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Short-term Forecasting with Business Surveys: Evidence for German IHK Data at Federal State Level

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1 | Introduction

Nowadays, policy-makers are expected to respond quickly to changes in the economic environment. Upcoming developments have to be anticipated before they interfere with policy aims. The success of macroeconomic policies is thus highly reliant on the efficiency of forecasting tools. Efficient forecasting requires that in addition to regular time patterns also sudden irregular developments are identified for which little past evidence is available. In this regard, business climate surveys can represent valuable complements to univariate statistical techniques. Typically, these surveys gather assessments made by leading actors in the market, which can expected to be the first to detect recent trends. Another advantage compared to indicators from national account data is that results are not challenged by data revisions.

At the regional level in Germany, currently a wide range of frequently updated business climate indicators exist. For a macroeconomist, this variety represents a promising opportunity to investigate region-specific fluctuations. However, to test the macroeconomic relevance of these high-frequency indicators, sub-annual production data at the regional level is required. Currently, these are not regularly published by the statistical offices in Germany. In addition, to gain some understanding of the underlying economics, theoretical pre-considerations on the nature of the relationship between production volumes and expectations of survey respondents are needed.

In this paper, we analyze the performance of the regional business climate index published by the Chambers of Commerce (IHKs) in Germany, henceforth called the IHK index. We examine its linkages to fluctuations in regional output within a consistent growth framework. To overcome the disaggregation issue, we start with generating quarterly production data for the northern states by means of a modified Chow-Lin approach. This data is then matched with the index score as part of a growth regression.

In doing this, we are the first to investigate the relationship of the IHK index to short-run growth and to assess its forecasting performance. Moreover, this is also the first attempt to examine the forecasting quality of business surveys with regard to sub-annual output fluctuations for Northern Germany.

The plan of the paper is as follows: first we give a short overview on previous attempts in this direction. Then, in section 3 we describe the construction of the IHK business climate index and explain our method to generate values for quarterly output at the level of federal states. In section 4 we derive our empirical framework and justify our estimation approach. In section 5 we present basic results on the explanatory power of the IHK index for short-run growth based on ex-post fits. In section 6, two slight modifications of the model are introduced to discuss alternative hypotheses.

Section 7 is then devoted to an evaluation of the actual forecasting performance of our model by applying a standard recursive scheme. Finally, section 8 summarizes our results and hints at promising future research strands.

2 | Previous evidence

The data-scarce environment has so far prevented the emergence of a broader literature on indicator-based forecasting of regional growth. Moreover, regional data application is further complicated by the German unification and the subsequent asymmetric shock. The majority of existing papers rely on scattered attempts to generate quarterly production data. Examples for these attempts include Bandholz & Funke (2003) for Hamburg, Dreger & Kholodilin (2006) for Berlin, Vullhorst (2008) for Baden-Württemberg and Nierhaus (2008) for Sachsen. The two last mentioned papers draw on the well-accepted Chow-Lin methodology. Consequently, these regions have been the focus of most of the recent literature.

Lehmann et al. (2010) investigated the performance of business survey data for Sachsen as a leading indicator through the crisis period around 2009. Additionally, quarterly growth forecasts are now published regularly (e.g. Arent et al., 2011) for Sachsen. Based on this, Lehmann & Wohlrabe (2012) forecast quarterly growth rates for Sachsen, Baden-Württemberg and Eastern Germany by pooling regression results from various specifications including over 300 explanatory variables.

Regional growth estimation using panel techniques has been an alternative approach. However, these attempts have so far relied on annual data. Kholodilin et al. (2007) use a simple autoregressive model with spatial dependence to forecast annual regional growth for all 16 federal states in Germany. Similarly, Wenzel (2013) uses business survey data from all federal states to test their forecasting performance for regional annual growth rates.

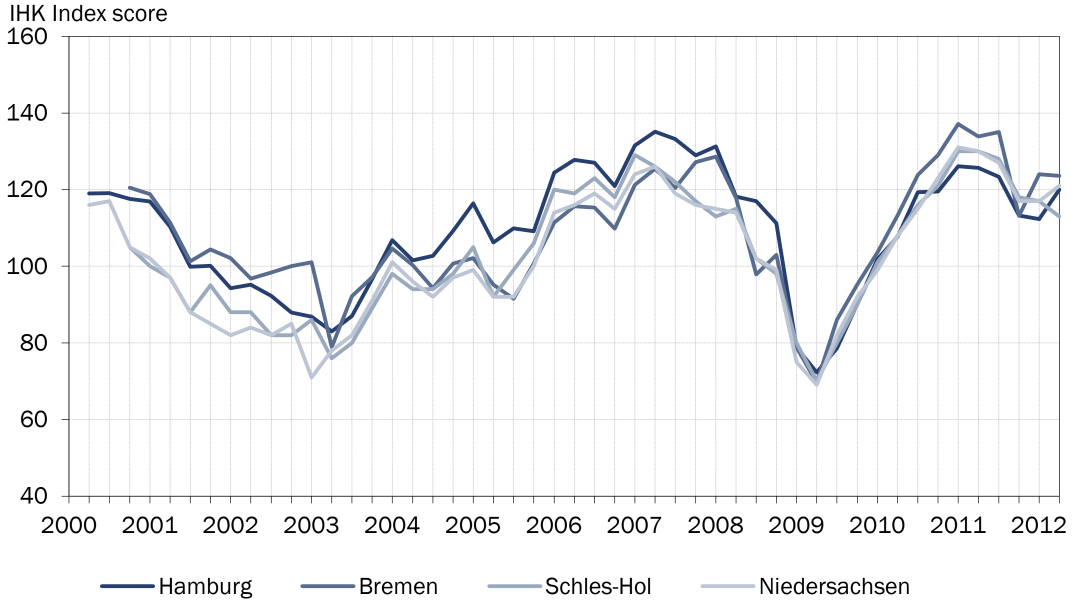
3 | Data sources

3.1 | The IHK business climate index

Principally, regional results for the IHK index are provided by chambers of commerce from all federal states in Germany on a regular basis. However, we choose to focus our analysis exclusively on the four northern Bundesländer of Bremen, Hamburg, Niedersachsen and Schleswig-Holstein. Beside geographical proximity, a reason is conceptual similarity. Due to the collaboration of the "Hamburger Gruppe", which includes the relevant regional chambers of commerce, the surveys and the subsequent index-generation are standardized in Northern Germany. This is not necessarily the case when including other regions.

The business climate is assessed through survey responses to questions about the current and expected (12-months horizon) business environment. An index is then generated, ranging from 0 to 200, which measures the available information on an interval scale. (The exact questions and formula for index calculation are listed in the Appendix). The business climate indicators in this analysis cover the time from 2000 to 2012 and are available on a quarterly basis. Figure 1 plots the IHK data over time.

