Jahrbücher f. Nationalökonomie u. Statistik (Lucius & Lucius, Stuttgart 2002) Bd. (Vol.) 222/3

Abhandlungen / Original Papers

Leading Indicators of German Business Cycles

An Assessment of Properties

Frühindikatoren der deutschen Konjunktur

Eine Beurteilung ihrer Eigenschaften

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JEL E32, C22, C32

Business cycle, leading indicators, Granger-causality test, spectral analysis.

Konjunktur, Frühindikatoren, Granger-Kausalitätstest, Spektralanalyse.

Summary

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 German data. We used frequency domain analysis, different Granger-causality tests and out-of sample forecasts. Only few indicators passed all tests. Their inclusion into VAR-based forecasts improves the forecast in the very short run. Further research should concentrate on the unsolved problem of the prediction of business cycle turning points.

Zusammenfassung

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 deutsche Daten. Dazu werden Methoden der Spektralanalyse, verschiedene Granger-Tests und Out-

* We would like to thank the participants of the "Seminar for Quantitative Economic Research" at the Freie Universität Berlin, especially Professor Jürgen Wolters, as well as our colleagues at the German Institute for Economic Research (DIW) in Berlin, especially Gustav-Adolf Horn, for helpful comments and fruitful discussions about the topic. We thank Jörg Döpke for sharing some of his programmes and benefitting from his ongoing research. Thanks to Jan Gottschalk for comments and to Kirsten Lommatzsch who not only helped to improve our English version but stimulated the discussion considerably. We thank the anonymous referees for very helpful comments.

of-sample-Prognosen verwendet. Nur wenige Indikatoren bestehen die Tests auf die geforderten Eigenschaften. Ihre Einbeziehung in VAR-basierte Prognosen verbessert die Prognoseleistung in der sehr kurzen Frist. Weitere Forschung sollte sich auf das ungelöste Problem der Wendepunktprognose des Konjunkturzyklus beziehen.

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]

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 fit of the estimation 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 "naive" prognosis).

Our analysis deals with tests for these requirements applied to German data. First of all we have to decide which of the potential indicators selected on theoretical grounds are related to the business cycle reference series. One approach to the investigation of time series properties, which is rarely used nowadays, is spectral analysis. This method is used as a test for meeting the first requirement, namely the test of co-movements in the indicator and reference series. The coherence measure used in the frequency domain approach enables us to measure the strength of the relationship between the business cycle reference series and the indicator series especially at the frequency relevant for business cycle movements. Only if the indicator series show the same somehow defined "normal" business cycle upswings and downturns as the reference series this indicator can serve as a reliable tool for business cycle forecasting.[2] In accordance with the significance band proposed by Koopmans, we confined the choice of potential leading indicators to those which have a significant relationship in the relevant interval. In our further investigations, we only included those indicators which passed the first test in the frequency domain.

[1] Indicators can be divided in leading, coincident and lagging indicators. Furthermore there are indicators which show the degree of "tightness" on markets. The first attempts to describe cyclical movement of economic activity based on a system of indicators date back to the early twenties. The "Harvard Barometer" – published between 1919 and 1922 – was one of the first well-known leading indicator systems. Its construction was based on 13 time series. The Deutsches Institut für Konjunkturforschung (later DIW) under the leadership of its first president Professor Ernst Wagemann established the first leading indicator system for Germany. The indicator-based research of Burns and Mitchell at NBER in the thirties and forties helped to establish the Anglo-Saxon view of the "business cycle as consensus". Cf. *Tichy* (1994), *Wagemann* (1928), *Burns/Mitchell* (1946), *Oppenländer* (1997), *Moore/Zarnowitz* (1986).

[2] According to the old practice of Burns and Mitchell, a "normal" business cycle is defined as a cycle of a length between six and 32 quarters. This is a standard setting which is common in business cycle research. Cf. *Zarnovitz* (1992).

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. We used the criterion of Granger-causality to decide which indicators meet the second requirement of our list. Because traditional pair-wise Granger-causality tests possess some pitfalls, we carried out a modified Granger-causality test as well.[3]

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, for indicators that passed all earlier tests, we examined their forecast performance using a procedure proposed by Davis and Fagan, thus testing for the third requirement for a reliable indicator.[4]

2. Data

2.1. Choice of Variables

For decades, the use of leading indicators in business cycle research has been criticised for being "measurement without theory".[5] There are however 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.

In particular, indicators are of crucial importance to applied business cycle forecasting. In recent years, examination of their properties has gained considerable attention from researchers. 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 the articles of Döpke/Krämer/Langfeldt (1994), Langfeldt (1994), Köhler (1994), Sauer/Scheide (1995), Funke (1997), Seifert (1999) and Langmantel (1999).

In determining the business cycle reference series, we relied on a "narrow" interpretation of the business cycle and chose the index of industrial production (excluding construction). The use of the index of industrial production as a proxy for business cycle movements can be justified for several reasons but this is nevertheless not undisputed. In general it seems to be useful to use a broader aggregate like GDP growth as a proxy for the business cycle. But in that case we would lose information content due to the lower frequency of quarterly GDP figures in comparison to monthly data. Furthermore industrial production seems to be more volatile than overall GDP figures. This is not surprising given the fact that industrial production is much closer to the "volatile" aggregates of GDP like investment and exports – which are at the heart of most busi-

[3] Cf. *Wolters* (1996).
[4] Cf. *Davis/Fagan* (1997).
[5] This is known as "The Koopmans Critique". Cf. *Koopmans* (1947), *Klein* (1997).
[6] Cf. *De Leeuw* (1991).

ness cycle theories. In contrast to the index of industrial production the figures for the value added of the service sector are much closer to the somehow smoother output aggregates like private consumption. Because we are interested in identifying business cycle leading indicators, however, the use of industrial production seems to be reasonable.

The construction sector was excluded from the reference series because this sector suffered from a somehow "policy-induced" extraordinary cycle in the 1990s in Germany.[7]

After the introduction of the new industrial classification (NACE or WZ 93 for Germany), the index of industrial production was re-estimated and prolonged by Eurostat back to 1978. This is why we used the year 1978 as the starting point of our analysis.

We basically included the same indicators in our analysis as Döpke/Krämer/Langfeldt (1994). These indicators are common in the German leading indicator discussion and the results can therefore be easily compared. However for our analysis some indicators were excluded as for example, the number of *Kurzarbeiter*.[8] Our choice of indicators can be justified for several reasons. One group, the order inflows, was chosen on the grounds of production technology, since on the macroeconomic (aggregate) level we expect a relatively stable relationship between the inflow of orders and production. The choice of other indicators is justified by the fact that these indicators contain information about market expectations. In particular, this applies to the *ifo* indicators (business climate and business expectations) and the consumer confidence indicator, which are designed to measure expectations. Furthermore, we included the spread between government bond yields (assumed to carry no risk) and private bond yields (which can reflect uncertainty regarding future economic activity).[9] This measure should provide information on confidence in the economy. For a number of indicators, namely the *ifo* indicators and the order inflows, we used indicators which refer to the manufacturing industry, to producers of investment goods and producers of intermediate inputs. This reflects the idea that some sectors of the economy are leading or lagging compared with the overall business cycle – a view popular already in traditional business cycle theory and taken up again by real business cycle approaches.[10]

The use of monetary indicators 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-

[7] Whereas in the early nineties tax exemptions and subsidies created an enormous boom, since 1996 the construction sector has been suffering from "overcapacities" and is still in a long-lasting recession period.

[8] The main problem with this variable is that, after German reunification, this was an instrument for reducing labour volume, which was intensively used especially in Eastern Germany due to a changed incentive structure for the enterprises. Thus, this is not the "traditional behaviour" that depends on the position within the business cycle. Technically speaking, one can find strong evidence of a structural break.

