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Leading Indicators of Euroland Business Cycles

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Leading Indicators of Euroland Business Cycles★

by Ulrich Fritsche* and Felix Marklein**

Abstract:

The introduction of a common monetary policy in eleven European countries increased the need for leading indicators for that area. A reliable leading indicator should possess the following properties: (1) The movements in the indicator series should resemble those in the business cycle reference series. (2) The relation between the reference series and the indicator should be statistically significant and stable over time. (3) The inclusion of the indicator in out-of-sample forecasting procedures should improve the predictive power. Our analysis deals with tests for these requirements applied to Euroland data. We use frequency domain analysis, Granger-causality tests and out-of sample forecasts. Only a few indicators pass all tests, while the non-monetary indicators perform best.

Konjunkturelle Frühindikatoren für Euroland

Die Einführung einer gemeinsamen Geldpolitik in elf europäischen Ländern erhöhte die Bedeutung von konjunkturellen Frühindikatoren für dieses Gebiet. Brauchbare Frühindikatoren sollten folgende Eigenschaften besitzen: (1) Die konjunkturellen Bewegungen des Frühindikators sollten denen der Referenzreihe folgen. (2) Die Beziehung zwischen den Reihen sollte stabil und signifikant sein. (3) Die Einbeziehung des Indikators sollte die Out-of-sample-Prognose verbessern. Unsere Untersuchung testet diese Anforderungen für Euroland-Daten. Dazu werden Methoden der Spektralanalyse, verschiedene Granger-Kausalitäts-Tests und Out-of-sample-Prognosen verwendet. Nur wenige Indikatoren bestehen die Tests auf die geforderten Eigenschaften, wobei die nichtmonetären Indikatoren besser abschneiden.

JEL Classification: E 32, L 60, L 70

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1. Introduction

The application of business cycle indicators has been a means of studying and forecasting cycle movements from the beginning of business cycle research. Among all indicators, leading indicators are of special interest since they can improve the power of business cycle forecasts.[1] In recent years, examination of indicator properties has once again gained considerable attention from researchers.[2]

After the introduction of a common monetary policy in eleven European countries, leading indicators of the European business cycle are of special interest. This is, in particular, due to the fact that monetary policy decisions are based on estimates of the development in the Eurozone as a whole. In addition it is to be expected that the common monetary policy and an intensified European integration will lead to a further synchronisation of the business cycles. Business decisions are increasingly being based on the assessment of the development of the entire currency area. In any case, there is a practical interest for the professional forecaster: Up to now, there has been a lack of experience of quantitative forecasts of the European business cycle. Therefore the characteristics of the relevant time series are of great interest.

As was stated in a companion paper (Fritsche/Stephan (2000)) a reliable leading indicator should possess the following properties:

(1) Movements in the indicator series should resemble those in the business cycle reference series.

(2) The relationship between the reference series and the indicator should be statistically significant and stable over time. Moreover, the inclusion of the indicator should improve the predictive power over that of a simple autoregressive process.

(3) The inclusion of the indicator in out-of-sample forecasting procedures should improve the predictive power (compared to a "naïve" prognosis).

Our analysis applies tests for these requirements to aggregated Euroland data. The implicit assumption behind our investigation is that there has already been significant synchronicity over the last cycles in economic activity all over the Eurozone. This can either be justified by empirical

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[1] Cf. Tichy (1994); Burns/Mitchell (1946); Oppenländer (1997); Moore/Zarnowitz (1986).

[2] Besides the often-cited American works of Stock and Watson (Stock/Watson 1989), there are a number of German examinations of leading indicators of business cycles. These include Döpke/Krämer/Langfeldt (1994), Langfeldt (1994), Köhler (1994), Sauer/Scheide (1995), Funke (1997) and Langmantel (1999). Current examinations of leading indicator properties for Euroland include the papers of Döpke (1998) and Seifert (1999).

evidence[3] or by the fact that over the last few decades integration in Europe became much stronger, especially after the introduction of the single market. But the process of European integration also complicates the analysis. This is especially true for the interest rates in Europe, which show a strong downward trend during the period prior to the European monetary union. This is, however, unlikely to persist.

First of all it has to be determined, which of the potential indicators selected on theoretical grounds are related to the business cycle reference series. One approach, which is used rather rarely nowadays, is frequency domain analysis. This method is used here as a test for meeting the first requirement, namely the test of a strong relationship between the indicator and the reference series at a frequency relevant for business cycle movements. The coherence measure used in the frequency domain approach enables us to measure the strength of this relationship between the business cycle reference series and the indicator series.

In addition, a reliable leading indicator should have a stable lead-structure relative to the movements of the cycle and should furthermore improve the forecasting power of cycle movements compared with simple autoregressive processes. After testing for possible lead-lag structures with cross-correlograms, we applied the Granger-causality criterion. Because traditional pair-wise Granger-causality tests possess some pitfalls, we carried out a modified Granger-causality test as well.[4]

Unfortunately, it is by no means certain that the indicators with the best in-sample performance perform equally well in out-of-sample forecasts. Therefore we examined their forecast performance using a procedure proposed by Davis and Fagan, thus testing for the third requirement for a reliable indicator.[5]

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[3] Cf. Döpke (1998).

[4] Cf. Wolters (1996).

[5] Cf. Davis/Fagan (1997).

2. The Data

2.1. Choice of Variables

There are a number of rationales that underlie indicator choice and justify research on leading indicators. The most important rationales are *production time* (time between ordering and production); *ease of adaptation* (some aggregates are affected by short-term fluctuations earlier and/or stronger than others); *market expectations* (some series reflect or react to anticipations of future economic activity) and *prime movers* (economic fluctuations are driven by measurable economic forces such as monetary policy).[6] Furthermore indicators are often chosen for their resistance against revisions, as well as early availability. For instance, monetary indicators are available sooner than most other indicators.

With reference to Euroland, there are basically two methods of analysis: aggregated or non-aggregated time series. We decided to use aggregated time series for the following reasons: The developments in Euroland, seen as a whole, are increasingly becoming the focus of economic policy discussions. The European Central Bank (ECB) is also orientating its monetary policy towards the European aggregate. In addition, we assume that the process of European integration will continue.

Previous work on Euroland indicators have required a lot of time and effort to calculate the aggregated time series. In the meantime aggregate time series, provided by Eurostat, the ECB, the European Commission and the OECD, have been developed for many of the indicators. These have also formed the basis of this investigation.

In determining the business cycle reference series, we relied on a "narrow" interpretation of the business cycle and chose the industrial production index as published in the OECD Main Economic Indicators database. The high frequency of monthly data allows the application of non-parametric approaches such as empirical frequency domain analysis.

For the indicator investigation we used two broad categories of indicators: monetary indicators (money supply, interest rates, exchange rates) and non-monetary indicators (survey indicators and indicators for economic activity such as car registrations).

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[6] Cf. De Leeuw (1991).

The use of monetary indicators[7] can be justified in several ways. On the one hand some business cycle theories emphasise the role of monetary developments in determining business cycle movements. In particular, this is the case in so-called "monetary over-production theories".[8] The argument that monetary developments influence business cycle movements can likewise be applied to the role of interest rates in determining economic decisions (for instance investment decisions) - especially in Keynesian business cycle theories. For this reason yield curves are often seen as very good indicators.[9] Because of their forward-looking nature it can be expected that they measure expectations which also imply adjustment reactions relevant for business cycle movements in the future. As Laidler recently stated,[10] the leading indicator role of real money balances can be explained by deviations of the market interest rate from a Wicksellian "natural rate" which leads to adjustment reactions relevant for business cycle movements. Furthermore monetary indicators are often available sooner than most other indicators. Nominal and real exchange rates were included to measure impulses or disturbances originating from the external value of money.

The second broad category of Euroland indicators contains a number of survey indicators. They are based on the EU Commission survey questionnaire.[11] By using these indicators we solve a lot of comparability problems that exist between different countries.[12] The EU Commission survey measures expectations and business climate for different economic sectors (retail, construction, industry), for different economic subjects (enterprises and households) for each country and for the Euroland area. That is why these indicators are natural candidates for leading indicator research. We used the different confidence indicators (the industry confidence indicator, the retail confidence indicator, the construction confidence indicator and the consumer confidence indicator) and the economic sentiment indicator. All these indicators are calculated using different time series about order book position, production expectation etc. The economic sentiment indicator summarises the information of the different confidence indicators. Furthermore we investigated two time series which affect the calculation of the industry confidence indicator: namely the order book position and the production expectations in

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[7] The real money balances, as well as the real interest rates were calculated using ex post consumer price inflation (CPI). From 1990 backwards the European CPI was calculated using fixed weights (based on gross domestic product, GDP) from 1990.

[8] Cf. Hayek (1931) and the survey in Haberler (1948[2]).

[9] Cf. Estrella/Mishkin (1997).

[10] Cf. Laidler (1999).

[11] Cf. European Commission (1997).

[12] Of course, this is provided that the commission solves these problems.

European industry. They are also used as an approximation for the overall European level of orders received, but which are not yet available. The choice of all these indicators is justified by the fact that these indicators contain information about market expectations.

The exchange rates were included because of the common argument stating that most booms, especially those in Germany (which is highly important for the Euroland area), are initiated by export-led upswings, which in turn are based on improved competitiveness due to a real depreciation of the currency.

Table 2.1 in the appendix gives an overview about the time series and their sources.

