Deviation Cycles in Manufacturing: Business Cycle Measurement and Leading Indicators

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Abstract

The deviation cycles in the manufacturing industry of nine OECD-countries are identified by applying the Christiano-Fitzgerald band-pass filter. Turning points, low- and high-growth phases and other descriptive statistics are derived from these deviation cycles. A regression based test statistic is applied to test for duration dependence. Moreover, the international linkage between the cyclical motions in the manufacturing industry of two countries is investigated by measuring the degree of synchronisation. In addition to measuring the cyclical fluctuation, a composite leading indicator is constructed which replicates and predicts the deviation cycle in the manufacturing industry. This composite leading indicator is a single index composed of economic, financial and expectation variables possessing leading properties.

Key Words: Business cycles, Turning points, Leading indicators, Band-pass filter

JEL Classification: C82, E32, E37

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1 Introduction

Under the second pillar of the European Central Bank's (ECB) monetary policy strategy, information on the cyclical position of the economy is an important element in the assessment of the outlook for future price developments. The cyclical instability of aggregate economic behaviour will sooner or later be reflected in similar patterns across various macroeconomic time series. The cyclical motions of the variables are mostly simultaneous or in a rapid succession of one another. This phenomenon of leading and lagging cyclical behaviour over time across macroeconomic variables can be exploited for the measurement and forecasting of the conjunctural position of the economy. The study of business cycles, which is of cyclical fluctuations in economic activity, goes back to the seminal contribution of Burns and Mitchell (1946), one of the earliest writings on the business cycle. As a starting point, it seems worthwhile to recall their definition:

"Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own."

This paper builds on the tradition of business cycle indicator research at De Nederlandsche Bank, see for instance Fase and Bikker (1985), Bikker and De Haan (1988), Berk and Bikker (1995) and De Haan and Vijselaar (1998). The first aim of this study is to identify cycles in the manufacturing industry for 9 OECD-countries: the Netherlands, Belgium, Germany, France, Italy, Spain, the United Kingdom, the United States and Japan. We will construct indicators for the nine OECD-countries with special attention to the Netherlands. Moreover, we will provide for each country descriptive statistics like the dating of cyclical turning points, moment properties like the amplitude describing the severity of the recessions and the strength of the booms. Moreover, we will test for duration dependence of low- and high-growth periods. These statistics are derived for each country separately. In addition, the international linkages of the cyclical motions in the manufacturing industries among countries can be measured by the fraction of time the cycles are simultaneously in an upturn and/or in a downturn. The second aim of this study is to forecast the cyclical motions in the manufacturing industries by exploiting the early signals provided by leading indicator variables. The cyclical movement of a broad set of macroeconomic variables will be evaluated on statistical grounds and accordingly selected to form the basis for the composite leading indicator. The selection criteria are a sufficient degree of similarity both in terms of correlation and in terms of turning points and, secondly, leading properties with respect to the cycle in the manufacturing industry.

2 Measuring Business Cycles

Business cycles can be described in general terms as the oscillating behaviour of economic activity. The business cycle consists of a peak in economic activity, a period of recession, followed by a trough and a period of expansion. Subsequent business cycles are therefore separated by the business cycle turning points. A recession of the classical cycle is by definition a period with a decline in the level of economic activity, see Harding and Pagan (2001, 2002, 2005). In effect, negative growth is a sufficient condition for a classical recession. A recession of the deviation cycle, or a low-growth phase, means that the level of economic activity is below its trend, or potential, level. Given that the potential trend growth is positive, classical cycle recessions are always a subset of deviation cycle recessions[1] and there can be multiple classical cycle recessionary episodes within one single period of deviation cycle recession. The durations of low- and high-growth periods of deviation cycles are symmetric: on average is the economy half of the time in recession. Contrarily, the duration of classical cycle recessions are typically much shorter than expansions. Since periods of declining economic activity were relatively scarce in Western Europe since the 2nd World War, deviation cycles are more in line with the fluctuations in the levels of employment and unemployment. Moreover, deviation cycles, or output gaps, gained much policy relevance for Taylor-rule driven monetary policy and for cyclically adjusted government budget deficits.

As the trend cannot be observed directly, the strategic choice concerning the deviation cycle is the methodology to filter the trend, and implicitly the cycle, out of a time series of observations. Canova (1998) provides an overview of the comparative properties of cyclical components obtained by using different trend estimators on a couple of commonly used macroeconomic time series. He concludes that the existence of a set of business cycle stylized facts that is robust to varying trend estimators is misleading, because different concepts of a business cycle, and correspondingly different trend estimators, generate different economic objects which not necessarily have similar properties. Basically two concepts of a business cycle can be distinguished, which originate from Koopmans' (1947) 'measurement without theory' debate on whether the economic considerations underlying a statistical based decomposition should be modelled explicitly? For the econometric model based approach, the optimal filter is the signal extracting device, which minimizes the mean squared error to the actual data generating process. Examples of filters based on econometric models are the exponential smoothing filter, the HP-filter and more recently, the Butterworth-filter known from electrical engineering, see Pollock (2000) and Gomez (2001).

1 If a variable x_t, say GDP, admits the log-additive decomposition: $x_t = u_t + \psi_t$, where u_t denotes the trend and ψ_t denotes the deviation cycle, then growth, Δx_t, can be decomposed into: $\Delta x_t = \Delta u_t + \Delta \psi_t$, that is potential growth Δu_t and cyclical change $\Delta \psi_t$. Deviation cycle recessions, $\Delta \psi_t < 0$, correspond to periods of growth below potential growth: $\Delta x_t < \Delta u_t$, which then encompasses the classical recessions, that is $\Delta x_t < 0$ (given that potential growth is at least positive, that is $\Delta u_t > 0$).