[9] We calculated the difference between the *Umlaufsrendite öffentlicher Anleihen* and the *Umlaufsrendite der Industrieobligationen*, Cf. *Friedman/Kuttner* (1992) for theoretical arguments.

[10] It is beyond the scope of this paper to identifiy the different transmission mechanisms as well as the sources of the German business cycle movements. Nevertheless there are strong arguments to assume that the time series for the producers of intermediate inputs and the producers of investment goods would have a "lead" compared to the overall cycle. Cf. *Haberler* (1948²), *Entorf* (1990).

production theories".[11] 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. On the other hand, it can be assumed that all monetary indicators reflect expectations regarding the future path of economic activity.[12] As mentioned above, monetary indicators are available sooner than most other indicators.

The real effective exchange rate was included because of a common argument which states that most booms in Germany are initiated by export-led upswings, which in turn are based on improved competitiveness.

The time series for order inflows were provided by Eurostat; *ifo* series for climate and expectations were calculated by the Munich based ifo-Institute. Monetary indicators, as well as interest rates were obtained from the Deutsche Bundesbank. The spread between government and private bond yields was calculated by the authors using data provided by the Deutsche Bundesbank. The consumer confidence indicator, as well as the real effective exchange rate are from the OECD database.

The usage of monthly data ensured that there were sufficient degrees of freedom available for non-parametric estimation in the frequency domain. All series are from 1978:1 to 1998:12. The estimations were carried out for that period.

The structural break caused by German reunification implies that econometric testing may face some difficulties. Eurostat, which provided the time series for the different production indices as well as for the order inflows, chained the time series for West Germany (up to 1990) and Germany (from 1991 onwards). A chaining procedure was also used for the monetary aggregates. The *ifo* indicator series are time series for West Germany only. All other time series refer to West German data until reunification and to German data afterwards.

2.2. Data Properties

Most of our procedures require stationarity assumptions. Therefore we tested all time series for unit roots using augmented Dickey-Fuller tests.[13] Seasonally unadjusted non-stationary variables were transformed into stationary variables by calculating annual growth rates. This strategy has the advantage that we could avoid complicated de-trending procedures, the results of which depend moreover on the assumed structure of the data generating process.[14] Furthermore, as some studies have shown, the chosen

[11] Cf. *Hayek* (1931), *Haberler* (1948[2]).

[12] For the monetary indicators we calculated nominal and "real" monetary aggregates, taking the contemporary consumer price index as the deflator. To calculate these measures more accurately in terms of mainstream monetary theory, "expected" inflation should be used instead of actual inflation. This is however rather difficult to measure. This argument holds both for monetary aggregates and for the calculation of real interest rates, but it is much more important in the latter case, if one considers the famous Fisher equation. One attempt to solve this problem is the approach of *Mishkin* (1981). Other authors calculate trend functions. In our analysis, we followed a compromise strategy. In the case of monetary aggregates we calculated "real" aggregates using the actual consumer price index. This can be justified because actual inflation matters in deciding about real balances. In the case of interest rates, we did not calculate real interest rates.

[13] Cf. *Dickey/Fuller* (1979).

[14] Cf. *Canova* (1998a,b).

filtering procedure has the advantage that a lot of spectral density remains in the region relevant for our topic.[15] 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 only exception in our investigation was the handling of the seasonally adjusted monetary aggregates. First, we calculated annual growth rates. But these transformed series did not pass the unit root tests. The reason might be a bias towards non-stationarity when already seasonally adjusted time series are transformed into growth rates. Because we needed stationary time series for frequency domain analysis, we calculated first differences (which passed the unit root tests). Fortunately, a main advantage of the spectral analysis is the fact that the coherence measure is invariant against any kind of linear transformation. That is why, for the spectral investigation, we could use first differences of the monetary aggregates instead of annual growth rates.[16]

All seasonally unadjusted variables which were already stationary in levels had been seasonally adjusted using the Berlin Method (Version 4, BV4).[17] The stationary properties did not change. The variables taken from the OECD database (the consumer confidence indicator as well as the real effective exchange rate) were only available on a seasonally adjusted basis (X-11). The relevant properties of the indicators are presented in Table 2.1.

3. Spectral Analysis

3.1. Methodological Approach

Traditionally, the cyclical properties of time series and lead-lag-structures between different time series are determined by cross-correlogram analysis.[18] However, this approach has some disadvantages: Overlapping oscillations of different periods and with different amplitudes can distort the properties of the correlogram. High auto-correlation complicates the analysis. Furthermore, new developments in time series analysis show that results depend to a large extent, on the kind of transformation used to attain stationary variables, e. g. trend deviations or growth rates. Ignoring the necessary transformation, i. e. the regression of independent non-stationary time series, may lead to spurious regression. On the other hand, 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.

For these reasons we followed a different approach: The first step in our research is the discrimination between series which show a significant relationship with the business cycle in the relevant period and those which do not. Spectral analysis proved to be a

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[15] Cf. *Wolters/Kuhbier/Buscher* (1990).

[16] Because of their insignificance in the frequency domain monetary aggregates were excluded from further research.

[17] Cf. *Nourney* (1983).

[18] Cf. *Döpke/Krämer/Langfeldt* (1994), *Lindlbauer* (1995).

helpful tool for this purpose.[19] That is why the spectral analysis is at the heart of our paper. *Only those indicators which show – irrespective of their lead and lag structure – a strong co-movement with the reference series at the relevant intervall can serve as indicators*. This information is given by spectral analysis.

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

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

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

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) the coherence is a measure for the stochastic relationship between different components of two processes at specific frequencies.[20]

In other words:

"...(T)he squared coefficient of coherence (...) can be interpreted as the proportion of the power at frequency λ in either time series (...) which can be explained by its linear regression on the other."[21]

Therefore, the measure is comparable to the well-known R^2 in traditional regression analysis. However, the application of spectral analysis allows some pitfalls of traditional regressions to be avoided, since coherence is a measure of the degree of *linear association, not of linear dependence*. 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. It is worth mentioning, that as Kirchgässner and Wolters (1994) have shown, a coherence of one at frequency zero indicates co-integration between two time series.[22] This finding is in line 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 between the indicator and the reference series.[23]

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

[20] *König/Wolters* (1972), pp. 120.

[21] *Koopmans* (1974), pp. 142.

[22] Cf. *Kirchgässner/Wolters* (1994).

[23] By inspecting the coherence estimates it can be seen that there is no co-integration between any of the indicator series and the reference series. If this would be the case, we would expect a coherence value very close to one at frequency zero which is not the case in any of these pictures.

Similar to all other non-parametric approaches, the empirical application of spectral analysis has disadvantages as well. Relatively long time series are required to get reliable results. Moreover, the analysis is complicated by the trade-off between bias and variance.

3.2. Results

The results of coherence estimation for the business cycle reference series and the indicators are shown in Figures 3.1 to 3.4.[24]

The null hypothesis of no significant influence (at a 5 % confidence level) was tested using a significance test statistic developed by Koopmans (1974). The horizontal line in our graphs represents the 5 % confidence band.[25] 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 can these results be interpreted? In traditional business cycle literature,[26] 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 period (that is, on the left side of our graphs).

Our tests lead to some interesting conclusions. All order inflows as well as the *ifo* climate and expectation indicators show significant coherence in the period under consideration (cf. Figures 3.1 and 3.2). Quite interestingly, all monetary aggregates (cf. Figures 3.3 and 3.4) – real and nominal – and the real effective exchange rate (cf. Figure 3.1) are insignificant, whereas both interest rates, as well as their spread have explanatory power, but only with little significance (cf. Figure 3.4).[27] This is the case for consumer confidence, as well as the spread between government and private bond yields (cf. Figure 3.1).