2.2. Data Properties: Unit Root Pre-tests

All of our procedures require some kind of stationarity assumptions.[13]

We therefore tested all time series for unit roots using augmented Dickey-Fuller tests.[14] Non-stationary variables were transformed by calculating annual growth rates.[15] This strategy has the advantage that highly arbitrary de-trending procedures are avoided, the results of which depend on the assumed structure of the data generating process.[16] Furthermore, as some studies have shown, the chosen filtering procedure has the advantage that a lot of spectral density remains in the region relevant for our topic.[17] In addition, annual growth rates are quite often used for forecasting purposes and economic policymaking in Germany. Furthermore, the transformation into annual growth rates serves as a simple method of seasonal adjustment. The relevant properties of the indicators are presented in table 2.2.[18]

Unfortunately some monetary indicators displayed some less pleasant properties. As the results show, annual growth rates of nominal interest rates as well as money balances are not likely to be

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[13] Of course some of the procedures can be specified in a error correction framework which implies the existence of co-integration. Therefore Sauer/Scheide (1995) carried out Granger tests with an error correction equation. Here we tested informally for co-integration between indicator and reference time series with the instrument of spectral analysis. We found no clear evidence except very high coherence at frequency zero between industrial production and production expectation. However, a simple co-integration test based on the Engle/Granger procedure for those time series did not confirm this.

[14] Cf. Dickey/Fuller (1979); MacKinnon (1991)

[15] The annual growth rates were calculated using the formula $\Delta_{12}Y = ([Y_t / Y_{t-12}] - 1) * 100$.

[16] Cf. Canova (1998a,b).

[17] Cf. Wolters/Kuhbier/Buscher (1990).

[18] All time series specified in levels are seasonally adjusted. Regarding the series which had to be specified in growth rates due to their stationarity properties, in most cases we used unadjusted time series where the transformation into annual growth rates served as a seasonal adjustment procedure. The reason for this was an observed bias towards non-stationarity when we transformed seasonally adjusted time series into growth rates.

stationary. For the real money balance M3 there is evidence of a trend-stationary process which could indicate a co-integration between money and prices which is not really surprising.

For this reason we chose the following strategy for the investigation: For time series which did not indicate the required stationarity characteristics in the annual growth rate we calculated secondary differences, which were stationary. At this stage we used an agreeable characteristic of coherence to our advantage, namely that it is invariant towards linear transformations. In this respect we could at least conduct a spectral investigation with these series. Because the unsuitability of these twice differenced series became apparent at this transformation (the money supply as well as the nominal interest rates were not significant in the relevant area), the further tests were not carried out for these time series.

3. Spectral Analysis

3.1. Methodological Approach[19]

Traditionally, the cyclical properties of time series and lead-lag-structures are determined by cross-correlogram analysis.[20] Overlapping oscillations of different periods and different amplitudes can distort the properties of the correlogram. High serial correlation complicates the analysis. Furthermore, new developments in time series analysis show that results depend to a large extent on the kind of transformations used to attain stationary variables, e.g. trend deviations or growth rates. As is well known the regression of independent non-stationary time series leads to spurious regression. At the same time, the specification of non-stationary time series in differences while these series are co-integrated leads to misspecification. The problems become even more complicated as the results are sensitive with regard to the assumed parametric model - a problem widely discussed in conjunction with de-trending procedures.

The first step in our research is the discrimination between series which show a significant relationship with the reference series for the business cycle in the relevant period and those which do not. Spectral analysis proved to be a helpful tool for this purpose. Analytically, a correlogram can be transformed to the frequency domain using Fourier transformation. The spectra functions indicate the contribution of every frequency component to overall variance. By applying spectral analysis to more than one time series, it is possible to calculate some useful measures such as squared coherence and gain, which allow the assessment of the underlying

[19] Cf. König/Wolters (1972); Wolters/Kuhbier/Buscher (1990); Wolters (1996); Kirchgässner/Wolters (1994); Wolters/Lankes (1989); Koopmans (1974).

[20] Cf. Döpke/Krämer/Langfeldt (1994); Lindlbauer (1995).

relationship between different time series. In addition, the coherence is invariant to any kind of linear transformation.

Frequency domain analysis allows us to calculate the *squared coherence* as a function of *spectra* and *cross spectra:*

$$K_{xy}(\lambda) = \frac{\left|f_{xy}(\lambda)\right|^2}{f_{xx}(\lambda)f_{yy}(\lambda)}$$

where $f_{aa}(\lambda), a = x, y, u$ is called *spectrum* at frequency λ and $f_{xy}(\lambda)$ is called *cross spectrum* (between x and y).

According to König/Wolters (1972) this is a measure for the stochastic relationship between different components of two processes at specific frequencies.[21] Therefore, the measure is comparable to the well-known R^2 in traditional regression analysis. But, no causal relationship between the two variables has to be assumed, as is implicitly the case in regression analysis. Furthermore, no specific model needs to be specified for the determination of the direction of dependence. One of the most important advantages is the invariance against any kind of linear transformation, including that to growth rates. It is worth mentioning that, as Kirchgässner and Wolters (1994) have shown, a coherence of one at frequency zero indicates a co-integration relationship between two time series.[22] This finding corresponds with a popular interpretation of co-integration in the sense that *in the long run* (a frequency of zero corresponds to a cycle of infinite length) both time series *are strongly related and do not diverge from each other*. Our coherence estimations can therefore be regarded as an informal test for co-integration relationships between the indicator and the reference series.

3.2. Results

The results of the estimation of squared coherence for the business cycle reference series and the indicators are shown in figures 3.1 to 3.5.[23]

The null hypothesis of no significant influence (at a 5 % confidence level) was tested using a significance test statistic proposed by Koopmans (1974). The horizontal line in our graphs

[21] König/Wolters (1972: 120).

[22] Cf. Kirchgässner/Wolters (1994).

[23] For the empirical estimation we used the program RATS.

represents the 5% confidence band.[24] Coherence values *above* this level show *significant association* between these two series at specific frequencies (which were transformed into periods for better understanding, e.g. months).

How are these results to be interpreted? In traditional business cycle literature[25], a period of one year up to six or eight years is regarded as relevant for business cycle movements. Hence, coherence tests were carried out for this time series (that is, on the very left side of our graphs, as the figure must be read from right to left). It is the interval from 12 months to near infinity, which is of interest here.

The squared coherence shows a high and significant connection in the field relevant for business cycle research for all the survey indicators. This is especially high in the case of the production expectations, the industry confidence indicator, the economic sentiment and the OECD leading indicator. The real short-term rate also performs well. However, the frequency domain analysis also shows that no indicator is co-integrated with the reference series (with production expectations possibly being an exception). Fortunately, co-integration is not necessary for the variable to be suitable as an indicator. Within the framework of this investigation, a high and significant coherence in the period of one to eight years is sufficient.

Less convincing are the traits of the money supply aggregate, exchange rates, the nominal interest rate, the stock market index, and the interest rate spread. The poor results of the coherence investigation justify in retrospect that the time series with unsatisfactory stationarity characteristics (as discussed above) were excluded from the analysis.

4. Analysis of Lead-Lag Structures

In the second part of our analysis, we examined the lead-structure between the indicator and the reference series. Basically, the *phase* can be determined within multivariate frequency domain analysis. However, this procedure has some disadvantages. Owing to the ambiguous nature of trigonometric functions, these measures are difficult to interpret. Furthermore, estimates are imprecise if the coherence is rather small.[26]

Consequently, we decided to apply other techniques. First we used cross-correlograms to identify - via the maximum of the coefficient of correlation calculated at different lags - possible lead-lag-

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[24] Koopmans (1974), annex, table A9.6. The critical values depend on the degrees of freedom of the empirical estimation.

[25] Cf. Zarnowitz (1992).

[26] Cf. Wolters (1996).

structures. We then asked whether the inclusion of past values of the indicator variable would improve the forecast of the reference series, that is, we performed Granger-causality tests.

4.1. Cross Correlation

As a first approximation of lead-lag structures between the chosen reference series and those indicators that passed the spectral analysis criterion, cross correlation can be calculated. Traditionally, the maximum of the coefficient of correlation is seen as the "lead" or "lag" of the indicator in relation to a reference series. But these measures should be interpreted cautiously, as they can be distorted by overlapping oscillations. We estimated the coefficient of correlation between the reference and indicator series with a lag length of 24 on each side. The thin lines in our graphs represent a rough estimation of the 5% significance band.[27] Values outside this band indicate a "significant" correlation. Results are plotted in Figures 4.1 to 4.3.

In many cases, when used with the survey indicators, the traditional cross-correlograms indicate coincidence between indicator and reference series. This comes as little surprise, as most surveys focus on the assessment of the current situation. However, some indicators, as e.g. the order volumes, show a lag. The real exchange rate shows a lead of around 6 months, while the lead of the nominal exchange rate lies between 6 and 12 months. Short- as well as long-term real interest rates are lagging behind the reference series. The OECD leading indicator shows a clear lead of around 6 months as it was designed to do. However, the overlapping oscillations mentioned above can also lead to misleading results. Investigations were extended in order to further our knowledge.

4.2. Pair-wise Granger-Causality Tests

Determining whether movements in the indicator series "lead" movements in the reference series is of crucial importance in identifying reliable indicators. Granger-causality tests were developed for the assessment of such questions. The test for Granger-causality attempts to determine whether changes in the indicator series precede changes in the reference series or vice versa: We extend a regression of the stationary reference series on its own lagged variables by including past values of a stationary indicator series. If the fit is improved significantly by this inclusion, the

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[27] The significance band is calculated as $\pm 2/\sqrt{T}$, where T is the number of observations (this procedure is quite common in most econometric software packages, see EViews 3.1 help).

indicator series is Granger-causal. This, however, does not mean that a "true" causality between the time series exists.[28]

A common difficulty in performing such tests is the choice of lag length, because the results are not independent from the chosen lag structure.[29] Other authors state that quite often the equations do not pass stability tests on parameter constancy like CUSUM-square tests or Chow breakpoint tests.[30] Furthermore, standard econometric software packages carry out these tests with fixed length on both sides, which is sometimes criticised as leading to mis-specification. We chose a twofold strategy. First, we estimated a VAR including the indicator and the reference series and identified the best model specified by the minimum of the Hannan-Quinn criterion considering up to 24 months. We used this lag-length to specify Granger-tests. This strategy has the disadvantage that the equation contains variables which need not be statistically significant, so that the results may be biased. Furthermore, we violate the principle of parsimonious parameter inclusion.

