“In-sample and out-of-sample performance of alternative business cycle indicators in core European countries”

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1 Introduction

This study includes two different but related research questions. The first one is to compare the explanatory power of several popular business cycle indicators for the industrial production (in-sample analysis) in the three core European countries Germany, France and Italy. This in-sample analysis also asses the question whether structural differences in explaining industrial production exist. The second question is if leading indicators help to improve the accuracy of short-term industrial production forecasts (out-of-sample analysis) for the same set of countries.

Germany, France and Italy are the three biggest economies in the Euro area. In 2010, these countries accounted for more than 60% of the real gross domestic product (GDP) in the Euro area (Eurostat, 2011). Moreover Germany, France and Italy are the only Euro area member states which join the meetings of the “Group of Eight” (forum for the governments of eight of the world’s largest economies).

Most of the literature reviewed so far evaluates the in-sample or/and out-of-sample performance of different leading indicators for either only one of the three countries (e.g. Hüfner and Schröder, 2002; Fritsche and Stephan, 2002; Funke, 1997; Marchetti and Parigi, 2000; Bruno and Lupi, 2004; Dreger and Schumacher, 2005) or for the Euro area aggregation (Marcellino et al., 2003; Ozyldirim et al., 2010; Carstensen et al., 2011; Forni et al., 2001). Two exceptions are the papers by Bodo et al. (2000) and Camba-Mendez et al. (2002). Bodo et al. (2000) found out that for Germany, France, Italy and Spain, the forecasting ability of Vector Autoregression (VAR) models that include the Business Confidence Indicator published by the European Commission, outperform that of standard ARIMA models. Camba-Mendez

et al. (2002) showed that by using the OECD leading indicator as an additional exogenous variable, the forecast results of different VAR models can be improved for Germany, France, Italy and the U.K. However, instead of comparing a large set of different business cycle indicators, both papers focused on one leading indicator only. Therefore, the intention of this study is to extend the existing literature in a way that several business cycle indicators will be compared for three different (major) European countries and over the same time period.
The recent European debt crisis has led to political will for the introduction of debt brakes in the member states (The Economist, December 2011, 56-57; Begg et al., 2011).

In March 2011, the General Secretary of the European Council wrote:

"Participating Member States commit to translating EU fiscal rules as set out in the Stability and Growth Pact into national legislation. Member States will retain the choice of the specific national legal vehicle to be used, but will make sure that it has a sufficiently strong binding and durable nature (e.g. constitution or framework law). The exact formulation of the rule will also be decided by each country (e.g. it could take the form of a 'debt brake', rule related to the primary balance or an expenditure rule), but it should ensure fiscal discipline at both national and sub national levels." (European Council, 2011a, 19).

Most of the European governments either plan a referendum about the eurozone fiscal treaty or already introduced it into their constitutions (e.g. The Guardian, February, 2012; European Council, 2011b). The fiscal treaty includes a national debt brake. This policy instrument requires to generate reliable forecasts about the future development of tax revenues which are mostly based on GDP forecasts. Moreover, the current economic situation of the Euro area member states seems to suggest that, in contrast to an optimal currency area (Mundel, 1961), there is not one common European business cycle. While the economies of Germany, the Netherlands or Finland still grow, other countries like Spain, Portugal, Greece or even Italy suffer a severe recession (International Monetary Fund, 2011). These facts illustrate that there exist an increasing demand for accurate *country-specific* forecasts from

institutions like the European Commission, the European Central Bank or the national governments.

Furthermore, industrial production which is available on a monthly basis is widely used as a hard indicator of aggregate output (e.g. Breitung, Jagodzinski, 2001; Bodo et al., 2000; Carstensen et al., 2011; Camba-Mendez et al., 2002; Hinze, 2003). This is due to the fact that the economic cycle is influenced mainly by the activity of the industrial sector (Bodo et al., 2000; Rossen, 2012).

For these reasons, I want to study whether there exist structural differences in explaining industrial production by the help of alternative leading indicators between the three EU member states (in-sample analysis). Additionally, I want to find out which leading indicator predicts industrial production most accurately for each of the selected countries (out-of-sample analysis).

2 Data

The study will consider a wide range of different business cycle indicators published by various institutions like national statistical offices, central banks or research institutes (for more details see Appendix A) over the time period 1993*M02* to 2011*M10*. The indicators differ in their aggregation level (survey or macroeconomic data) and in their composition (raw data or combination of different data sets). The target series is the year-over-year growth rate of the industrial production index for the three European countries as published by Eurostat. As shown in other studies business cycle indicators are useful instruments for explaining and predicting industrial production especially in the short-run (e.g. Hinze, 2003; Rossen, 2012).

For Germany, nine alternative business cycle indicators will be used, eight for France and five for Italy. All variables are transformed into stationary series. Appendix A shows if levels or first differences of the indicator variables reject the null hypothesis of non-stationarity at a significant level of 10% when applying generalized least squares-based unit root tests. The growth rate series of the industrial production index rejects the null hypothesis at the same 10%-significant level for all three countries.

Figure 1 shows the one-year percentage change of the industrial production indices for Germany, France, Italy and the Euro area over the time period 1993*M02* to 2011*M10*. Table 1 reports descriptive statistics of these series.

All four industrial production growth rates follow more or less the same pattern: A strong cyclical behavior between 1992 and 2007, the deep recession in 2009 due to the world economic crisis and a strong recovery afterwards. All four industrial production indices show there strongest decrease in 2009*M04*.

Only the German industrial production grew, on average, faster than the industrial production of the Euro area. Italy suffered the lowest percentage changes of the industrial production for the three considered countries. The growth rate of the German industrial production also shows the highest volatility (measured as the standard deviation) of all the four series. On the other hand, for the percentage change of the industrial production of France, the lowest standard deviation can be observed. Surprisingly, while showing the lowest average growth rate, the Italian industrial production series is more volatile than those series for France and the Euro area. In the recovery period of the world economic crisis (2010*M04* or 2010*M05*), the industrial production indices of Germany, France and the Euro area show their highest growth rates (14.35%, 8.59%, and 9.57%). In contrast, the Italian industrial production grew the most in 1994*M12* (11.66%).

Figure 1: One-year percentage change of industrial production

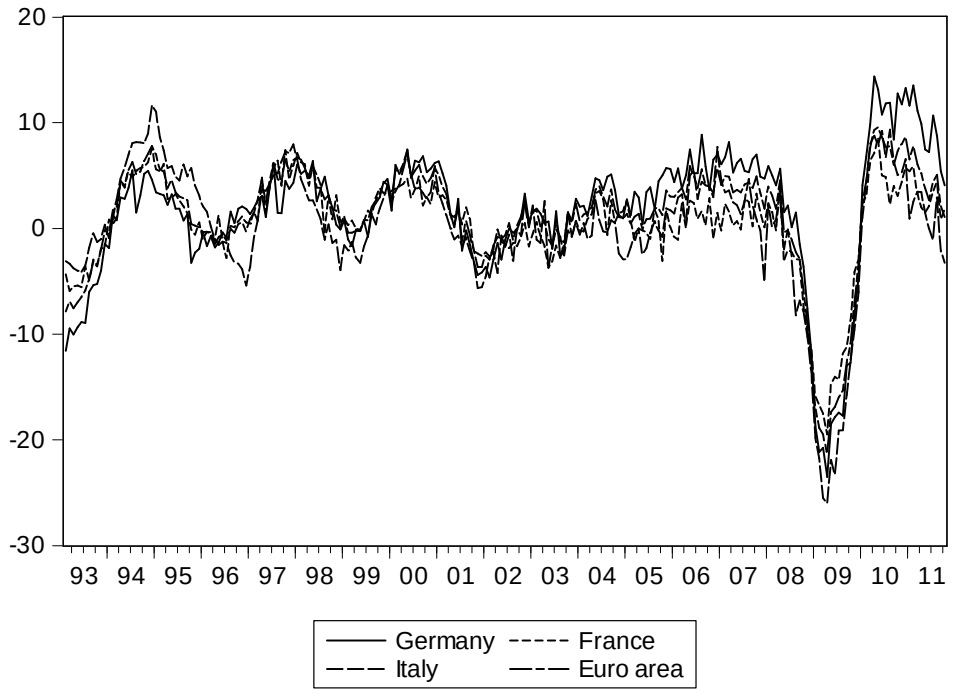


Table 1: Descriptive statistics of the one-year percentage change of the industrial production indices (1993*M02* to 2011*M10*)

	Germany	France	Italy	Euro area
Mean	1.66	0.52	0.22	1.30
Standard Deviation	6.25	4.50	6.04	5.26
Minimum	-23.51 (2009*M04*)	-19.50 (2009*M04*)	-25.99 (2009*M04*)	-21.33 (2009*M04*)
Maximum	14.35 (2010*M04*)	8.59 (2010*M05*)	11.66 (1994*M12*)	9.57 (2010*M05*)
Observations	225	225	225	225

3 Methodology

As suggested by Goodhardt et al. (2004), Stock and Watson (1996) and Carstensen et al. (2011) rolling regressions with a fixed window size will be employed to identify structural differences between the leading indicators for each country and between the countries. Rolling regression with a fixed window size means that the length of the estimation period is held fixed by rolling both initial date and ending date one at a time. In this study, structural differences are understood as differences in "lagged causality" or Granger-Causality (for more details see next subsection).

In addition to that and in line with the recent literature on business cycle forecasts, these rolling regressions will be used to generate short-term (one month) out-of-sample forecasts (Marcellino et al., 2003; Ozyldirim et al., 2010; Carstensen et al., 2011; Stock and Watson, 1996; Dreger and Schumacher, 2005). To compare the forecasting ability of different models, the standard root mean squared error will be considered.

3.1 In-Sample Analysis

The following regression model will be employed for the in-sample analysis:

$$y_t = \alpha_{t_*} + \sum_{i=1}^{p} \emptyset_{i,t_*} y_{t-i} + \theta_{t_*} x_{t-1} + \varepsilon_t \qquad (1)$$

where y_t is the (country-specific) year-over-year growth rate of the industrial production index for the three European countries Germany, France and Italy. x_t denotes one of the aforementioned business cycle indicators which are taken as

exogenous or predetermined. t represents the month and ε_t is an error term which is assumed to be independent and identically distributed (i.i.d.). t_* stands for the observation period of the calculated rolling regression. The initial observation period ranges from 1993*M02* to 2001*M01* ($T = 96$) and the sample of the last regression is 2003*M10* to 2011*M09*. It follows that for every specification of equation (1) 129 different regressions will be calculated.

$\alpha_{t_*}, \emptyset_{t_*}$ and θ_{t_*} are (time-varying) coefficients of the specific observation period t_* that have to be estimated by using ordinary least squares. Equation (1) will be estimated for each country and indicator separately.

The model with a θ_{t_*} unequal to zero implies that the business cycle indicator of the last period includes information that helps explaining the current period industrial production. In other words, the underlying assumption of the model is that the business cycle indicator (x_t) helps predicting the growth rate of the industrial production in the sense of Granger (Granger, 1969).

Confidence bands, t-values and Bayesian Information Criteria will be used to identify differences in Granger-Causality between the models and within the countries. These differences in Granger-Causality will be seen as structural differences in explaining industrial production, which is in line with the strategies of Carstensen et al. (2011) and Marcellino et al. (2003).

Similar to the studies by Carstensen et al. (2011) and Fritsche and Stephan (2002) the maximum number of lags for the endogenous variable is equal to 13 ($p = 13$). The reason for it is justified by the assumption that an exogenous shock, on average, influences the endogenous variable for about one year (e.g. Dedola and Neri, 2007). An observation period of 96 months or eight years is considered because a common assumption states that business cycles last about four years (e.g. Canova, 1998; Carstensen et al., 2011). From this it follows that two consecutive business cycles form the basis for the rolling regression estimations. In a later paragraph ("Robust analysis") it will be tested if the out-of-sample results change significantly when a larger window size of 120 months or 10 years is used.

At each point in time the rolling regressions generate specific parameters and t-values for the coefficients $\alpha_{t_*}, \emptyset_{t_*}$ and θ_{t_*}. The main interest of this study lies in the time-varying coefficients of the one period lagged business cycle indicators (θ_{t_*}). For each leading indicator it will be studied how this parameter and its statistical significance (t-values) change over time. Therefore, the hypothesis that has to be

tested for all the different business cycle indicator models at each point in time (one-point-wise testing) t_* is:

$$H_0: \theta_{t_*} = 0, \forall\, t_* \qquad .$$

If θ_{t_*} is not statistical significant, this would imply that the business cycle indicator of the last month does not include information that helps explaining today's industrial production or, as mentioned before, that the business cycle indicator does not "Granger cause" the growth rate of the industrial production.

While this approach allows statements about the specific parameters of the business cycle indicators and its statistical significance only, time-dependent Bayesian Information Criteria of the different regression models will be calculated also (Clark and McCracken, 2010). As long as the sample size is the same, which is given for rolling regressions with a fixed window size, the Information Criterion allows comparing models with different degrees of freedom (Lütkepohl and Krätzig, 2004, 111). The Bayesian Information Criterion places a "premium on achieving a given fit with a smaller number of parameters per observation" (Greene, 2003, 160). By doing so, the different business cycle indicator models can be evaluated for each country and indicator separately. As shown by Lütkepohl (1985) and Stock and Watson (1999), the Bayesian Information Criterion often selects better forecasting models than the Akaike Information Criterion.

In line with the study by Bodo et al. (2000), the Ljung-Box test will help to study if the error terms of the rolling regression models suffer from autocorrelation. If the error terms show serial correlation, the lag structure (p) of the specific regression model will be adjusted by changing the maximum number of lags for the endogenous variable.

As benchmark, a model which includes no business cycle indicator and therefore a constant and 13 lags of the endogenous variable (13 lags of the industrial production index) only will be employed for the three countries.

3.2 Out-of-Sample Analysis

For the out-of-sample analysis, short-term (one month) forecasts of the industrial production will be generated by using the rolling regression results of equation (1):

$$y_t^f = \hat{\alpha}_{t_*} + \sum_{i=1}^{p} \hat{\emptyset}_{i,t_*} y_{t-i} + \hat{\theta}_{t_*} x_{t-1} \tag{2}$$

$\hat{\alpha}_{t_*}$, $\hat{\emptyset}_{t_*}$ and $\hat{\theta}_{t_*}$ are the estimated coefficients of equation (1) and y_t^f is the predicted value of the current industrial production given the 13 lags of the endogenous variable and the last period value of the specific business cycle indicator. As mentioned by Hinze (2003) leading business cycle indicators are an adequate instrument for predicting industrial production especially in the short-run. Given that the initial observation period ranges from 1993*M02* to 2001*M01*, the first forecast date is 2001*M02*. It follows that the last forecast is calculated for 2011*M10*.

To compare the forecasting ability of different regression models, root mean squared errors (RMSE) will be computed. The RMSE is defined as follows (e.g. Armstrong and Collopy, 1992; Fildes and Ord, 2002; Franses, 1998; West, 2006):

$$RMSE_i = \sqrt{\frac{1}{P} \sum_{t=T+1}^{T+P} \left(y_t - y_{i,t}^f\right)^2} \tag{3}$$

where y_t is the realization of the target variable (year-over-year growth rate of industrial production) and $y_{i,t}^f$ is the value predicted by model i. Therefore $y_t - y_{i,t}^f$ represents the forecast error of model i. The forecast period ranges from $T+1$ (*2001M02) to* $T+P$ (2011*M10*), which implies that 129 different forecasts will be calculated for every business cycle indicator model ($P = 129$).