These findings correspond with the research of Bernanke and Blinder (1992) or Friedman and Kuttner (1992), who showed that the information content of money – however defined – is to a large extent obsolete if interest rates are taken into account.

In our further research we decided to exclude all monetary aggregates as well as the real effective exchange rate and to examine only the relationships between the reference series and indicators with significant coherence in the interval relevant for business cycle research. This strategy was chosen since one of the basic properties which a reliable indicator should possess is that movements in the indicator series should resemble those of the reference series. Nevertheless, we included the spread which showed only small signs of significance in the frequency domain tests into further investigations because of its dominant role in leading indicator literature.[28]

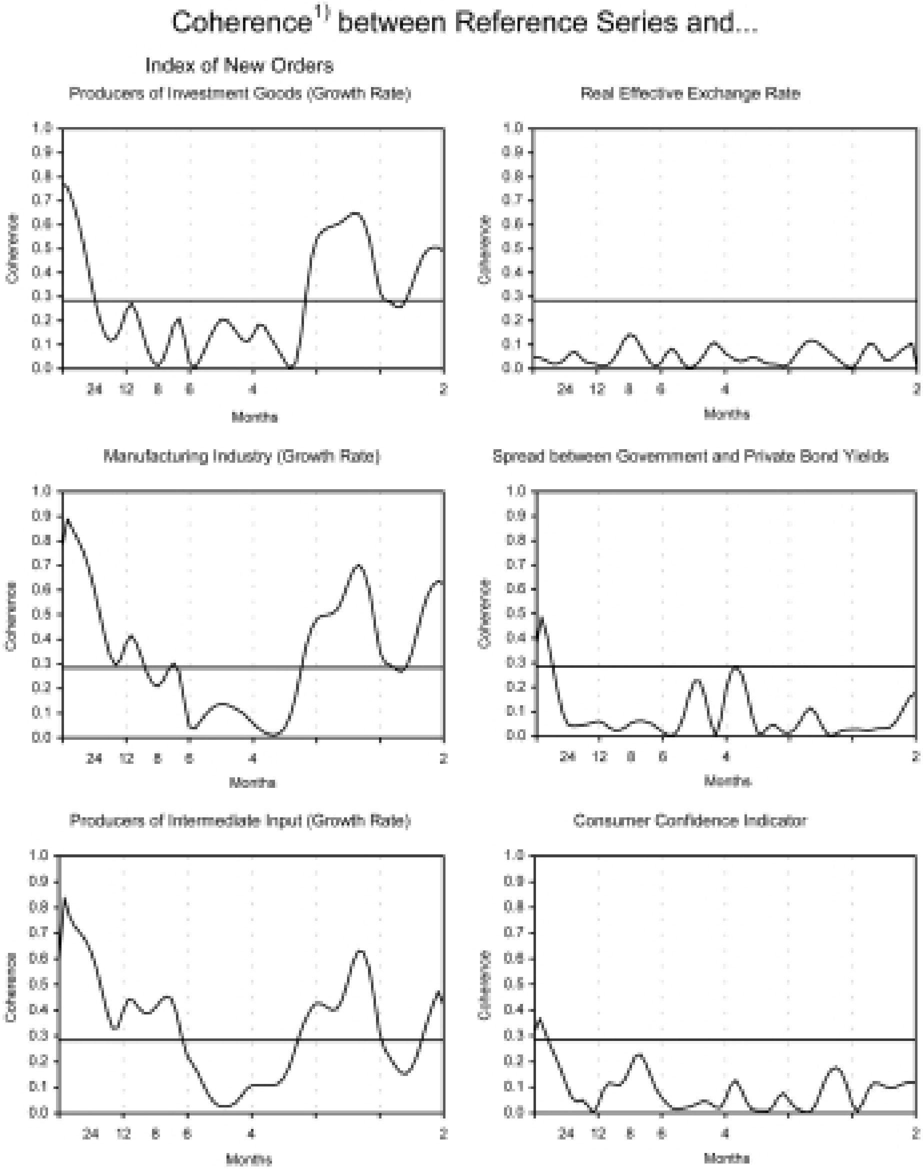
[24] For the empirical estimation we used the program SPEKTRAL, developed at the Freie Universität Berlin, Faculty of Economics, chair of Professor Jürgen Wolters. The following parameters were used: length of the time series: 240 data points, number of estimated function values: 72, covariances: 36. Applying a Parzen window the estimation has 24 degrees of freedom (Cf. *König/Wolters* (1972), pp. 72). We thank Professor Jürgen Wolters for sharing the programme files.

[25] *Koopmans* (1974), annex, table A 9.6.

[26] Cf. *Zarnowitz* (1992).

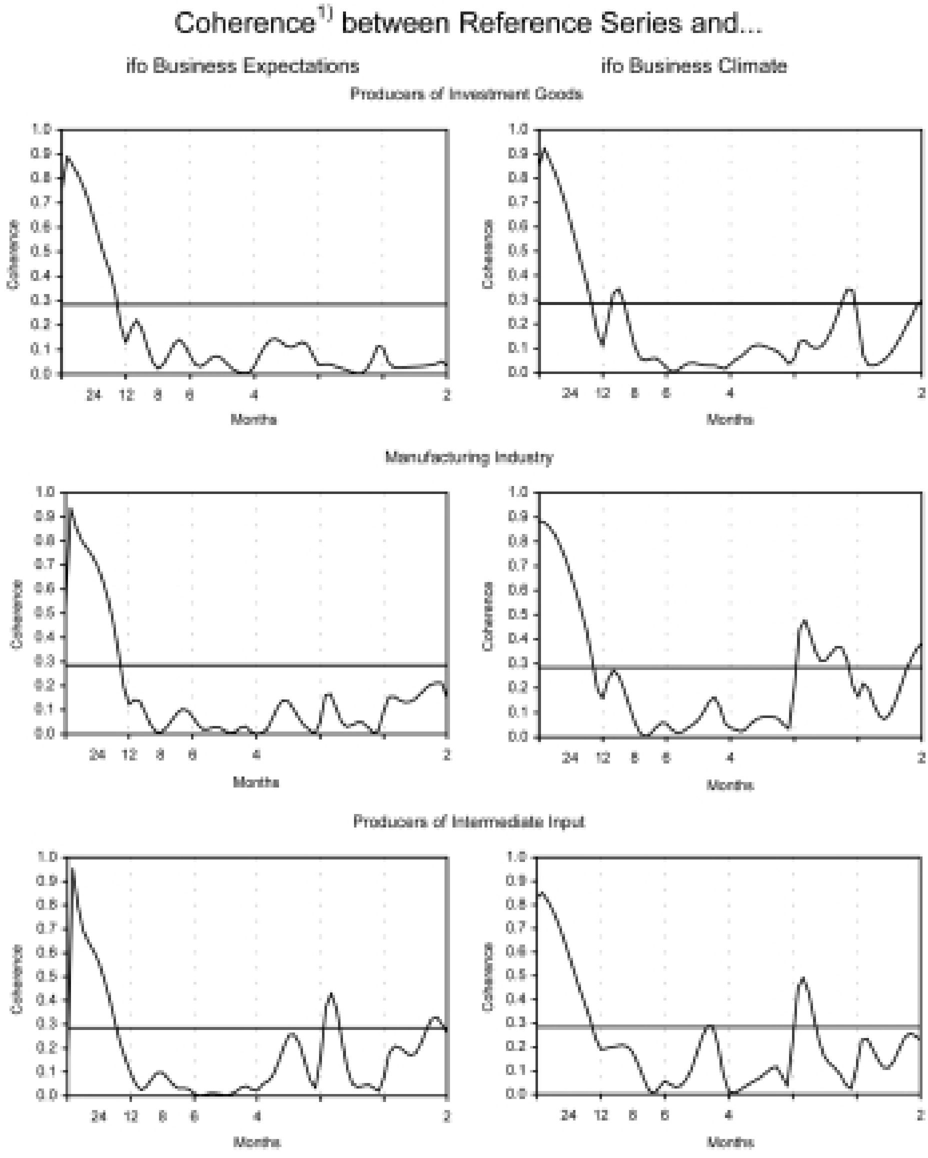
[27] In other analyses interest rates show very good indicator properties. Cf. *Kirchgässner/Savioz* (1998).

