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Forecasting gross value-added at the regional level: Are sectoral disaggregated predictions superior to direct ones?

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Abstract

In this paper, we ask whether it is possible to forecast gross value-added (GVA) and its sectoral subcomponents at the regional level. With an autoregressive distributed lag model we forecast total and sectoral GVA for one German state (Saxony) with more than 300 indicators from different regional levels (international, national and regional) and additionally make usage of different forecast pooling strategies and factor models. Our results show that we are able to increase forecast accuracy of GVA for every sector and for all forecast horizons (one up to four quarters) compared to an autoregressive process. Finally, we show that sectoral forecasts contain more information in the short term (one quarter), whereas direct forecasts of total GVA are preferable in the medium (two and three quarters) and long term (four quarters).

JEL Code: C32, C52, C53, E37, R11.
Keywords: Regional forecasting, gross value-added, forecast combination, disaggregated forecasts, factor models.

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1 Motivation

Fiscal policy at the sub-national level is one of the major fields in the decision-making of policy makers. For this purpose, reliable forecasts of economic aggregates (as gross domestic product or gross value-added) are necessary. At the regional level, e.g. states or counties, data limitations or a low publication frequency of national accounts make it difficult to predict macroeconomic aggregates and may cause higher forecast errors in comparison to countries' aggregate, e.g., total German gross domestic product (GDP). Additionally, the forecast for Germany may not be a good approximation for the economic development of sub-national (e.g., states) aggregates. The reasons are a high heterogeneity in regional economic structures and different regional business cycles. Whenever a shock such as the economic crisis of 2009 hits the German economy, not all states have to develop in the same way. Therefore, separate regional forecasts are needed. Only few attempts have been made to forecast regional macroeconomic aggregates. Bandholz and Funke (2003) predict turning points for the German state[1] Hamburg with a newly constructed leading indicator. The study by Dreger and Kholodilin (2007) employs a set of regional indicators to forecast the GDP of the German state Berlin. Kholodilin *et al.* (2008) predict the GDP of all German states simultaneously and account for spatial effects in a dynamic panel setup. Lehmann and Wohlrabe (2013) showed for three different regional units in Germany (the Free State of Saxony, Baden-Württemberg and Eastern Germany[2]) that forecast accuracy of GDP at the regional level can be improved with a huge data set of indicators in comparison to simple benchmark models. At the level of Canadian provinces, Kopoin *et al.* (2013) evaluate the forecasting information of national (Canadian) and international indicators.

While these few prominent studies focus on the prediction of aggregated GDP directly, this paper mainly concentrates, from a regional point of view, on the question whether it is possible to forecast gross value-added (GVA) for different sectors (e.g., manufacturing, construction etc.). Regional policy makers or credit institutes (e.g., for granting of credits) are not only interested in the development of the economy as a whole but also in forecasts for different branches of the economy. From a practioners point of view it is necessary to know which branches or aggregates drive future economic development, so that predicting sub-components makes the state of the economy more tangible. Another important point for disaggregated forecasts is the consideration that several indicators (e.g., the EU business survey for manufacturing) might be linked to sub-components even stronger than to macroeconomic aggregates (e.g., GDP or GVA). As mentioned above, missing quarterly sectoral GVA data at the regional level makes such an analysis impossible until yet. But our data set enables us to carry out such an analysis, since we have quarterly GVA data for one

[1]Germany consists of 16 different states which are categorized as NUTS 1 for statistics of the European Union. In comparison, Germany is classified as NUTS 0.

[2]Eastern Germany is the aggregation of five German states: Brandenburg, Mecklenburg-West Pomerania, the Free State of Saxony, Saxony-Anhalt and the Free State of Thuringia.

German state (Free State of Saxony). To the best of our knowledge, this is the only German state where quarterly GVA data for different sectors is available.

Additionally, this paper evaluates whether it is preferable to forecast an aggregate directly (total GVA) or to sum up its weighted sub-components (sectoral GVA) at the regional level. Recently, this question has become more and more attractive in the field of economic forecasting. For the euro area as a whole, forecast performance for different sub-somponents of GDP is analyzed by Hahn and Skudelny (2008) and Angelini *et al.* (2010). Barhoumi *et al.* (2008) and Barhoumi *et al.* (2012) study this question for the French economy. A comparison of forecast accuracy of sub-components for Germany is made by Cors and Kuzin (2003) or Drechsel and Scheufele (2012a). Whereas the first article only studies the production side (aggregation of sectoral GVA) of the German economy, the second study compares the different outcomes from the demand (e.g., private consumption, exports etc.) and supply side with those of aggregated German GDP. For the German labor market, the study by Weber and Zika (2013) finds an improvement of forecast accuracy for employment figures through disaggregation in the short term. They show that the aggregation of forecasts for different branches of the economy can produce lower forecast errors in comparison to the prediction of total employment. Studies for regional units, which evaluate aggregate vs. disaggregate forecasts, are missing.

The contribution of our paper is manifold. First, we evaluate forecast accuracy of different indicators for several branches of the economy and forecast horizons (one up to four quarters). With such an analysis we make the state of the economy more tangible and can clearly specify what drives future economic development. Second, we apply different pooling strategies. It is well-known in the forecasting literature that the combination of forecasting output from competing models can yield lower forecast errors (Stock and Watson, 2006; Timmermann, 2006). In numerous studies, the advantage of pooling was confirmed (Drechsel and Maurin, 2011; Eickmeier and Ziegler, 2008). For three German regions, Lehmann and Wohlrabe (2013) find that pooling significantly produces lower forecast errors for regional GDP than an univariate benchmark model. Sub-national studies for different sectors are still missing. Third, this paper applies factor models as well. Several studies at the national level find significant improvements of forcast accuracy for this class of models (see, e.g., Schumacher (2007) and Schumacher (2010) for Germany, or Stock and Watson (2002) for the US). At the regional level, Lehmann and Wohlrabe (2013) find that factor models show no significant improvement for regional GDP in Germany. Finally, we compare direct and disaggregated forecasts of gross value-added with each other and ask whether there is an information gain when predicting sub-components. To carry out this analysis we use a huge data set at the regional level which incorporates quarterly national accounts for one German state (Saxony). We have information on GDP, total GVA and its sub-components as well as 317 different indicators from the international (USA, EU etc.), national (Germany) and regional level (Saxony). This study is closely linked to the one by Lehmann and Wohlrabe (2013), since it focuses on regional forecasts. But in contrast, it studies sectoral forecasts instead of GDP and additionally asks whether it is preferable to predict sub-components instead of aggregates.

The paper is organized as follows. Section 2 describes our data, the aggregation method and our empirical setup. The results are discussed in Section 3. The last Section concludes our main findings.

2 Data and Methodology

2.1 Data

In general there are no temporal disaggregated macroeconomic data (e.g., quarterly GVA) available at the regional level in Germany. It is possible to use annual information, but this causes the problem of an insufficient number of observations. To the best of our knowledge, only Nierhaus (2007) provides quarterly data on GVA for different sectors. He calculates national accounts for the German state Saxony, which we use in this paper.[3] Gross value-added in real terms is available for six aggregated sectors: (i) agriculture, hunting and forestry; fishing (AGFI), (ii) mining and quarrying; manufacturing; electricity, gas and water supply (industry; IND), (iii) construction (CON), (iv) wholesale and retail trade; hotels and restaurants; transport (basic services; BS), (v) financial intermediation; real estate, renting and business activities (advanced services; AS), (vi) public administration; education; health and social work; private households (public and private services; PPS).[4] The methodological background for the computation of the quarterly data is the temporal disaggregation method developed by Chow and Lin (1971). They suggest to employ a stable regression relationship between annual aggregates and indicators with a higher frequency (e.g., quarterly data). With this relationship it is possible to convert annual into quarterly data. But these quarterly information have to fulfill two restrictions: horizontal and temporal aggregation (see Nierhaus, 2007). This means that first the sum of GVA of all sectors has to result in total GVA for every time period. Second, the average index of four quarterly data points has to equal the annual aggregate. We exclude those indicators from our analysis which were used for temporal disaggregation by Nierhaus (2007). These indicators have to perform well for predicting sector-specific GVA. To avoid such a bias, the following indicators for Saxony are not part of the analysis: turnovers in the manufacturing and construction sector, turnovers for retail sale and wholesale trade. All GVA target variables are available in real terms and for the period 1996:01 to 2010:04. The data are seasonally adjusted with Census X-12-ARIMA and we transformed these into quarter-on-quarter (qoq) growth rates.