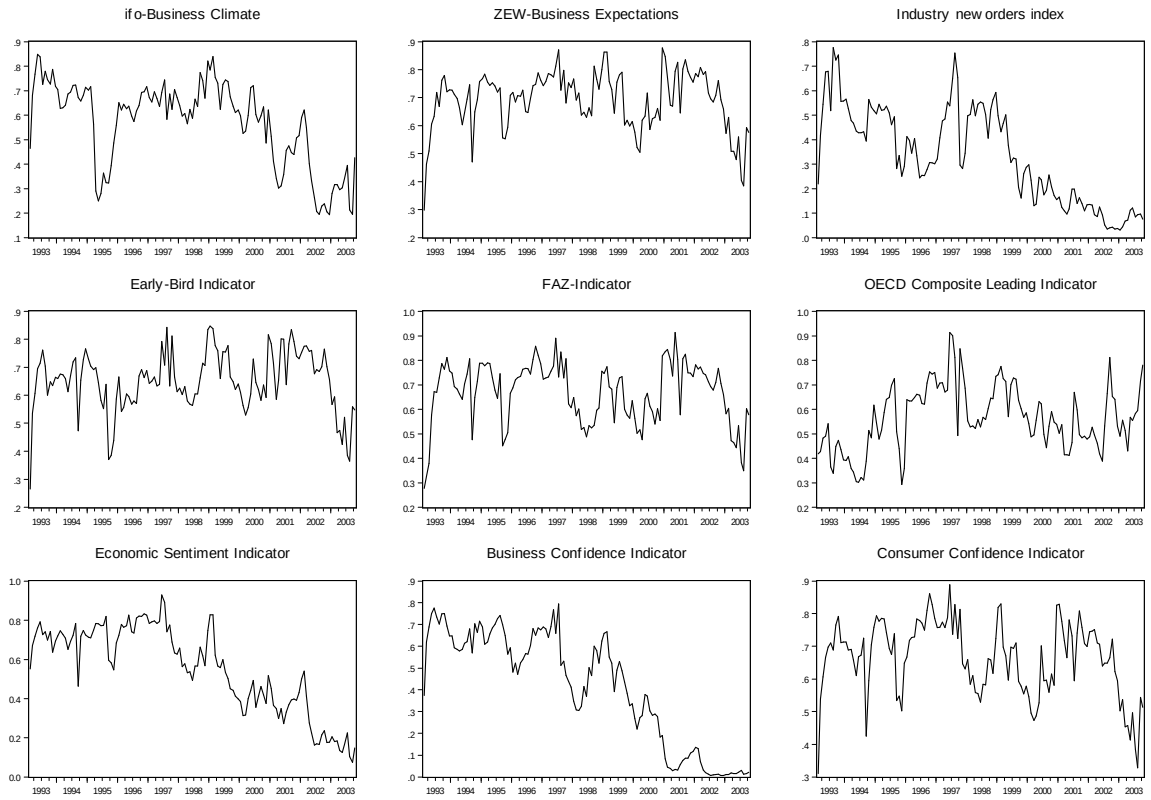
The RMSE allows statements about the forecasting performance of the different regression models. By comparing two competing models, the model with the smaller RMSE should be chosen. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors.

Similar to the in-sample analysis, a model with a constant and 13 lags of the endogenous variable only, will be used as a benchmark model. For Germany, 10 different RMSE will be calculated (nine for the alternative business cycle indicator models and one for the benchmark model), nine for France (eight, one) and six for Italy (five, one).

4 First round of business cycle indicator models

Before comparing the specific results for each indicator and country separately, it should be tested if the estimated error terms of the models suffer from serial autocorrelation. Therefore, the Ljung-Box test is calculated for the error terms of every rolling regression model, whereby the maximum number of lags included in the test is equal to 13. The Ljung-Box test assesses the null hypothesis that a series of residuals exhibits no autocorrelation for a fixed number of lags (here 13) (Ljung and Box, 1978).

Figure 2: Minimum probabilities for the Q-statistic of the rolling regressions* (Germany)

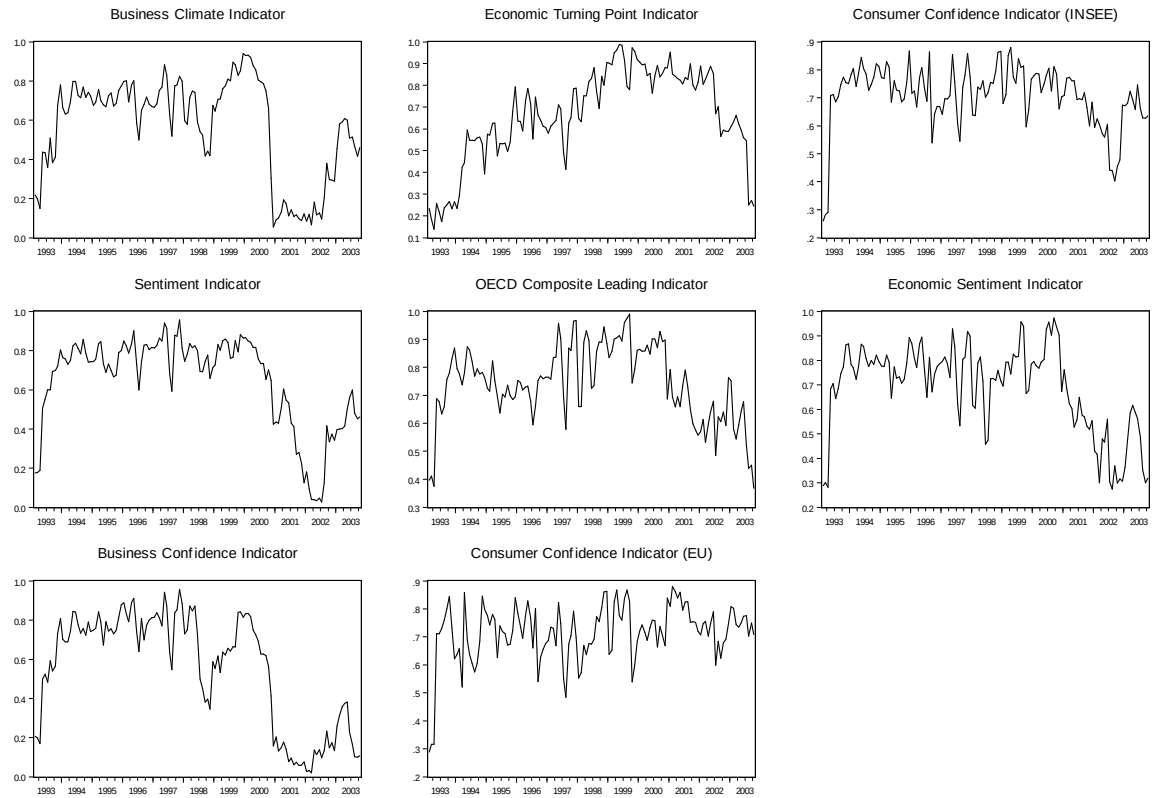


* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Maximum number of lags included in the Ljung-Box test is equal to 13.

Figures 2-4 show the minimum of the probabilities for the Q-statistic associated with the aforementioned fixed number of lags for every business cycle indicator model and at every point in time for the three countries of interest. For these and the following figures, the starting dates of the rolling regressions are represented on the time axes. To give an example, the values at 1995*M02* correspond to the minimum probabilities for the Q-statistic from the regression estimated over the period 1995*M02* to 2003*M01*.

It turns out that in general the residuals of the individual business cycle models are not serial correlated. Hence, autocorrelation of the error terms seems not to be a problem for the estimated regressions.

Figure 3: Minimum probabilities for the Q-statistic of the rolling regressions* (France)

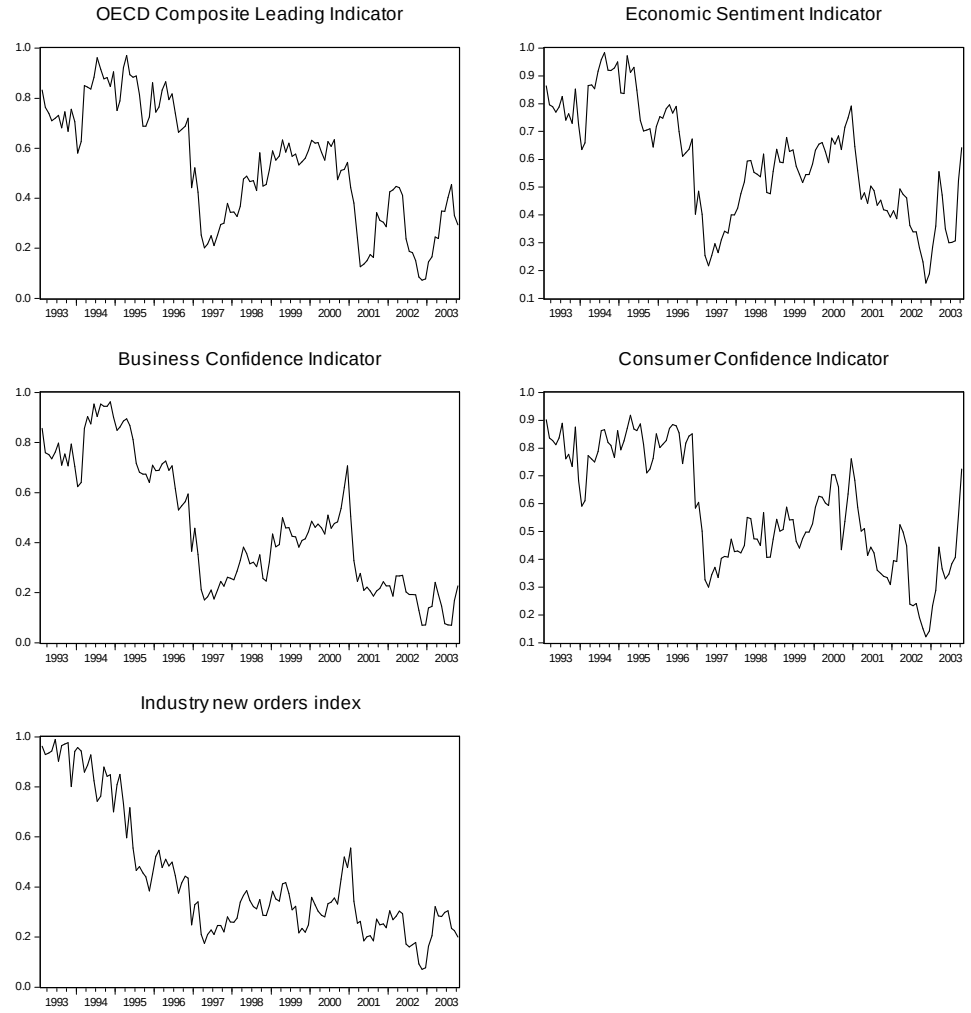


* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Maximum number of lags included in the Ljung-Box test is equal to 13.

In the case of Germany (Figure 2), for seven of the nine regression models the minimum probabilities for the Q-statistic lie above a critical value of 5% at each of the 129 observations (1993*M02* to 2003*M10*). Only for the two models which include the Industry new orders index or the Business Confidence Indicator respectively the

probabilities fall below the 5% level at the end of the sample period. For France (Figure 3), the rolling regressions using the Sentiment Indicator and the Business Confidence Indicator show probabilities below 5%, while all regression models for the Italian industrial production (Figure 4) show Q-statistics above 5% at each point of the observation period.

Figure 4: Minimum probabilities for the Q-statistic of the rolling regressions* (Italy)



* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Maximum number of lags included in the Ljung-Box test is equal to 13.

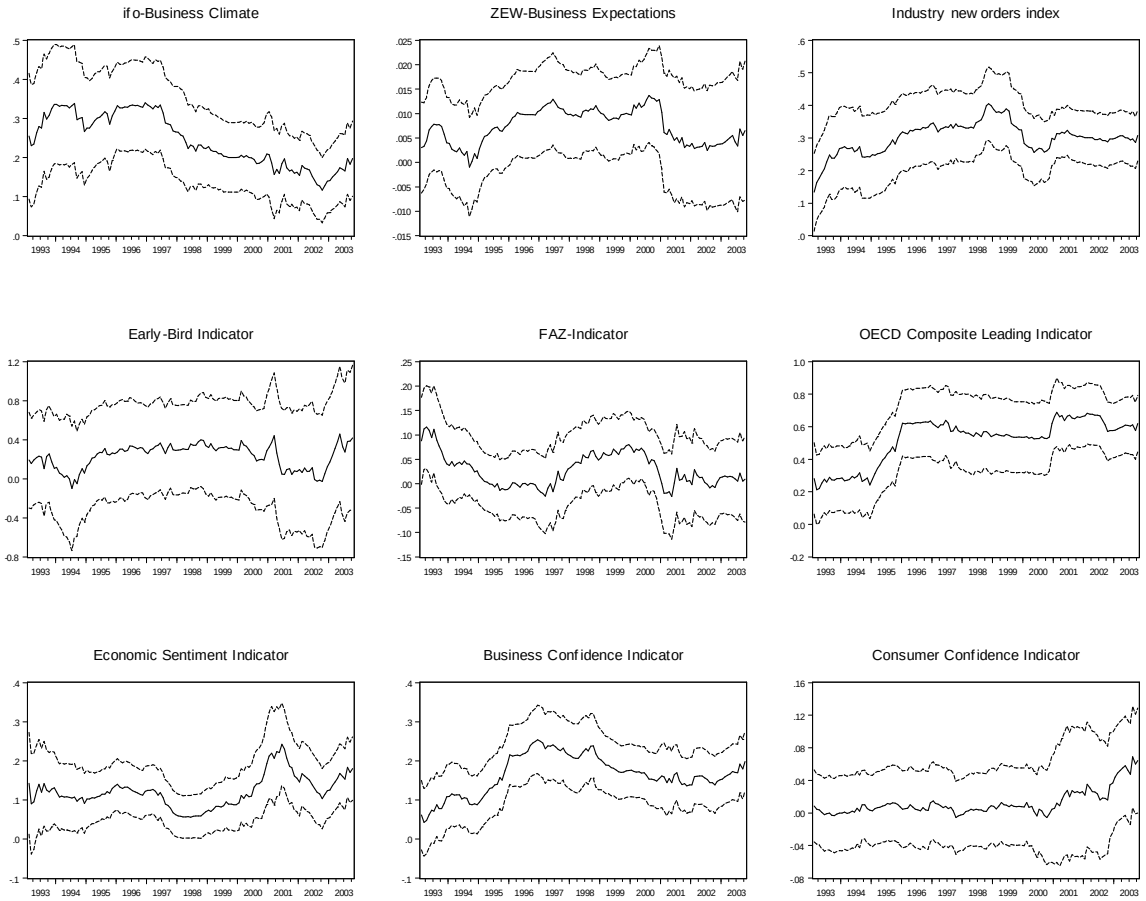
The minimum probabilities for the Q-statistic of nearly all considered models decrease at the end of the sample period. The reason for it could be seen in the economic downturn of the economies under study between 2007 and 2009, which is included in regressions starting 2001 and later. The results indicate that for the models estimated here, autocorrelation of the error term could be a problem for

regressions that take only data of the world economic crisis into consideration. However, adjusting the maximum number of lags included in the business cycle indicator models seems not to be necessary.

4.1 Germany

Figure 5 presents the estimated (time-varying) coefficients $\hat{\theta}_{t_*}$ and its upper/lower 95% confidence bands for every of the nine German business cycle indicator models. In what follows, coefficient uncertainty is understood as the case in which the lower and upper confidence bands show different signs. A negative business cycle indicator coefficient seems to be meaningless, because all indicators are constructed in a way that a higher (lower) value would indicate a future economic upturn (downturn).