[28] Cf. *Davis/Fagan* (1997), *Langfeldt* (1994), *Sauer/Scheide* (1995).



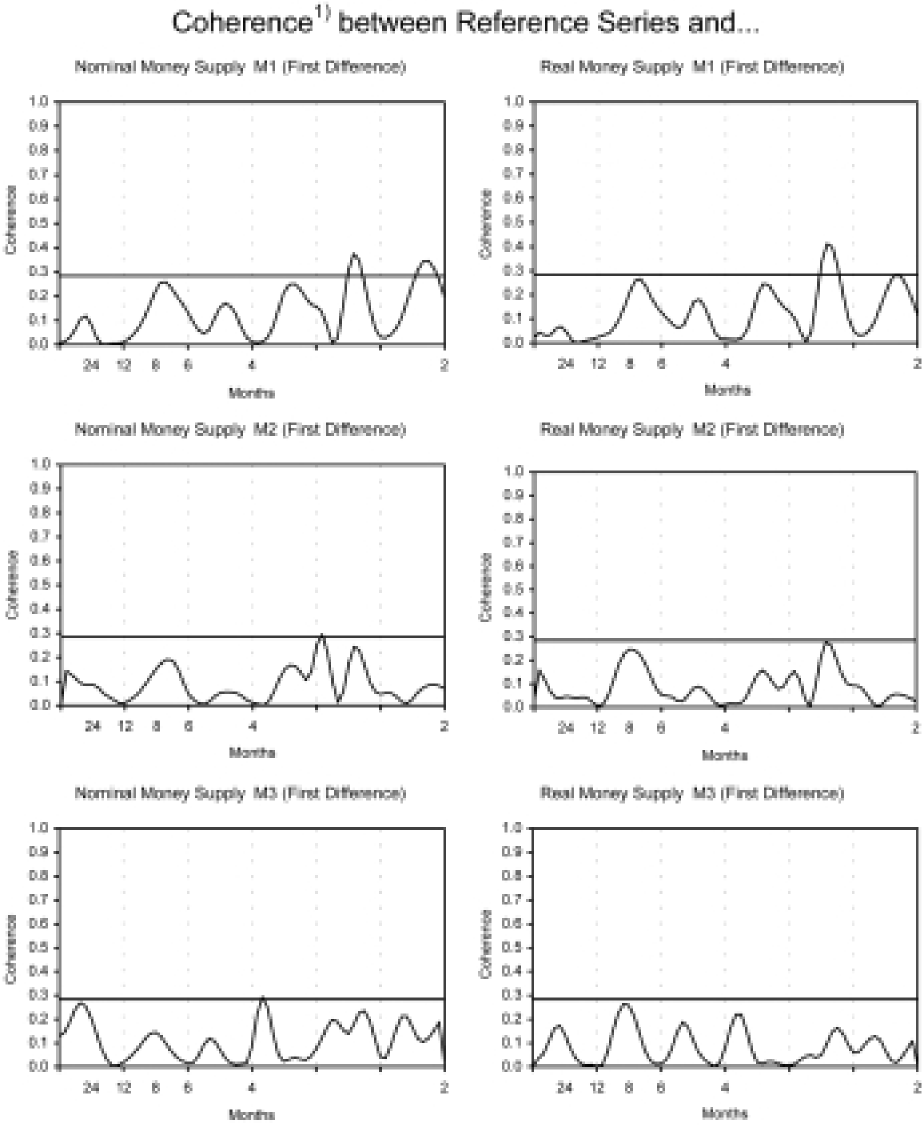
1) The coherence was estimated using 72 datapoints and 36 covariances which implies 24 degrees of freedom (Parzen window)

Figure 3.1.



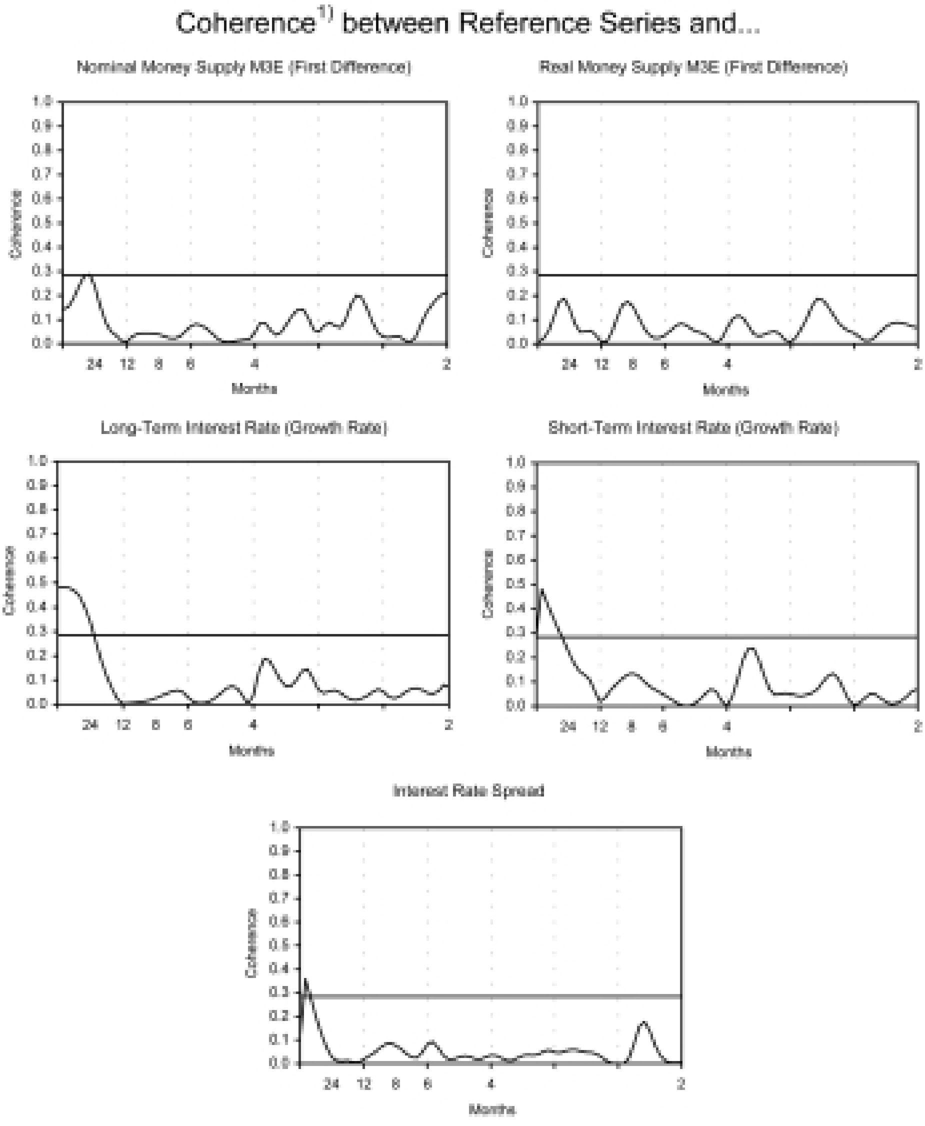
1) The coherence was estimated using 72 datapoints and 36 covariances which implies 24 degrees of freedom (Parzen window)

Figure 3.2.