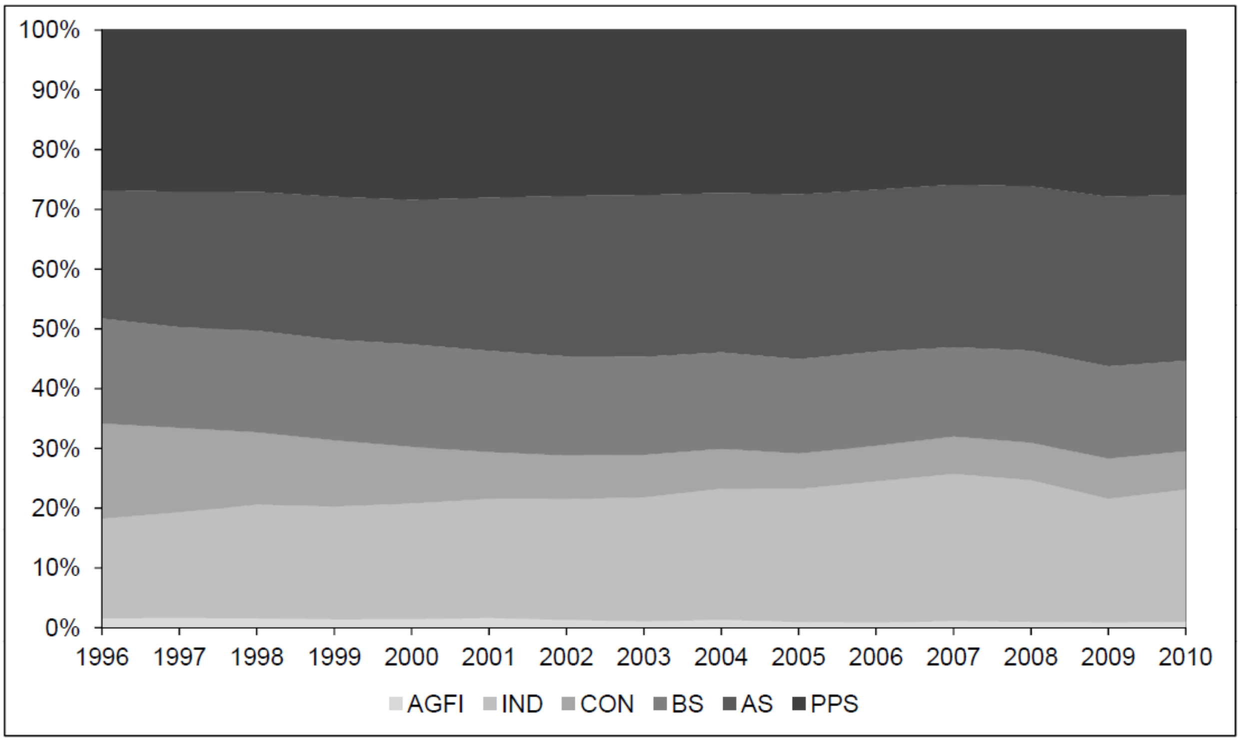
To get an impression on how the different sectors contribute to total GVA, Figure 1 shows

[3] The data are available upon request from dresden@ifo.de.

[4] These six sectors describe the whole economy so that the sum of these sectors equals total GVA.

the sectoral structure of Saxony. The figure shows the share of our six sectors of interest in total GVA for the years 1996 to 2010. For all years, the share of agriculture, hunting and forestry; fishing (AGFI) is negligible (in 2010: 1%). The share of the industry (IND) is approximately 22% of total GVA in 2010 (for comparison: Germany 24%). The construction sector (CON) is traditionally large in Eastern German states, because a building boom was initiated in Eastern Germany after reunification. Since the mid 1990s, the construction sector lost its importance for total GVA in Eastern Germany. The share of construction in Saxon GVA was 6.5% in 2010 (Germany: 4%). Basic services (BS) have a share in total GVA of about 15% (Germany: 17%). With a share of 28% of total GVA the sector advanced services (AS) is of a smaller magnitude than in Germany (30.5%). The public sector (PPS) is traditionally overrepresented in Eastern Germany (in comparison to Germany); the share of PPS in total GVA is 27.5% in Saxony and 24% in Germany.

Figure 1: Sectoral shares in total GVA for Saxony

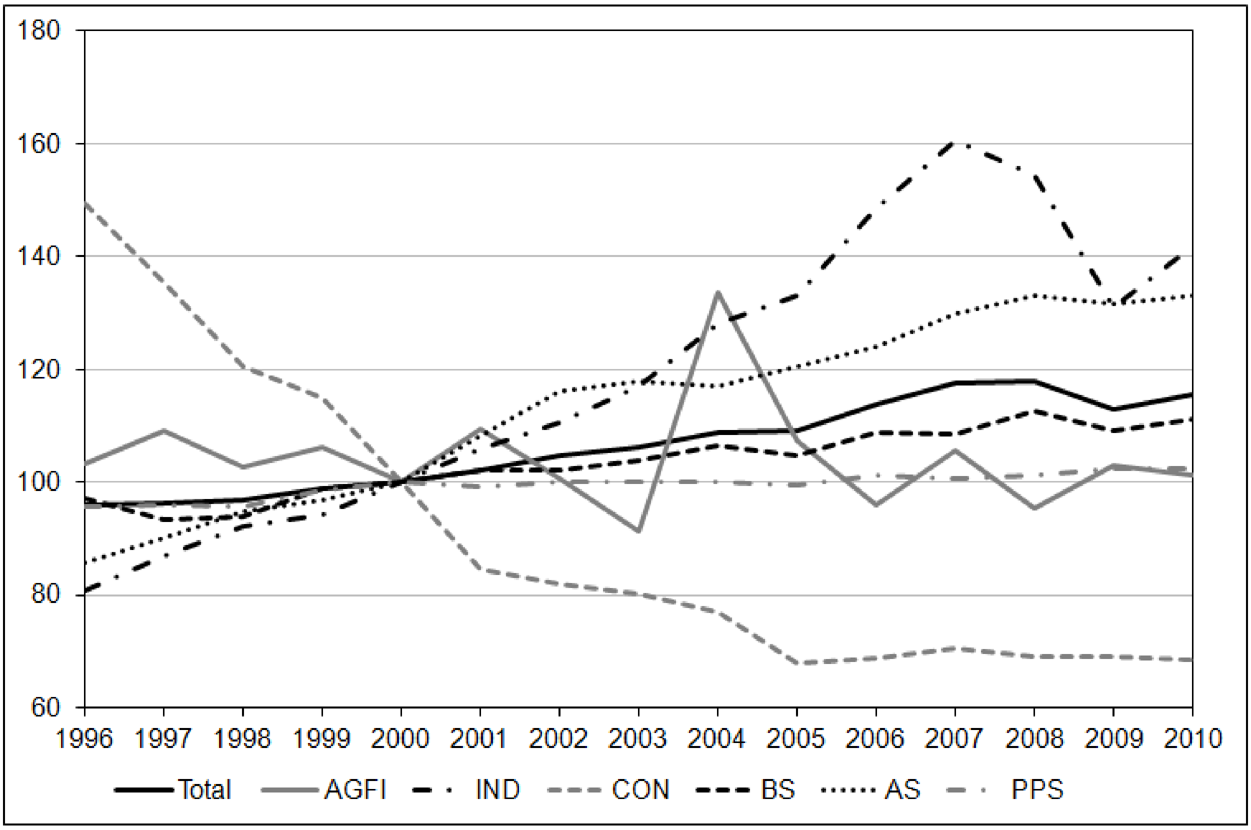


Acronyms: AGFI...agriculture, hunting and forestry; fishing, IND...industry, CON...construction, BS...basic services, AS...advanced services, PPS...public and private services.

Source: Working Group Regional Accounts VGRdL (2011), author´s illustration.

After presenting the sectoral weights, Figure 2 shows the development of total and sectoral real GVA for our period of investigation. The most volatile figure is the one for the primary sector (AGFI). Mainly special events drive real GVA growth in this branch of the economy. The public sector (PPS) is the branch with no dynamics at all. Real GVA in the Saxon construction sector (CON) shrinks throughout until the year 2005. Afterwards this branch stabilizes and shows a lateral movement in growth rates. The two service sectors (basic services – BS and advanced services – AS) experienced a positive trend in real GVA growth for the whole period under observation. After the base year 2000, GVA in advanced services grew faster than value-added for basic services. The industrial sector (IND) is the branch with the highest growth rates in real GVA. The reason is the high export dependence of this sector. But on the opposite, the export dependence makes the industrial sector prone to negative external shocks such as the one observed in the global downturn years 2008 and 2009. Total Saxon GVA is mainly driven by the development in the industrial sector.

Figure 2: Total and sectoral real GVA for the Saxon economy



Acronyms: AGFI...agriculture, hunting and forestry; fishing, IND...industry, CON...construction, BS...basic services, AS...advanced services, PPS...public and private services.
Note: The axis of ordinates shows the real Chain Index with the year 2000 = 100.

Source: Working Group Regional Accounts VGRdL (2011), author´s illustration.

To forecast sectoral GVA we use a huge data set containing **317** indicators which are grouped into seven categories: macroeconomic (95), finance (31), prices (12), wages (4), surveys (74), international (32) and regional (69). The category macroeconomic indicators contain German industrial production, new orders in manufacturing or foreign trade figures. Financial variables are, e.g., interest rates, exchange rates and government bond yields. Furthermore, we have price indices for exports and imports as well as consumer and producer prices. Qualitative measures are collected from different survey results. We have information from consumer surveys (Society for Consumer Research – GfK), business surveys (Ifo institute or European Commission) or expert surveys (Centre for European Economic Research

– ZEW). Additionally, we add composite leading indicators for Germany obtained from the OECD and the Early Bird of the Commerzbank to this group. International indicators cover a wide range of information from large economies (US, China, France or Italy). Finally, we have qualitative (Ifo business survey results) and quantitative indicators (e.g., new orders or prices) from the regional level. As mentioned before, we excluded regional indicators which were used for temporal disaggregation of sector-specific GVA.

Most of the indicators are available on a monthly basis. To obtain quarterly information, we first seasonally adjust the data with Census X-12-ARIMA and then calculate a three-month average. Stationarity is warranted through different transformations (either first differences or qoq growth rates), whenever the levels are non-stationary. For a complete description of our data set as well as the applied transformation for each indicator, see Table 4 in the Appendix.