Figure 1: IHK Indices over time



Source. IHK Bremen, Hamburg, Niedersachsen, Schleswig-Holstein (2013)

Sectoral structure of a region is accounted for by weighting the survey responses according to the size of the corresponding sectors. Seasonality is also accounted for in the final business climate indicators. However, the surveys focus principally on large enterprises and do not manage to survey many small enterprises, which would probably more strongly reflect regional dynamics. Additionally, the weighting of survey replies is primarily done by company turnover and employment, which gives more weight to companies with a superregional scope. Thus, it is possible that the IHK data contains a national or even supranational bias which is partly due to selection and partly due to construction (a fact that we will consider later on in empirical analysis),. Nonetheless, the business survey data is interesting, particularly in the forecasting context, as it is sub-annual, readily available at the regional level and is not revised.

3.2 | Quarterly disaggregation of production series

Given the quarterly frequency of the IHK surveys, testing their relevance based on annual production data would most likely result in estimation biases and misinterpretation of results. Unfortunately, statistical agencies in Germany merely publish sub-annual production volumes at the national, not at the regional level. In recent years, attempts have been made to create sub-annual series for regional GDP with the help of statistical techniques. The by far most popular method is an indicator-based regression approach developed by Chow and Lin (Chow & Lin, 1971). In this technique, the target low-frequency series (e.g. GDP) is regressed on the low-frequency series of related indicators for which also values at the desired high-frequency level are available. The fit is used to distribute low-frequency values of the target variable across the high-frequency dimension. In addition, residuals are distributed in a way that matches observed autocorrelation patterns of the target variable.

Recent applications for German GDP at the level of federal states have been made by Nierhaus (2007) for Saxony and Vullhorst (2008) for Baden-Wurttemberg. They both disaggregate annual GDP to quarterly values. For the northern federal states in Germany (Bremen, Hamburg, Lower Saxony, Schleswig-Holstein), this procedure has so far not been systematically applied. Hence, to obtain quarterly production data, we carried out own estimations based on the Chow-Lin method. Concerning indicator choice, structural breaks during the time span (changes in the classification of economic activities, changes in sample composition) made it impossible for us to use regional indicators. In contrast, for quarterly national GDP consistent series for the whole sampling period are at hand. We therefore resorted to national indicators of production. Precisely, since our focus is on fluctuations in real production volumes, our measure is deflated Gross Value Added (GVA), which was obtained from the federal statistical office in Germany. To avoid distortions due to seasonal influence, we chose a seasonally adjusted series, were adjustments were based on a standard Census X-12-ARIMA procedure.

In line with Nierhaus (2007) and Vullhorst (2008), we estimated the relationships at a sectorally disaggregated level in order to account for sectoral heterogeneity in the diffusion of aggregate shocks. To this end, the same six sectors as in Vullhorst (2008) were defined (see Appendix) and sectoral estimates for each state were gained by regressions of annual sectoral GVA at state level on annual sectoral GVA at national level.[1] Afterwards, estimates were sectorally aggregated to arrive at total quarterly GVA at state level.

Across all states and sectors, our national indicators proved to be highly significant. Apart from this, however, appropriateness of the Chow-Lin method also hinges upon the stationarity of residuals, i.e. the existence of a co-integration relationship between target variable and indicator. In case this condition fails, Rodriguez (1982) has proposed an alternative estimator based on first-differencing the target and the indicator series. For our data, ADF-tests proved unable to reject non-stationarity of residuals for some sectors in some regions. We therefore implemented an iterative econometric procedure to arrive at quarterly estimates of GVA, which is outlined in the Appendix. Likewise, the resulting (sectorally aggregated) values are graphed together with quarterly index scores for the single states in the Appendix.

4 | Empirical setup

4.1 | Basic framework

In the following, we consider aggregate output Y during period t in region r to be a function of two basic components:

$$Y_{r,t} = \mathrm{E}_{r,t}\tilde{Y}_{r,t} \ . \tag{1}$$

The factor E represents a random variable reflecting short-term fluctuations in regional output. $\tilde{Y}$ on the other hand represents a deterministic trend in output which is supposed to capture fundamentals like technological progress, regional population growth and capital accumulation determining long-term growth of region r. Since our focus is on short-term evolutions, we will refrain from a decomposition of this factor.

[1] Note that even though we choose the same indicators for all four states, there is still plenty of room for regional heterogeneity. First, the nature of the relationship to the indicator series differs between regions Second, our approach accounts for differences in sectoral structure and third, region-specific autocorrelation patterns are considered by the Chow-Lin methodology.

To facilitate empirical implementation, it will be useful to reformulate relation (1) in logs, where lower-case letters symbolize log expressions:

$$y_{r,t} = \varepsilon_{r,t} + \tilde{y}_{r,t} \,. \tag{2}$$

We assume ε to follow an AR(1)-Process governed by time- and region-specific shocks u. For the moment, we additionally assume regional trend output to grow at a constant rate g_r.

$$\varepsilon_{r,t} = \phi_r \varepsilon_{r,t-1} + u_{r,t} \quad 0 \leq \phi_r < 1 \quad u_{r,t} \ i.i.d. \ with\, E(u_{r,t}) = 0$$

$$\Delta\tilde{y}_{r,t} = g_r$$

Hence, short-term fluctuations in output are viewed to be driven by independent stochastic shocks which taper off over time at some given speed. Accordingly, forecasting short-term output growth in t at the beginning of period t involves the task of determining the strength of shock $u_{r,t}$. In this regard, business survey results can represent useful indicators. As explained in the previous section, the IHK business climate indices are constructed as a combination of assessments on the current economic situation of the firms and future economic outlooks. In the following, we assume managers and entrepreneurs to be both rational and well-informed on current and past market conditions. Particularly, this includes knowledge on long-term trends as well as on common time patterns of short-term shocks. As a consequence, we can define the regional index score $BSI_{r,t}$ obtained from surveys carried out during period t as a (not further restricted) function of the trend deviation in the previous period and current stochastic shocks:

$$BSI_{r,t} = f(y_{r,t-1} - \tilde{y}_{r,t-1}, u_{r,t}).$$

Hence, the index score provides a judgement based on the current position in the business cycle and recent exogenous events.[2] To see in which form it can be utilized in estimation, we rewrite (2) in first differences:

$$\begin{aligned}\Delta y_{r,t} = \Delta\varepsilon_{r,t} + \Delta\tilde{y}_{r,t} &= (\phi_r - 1)\varepsilon_{r,t-1} + u_{r,t} + g_r \\ &= (1 - \phi_r)(\tilde{y}_{r,t-1} - y_{r,t-1}) + u_{r,t} + g_r. \end{aligned} \tag{3}$$

Current period-to-period output growth is thus represented as an additive combination of long-term growth, a current exogenous shock and an error correction mechanism whose speed of adjustment is the larger the smaller autocorrelation parameter ϕ_r. The only inherently unobservable determinant in this equation is $u_{r,t}$. Hence, by using the index score as a proxy for this measure, one gains a coherent estimation framework provided that values for the remaining measures are made

[2] Note that shocks from the past are already processed in y_{t-1}, so u_t represents the only new information available for evaluating future prospects.

available during t. An empirical advantage of estimating the relationship between output growth and index score via this modeling framework is the ability to control for the economy's position in the business cycle. Given the dependence of both current growth and index score on this position, we thereby avoid an essential source of omitted variable bias in estimating the forecasting performance of the IHK index.