That is why, for the second strategy, we estimated a univariate equation and added individual lags of the indicator series. We chose the Schwartz information criterion to assess improvements in specification. The second strategy helps to avoid mis-specification by allowing for a more flexible specification of the lag structure.

The results of the first approach are summarised in Table 4.1.

Some indicators have clear leading indicator characteristics. This is especially the case with the industry confidence, the order book position, the production expectations or the OECD leading indicators. They do not only indicate a clear one-way direction of Granger-causality, but the values of the F-statistic are also very significant.

Feedback relationships cannot be rejected for many of the indicators. In particular in those cases where the "opposite direction" (causality leading from the reference series towards the indicator) of causality is found and the F-statistic value is very high, some doubts remain as to whether these indicators are really useful leading indicators.[31]

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[28] Cf. Salazar et. al. (1996: 50).

[29] Cf. Gujarati (1995: 622).

[30] Cf. Döpke/Krämer/Langfeldt (1994); Döpke (1998).

[31] The application of Granger-tests for the assessment of leading indicator suitability is difficult. A common example is the relation between the sales of Christmas postcards and the occurance of Christmas. A Granger-Test would find that the sales of Christmas postcards (some one or two months ahead of Christmas) is causal for the occurance of Christmas. As we know, this cannot be true. Christmas occurs even without Christmas postcard sales. Nevertheless, stable relationships can be statistically proved. In addition, feed-back relationships show interdependence between

4.3. Individual Granger-Causality Tests

Due to the above-mentioned disadvantages of the standard Granger-causality tests carried out by standard econometric software, we performed individual tests as well.[32] Contrary to the pair-wise tests, we tested for one direction of causality only.[33]

First, we estimated the best univariate specification for the annual growth rate of the reference series (t-values in parentheses):

$$y = \underset{(2.13)}{0.29} + \underset{(4.56)}{0.35}\, y_{-1} + \underset{(5.05)}{0.39}\, y_{-2} + \underset{(4.35)}{0.36}\, y_{-3} - \underset{(-5.59)}{0.26}\, y_{-9}$$

with:

$\overline{R}^2 = 0.82$

$DW = 1.95$

$SIC = 0.753$

where DW denotes the Durbin-Watson statistic and SIC the Schwartz information criterion. No serial correlation remained in the residuals. In a second step we estimated regressions specified in the form of Granger-tests. Here, we could add individual lags (always one) of the indicator series to the univariate regression. In general, the above-mentioned equation was modified to:

$$y = \beta^0 + \beta^1 y_{-1} + \beta^2 y_{-2} + \beta^3 y_{-3} + \beta^4 y_{-9} + \gamma^1 x_{-t}$$

where t = 1,2,....24.

The value of the Schwartz information criterion of the latter equation was compared with the value of the Schwartz information criterion of the univariate equation (the dotted line in figures 4.4 to 4.6), for equations from the first up to and including the 24th lag. As proposed in Wolters (1996), an improved information criterion in comparison with the information criterion of the univariate estimation was interpreted as a sign of Granger-causality. Because only individual lags were used, the absolute minimum of the criterion served as a means of identifying the most significant "lead" between reference and indicator series. The results are summarised in Figures 4.4 to 4.6.

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the indicator and the reference series. In this case indicators reflect a correct anticipation of business cycle movements by the economic agents, whereas the business cycle itself reflects the economic sentiment. Both are determined inter-dependently (feed-back). However, if one believes that only unanticipated shocks can cause changes in the business cycle (as most business cycle theories state), only "true" Granger causality relationships can be admitted as suitability criteria for indicators. In our investigation, however, we did not reject feed-back relationships for the assessment of the suitability of an indicator variable.

[32] Cf. Wolters (1996).

[33] Cf. footnote 31.

Only a few of the survey indicators pass this, admittedly, demanding test. Industry confidence, retail trade confidence and, in particular, production expectations show the expected results. This is also true for the OECD leading indicator. The inclusion of short- and long-term real interest rates in the range of around five months shows an improvement of the estimation characteristics. It is interesting that all results suggest that the indicators have mainly short-term characteristics, which in turn confirms the earlier observation of widespread coincidence between the series. At the same time the limitations for the use of these indicators in actual forecasts also becomes apparent.

5. Out-of-Sample Forecasts

One important question remains to be answered. Are the indicators with the best in-sample performance also the indicators with the best out-of-sample performance? The answer is by no means obvious.

In general, exercising out-of-sample forecasts requires forecasts of the exogenous variables, which is sometimes done by AR processes. However, we chose another strategy.

To generate an endogenous forecast for the indicator variable, we constructed a VAR that includes the reference series and the indicator series. The maximum lag was restricted to 12 months and single VARs were specified according to significant t-values. The specifications of the VARs can be found in Table 5.1.

Theil's U is well-known as a measure of forecast accuracy. We calculated a modified Theil's U, as proposed by Davis and Fagan.[34] This measure is defined as the relation of the root mean squared error of a structural forecast (here: the root mean squared error of the VARs or $RMSE^{VAR}$) to the root mean squared error of a "naïve" forecast (here: the root mean squared error of the above-mentioned univariate AR-process or $RMSE^{AR}$).

$$\text{Theil's } U = \frac{RMSE^{VAR}}{RMSE^{AR}}$$

A range of Theil's U between zero (perfect prediction) and less than one (a value of one indicates no improvement in comparison with a "naïve" forecast) is of special interest for our investigation. Values larger than one can be interpreted as a worsening of the forecast quality compared to the above-mentioned "naïve" prognosis. Furthermore, the root mean squared error

[34] Davis/Fagan (1997); Döpke (1998).

can be decomposed into a bias, a variance and a covariance proportion.[35] The bias proportion tells us how much the mean of the forecast differs from the mean of the actual series. The variance proportion indicates the differences in variation of the forecast and variation of the actual series. The covariance proportion measures the remaining unsystematic forecasting errors. For a "good" forecast, the bias and variance proportion should be small, whereas most of the remaining errors should concentrate on the covariance proportion.

Regressions were run for the period from 1986:1 to 1995:12. Dynamic three- and six- month forecasts were carried out for the period from 1996 to 1998. In addition, the root mean squared errors for both forecasting methods were calculated and decomposed into bias, variance and covariance. The results are shown in Table 5.1. and allow some interesting conclusions to be drawn.

On the one hand it can be observed that only few indicators significantly improve the prognosis over that of a simple univariate AR-prognosis and even this holds only for a period of up to 3 months. In particular the VARs including the economic sentiment indicator and the OECD leading indicator – both constructed from a number of series and therefore close to the idea of an overall indicator – point towards an improved forecast over a time period of 6 months. On the other hand, it cannot be ruled out that the indicators can produce substantially false prognoses. The result of the estimation of the industry confidence indicator, which until now was one of the better performing indicators, is particularly noticeable. All in all the performance of all other indicators was rather dissatisfactory. These results confirm the general scepticism of the usefulness of leading indicator relations.[36]

6. Conclusion

In our analysis we tested a number of potential indicators using spectral analysis, Granger-tests and out-of-sample forecasts. We tested two large groups of indicators on their suitability as economic leading indicators for the European business cycle: monetary and non-monetary (mainly survey-based) indicators. The results are summarised in Table 5.2. It is apparent that all survey indicators, such as production expectations, different confidence indicators and combined indicators such as the economic sentiment indicator or the OECD leading indicator perform quite well. They show significant coherence in the relevant region. Furthermore, their leading

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[35] Cf. Pindyck/Rubinfeld (1998[4]), chapter 8.

[36] As an example for the scepticism concerning Euroland, see Döpke (1998).

indicator qualities are confirmed by Granger-tests and by out out-of-sample forecasts, even though the latter also show the limits of the indicator approach.

A surprising result is that monetary indicators such as money supply aggregates and nominal interest rates do less well. Their stationarity properties are insufficient for the indicator approach as they do not fulfil the minimum requirements for a reliable indicator, which is proven by the coherence test in the spectral analysis. For this reason, they were omitted from the following investigations. Real interest rates as well as the interest rate spread did not show very convincing characteristics but the real effective exchange rate seems to have some leading indicator properties according to the out-of-sample forecast.

In sum, our findings are rather sobering in the sense that there are only some indicators that improve the forecasts and they do this for the very short term only.

Nevertheless, indicators with a small lead or those which are coincident can still provide an important contribution to the assessment of the overall European economic development. This is in particular the case of the survey-based indicators of the European commission. However, improvements in the forecasts for a time period of over 6 months should not be expected.