2.2 Aggregation of GVA sub-components

National accounts provide two concepts for disaggregating GDP: (i) demand side and (ii) supply side. The first concept uses the identity that total production in an economy equals total domestic demand. So GDP is the sum of private and public consumption, investments, inventories and net exports (exports minus imports). The second concept looks at the production side of an economy. GDP is therefore the sum of gross value-added of every industry plus taxes minus subsidies. In our data set no information about quarterly demand side variables are available. Therefore we can only look at the supply side. Since the aggregate taxes minus subsidies is difficult to forecast, we concentrate on GVA rather than GDP. The qoq growth rate of total Saxon GVA (y_t^{GVA}) could be expressed, for all $t = 1, 2, ..., T$, as:

$$y_t^{GVA} = \omega_t^{AGFI} y_t^{AGFI} + \omega_t^{IND} y_t^{IND} + \omega_t^{CON} y_t^{CON} + \omega_t^{BS} y_t^{BS} + \omega_t^{AS} y_t^{AS} + \omega_t^{PPS} y_t^{PPS}. \qquad (1)$$

Therefore, the total growth rate is a sectoral-weighted sum of the single sectoral GVA growth rates (ω_t^s). As we can see from Equation (1), the weights are time-varying and we assume that the sum of all weights has to equal unity. Whenever a forecast is made, the weights are ex ante unknown to the forecaster. In our forecasting exercise we assume that the weights in every forecasting period are constant with respect to the last known value.[5] For example, imagine we want to make a forecast for the first quarter of 2010 and information are available until 2009:04. Then we use the last known shares in total GVA from 2009:04 and apply them to aggregate sector-specific GVA forecasts in 2010:01.

[5]Drechsel and Scheufele (2012a) state that in most cases simple averages are used for weighting sub-components. In contrast, they use a moving average over the last four quarters to obtain their estimated weights. Since the shares in our sample are relatively persistent, the results should not differ dramatically by applying another approach.

2.3 Forecast procedure

We employ the autoregressive distributed lag (ADL) model,

$$y_{t+h}^{s,k} = \alpha + \sum_{i=1}^{p} \beta_i y_{t+1-i}^{s} + \sum_{j=1}^{q} \gamma_j x_{t+1-j}^{k} + \varepsilon_t^{s,k} \,, \tag{2}$$

to generate our forecasts, where $y_{t+h}^{s,k}$ denotes the h-step-ahead forecast of real GVA for sector s (including total) and x_t^k stands for one of our 317 exogeneous indicator. The variable k relates to one of these indicators. We allow a maximum of 4 lags, both for the endogeneous and exogeneous variables. The Schwarz Information Criteria (BIC) is used for the optimal lag length selection of p and q. Equation (2) is estimated in a recursive way and we use the data from 1996:01 to 2002:04 ($T_E = 28$) as the initial estimation period. Afterwards we enlarge the estimation period successively by one quarter, at which the model of Equation (2) is respecified. So we obtain for every forecast horizon h the first forecast for our target variables at 2003:01 and the last at 2010:04. h is defined as $\{1, 2, 3, 4\}$.[6] We apply a direct-step forecasting approach, so that for every forecasting horizon and indicator $T_F = 32$ forecasts are generated. This is obtained by adjusting Equation (2) in such a way that for each forecast horizon the first forecast is calculated for the first quarter 2003. Our benchmark model is a standard AR(p) process. We define $y_{t+h}^{agg,k}$ if the forecast is generated directly for total GVA and $y_{t+h}^{dis,k}$ for a weighted forecast from all sub-components.

2.4 Pooling

The outcome of a pooling-based forecast $\widehat{y}_{t+h}^{s,Pool}$ for sector s is the product of single indicator forecasts $\widehat{y}_{t+h}^{s,k}$ and a specific weighting scheme $w_{t+h}^{s,k}$:

$$\widehat{y}_{t+h}^{s,Pool} = \sum_{k=1}^{K} w_{t+h}^{s,k} \widehat{y}_{t+h}^{s,k} \quad \text{with} \sum_{k=1}^{K} w_{t+h}^{s,k} = 1 \,. \tag{3}$$

As Equation (3) shows, the weights are indexed by time and thus varying with every estimation of our model. K stands for the number of models which are used for pooling.

We apply six different weighting schemes. A very simple scheme are (i) equal weights: $w_{t+h}^{s,k} = 1/K$. For this weighting scheme, the sheer number of models is important. To control for outliers, we additionally apply (ii) a median approach. We follow the studies by Drechsel and Scheufele (2012b) or Lehmann and Wohlrabe (2013) and calculate weights from two additional categories: in-sample and out-of-sample measures. Whereas weights from in-sample measures use criteria on how good the model fits the data, weights from out-of-sample measures are based on past forecast errors.

[6] In this paper we denote one quarter ($h = 1$) as short term, two and three quarters ($h = 2, 3$) as medium term and four quarters ($h = 4$) as long term. These definitions are in line with the forecasting literature and do not reflect time horizons in macroeconomic theory.

We apply two in-sample measures: (iii) BIC and (iv) R^2. The weights from these two measures are time-varying and have the following form:

$$w_{t+h}^{k,BIC} = \frac{\exp\left(-0.5 \cdot \Delta_k^{BIC}\right)}{\sum_{k=1}^{K} \exp\left(-0.5 \cdot \Delta_k^{BIC}\right)} \tag{4}$$

$$w_{t+h}^{k,R^2} = \frac{\exp\left(-0.5 \cdot \Delta_k^{R^2}\right)}{\sum_{k=1}^{K} \exp\left(-0.5 \cdot \Delta_k^{R^2}\right)}\ , \tag{5}$$

with $\Delta_k^{BIC} = BIC_{t+h}^k - BIC_{t+h,min}$ and $\Delta_k^{R^2} = R^2_{t+h,max} - R^2_{t+h,k}$. The difference between the two schemes is straightforward. Whereas a model with a lower BIC gets a higher weight, the importance of a single model for pooling increases with higher values of R^2.

For the application of out-of-sample weights, it is appropriate to use past forecast errors from different models. First, we apply a so called (v) trimmed mean. Indicators with a bad performance are filtered and not considered for pooling. In accordance with the existing literature, we include the best 25%, 50% or 75% performing indicators. The outcome of all remaining indicators are combined with equal weights. Second, (vi) discounted mean squared forecast errors (MSFE) are applied to calculate the weights, which have the following form:

$$w_{t+h}^k = \frac{\lambda_{t+h,k}^{-1}}{\sum_{k=1}^{K} \lambda_{t+h,k}^{-1}}\ . \tag{6}$$

$\lambda_{t+h,k} = \sum_{n=1}^{T_F} \delta^{t-h-n} \left(FE_{t+h,n}^k\right)^2$ represents the sum of discounted[7] (δ) forecast errors of the single–indicator model k. As the weighting scheme indicates, more recent forecast errors get a higher weight than older ones. Since the weighting schemes depend on the number of indicators considered for pooling, we either combine forecasts from all indicators of the full sample (FS) or only use indicators for Saxony (S).

2.5 Factor models

Next to pooling, another way of dealing with large cross–sectional data sets are static and dynamic factor models. The literature finds that these class of models perform very well (see, e.g., Stock and Watson, 2002; Marcellino *et al.*, 2003; Forni *et al.*, 2005). The idea behind factor models is straightforward. Because standard econometric approaches cannot handle all available indicators (in our paper: 317) at the same time, factor models summarize the information of many time series in few common factors. With this approach we are able to specifiy a parsimonious model, thereby reducing the biases in parameter estimates (see Giannone *et al.*, 2008). In this paper, we apply three different methodologies to extract the common factors from our indicator series. For details, see the cited literature for each

[7] The literature has not found a consesus yet about the level of the discount rate. We apply different values ($\delta \in \{0, 0.1, 0.2, ..., 1\}$) and find similar results. Because of this and to avoid long tables, we only report the outcome for a discount rate equal to **0.1**.

approach. First, the standard principal components (PC) method is the easiest way to extract the common factors. In line with Giannone *et al.* (2008), the second approach is the two–step estimator proposed by Doz *et al.* (2011). This procedure uses principal components and Kalman filtering (PCKF) and shows efficiency improvements over standard PC methods. Third, we extract the common factors via quasi-maximum likelihood estimation (see Doz *et al.*, 2012).[8]

For all three approaches we have to decide how many factors to extract from the series. We decide to choose a maximum of three common factors. The factors can either be estimated from the full sample of indicators (FS) of only extracting them from the regional series (S). Another decision has to be made according to the frequency. We extract the factors from the quarterly series (Q). To generate the forecasts for real GVA, we have another two possibilities. First, we can directly put the factors in the ADL model from equation (2), instead of using single indicators (ADL). Second, as proposed by Giannone *et al.* (2008), we can run a simple OLS estimation, where real GVA is explained by a constant and the extracted factors available at different points in time (OLS). Whereas the first method considers lagged values of the dependent variable and the factors, the OLS approach does not. In the end, this gives us 36 factor models for every Saxon branch of the economy as well as total GVA.[9]

2.6 Forecast accuracy

To evaluate how good different indicators perform, we calculate forecast errors in a first step. The forecast of model k in sector s for the forecasting horizon h is denoted as $\widehat{y}^{s,k}_{t+h}$. The resulting forecast error is defined as $FE^{s,k}_{t+h} = y^{s,k}_{t+h} - \widehat{y}^{s,k}_{t+h}$ and $FE^{s,AR}_{t+h}$ is the forecast error from the autoregressive benchmark model. In a second step, we choose the root mean squared forecast error (RMSFE),

$$RMSFE^{s,k}_{h} = \sqrt{\frac{1}{T_F}\sum_{n=1}^{T_F}\left(FE^{s,k}_{t+h,n}\right)^2}\,, \tag{7}$$

as the loss function to get an assessment of the overall forecast accuracy of model k. The RMSFE for the AR(p) process is $RMSFE^{s,AR}_{h}$. With the ratio

$$rRMSFE^{s,k}_{h} = \frac{RMSFE^{s,k}_{h}}{RMSFE^{s,AR}_{h}}\,, \tag{8}$$

[8] We do not take into account the ragged edge problem (see Wallis, 1986) and extract the factors from the information set up to $t-1$.