4.2 | Econometric approach

Utilizing the IHK index scores as indicators for recent shocks leads to the following basic regression equation:

$$\Delta y_{r,t} = \beta_r^0 + \beta_r^1 \left(y_{r,t-1} - \tilde{y}_{r,t-1} \right) + \beta_r^2 g\left(BSI_{r,t} \right) + v_{r,t} \tag{4}$$

with regression parameters denoted by β_r^0, β_r^1 and β_r^2. Applied to our data, t now marks single quarters and r marks federal states. To facilitate interpretation, we include index scores BSI in the form of deviations from their region-specific means $\left(g\left(BSI_{r,t} \right) = BSI_{r,t}^m = BSI_{r,t} - \overline{BSI_r} \right)$. In this way, intercepts β_r^0 are identical to the long-term growth rates of regional output included in equation (3). For an empirical implementation, the task remains to determine regional trend output over time. Consistent with our basic concept of constant long-term growth would be a derivation of region-specific log-linear trend functions. To this end, the following auxiliary regressions are performed for each region r:

$$\begin{aligned} y_{r,t} &= \alpha_r^0 + \alpha_r^1 t + \vartheta_{r,t} \\ \tilde{y}_{r,t} &= \widehat{\alpha_r^0} + \widehat{\alpha_r^1} t. \end{aligned} \tag{5}$$

Then, the information gathered could principally be used for region-specific regressions designed to test the significance of the IHK indices as growth indicators. However, given that sample sizes for each region are rather small ($n = 49$), we have to acknowledge the efficiency gain of a combined estimation. Hence, we prefer to test the general significance within a Panel approach:[3]

$$\Delta y_{r,t} = \beta^0 + \beta^1 \left(y_{r,t-1} - \tilde{y}_{r,t-1} \right) + \beta^2 BSI_{r,t}^m + \lambda_r + v_{r,t}$$

where λ_r symbolizes regional heterogeneity in long-term growth and $v_{r,t}$ the part of short-term fluctuations that is not captured by survey responses. Note that by construction $\Delta \tilde{y}_{r,t} = \widehat{\alpha_r^1} = \widehat{\beta^0} + \widehat{\lambda_r}$ holds. Hence, regional fixed effects are predetermined through the estimation of long-term growth in this setup. Given our knowledge from (5), we can thus eliminate time-invariant heterogeneity by shifting it

[3] Considering our model formulation (3), this involves the assumption that adjustment speeds of regional output are identical among the northern states.

to the left hand-side and estimating the determinants of deviations from long-term growth:

$$\begin{aligned}(\Delta y_{r,t} - \Delta\tilde{y}_{r,t}) &= \beta^1(y_{r,t-1} - \tilde{y}_{r,t-1}) + \beta^2 BSI^m_{r,t} + \varsigma_{r,t} \\ \Delta(y_{r,t} - \tilde{y}_{r,t}) &= \beta^1(y_{r,t-1} - \tilde{y}_{r,t-1}) + \beta^2 BSI^m_{r,t} + \varsigma_{r,t} \qquad (6)\end{aligned}$$

with $\varsigma_{r,t}$ denoting the residuals of the modified model. In the following, we will call this setup **model 1**.

A critical feature is the identification of the trend component. In this regard, fitting a log-linear trend is subject to the notion of trend as a long-term average placing equal weights on developments materializing in past and future. If, instead, a trend is rather interpreted as capturing current knowledge on the fundamentals influencing long-term growth, any new information in this regard should lead to major trend revisions. Hence, larger weights should be placed on current developments in determining current trend components. Applied to our framework, this means managers are expected to update their views on economic long-term prospects over time. A statistical implication is that growth of trend output can no longer be viewed as constant over time. Instead of applying ordinary regression over the whole sample period, this requires the use of filter techniques like Hodrick & Prescott (1997) and Baxter & King (1999) or spline regression approaches.

In the end, the question of an appropriate trend definition is a philosophical one and cannot be satisfyingly answered by means of statistical analysis. For this reason, we choose not to take sides and simply complement estimation of model 1 by an alternative version referred to as **model 2**. Here, the trend component is determined by applying a Hodrick-Prescott filter (HP) with a standard value of 1600 for the smoothing parameter. A consequence is that the change in long-term output as the second component of the dependent variable in () varies both across time and regions in this model version: $\Delta\tilde{y}_{r,t} = g_{r,t}$.

In the following, we estimate both model versions as pooled cross-sections via OLS for the sampling period 3:2000 (quarter:year) to 4:2012. As explained above, we choose quarterly disaggregated data on Gross Value Added (GVA) (both deflated and seasonally adjusted) at the level of the four northern states as measures of production value. Given that patterns of short-term fluctuations are likely to differ between states, we should not expect our residuals to be homoscedastic. White-Hubert standard errors are therefore applied in inference.

5 | Basic results

Table 1 lists estimated coefficients for the two model variants (linear trend and HP). For both variants, a truncated version including just the (mean-subtracted) IHK index as explanatory variable and the full model were estimated.

Table 1: Estimation results for the two basic model variants

	Model 1 (Linear trend)		**Model 2 (HP-Filter)**	
$\boldsymbol{\beta^1}$	-	-.1267858***	-	-.1630146***
		(-4.96)		*(-5.00)*
$\boldsymbol{\beta^2}$	.0003075***	.0003107***	.0002745***	.0002789***
	(5.89)	*(6.27)*	*(5.21)*	*(5.61)*
$\boldsymbol{R^2}$	.2869	.3569	.2415	.3291
Adj. $\boldsymbol{R^2}$	.2834	.3505	.2378	.3224
No. Obs.	203	203	203	203

t-values in parentheses; ***significant at a 1%-level
Source. own calculations

For model 1, estimation of the truncated version reveals a significantly positive relationship between the regional index score and current regional quarter-to-quarter GVA growth. More interestingly, the significance of this linkage remains unimpaired by introducing current trend deviation as a control variable in the full model. The size of the coefficient is even slightly increased. This documents the relevance of the IHK index as an indicator of short-run growth in the northern states: even having the information on the current position in the business cycle at hand, the index score provides additional insights into subsequent movements. Precisely, a ten-point increase in the index score is on average associated with a 0.31% increase in the current quarter-to-quarter growth rate of GVA. Hence, survey responses indeed seem to offer first-hand information on current shocks.

In addition, we also observe for the estimate of β^1 significance with the expected negative sign, indicating actual convergence to trend output for the sample period. Analyzing the time patterns of the residuals in the full model confirms this impression:

separate ADF-tests for the residuals in the four states all strongly reject the null-hypothesis of non-stationarity.

For model 2, results are qualitatively very similar. Here, the interpretation of estimates is a slightly different one, given that the second term in the target variable is no longer time-invariant. In this variant, coefficients merely indicate the effect on deviations of actual GVA growth from current trend growth (or equivalently the change in the level of trend deviation). Hence, $\widehat{\beta^2}$ says that a ten-point increase in the index score is on average associated with a 0.27% increase in the deviation of short-run from trend growth of GVA.