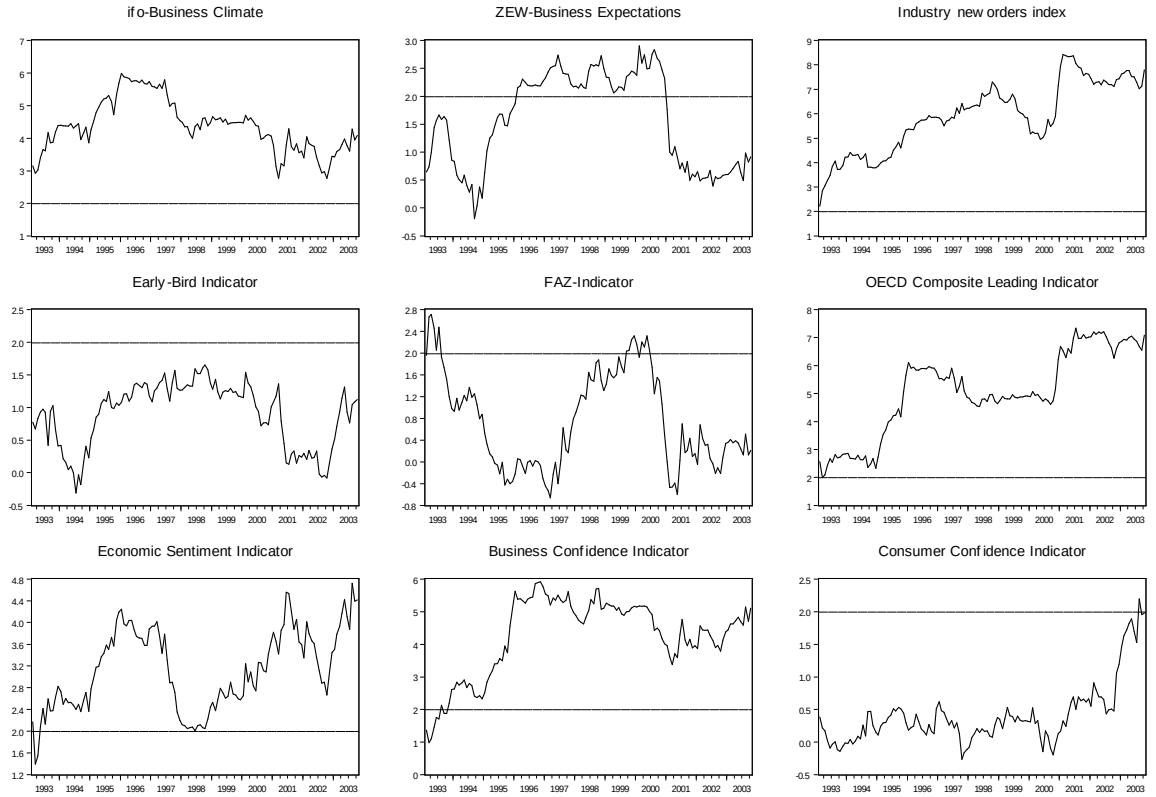
Figure 5: Estimated business cycle indicator coefficients and 95% confidence bands* (Germany)



* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Solid line: estimated business cycle indicator coefficient. Dashed line: 95% confidence bands of the estimated business cycle indicator coefficient.

The models that include the ifo-Business Climate, the Industry new orders index and the OECD Composite Leading Indicator do not suffer from coefficient uncertainty. In other words their lower and upper confidence bands take always positive values. In contrast, the rolling regressions of the ZEW-Business Expectations, the Early-Bird Indicator, the FAZ-Indicator, and the Consumer Confidence Indicator show large coefficient uncertainty problems. For the Early-Bird Indicator specification and also for the Consumer Confidence Indicator model, the upper confidence bands are always positive while the lower ones are always negative. The lower confidence bands of the Business Confidence Indicator and the Economic Sentiment Indicator model are most of the time positive. Nevertheless, there are some periods for which the signs of the two confidence bands differ.

Figure 6: T-values for the business cycle indicator coefficients of the rolling regressions* (Germany)



* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Solid line: t-value for the business cycle indicator coefficient. Dashed lines: 95% critical t-value (1.99).

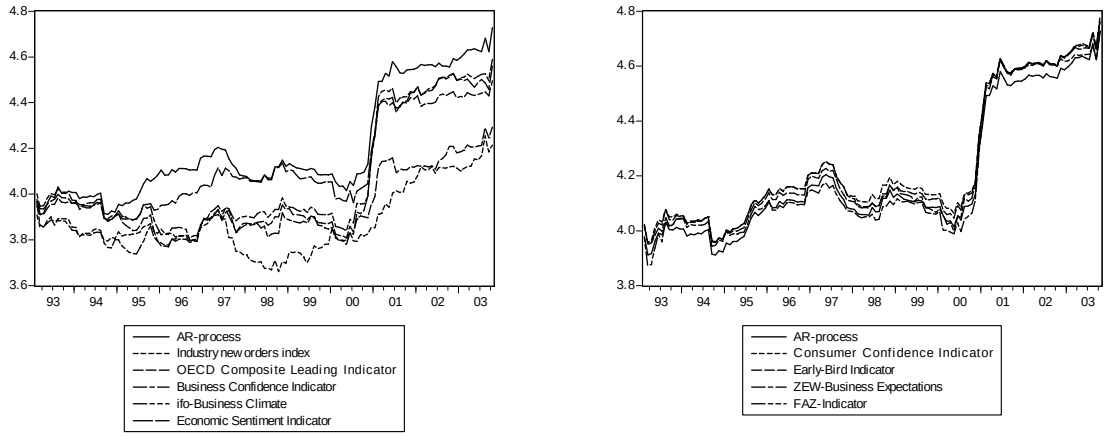
In addition to that, Figure 6 shows the time-dependent t-values for the business cycle indicator parameters of each estimated model. Given a sample range of 96 periods for every rolling regression and 15 parameters to estimate (one constant, 13

autoregressive coefficients, and one business cycle indicator coefficient), the 95% critical t-value is equal to 1.99.

The results are in line with those already mentioned for Figure 5. The specific business-cycle indicator parameters of the ifo Business Climate, the Industry new orders index and the OECD Composite Leading Indicator are significantly different from zero at each period. This means that these three indicators cause the German industry production in the sense of Granger at each point of the observation period. On the other hand, the Early-Bird Indicator is not significant at every point in time which implies that this indicator does not include information that helps explaining the German industrial production within the econometric framework considered here. For most of the time periods the ZEW Business Expectations, the FAZ-Indicator and the Consumer Confidence Indicator show no significant influence on the German industrial production. The Economic Sentiment Indicator and the Business Confidence Indicator are statistically significant for most of the time points. However, both indicators do not influence the industrial production significantly at the beginning of the sample range.

The analysis so far allows statements about the specific parameters of the different business cycle indicator models only. Therefore, Figure 7 shows the time-varying Bayesian Information Criterion of the alternative business cycle indicator models. This procedure follows the work by Clark and McCracken (2010). For optical reasons, the models are separated in two different groups. The first graph represents the results for the rolling regressions of the ifo Business Climate, the Industry new orders index, the OECD Composite Leading Indicator, the Economic Sentiment Indicator and the Business Confidence Indicator, while the results of the remaining models are shown in the second graph. As a benchmark, the Bayesian Information Criterion of the specification with a constant and 13 lags of the industrial production only is also illustrated (“AR-process”).

Figure 7: Bayesian Information Criteria of the rolling regressions* (Germany)



* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. AR-process does not include any business cycle indicator in the estimated regressions.

All the models show a strong increase in the Bayesian Information Criterion for regressions starting 2000 and later. This observation implies that the model fit of all specifications decreases at the end of the observation period. The reason for this seems to be the world economic crisis that began at the end of 2008. These data are included in rolling regressions with a beginning period of 2000 and later.

Over almost the whole observation period, the rolling regressions of the ifo Business Climate, the Industry new orders index, the OECD Composite Leading Indicator, the Economic Sentiment Indicator and the Business Confidence Indicator show lower Information Criteria compared to the benchmark autoregressive model. This suggests that these models outperform the autoregressive one. Only at the beginning of the sample range, the Information Criteria of the models including the Economic Sentiment Indicator and the Business Confidence Indicator are higher than those of the benchmark. The Information Criteria of the Industry new orders index specification is the lowest for most of the time periods. However, at the beginning of the sample range the ifo Business Climate model provides smaller Information Criteria than the Industry new orders index specification. Nevertheless the regressions including the Industry new orders index show, on average, the highest model fit.

For almost all time periods, the model fits of the Consumer Confidence Indicator, the Early-Bird Indicator, the ZEW Business Expectations and the FAZ-Indicator specifications are lower than that of the benchmark AR-process.

Turning to the out-of-sample analysis, Table 2 presents the RMSE of the alternative business cycle indicator specifications and the benchmark model. The regressions including the Industry new orders index, the OECD Composite Leading Indicator and the Business Confidence Indicator show the lowest RMSE or the best forecasting performances. Six of the considered nine business cycle indicator models outperform the naive forecast by the AR-process. However the FAZ-Indicator, the ZEW-Business Expectations and the Early-Bird Indicator models perform poorer out-of-sample than the autoregressive benchmark process.

Table 2: RMSE of the rolling regressions (Germany)

Model (specification)	RMSE
Industry new orders index	1.65
OECD Composite Leading Indicator	1.72
Business Confidence Indicator	1.97
ifo-Business Climate	1.99
Economic Sentiment Indicator	2.00
Consumer Confidence Indicator	2.05
AR-process	2.08
Early-Bird Indicator	2.09
ZEW-Business Expectations	2.10
FAZ-Indicator	2.18

For the analysis of the German industrial production index the in-sample results are (more or less) the same as the out-of-sample analysis. The model including the Industry new orders index shows (on average) the best in-sample and out-of-sample performance. Most of the considered models outperform the AR-process in-sample and out-of-sample.

4.2 France

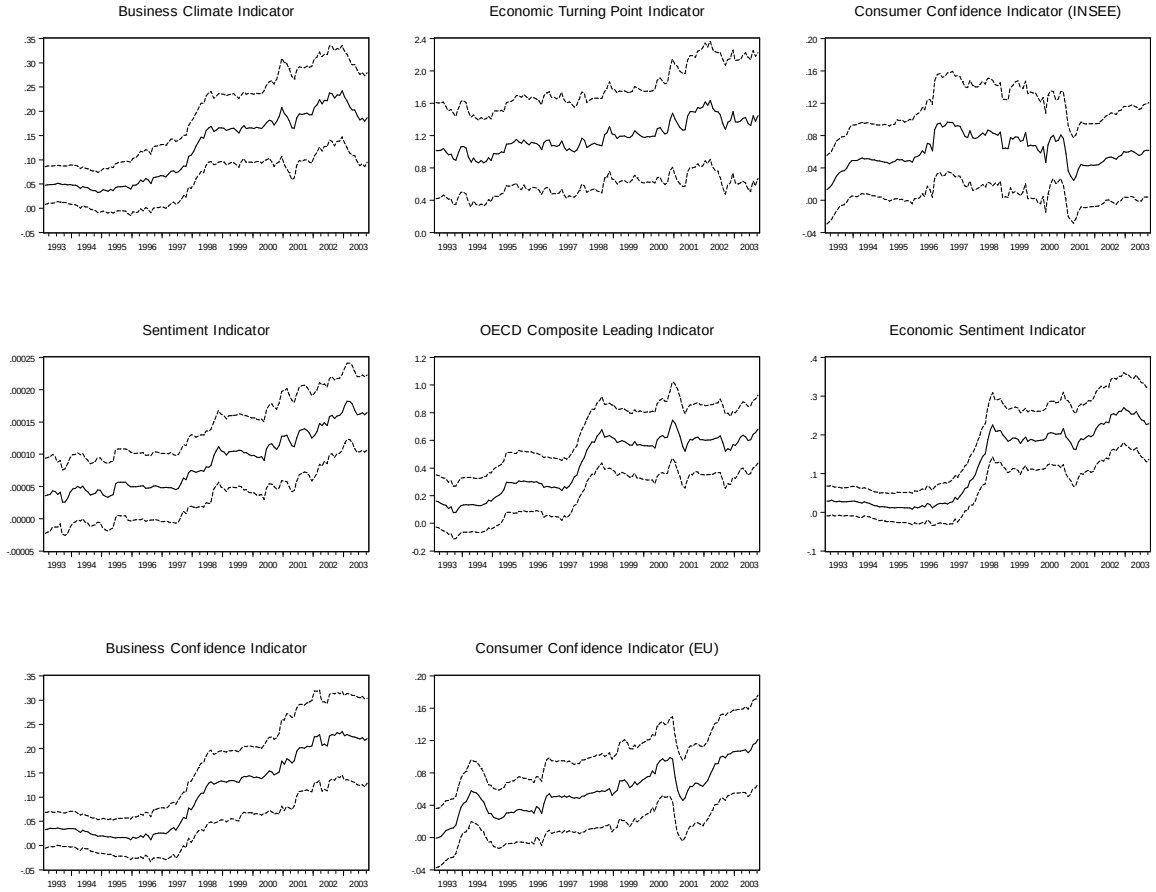
Figure 8 shows the estimated time-varying business cycle indicator coefficients ($\hat{\theta}_{t_*}$) and its 95% confidence bands for France. The Economic Turning Point Indicator specification is the only one for which both confidence bands have the same (positive) sign at each observation. In other words, while all the other indicators suffer from more or less serious coefficient uncertainty, the relationship between the

Economic Turning Point Indicator and the industrial production seems to be quite stable.

In contrast to its upper confidence bands, the lower confidence bands of the OECD Composite Leading Indicator are negative for some points at the beginning of the observation period. However, for all rolling regressions with a starting date of 1995 and later, the OECD Composite Leading Indicator does not show any further coefficient uncertainty. The same applies for the Business Climate Indicator (1997 and later), the Economic Sentiment Indicator and the Business Confidence Indicator (for both 1998 and later). On the other hand, the confidence bands of the two Consumer Confidence Indicator (published by the National Institute of Statistics and Economic Studies (INSEE) and the European Commission) coefficients have different signs for most of the time periods. This suggests that coefficient uncertainty seems to be a serious problem especially for the two Consumer Confidence Indicators.

The t-values for the business cycle indicator coefficients of the rolling regressions presented in Figure 9 confirm the former findings. The Economic Turning Point Indicator is highly significant at each date of the observation period. For the rolling regressions with a sample range starting 1995 (1997) and later, the OECD Composite Leading Indicator (Business Climate Indicator) shows a significant influence on the French industrial production growth rate. The specific t-values of each of the rolling regressions including the Sentiment Indicator, the Economic Sentiment Indicator and the Business Confidence Indicator are higher than the critical value for estimation periods starting after 1998. Additionally, the coefficients of both Consumer Confidence Indicators are also significantly different from zero for most of the considered time periods.