[9] To understand the notation in the results section, the following example should make it clear. Imagine a factor model is abbreviated with QML1QSOLS. Then one common factor (1) is extracted via quasi-maximum likelihood (QML) from quarterly data (Q) and the forecast is generated from an OLS estimation. In this case, the factors are obtained from the set of Saxon indicators (S).

we can assess the performance of a single indicator forecast in comparison to the autoregressive benchmark. If the $rRMSFE$ is smaller than one, the specific indicator is performing better than the AR(p) process and therefore preferable.

To test whether an indicator-based forecast produces lower forecast errors in comparison to the benchmark model, we apply the Diebold-Mariano test (Diebold and Mariano, 1995). Since we have a relatively small sample, we use the correction proposed by Harvey *et al.* (1997). The null hypothesis states the equality of expected forecast errors for two competing models. Or in other words, the expected difference between the forecast errors is zero,

$$H_0 : E\left[FE_{t+h}^{s,k} - FE_{t+h}^{s,AR}\right] = E\left[d_{t+h}^{s,k}\right] = 0\,. \tag{9}$$

Whenever the null can be rejected, the specific indicator or combination strategy produces smaller forecast errors than the autoregressive benchmark.

To conclude whether the direct or disaggregated approach performs better, we only consider the forecasts from our several pooling strategies. Therefore, we compare the forecast errors from the predictions $\widehat{y}_{t+h}^{agg,Pool}$ and $\widehat{y}_{t+h}^{dis,Pool}$ with each other. The modified Diebold-Mariano test (MDM) is used again for testing the difference in the produced forecast errors. Additionally, we apply a forecast encompasing test to check whether disaggregated forecasts have more information content than the direct approach. Granger and Newbold (1973) showed that it is insufficient to compare only the forecast mean squared errors of competing forecasts. They suggest that a preferred forecast is not necessary optimal and does not have to comprise all available information. This is known as “conditional efficiency”. If a competing forecast has no more additional information, then the preferred forecast encompasses the competitor (see Clements and Hendry, 1993). In our setup we examine whether the disaggregated approach ($\widehat{y}_{t+h}^{dis,Pool}$) contains more information than the direct one ($\widehat{y}_{t+h}^{agg,Pool}$). For this purpose we use a modified version proposed by Harvey *et al.* (1998). A regression of the form

$$FE_{t+h}^{agg,Pool} = \lambda\left(FE_{t+h}^{agg,Pool} - FE_{t+h}^{dis,Pool}\right) + \nu_t \tag{10}$$

is performed, using corrected standard errors with the method of Newey and West (1987). The null hypothesis of this test is than $H_0 : \lambda = 0$. If the tests rejects the null, the disaggregated approach contains more information beyond the direct one.

3 Results

We start by presenting our disaggregated results for the six different sectors: (i) agriculture, forestry and hunting; fishing, (ii) industry, (iii) construction, (iv) basic services, (v) advanced services as well as (vi) public and private services. Then we show the results for the aggregated forecasts of total GVA. Finally, we discuss the findings of the comparison between direct and disaggregated predictions.

3.1 Disaggregated Results

Table 1 shows the forecasting results for our six considered sectors. In order to show the results for our disaggregated forecasts in a compact way, we present the different sectors in one single table. We divide this table into sectoral parts, separated by a double line, an empty row as well as new denotations of the target variables. We start with the results of agriculture, forestry and hunting; fishing. The last sector are public and private services. For every sector and forecast horizon (h) the Table presents the top 5 indicators, pooling strategies or factor models. The $rRMSFE$ are presented in the column Ratio. Whenever the average forecasting errors differ significantly, asteriks are shown in the column MDM. To make the tables easier to read, we add acronyms by the indicator categories, pooling strategies and factor models. Indicators from the national (German) level are denoted with (N). The acronyms for international and regional indicators are (I) and (R) respectively. The combination strategies are indicated by (C) and factor models with (F). Acronyms for the indicators can be found in Table 4 in the Appendix.

Table 1: Disaggregated Results

Target variable – qoq growth rate GVA: *Agriculture and Fishing*							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
Trimmed 25 (FS)	(C)	0.986		MSFE weighted (FS)	(C)	0.953	
TRWIT	(N)	0.991		IFOBCBUENSAX	(R)	0.967	
Trimmed 25 (S)	(C)	0.991		Trimmed 25 (FS)	(C)	0.971	*
ICTOSAX	(R)	0.993	*	Trimmed 25 (S)	(C)	0.971	*
QML1QFSOLS	(F)	0.995		IFOBSBUENSAX	(R)	0.985	
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
WDAYS	(N)	0.988		IFOBECONDUR	(N)	0.958	
IFOBCCONSAX	(R)	0.988		Trimmed 25 (FS)	(C)	0.972	
IFOBCBUENSAX	(R)	0.993		MSFE weighted (FS)	(C)	0.980	
IFOBSBUENSAX	(R)	0.994		Trimmed 25 (S)	(C)	0.981	
MSFE weighted (FS)	(C)	0.994		DREUROREPO	(N)	0.985	

Target variable – qoq growth rate GVA: *Industry*							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
Trimmed 25 (FS)	(C)	0.849	**	WTCHEM	(N)	0.843	*
IFOBCMANSAX	(R)	0.849		Trimmed 25 (FS)	(C)	0.882	**
IFOBCCAPSAX	(R)	0.851		MSFE weighted (FS)	(C)	0.885	***
MSFE weighted (FS)	(C)	0.859	***	NOMANINTD	(N)	0.889	*
Trimmed 25 (S)	(C)	0.863	**	Trimmed 25 (S)	(C)	0.890	**
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
Trimmed 25 (FS)	(C)	0.909	**	IFOEOARS	(N)	0.888	*
IPCONG	(N)	0.909		MSFE weighted (FS)	(C)	0.912	***
Trimmed 25 (S)	(C)	0.919	**	Trimmed 25 (FS)	(C)	0.919	*
IFOBERS	(N)	0.921	*	IFOBERS	(N)	0.924	
MSFE weighted (FS)	(C)	0.922	***	YLFBOML	(N)	0.929	

Target variable – qoq growth rate GVA: *Construction*							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
IFOEMPECONSAX	(R)	0.844		MSFE weighted (FS)	(C)	0.909	***
IFOBSCONSAX	(R)	0.867	*	Trimmed 25 (FS)	(C)	0.921	***
IFOBCBUENSAX	(R)	0.888		IFOBEFBTSAX	(R)	0.927	**
MSFE weighted (FS)	(C)	0.889	***	Trimmed 25 (S)	(C)	0.931	***
Trimmed 25 (FS)	(C)	0.900	***	HCTOSAX	(R)	0.958	*
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.892	***	MSFE weighted (FS)	(C)	0.931	**
Trimmed 25 (FS)	(C)	0.927	***	Trimmed 25 (FS)	(C)	0.943	*
Trimmed 25 (S)	(C)	0.943	***	WTSLGF	(N)	0.949	

Table 1: Disaggregated Results – continued

TOCON	(N)	0.946		Trimmed 25 (S)	(C)	0.963	
GFKSE	(N)	0.948	**	TOCONNDURF	(N)	0.968	

Target variable – qoq growth rate GVA: *Basic Services*							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
NOVEMF	(N)	0.947		MSFE weighted (FS)	(C)	0.880	**
MSFE weighted (FS)	(C)	0.949	***	Trimmed 25 (FS)	(C)	0.931	***
Trimmed 25 (FS)	(C)	0.950	***	Trimmed 25 (S)	(C)	0.939	***
PCNOSAX	(R)	0.958	**	EUBSSSCI	(N)	0.939	
Trimmed 25 (S)	(C)	0.965	***	IFOBCMOTSAX	(R)	0.946	
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.922	***	PCWHSAX	(R)	0.891	*
Trimmed 25 (FS)	(C)	0.824	**	MSFE weighted (FS)	(C)	0.918	***
EUBSSSCI	(N)	0.932		Trimmed 25 (FS)	(C)	0.945	***
Trimmed 25 (S)	(C)	0.936	**	Trimmed 25 (S)	(C)	0.951	***
IFOOOHCONSAX	(R)	0.954		NOMANCAPD	(N)	0.954	

Target variable – qoq growth rate GVA: *Advanced Services*							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.659	**	MSFE weighted (FS)	(C)	0.608	**
Trimmed 25 (FS)	(C)	0.826	**	Trimmed 25 (FS)	(C)	0.848	*
Trimmed 25 (S)	(C)	0.841	***	Trimmed 25 (S)	(C)	0.868	*
DJESI50	(I)	0.856	*	Trimmed 50 (FS)	(C)	0.902	*
SPUSSPI	(I)	0.884	*	SPUSSPI	(I)	0.916	
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.649	**	MSFE weighted (FS)	(C)	0.595	**
GFKSE	(N)	0.849		Trimmed 25 (FS)	(C)	0.839	
Trimmed 25 (FS)	(C)	0.863		Trimmed 25 (S)	(C)	0.857	
GFKIE	(N)	0.866		IFOBCCONNDURSAX	(R)	0.882	
Trimmed 25 (S)	(C)	0.890		ZEWES	(N)	0.885	**

Target variable – qoq growth rate GVA: *Public and Private Services*							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
QML1QFSOLS	(F)	0.943		MSFE weighted (FS)	(C)	0.796	***
Trimmed 25 (FS)	(C)	0.958	***	Trimmed 25 (FS)	(C)	0.880	***
MSFE weighted (FS)	(C)	0.960		Trimmed 25 (S)	(C)	0.890	***
Trimmed 25 (S)	(C)	0.963	***	Trimmed 50 (FS)	(C)	0.931	***
M2MS	(N)	0.982		QML1QSOLS	(F)	0.932	
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.672	***	MSFE weighted (FS)	(C)	0.657	***
Trimmed 25 (FS)	(C)	0.835	***	Trimmed 25 (FS)	(C)	0.852	***
Trimmed 25 (S)	(C)	0.839	***	Trimmed 25 (S)	(C)	0.856	***
Trimmed 50 (S)	(C)	0.890	**	MSFE weighted (S)	(C)	0.896	**
Trimmed 50 (FS)	(C)	0.898	**	Trimmed 50 (FS)	(C)	0.898	**

Note: This Table reports the best five indicators due to the smallest rRMSFE for single indicator forecasts, pooling or factor model for every sector. MDM presents significance due to the modified Diebold-Mariano test.
Acronyms: FS: Full Sample, S: Saxony and GVA: gross value-added.
(I) international, (N) national, (R) regional indicators, (C) combinations and (F) factor models.
Table 4 in the Appendix shows the acronyms used for the different indicators.
***, ** and * indicates significant smaller forecast errors at the 1%, 5% and 10% level.