7. Literature

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Appendix

Table 2.1

Time Series under Investigation

Time Series	Dimension	Source
Industry Production Index (IIP)	1995=100	OECD: Main Economic Indicators
Industry Confidence Indicator	% balance	EU Commission
Order Book Position	% balance	EU Commission
Production Expectation for months ahead	% balance	EU Commission
Construction Confidence Indicator	% balance	EU Commission
Retail Confidence Indicator	% balance	EU Commission
Consumer Confidence Indicator	% balance	EU Commission
Economic Sentiment Indicator	% balance	EU Commission
EMU-11 Stock Index	1990=100	EU Commission
OECD Leading Indicator	1990=100	OECD: Main Economic Indicators
Euro Dollar Exchange Rate	Euros per Dollar	OECD: Main Economic Indicators
Real Effective Exchange Rate	1995 = 100	OECD: Main Economic Indicators
New Car Registrations, sa	in 1.000	OECD: Main Economic Indicators
Money Supply M1	Euros Billion	OECD: Main Economic Indicators
Money Supply M3	Euros Billion	OECD: Main Economic Indicators
Short-Term Interest Rate	% p.a.	OECD: MEI / Own Calculations
Long-Term Interest Rate	% p.a.	OECD: MEI / Own Calculations
Short-Term Interest Rate, real	% p.a.	Own Calculations
Long-Term Interest Rate, real	% p.a.	Own Calculations
Interest Rate Spread	% p.a.	Own Calculations
Money Supply M1, real	Euros Billion	Own Calculations
Money Supply M3, real	Euros Billion	Own Calculations

Table 2.2

Unit Root Test (Augmented Dickey-Fuller)

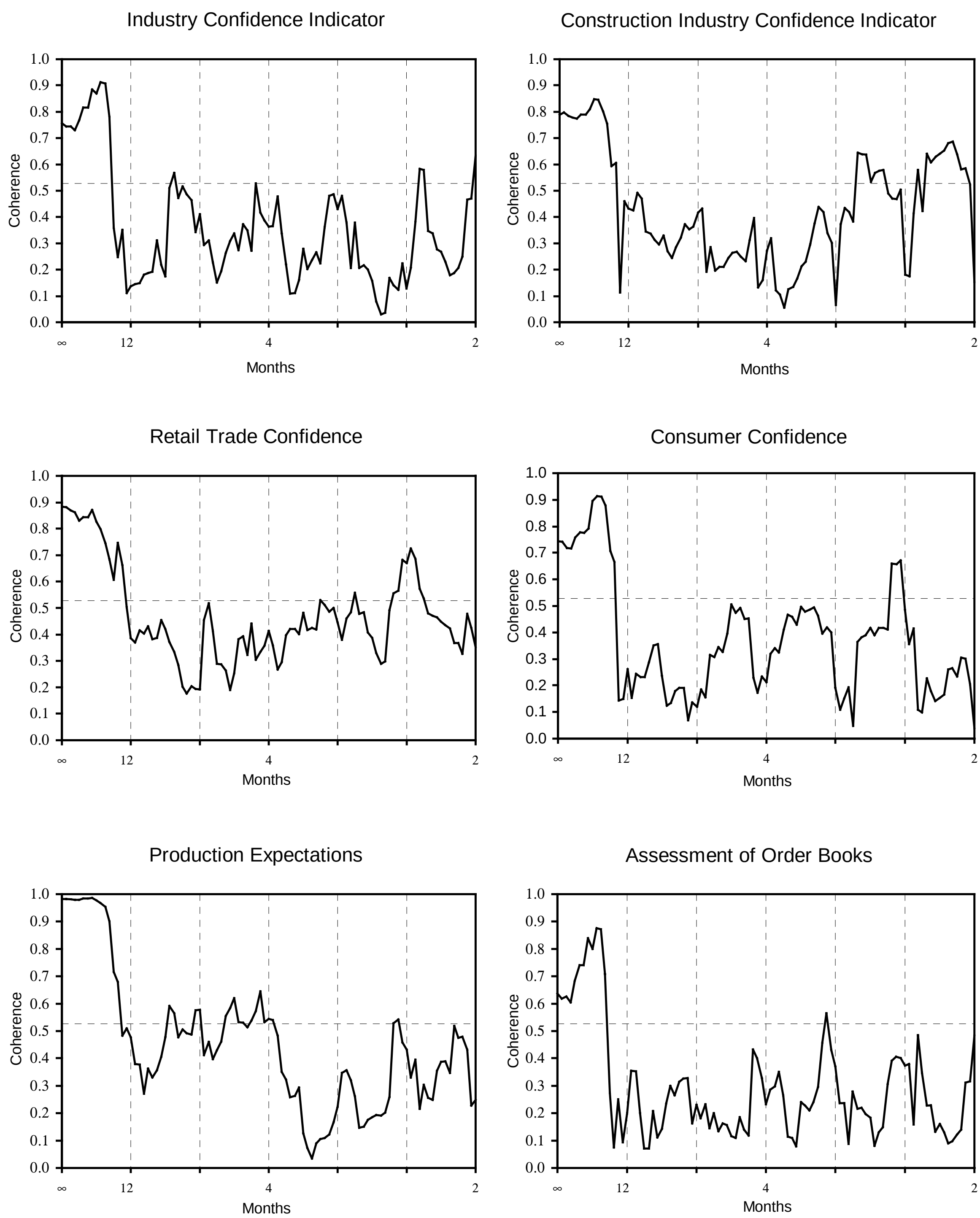
Transformation	Level		Yearly Growth Rate		1st Difference		Degree of
Series	t-Value	Specification	t-Value	Specification	t-Value	Specification	Integration
Industry Production Index (IIP)	-1,83	c, t, 1-12	-2,94 **	c, 1-12	-	-	I (1)
Industry Confidence Indicator	-2,78 *	c, 1-5, 12	-	-	-	-	I (0)
Order Book Position	-2,63 *	c, 1-3, 5-6, 11	-	-	-	-	I (0)
Production Expectation for months ahead	-3,52 ***	c, 1-12	-	-	-	-	I (0)
Euro Dollar Exchange Rate	-3,41 **	c, 1-12	-	-	-	-	I (0)
Real Effective Exchange Rate	-3,57 ***	c, 1-12	-	-	-	-	I (0)
Construction Confidence Indicator	-2.19	c, 1, 3-7, 9-12	-2,68 ***	1-12	-	-	I (1)
Retail Confidence Indicator	-1.41	c, 1-12	-2,33 **	1-12	-	-	I (1)
Consumer Confidence Indicator	-1.89	c, 1-7, 9-12	-1,96 **	1-12	-	-	I (1)
Economic Sentiment Indicator	-2.46	c, 1, 3-7, 9, 11-12	-2,30 **	1-12	-	-	I (1)
EMU-11 Stock Index	2,10	1-12	-2,98 **	c, 1, 3, 7-12	-	-	I (1)
OECD Leading Indicator	-2,83	c,t,1,7-8	-3,92 ***	c,1			I (1)
New Car Registrations	-2.11	c, 1-7, 9-10, 12	-2,89 **	1-12	-	-	I (1)
Real Short-Term Interest Rate	-1,21	1-2,4,6,9,12	-3,19 ***	1,2,4,7-9,10,12	-	-	I (1)
Real Long-Term Interest Rate	-2,28	c,t,1,3,5-7,9,10-12	-2,16 **	1-3,5-6,8-9,11-12	-	-	I (1)
Interest Rate Spread	-1,75 *	1-2	2,18 **	1-2,5-6,11-12	-	-	I (1)
Short-Term Interest Rate	-1,52	c,t,1,3,7-9	-2,28	c,t,1-2,4,7.8-10,12	-2,95 ***	1-12	I (1)
Long-Term Interest Rate	-1,04	c,t,1,3,7,10-12	-2,44	c,t,1-3,7,11,12	-3,61 ***	1-12	I (1)
Money Supply M1	-1,30	c,t,1,3,7-9	-2,43	c,t,1-3,5,9,12	-0,86	c, 1-12	I (2)
Money Supply M3	-2,49	c, t, 1-12	-2,20	c,t,1,3,6,9,12	-23,04 ***	c, 2-11	I (1)
Real Money Supply M1	-0,65	c,t,1,2,6,9,10-12	-1,77	c,t,1-3,5,9,10,12	-0,76	c, 1-12	I (2)
Real Money Supply M3	-3,08 1)	c,t,9-12	-1,84	c,1,3,6,9,12	-23,02 ***	c, 2-11	I (1)

1) Significant at 12 per cent level. *,**,*** denote siginificance at 10, 5 and 1 per cent level.

Critical Values according to McKinnon (1991).

Figure 3.1

Coherence[1)] between Reference Series and...