1) The coherence was estimated using 72 datapoints and 36 covariances which implies 24 degrees of freedom (Parzen window)

Figure 3.3.



1) The coherence was estimated using 72 datapoints and 36 covariances which implies 24 degrees of freedom (Parzen window)

Figure 3.4.

4. Analysis of Lead-Structures

In the second part of our analysis, we examined the lead-structure between indicator and reference series. Basically, the *phase* can be determined within multivariate spectral 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 quite small.[29]

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. As a result we decided to use other techniques. We asked whether the inclusion of past values of the indicator variable would improve explanatory power of the estimation in comparison to a simple autoregressive estimation of the reference series. To achieve this we performed different Granger-causality tests.

4.1. 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 on Granger-causality attempted to determine whether changes in the indicator series precede changes in the reference series or vice versa: We included past values of a stationary indicator series to a regression of a stationary reference series on its own lagged variables. If the fit improves significantly by this inclusion, the indicator series is Granger-causal.[30]

A common difficulty in performing such tests is the choice of lag length, because the results are not independent from the chosen lag structure.[31] Furthermore, standard econometric software packages carry out these tests with fixed lag-length for both variables, something that is criticised as it may lead to misspecification. We chose a twofold strategy. First we carried out standard pair-wise Granger-causality tests with lags of up to 3, 6 and 12 months for both variables. This helped to identify possible "causality" relations in the above-mentioned sense. Then we estimated a univariate equation and added individual lags of the indicator series. We chose the Schwarz information criterion to assess improvements in specification. The second strategy helps to avoid misspecification and serves as a means of determining the lag structure.

The results of the first approach are summarised in Table 4.1. The order inflow to producers of investment goods, as well as the order inflow in manufacturing industry and all *ifo* indicators show strong signs of Granger-causality. Short-, as well as long-term interest rates are Granger-causal, if a lag structure of three or six months is cho-

[29] Cf. *Wolters* (1996).

[30] "Granger-Causality tests are in fact something of a misnomer: in practice all such tests simply examine whether movements in one variable regularly precede those in another variable. There can be no valid test of true causality on this basis in a world where individuals are forward-looking. A simple example is the purchase of anti-freeze in the months leading up to winter: it is clear that winter causes antifreeze purchases; but a typical Granger-Causality Test would suggest the reverse causation, since the antifreeze purchases come first. However, in the context of the search for potential leading indicators, this problem does not arise: in our example, anti-freeze purchases are a good *leading indicator* of winter." Cf. *Salazar* et al. (1996), pp. 50.

[31] Cf. *Gujarati* (1995), pp. 622.

sen. Both spreads as well as the consumer confidence are insignificant with a lag length of 6 or 12 months, but slightly significant if a range of three months is chosen.

For most of the indicators in our investigation, the pair-wise Granger-tests show that causality runs from the indicator to the reference series. In some cases, feedback relationships cannot be rejected.

4.2. Parsimonious Granger-causality Tests

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

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

$$y_t = \underset{(1.61)}{0.002} + \underset{(5.43)}{0.33}\, y_{t-1} + \underset{(5.05)}{0.31}\, y_{t-2} + \underset{(4.17)}{0.27}\, y_{t-3} + \underset{(2.04)}{0.12}\, y_{t-11} - \underset{(-4.87)}{0.28}\, y_{t-12}$$

with:

$$\bar{R}^2 = 0.67$$
$$DW = 1.87$$
$$SIC = -4.51$$

where DW denotes the Durbin-Watson statistic and SIC the Schwarz information criterion. No serial correlation remained in the residuals. In the 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:

$$y_t = \beta_1 + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + \beta_5 y_{t-11} + \beta_6 y_{t-12} + \gamma_1 x_{t-i}$$

where $i = 1,2,....24$.

The value of the Schwarz information criterion of the latter equation was compared with the value of the Schwarz information criterion of the univariate equation (the dotted line in Figures 4.1 to 4.3), for equations from the first up to and including the 24th lag. An improved information criterion in comparison with the information criterion of the univariate estimation was interpreted as a sign of Granger-causality and 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 illustrated in Figures 4.1 to 4.3.

The modified Granger-tests show that the inclusion of the order inflows to producers of investment goods and in manufacturing industry improve the equation in the very short run (cf. Figure 4.1). In the case of *ifo* indicators, the inclusion of the respective indicator improved the fit in the first month up to half a year (cf. Figure 4.2). The only exceptions were order inflows to and *ifo* business expectations of producers of intermediate input. In these cases, no significant improvement was achieved.

[32] Cf. *Wolters* (1996).

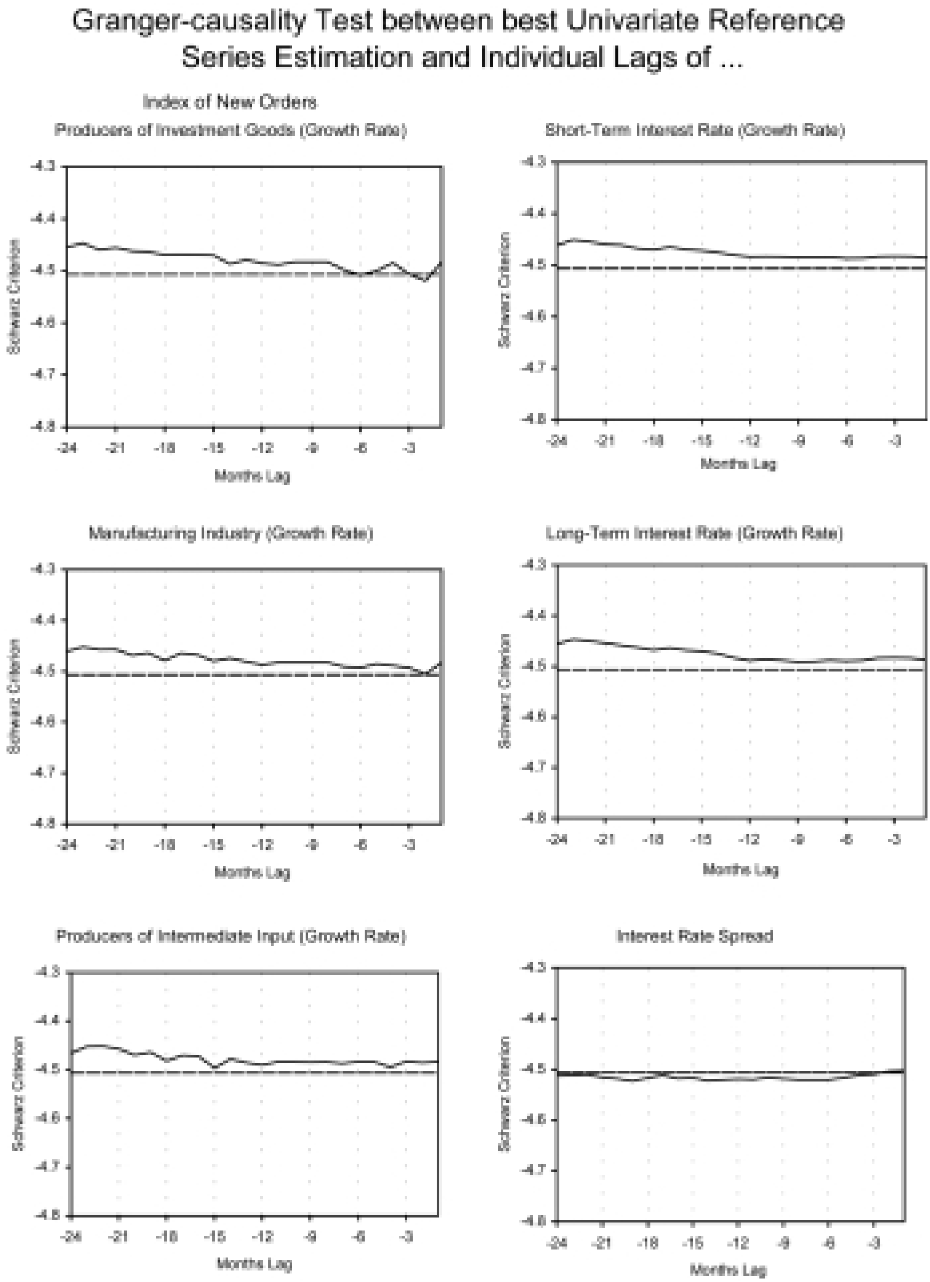

Granger-causality Test between best Univariate Reference Series Estimation and Individual Lags of ...
Index of New Orders
Producers of Investment Goods (Growth Rate)
Short-Term Interest Rate (Growth Rate)
Manufacturing Industry (Growth Rate)
Long-Term Interest Rate (Growth Rate)
Producers of Intermediate Input (Growth Rate)
Interest Rate Spread
Schwarz Criterion
Months Lag
-4.3
-4.4
-4.5
-4.6
-4.7
-4.8
-24
-21
-18
-15
-12
-9
-6
-3