In general it is possbile to forecast GVA more accurately than the autoregressive benchmark model. This holds for every forecasting horizon. But there exists a large heterogeneity in forecast accuracy between the sectors. Indicators from each level (international, national and regional) are able to predict GVA and beat the AR process. In the short term ($h = 1$), forecasting signals predominantly come from regional (R) or international (I) indicators, whereas national (N) ones are important for medium and long term predictions ($h = 2, 3, 4$). As we can conclude from the table, the forecasting performance of different pooling strategies is overwhelming. For all sectors and forecasting horizons, at least one forecast outcome from pooling is within the top five. Mainly MSFE weights or trimming (25% or 50% either with the full sample or only with regional indicators) produce significantly lower forecast errors than the autoregressive benchmark. In comparison to that, factor models are not that competitive at all. This class of models produce lower forecast errors than the benchmark only in some cases, but are not able, with some exceptions, to reach a higher forecast accuracy than indicator models or pooling. Since the results differ notably between the sectors, we will briefly discuss sectoral results subsequently.[10]

The improvement of forecast accuracy with indicator–based models for the Saxon *Agricultural Sector* is only minor, as the results for GVA in Table 1 suggest. We have ratios which are smaller than one, but in most cases, forecast errors from indicators or pooling are not statistically different from those of the autoregressive benchmark. International indicators are negligible for this sector. The best performance have regional indicators or pooling strategies (MSFE weighted or trimming). Factor models are only in the top five in the short forecasting horizon. However, the improvement against the AR process is not very large.

For the Saxon *Industrial Sector*, regional and national indicators are important for predicting GVA one quarter ahead (see $h = 1$ for GVA industry). International indicators are able to forecast industrial GVA in Saxony for all forecasting horizons better than the benchmark. Considering pooling, we see that trimming (25%) and MSFE weights significantly beat the AR(p) process. Factor models show no significant improvement at all. A closer look reveals that regional surveys send important forecast signals. For example, the Ifo business climate for Saxon manufacturing (IFOBCMANSAX, $rRMSFE = 0.849$) or the Ifo business expectations in the manufacturing sector (IFOBEMANSAX, $rRMSFE = 0.889$) produce lower forecast errors in comparison to the autoregressive benchmark. Macroeconomic variables such as domestic new orders of German intermediate good producers (NOMANINTD) or domestic turnovers from German capital goods producers significantly improve forecast accuracy. These results are straightforward, because the Saxon manufacturing sector is dominated by intermediate and capital goods producers. Approximately 82% of total turnovers in 2011 were achieved by firms from these two main groups, whereas capital goods producer have the highest share (45%) of total turnovers.

The third part of Table 1 shows the results for the Saxon *Construction Sector*. As for the agricultural sector, regional and national indicators yield the best forecasting results for construction. In the short term, regional indicators produce the lowest forecast errors. National indicators are more important for long term predictions. In contrast, international indicators are more or less negligible. This result is not surprising, because construction firms mainly operate on domestic markets. As we could see from the manufacturing sector, pooling (trimming 25% and MSFE weights) is also favorable to forecast GVA of the Saxon construction sector. In addition to these more general results, there are some specific indicators that have to be highlighted. Regional survey indicators such as the Ifo assessement of the

[10] Detailed results for all sectors are available upon request.

business situation for the Saxon construction sector (IFOBSCONSAX, $rRMSFE = 0.867$) or the Ifo business climate either for building engineering or civil engineering (IFOBCBUENSAX, IFOBCCIENSAX) have a higher forecast accuracy than the autoregressive benchmark model. Turnovers from housing construction in Saxony, with a share of approximately 9% of all regional turnovers, significantly produce lower forecast errors.

As for construction, regional and national indicators produce the lowest forecast errors in *Basic Services*; international indicators do not play a role. These results are in line with the focus of this sector, because basic services are predominantly traded in a certain region. Gross value-added in retail trade, tourism or restaurants is mainly generated by regional demand. Survey indicators obtained from regional or national business surveys (Ifo and European Commission) are again important for the prediction of GVA in this aggregated sector (see, e.g., IFOBCMOTSAX). These findings are also reflected in forecast accuracy of macroeconomic variables. For example, new orders from public (PCNOSAX) and industrial construction in Saxony or domestic new orders from German capital goods producers (NOMANCAPD) produce lower forecast errors in comparison to the autoregressive benchmark. Wholesale and retail trade as well as the transport sector react with a time lag to the development in manufacturing and construction. Since GVA in basic services is mainly generated by regional demand, consumer surveys should perform really well. The national indicators obtained by the GfK significantly beat the autoregressive benchmark.

Advanced Services comprise the sectors financial intermediation, real estate, renting and business activities. Therefore, credit institutes as well as research and development are part of this aggregate. The best forecasting results are observed for advanced services. Here, we are able to produce approximately 40% lower forecast errors than the autoregressive benchmark model. These results are obtained with MSFE weighted combination approaches. Another result is the importance of international and national indicators for this sector. This importance is described by two reasons. First, regional credit institutes and other services highly depend on decisions of the European Central Bank (ECB) or the Central Bank of Germany (DB). This is why, e.g., financial indicators such as money supply produce lower forecast errors than the AR(p) process. Second, regional indicators for different subsectors are missing. However, regional survey results from the Saxon manufacturing sector have a good forecasting performance. Since business activities such as tax or business consultancy depend on the development in the manufacturing sector with a specific time lag, indicators from the industrial sector have important forecasting signals. In addition, consumer surveys have good forecasting properties. Saving or income expectations of private households can significantly increase forecast accuracy. A reason for this result is the fact that regional credit institutes (e.g., saving banks) mostly lend money to private persons, inter alia (see German Council of Economic Experts, 2008).

Our last aggregate is *Public and Private Services*. This is the only sector in our sample, where factor models show the lowest forecast errors in comparison to the benchmark. But this result only holds for the short term. Forecast accuracy for this sector can also significantly be improved by pooling. Almost all weighting schemes, either for the full sample or only with Saxon indicators, produce lower forecast errors than the autoregressive benchmark model. There is no indicator (international, national or regional) which beats the forecasting outcome of pooling. Especially in the medium and long term ($h = 3, 4$), no indicator is in the top 10. The reason for this is that there are no indicators available for this sector. Only consumer surveys produce lower forecast errors than the autoregressive process for public and private services. This result ist straightforward because GVA of clubs, culture, sports and education are part of this sector and demand for these services is mainly generated by private households.

3.2 Aggregated results

Our results for total GVA are presented in Table 2. The structure of this table is the same as for our disaggregated results.

Table 2: Aggregated Results

Target variable – qoq growth rate GVA: *total*							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
IFOBEWTSAX	(R)	0.858	*	GOVBY	(N)	0.912	
MSFE weighted (FS)	(C)	0.869	***	YLFBOML	(N)	0.919	*
Trimmed 25 (FS)	(C)	0.886	**	IFOEOARS	(N)	0.922	
Trimmed 25 (S)	(C)	0.889	**	MSFE weighted (FS)	(C)	0.924	***
IFOBCITSAX	(R)	0.921		WTCHEM	(N)	0.933	
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.902	**	MSFE weighted (FS)	(C)	0.895	*
IFOEOARS	(N)	0.928		Trimmed 25 (FS)	(C)	0.943	***
Trimmed 25 (FS)	(C)	0.935	***	IFOBERSSAX	(R)	0.951	
Trimmed 25 (S)	(C)	0.949	**	ICTOSAX	(R)	0.956	
GOVBY	(N)	0.968		Trimmed 25 (S)	(C)	0.961	*

Note: This Table reports the best five indicators due to the smallest rRMSFE for single indicator forecasts, pooling or factor models for total GVA. MDM presents significance due to the modified Diebold-Mariano test.
Acronyms: FS: Full Sample, S: Saxony and GVA: gross value-added.
(I) international, (N) national, (R) regional indicators, (C) combinations and (F) factor models.
Table 4 in the Appendix shows the acronyms used for the different indicators.
***, ** and * indicates significant smaller forecast errors at the 1%, 5% and 10% level.

We are able to beat a simple autoregressive benchmark model for all forecast horizons. In the short and long term, especially regional indicators and pooling lead to a higher forecast accuracy than the AR(p) process. The medium term is dominated by national indicators and combination strategies. An important leading indicator[11], namely the Ifo business climate for industry and trade in Saxony (IFOBCITSAX), is within the top 5 in the short term forecasts. As for the disaggregated results, MSFE weights or trimming (25% and 50%), either for the full set of indicators or the Saxon sample, perform best within our considered pooling strategies. Our results are in line with the existing pooling literature. The improvement

[11]See Abberger and Wohlrabe (2006) for a recent survey for Germany. For an analysis for Saxony, see Lehmann *et al.* (2010).

of factor models is negligible. In the end, the aggregated results are perfectly in line with those of Lehmann and Wohlrabe (2013). The top 5 indicators shown in Table 2 can be found within the top 20 for Saxon GDP. Whereas the ranking and the ratios of the indcators or combination strategies differ between the two studies, all qualitative results (e.g., that factor models are not that competitive) remain the same. The differences between our results and those found by Lehmann and Wohlrabe (2013) are explained by the fact that we consider GVA instead of GDP.