While estimating the effects for all four northern states within a joint model raises our degrees of freedom, it could be seen as too restrictive in the sense that regional indices might differ in their capabilities to predict regional growth. Apart from issues related to data collection, this could be triggered by differences in the regional focus of enterprises, leading survey responses in some regions to be better indicators of national than of regional growth. In the following, we compare the performance of the IHK indices across northern states by estimating our model separately for each state. Hence, we carry out four time series estimations instead of one pooled estimation. Results in table 2 show that there is indeed a regional spread in index performance to be observed.[4]

Table 2: Estimation of basic model (variant 1) based on regional subsamples

	Bremen	Hamburg	Lower Saxony	Schlesw.-Hol.
$\boldsymbol{\beta^1}$	-.1649112***	-.0314687	-.2002075***	-.1050081**
	(-2.87)	*(-.62)*	*(-4.74)*	*(-2.09)*
$\boldsymbol{\beta^2}$	.0004298***	.0002611***	.0003824***	.0002506***
	(2.83)	*(3.38)*	*(3.89)*	*(3.83)*
$\boldsymbol{R^2}$	.3962	.2785	.5056	.3646
No. Obs.	50	51	51	51

t-values in parentheses; ***significant at a 1%-level; **significant at a 5%-level
Source. own calculations

[4] Again results for the two model variants are qualitatively, we therefore do not report estimation results for the second model variant here.

Among the northern states, the largest R^2 is achieved in Lower Saxony. This is also the region where the indicator reaches its highest level of significance. The worst overall fit is observed for Hamburg, the lowest significance of the index score for Bremen. The estimated quantitative effects of a 10-point increase in index scores on current growth range from 0.25% in Schleswig-Holstein to 0.43% in Bremen. Nevertheless, high significance can be detected for index scores within all states, pointing to a cross-regional relevance of the IHK survey.

6 | Model modifications

Our model structure so far assumed that assessments of managers are rational and primarily rest on local market conditions. This might be questioned, given that the survey sample consists of large firms that participate in national or even international markets. And even if there is no national focus, shocks on the national level might nevertheless be relevant as they are apt to spill over to the level of single regions.

Note that we have to refrain from inserting levels of national output directly as a control variable: since we constructed regional quarterly output from this data, this strategy would surely result in strong multicollinearity. However, at least we can add changes in national output on the right-hand side of (6). Precisely, we add the change in the trend deviation of national log GVA:

$$\Delta\left(y_{r,t}-\tilde{y}_{r,t}\right) \;=\beta^1\left(y_{r,t-1}-\tilde{y}_{r,t-1}\right)+\beta^2 BSI_{r,t}^m+\beta^3\Delta\left(y_{t-1}^n-\tilde{y}_{t-1}^n\right)+\varsigma_{r,t}$$

with y^n now denoting national log values. Analogous to our first approach for regional trends, the national trend component $\tilde{y}_t^n$ is estimated in advance as a log-linear trend function over the national quarterly series. In words, this model formulation means we control for a potential effect of lagged national shocks on current regional growth. Table 3 first reports estimates for the case where the IHK index is omitted and second results for the full model.

Results in the first column confirm that there is some association between current regional and lagged national short-term fluctuations of output in our data. Since we control for the position in the business cycle, this is not plainly the result of common business cycle regularities. However, reintroducing the IHK index into the regression equation renders this effect completely insignificant. The index score exhibits a similar explanatory power as in previous estimations. Given the strong increase in R^2, this result does not simply represent a statistical artifact, e.g. due to multicollinearity. Instead, it indicates that the index score indeed conveys some of the signals already materialized at the national level, but apart from this also a lot of additional relevant information. Whether this is because firms tend to be rather nationally oriented or because they correctly anticipate the future impact of national shocks on the regional level cannot be answered by our analysis. What we can conclude is that the IHK index seems to maintain its explanatory power when accounting for national developments.

Table 3: Results for modified model including national lags

	Model 1 (Linear trend)		Model 2 (HP-Filter)	
$\boldsymbol{\beta^1}$	-.1995633***	-.1063146***	-.2719683***	-.1719536***
	(-4.52)	*(-2.90)*	*(-4.50)*	*(-3.27)*
$\boldsymbol{\beta^2}$	-	.0003166***	-	.0002772***
		(6.06)		*(5.36)*
$\boldsymbol{\beta^3}$	.0902748**	-.0243803	.119025***	.0093342
	(2.51)	*(-.65)*	*(2.77)*	*(.21)*
$\boldsymbol{R^2}$	.0862	.3607	.1026	.3292
Adj. $\boldsymbol{R^2}$	.0771	.3511	.0936	.3191
No. Obs.	203	203	203	203

t-values in parentheses; ***significant at a 1%-level; **significant at a 5%-level
Source. own calculations

Concerning the rationality of assessments, an interesting type of behavioral anomaly would be an asymmetry in explanatory power for different positions in the business cycle. Managers might be systematically better or worse in predicting short-term growth during a boom than during a recession. Psychological explanations for these phenomena are provided by theories like representativeness (Kahneman & Tversky, 1973) and anchoring (Lichtenstein & Slovic, 1971). Simple tests for this specific kind of asymmetry can be conducted by splitting up the sample in periods of boom and depression. Alternatively, we can examine how the extent of linkages between index scores and short-term fluctuations interacts with business cycle dynamics by including a business cycle dummy D^{BC}:

$$\Delta(y_{r,t} - \tilde{y}_{r,t}) = \beta^1(y_{r,t-1} - \tilde{y}_{r,t-1}) + \beta^2 BSI^m_{r,t} + \beta^{BC} D^{BC} BSI^m_{r,t} + \varsigma_{r,t}$$

$$\text{with } D^{BC} = \begin{cases} 1 & iff \; (y_{r,t-1} - \tilde{y}_{r,t-1}) \geq 0 \\ 0 & else \end{cases}$$

Hence, $\beta^2 + \beta^{BC}$ measures the relationship in case output had been located above the trend line in the previous period and $\beta^2$the relationship in times where actual output did not reach its trend value. Table 4 shows results for this extended setup as well as for the strategy of sample splitting.

Table 4: Differences in model fit between boom and depression (for model 1)

	Full model	$\boldsymbol{D^{BC} > 0}$	$\boldsymbol{D^{BC} < 0}$
$\boldsymbol{\beta^1}$	-.1131569***	-.0831771**	-.1490427***
	(-4.58)	*(-2.41)*	*(-4.52)*
$\boldsymbol{\beta^2}$	.0001874***	.0004017***	.0001966***
	(5.57)	*(5.26)*	*(5.72)*
$\boldsymbol{\beta^{BC}}$	.0002101**	-	-
	(2.54)		
$\boldsymbol{R^2}$	.3912	.4253	.3070
Adj. $\boldsymbol{R^2}$	.3820	.4135	.2934
No. Obs.	203	99	104

t-values in parentheses; ***significant at a 1%-level; **significant at a 5%-level
Source. own calculations

The coefficient of the interaction term is positive and at least at a 5%-level significant. Hence, in the sampling period, the same quarterly changes in index scores where followed by stronger fluctuations of output in periods of boom than in periods of depression. Estimates for the subsamples in columns 2 and 3 reveal that this was also coupled with a moderately better overall fit in the boom stage. This is the case even though on average trend adjustment happened faster in recession. This indicates that the IHK index played a more substantial role in boom phases within this sampling period.