Figure 4.1.

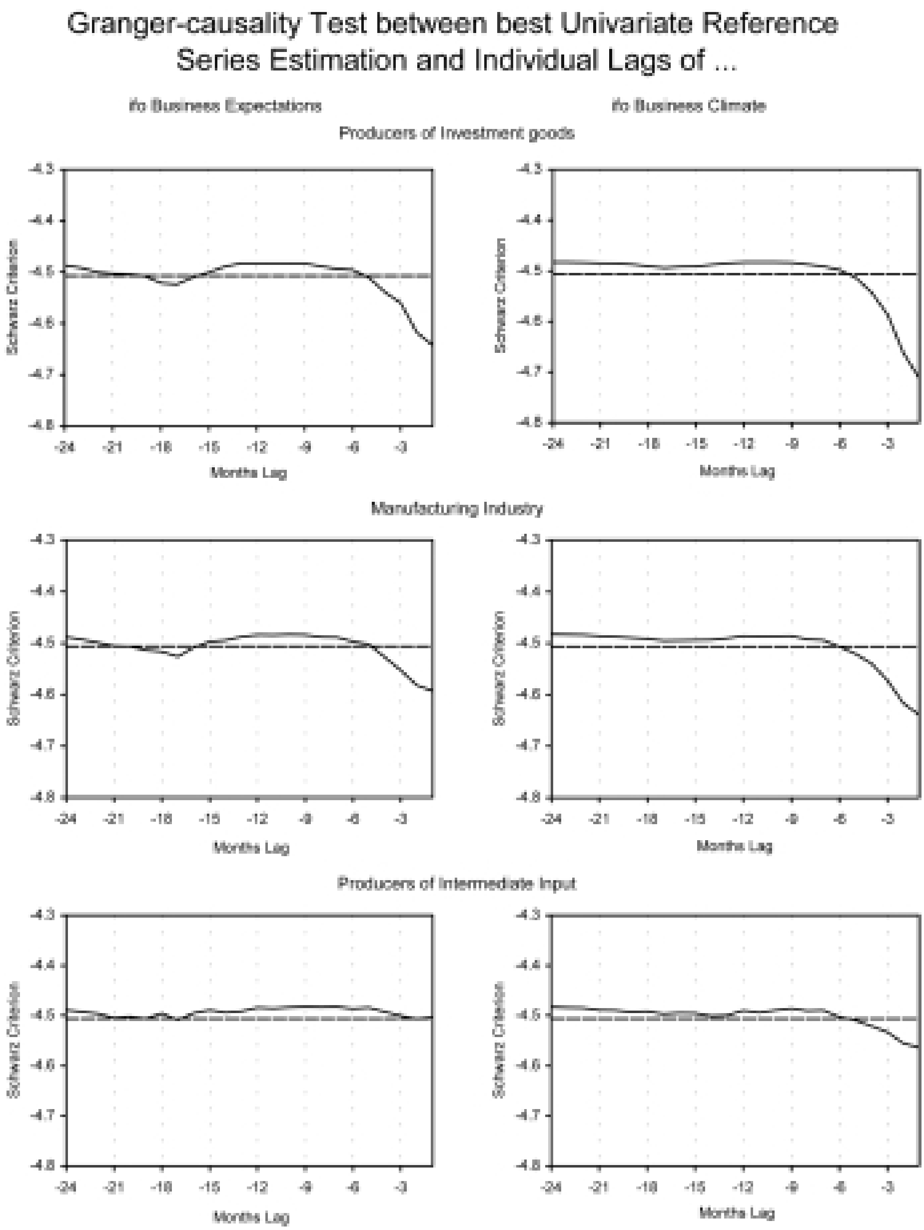

Granger-causality Test between best Univariate Reference Series Estimation and Individual Lags of ...
ifo Business Expectations
ifo Business Climate
Producers of Investment goods
Manufacturing Industry
Producers of Intermediate Input
Schwarz Criterion
Months Lag
-4.3
-4.4
-4.5
-4.6
-4.7
-4.8
-24
-21
-18
-15
-12
-9
-6
-3

Figure 4.2.