3.3 Comparison of the two approaches

This section presents the comparison of our results from the aggregated and the disaggregated approach. Table 3 shows the $rRMSFE$ of $\widehat{y}_{t+h}^{dis,Pool}$ and $\widehat{y}_{t+h}^{agg,Pool}$ for our different forecast horizons and pooling techniques. The structure of Table 3 differs in several ways from the tables shown in the former sections. First, we present the ratios for all considered combination approaches either for the whole sample of indicators (FS) or for the Saxon indicators (S) only. This means that we combine either the forecast outcomes of all indicators with each other or use forecasts produced with Saxon indicators. Second, columns two till four present the results for each of our four forecasting horizons. Third, the presented $rRMSFE$ are always calculated as follows: $RMSFE^{dis,Pool}/RMSFE^{agg,Pool}$. So we always make a pairwise comparison (e.g., $RMSFE^{dis,Mean}/RMSFE^{agg,Mean}$). A ratio smaller than one means that the disaggregated approach is favorable in comparison to a direct forecast of Saxon GVA. Fourth, significance due to the MDM and the forecast encompassing test is separated by asteriks ($*$) and daggers (†). Asteriks indicate that a disaggregated forecast produce lower forecast errors then a aggregated one and daggers show that disaggregated predictions comprise more information beyond a direct forecast of total GVA.

Table 3: Comparison of aggregated and disaggregated Results

Target variable – qoq growth rate GVA: ***total***				
Strategy	**h=1**	**h=2**	**h=3**	**h=4**
Mean (FS)	$0.948^{*,\dagger\dagger}$	1.029	1.039	1.035
Median (FS)	$0.948^{*,\dagger\dagger}$	1.040	1.044	1.045
BIC (FS)	$0.947^{*,\dagger\dagger}$	1.028	1.039	1.033
R^2 (FS)	$0.947^{*,\dagger\dagger}$	1.029	1.039	1.034
Trimmed 25 (FS)	$0.918^{**,\dagger\dagger\dagger}$	1.025	1.036	1.028
Trimmed 50 (FS)	$0.926^{**,\dagger\dagger}$	1.038	1.080	1.041
Trimmed 75 (FS)	$0.937^{*,\dagger\dagger}$	1.039	1.082	1.046
MSFE weighted (FS)	$0.948^{\dagger\dagger}$	1.026	1.081	1.040
Mean (S)	$0.943^{*,\dagger\dagger}$	1.036	1.046	1.048
Median (S)	$0.958^{\dagger}$	1.048	1.058	1.063
BIC (S)	$0.942^{*,\dagger\dagger}$	1.037	1.044	1.048
R^2 (S)	$0.943^{*,\dagger\dagger}$	1.036	1.045	1.048
Trimmed 25 (S)	$0.928^{**,\dagger\dagger}$	1.023	1.038	1.024
Trimmed 50 (S)	$0.928^{**,\dagger\dagger}$	1.023	1.037	1.038
Trimmed 75 (S)	$0.939^{*,\dagger\dagger}$	1.026	1.038	1.042
MSFE weighted (S)	$0.949^{\dagger}$	1.034	1.044	1.038

Acronyms: FS: Full Sample, S: Saxony and GVA: gross value-added.
***, ** and * indicates significance (MDM) at the 1%, 5% and 10% level.
†††, †† and † indicates significance due to the forecast encompassing test at the 1%, 5% and 10% level.

As our forecast outcome shows, a disaggregated approach is preferrable for short term predictions. Nearly all combination strategies (with all indicators as well as only with Saxon ones) significantly beat the direct approach. For medium and long term predictions, a direct approach produces lower forecast errors in comparison to disaggregated predictions. However, the ratios are not statistically significant. The forecast encompassing tests clearly state that there is an information gain from disaggregated forecasts in comparison to direct ones for all considered pooling techniques in the short term. We can conclude that direct predicitions of GVA significantly neglect information. Our results are in line with the existing literature. Drechsel and Scheufele (2012a) find that the supply-side approach produces in some cases lower forecasts errors. This holds especially for the short term. We think that the disaggregated approach loses its power against the direct one in the medium and long term since many indicators (e.g., surveys or new orders) only have a lead of up to three months or provide forecasting signals contemporaneously. Whenever the forecast horizon becomes larger, the performance of those indicators for sector-specific forecasts is negligible. We leave this for future research.

The pooling results suggest that it makes no difference whether to use the whole set of indicators (FS) or just the one restricted to Saxon indicators (S). We find no systematic pattern so that either FS or S lead to a higher forecast accuracy for the disaggregated approach. This holds for all combination strategies and forecast horizons. However, out-of-sample weighted combination strategies perform better than in-sample weights or simple averages. Using a trimmed mean for the 25% best performing indicators in the full sample, a disaggregated approach produces on average nearly 8% smaller forecast errors than the direct approach (Trimmed 25 (FS), $rMSFE = 0.918$).

For short term predictions we can conclude that disaggregated forecasts have a higher forecast accuracy than direct ones. Since we are able to predict sectoral GVA with different indicators better than an autoregressive benchmark model, practitioners and forecasters should use the available information to forecast the state of the economy in the short term. For long term predictions, they should predict the whole aggregate directly in addition to sectoral forecasts.

4 Conclusion

With our empirical setup, we are able to predict sectoral GVA (e.g., for manufacturing) more accurately than a benchmark model. But forecast accuracy significantly differs between different sectors of the economy. These results are important for regional policy makers, practitioners or regional credit institutes. We are able to make the state of the economy more tangible. If external shocks only hit a few sectors, regional policy makers can systematically align their future policy. For credit institutes it is important to know how different sectors will develop in the near future. Especially for granting credit, such information are necessary.

All in all, we find that for short term predictions (one quarter ahead) disaggregated forecasts for GVA are preferable in comparison to direct ones. The resulting forecast errors could be reduced by about 8% on average. This outcome is straightforward, because we find that different indicator are linked to sectoral GVA even stronger than to total outcome. To predict GVA in the medium (two and three quarters) and long term (four quarters), a direct approach for total GVA produces lower forecast errors.

Regional indicators (e.g., business surveys) produce significantly lower forecast errors than the benchmark, especially in the short term. This result may explain, why the weighted sum of disaggregated predictions is more accurate than a direct forecast of total GVA, since the information surplus of these regional indicators is most present in the short term. National and international indicators are more important in the medium and long term. Whenever it is possible to use regional indicators, forecasters should include those information in their analysis. Pooling performs really well for the different sectors and total GVA, too. Factor models are not that competitive at the regional level.

Our analysis has shown that indicator–based sectoral forecasts produce smaller forecast errors and that forecast accuracy of total GVA can be improved by disaggregated forecasts. This gives a more detailed picture of the development of the economy and makes economic policy more assessable. Due to data limitations, our paper focuses exclusively on the Free State of Saxony. To the best of our knowledge, this is the only German state for which quarterly national accounts for different sectors are available. However, we think that such forecast improvements can be found for other German states or other regions too. If official statistics are able to provide quarterly data at the regional level, then such an analysis could be extended to other regional units. In the end, the results of our analysis suggest that forecasts for total German GDP could be improved by aggregation of state level GDP predictions. We leave this for future research.

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Appendix

Table 4: Indicators, Acronyms and Transformations

Acronym	Indicator	Transformation
Dependent Variables		
GVAAGFISAX	gross value-added (GVA): agriculture, hunting and forestry; fishing, Saxony	1
GVAINDSAX	GVA: industry, Saxony	1
GVACONSAX	GVA: construction, Saxony	1
GVABSSAX	GVA: basic services, Saxony	1
GVAASSAX	GVA: advanced services, Saxony	1
GVAPPSSAX	GVA: public and private services, Saxony	1
Macroeconomic Variables		
IPTOT	industrial production (IP): total (incl. construction)	1
IPCON	IP construction: total	1
IPENY	IP energy supply: total	1
IPMQU	IP manufacturing: mining and quarrying	1
IPMAN	IP manufacturing: total	1
IPCAP	IP manufacturing: capital goods	1
IPCONDUR	IP manufacturing: consumer durables	1
IPCONNDUR	IP manufacturing: consumer non-durables	1
IPINT	IP manufacturing: intermediate goods	1
IPCONG	IP manufacturing: consumer goods	1
IPCHEM	IP manufacturing: chemicals	1
IPMET	IP manufacturing: basic metals	1
IPMECH	IP manufacturing: mechanical engineering	1
IPMOT	IP manufacturing: motor vehicles, trailers	1
IPEGS	IP manufacturing: energy, gas etc. supply	1
IPVEM	IP manufacturing: motor vehicles, trailers etc.	1
TOCON	turn over (TO): construction	1
TOMQD	TO: mining and quarrying, domestic	1
TOMQF	TO: mining and quarrying, foreign	1
TOMAND	TO: manufacturing total, domestic	1
TOMANF	TO: manufacturing total, foreign	1
TOCAPD	TO: capital goods, domestic	1
TOCAPF	TO: capital goods, foreign	1
TOCONDURD	TO: consumer durables, domestic	1
TOCONDURF	TO: consumer durables, foreign	1
TOCONNDURD	TO: consumer non-durables, domestic	1
TOCONNDURF	TO: consumer non-durables, foreign	1
TOINTD	TO: intermediate goods, domestic	1
TOINTF	TO: intermediate goods, foreign	1
TOCONGD	TO: consumer goods, domestic	1
TOCONGF	TO: consumer goods, foreign	1
TOCEOD	TO: computer, electronic and optical products, domestic	1
TOCEOF	TO: computer, electronic and optical products, foreign	1
TOCHEMD	TO: chemicals, domestic	1
TOCHEMF	TO: chemicals, foreign	1
TOMECHD	TO: mechanical engineering, domestic	1
TOMECHF	TO: mechanical engineering, foreign	1
TOVEMD	TO: motor vehicles, trailers etc., domestic	1
TOVEMF	TO: motor vehicles, trailers etc., foreign	1
TOEGSD	TO: energy, gas etc. supply, domestic	1
TOEGSF	TO: energy, gas etc. supply, foreign	1
NOCON	new orders (NO): construction	1
NOMANTOT	NO: manufacturing total	1
NOMANTOTD	NO: manufacturing total, domestic	1
NOMANTOTF	NO: manufacturing total, foreign	1
NOMANCAP	NO: capital goods	1
NOMANCAPD	NO: capital goods, domestic	1
NOMANCAPF	NO: capital goods, foreign	1
NOMANCONG	NO: consumer goods	1
NOMANCONGD	NO: consumer goods, domestic	1
NOMANCONGF	NO: consumer goods, foreign	1
NOMANINT	NO: intermediate goods	1
NOMANINTD	NO: intermediate goods, domestic	1
NOMANINTF	NO: intermediate goods, foreign	1
NOCHEMD	NO: chemicals, domestic	1
NOCHEMF	NO: chemicals, foreign	1
NOMECHD	NO: mechanical engineering, domestic	1
NOMECHF	NO: mechanical engineering, foreign	1
NOVEMD	NO: motor vehicles, trailers etc., domestic	1
NOVEMF	NO: motor vehicles, trailers etc., foreign	1
NOCEOD	NO: computer, electronic and optical products, domestic	1
NOCEOF	NO: computer, electronic and optical products, foreign	1