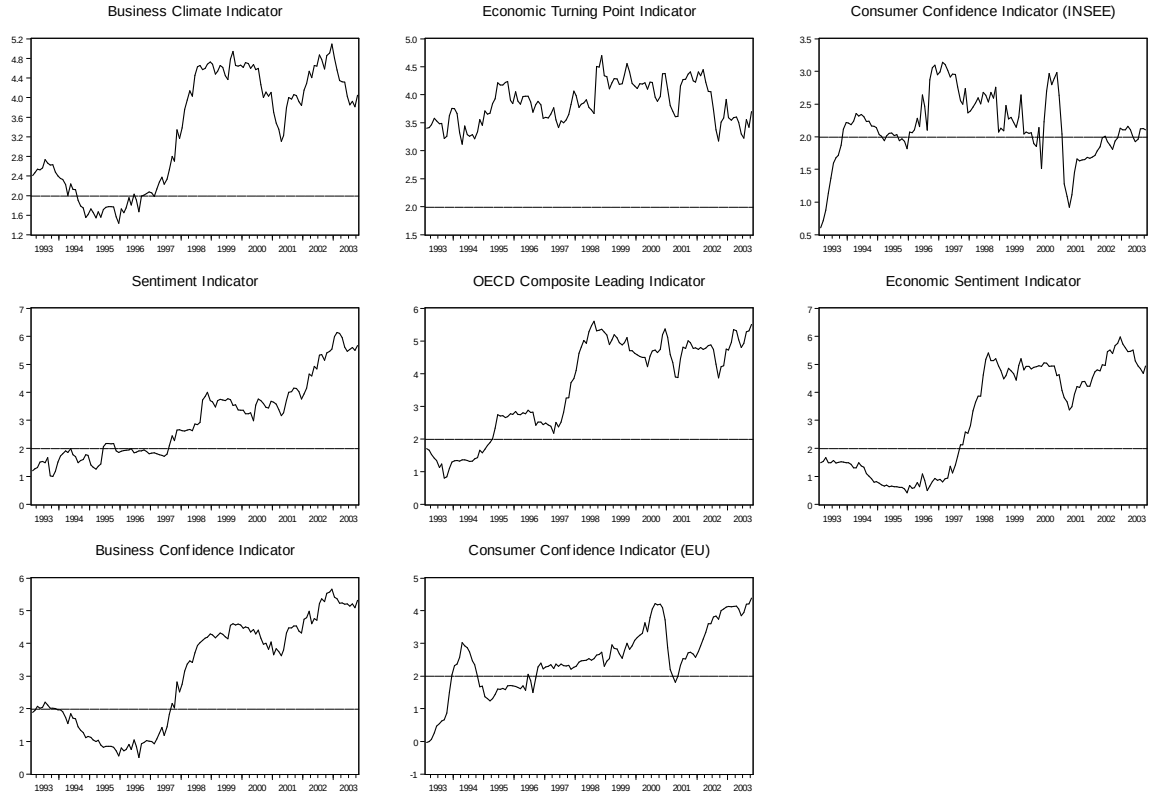
Figure 8: Estimated business cycle indicator coefficients and 95% confidence bands* (France)



* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Solid line: estimated business cycle indicator coefficient. Dashed line: 95% confidence bands of the estimated business cycle indicator coefficient.

By comparing the Bayesian Information Criteria of the rolling regressions in Figure 10 it turns out that, similar to the German case, the Information Criteria of all estimated models increase over time. In other words, the fit of each model decreases. Furthermore, most of the models show a more or less strong increase in the model fit at the end of 1998. Nearly all the models outperform the benchmark autoregressive process in-sample. For the first part of the observation period (until 1999), the specification including the Economic Turning Point Indicator shows the lowest Information Criteria, respectively the best in-sample fit. However, for regressions starting 1999 and later, the OECD Composite Leading Indicator model achieves, on average, the lowest Information Criteria.

Figure 9: T-values for the business cycle indicator coefficients of the rolling regressions* (France)

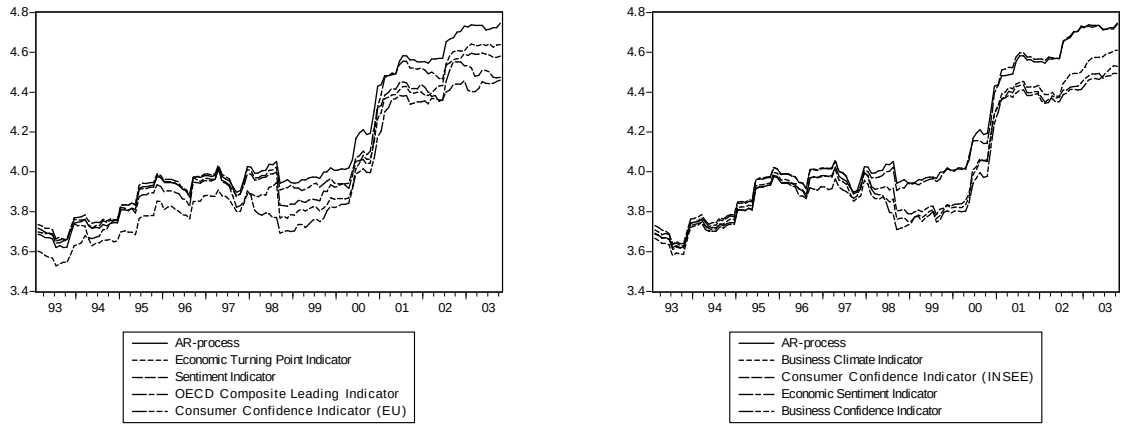


* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Solid line: t-value for the business cycle indicator coefficient. Dashed lines: 95% critical t-value (1.99).

As shown in Table 3, the Sentiment Indicator, the Business Confidence Indicator and the OECD Composite Leading Indicator models perform best out-of-sample. Moreover all specifications show a lower RMSE than the benchmark autoregressive model. However, the rolling regressions including the Consumer Confidence Indicator published by the INSEE lead to the lowest forecast accuracy of all considered French business cycle indicator equations.

In contrast to the German results, differences between the in-sample and out-of-sample performance of the alternative models can be observed for the French industrial production index. While the specifications including the Economic Turning Point Indicator and the OECD Leading Indicator perform best in-sample, the models using the Sentiment Indicator and the Business Confidence Indicator show the highest out-of-sample accuracy. As already shown by Chatfield (1995), the difference between the in-sample and the out-of-sample performance of a model can be quite substantial.

Figure 10: Bayesian Information Criteria of the rolling regressions* (France)



* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. AR-process does not include any business cycle indicator in the estimated regressions.

Table 3: RMSE of the rolling regressions (France)

Model (specification)	RMSE
Sentiment Indicator	1.91
Business Confidence Indicator	1.91
OECD Composite Leading Indicator	1.95
Economic Turning Point Indicator	1.98
Business Climate Indicator	1.99
Economic Sentiment Indicator	2.01
Consumer Confidence Indicator (EU)	2.04
Consumer Confidence Indicator (INSEE)	2.08
AR-process	2.09

4.3 Italy

In Figure 11 one can see the estimated business cycle indicator coefficients and its 95% confidence bands for the Italian specifications. For none of the five considered business cycle indicators, both confidence bands show a positive sign at every date of the observation period. This means that all the Italian leading indicators suffer in some way from coefficient uncertainty. For almost every point in time, the lower confidence bands of the Consumer Confidence Indicator coefficient are negative while the upper ones are positive. The results also suggest that coefficient uncertainty represents a serious problem for the specification including the Economic Sentiment Indicator. The three rolling regressions using the OECD Composite

Leading Indicator, the Business Confidence Indicator and the Industry new orders index as leading indicators, show different sings for the two confidence bands for most of the time periods. Nevertheless, it seems that coefficient uncertainty is a serious problem for explaining the Italian industrial production by the help of alternative business cycle indicators within the econometric framework applied in this study.

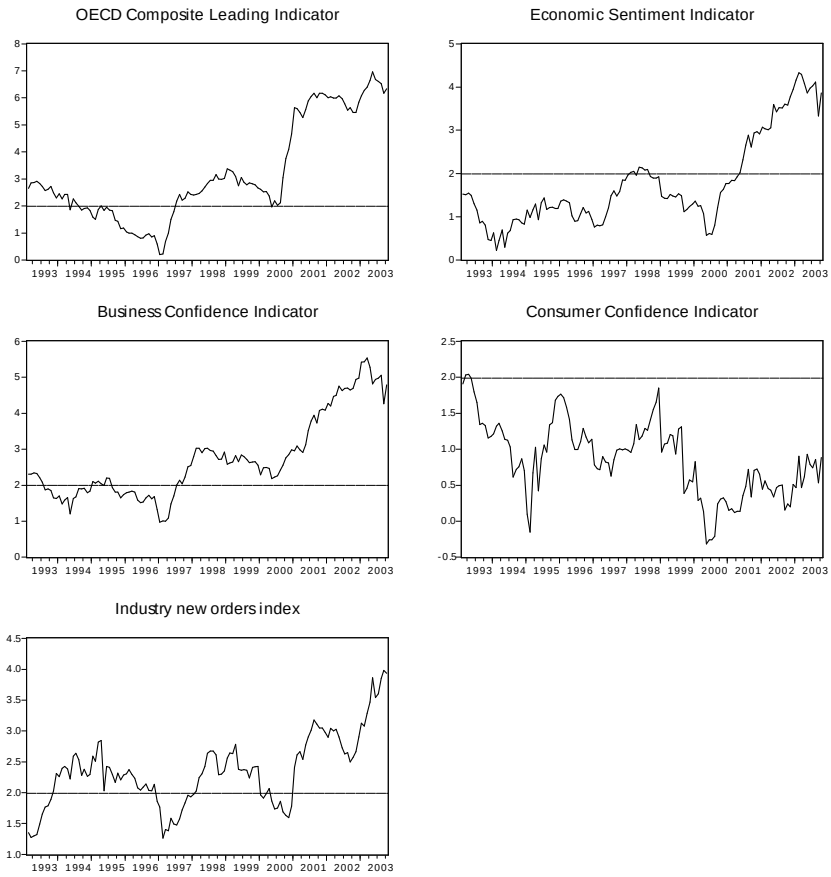
Figure 11: Estimated business cycle indicator coefficients and 95% confidence bands* (Italy)

* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Solid line: estimated business cycle indicator coefficient. Dashed lines: 95% confidence bands of the estimated business cycle indicator coefficient.

Figure 12 presents the t-values for the Italian business cycle indicator coefficients. For a given 95% critical value, the Consumer Confidence Indicator is statistically not significant at nearly every month of the estimation period. For regressions with a

starting date of 2001 and later the OECD Composite Leading Indicator, the Business Confidence Indicator, the Industry new orders index and the Economic Sentiment Indicator influence the industrial production of Italy significantly. This finding suggests that these four indicators include information that help explaining the industrial production especially over the last three years of the considered observation period respectively for regressions with ending dates from 2009-2011.

Figure 12: T-values for the business cycle indicator coefficients of the rolling regressions* (Italy)

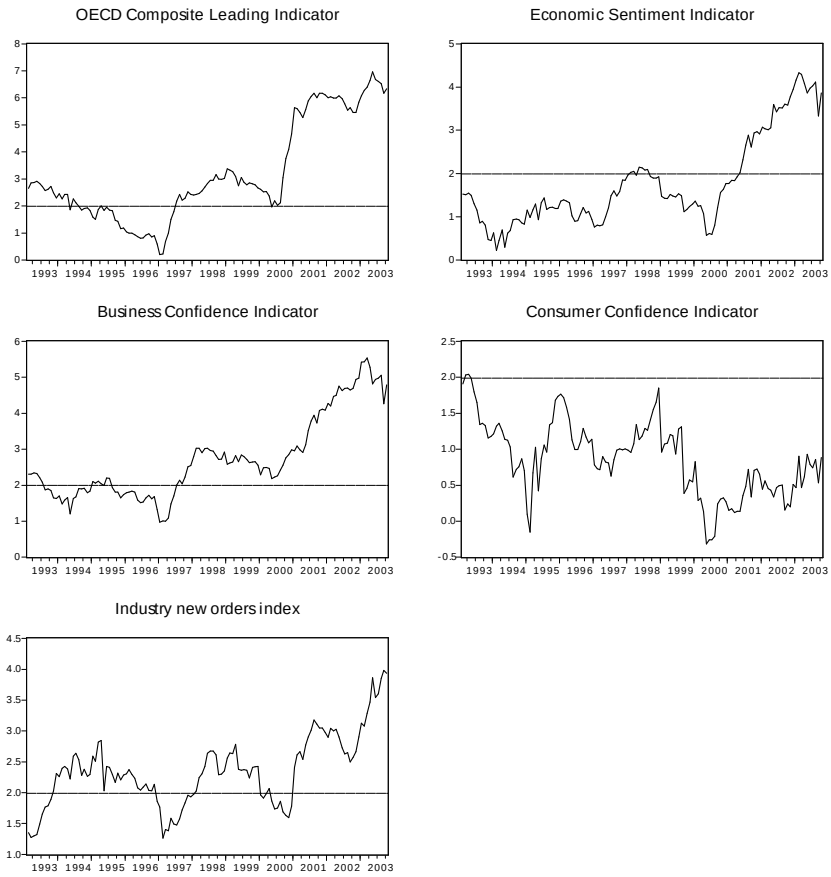


* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Solid line: t-value for the business cycle indicator coefficient. Dashed lines: 95% critical t-value (1.99).

Turning to the fit of the models shown in Figure 13, it turns out, that not all of the five estimated business cycle indicator specifications outperform the autoregressive benchmark process for regressions with a starting date of 2001 and earlier. However, for regressions starting after 2001 the models including the OECD Composite Leading indicator, the Business Confidence Indicator, the Industry new orders index and the Economic Sentiment Indicator take lower Bayesian Information Criteria

values than the benchmark process. On average, the OECD Composite Leading Indicator specification shows the best in-sample fit. On the other hand, the Information Criteria of the Consumer Confidence Indicator regressions are higher than those of the benchmark model for almost the whole observation period. As well as for the German and the French results, the Bayesian Information Criteria of all regressions of the Italian industrial production rise sharply after 2000.

Figure 12: T-values for the business cycle indicator coefficients of the rolling regressions* (Italy)

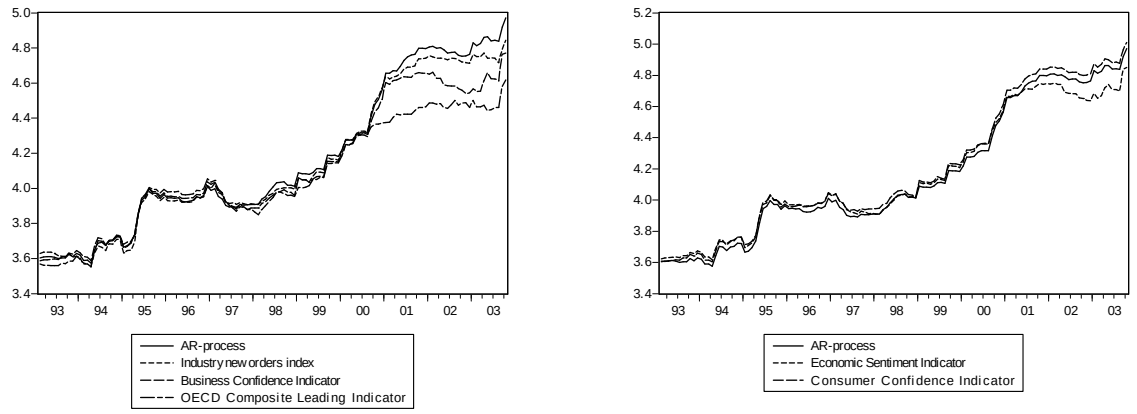


* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Solid line: t-value for the business cycle indicator coefficient. Dashed lines: 95% critical t-value (1.99).

Table 4 reports the RMSE of the different models for the Italian industrial production. The rolling regressions including the OECD Composite Leading Indicator as additional explanatory variable show the best out-of-sample accuracy, followed by those including the Business Confidence Indicator and the Industry new orders index. Four out of five business cycle indicator models lead to a lower forecast error than the AR-process. The only model that has a poorer forecasting ability than the

benchmark autoregressive process is the one including the Consumer Confidence Indicator.

Figure 13: Bayesian Information Criteria of the rolling regressions* (Italy)



* Rolling regressions of equation (1) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. AR-process does not include any business cycle indicator in the estimated regressions.