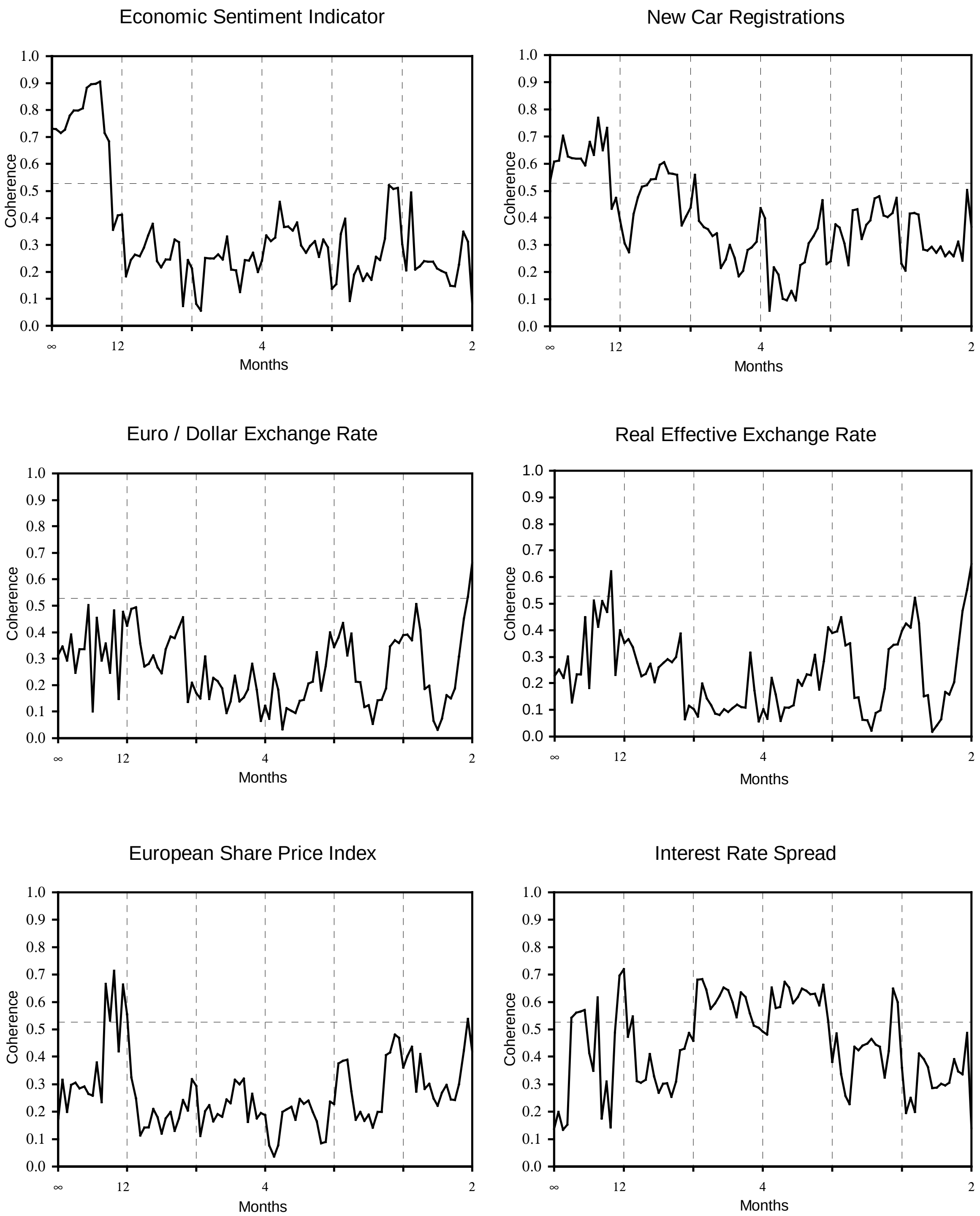


1) The coherence was estimated using 96 datapoints and 11 degrees of freedom.

Source: Calculations of DIW.

Figure 3.2

Coherence[1)] between Reference Series and...



1) The coherence was estimated using 96 datapoints and 11 degrees of freedom.

Source: Calculations of DIW.

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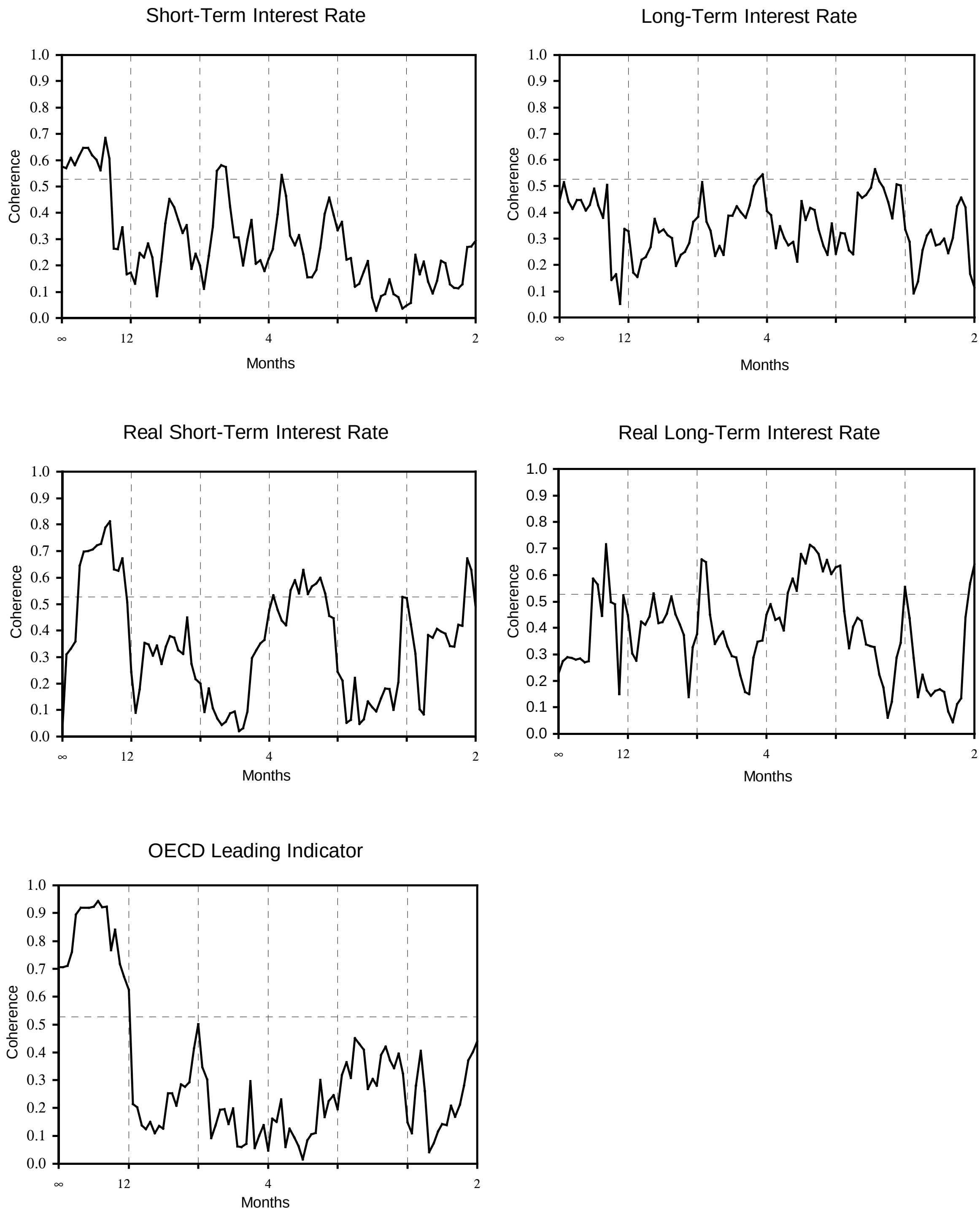
Figure 3.3

Coherence[1)] between Reference Series and...



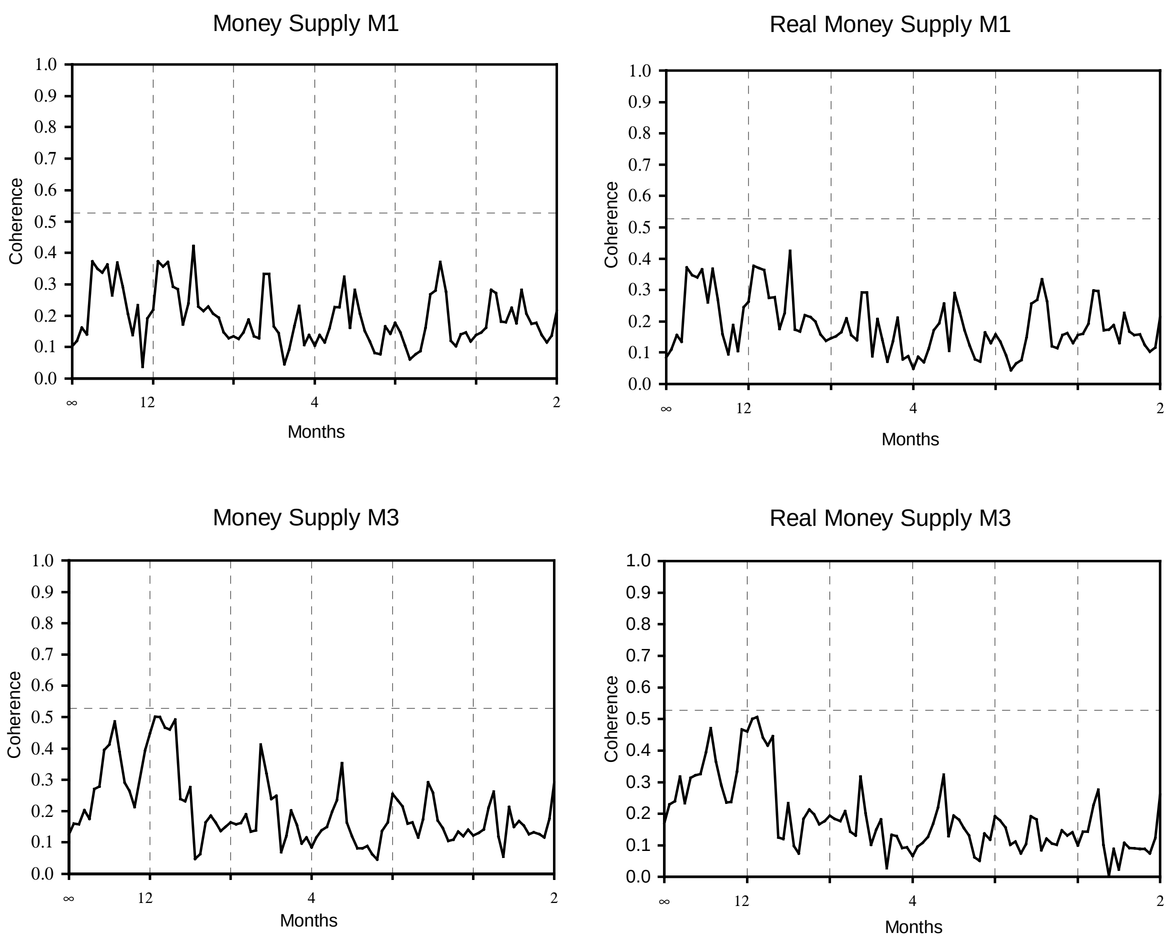
1) The coherence was estimated using 96 datapoints and 11 degrees of freedom.