The statistical based approach assumes the existence of an ideal band-pass filter, often characterized by isolating a pre-specified frequency interval, which is then used as a benchmark for finite sample approximations. The choice of the ideal band-pass filter as a reference model is justified by the definition of Burns and Mitchell (1946) of business cycles as recurrent waves lasting longer than a minimum and shorter than a maximum duration. This wave length interval corresponds one-to-one with the business cycle frequencies. Examples of filters based on the ideal band-pass filter are Baxter and King (1999) (BK-filter), Christiano and Fitzgerald (2003) (CF-filter) and Pedersen (2001).

These papers focus on the optimal approximation to the ideal filter of a finite sample of data that is possibly non-stationary and auto-correlated. Harvey and Trimbur (2003) combine both approaches within a unified framework. They show that the least squares linear estimator of an Unobserved Components model (UC-model, cf Harvey and Jaeger, (1993)) corresponds to a generalized Butterworth filter, which is a specific type of band-pass filter. Conventional econometric specification of the UC-model implies a sub-optimal parameterization of the Butterworth-filter, as the ideal band-pass filter emerges only as the limiting case. Equivalently, the implied cyclical model corresponding to the ideal band-pass filter has no direct economic interpretation. A more general disadvantage of UC-model based filtering is that adding additional new data may result in a higher likelihood for an alternative model specification. Since the decomposition in trend and cycle is model specific, the alternative model can then induce a radical change in the historical shape of the business cycle. This unreliability of the output gap estimates is undesirable from a practical policy making perspective. Orphanides and Van Norden (2002) conclude that the reliability, that is the extent to which output gap estimates are revised over time as more information arrives, is quite low for a broad class of detrending methods. As more data are released however, the estimate of the non-model based band-pass filtered cycle will eventually converge to its final value as the approximation converges to the ideal band pass, regardless of the specific choice of the approximation filter. Therefore, this study defines the cycle to be the optimal band-pass filtered component of the observed variable and remains agnostic about the structural model.

The BK-filter is an approximation to the ideal band-pass filter under side constraints and renders a series stationary without inducing a phase shift. So, it does not shift the filtered cycles forward or backward in time. The CF-filter is a weighted approximation, which takes into account the empirical property of macroeconomic data known as Granger's (1966) typical spectral shape. The approximation of the ideal band-pass filter at the lower frequencies is consequently more important than at the higher frequencies. Schleicher (2004) confirms theoretically and empirically the optimality of the CF-filter, especially concerning the end-of-sample performance for current analysis.[2] For these reasons, this study will use the CF-filter to extract cycles from time series.

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2 Even though the CF-filter might show the best end-of-sample performance, this filter exhibits considerable more instability if it is applied to not-seasonally adjusted data. The (seasonal) instability is corrected for by averaging over (maximum) half a cycle (which is 60 months). More precisely: the definitive deviation cycle indicator DCI^{def} for $i = 1,...,60$ for the period $t-i$ given data up until period t, equals to: $DCI^{def}_{t-i/t} = \sum_{j=1}^{i} DCI_{t-i/t-i+j}$, where $DCI_{./t-i+j}$ is the CF-filtered cyclical component at period $t-i+j$.

A starting point in defining the range of business cycle periodicities is given in the introduction's quote of Burns and Mitchell (1946) saying between one year and ten or twelve years. Stock and Watson (1999) and Baxter and King (1999) apply the BK-filter using the convention of business cycles as variations in GDP between 6 and 32 quarters. This is based on the NBER business cycle reference dates, for which the shortest cycle since 1858 lasted 6 quarters and the longest ones are mostly shorter than 8 years. However, the latest two US-cycles lasted more than eight years. Agresti and Mojon (2001) use for the euro area business cycle the BK-filter with a periodicity band of 1.5 years and 10 years. They arrive at this higher upper bound by stating that the euro area experienced only three recessions over the last thirty years. This study adopts the 1.5-10 years convention of business cycle frequencies[3], see also Kranendonk *et al.* (2004) concerning the Netherlands.

3 Detecting and Dating Dutch Deviation Cycles

GDP is the aggregate statistic of all economic activity and provides the broadest coverage of the economy. As the accounting identity holds, GDP is the aggregate of both production and expenditures and of income. Deviation cycles as recurrent periods of above- and below-trend growth are visible in many economic activities and should therefore be visible in GDP as the aggregate of all activity as well. However, not all economic activity is affected simultaneously by the deviation cycle. Some macroeconomic variables lead the cycle, a feature that will be exploited in the next section, and other variables are coincident or lag the cycle. The non-synchronized cyclical behaviour of some sub-components partly cancels in the aggregate GDP. For instance, the expenditure component government consumption is well-known to act as an automatic stabilizer of the general cycle due to counter-cyclical and lagging patterns of tax revenues and social security payments. The expenditure component exports tends to pro-cyclically lead the general cycle, particularly so for a small open economy as the Netherlands.

Since the cyclical motion of GDP does not parallel the ones of its underlying components, the business cycle dating committees of the European CEPR[4] and the American NBER[5] look at more macroeconomic variables for dating the turning points of the classical cycle. Apart from GDP, both committees analyse industrial production and total employment. The CEPR committee considers moreover investment and consumption while the NBER committee considers instead real disposable income and the wholesale and retail sales, see Hall *et al.* (2003). Business cycle committees officially establish a turning point of the classical cycle only after a considerable time period has elapsed since its occurrence. Since the cyclical indicator is used for current analysis policy purposes, it is of practical

3 Noteworthy, Ravn and Uhlig (2002) show that the HP-filter is equivalent to a one sided band-pass filter. The standard parameter value of λ=1600 for quarterly data filters out cycles of duration longer than 8 years.

4 http://www.cepr.org/data/Dating

5 http://www.nber.org/cycles.html

importance to base the indicator on monthly data that are released with a short publication delay and are only to a minor extent subject to revisions.