Finally, we need to stress that general significance of the IHK index for regional output does not rest on our chosen model specification. Alternative specifications of output in absolute levels, log levels and absolute differences have been tested and the index score proved to be significant throughout. In order to allow for some real economic interpretation, however, it seems appropriate to stick to a consistent estimation framework.

7 | Performance in forecasting

In the forecasting literature, researchers are aware that models with good within-sample fits are not necessarily successful in forecasting future values. Our results so far thus do not represent evidence on the predictive quality of the IHK index. A standard procedure to determine forecasting performance based on past data is recursive out-of-sample forecasting (Tashman (2000)). Here, the total sample is split in subsamples across the time dimension: one part is used to fit the model, a subsequent one to evaluate forecasts generated from the fitted model. To obtain a sufficient number of predictions for some forecast horizon out of just one dataset, a rolling scheme is implemented. Forecasts are undertaken repeatedly. Each turn the model subsample used for model fitting is extended by one period, inducing an update of model fit and forecast value. Differences between these out-of-sample predictions and actual values (Forecast errors (FE)) are then accumulated to determine the mean squared forecast error (MSFE):

$$MSFE_h = \frac{1}{N}\sum_{r=1}^{4}\sum_{n=1}^{N}\left(FE_{r,t+h,n}\right)^2$$

with N denoting the number of forecasts for horizon h. The square root of this measure is called the root mean squared forecast error (RMSFE). In the following, we will compute RMSFEs for our two model variants and compare them to RMSFEs observed for benchmark models. Unlike in the previous section, we will do this based on model fits applied to the single regions instead of estimating just one pooled model: given the regional discrepancies in estimated coefficients observed in the previous section, this proves to enhance overall forecasting performance. In addition, we have to specify the exact point in time during period t at which forecasts are made. Since our aim is to test the performance of the IHK index, we define this to be a point where surveys have been undertaken. $BSI_{r,t}$ is thus principally known. Yet unknown is the level of output for the current period. Expectations at this point are marked by E_t. Then, we can compute expected values for current and future output by means of backward operations on model equation (6):

$$E_t y_{r,t} = E_t \tilde{y}_{r,t} + (1+\beta^1)\left(y_{r,t-1} - \tilde{y}_{r,t-1}\right) + \beta^2 BSI_{r,t}^m$$

$$E_t y_{r,t+1} = E_t \tilde{y}_{r,t+1} + (1+\beta^1)^2\left(y_{r,t-1} - \tilde{y}_{r,t-1}\right) + (1+\beta^1)\beta^2 BSI_{r,t}^m$$

$$E_t y_{r,t+h} = E_t \tilde{y}_{r,t+h} + (1+\beta^1)^{h+1}\left(y_{r,t-1} - \tilde{y}_{r,t-1}\right) + (1+\beta^1)^h\beta^2 BSI_{r,t}^m$$

In addition to the current index score, rational forecasting involves expectations on future trends as well as knowledge of the position in the business cycle. Hence, our forecasting strategy is first to predict the trend component, which then enters the prediction of actual log output. For a consistent ex-post evaluation, only values have to enter forecasting which belong to the time span for model fitting, i.e. which are assumed to be known at that time. This also holds for the trend forecasts. Actual forecasts for horizon h are thus calculated in the following way:

$$\widehat{y_{r,t+h}}|_t = \widehat{\tilde{y}_{r,t+h}}|_t + \left(1 + \widehat{\beta_r^1}|_t\right)^{h+1} \left(y_{r,t-1} - \tilde{y}_{r,t-1}\right) + \left(1 + \widehat{\beta_r^1}|_t\right)^h \widehat{\beta_r^2}|_t BSI_{r,t}^m$$

with $\widehat{\beta_r}|_t$ denoting parameter estimates obtained from the (region-specific) model fit at forecasting time in t (i.e. excluding current output $y_{r,t}$). Equivalently, estimates of the trend component $\tilde{y}_{r,t+h}$ are obtained based on output levels of periods no later than $t-1$. Concerning the first model variant, this implies that each forecasting turn we update our parameter estimates for the region-specific trend functions by including an additional observation. Future trend values are estimated by extrapolating the log-linear trend functions into the future. Concerning the second model variant, it means we update the HP-Filter based on the additional observation. Future values are obtained by assuming that estimated trend growth between the two last estimation periods persists in the future,

As the initial time span used to fit the model, we choose a range from 3:2000 to 3:2006. Hence, applying a rolling strategy provides us with a total of $26 \cdot 4 = 104$ estimates for output in the current quarter ($h = 0$), namely for each northern state from 3:2006 to 4:2012. For one-period-ahead forecasts ($h = 1$) we obtain 100 estimates, for two-period-ahead forecasts ($h = 2$) 96 estimates etc. Since our focus is on short-run performance, we refrain from forecasting more than three quarters ahead. The data structure does anyway not suggest a substantial long-run predictive power. The resulting RMSFEs of the two model variants for the four forecasting horizons are reported in table 5.

Table 5: Calculated RMSFEs for different forecast horizons

	h=0	h=1	h=2	h=3
Model 1 (log-lin)	.00946	.01837	.02479	.02957
Model 2 (HP)	.00983	.01997	.02725	.03303
No. Forecasts	104	100	96	92

Source: own calculations

As one should expect, forecasting accuracy shrinks with increasing forecast horizon. For all time spans, model variant 1 performs slightly better. This efficiency gap grows with larger h. Postulating a log-linear trend thus seems to be more appropriate, especially for forecasting more than one quarter ahead. This can be explained by the fact that more long-term information is processed by applying this trend filter. In the following, we will therefore restrict our analysis to the first model variant.

Assessing the suitability of the general model structure requires comparison with a benchmark model. The choice of a benchmark should depend on what one actually prefers to evaluate. If one is interested in evaluating overall forecasting performance compared to an intuitive guess, a standard naïve $AR(q)$-process represents an appropriate choice. However, in our case, the pure contribution of the business survey indicator is also of interest. We therefore present comparisons to two benchmarks, an $AR(q)$-process in log-levels ($B1$) and a restricted version of our model excluding the IHK index ($B2$):

$$B1: \quad y_{r,t} = \beta_r^0 + \sum_{p=1}^{q} \beta_r^p y_{r,t-p} + \varsigma_{r,t}^1$$

$$B2: \quad \Delta\left(y_{r,t} - \widetilde{y}_{r,t}\right) = \beta_r \left(y_{r,t-1} - \widetilde{y}_{r,t-1}\right) + \varsigma_{r,t}^2$$

where the optimal number of lags q in $B1$ is determined based on the Schwarz information criterion. Estimates for the benchmark models are computed based on the same recursive strategy and are used to generate predictions and calculate forecast errors.