The in-sample and out-of-sample analysis of the Italian industrial production lead to similar results. While the specification including the OECD Composite Leading Indicator shows the best in-sample and out-of-sample fit, the model using the Consumer Confidence Indicator as leading indicator performs poorest in-sample and out-of-sample.

Table 4: RMSE of the rolling regressions (Italy)

Model (specification)	RMSE
OECD Composite Leading Indicator	2.00
Business Confidence Indicator	2.18
Industry new orders index	2.26
Economic Sentiment Indicator	2.26
AR-process	2.38
Consumer Confidence Indicator	2.40

5 Granger-Causality

As shwon by Bodo et al. (2000), the in-sample and out-of-sample performances of alternative econometric models can be improved by modelling the interrelationships among core European countries. Therefore, it will be tested if the lags of the industrial production index of a foreign country helps to improve the in-sample and out-of-sample fit of one of the three countries of interest. To answer this question Granger-Causality-tests are considered for the observation period 1993*M02* to 2011*M10*. The Granger-Causality-test checks if the lags of an exogenous variable, here the industrial production index of a foreign country, help to explain the industrial production index of the country of interest when lags of the endogenous variable are already included. In this part, business cycle indicators will not be used as exogenous variables in the estimated equations.

5.1 Test design

The test equations take the following form:

Germany:

$$y(GER)_t = \alpha(GER) + \sum_{i=1}^{j} \emptyset(GER)_i y(GER)_{t-i} + \sum_{i=1}^{j} \varphi(GER)_i y(ITA)_{t-i} + \sum_{i=1}^{j} \omega(GER)_i y(FRA)_{t-i} + \varepsilon_t \quad (4)$$

Italy:

$$y(ITA)_t = \alpha(ITA) + \sum_{i=1}^{j} \emptyset(ITA)_i y(ITA)_{t-i} + \sum_{i=1}^{j} \varphi(ITA)_i y(GER)_{t-i} + \sum_{i=1}^{j} \omega(ITA)_i y(FRA)_{t-i} + \varepsilon_t \quad (5)$$

France:

$$y(FRA)_t = \alpha(FRA) + \sum_{i=1}^{j} \emptyset(FRA)_i y(FRA)_{t-i} + \sum_{i=1}^{j} \varphi(FRA)_i y(GER)_{t-i} + \sum_{i=1}^{j} \omega(FRA)_i y(ITA)_{t-i} + \varepsilon_t \quad (6)$$

where GER, ITA and FRA represent Germany, Italy and France. $\emptyset$, φ and ω are coefficients that has to be estimated by applying ordinary least squares. Similar to the former analyses the maximal number of lags included in the equations is equal to 13 ($j = 13$).

The underlying hypotheses of the Granger-Causality tests are:

Germany: $H_0: \varphi(GER)_1 = \varphi(GER)_2 = \cdots = \varphi(GER)_j = 0$ and

$H_0: \omega(GER)_1 = \omega(GER)_2 = \cdots = \omega(GER)_j = 0$

Italy: $H_0: \varphi(ITA)_1 = \varphi(ITA)_2 = \cdots = \varphi(ITA)_j = 0$ and

$H_0: \omega(ITA)_1 = \omega(ITA)_2 = \cdots = \omega(ITA)_j = 0$

France: $H_0: \varphi(FRA)_1 = \varphi(FRA)_2 = \cdots = \varphi(FRA)_j = 0$ and

$H_0: \omega(FRA)_1 = \omega(FRA)_2 = \cdots = \omega(FRA)_j = 0$

By using the standard F-distribution these hypotheses can be tested.

5.2 Test results

Table 5 reports the estimation results of the Granger-Causality tests. It turns out that the German industrial production is not influenced significantly by the lags of the industrial productions of Italy or/and France. The hypotheses that the specific coefficients are equal to zero cannot be rejected for a confidence level of 95%. Therefore, the lags of the Italian or/and the French industrial production indices do not help explaining the German index.

Table 5: Estimation Results of the Granger-Causality Tests*

Sample: 1993*M02* 2011*M10* (225 observations)		
Dependent variable: y(GER)		
Hypothesis**	f-value	Prob.
y(ITA) -> y(GER)	6.44	0.93
y(FRA) -> y(GER)	16.52	0.22
y(ITA) + y(FRA) -> y(GER)	27.38	0.39
Dependent variable: y(ITA)		
Hypothesis**	f-value	Prob.
y(GER) -> y(ITA)	23.11	0.04
y(FRA) -> y(ITA)	19.30	0.11
y(GER) + y(FRA) -> y(ITA)	50.19	0.003
Dependent variable: y(FRA)		
Hypothesis**	f-value	Prob.
y(GER) -> y(FRA)	36.15	0.001
y(ITA) -> y(FRA)	30.93	0.004
y(GER) + y(ITA) -> y(FRA)	63.80	0.0001

* Granger-Causality Tests of equation (4), (5) and (6). y stands for the (monthly) year-over-year growth rate of the industrial production indices for Germany (GER), France (FRA) and Italy (ITA). 13 lags included in the estimated equations. ** Null-hypothesis states that all the coefficients are equal to zero.

A different view can be observed for the Italian industrial production. While the lags of the French industrial production show no significant influence, the lagged German ones have a statistical significant impact on the industrial production of Italy. In other words, the industrial production index of France does not Granger cause the Italian industrial production, while the German industrial production does Granger cause the Italian one. Also the hypothesis that the lags of both industrial productions (Germany

and France) are equal to zero at the same time can be rejected for a confidence level of 95%. Moreover the Italian and the German industrial production indices cause the industrial production of France in the sense of Granger.

To summarize the results:

1.) The German industrial production seems to be independent of the lags of the Italian and French indices.
2.) The industrial production of Italy is influenced by the lags of the German but not by the French production.
3.) Both, the lagged German as well as the lagged Italian industrial production do Granger cause the French index.

These findings seem to confirm the hypothesis that Germany is Europe's economic "locomotive" (The Economist, August 2011, 45-46)

5.3 In-sample and out-of-sample performance

The former findings will be used trying to improve the in-sample explanation and out-of-sample fit of the industrial production indices. As the German industrial production is not influenced significantly by the lags of the French or the Italian industrial production indices, the following analysis concentrates on the industrial productions of Italy and France.

The new regression models take the following form:

Italy:

$$y(ITA)_t = \alpha(ITA)_{t_*} + \sum_{i=1}^{l} \emptyset(ITA)_{i,t_*} y(ITA)_{t-i} + \sum_{i=1}^{l} \varphi(ITA)_{i,t_*} y(GER)_{t-i} + \varepsilon_t \quad (7)$$

France: $$y(FRA)_t = \alpha(FRA)_{t_*} + \sum_{i=1}^{l} \emptyset(FRA)_{i,t_*} y(FRA)_{t-i} + \sum_{i=1}^{l} \varphi(FRA)_{i,t_*} y(GER)_{t-i} + \sum_{i=1}^{l} \omega(FRA)_{i,t_*} y(ITA)_{t-i} + \varepsilon_t \quad (8)$$

Once again, rolling regressions with a fixed window size of 96 months are calculated over the observation period 1993*M02* to 2011*M10*. $\alpha_{t_*}, \emptyset_{t_*}, \varphi_{t_*}$ and ω_{t_*} are time-varying coefficients representing the specific observation period of the estimated rolling regression (t_*). Similar to the studies by Stock and Watson (1996) and Clark and McCracken (2010), the optimal lag-length (l) is chosen via the Bayesian Information Criteria.[1]

In line with the previous analysis, the time-dependent Bayesian Information Criterion of the estimated regressions will be depicted. In addition to that series of the (time-varying) f-values for the Granger-Causality-tests as stated above are represented also. As a benchmark for these two models (equation (7) and equation (8)), the specific autoregressive processes which include only a constant and 13 lags of the endogenous variable are used once again. Similar to the former procedure RMSE are calculated for the out-of-sample analysis.

Figure 14 shows the calculated (time-varying) f-values of the rolling regressions for the Granger-Causality tests as already described before. The results indicate that the Italian industrial production is not influenced significantly by the lags of the industrial production index of Germany for all regressions with a starting point of 1998 and earlier. In contrast, for all regressions starting after 1998 the null-hypothesis stating that the lags of the German industrial production do not have a significant influence on the industrial production of Italy can be rejected at a confidence level of 95%. Turning to the Granger-Causality-tests concerning the change of the industrial production of France, it turns out that the lagged German industrial production has a statistical significant impact on the French one for each rolling regression starting 1995*M01* and earlier as well as for regressions with a starting point of 2001*M06* and

[1] Given the Granger-Causality test results of Table 5, the optimal lag length for the whole observation period (1993*M02* to 2011*M10*) is equal to four.

later. The f-statistics for all regressions beginning between 1995 and 2001*M05* lie below the 95%-critical value.

Only for regressions starting 1995*M01* and earlier, the lags of the Italian industrial production show a significant influence on the industrial production index of France. For almost all estimated equations with a starting point later than 1995, the null-hypothesis of the Granger-Causality-test cannot be rejected. Both the lags of the German and the Italian industrial production are not statistically significant for regressions with starting points between 1996 and 2001. For regressions starting 1996*M01* and earlier or later than 2000, the calculated f-statistics lie above the critical 95%-value. In other words, for these rolling regressions the lags of the industrial production of Germany and Italy influence the French industrial production significantly.

These findings should be summarized: The lags of the German industrial production have a statistical significant impact on the industrial productions of France and Italy for regressions including data of the world economic crisis (regressions starting after 2001). In comparison, the influence of the lagged Italian industrial production on the French one is statistical significant only for regressions starting at the beginning of the observation period (for regressions starting earlier than 1995).

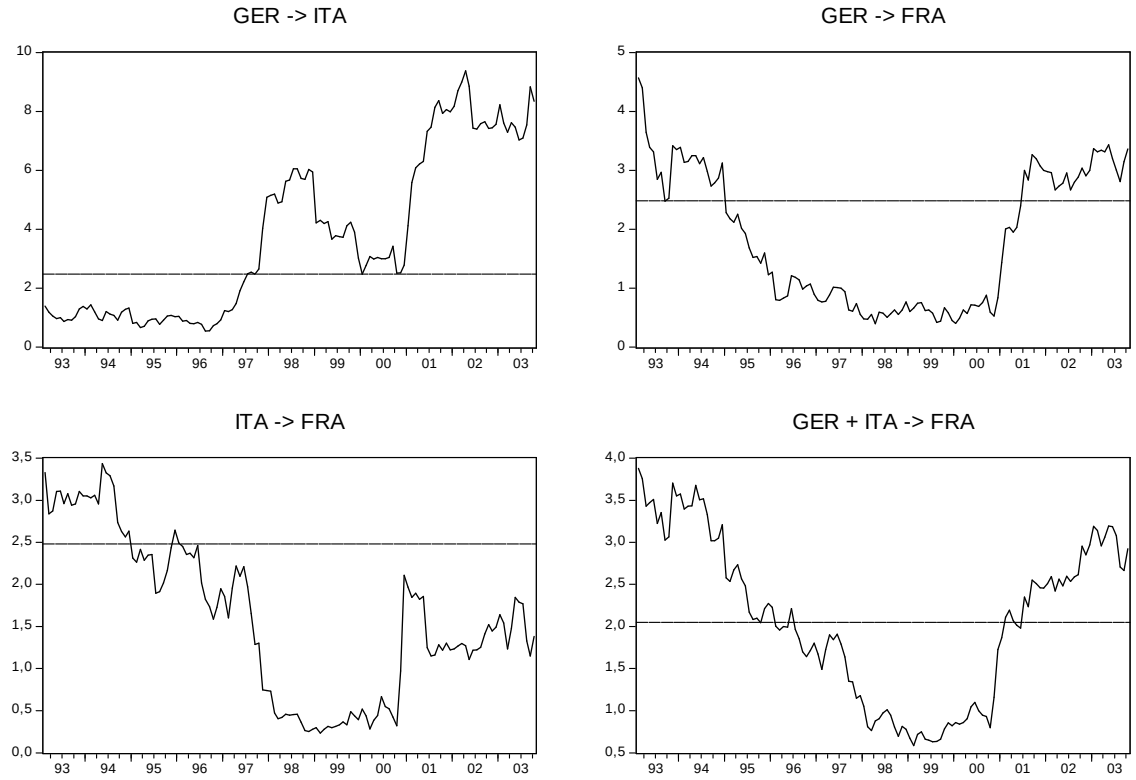
These results can be interpreted in a way that the influence of the German economy, here measured via the lagged industrial production index, on the other two core member states of the European Union has increased after the world economic downturn. On the other hand the impact of the lagged Italian industrial production on the French index has decreased over time.

Figure 15 presents the time-dependent Bayesian Information Criteria calculated for rolling regressions of equation (7), (8) and of the AR-process as described above. For France the differences between the two Information Criteria series are quite small. At the beginning of the sample or for regressions starting at 1996*M06* and earlier, the Bayesian Information Criteria of the AR-process lie below that of equation (8) ("Granger-causality equation"). For regressions with a starting point between 1996*M07* and 2001 no significant difference between the two Information Criteria can be observed. Equation (8) shows a better model fit compared to the AR-process for regressions starting at 2001 and later. This result confirms the former findings of Figure 14. Including lags of the German and the Italian industrial production helps

explaining the change of the industrial production of France when data of the world economic crisis are included in the regressions.

The picture for Italy is slightly different. At the beginning of the observation period, the Information Criteria of the AR-process and of equation (7) are fairly the same, whereas for regressions with a starting point between 1995*M06* and 1998, the model fit of the AR-process is better. Between 1998 and 2001, the Bayesian Information Criteria show again similar results.

Figure 14: F-values of the rolling regressions (Granger-Causality-Test)*



* Rolling regressions of equations (7) and (8) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Solid line: f-value of the rolling regressions (Granger-Causality-Test). Dashed lines: 95% critical f-value.

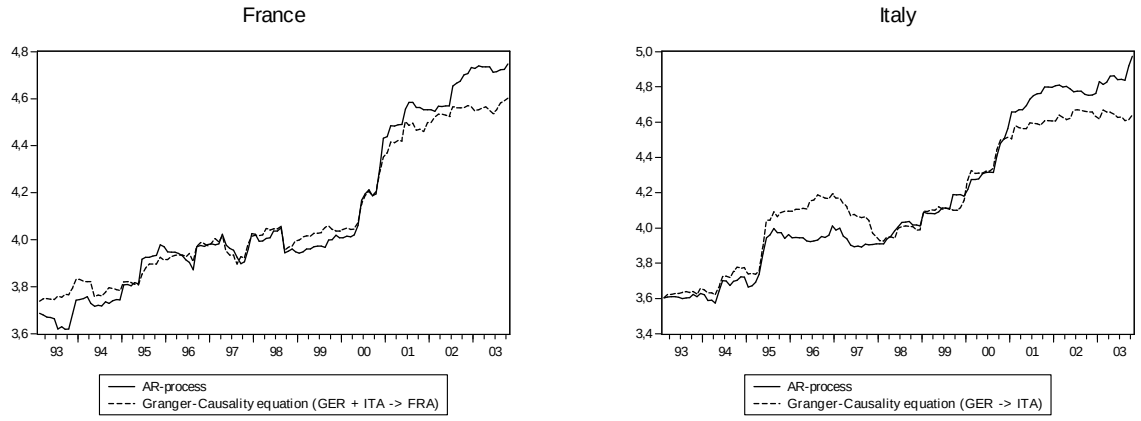
For regressions starting 2001 and later, the “Granger-Causality equation” (7) outperforms the AR-process. This means that after the crisis, lags of the German industrial production index include information that help increasing the model fit for the industrial production of Italy.