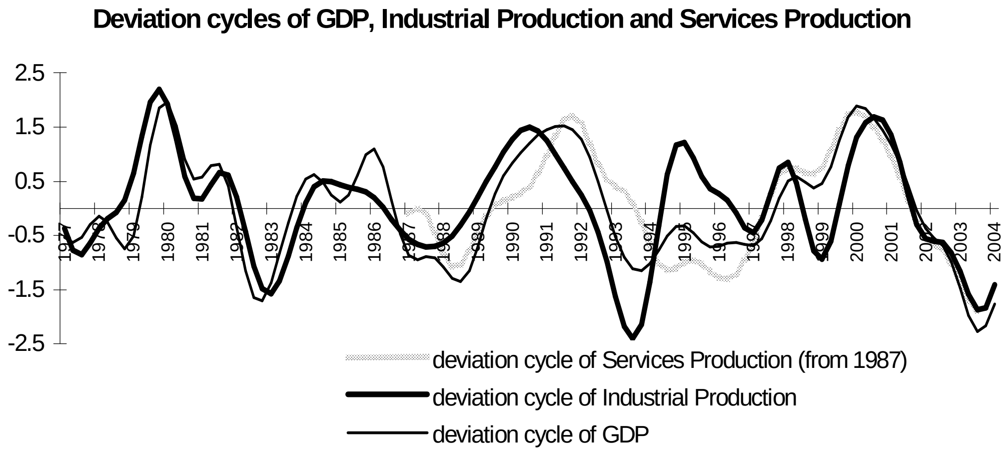
Stock and Watson (1989) provide a formal statistical framework to construct a coincident indicator for the United States based on the four macroeconomic variables analysed by the NBER dating committee. The indicator closely resembles The Conference Board´s (2000) (TCB) one, which is a contemporaneous weighted average of the same four variables. TCB does not straightforwardly construct similar indicators for other countries due to data availability and issues of data definitions. The international indicators of TCB rely on proxy data such as surveys for sales and unemployment rates for payroll employment. Moreover, personal income data is notoriously tedious to obtain at a high sampling frequency without a substantial publication delay. Only the industrial production series is an internationally widely available and comparable statistic.

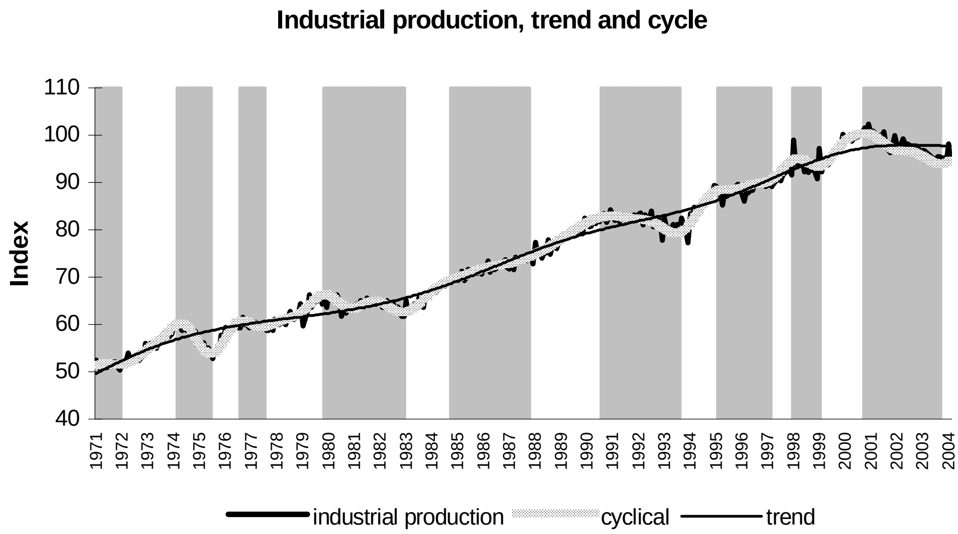
In accordance with practices at the OECD (2002) and at De Nederlandsche Bank, see Berk and Bikker (1995), this study will use the manufacturing output volume as the reference series from which the cyclical indicator is filtered. Like GDP, industrial production is a main focus variable of both the CEPR and NBER business cycle dating committees. However, industrial production is available on a higher, that is monthly, frequency, the publication lag is considerably shorter and the revision of the numbers after the first publication is smaller than for GDP. The standardized CF-filtered deviation cycles of GDP, services production and industrial production on a quarterly basis for the Netherlands are displayed in Figure 1. The industrial production is, with a cross-correlation with cyclical GDP of 0.77, only approximately cyclically representative. Especially the mid-nineties show discrepancy between the cycles of services production and industrial production. These two types of production constitute 70% respectively 25% of GDP and agriculture producing the remaining 5% for the highly developed countries considered in this paper.

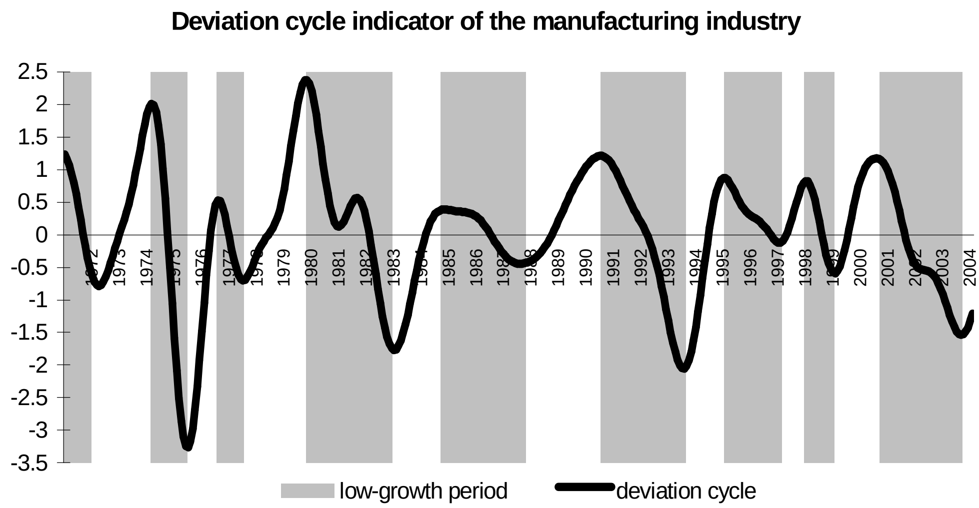
The periods between a peak and a trough of the deviation cycle of manufacturing industry are the low-growth phases and are indicated in the graphs of Figure 1 by the shaded areas. The collection of peaks and troughs, the turning points, are derived from the deviation cycle according to the procedure outlined below.