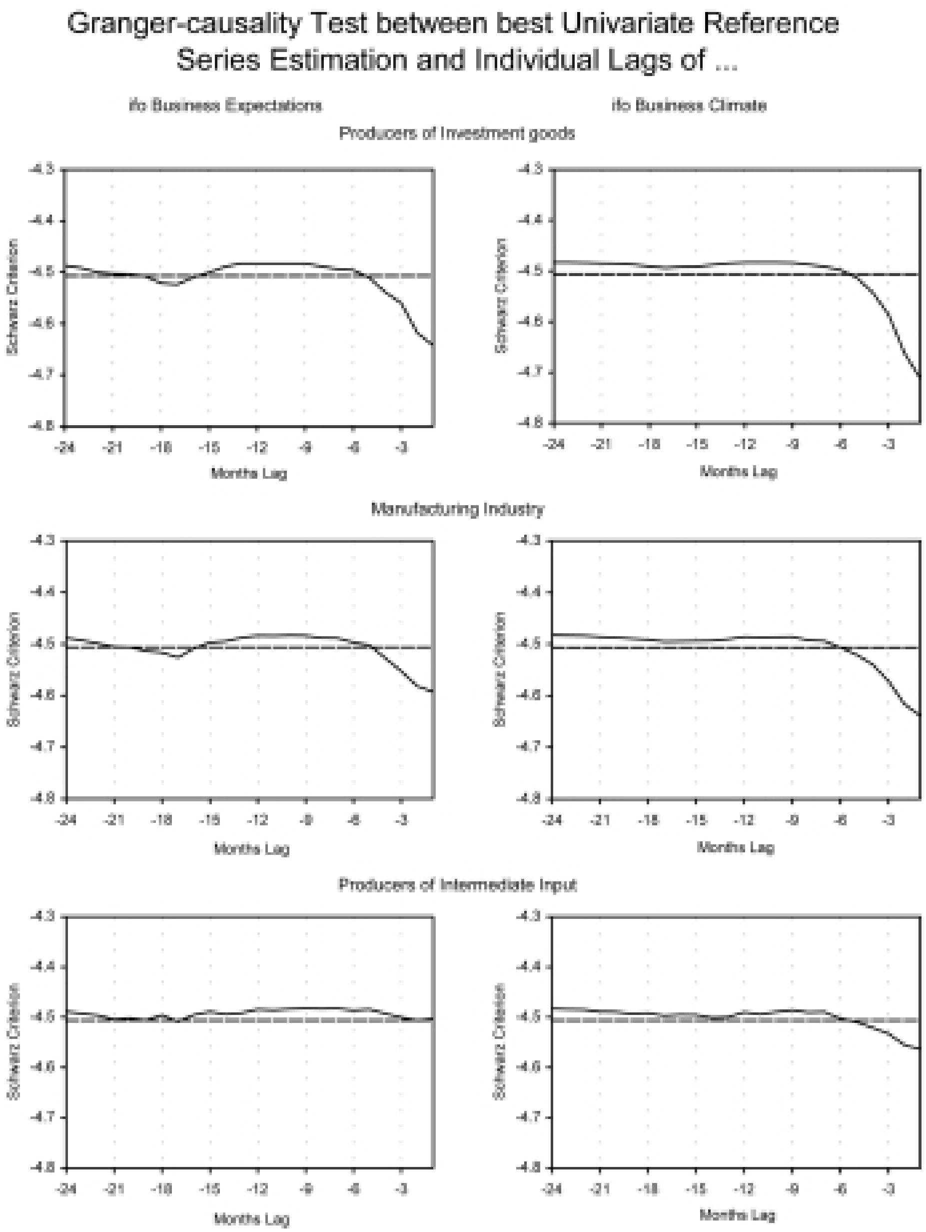

Granger-causality Test between best Univariate Reference Series Estimation and Individual Lags of ...
ifo Business Expectations
ifo Business Climate
Producers of Investment goods
Manufacturing Industry
Producers of Intermediate Input
Schwarz Criterion
Months Lag
-4.3
-4.4
-4.5
-4.6
-4.7
-4.8
-24
-21
-18
-15
-12
-9
-6
-3

Figure 4.3.

Both interest rates have no additional explanatory power. However, only the inclusion of the interest rate spread improves the fit of equation into the period from 4 to 24 months, but without a clearly defined local minimum (cf. Figure 4.1). The spread between government bond and private bond yields as well as the consumer confidence indicator improve the fit in the very short run (cf. Figure 4.3).

To a large extent, the results of the parsimonious specified Granger-tests confirm the results found earlier. It is quite interesting that the inclusion of *ifo* indicators leads to the lowest values of the Schwarz information criterion. This means, since we held all other parameters (number of regressors and estimation period) constant, that, compared with all other indicators, their inclusion improved the fit of the estimation most.

Because the parsimonious specified Granger-test did not find causality in the case of order inflows to producers of intermediate inputs, as well as for the interest rates, we decided to exclude these variables from further investigations. But, in the case of *ifo* business expectations of producers of intermediate input, we decided to retain this series, since the pair-wise Granger-test supported the hypothesis of causality.

5. Out-of-Sample Forecasts

One interesting 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.

For most of the indicators examined, the fit of bivariate equations experienced the greatest improvement in the very short run (in most cases, and especially for *ifo* indicators, the most significant lag structure is one or two lags). In this case, exercising out-of-sample forecasts requires forecasts of the exogenous variables, which is sometimes done by AR processes.

The pair-wise Granger causality tests showed that, for many cases, a "feed-back" relation cannot be rejected. For this reason, we chose a different strategy.

First, 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.[33] 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 "naive" forecast (here: the root mean squared error of the above-mentioned 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 "naive" 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 "naive" prognosis. Furthermore, the root mean squared error can be decomposed into a bias, a variance and a covar-

[33] *Davis/Fagan* (1997), *Döpke* (1998).

iance proportion.[34] 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 1978:1 to 1990:12. Dynamic three- and six-month forecasts were carried out for the period from 1991 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 5.2 and allow some interesting conclusions to be drawn. Four indicators show satisfactory performance: the order inflow to producers of investment goods, the *ifo* business climate of producers of investment goods and both spreads. The performance of all other indicators was rather dissatisfactory.

6. Conclusion

In our analysis we tested a number of potential indicators using spectral analysis, Granger-tests and out-of-sample forecasts (see Table 6.1 for a summary). After each test, we reduced the number of indicators to qualify the rest as reliable leading indicators. The results are satisfactory in that *ifo* indicators, as well as order inflows perform quite well. They show significant coherence in the relevant region, they are qualified by the Granger-tests and in particular the indicators for producers of investment goods, are also qualified by out-of-sample forecasting power. Both spreads show only little significance in the frequency domain, but show signs of Granger-causality and are well qualified by the out-of sample forecast.

To sum up, *ifo* indicators as well as order inflows showed the best results in our tests. Interest rate spreads can also be used as reliable leading indicators. In contrast to other studies monetary aggregates showed a bad performance. Interest rates showed significant coherence in the spectral analysis, but performed badly in the out-of sample performance.

In sum, our findings are a bit sobering as regards the use of leading indicators for business cycle forecasts. This is clearly revealed by the fact that it proved difficult to significantly increase the explanatory power of autoregressive equations by including leading indicators. This can be proved by inspecting the results of the Granger-Tests – especially the parsimonious specified tests – where we performed in-sample tests as well as by the results of the out-of-sample forecasts. In the out-of-sample forecasts we found that there are some indicators which improve the forecasts for the very short term significantly.

But perhaps there could be another role for leading indicators: the signalling of coming business cycle turning points. Further examinations will have to concentrate on turning points, since publicly used forecasts of annual growth rates depend crucially on the correct prediction of the turning points. This could possibly be done by the use of probit models. We will publish such results soon.

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

Appendix

Table 2.1: Augmented Dickey-Fuller Tests

Transformation	Level		Annual Growth Rate[1)]		First Difference		Original time series is integrated of order …	Source
Series	t-value	Specification	t-value	Specification	t-value	Specification		
Industry Production Index			–3.584668***	1, 3, 6–8, 12			I(1)	Eurostat
Index of New Order								
Producers of Investment Goods			–5.407373***	1–2, 6–11, c			I(1)	Eurostat
Manufacturing Industry			–3.971640***	1–3, 6, c			I(1)	Eurostat
Producers of Intermediate Goods			–5.209718***	1, 3–6, 9, 12–13, 15, c			I(1)	Eurostat
ifo Business Expectations								
Producers of Investment Goods	–3.376961***	1–2, 6, 8, 10					I(0)	ifo Institute
Manufacturing Industry	–3.836831***	1–2, 6, 8, 10–11					I(0)	ifo Institute
Producers of Intermediate Goods	–3.474097***	2–3, 11, 16					I(0)	ifo Institute
ifo Business Climate								
Producers of Investment Goods	–2.411094**	1, 4, 10, 12, 14, 16					I(0)	ifo Institute
Manufacturing Industry	–3.782048***	1–3, 6, 11					I(0)	ifo Institute
Producers of Intermediate Goods	–3.782048***	1–3, 6, 11					I(0)	ifo Institute
Nominal Money Supply								
M1					–4.961298***	1–4, c	I(1)	Bundesbank
M2					–3.549529***	1–4, c	I(1)	Bundesbank
M3					–7.325750***	1, 9, 10, c	I(1)	Bundesbank
M3 enlarged					–3.980041***	1–4, 9, 10, c	I(1)	Bundesbank
Real Money Supply								
M1					–5.190840***	1–4, c	I(1)	Bundesbank
M2					–5.663593***	1, 2, 4, c	I(1)	Bundesbank
M3					–12.14376***	c	I(1)	Bundesbank
M3 enlarged					–8.798584***	11–12, c	I(1)	Bundesbank

Table 2.1: Augmented Dickey-Fuller Tests

Transformation	Level		Annual Growth Rate[1)]		First Difference		Original time series is integrated of order …	Source
Series	t-value	Specification	t-value	Specification	t-value	Specification		
Short-Term Interest Rate (3 month FIBOR)			−3.034274***	1, 3, 10, 12, 16			I(1)	Bundesbank
Long-Term Interest Rate (Umlaufsrendite)			−2.102232**	1–3, 9, 12			I(1)	Bundesbank
Interest Rate Spread	−2.864696***	1, 3, 7					I(0)	Bundesbank
Spread between Government and Private Bond Yields	−3.673450***	2, 11, c					I(0)	Bundesbank
Consumer Confidence Indicator	−3.616756***	4, 5, 10, c					I(0)	OECD
Real Effective Exchange Rate	−2.722615*	1, c					I(0)	OECD

1) Annual growth rates = $\log(x) - \log(x(-12))$
*, **, *** denote significance at 10, 5 and 1 per cent level.