To judge whether these models are inferior with respect to forecasting performance, we draw on the Diebold-Mariano (DM) test (Diebold & Mariano, 1995), precisely on the modification proposed by Harvey et al. (1997) for small sample sizes. It is a two-sided test static that compares the size of forecast errors for two competing models, where the null hypothesis is that differences in errors are negligible. The test is originally designed for single time series. Since we analyze performance by pooling several time series, we draw on an additional modification proposed by Bernoth & Pick (2011) for forecasting with panel data. The test statistic in this case is:

$$s(h) = \frac{1}{\sqrt{P}} \sum_{r=1}^{P} s_r(h) = \frac{1}{2} \sum_{r=1}^{4} s_r(h)$$

where $P = 4$ is the number of panels and $s_r(h)$ denotes DM-test results for the time series of the single federal states. Under the null hypothesis, the statistic has a standard normal limiting distribution. We use the test to compare our model variant 1 pairwise with our two benchmarks. Table 6 confronts the resulting MSFEs and presents the two test statistics including p-values for the different forecasting horizons.

Table 6: Benchmark comparisons based on RMSFEs and DM-tests

	h=0	h=1	h=2	h=3
		RMSFE		
Model 1	.00946	.01837	.02479	.02957
Benchmark B1	.01116	.02504	.03539	.04382
Benchmark B2	.01137	.02030	.02634	.03089
		Test-statistic modified DM-test		
Model 1 vs. B1	-2.6644***	-4.0474***	-6.2565***	-8.3623***
	(.0090)	*(.0001)*	*(.0000)*	*(.0000)*
Model 1 vs. B2	-3.9389***	-3.7865***	-2.7389***	-2.2081**
	(.0002)	*(.0003)*	*(.0073)*	*(.0295)*
No. Forecasts	104	100	96	92

p-values of test statistics in parentheses; ***significant at a 1%-level; **significant at a 5%-level
Source: own calculations

Compared to benchmark $B1$, our model exhibits a persistently better performance, where the advantage is large enough to be highly significant. Differences in forecasting accuracy even increase with longer forecasting horizons. However, we also see that this pattern is not exclusively due to the presence of the IHK indicator. With increasing horizon, the autoregressive benchmark is likewise more and more outperformed by the truncated version of our model. This is rather intuitive: compared to the AR-structure, model $B2$ takes more explicit account of medium-run dynamics through the extrapolated trend function. At the same time, the reduction in forecasting error achieved by including the IHK indicator into our model loses significance with larger h, even though performance of this full model in relation to $B1$ further improves. Trend dynamics thus seem to gain in importance compared to assessments at forecasting time for larger h. In the end, this confirms our notion of the IHK index as a signaling tool for short-run shocks in the business cycle.

Given that these numbers were derived from forecasts for the single time series, we are also able to report comparative forecasting results at state level, being aware that observation numbers are here too low for test-based inference. Signs of regional heterogeneity are nevertheless detectable. Within this sample, our model has performed best in Hamburg and Lower Saxony regarding both reported horizons. However, comparing performance of the truncated model $B2$ leads to an equivalent ranking, indicating that this heterogeneity is not necessarily an outcome of differences in the forecasting power of the IHK index. Comparing $B2$ with the full model, a main result is nevertheless that the inclusion of the index score has lowered average forecast errors in all single states.

Table 7: RMSFEs reported for forecasts in the single states

	Bremen	Hamburg	Lower Saxony	Schlesw.-Hol.
		RMSFE (h=0)		
Model 1	0.01279	0.00704	0.00733	0.00951
Benchmark B1	0.01490	0.00897	0.00925	0.01226
Benchmark B2	0.01514	0.00874	0.00863	0.01170
No. Forecasts	26	26	26	26
		RMSFE (h=1)		
Model 1	0.02540	0.01410	0.01326	0.01817
Benchmark B1	0.03439	0.01901	0.01775	0.02547
Benchmark B2	0.02787	0.01585	0.01466	0.02015
No. Forecasts	25	25	25	25

Source: own calculations

8 | Conclusion

We have tested the usefulness of the regional IHK business climate index as an indicator for short-run output growth in Northern Germany. In this way, we have contributed to the emerging literature on survey-based forecasting techniques concerning production at the regional level. Estimates of our theoretical framework have pointed to a significant explanatory power of the index score, which cannot be traced back to information already implicit in the position within the business cycle. Tests of forecast accuracy based on out-of-sample predictions have confirmed this impression. Compared to a standard autoregressive benchmark, our model performs significantly better for all tested time horizons. This observation can also be made at the level of all single northern states.

Furthermore, modifications of our basic setup have brought relevant insights. We could detect some signs for a structural difference in the relationship between indicator and output growth when comparing times of boom with times of recession. Furthermore, national shocks seem to have partly been absorbed by regional survey responses, but do surely not represent the only source of the surveys' information content. This suggests the presence of complex mechanisms of shock transmission, which might be identifiable by a simultaneous equation approach.

For the future, an obvious task is to examine the relative performance of the IHK index by letting it compete against other regional business surveys, preferably at a wider regional level. However, following this road requires improvements in data availability. On the parts of statisticians, efforts have to be made in two directions. First, techniques of sample selection and data collection should be further harmonized among different regional indices. Otherwise it is hard to say whether the bad forecasting performance of an indicator is due to a flawed sample design or due to differences in the economic agenda of the survey respondents. Second, more temporarily disaggregated data on regional output is needed. In this regard, appropriate methods for disaggregation are at hand, what is missing are sufficiently long time series for disaggregation indicators at the regional level. Data updates and harmonization in the course of changes in classification schemes should thus be intensified.