Equivalent to the standard calculus rule for finding extreme values, i.e. setting the first derivative of a function with respect to a variable equal to zero, a local peak in (the log of) a macroeconomic time series variable, x_t, occurs at time t if x_t exceeds values x_s for $t-k<s<t$ and $t+k>s>t$, where k delineates some symmetric window in time around t. This simple idea is the basis of the NBER procedures summarized in the Bry and Boschan (1971) dating algorithm. In practice, the Bry-Boschan algorithm with $k=5$ for monthly data also applies some censoring rules ensuring a minimum cycle duration of 15 months and alternation of peaks and troughs. This algorithm has been applied on time series data in levels and so produces the dating of classical cycles. Now consider the deviation cycle variable $DCI_t = y_t - g_t$. The variable DCI_t is now the deviation of the log of a macroeconomic time series variable, x_t, form its long run CF-trend, g_t, and a similar turning point algorithm can be applied on this deviation series.

Figure 1 **Deviation cycles of the Netherlands**







The Bry-Boschan algorithm has been adapted by Harding and Pagan (2002) to date growth cycles. We perform our dating in this spirit and apply an algorithm that obeys the following rules:

- peaks and troughs must alternate,
- a peak (trough) must represent above (below) trend growth and so the corresponding $DCI_t > (<) 0$,
- the turning point must be a local optimum:

$$\text{a peak at } t \text{ if } \left(DCI_{t-p},...,DCI_{t-1} < DCI_t > DCI_{t+1},...,DCI_{t+q}\right), DCI_{t'} > 0 \text{ for } t' \in [-p,...,q], \tag{1}$$

$$\text{a trough at } t \text{ if } \left(DCI_{t-p},...,DCI_{t-1} > DCI_t < DCI_{t+1},...,DCI_{t+q}\right), DCI_{t'} < 0 \text{ for } t' \in [-p,...,q].$$

Since the CF-filter parameters are set such that the shortest possible cycle lasts at least 18 months, no two peaks or troughs can coexist within this time frame. Moreover, a deviation cycle is approximately symmetric; the cycle is roughly half of the time below trend level. The study therefore sets $p = q = 9$, which defines a symmetric window consistent with the a priori definition of the minimum duration of the deviation cycle of 18 months. The dating procedure provides the collection of dates at which the deviation cycle reaches a peak or a trough. A low-growth (high-growth) period is straightforwardly defined as the period between a peak (trough) and a trough (peak).

Applying the dating rules (1) to a couple of different deviation cycles for the Netherlands results in the collection of deviation cycle turning points which are represented in Table 1. It shows both the results of filtered GDP on quarterly basis and of filtered industrial production on monthly basis. Moreover, the filters applied are the CF-filter used in this study, the HP-filter used by De Haan and Vijselaar (1998) and the Phase Average Trend (PAT) filter used by the OECD (2002). The last column of the table shows the chronology of turning points by the OECD of the Dutch deviation cycle. This chronology results from the comparison of turning points of PAT-filtered GDP and industrial production combined with expert judgement by country specialists. As shown in the last row, the turning points of both the CF- and the HP-filtered industrial production series produces deviation cycle turning points, as defined by (1), which closely match the OECD's final chronology. The mean absolute difference of the timing of the turning point dates as compared to this chronology is close to 3 months for all filtered series considered.

Table 1 **Dutch deviation cycle turning points of industrial production and GDP**

	Industrial Production index (manufacturing)			GDP		Dating[1)2)]
	Hodrick-Prescott[3)]	Christiano-Fitzgerald[4)]	Phase Average Trend[1)]	Christiano-Fitzgerald[4)]	Phase Average Trend[1)]	
Through	67m07	67m06	67m05		67q2	67m08
Peak	70m09	69m12	70m03		70q4	70m06
Through	72m06	72m01	71m12		72q3	72m06
Peak	74m04	74m03	74m08		74q3	74m01
Through	75m07	75m07	75m08		75q1	75m07
Peak	76m11	76m08	76m09			[76m09]
Through	78m01	77m08	78m05	79q1		[78m05]
Peak	79m11	79m11	79m11	80q2	79q4	79m10
Through	83m05	83m01	82m11	83q1	82q4	82m12
Peak	85m12	84 m10	85m01	86q2	86q2	84m10
Through			86m05			[86m05]
Peak			87m01			[87m01]
Through	87m07	87m11	88m04	88q4	88q1	87m08
Peak	90m05	90m08	91m02	91q4	90q4	90m12
Through					91q3	
Peak					92q1	
Through	93m08	93m09	93m06		93q4	93m12
Peak	95m06	95m02	95m06		95q4	95m02
Through	96m08	97m03	98m08	97q2	96q4	96m12
Peak	98m03	98m01			98q1	[98m01]
Through	99m01	99m02			99q1	[98m12]
Peak	00m10	00m10	00m06	00q2	99q4	00m06
Through	04m01	03m10		03q4		
MAD[5)]	3.3	2.6	2.7			

1) OECD (2002)

2) [ ] = minor cycle

3) De Haan and Vijselaar (1998)

4) with lower bound and upper bound of 1.5 and 10 years respectively

5) *MAD* = mean absolute difference in months of the timing of the turning point dates as compared to the OECD´s chronology that is shown in the last column.