Source: Calculations of DIW.

DIW Deutsches Institut für Wirtschaftsforschung

Figure 3.4

Coherence[1)] between Reference Series and...



1) The coherence was estimated using 96 datapoints and 11 degrees of freedom.

Source: Calculations of DIW.

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Figure 4.1

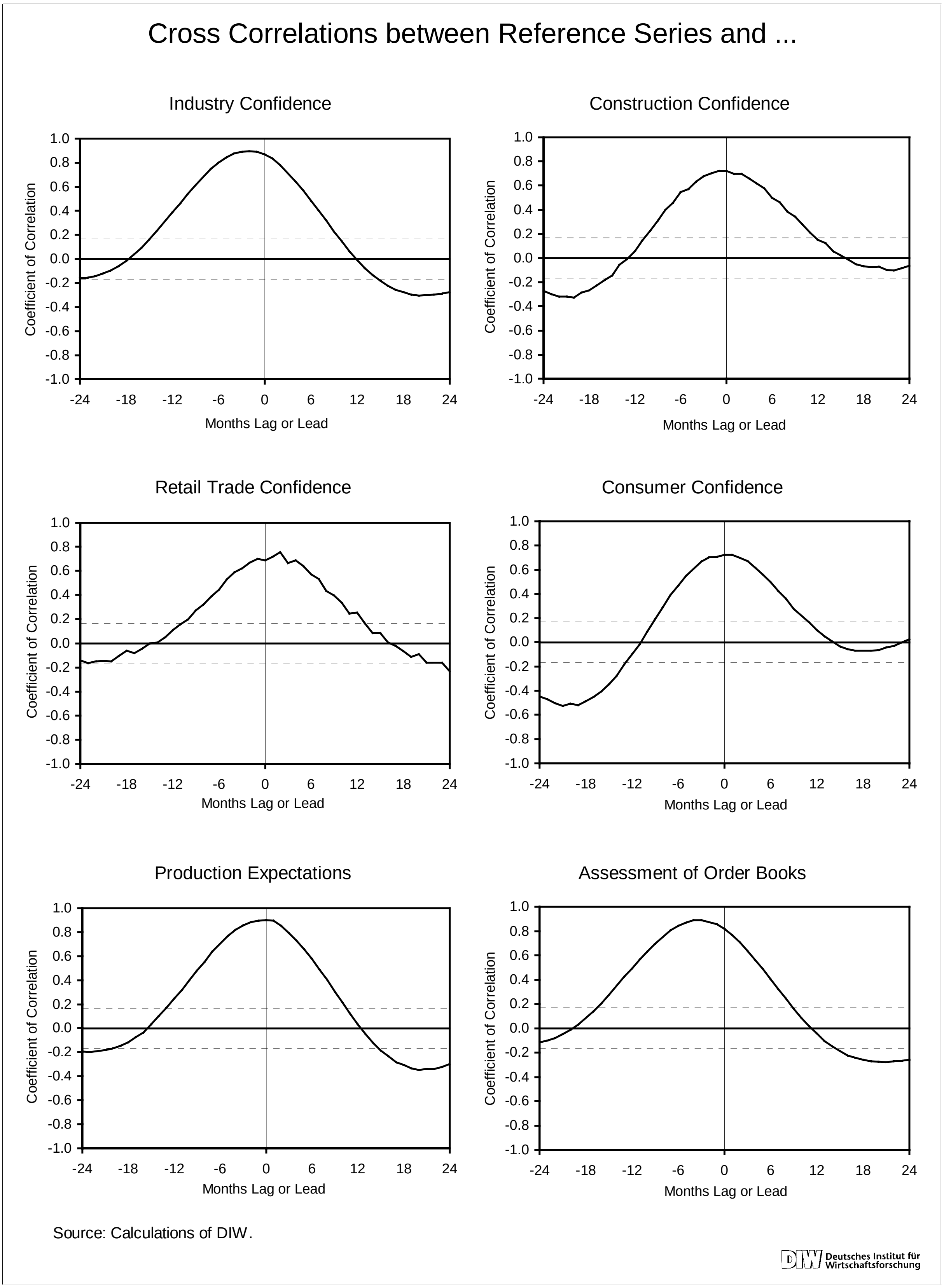
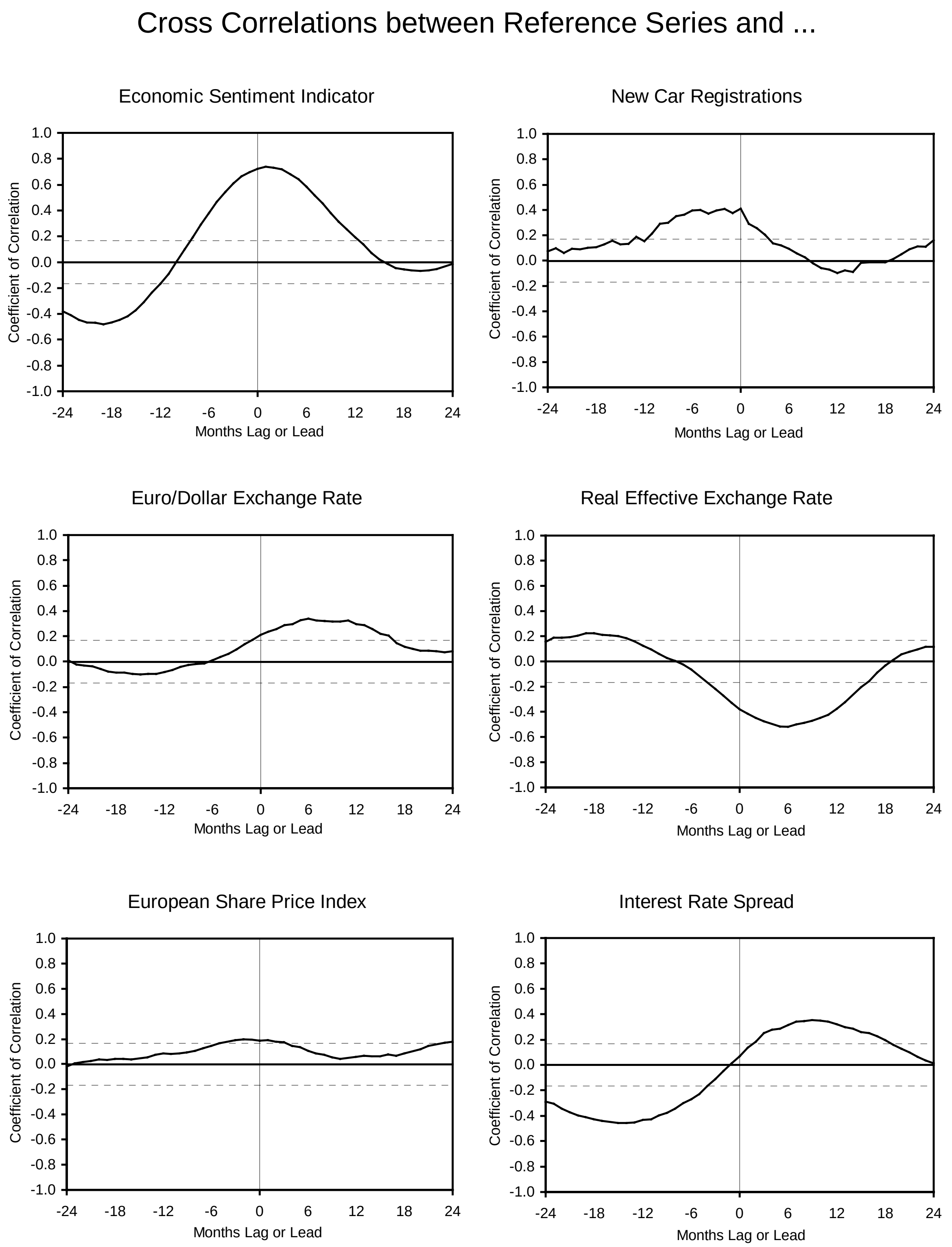
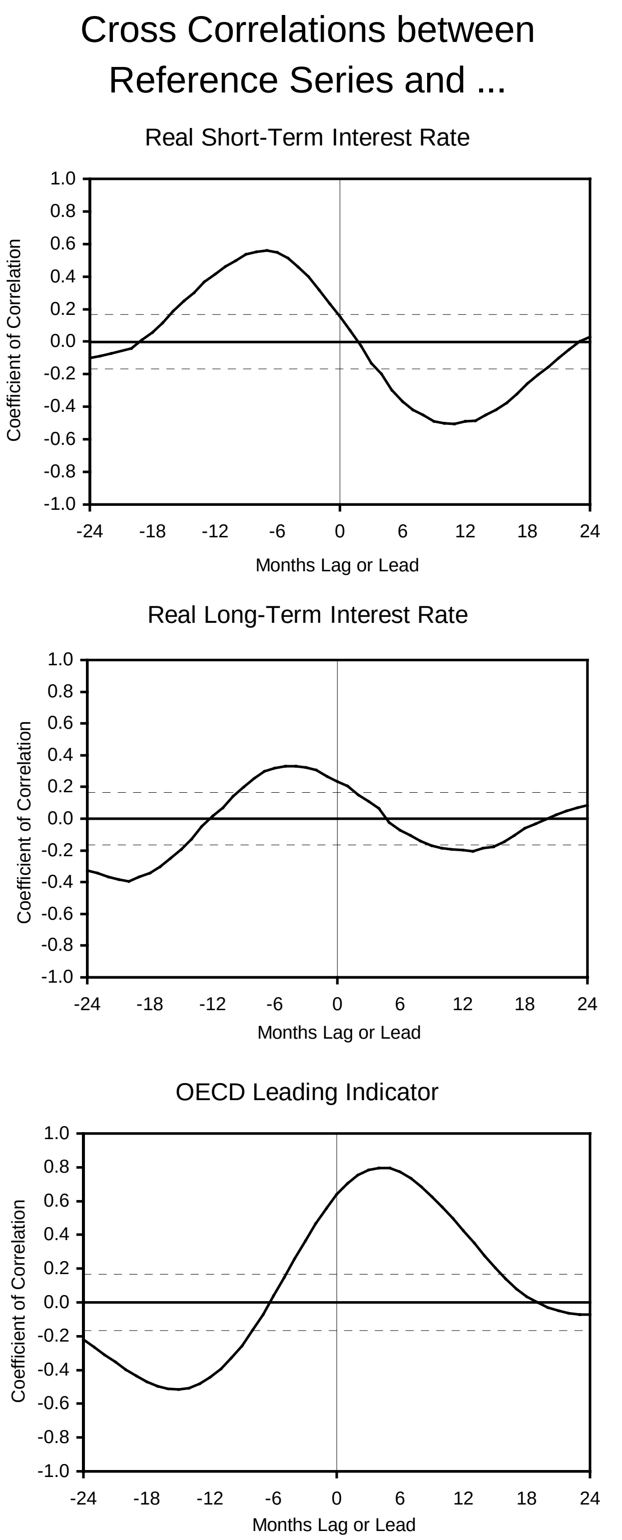