Table 6 illustrates the forecast errors of equations (7) and (8) compared those of the AR-processes and the most accuracy model of the first approach (“First round of business cycle indicator models”) for France Italy. For France as well as for Italy the

“Granger-Causality equations” lead to a smaller RMSE than the specific AR-processes. Nevertheless, the rolling regressions including the Sentiment Indicator for France and the OECD Composite Leading Indicator for Italy show a better out-of-sample fit than equations (7) and (8).

Comparing Table 6 to Table 3 and Table 4 respectively, it turns out that equation (7) leads to a lower RMSE than five of the business cycle indicator models estimated in the first part of this study, whereas equation (8) does not show a better forecast accuracy than the five business cycle indicator specifications considered above.

Figure 15: Bayesian Information Criteria of the rolling regressions*



* Rolling regressions of equations (7) and (8) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. AR-process does not include any business cycle indicator in the estimated regressions.

While the “Granger-Causality equations” outperform the naive AR-process for France and for Italy, they do not overcome the out-of-sample performance of the best business cycle indicator equations found so far.

Table 6: RMSE of the rolling regressions (France and Italy)

	Model (specification)	RMSE
France		
	Sentiment Indicator	1.91
	Granger-Causality equation (8)	1.97
	AR-process	2.09
Italy		
	OECD Composite Leading Indicator	2.00
	Granger-Causality equation (7)	2.28
	AR-process	2.38

6 Second round of business cycle indicator models

The findings of the Granger-Causality tests described in the previous section will be used for trying to improve the in-sample and out-of-sample fit of the different business cycle indicator specifications estimated in the fourth part of this study ("First round of business cycle indicator models"). Because the test results indicated that the German industrial production is not influenced statistically significant by lags of the two other indices, the analysis concentrates once again on the industrial productions of France and Italy.

Rolling regressions of the following equations will be estimated:

France:
$$y(FRA)_t = \alpha(FRA)_{t_*} + \sum_{i=1}^{l} \emptyset(FRA)_{i,t_*} y(FRA)_{t-i} + \sum_{i=1}^{l} \varphi(FRA)_{i,t_*} y(GER)_{t-i} + \sum_{i=1}^{l} \omega(FRA)_{i,t_*} y(ITA)_{t-i} + \theta(FRA)_{t_*} x_{t-1} + \varepsilon_t \quad (9)$$

Italy:
$$y(ITA)_t = \alpha(ITA)_{t_*} + \sum_{i=1}^{l} \emptyset(ITA)_{i,t_*} y(ITA)_{t-i} + \sum_{i=1}^{l} \varphi(ITA)_{i,t_*} y(GER)_{t-i} + \theta(ITA)_{t_*} x_{t-1} + \varepsilon_t \quad (10)$$

It follows that equation (1) is augmented by the lags of the German and the Italian industrial production indices for France and by the German industrial production index for Italy.

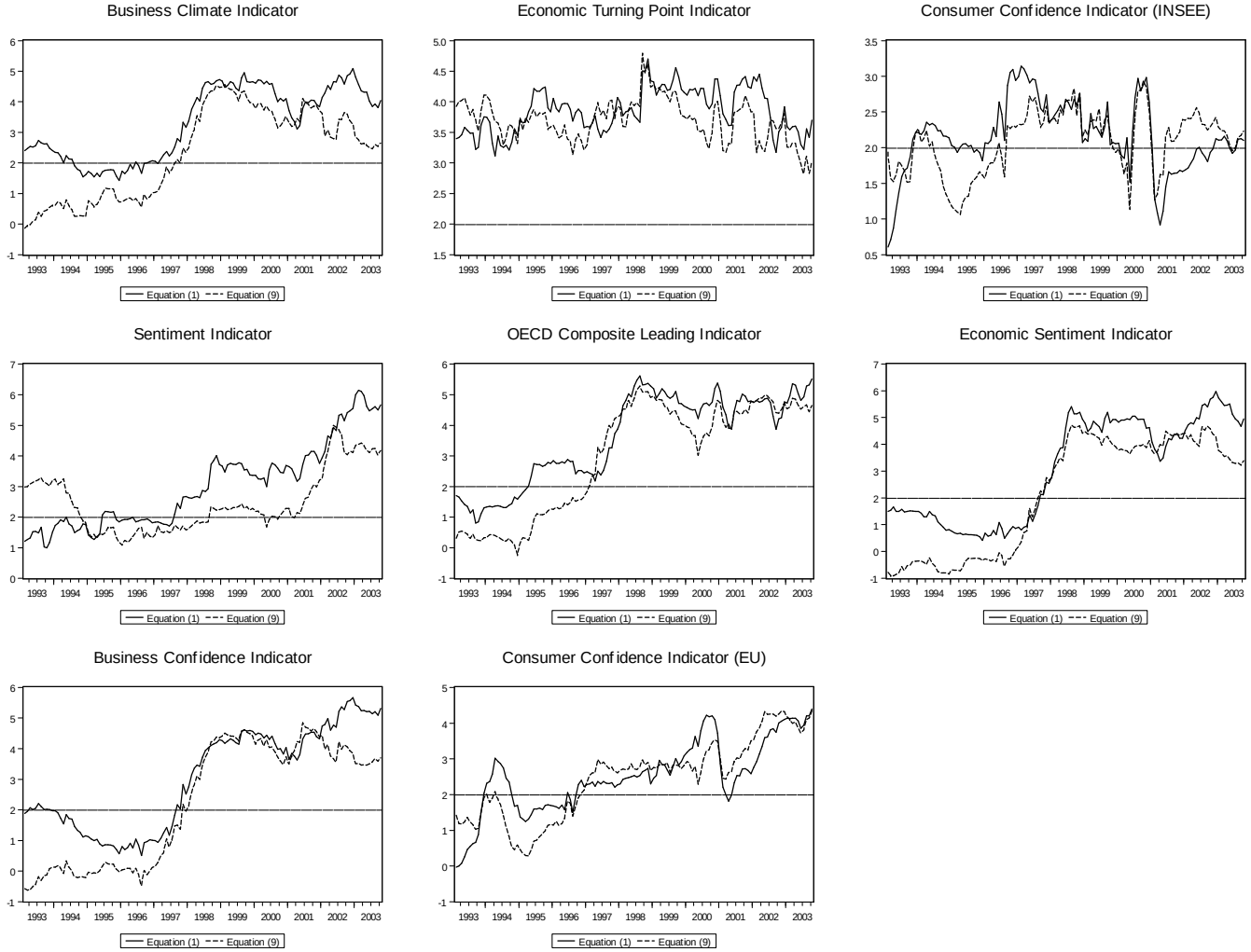
As in the previous section, the optimal lag-length (l) is chosen via the Bayesian Information Criterion. The 95% critical t-value for equation (1) (80 degrees of freedom), equation (9) (81 degrees of freedom) and equation (10) (85 degrees of freedom) is equal to 1.99.

6.1 France

The t-values obtained by estimating rolling regressions of equation (1) and (9) for explaining the French industrial production are shown in Figure 16. For the specification including the Business Climate Indicator, the specific business cycle indicator t-values of equation (1) are higher at almost every point of the observation period. This implies the following: If lags of the German and Italian industrial production are taken into consideration for explaining the industrial production of France, the statistical significance of the one-month lagged Business Climate Indicator decreases. For the Economic Turning Point Indicator both, periods for which the t-values of equation (1) are higher than those of equation (9) (for example regressions starting between 1995 and 1997) can be observed as well as periods for which the t-values of equation (9) exceed those obtained by equation (1). However for nearly every regression with a starting point of 1999 and later, the statistical significance of the Economic Point Indicator resulting when estimating equation (1) outperforms that obtained by equation (9). For the beginning of the observation period (regressions starting 1994 and earlier), the t-values of the rolling regressions including the Consumer Confidence Indicator published by the INSEE, are lower when lags of the German and Italian industrial production are not considered. In contrast, for regressions with a starting point between 1994 and 1998, the statistical significance of the Consumer Confidence Indicator is higher when estimating equation (1). For the time period 1998 to 2001, the two different t-value series are fairly the same. After 2001, the t-values for the Consumer Confidence Indicator are higher when rolling regressions of equation (9) are estimated.

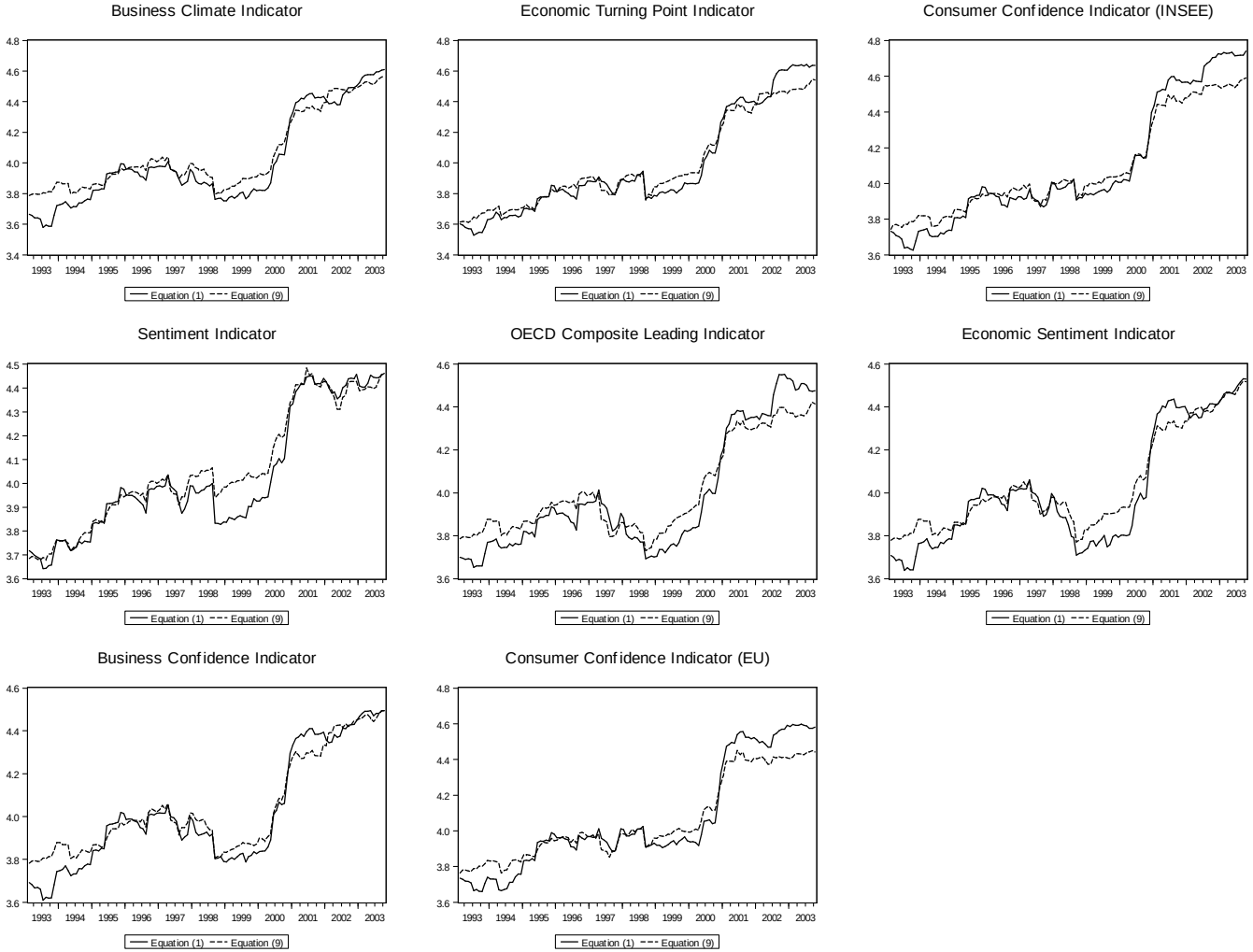
Turning to the specification including the Sentiment Indicator, it turns out that the t-values calculated by equation (9) are higher at the beginning of the observation period (regressions starting at 1995 and earlier). Nevertheless, for all rolling regressions with a starting point at 1995 and later the statistical significance of the Sentiment Indicator is higher when equation (1) is estimated. For almost every point of the observation period, the t-values of the OECD Composite Leading Indicator cannot be increased when equation (9) is considered. The same can be observed for the Economic Sentiment Indicator and the Business Confidence Indicator.

Figure 16: T-values for the business cycle indicator coefficients of the rolling regressions* (France)



* Rolling regressions of equation (1) and equation (9) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Dashed lines: 95% critical t-value (1.99).

Figure 17: Bayesian Information Criteria of the rolling regressions (France)*



* Rolling regressions of equations (1) and (9) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes.

While the t-values of equation (1) exceed those of equation (9) for the beginning of the sample period when the Consumer Confidence Indicator (published by the European Union) is included, the statistical significances of the indicator obtained by equation (9) are higher at the end of the observation period (regressions starting 2001 and later).

Figure 17 presents the Bayesian Information Criteria for explaining the industrial production index of France obtained by equation (1) and (9). Overall the differences between the two Information Criteria are fairly small. Nevertheless, some observations can be made.

For all eight business cycle indicator specifications, equation (1) leads to a better model fit compared to equation (9) at the beginning of the sample period (regressions starting 1994 and earlier). The same can be observed for regressions with a starting point between 1999 and 2001.

On the other hand, for almost every specification equation (9) shows lower Information Criteria at the end of the observation period (regressions starting 2001 and later). This difference is quite obvious for the rolling regressions including the Consumer Confidence Indicator published by the INSEE and that published by the European Commission. These findings indicate that for regressions including data of the world economic crisis, the explanation of the French industrial production can be improved when additionally to the own lags and the specific business cycle indicator, lagged values of the industrial production of Germany and Italy are taken into consideration.

Table 7 shows the different RMSE and the associated rank order obtained when estimating rolling regressions of equation (1) and equation (9). The out-of-sample accuracy increases for seven out of eight specifications, when lags of the German and the Italian industrial production are additionally included in the estimated regressions. Only for the rolling regressions using the Business Confidence Indicator, the RMSE still takes on the same value.

When estimating rolling regressions of equation (1) the RMSE of five business cycle indicator models lies below two. However the forecast errors of all eight specifications show a value below two when rolling regressions of equation (9) are estimated. Furthermore the rank order concerning the best out-of-sample fit of the different specifications changes when turning from equation (1) to equation (9). While the rolling regressions including the Sentiment Indicator show the lowest RMSE, followed

by the Business Confidence Indicator and the OECD Composite Leading Indicator for equation (1), the specifications of the OECD Composite Leading Indicator, the Consumer Confidence Indicator published by the European Commission and the Economic Turning Point Indicator reach the best forecasting accuracy when estimating equation (9). One result does not depend on the specific equation that is estimated. The rolling regressions including the Consumer Confidence Indicator published by the INSEE take on the highest RMSE for both tested equations.

While the rolling regressions including the Sentiment Indicator show the lowest RMSE, followed by the Business Confidence Indicator and the OECD Composite Leading Indicator, for equation (1), the specifications of the OECD Composite Leading Indicator, the Consumer Confidence Indicator published by the European Commission and the Economic Turning Point Indicator reach the best forecasting accuracy when estimating equation (9).

One result does not depend on the specific equation that is estimated: the rolling regressions including the Consumer Confidence Indicator as published by the INSEE assign the highest RMSE for both tested equations.