4 The Empirics of International Deviation Cycles in Manufacturing

The indicators of the deviation cycle in the manufacturing industry of the nine countries are calculated by applying the CF-filter and standardising the resulting cyclical series. Subsequently, the dating is performed by applying the dating rules (1) to the indicators. The successive above- and below-trend growth periods are shown together with the deviation cycle indicators (DCI) in the manufacturing industry in Figure A1 in the appendix. The deviation cycles are represented by the bold lines and the low-growth phases by the shaded areas. The construction of the composite leading indicators, which are shown in the graphs by the dashed lines, will be explained in the next section. In order to derive descriptive statistics and measure synchronization among the deviation cycles in the manufacturing industry, we construct a state variable S_t, which equals one in high-growth periods and zero otherwise. The information $\{DCI_t, S_t\}$ provides for each country a picture of the characteristics of the cyclical motion and can be used to produce descriptive statistical measures as duration, amplitude, steepness and sharpness of high- and low-growth phases, see for instance Harding and Pagan (2002). Moreover, the information $\{DCI_t, S_t\}$ can be used to assess synchronization among deviation cycles in the manufacturing industry of different countries, see Harding and Pagan (2005).

The most commonly used descriptive statistics are the standard deviation, skewness and kurtosis. The standard deviation measures the variability of the indicator. Skewness measures the one-sided fattailedness of the probability distribution of the indicator. So, it measures whether high-growth phases are relatively more exuberant than low-growth phases are severe. Kurtosis measures the two-sided fattailedness and indicates whether large cyclical movements are relatively more common.

The state variable S_t separates above- and below-trend growth phases. A peak (trough) occurs at time t when $S_t = 1$ $(S_t = 0)$ and $S_{t+1} = 0$ $(S_{t+1} = 1)$. A high- (low-)growth phase consists of the period beginning the month after the date of a trough (peak) and ending at the date of a peak (trough). High growth phases and TP (trough-to-peak) and low-growth phases and PT (peak-to-trough) will be used interchangeably. The average duration[6] of high- and low-growth phases[7] are:

$$DUR_{TP} = \frac{\sum_{t=1}^{T} S_t}{\sum_{t=1}^{T-1} \left(1 - S_{t+1}\right) S_t}. \tag{2}$$

6 In calculating average of high- and low-growth phases one has to deal with uncompleted phases at both ends of the sample. The statistics will only be based on completed phases and therefore the summation runs from the beginning of the first completed phase until the end of the last one rather than over $1,...,T$.

7 The corresponding formulas for low-growth phases, PT, are obtained by replacing S_t by $(1 - S_t)$.

The numerator in (2) measures the total time spent in low-growth phases and the denominator counts the number of peaks. The average amplitude straightforwardly equals:

$$AMP_{TP} = \frac{\sum_{t=1}^{T} S_t \Delta DCI_t}{\sum_{t=1}^{T-1} \left(1 - S_{t+1}\right) S_t}. \tag{3}$$

Thinking of a phase as a triangle with as base its duration and as height its amplitude, then the steepness of a phase is naturally measured by the slope of the triangle:

$$STEEP_{TP} = {AMP_{TP}}\big/{DUR_{TP}}. \tag{4}$$

In addition to looking at the steepness over the phases, one might want to compare the shape of the cycle in the early part of the cycle to that in the later part. A simple way of capturing this shape is to divide a phase into two parts and to compare the average growth rates in the first part to those in the second part. This statistic is called sharpness and essentially measures a degree of convexity of the indicator, which is the relative steepness of the early stage in the cycle. Let i be the i^{th} phase and d_i be the duration of this phase, starting at time t_i. The measure of the shape of a single phase can then be defined as:

$$v_i = \frac{1}{\lfloor d_i/2 \rfloor} \left[\sum_{k=1}^{\lfloor d_i/2 \rfloor} \left(DCI_{k+t_i} - DCI_{k+t_i-1} \right) - \sum_{k=\lfloor d_i/2 \rfloor+1}^{d_i} \left(DCI_{k+t_i} - DCI_{k+t_i-1} \right) \right]. \tag{5}$$

Thus, if in a TP-phase the growth is faster in the first half of its duration than in the second half, then this measure will be positive. If in a PT-phase the decline is slower in the first half of its duration than in the second half, then this measure will be positive. If a cyclical indicator shows these two positive measurements it implies that the peaks are relatively long lasting and rounded and the troughs are relatively short lasting and pointed.

Averaging (5) over all similar phases can be defined as:

$$SHARP_{TP} = \sum_i S_{t_i} \left(\frac{d_i}{\sum_t S_t} \right) v_i . \tag{6}$$

In equations (6), S_{t_i} serves as an indicator function which equals one if the i^{th} cyclical phase starting at time t_i is a high-growth phase. Moreover, the equation is a weighted moving average of (5) over respectively high- and low-growth phases. The weight for a particular high-growth phase is the duration of that phase divided by the total time spent in

TP-phases over the sample. So, this weighting scheme gives more weight to longer phases and the sum of the weights is equal to one.

The descriptive statistics for the nine deviation cycle indicators of the manufacturing industry are presented in Table 2. Almost all countries tend to display kurtosis indicating that large cyclical movements in the manufacturing industry are relatively common. The Netherlands and to a lesser extent Belgium stand out on stability, but not on moderateness. Stability is revealed by the volatility of the cyclical behaviour around the trend and by the amplitude. This is the absolute deepness of a cycle decomposed into the ones belonging to low- and high-growth phases. Both the Netherlands and Belgium show the lowest numbers for all nine countries on the standard deviation and the amplitude. Moderateness is revealed by the steepness statistic. Steepness can be interpreted as the motion deepness of a low- or high-growth phase like amplitude can be seen as the absolute deepness of a low- or high-growth phase. For both phase types, the Netherlands and to a lesser extent Belgium show among the highest numbers for the steepness statistic indicating that the deviation cycle of the manufacturing industries for both countries move quickly from one turning point to another. Japan’s manufacturing sector acts as the mirror image of the ones of these two countries by showing the highest cyclical volatility and the highest cyclical severity both in terms of amplitude and steepness for both PT- and to a lesser extent TP-phases. The deviation cycle of the manufacturing industry of the U.S. also display high cyclical volatility and severity. The negative skewness indicates contraction phase outliers indicating at relatively severe recessions. The large slowdown sharpness and the large acceleration sharpness for the U.S. reveals a pattern of smooth rounded peaks and pointed deep troughs. Italy’s manufacturing industry demonstrates the largest positive skewness and among the highest peaks, that is the average amplitude of the high-growth phase. Both statistics indicate large upward cyclical outliers. The quite moderate sharpness statistic reveals that the Italian cyclical pattern surrounding turning points is particularly smooth. Germany’s manufacturing industry shows a cycle with a relatively long TP-phase compared as to the PT-phase. On the other hand the motion of the low-growth phases is relatively fast according to the steepness statistic and relatively deep according to the negative skewness. The sharpness statistic reveals that the German turning points are the most sharply pointed ones of the nine countries. Therefore, the German indicator looks somewhat like a saw tooth.