Continued on next page...

Table 4: Indicators, Acronyms and Transformations – continued

Acronym	Indicator	Transformation
CONEMPL	construction: total employment	1
CONTOT	construction: permits issued, total	1
CONHOPE	construction: housing permits issued for building	1
CONNREPE	construction: non-residential permits	1
CONBPGTOT	construction: building permits granted, total	1
CONBPGHO	construction: building permits granted, new homes	1
CONBPGNRE	construction: building permits granted, non-residentials	1
CONHW	construction: hours worked	1
WTEXMV	wholesale trade (WT): total (excl. motor vehicles)	1
WTCLFW	WT: clothing and footwear	1
WTCHEM	WT: chemicals	1
WTCONMA	WT: construction machinery	1
WTSLGF	WT: solid, liquid, gaseous fuels etc.	1
WTEMPL	WT: total employment	1
RSEXC	retail sales (RS): total (excl. cars)	1
NRTOT	new registrations (NR): all vehicles	1
NRCARS	NR: cars	1
NRHT	NR: heavy trucks	1
EXVOL	exports: volume index, basis 2005	1
IMVOL	imports: volume index, basis 2005	1
UNPTOT	unemployed persons (UNP): total, % of civilian labor	2
EMPLRCTOT	employed persons (EMPL): residence concept, total	1
EMPLWPCTOT	EMPL: work-place concept, total	1
WDAYS	working days: total	1
VACTOT	vacancies: total	1
MANHW	manufacturing: hours worked (excl. construction)	1
TREUCD	tax revenues (TR): EU customs duties	1
TRITTOT	TR: income taxes, total	1
TRVAT	TR: value added tax	1
TRVATIM	TR: value added tax on imports	1
TRVATTOT	TR: value added tax, total	1
TRWIT	TR: wage income tax	1
Finance		
MMRDTD	money market rate (MMR): day-to-day, monthly average	2
MMRTM	MMR: three-month, monthly average	2
DREUROREPO	discount rate - short term euro repo rate	2
GOVBY	long term government bond yield, 9-10 years	2
YFTBOPB	yields on fully taxed bonds outstanding (YFTBO): public bonds	2
YFTBOCB	YFTBO: corporate bonds	2
YLFBOMS	yields on listed fed. bonds outstand. mat. (YLFBOM): 3-5 years	2
YLFBOML	yields on listed fed. bonds outstand. mat. (YLFBOM): 5-8 years	2
TSPI	term spread (TS): 10 years, policy inst	0
TSDAY	TS: 10 years, 1Day	0
TSMTH	TS: 10 years, 3Month	0
SPRDAYPR	1Day - policy rates	0
SPRCTB	corporate - treasury bond	0
GPC23CPI	german price competition: 23 industrialized countries, basis: cpi	1
DAXSPI	DAX share price index	1
NEER	nominal effective exchange rate	1
VDAXNVI	VDAX: new volatility index, price index	2
VDAXOVI	VDAX: old volatility index, price index	2
M1OD	M1, overnight deposits	1
M2MS	M2, money supply	1
M3MS	M3, money supply	1
EMMSM1EP	EM money supply: M1, ep	1
EMMSM1F	EM money supply: M1, flows	2
EMMSM2M1I	EM money supply: M2-M1, index	1
EMMSM2M1F	EM money supply: M2-M1, flows	2
EMMSM3M2EP	EM money supply: M3-M2, ep	1
EMMSM3M2F	EM money supply: M3-M2, flows	2
BLDNB	bank lending to domestic non-banks, short term	1
BLDEI	banl lending to enterprises and individuals, short term	1
TDDE	time deposits of domestic enterprises	1
SDDE	saving deposits of domestic enterprises	1
Prices		
CPI	consumer price index	1
CPIEE	consumer price index (excl. energy)	1
HWWAPITOT	HWWA index of world market prices: eurozone, total	1
HWWAPIEY	HWWA index of world market prices: eurozone, energy	1
HWWAPIEEY	HWWA index of world market prices: eurozone, excl. energy	1
OIL	oil prices, euro per barrel	1
OILUK	brent oil price, UK average	1
LGP	London gold price, per US $	1
IMPI	import price index	1
EXPI	export price index	1

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Table 4: Indicators, Acronyms and Transformations – continued

Acronym	Indicator	Transformation
WTPI	wholesale trade price index, 1975=100	1
PPI	producer price index	1
Wages		
WSLTOTHOU	wage and salary level (WSL): overall economy, basis: hours	1
WSLTOTMTH	WSL: overall economy, basis: monthly	1
WSLMANHOU	WSL: manufacturing, basis: hours	1
WSLMANMTH	WSL: manufacturing, basis: monthly	1
Surveys		
ZEWPS	ZEW: present economic situation	0
ZEWES	ZEW: economic sentiment indicator	0
IFOBCIT	ifo business climate industry and trade, index	0
IFOBEIT	ifo: business expextations industry and trade, index	0
IFOBSIT	ifo: assessment of business situation industry and trade, index	0
IFOBCMAN	ifo: business climate manufacturing, index	0
IFOBEMAN	ifo: business expextations manufacturing, index	0
IFOBSMAN	ifo: assessment of business situation manufacturing, index	0
IFOEXEMAN	ifo: export expectations next 3 months manufacturing, balance	0
IFOOOHMAN	ifo: orders on hand manufacturing, balance	0
IFOFOOHMAN	ifo: foreign orders on hand manufacturing, balance	0
IFOIOFGMAN	ifo: inventory of finished goods manufacturing, balance	0
IFOBCCAP	ifo: business climate capital goods, balance	0
IFOBECAP	ifo: business expectations capital goods, balance	0
IFOBSCAP	ifo: assessment of business situation capital goods, balance	0
IFOBCCONDUR	ifo: business climate consumer durables, balance	0
IFOBECONDUR	ifo: business expectations consumer durables, balance	0
IFOBSCONDUR	ifo: assessment of business situation consumer durables, balance	0
IFOBCCONNDUR	ifo: business climate consumer non-durables, balance	0
IFOBECONNDUR	ifo: business expectations consumer non-durables, balance	0
IFOBSCONNDUR	ifo: assessment of business situation consumer non-durables, balance	0
IFOBCINT	ifo: business climate intermediate goods, balance	0
IFOBEINT	ifo: business expectations intermediate goods, balance	0
IFOBSINT	ifo: assessment of business situation intermediate goods, balance	0
IFOBCCONG	ifo: business climate consumer goods, balance	0
IFOBECONG	ifo: business expectations consumer goods, balance	0
IFOBSCONG	ifo: assessment of business situation consumer goods, balance	0
IFOBCCON	ifo: business climate construction, index	0
IFOBECON	ifo: business expectations construction, index	0
IFOBSCON	ifo: assessment of business situation construction, index	0
IFOOOHCON	ifo: orders on hand construction, balacne	0
IFOUNFWCON	ifo: unfavourable weather situation	0
IFOBCWT	ifo business climate wholesale trade, index	0
IFOBEWT	ifo: business expextations wholesale trade, index	0
IFOBSWT	ifo: assessment of business situation wholesale trade, index	0
IFOAOIWT	ifo: assessment of inventories wholesale trade, balance	0
IFOEOAWT	ifo: expect. with regard to order activity next 3 months WT, balance	0
IFOBCRS	ifo business climate retail sales, index	0
IFOBERS	ifo: business expextations retail sales, index	0
IFOAOIRS	ifo: assessment of inventories retail sales, balance	0
IFOEOARS	ifo: expect. with regard to order activity next 3 months RS, balance	0
GFKBCE	GfK consumer survey (GfK): business cycle expectations	0
GFKIE	GfK: income expectations	0
GFKWTB	GfK: willingness to buy	0
GFKPL	GfK: prices over the last 12 months	0
GFKPE	GfK: prices over the next 12 months	0
GFKUE	GfK: unemployment situation over next 12 months	0
GFKFSL	GfK: financial situation over the last 12 months	0
GFKFSE	GfK: financial situation over the next 12 months	0
GFKESL	GfK: economic situation over the last 12 months	0
GFKESE	GfK: economic situation over the next 12 months	0
GFKMPP	GfK: major purchases at present	0
GFKMPE	GfK: major purchases over the next 12 months	0
GFKSP	GfK: savings at present	0
GFKSE	GfK: savings over the next 12 months	0
GFKCCI	GfK: consumer confidence, index	0
GFKCCC	GfK: consumer confidence climate, balance	0
GFKCCIN	GfK: consumer confidence indicator	0
EUCSUE	EU consumer survey (EUCS): unemploy. expect. over next 12 months	0
EUCSFSP	EUCS: statement on financial situation	0
EUCSCCI	EUCS: consumer confidence indicator	0
EUCSESI	EUCS: economic sentiment indicator	0
EUBSPTIND	EU business survey (EUBS): prod. trends recent month, industry	0
EUBSOBLIND	EUBS: assessment of order-book levels, industry	0
EUBSEXOBLIND	EUBS: assessment of export oder-books level, industry	0
EUBSSFGIND	EUBS: assessment of stocks of finished products, industry	0
EUBSPEIND	EUBS: production expectations for the month ahead, industry	0