Table 7: RMSE of the rolling regressions (France)

	Equation (1)		Equation (9)	
Model (specification)	**RMSE**	**Rank**	**RMSE**	**Rank**
Sentiment Indicator	1.91	1	1.89	4
Business Confidence Indicator	1.91	2	1.91	5
OECD Composite Leading Indicator	1.95	3	1.81	1
Economic Turning Point Indicator	1.98	4	1.89	3
Business Climate Indicator	1.99	5	1.93	6
Economic Sentiment Indicator	2.01	6	1.92	5
Consumer Confidence Indicator (EU)	2.04	7	1.89	2
Consumer Confidence Indicator (INSEE)	2.08	8	1.95	8

6.2 Italy

Figure 18 shows the time-varying t-values obtained when estimating the rolling regressions of equation (1) and (10) for the Italian industrial production index. For almost every time point of the observation period, the t-values referring to equation (1) are higher than those referring to equation (10) when the OECD Composite Leading Indicator is used as business cycle indicator. Only for regressions starting

between 1995*M06* and 1997*M06* the t-values of equation (10) lie above the calculated t-values of equation (1). As a result including lags of the German industrial production does on average not increase the statistical significances of the OECD Composite Leading Indicator.

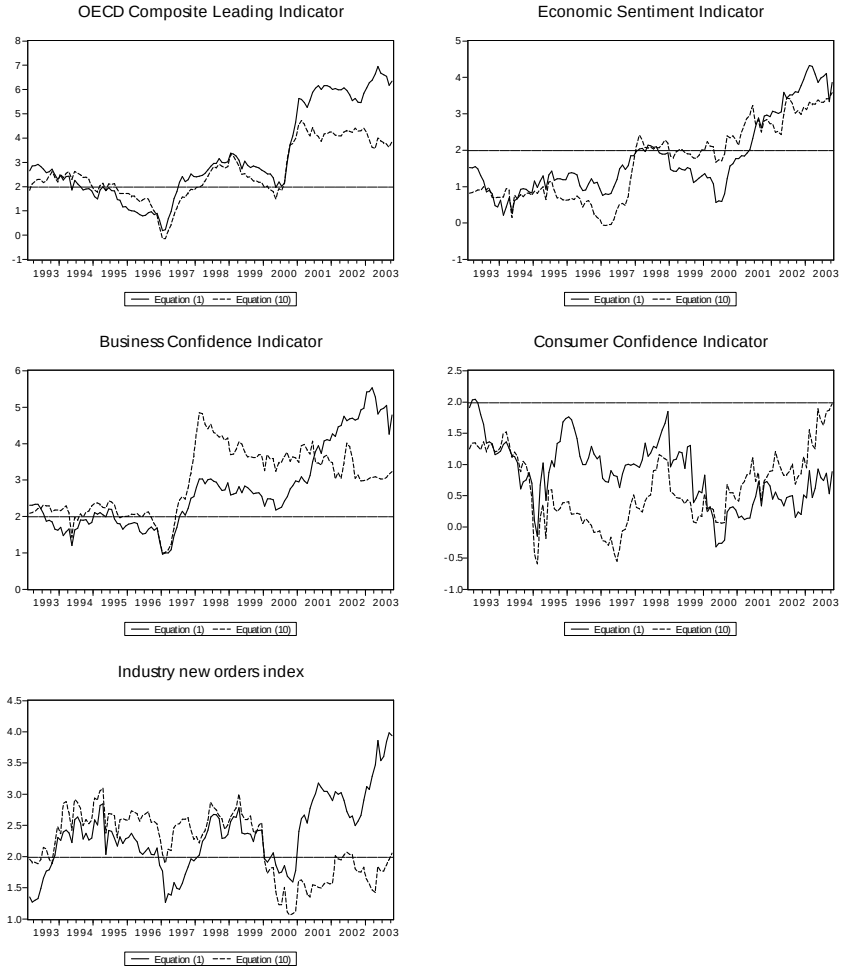
For the specifications including the Economic Sentiment Indicator, the t-values for regressions with a starting point between 1998 and 2002 are higher when estimating equation (10) compared to equation (1). However for the rest of the observation period the t-values obtained by estimating equation (10) lie below those of equation (1). For nearly every rolling regression using the Business Confidence Indicator as exogenous variable, equation (10) leads to higher t-values for the business cycle indicator than equation (1) (especially when the regression starts at 2002 or earlier). In contrast, for regressions starting later than 2002, the opposite result can be observed. Turning to the Consumer Confidence Indicator specifications, the business cycle indicator t-values of equation (10) are higher than those of equation (1) only for regressions with a starting point at 2001 and later. Nevertheless, for both specifications (equation (1) and equation (10)) the Consumer Confidence Indicator shows no significant influence on the industrial production of Italy at almost every time point.

The models including the Industry new orders index show lower t-values for equation (1) when regressions start earlier than 2000. However the business cycle indicator t-values obtained by estimating equation (1) are higher for regressions starting later than 2000. While the Industry new orders index shows no significant impact for this period when following equation (10), it is highly significant when equation (1) is estimated.

In Figure 19 the different Bayesian Information Criteria explaining the industrial production of Italy obtained when estimating equation (1) and equation (10) can be seen. For the rolling regressions including the OECD Composite Leading Indicator, using lags of the German industrial production does not lead to a significant increase in the model fit. Equation (1) shows lower Information Criteria for almost every time point of the observation period.

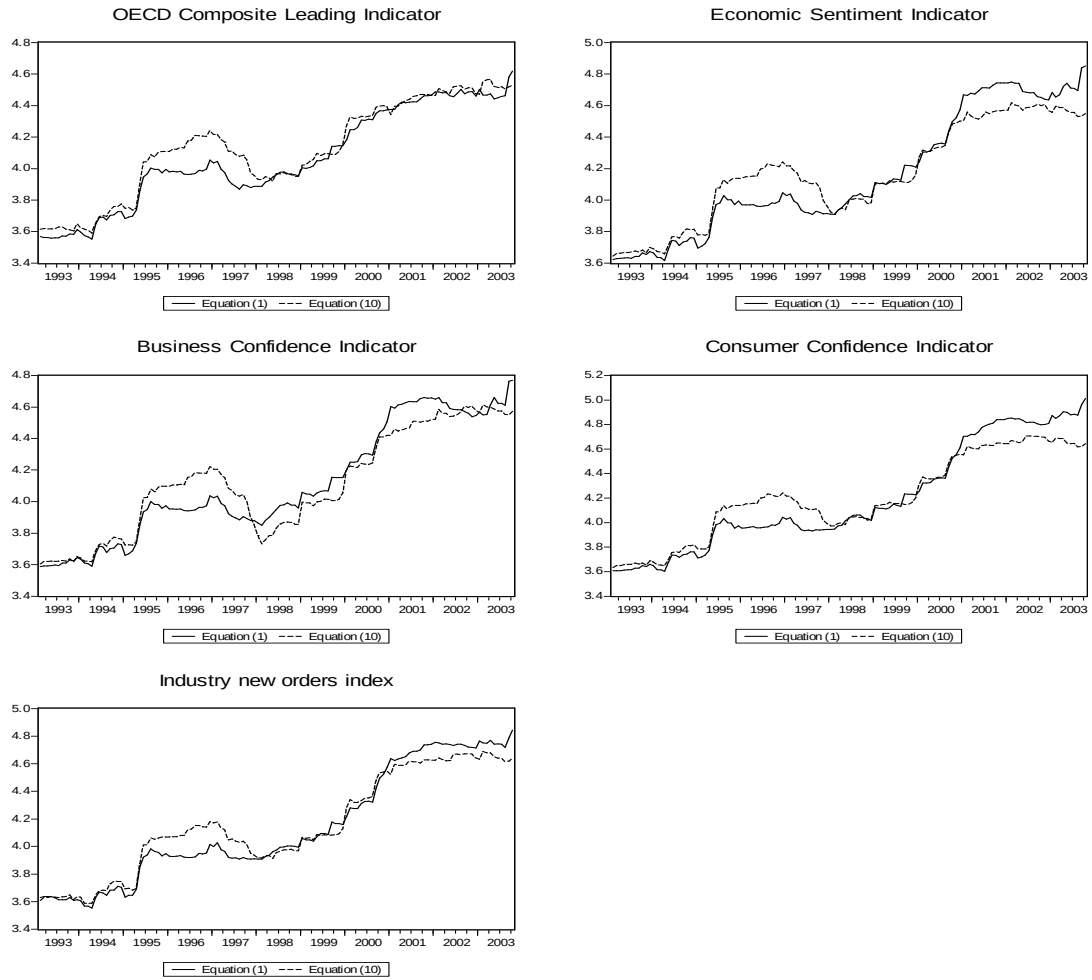
For the remaining four business cycle indicator specifications, equation (10) leads to a better model fit compared to equation (1) at the end of the observation period (regressions starting after 2001).

Figure 18: T-values for the business cycle indicator coefficients of the rolling regressions* (Itay)



* Rolling regressions of equation (1) and equation (9) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes. Dashed lines: 95% critical t-value (1.99).

Figure 19: Bayesian Information Criteria of the rolling regressions (Italy)*



* Rolling regressions of equations (1) and (9) with an observation period of 96 months (8 years). Starting dates of the rolling regressions are represented on the time axes.

Similar to the previous (French), findings using lags of the German industrial production index results in lower Bayesian Information Criteria for rolling regressions that include data of the world economic crisis. However, for regressions starting between 1995*M06* and 1998 equation (10) shows a poorer model fit than equation (1) for all estimated models. For the remaining time periods (1995*M06* and earlier, between 1998 and 2000) the differences between the two Bayesian Information Criteria are quite low for the considered equations.

Table 8 presents the forecasting errors of equation (1) and (10) and the specific rank order for every estimated specification. The results are not as clear as those described for the French industrial production.

For two out of five specifications (OECD Composite Leading Indicator, Business Confidence Indicator), the forecasting accuracy decreases when lags of the German industrial production are used as additional explanatory variables. However the remaining three specifications show an improvement in their forecasting performances.

Although the out-of-sample performance of the OECD Composite Leading Indicator model is poorer when turning from equation (1) to equation (10), it remains the best prediction of the Italian industrial production among all specifications considered. The models including the Consumer Confidence Indicator lead to the highest RMSE when estimating equation (1) but also when equation (10) is applied.

Table 8: RMSE of the rolling regressions (Italy)

	Equation (1)		**Equation (10)**	
Model (specification)	**RMSE**	**Rank**	**RMSE**	**Rank**
OECD Composite Leading Indicator	2.00	1	2.16	1
Business Confidence Indicator	2.18	2	2.21	3
Industry new orders index	2.26	3	2.24	4
Economic Sentiment Indicator	2.26	4	2.20	2
Consumer Confidence Indicator	2.40	5	2.27	5

7 Robust analysis

In the second last paragraph of this study, it will be tested how sensible the out-of-sample performances of the different models are to changes in the estimation framework. More precise, it will be studied if the results differ significantly when a

larger fixed window size of the rolling regressions is used. As suggested by Stock and Watson (1996) and Clark and McCracken (2010), all equations will be reestimated for a window size of 120 months or 10 years ($T = 120$).

Table 9 reports the RMSE obtained when estimating rolling regressions with a window size of 96 months and 120 months for all German specifications. It is obvious that the rank order depends only slightly on the length of the observation period of the rolling regressions. The specifications including ifo-Business Climate and the Economic Sentiment Indicator switch their specific orders when turning to a larger window size. For the rest of the estimated models the specific rank order does not change. Similar to the window size of 96 months, the specifications including the Early-Bird Indicator, the ZEW-Business Expectations and the FAZ-Indicator are the only three models that perform poorer than the AR-process when the window size is enlarged to 120 months.

The next striking result is the fact that the forecasting accuracy of all estimated specifications decreases when turning to a window size of 120 months. This implies that for all German models, rolling regressions with a shorter length of the observation period lead to better forecasting performances.

Table 9: RMSE of the rolling regressions – robust analysis (Germany)

	T=96		T=120	
Model (specification)	**RMSE**	**Rank**	**RMSE**	**Rank**
Industry new orders index	1.65	1	1.69	1
OECD Composite Leading Indicator	1.72	2	1.83	2
Business Confidence Indicator	1.97	3	2.05	3
ifo-Business Climate	1.99	4	2.13	5
Economic Sentiment Indicator	2.00	5	2.11	4
Consumer Confidence Indicator	2.05	6	2.16	6
AR-process	2.08	7	2.21	7
Early-Bird Indicator	2.09	8	2.21	8
ZEW-Business Expectations	2.10	9	2.22	9
FAZ-Indicator	2.18	10	2.22	10

In the next table (Table 10) one can see the results of the robust out-of-sample analysis for the French specifications. For equation (1), turning from a window size of 96 months to one of 120 months changes the rank order only slightly. The rolling regressions including the Sentiment Indicator (Consumer Confidence Indicator as published by the INSEE) as business cycle indicator still show the smallest (largest)

forecast error. Although the value of the RMSE for the specification of the Consumer Confidence Indicator published by the EU is the same for both window sizes, the rank number increase by four positions when estimating with a larger length of the observation period.

When estimating equation (9), the rank order depends heavily on the length of the fixed window size. For all specifications the specific rank number changes when estimating rolling regressions with a window size of 120 months. While the model including the OECD Composite Leading Indicator shows the best out-of-sample accuracy for a window size of 96 months, the rolling regressions using the Consumer Confidence Indicator as published by the EU lead to the lowest RMSE when turning to a window size of 120 months. The Business Climate Indicator model performs poorest when estimating with the larger window size.

The result already mentioned before that the forecast error for every of the eight business cycle indicator specifications decreases when estimating equation (9) instead of equation (1) still holds for the larger window size. Once again including lags of the German and the Italian production indices in the business cycle indicator rolling regressions leads to better forecasts for the industrial production of France. Similar to the German findings as described above, the forecasting performances of 15 out of 16 regressions (eight for equation (1) and eight for equation (9)) decrease when estimating with a window size of 120 months.

Table 10: RMSE of the rolling regressions – robust analysis (France)

	T=96				T=120			
	Equation (1)		Equation (9)		Equation (1)		Equation (9)	
Model (specification)	**RMSE**	**Rank**	**RMSE**	**Rank**	**RMSE**	**Rank**	**RMSE**	**Rank**
Sentiment Indicator	1.91	1	1.89	4	2.01	1	1.95	2
Business Confidence Indicator	1.91	2	1.91	5	2.04	2	2.02	6
OECD Composite Leading Indicator	1.95	3	1.81	1	2.04	4	1.97	3
Economic Turning Point Indicator	1.98	4	1.89	3	2.06	5	1.97	5
Business Climate Indicator	1.99	5	1.93	6	2.12	7	2.05	8
Economic Sentiment Indicator	2.01	6	1.92	5	2.07	6	2.04	7
Consumer Confidence Indicator (EU)	2.04	7	1.89	2	2.04	3	1.93	1
Consumer Confidence Indicator (INSEE)	2.08	8	1.95	8	2.13	8	1.97	4

In Table 11 the results of the robust analysis for the Italy are shown. When estimating equation (1) for a window size of 96 months and for a window size of 120, the

specific rank number of every business cycle indicator models is still the same. For equation (10) the rank order also changes only slightly when turning to the larger window size of the rolling regressions. Only the two specifications including the Business Confidence Indicator and the Consumer Confidence Indicator switch their rank numbers.

One result seems to be quite stable and is independent neither on the specific equation that is estimated nor on the window size of the rolling regressions. The models including the OECD Composite Leading Indicator lead to the lowest RMSE within all four estimated set ups. Additionally, the specifications of the Consumer Confidence Indicator show the poorest forecasting accuracy in three out of four cases.

Turning from equation (1) to equation (10) when estimating rolling regression with a fixed window size of 120, months the out-of-sample performance of three out of five models increases. Similar to the window size of 96 months, the forecast error of the specification including the OECD Composite Leading Indicator decreases when using lags of the German industrial production as additional exogenous variables (turning from equation (1) to equation (10)).