The descriptive statistics show the idiosyncrasy of the deviation cycle of each individual country’s manufacturing industry as compared to a sinusoid cyclical motion. This stylized cyclical pattern implies a deterministic periodicity. The periodicity of the cycle is the amount of time between two peaks, or two troughs. A complete cycle covers therefore two consecutive phases, which is either a PT-TP or a TP-PT period. The theoretical literature considers the cycle as the total sum of sub-cycles identified by theoretically founded durations. Impulses from inventory holdings, (infrastructural) investments and technological breakthrough innovations are the driving forces behind respectively the Kitchin, Juglar, Kuznets and the Kondratieff cycles.

Table 2 **Summary statistics for the deviation cycle indicators of the manufacturing industry**

		NLD	BEL	FRA	DEU	ITA	ESP	JPN	GBR	USA
Standard deviation		1.67	2.16	2.50	2.64	2.67	2.33	3.38	2.47	2.82
Skewness		-0.38	-0.0091	-0.56	-0.25	0.21	-0.68	0.16	-0.13	-0.35
Kurtosis		3.51	4.08	4.78	2.68	3.25	3.69	2.67	3.14	3.55
Duration	TP	26.00	22.00	24.83	24.90	33.40	38.83	26.00	36.75	27.00
	PT	22.00	28.13	22.33	28.00	33.50	30.67	39.00	33.40	36.50
Amplitude	TP 1)	2.87	2.67	2.44	2.93	3.40	3.02	3.39	3.00	2.74
	PT	2.42	2.38	2.59	2.31	2.83	2.97	3.12	2.39	2.51
Steepness	TP 1)	0.11	0.12	0.098	0.12	0.10	0.078	0.13	0.098	0.10
	PT	0.11	0.085	0.12	0.083	0.085	0.097	0.080	0.072	0.069
Sharpness	TP	0.015	-0.017	-0.038 2)	-0.023	-0.66 2)	0.053	-0.14 2)	0.14 2)	0.083
	PT	0.015	-0.012	-0.042 2)	-0.017	-0.55 2)	0.067	-0.097 2)	0.10 2)	0.061

Notes: The statistics are calculated over the sample 1965:1-2001:9 and represent the deviations from trend series which are not standardised. The mean of the deviation cycle is by construction approximately zero. So, standardising approximately only implies dividing the deviation time series by its standard deviation. PT means the phase Peak-to-Trough and is therefore synonym to low-growth phase. Equivalently, TP is synonym to high-growth phase. The skewness measure is $u_3/(u_2)^{1.5}$ and the kurtosis measure is $\mu_4/(\mu_2)^2$, where μ_r is the r^{th} central moment. The skewness of a symmetrical distribution, such as the normal distribution, is zero. Similarly, the kurtosis of the normal distribution is 3.

1) The numbers are presented with opposite signs for the sake of comparison with periods of high growth.

2) These numbers are multiplied by 100.

The elapsed time between two consecutive peaks would then be a fixed period T, for which the duration depends on the type of the subcycle. So, if DCI_t is identified as a peak, then $DCI_{t+\tau}$ must also be a peak with fixed duration time of $\tau = T$ periods, whereas in case of weak periodicity τ is considered as a stochastic duration variable with a mean of T. For $\tau > T$, the probability that the cycle switches to the other phase increases then with the ongoing duration of the current phase. Diebold and Rudebusch (1990) refer to the feature that the probability of a turning point is some function of the age of the cycle as duration dependence. Their evidence for the existence of some duration dependence is corroborated by Ohn *et al.* (2004) using novel discrete-time test statistics. A minimum duration on the complete deviation cycle in the manufacturing industry of 18 months is imposed in this study by the parameter settings of the CF-filter. The appendix shows that Ohn's *et al.* (2004) discrete test statistic is still valid to test duration dependence if the cycle is subject to minimum duration requirements. The hypothesis of no duration dependence is for both low- and high-growth phases for almost all countries rejected, according to the reported statistics in Table 3.

Table 3 **Statistics of duration dependence of the deviation cycle in the manufacturing industry**

	NLD	BEL	FRA	DEU	ITA	ESP	JPN	GBR	USA
TP	-4.35	-7.98	-1.93	-5.13	-1.25*	-3.74	-4.53	-4.48	-7.58
PT	-6.04	-2.75	-1.86	-3.82	-2.71	-2.71	-5.91	-2.8	-4.62

Note: The sample period is 1965:1-2004:2. The numbers are the Newey-West t-statistics for the null hypothesis of no duration dependence. PT means the phase Peak-to-Trough and is therefore synonym to low-growth phase. Equivalently, TP is synonym to high-growth phase.

The next step after examining the characteristics of the deviation cycle in the manufacturing industry is to analyze the relationships between them. More precisely, we want to examine how closely the cycles of individual countries are synchronized to one another. Harding and Pagan (2001) propose the index of concordance, which measures the fraction of time that two cycles spend in the same phase. Let S^i and S^j denote the state variables of the deviation cycle in the manufacturing industry of countries *i* and *j*. The index of concordance is defined as:

$$IC_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left\{S_t^i S_t^j + \left(1-S_t^i\right)\left(1-S_t^j\right)\right\}. \tag{7}$$

For all nine countries the results for the index of concordance are presented in the upper triangle of Table 4. The italic numbers in the lower triangle are the cross correlation coefficients of the two concerning deviation cycles in the manufacturing industry.