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10 | Appendix

10.1 | Construction of the IHK business climate index

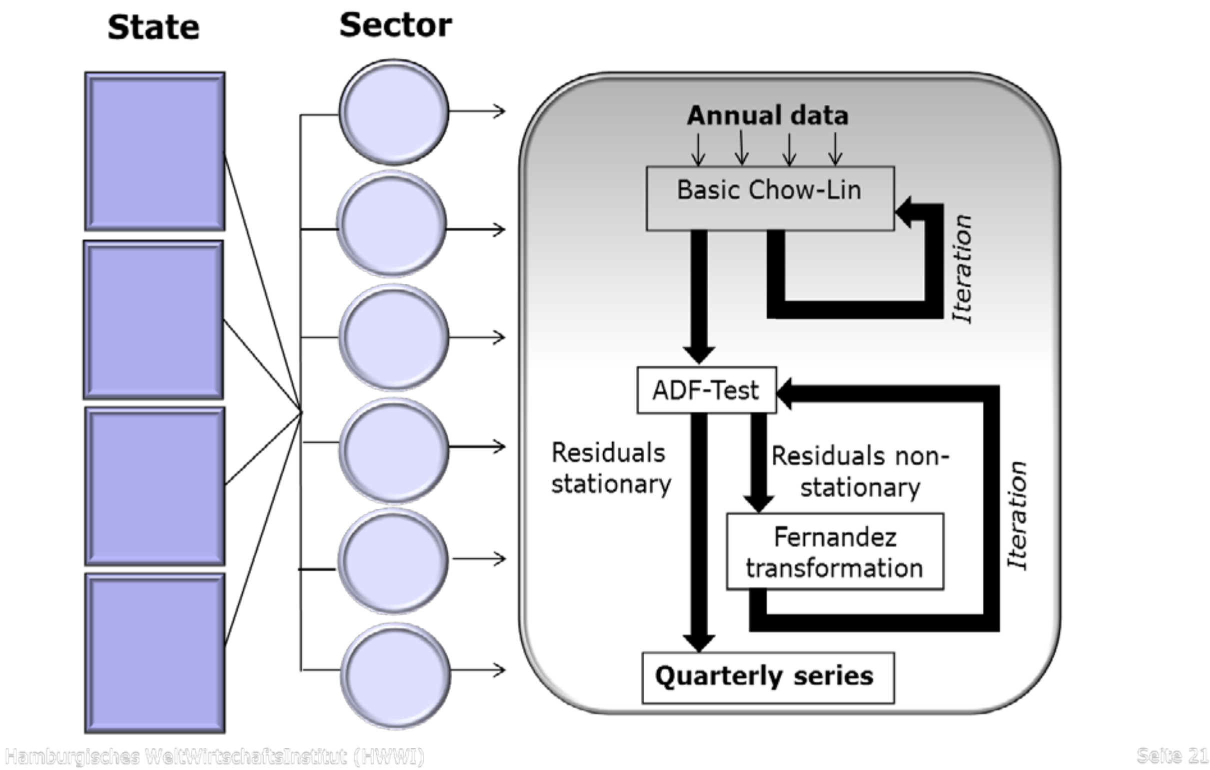
Questions:
1. "How does your company assess its current situation?"
2. "Which developments does your company expect in the next 12 months?"

a. Good b. Satisfactory c. Bad

Answers weighted

BSD Indicator = $\sqrt{\left(\left(\frac{(1a-1c)*100}{Total\ Replies}\right)+100\right)*\left(\left(\frac{(2a-2c)*100}{Total\ Replies}\right)+100\right)}$

10.2 | Disaggregation methodology

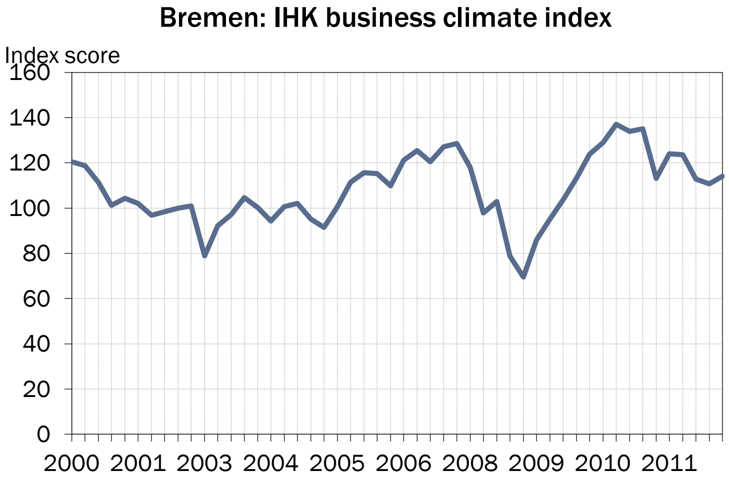


Source: own representation

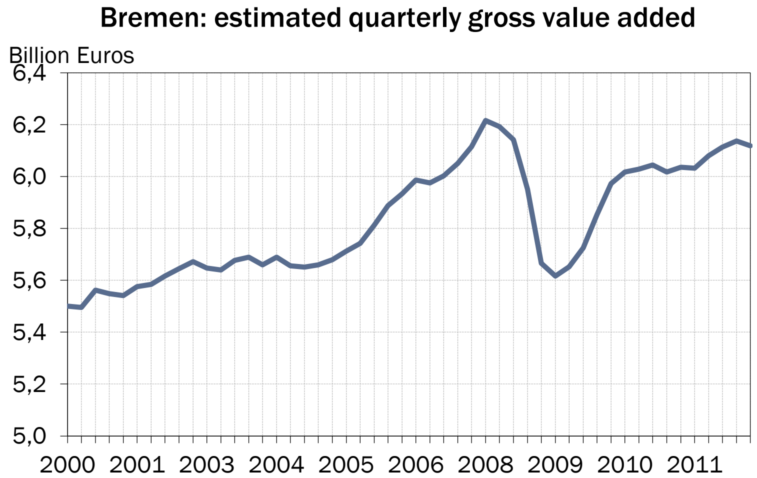
Steps undertaken to generate quarterly production data at federal state level:

1. For the four northern states, annual data on (deflated) sectoral gross value added (GVA) was organized for the time span 1991-2012. The sectoral decomposition consisted of the following six sectors (s) : agriculture and fisheries, manufacturing and energy, construction, trade and transport, financial services and insurance, public and remaining private services.
2. For the same six sectors, quarterly data on (deflated and seasonally adjusted) GVA at the national level was organized for 1991-2012 as indicator series.
3. The relationship between regional values (Y_r) and national values (Y^n) at annual level was estimated based on a simple linear model for each sector in each state separately:
$$Y_{s,r,t} = \beta_{s,r} Y_{s,t}^{n} + \upsilon_{s,r,t}$$
4. Preliminary estimates for $\beta_{s,r}$ were gained based on the BLUE estimator described in Chow & Lin (1971).
5. Stationarity of residuals $\upsilon_{s,r,t}$ was checked by means of ADF-tests.
6. In case the null-hypothesis of non-stationarity could be rejected, the estimates of $\beta_{s,r}$ gained from basic Chow-Lin were used together with estimates of residual autocorrelation to distribute annual sectoral GVA between quarters.
7. In case the null hypothesis could not be rejected, the first-difference transformation suggested by Fernandez (1981) was undertaken and alternative estimates were gained based on the transformed model:
$$\Delta Y_{s,r,t} = \beta_{s,r} \Delta Y_{s,t}^{n} + \upsilon_{s,r,t}^{Fer}$$
8. Residuals of the transformed models $\upsilon_{s,r,t}^{Fer}$ again entered ADF-tests. If they could be identified as stationary, these models were used to generate quarterly data as described in Fernandez (1981). If stationarity still could not be confirmed, the first-difference transformation was repeated for the given sector in the given region and newly gained residuals tested until stationarity was achieved.
9. The resulting sectoral output estimates were aggregated to quarterly GVA for the northern states for 1991-2012.