As already observed in the two previous tables, the RMSE increases when the larger window size is used. For all ten estimated business cycle indicator models the forecasting accuracy falls when turning from a window size of 96 months to a window size of 120 months.

Table 11: RMSE of the rolling regressions – robust analysis (Italy)

	T=96				T=120			
	Equation (1)		Equation (10)		Equation (1)		Equation (10)	
Model (specification)	**RMSE**	**Rank**	**RMSE**	**Rank**	**RMSE**	**Rank**	**RMSE**	**Rank**
OECD Composite Leading Indicator	2.00	1	2.16	1	2.11	1	2.19	1
Business Confidence Indicator	2.18	2	2.21	3	2.36	2	2.36	5
Industry new orders index	2.26	3	2.24	4	2.40	3	2.34	4
Economic Sentiment Indicator	2.26	4	2.20	2	2.44	4	2.31	2
Consumer Confidence Indicator	2.40	5	2.27	5	2.54	5	2.32	3

Two striking results of the out-of-sample robust analysis should be summarized: First, at least for Germany and Italy the specific RMSE rank orders are influenced only slightly when estimating rolling regressions with a window size of 120 months instead

of 96 months. Second, in 35 out of 36 cases (10 specifications for Germany, 16 for France and 10 for Italy) the forecasting accuracy decreases when turning to the larger window size. Therefore, the results seem to indicate that for (short-term) predicting exercises on the industrial productions of Germany, France and Italy rolling regressions with a shorter (96 months) window size should be preferred in contrast to rolling regression with a larger (120 months) window size.

8 Conclusion

The recent European debt crisis and the resulting political will for the introduction of debt brakes in the Euro area member states has led to an increasing demand for country-specific forecasts for economic developments. There exist several business cycle indicators for every Euro area member states published by different institutions like national statistical offices, central banks or research institutes.

This paper has studied the in-sample and out-of-sample performance of alternative business cycle indicators for the three major European economies Germany, France and Italy. The target series is the year-over-year growth rate of the industrial production index which is available on a monthly basis and is widely seen as hard indicator of aggregate output.

In line with the recent literature on empirical business cycle analysis, rolling regressions with a fixed window size of 96 months (8 years) were applied separately for every leading indicator and every country for the time period 1993*M02* to 2011*M10*. All variables were transformed into stationary series.

The underlying assumption of the estimated equations states that the specific business cycle indicators Granger cause ("lagged causality") the industrial production. While time varying confidence bands, t-values and Bayesian Information Criteria helped to evaluate the in-sample performances of the different estimated regressions, the RMSE of short-term (one month) forecasts allowed statements about the out-of-sample quality of the different business cycle indicator models.

By using the Ljung-Box test, all models were controlled for autocorrelation in the error terms. The results suggested that in general the residuals of the individual business cycle models are not serial correlated.

For Germany, the model including the Industry new orders index as additional exogenous variable shows, on average, the best in-sample and out-of-sample fit.

While the OECD Composite Leading Indicator and the Economic Sentiment Indicator perform best in-sample for the French industrial production, the Sentiment Indicator and the Business Confidence Indicator reach the lowest RMSE. The OECD Composite Leading indicator leads both categories (in-sample and out-of-sample performance) for Italy.

Moreover it turned out that most of the indicator models outperform the standard (naive) autoregressive process in-sample and out-of-sample. However, for Germany, France and Italy, the in-sample fit of the considered models, measured via time-varying Bayesian Information Criteria, decreases over time. The reason for this observation can be seen in the world economic crisis which was hard to predict by the different business cycle indicators.

Results of Granger-Causality tests suggested that the industrial production of France is influenced significantly by lags of the German and the Italian production indices while lags of the German industrial production has a significant impact on the Italian one. In contrast, the industrial production of Germany seems to be independent of lags of the French and the Italian indices. Nevertheless, time-varying F-tests indicated that the influence of the Italian economy on the French industrial production has decreased over the observation period. Moreover, an increasing impact of the lagged German industrial production on the indices of the two other core member states of the European Union can be observed. Using these findings in a second round of business cycle indicator models, the out-of-sample performances of most of the French and Italian specifications could be improved.

As recommended by Stock and Watson (1996) and Clark and McCracken (2010), all equations were reestimated for a fixed window size of 120 months or 10 years. This robust analysis led to the result that in 35 out of 36 cases, the forecasting accuracy decreases when turning to the larger window size. Given the specific econometric framework of this study, rolling regressions with a shorter (96 months) window size should be preferred to regressions with a larger (120 months) window size.

One further improvement of this study could consist in taking different forecast horizons into account. So far, short-term forecasts were calculated and evaluated only. Nevertheless, the accuracy of mid-term (6 month) or even long-term (1 year) forecasts seems to be interesting as well. Furthermore, by using multiple equation VAR models the in-sample and out-of-sample fit could be increased.

Although combining different indicators (“Factor analysis”) is a recent research area in empirical economics (e.g. Forni et al., 2001), it was not the goal of this study. Ultimately, the focus was to compare the in-sample and out-of-sample performance of alternative business cycle indicators separately for Germany, France and Italy.

I References

Armstrong, J.S., F. Collopy (1992): Error Measures For Generalizing About Forecasting Methods: Empirical Comparisons, *International Journal of Forecasting,* 8, 69-80.

Begg, I., A. Belke, S. Dullien, D. Schwarzer, R. Vilpišauska (2011): *European Economic Governance. Impulses for Crisis Prevention and New Institutions,* Gütersloh.

Bodo, G., R. Golinelli, G. Parigi (2000): Forecasting industrial production in the euro area, *Empirical Economics*, 25, 541-561.

Breitung, J., D. Jogodzinski (2001): Prognoseeigenschaften alternativer Indikatoren für die Konjunkturentwicklung in Deutschland, *Konjunkturpolitik,* 47, 292-314.

Bruno, G., C. Lupi (2004): Forecasting industrial production and the early detection of turning points, *Empirical Economics,* 29, 647-671.

Camba-Mendez, G., G. Kapetanios, M. Weale, R.J. Smith (2002): The Forecasting Performance of the OECD Leading Indicators for France, Germany, Italy, and the U.K, in *A companion to Economic Forecasting,* eds. M.P. Clements, D.F. Hendry, Oxford, 386-408.

Canova, F. (1998): Detrending and business cycle facts, *Journal of Monetary Economics,* 41, 475-512.

Carstensen, K., K. Wohlrabe, C. Ziegler (2011): Predictive Ability of Business Cycle Indicators under Test: A Case Study for Euro Area Industrial Production, *Journal of Economics and Statistics*, 231, 82-106.

Chatfield, C. (1995): Model Uncertainty, Data Mining and Statistical Inference, *Journal of the Royal Statistical Society,* 158, 419-466.

Clark, T., M. McCracken (2010): Averaging forecasts from VARs with uncertain instabilities, Journal of *Applied Econometrics,* 25, 5-29.

Dedola, L., S. Neri (2007): What does a technology shock do? A VAR analysis with model-based sign restrictions, *Journal of Monetary Economics,* 54, 512-549.

Dreger, C., C. Schumacher (2005): Out-of-sample Performance of Leading Indicators for the German Business Cycle, *Journal of Business Cycle Measurement and Analysis,* 2, 71-87.

European Council (2011a): *European Council 24/25 March 2011. Conclusions,* Brussels.

European Council (2011b): *Statement By The Euro Area Heads Of State Or Government,* Brussels, 9 December 2011.

Eurostat (2011): *Europe in Figures – Eurostat Yearbook 2011*, Luxemburg.

Fildes, R., K. Ord (2002): Forecasting Competitions: Their Role in Improving Forecasting Practice and Research, in *A companion to Economic Forecasting,* eds. M.P. Clements, D.F. Hendry, Oxford, 322-353.

Forni, M., M. Hallin, M. Lippi, L. Reichlin (2001): Coincident and Leading Indicators for the Euro Area, *The Economic Journal,* 111, C62-85.

Franses, P.H. (1998): *Time series models for business and economic forecasting,* Cambridge.

Fritsche, U., S. Stephan (2002): Leading Indicators of German Business Cycles: An Assessment of Properties, *Journal of Economics and Statistics*, 222, 289-315.

Funke, N. (1997): Predicting Recessions: Some Evidence for Germany, *Weltwirtschaftliches Archiv*, 133, 90-102.

Goodhart, C., B. Hofmann, M. Segoviano (2004): Bank Regulation and Macroeconomic Fluctuations, *Oxford Review of Economic Policy,* 20, 591-615.

Granger, C.W. (1969): Investigating causal relations by econometric models and cross-spectral methods, *Econometrica,* 37, 424-438.

Greene, W.H. (2003): *Econometric Analysis,* New Jersey.

Hinze, J. (2003): Prognoseleistung von Frühindikatoren. Die Bedeutung vpn Frühindikatoren für die Konjunkturprognose – Eine Analyse für Deutschland, *HWWA Discussion Paper,* 236.

Hüfner, F.P., M. Schröder (2002): Forecasting German Industrial Production: An Econometric Comparision of ifo- and ZEW-Business Expectations, *Journal of Economics and Statistics*, 222, 316-336.

International Monetary Fund (2011): *World Economic Outlook – Slowing Growth, Rising Risk,* Washington.

Ljung, G.M., G.E. Box (1978): On a measure of lack of fit in time series models, *Biometrika,* 65, 297-303.

Lütkepohl, H. (1985): Comparison of criteria for estimating the order of a vector autoregressive process, *Journal of Time Series Analysis,* 6, 35-52.

Lütkepohl, H., M. Krätzig (2004): *Applied Time Series Econometrics,* Cambridge.

Marcellino, M., J.H. Stock, M. Watson (2003): Macroeconomic forecasting in the Euro area: Country specific versus area-wide information, *European Economic Review*, 47, 1-18.

Marchetti, D.J., G. Parigi (2000): Energy Consumption, Survey Data and the Prediction of Industrial Production in Italy: A Comparison and Combination of Different Models, *Journal of Forecasting,* 19, 419-440.

Mundel, R.A. (1961): A Theory of Optimum Currency Areas, *American Economic Review,* 51, 657-665.

Ozyldirim, A., B. Schaitkin, V. Zarnowitz (2010): Business cycles in the euro area defined with coincident economic indicators and predicted with leading economic indicators, *Journal of Forecasting*, 29, 6-28.

Rossen, A. (2012): Frühindikatoren: gute Vorlaufeigenschaften, *Wirtschaftsdienst – Zeitschrift für Wirtschaftspolitik,* 92, 575-576.

Stock, J.H., M. Watson (1996): Evidence on Structural Instability in Macroeconomic Time Series Relations, *Journal of Business & Economic Studies,* 14, 11-30.

Stock, J.H., M. Watson (1999): A comparison of linear and nonlinear univariate models for forecasting macroeconomic time series, in *Cointegration, Causality, and Forecasting. A Festschrift in Honour of Clive W.J. Granger,* eds. R.F. Engle, H. White, Oxford, 1-44.

The Economist (2011): *The German growth engine stutters,* Vol. 401, August, Nr. 33, 46-46.

The Economist (2011): *Tie your hands, please*, Vol. 401, December, Nr. 51, 56-57.

The Guardian (2012): *Ireland set for referendum on eurozone fiscal treaty,* available from http://www.guardian.co.uk/business/2012/feb/28/irish-referendum-eurozone-fiscal-compact, accessed 28th February 2012.

West, K.D. (2006): Forecast Evaluation, in Handbook Of Economic Forecasting – Volume 1, eds. G. Elliot, C.W. Granger, A. Timmermann, Amsterdam, 99-134.

II Appendix

Appendix A: Overview over the business cycle indicators

Indicator	Available for	Source	Stationary in*	Definition
ifo-Business Climate	Germany	ifo-institute	Levels	Index (2005=100), trade and industry, seasonal adjusted, transformed mean of the balances of the business situation and the expectations
ZEW-Business Expectations	Germany	Centre for European Economic Research	First differences	ZEW Indicator of Economic Sentiment, balances, calculated from the results of the ZEW Financial Market Survey; constructed as the difference between the percentage share of analysts that are optimistic and the share of analysts that are pessimistic for the German economy in six months
Industry new orders index	Germany, Italy	Eurostat	First differences	Volume index of new orders in manufacturing, calendar and seasonal adjusted (X12-ARIMA), 2005=100
Early-Bird Indicator	Germany	Commerzbank	First differences	Weighted sum of the short-term real interest rate, the real external value of the euro and the Purchasing Manager Index
FAZ-Indicator	Germany	Kiel Institute for the World Economy	Levels	Components: the ifo Business Climate (0.13), new orders in manufacturing industries, (0.56), the real effective exchange rate (0.06) of the euro, the interest rate spread (0.08), the stock market index DAX (0.01), the number of job vacancies (0.05) and lagged industrial production (0.11)
OECD Composite Leading Indicator	Germany, France, Italy	Organsiation for Economic Co-operation and Development	Levels	Amplitude adjusted, Edition: October 2011, main sources: GDP and its components and industrial production, selected commodity output variables (crude steel, crude petroleum etc.), business and consumer tendency survey series, selected manufacturing variables (deliveries, stocks, new orders etc.), Construction, domestic trade, labour market series, consumer and producer prices, money aggregates, interest rates, financial variables, exchange rates, international trade and balance of payments
Economic Sentiment Indicator	Germany, France, Italy	European Commission	Levels	Seasonal adjusted, total sector, surveys: industrial confidence indicator (40%), services confidence indicator (30 %), consumer confidence indicator (20%), retail trade confidence indicator (5%), construction confidence indicator (5%); the Economic Sentiment Indicator is a composite measure (average = 100)
Business Confidence Indicator	Germany, France, Italy	European Commission	Levels	Seasonal adjusted, total manufacturing, questions: production trend observed in recent months; assessment of order-book levels; assessment of export order-book levels; assessment of stocks of finished products; production expectations for the months ahead; selling price expectations for the months ahead; employment expectations for the months ahead

Consumer Confidence Indicator	Germany, France, Italy	European Commission	Levels (Germany) First differences (France, Italy)	Seasonal adjusted, total sector, questions: financial situation over last 12 months; financial situation over next 12 months; general economic situation over last 12 months; general economic situation over next 12 months; price trends over last 12 months; price trends over next 12 months; unemployment expectations over next 12 months; major purchases at present; major purchases over next 12 months; savings at present; savings over next 12 months; statement on financial situation of household
Business Climate Indicator	France	National Institute of Statistics and Economic Studies	Levels	Seasonal adjusted, manufacturing industry, computed as the difference between the percentages of positive and negative responses: Change in production, Demand level, Finished-product inventories (stocks) (products ready for sale), Likely change in selling prices (net of taxes), Expectations for total French goods-producing industries
Economic Turning Point Indicator	France	National Institute of Statistics and Economic Studies	Levels	Seasonal adjusted, manufacturing industry, Markov switching indicator constructed with the same database as the Business Climate Indicator
Consumer Confidence Indicator	France	National Institute of Statistics and Economic Studies	First differences	Seasonal adjusted, questions: general economic situation, past 12 months; general economic situation, next 12 months; unemployment, next 12 months; consumer prices, past 12 months; consumer prices, next 12 months; major purchases intentions, next 12 months; savings intentions, next 12 months; current saving capacity; financial situation, past 12 months; financial situation, next 12 months; expected saving capacity
Sentiment Indicator	France	Bank of France	First differences	Seasonal adjusted, business survey in industry, nationwide assessment is drawn up: using monthly balances of opinion for industry and market services; using turnover volume indices for retail trade

* Rejects the null hypothesis of non-stationary at a significance level of 10%, if GLS-based unit root test are applied.