Six of the nine countries examined in this study are part of the euro area and account for more than 90% of euro area GDP. These six countries can form 15 unique couples[8] which provides 15 indices of concordance (ICs) measuring euro area synchronization of deviation cycles in the manufacturing industry. The average of these 15 indices is 0.74 and the average correlation is 0.66. As can be calculated from Table 3, the manufacturing industries of two euro area countries are on average roughly three quarters of the time in the same conjunctural state. Both the correlation and the IC of the big euro area countries Germany and France are both 0.68 and those between Germany and Italy only 0.32 respectively 0.65. The average IC and correlation of the potential euro area member the United Kingdom and the five euro area countries equal 0.64 respectively 0.56, which is even worse than the average IC of 0.67 between the United States and the euro area countries and slightly better than the average correlation of 0.54 between these two economic blocks. Moreover, the IC and the correlation between the United Kingdom and the United States equal 0.75 and 0.71 respectively. This indicates that the United Kingdom's deviation cycle in the manufacturing industry is more synchronized with the United States' one than with the cycle of the euro area.

8 One could also construct an index of concordance which only measures the simultaneity of more than two countries together. It then measures the fraction of time that all countries are in the same state. For example, the concordance of Germany, France and Italy together is 0.57

Table 4 **Index of concordance and correlation between indicators of deviation cycles in the manufacturing industry**

	NLD	BEL	FRA	DEU	ITA	ESP	JPN	GBR	USA
NLD		0.81	0.68	0.81	0.70	0.67	0.82	0.63	0.63
BEL	*0.82*		0.77	0.68	0.71	0.8	0.71	0.68	0.71
FRA	*0.76*	*0.86*		0.68	0.81	0.86	0.61	0.59	0.65
DEU	*0.80*	*0.66*	*0.67*		0.65	0.69	0.76	0.66	0.67
ITA	*0.64*	*0.64*	*0.66*	*0.31*		0.76	0.68	0.62	0.63
ESP	*0.58*	*0.67*	*0.81*	*0.47*	*0.61*		0.65	0.65	0.74
JPN	*0.74*	*0.76*	*0.65*	*0.52*	*0.65*	*0.52*		0.63	0.65
GBR	*0.66*	*0.72*	*0.58*	*0.37*	*0.47*	*0.53*	*0.60*		0.75
USA	*0.55*	*0.6*	*0.59*	*0.40*	*0.51*	*0.57*	*0.58*	*0.71*	

Notes: The sample period is 1965:1-2001:9. The indices of concordance are represented in the upper triangle of the table. The correlation coefficients are represented in *italic* in the lower triangle of the table.

5 Leading Indicators

The deviation cycles provide a signal for the current conjunctural state in the manufacturing industry. Cyclical motion in the economy is reflected in various macroeconomic time series. Depending on the timing behaviour of their cyclicality vis-à-vis the deviation cycle in the manufacturing industry, variables can be classified as leading, coincident or lagging. Leading variables give by nature an early signal on the conjunctural position. We will exploit this feature by selecting a set of leading variables and transform them into a single composite leading indicator that replicates and predicts the deviation cycle in the manufacturing industry. The combination of leading indicators is useful to pick up signals from different sectors of the economy. Stock and Watson (2003) conclude in their empirical literature review on the usefulness of financial indicators to forecast GDP growth and inflation that some asset prices predict inflation or output growth in some countries during some periods, but which series predicts what, when, and where is difficult to predict. As the forecasting literature moreover suggests that the simplicity of a model often implies forecasting power, this study aims to predict the deviation cycle in the manufacturing industry in a non-model based framework. Marcellino (2006) notes the overall good forecasting performance of the simple non-model based leading indicators concerning the latest two recessions in the U.S. in an overview of the different approaches and methods for the construction, use and evaluation of leading indicators, both in the academic literature and in the forecasting practice.

Potential leading variables that can be expected to lead and predict the general business climate are gathered and will be called basic indicators. The set of potential basic indicators is then screened in the spirit of the formalized scoring system of Moore and Shiskin

(1967). The collection of basic leading indicators should be a balanced representation of the total economy. Each basic indicator should be economically plausible, so it possibly causes the deviation cycle in the manufacturing industry or it reacts quicker to shocks. Moreover, the series should be statistically reliable, that is a long history of observations with as few interruptions and definition alterations as possible. The data should be available with a minimum publication delay and not be subject to substantial revisions after the first publication. The basic indicator should conform to the deviation cycle; it has good forecasting properties, not only at peaks and troughs. Finally, the basic indicator should posses a consistent timing as a leading indicator; systematically anticipate peaks and troughs with a rather constant lead time. The cyclical parts of all basic indicators are compared to the deviation cycle indicator of the manufacturing industry in order to determine the numbers of months by which the basic indicators lead the cycle, i.e. the timing. The measure of this timing is the lead in number of months corresponding to the maximum cross correlation coefficient between the deviation cycle indicator and the lagged basic leading indicator (BI):

$$\rho(l) = \tfrac{1}{T}\sum_t \left(DCI_t - \overline{DCI}\right)\left(BI_{t+l} - \overline{BI}_l\right) \Big/ \left(\sum_t \left(DCI_t - \overline{DCI}\right)^2 \sum_t \left(BI_{t+l} - \overline{BI}_l\right)^2\right)^{0.5}, \qquad (8)$$

$$l^* = \arg\max_l \rho(l). \qquad (9)$$

In equation (8) $\overline{DCI_t}$ and $\overline{BI_l}$ are the averages of DCI_t and BI_{t+l} respectively, over t. The magnitude of the correlation coefficient (8) measures the degree of cyclical similarity of the deviation cycle indicator of the manufacturing industry and the basic indicator. Moreover, the corresponding lead of l^* is determined in (9) and represents the optimal lead of the basic indicator. Analogous to Berk and Bikker (1995), we screen a set of potential leading variables consisting of about 40 monthly time series for each country on the criteria of a cross correlation $\rho(l^*)$ of at least 0.5 and a corresponding maximum lead l^* of at least 5 months. These boundaries are chosen as high as possible under the restriction that a sufficient number of basic leading indicators are selected. The selection statistics for the selected basic leading indicators are presented in Table 5. The first number in each cell is the optimal fine tuned lead l^* and the second number is the maximum cross correlation $\rho(l^*)$ for the concerning leading indicator and country. The selected leading indicators are of an economic, financial and monetary nature and confidence and expectations surveys.