Cross Correlations between Reference Series and ...
Industry Confidence
Construction Confidence
Retail Trade Confidence
Consumer Confidence
Production Expectations
Assessment of Order Books
Coefficient of Correlation
Months Lag or Lead
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-24
-18
-12
-6
0
6
12
18
24
Source: Calculations of DIW.
DIW Deutsches Institut für Wirtschaftsforschung

Figure 4.2



Source: Calculations of DIW.

Figure 4.3



Source: Calculations of DIW.

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Table 4.1

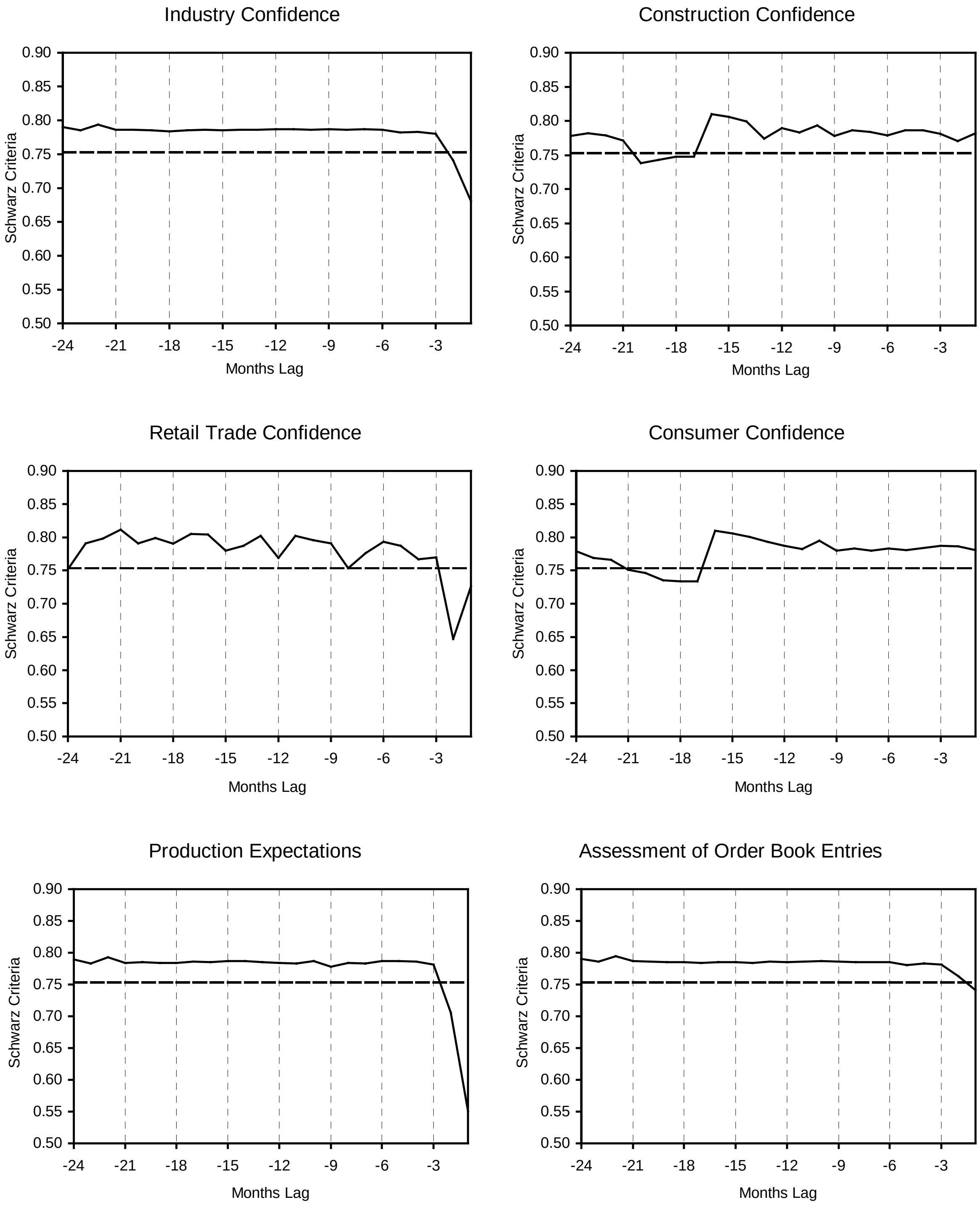
Pairwise Standard Granger-Causality Test

Indicator	Transformation	VAR Lag-Length	H0: Indicator not Granger-causal	H0: IIP not Granger-causal	Result
Industry Confidence	Level	4	16,63 ***	1,43	I --> R
Order Book Position	Level	4	11,62 ***	1,89	I --> R
Production Expectations	Level	4	17,42 ***	4,81 ***	Feedback
Euro / Dollar Exchange Rate	Level	2	1,39	0,20	No Causality
Real Effective Exchange Rate	Level	2	3,34 **	0,45	I --> R
OECD Leading Indicator	Growth Rate	3	17,49 ***	0,44	I --> R
Construction Confidence	Growth Rate	9	3,16 ***	3,36 ***	Feedback
Consumer Confidence	Growth Rate	4	5,09 ***	5,31 ***	Feedback
Retail Trade Confidence	Growth Rate	4	6,16 ***	2,47 **	Feedback
Economic Sentiment Indicator	Growth Rate	5	4,98 ***	2,88 **	Feedback
European Share Price Index	Growth Rate	12	2,16 **	1,66 *	Feedback
New Car Registrations	Growth Rate	2	2,98 *	4,41 **	Feedback
Real Short-Term Interest Rate	Growth Rate	3	9,09 ***	4,01 ***	Feedback
Real Long-Term Interest Rate	Growth Rate	2	2,04	1,71	No Causality
Interest Rate Spread	Growth Rate	4	4,19 ***	1,57	I --> R

VAR Lag-Length determined via the minimum of Hannan-Quinn-Criterion.

Figure 4.4

Granger Causality Test between best Univariate Reference Series Estimation and Individual Lags of ...



Source: Calculations of DIW.