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Table 4: Indicators, Acronyms and Transformations – continued

Acronym	Indicator	Transformation
EUBSSPEIND	EUBS: selling price expectations for the month ahead, industry	0
EUBSEMPEIND	EUBS: employment expectations for the month ahead, industry	0
EUBSINDCI	EUBS: industrial confidence indicator	0
EUBSSSCI	EUBS: service sector confidence indicator	0
EUBSRTCI	EUBS: retail trade confidence indicator	0
EUBSCONCI	EUBS: construction confidence indicator	0
COMBAEB	Commerzbank EarlyBird	0
International		
BGBIS	Belgium business indicator survey, whole economy	0
BGBISMAN	Belgium business indicator survey, manufacturing (not smoothed)	0
UMCS	University of Michigan US consumer sentiment, expectations	0
USISMP	US ISM production	0
EUCSFRESI	EUCS: economic sentiment indicator, France	0
EUCSESESI	EUCS: economic sentiment indicator, Spain	0
EUCSPOESI	EUCS: economic sentiment indicator, Poland	0
EUCSCZESI	EUCS: economic sentiment indicator, Czech Republic	0
EUCSITESI	EUCS: economic sentiment indicator, Italy	0
EUCSUKESI	EUCS: economic sentiment indicator, United Kingdom	0
DJESI50	EM Dow Jones EUROSTOXX index, benchmark 50	1
DJIPRI	Dow Jones industrials, price index	1
SPUSSPI	Standard & Poor´s 500 stock price index	1
GOVBYUK	government bond yield long term, United Kingdom	2
GOVBYUS	government bond yield long term, United States	2
USIPTOT	IP: United States, total	1
CLIAA	OECD Composite Leading Indicator (CLI): OECD, amplitude adjusted	0
CLITR	CLI: OECD, trend restored	1
CLINORM	CLI: OECD, normalised	0
CLIASAA	CLI: Asia, amplitude adjusted	0
CLIASTR	CLI: Asia, trend restored	1
CLIASNORM	CLI: Asia, normalised	0
CLICAA	CLI: China, amplitude adjusted	0
CLICTR	CLI: China, trend restored	1
CLICNORM	CLI: China, normalised	0
CLIEUAA	CLI: Euro Area, amplitude adjusted	0
CLIEUTR	CLI: Euro Area, trend restored	1
CLIEUNORM	CLI: Euro Area, normalised	0
CLIUSAA	CLI: United States, amplitude adjusted	0
CLIUSTR	CLI: United States, trend restored	1
CLIUSNORM	CLI: United States, normalised	0
ECRTE	Euro-Coin real time estimates	0
Regional – Free State of Saxony		
IFOBCITSAX	ifo business climate industry and trade Saxony, balance	0
IFOBEITSAX	ifo: business expextations industry and trade Saxony, balance	0
IFOBSITSAX	ifo: assessment of business sit. indus. and trade Saxony, balance	0
IFOBCMANSAX	ifo: business climate manufacturing Saxony, balance	0
IFOBEMANSAX	ifo: business expextations manufacturing Saxony, balance	0
IFOBSMANSAX	ifo: assessment of business sit. manufacturing Saxony, balance	0
IFOBCCONSAX	ifo: business climate construction Saxony, balance	0
IFOBECONSAX	ifo: business expectations construction Saxony, balance	0
IFOBSCONSAX	ifo: assessment of business situation construction Saxony, balance	0
IFOEMPECONSAX	ifo: employment expect. over next 3 months constr. Saxony, balance	0
IFOBCWTSAX	ifo business climate wholesale trade Saxony, balance	0
IFOBEWTSAX	ifo: business expextations wholesale trade Saxony, balance	0
IFOBSWTSAX	ifo: assessment of business situation wholesale trade Saxony, balance	0
IFOEMPEWTSAX	ifo: employment expect. over next 3 months WT Saxony, balance	0
IFOBCRSSAX	ifo business climate retail sales Saxony, balance	0
IFOBERSSAX	ifo: business expect. retail sales Saxony, balance	0
IFOBSRSSAX	ifo: assessment of business situation retail sales Saxony, balance	0
IFOEMPERSSAX	ifo: employment expect. over next 3 months RS Saxony, balance	0
IFOBCINTSAX	ifo business climate intermediate goods Saxony, balance	0
IFOBEINTSAX	ifo: business expextations intermediate goods Saxony, balance	0
IFOBSINTSAX	ifo: assess. of busin. sit. intermediate goods Saxony, balance	0
IFOBCCAPSAX	ifo: business climate capital goods Saxony, balance	0
IFOBECAPSAX	ifo: business expextations capital goods Saxony, balance	0
IFOBSCAPSAX	ifo: assessment of busin. sit. capital goods Saxony, balance	0
IFOBCCONDURSAX	ifo: business climate consumer durables Saxony, balance	0
IFOBECONDURSAX	ifo: business expectations consumer durables Saxony, balance	0
IFOBSCONDURSAX	ifo: assessment of business sit. consumer durables Saxony, balance	0
IFOBCCONGSAX	ifo business climate consumer goods Saxony, balance	0
IFOBECONGSAX	ifo: business expextations consumer goods Saxony, balance	0
IFOBSCONGSAX	ifo: assessment of business situation consumer goods Saxony, balance	0
IFOBCFBTSAX	ifo business climate food, beverage and tobacco Saxony, balance	0
IFOBEFBTSAX	ifo: business expextations food, beverage and tobacco Saxony, balance	0
IFOBSFBTSAX	ifo: assessment of business situation FBT Saxony, balance	0
IFOBCCHEMSAX	ifo business climate chemicals Saxony, balance	0

Continued on next page...

Table 4: Indicators, Acronyms and Transformations – continued

Acronym	**Indicator**	**Transformation**
IFOBECHEMSAX	ifo: business expextations chemicals Saxony, balance	0
IFOBSCHEMSAX	ifo: assessment of business situation chemicals Saxony, balance	0
IFOBCMECHSAX	ifo business climate mechanical engineering Saxony, balance	0
IFOBEMECHSAX	ifo: business expextations mechanical engineering Saxony, balance	0
IFOBSMECHSAX	ifo: assessment of busin. sit. mechanical engineering Saxony, balance	0
IFOBCMOTSAX	ifo business climate motor vehicles Saxony, balance	0
IFOBEMOTSAX	ifo: business expextations motor vehicles Saxony, balance	0
IFOBSMOTSAX	ifo: assessment of business sit. motor vehicles Saxony, balance	0
IFOBCBUENSAX	ifo business climate building engineering Saxony, balance	0
IFOBEBUENSAX	ifo: business expextations building engineering Saxony, balance	0
IFOBSBUENSAX	ifo: assessment of busin. sit. building engineering Saxony, balance	0
IFOBCCIENSAX	ifo business climate civil engineering Saxony, balance	0
IFOBECIENSAX	ifo: business expextations civil engineering Saxony, balance	0
IFOBSCIENSAX	ifo: assessment of busin. sit. civil engineering Saxony, balance	0
NOMANSAXTOT	NO: manufacturing Saxony, total	1
HCNOSAX	housing construction (HC): new orders Saxony	1
HCWHSAX	HC: working hours Saxony	1
HCTOSAX	HC: turnover Saxony	1
ICNOSAX	industry construction (IC): new orders Saxony	1
ICWHSAX	IC: working hours Saxony	1
ICTOSAX	IC: turn over Saxony	1
PCNOSAX	public construction (PC): new orders Saxony	1
PCWHSAX	PC: working hours Saxony	1
PCTOSAX	PC: turn over Saxony	1
CONNOSAX	construction: new orders Saxony	1
CONWHSAX	construction: working hours Saxony	1
CONFIRMSAX	construction: firms Saxony	1
CONEMPSAX	construction: employed people Saxony	1
CONFEESAX	construction: fees Saxony	1
IFOCUCONSAX	ifo: capacity utilization construction, Saxony	2
IFOOOHCONSAX	ifo: orders on hand construction, Saxony	0
TOHRSAX	TO: hotels and restaurants Saxony, total	1
CPISAX	consumer price index, Saxony	1
EXVALUESAX	exports: value, Saxony	1
IMVALUESAX	imports: value, Saxony	1

Note: 0 = three-month-average in levels; 1 = three-month-average and qoq growth rate; 2 = three-month-average and Δ
Industry: Mining and quarrying; manufacturing; electricity, gas and water supply.
Basic services: Wholesale and retail trade; hotels and restaurants; transport.
Advanced services: Financial intermediation; real estate, renting and business activities.
Public and private services: public administration; education; health and social work; private households.
Source: Drechsel and Scheufele (2012a), author´s extensions and calculations.

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