Table 4.1: Pair-wise Granger-causality Tests

Y (reference series)	X (indicator series)	Transformation	H_O: Indicator not Granger-causal			H_O: Reference series not Granger-causal			Result
			3 Months	6 Months	12 Months	3 Months	6 Months	12 Months	
Industrial Production without Construction		Annual Growth Rate							
	Index of New Orders, Producers of Investment Goods	Annual Growth Rate	3.40**	2.89***	2.55***	7.13***	4.84***	2.97***	Feedback
	Index of New Orders, Manufacturing Industry	Annual Growth Rate	4.38***	2.89***	1.98**	0.85	2.23**	1.89**	X → Y
	Index of New Orders, Producers of Intermediate Input	Annual Growth Rate	1.90	1.82*	1.47	0.48	1.08	1.77*	X → Y
	Ifo Business Climate, Producers of Investment Goods	Level	18.75***	10.80***	5.65***	2.22*	1.77	1.18	X → Y
	Ifo Business Climate, Manufacturing Industry	Level	15.92***	8.37***	4.88***	2.22*	2.71**	1.51	X → Y
	Ifo Business Climate, Producers of Intermediate Input	Level	10.91***	5.40***	4.18***	0.62	2.70**	1.83**	Feedback
	Ifo Business Expectations, Producers of Investment Goods	Level	17.88***	9.65***	2.72***	1.87	0.49	1.39	X → Y
	Ifo Business Expectations, Manufacturing Industry	Level	12.54***	7.53***	4.03***	3.17**	1.76	0.68	X → Y
	Ifo Business Expectations, Producers of Intermediate Input	Level	5.58***	4.40***	2.72***	4.52**	3.36**	1.39	Feedback
	Short-term Interest Rate	Annual Growth Rate	2.69**	2.58**	1.08	2.14*	0.98	1.24	X → Y
	Long-term Interest Rate	Annual Growth Rate	2.24*	2.20**	1.09	1.29	1.20	0.77	X → Y
	Interest Rate Spread	Level	2.93**	1.51	0.92	1.45	1.14	1.15	X → Y
	Spread between Government and Private Bond Yields	Level	3.03**	1.58	1.65*	0.15	0.18	0.91	X → Y
	Consumer Confidence Indicator	Level	2.46*	1.60	1.20	0.16	0.99	0.70	X → Y

Note: ***,** and * denote significance at the 1, 5 and 10 percent level.

Table 5.1: Specification of VARs

Estimated VAR between the Reference Series and...	Lag Specification
Index of New Orders, Producers of Investment Goods	1–3, 6–7, 12
Index of New Orders, Manufacturing Industry	1, 3, 12
Ifo Business Climate, Producers of Investment Goods	1, 3, 5, 12
Ifo Business Climate, Manufacturing Industry	1, 3, 5, 12
Ifo Business Climate, Producers of Intermediate Input	1–3, 5–6, 12
Ifo Business Expectations, Producers of Investment Goods	1–3, 12
Ifo Business Expectations, Manufacturing Industry	1, 3, 5, 12
Ifo Business Expectations, Producers of Intermediate Input	1–3, 5, 7, 12
Interest Rate Spread	1–3, 12
Spread between Government and Private Bond Yields	1–3, 8–12
Consumer Confidence Indicator	1–3, 12

Sample: 1978:1–1990:12

Table 5.2: Out-of-sample Forecast Results for 1991–1998

VAR between Business Cycle Reference Series and...	3 Months VAR Forecast: Modified Theil's U[1)]	3 Months: Forecast Measures of $RMSE^{VAR}$ – Bias Proportion	3 Months: Variance Proportion	3 Months: Covariance Proportion	6 Months VAR Forecast: Modified Theil's U[1)]	6 Months: Forecast Measures of $RMSE^{VAR}$ – Bias Proportion	6 Months: Variance Proportion	6 Months: Covariance Proportion
Order Inflow, Producers of Investment Goods	0.92	0.051	0.15	0.80	0.94	0.090	0.18	0.73
Order Inflow, Manufacturing Industry	1.02	0.065	0.33	0.61	0.99	0.098	0.41	0.49
Ifo Business Climate, Producers of Investment Goods	0.79	0.13	0.17	0.69	0.80	0.12	0.18	0.70
Ifo Business Climate, Manufacturing Industry	0.99	0.24	0.29	0.47	0.94	0.21	0.25	0.54
Ifo Business Climate, Producers of Intermediate Inputs	1.39	0.50	0.15	0.35	1.31	0.48	0.11	0.41
Ifo Business Expectations, Producers of Investment Goods	1.02	0.43	0.013	0.56	1.00	0.39	0.018	0.59
Ifo Business Expectations, Manufacturing Industry	0.97	0.37	0.13	0.50	0.99	0.42	0.15	0.43
Ifo Business Expectations, Producers of Intermediate Inputs	0.99	0.18	0.12	0.70	1.01	0.24	0.19	0.58
Interest Rate Spread	0.91	0.099	0.27	0.63	0.86	0.16	0.35	0.49
Spread between Government Bonds and Private Bonds	0.94	0.064	0.16	0.77	0.88	0.12	0.27	0.61
Consumer Confidence Indicator	1.00	0.025	0.26	0.74	0.98	0.00001	0.33	0.67

1) Modified Theil's U is defined as $RMSE^{VAR}$ / $RMSE^{AR}$.

Table 6.1: Summary of Results

	Test Procedures				
	Spectral Analysis	Standard Pair-wise Granger-causality Tests	Parsimonious Granger-Tests	VAR-based Out-of-Sample Forecast (3 Months)	VAR-based Out-of-Sample Forecasts (6 Months)
	Criterion				
	significant coherence in the frequency domain relevant for business cycle analysis	inclusion of laged 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	
Index of New Orders					
Producers of Investment Goods	**X**	**X**	**X**	**X**	**X**
Manufacturing Industry	**X**	**X**	**X**	–	X
Producers of Intermediate Input	**X**	**X**	–	–	–
ifo Business Expectants					
Producers of Investment Goods	**X**	**X**	**X**	–	–
Manufacturing Industry	**X**	**X**	**X**	X	X
Producers of Intermediate Input	**X**	**X**	–	X	–
ifo Business Climate					
Producers of Investment Goods	**X**	**X**	**X**	**X**	**X**
Manufacturing Industry	**X**	**X**	**X**	X	X
Producers of Intermediate Input	**X**	**X**	**X**	–	–
Nominal Money Supply					
M1	–	–	–	–	–
M2	–	–	–	–	–
M3	–	–	–	–	–
M3 enlarged	–	–	–	–	–
Real Money Supply					
M1	–	–	–	–	–
M2	–	–	–	–	–
M3	–	–	–	–	–
M3 enlarged	–	–	–	–	–
Real Credit Supply	–	–	–	–	–
Short-Term Interest Rate (3 month FIBOR)	X	X	–	–	–
Long-Term Interest Rate	X	X	–	–	–
Interest Rate Stsread	X	X	**X**	**X**	**X**
Spread between Government and Private Bond Yields	X	X	**X**	**X**	**X**
Consumer Condifence Indicator	X	X	**X**	–	X
Real Effective Exchange Rate	–	–	–	–	–

X denotes strong significance, X denotes weak significance.

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