DIW Deutsches Institut für Wirtschaftsforschung

Figure 4.5

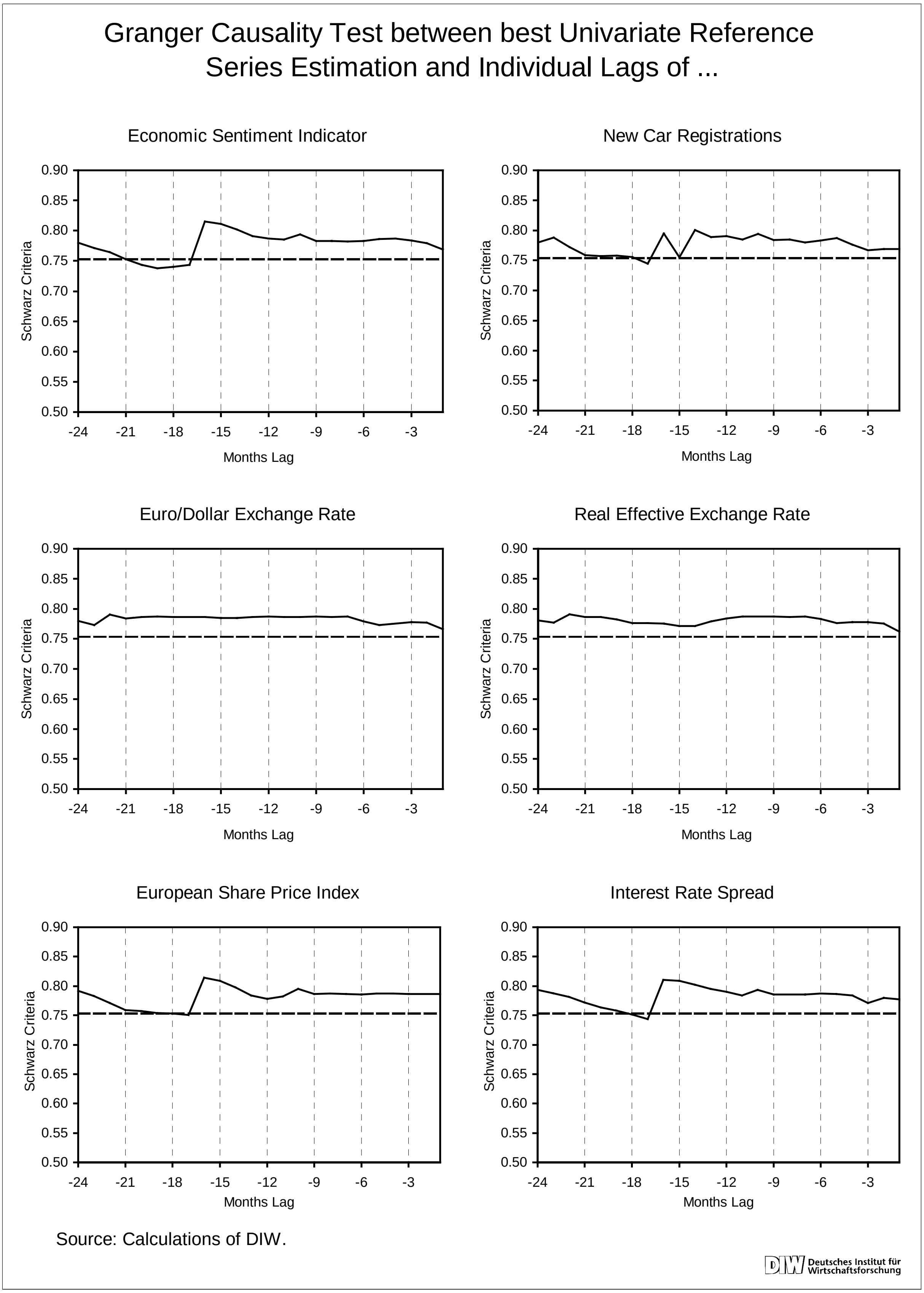

Granger Causality Test between best Univariate Reference Series Estimation and Individual Lags of ...
Economic Sentiment Indicator
New Car Registrations
Euro/Dollar Exchange Rate
Real Effective Exchange Rate
European Share Price Index
Interest Rate Spread
Schwarz Criteria
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
-24
-21
-18
-15
-12
-9
-6
-3
Months Lag
Source: Calculations of DIW.
DIW Deutsches Institut für Wirtschaftsforschung

Figure 4.6

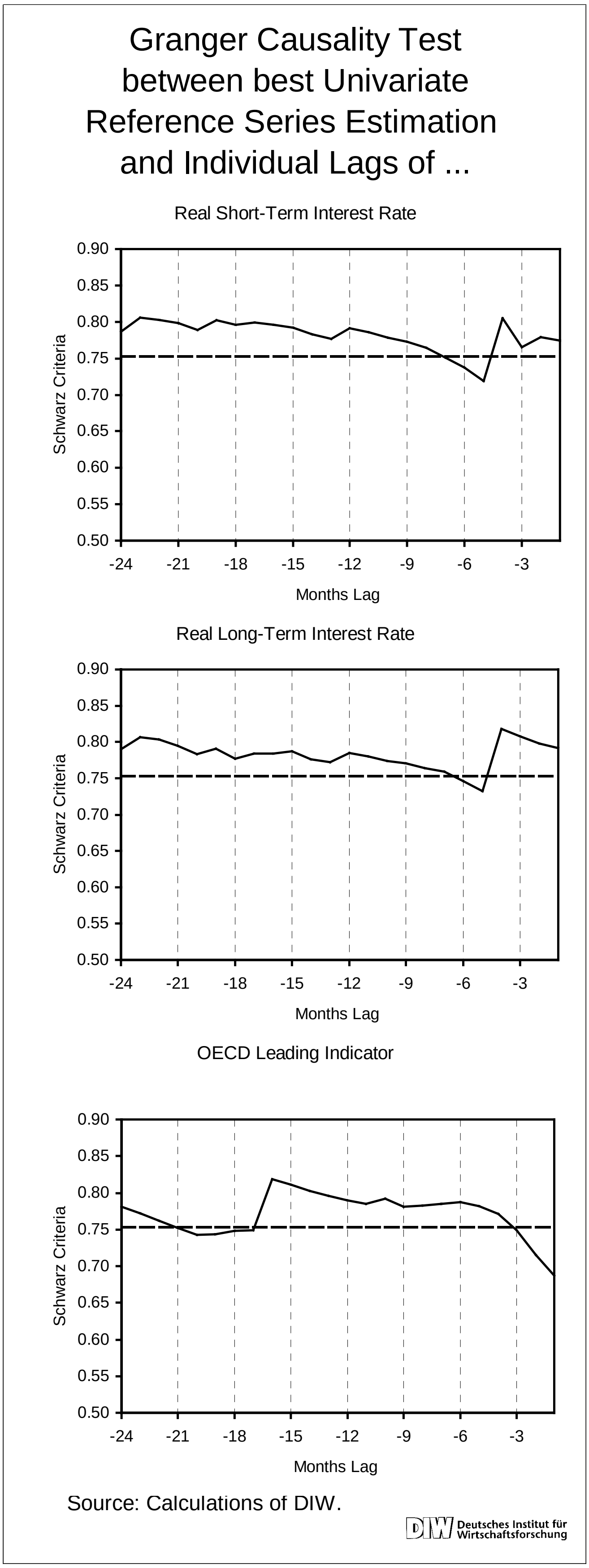

Granger Causality Test
between best Univariate
Reference Series Estimation
and Individual Lags of ...
Real Short-Term Interest Rate
Schwarz Criteria
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
-24 -21 -18 -15 -12 -9 -6 -3
Months Lag
Real Long-Term Interest Rate
Schwarz Criteria
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
-24 -21 -18 -15 -12 -9 -6 -3
Months Lag
OECD Leading Indicator
Schwarz Criteria
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
-24 -21 -18 -15 -12 -9 -6 -3
Months Lag
Source: Calculations of DIW.
DIW Deutsches Institut für Wirtschaftsforschung

Table 5.1

Out-of-Sample Forecast

VAR including Reference Cycle and...	VAR-Specification	3 Months VAR Forecast				6 Months VAR Forecast			
			Forecast Measures of RMSE ^{VAR}				Forecast Measures of RMSE ^{VAR}		
		Modified Theil´s U	Bias Proportion	Variance Proportion	Covariance Proportion	Modified Theil´s U	Bias Proportion	Variance Proportion	Covariance Proportion
Industry Confidence	c, 1, 9, 12	1,32	0,54	0,09	0,38	1,49	0,60	0,07	0,33
Construction Confidence	c, 1-2, 9	1,10	0,32	0,01	0,67	1,34	0,59	0,01	0,41
Retail Trade Confidence	c, 1-2, 11-12	0,95	0,06	0,02	0,93	1,18	0,26	0,01	0,73
Consumer Confidence	1-2, 5, 8-9	0,89	0,12	0,00	0,88	1,01	0,28	0,00	0,72
Production Expectations	1-3, 9	0,99	0,17	0,00	0,83	1,09	0,38	0,00	0,62
Assessment of Order Books	c, 1, 3-4, 10, 12	1,16	0,33	0,09	0,59	1,24	0,41	0,06	0,53
Economic Sentiment Indicator	c, 1-2, 5, 9	0,84	0,03	0,01	0,96	0,94	0,14	0,01	0,86
OECD Leading Indicator	c, 1-2, 8, 12	0,69	0,06	0,03	0,91	0,84	0,01	0,02	0,96
New Car Registrations	1-2, 12	1,04	0,26	0,02	0,72	1,28	0,44	0,05	0,52
Euro / Dollar Exchange Rate	c, 1-3, 9	0,92	0,05	0,02	0,93	1,06	0,18	0,02	0,80
Real Effective Exchange Rate	c, 1-2, 9	0,91	0,01	0,00	0,99	0,92	0,00	0,00	1,00
European Share Price Index	1-2, 5, 8-9, 12	0,95	0,09	0,03	0,89	1,15	0,24	0,03	0,74
Interest Rate Spread	1-3, 5, 7, 9	0,95	0,22	0,00	0,78	1,21	0,41	0,00	0,59
Real Short-Term Interest Rate	1-2, 5, 12	1,07	0,01	0,14	0,85	1,38	0,11	0,05	0,84
Real Long-Term Interest Rate	1-2, 5-6, 9, 12	0,94	0,17	0,00	0,83	1,22	0,40	0,00	0,60

Table 5.2

Summary of Results

	Test Procedures					
	Cross Correlation	**Spectral Analysis**	**Standard Pairwise Granger-Tests**	**Individual Granger-Tests**	**VAR-based Out-of-Sample Forecast (3 Months)**	**VAR-based Out-of-Sample Forecats (6 Months)**
	Criterion					
	maximum coefficient of correlation indicates a lead of the reference series	significant coherence in the frequency domain relevant for business cycle analysis	inclusion of lagged indicator values improves the estimation of the reference series significantly		improvement of the quality of the indicator-based forecast compared with the quality of a univariate (AR) forecast	
Industry Confidence	-	X	X	X	-	-
Construction Confidence	-	X	X	-	-	-
Retail Trade Confidence	-	X	X	X	X	-
Consumer Confidence	-	X	X	-	X	-
Production Expectations	-	X	X	X	X	-
Assessment of Order Books	-	X	X	-	-	-
Economic Sentiment Indicator	**X**	**X**	**X**	-	**X**	**X**
OECD Leading Indicator	**X**	**X**	**X**	**X**	**X**	**X**
New Car Registrations	-	X	X	-	-	-
Euro / Dollar Exchange Rate	X	-	-	-	X	-
Real Effective Exchange Rate	X	-	X	-	X	X
European Share Price Index	-	-	X	-	X	-
Interest Rate Spread	X	-	X	-	X	-
Real Short-Term Interest Rate	-	X	X	X	-	-
Real Long-Term Interest Rate	-	-	-	X	X	-