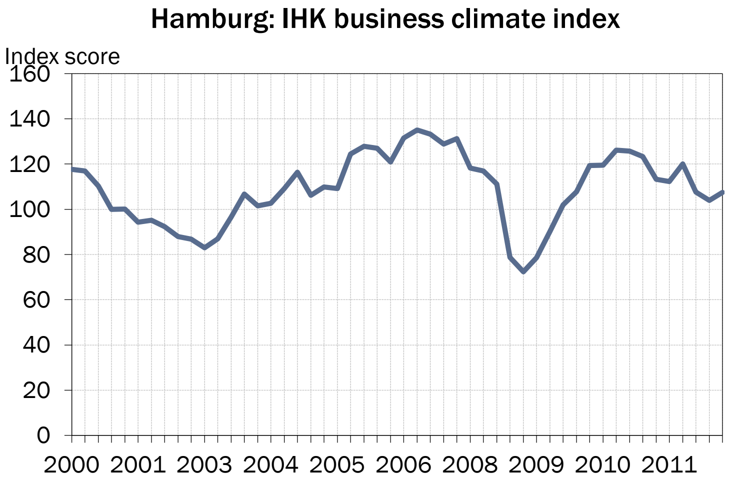
10.3 | Time series for disaggregated GVA and scores of the IHK index



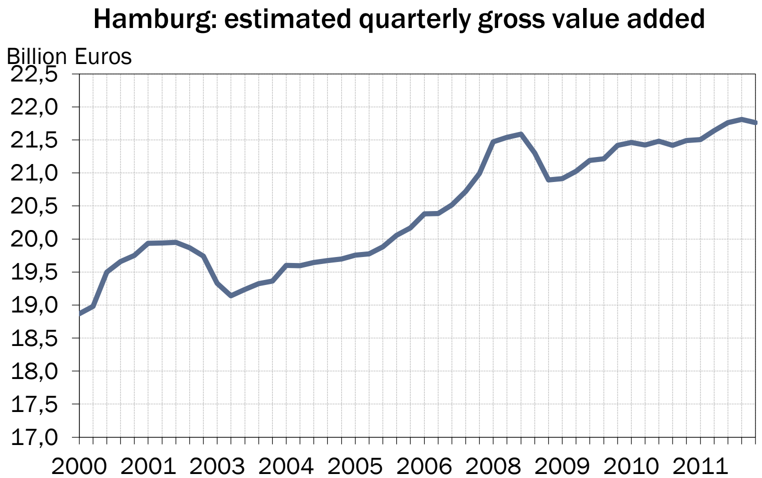
Source: IHK Bremen



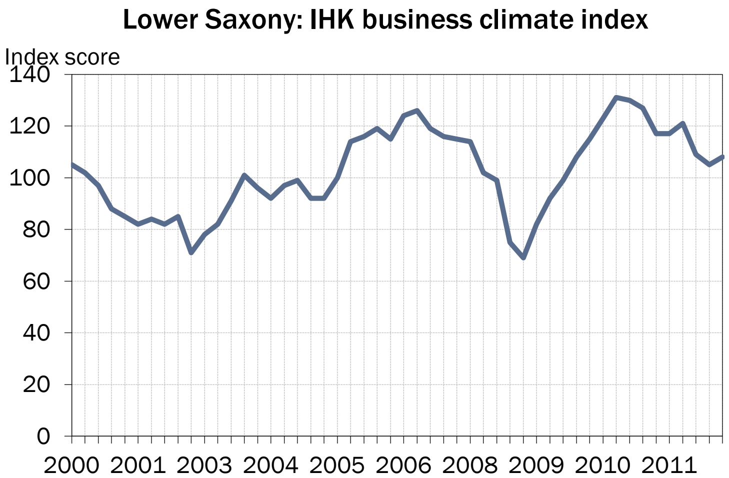
Source: I Federal statistical office (2013); own calculations



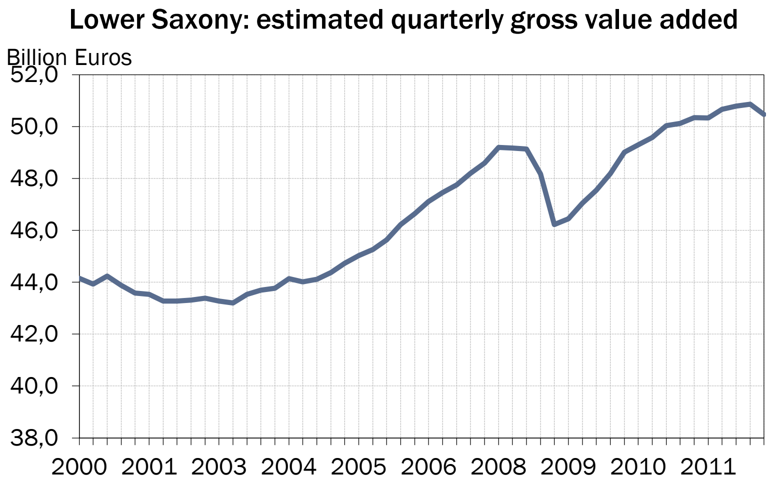
Source: IHK Hamburg



Source: I Federal statistical office (2013); own calculations



Source: IHK Lower Saxony



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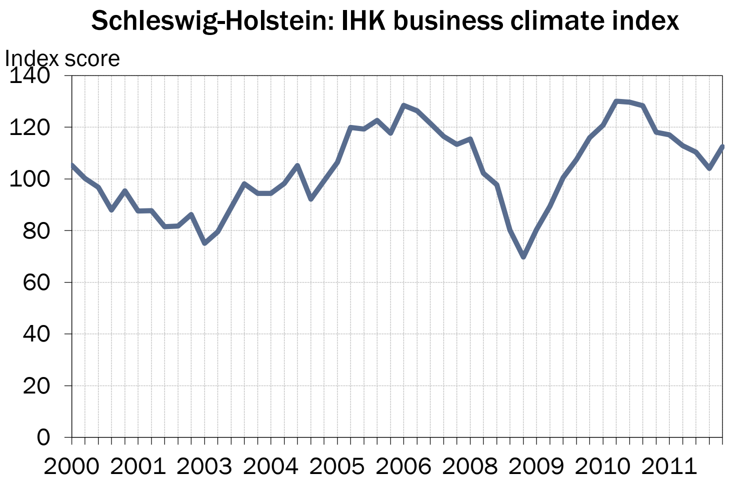
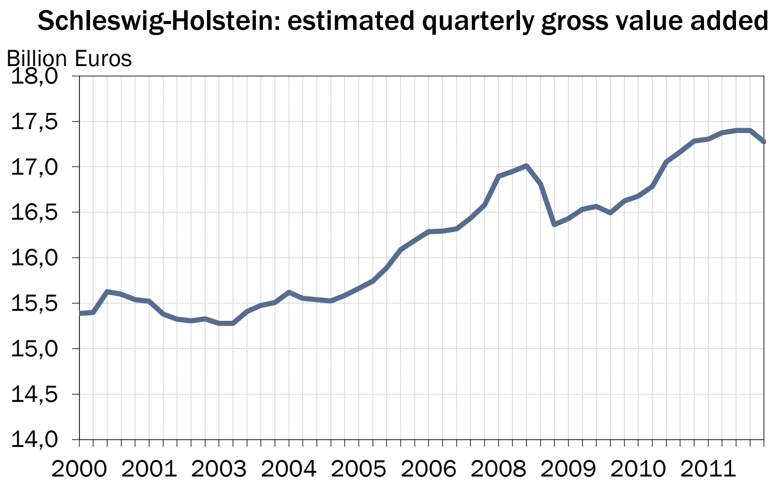


Source: IHK Schleswig-Holstein



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