Of the economic flow variables consumption, investment, exports and imports only the consumption in Japan shows a leading cyclical pattern. Consumption can straightforwardly be seen as a demand pull trigger for industrial activity. Inventories are a result of non-matching economic flows and for most countries the storage of final products provides an early signal for production activity. According to De Haan and Vijselaar (1998) there exists a one-way Granger-causality from the storage of final products towards industrial production for the Netherlands. Other types of inventories are those at the start of the production process, like the level order positions and issued building permits. Both variables pro-cyclically lead the deviation cycle in the manufacturing industry.

Prices and wages are a fundamental part in every economic model describing cyclical fluctuation. Following Stock and Watson (1999), a general pattern emerges of leading, countercyclical price levels and lagging, pro-cyclical rates of inflation. The nominal wage index exhibits a pattern quite similar to consumer prices, probably due to the contractual indexing of wages. Consumer prices, sales prices, total wages and hourly wages emerge in this study as cyclical leaders. Moreover, labour costs per unit product are a combination of wages and productivity and on average leads the cycle countercyclically. The same pattern shows up for the world market prices of commodities, which basically is a cost variable for production.

Dominant classes of leading variables concerning business cycles are those specifically related to the future. Survey variables that pro-cyclically lead the general cycle are consumer and producer confidence, expected future industrial production, prospects total economy, judgment of order arrivals and the IFO-indicator[9] for Germany. Financial variables deal with consumption and investment possibilities and therefore also with the choices made by private and public agents. As the sum of discounted expected future cash flows, share prices are, like surveys, future linked variables. Interest rates are a cost of capital and therefore partly determine the budget constraint. Both short term and long term interest rates lead the cycle with positive interest rates associated with cyclical declines in output. The lead of the short term interest rate is approximately 1.5 years for most countries to over two years for Japan, see Table 5. The connection between short term interest rate movements and the output gap is well established in the Taylor rule. The spread between the short and long term interest rates has long been recognized as a leading indicator. However, we prohibit taking this variable into the model together with both the short and the long term interest rates.

Monetary aggregates play an important role in the determination of price levels since nominal frictions in the economy can cause movements of real quantities. Following the time inconsistency literature, in the short run a monetary expansion creates a boost in employment and output that causes in the long run only a rise in the price level. We consider three monetary aggregates, if available, namely M1, M2 and M3 and test them both in nominal and real terms and in levels and growth rates. However, we find only for Spain a monetary aggregate functioning as a leading indicator. Stock and Watson (2003) note that the contemporaneous cross correlation between the cyclical components of nominal M2 and output has drastically declined since the early eighties for the United States.

The aim is to transform the selected basic leading indicators into a single composite index which replicates and predicts the deviation cycle indicator of the manufacturing industry. The replication property is ensured by the minimum correlation requirement. The prediction property is ensured by the criterion of minimum lead. A single composite index is then constructed as an optimal linear combination of normalized and synchronized selected basic leading indicators. The normalization procedure makes indicators exhibiting weak

9 We choose a sub index of the IFO-indicator which refers to future developments.

cyclical variation, for instance wages, comparable to indicators exhibiting strong cyclical variation, for instance confidence indicators and prevents the latter ones from dominating the former ones in a single composite index. The selected basic leading indicators are synchronized with the deviation cycle indicator of the manufacturing industry by shifting them forward with their respective leads as determined by (9) and reported in Table 5. Shifting a basic leading indicator variable forward by a number of months equal to its lead means that the shifted basic leading indicator variable no longer leads, but instead coincides with the cyclical phase of the manufacturing industry. Because of the shifting, the series extends beyond the observation period and provides a predictive signal for the near future cyclical development. Each selected basic leading indicator variable provides its own early signal. A one-dimensional single signal is obtained by constructing an optimal linear combination of the individual normalized and synchronized basic leading indicator variables by means of principal component analysis. The first principal component reflects the composite leading indicator since it captures the maximum common variation across the set of leading indicators.

According to Moore and Shiskin´s (1967) formalized criteria, the composite leading indicator is not only supposed to reflect the motion of the deviation cycle indicator of the manufacturing industry, but also to provide an early signal of upcoming turning points. As a linear combination of synchronized basic variables, the composite leading indicator’s turning points not necessarily coincide optimally with the corresponding ones of the deviation cycle indicator of the manufacturing industry. The lead of the composite leading indicator will therefore be fine tuned by matching the corresponding turning points of both indicators and minimizing a distance metric. The turning points of both indicators are dated using the procedures as stated in (1). The metric is the sum of the differences measured in months between all corresponding peaks and troughs of both indicators. The optimal leads of the synchronized composite leading indicators and their corresponding cross correlations with the deviation cycle indicators of the manufacturing industries are displayed in the last two rows of Table 5. Moreover, both indicators of each country are graphed in Figure A1 in the appendix. The shaded areas in the graphs correspond to the below-trend growth periods S_t. Table 6 presents the dating of the cyclical turning points of both indicators for all countries. The composite leading indicator sometimes misses turning points or sometimes gives false alarms, which means that the leading indicator signals a turning point that is not present in the deviation cycle indicator of the manufacturing industry. Missed signals and false alarms are mostly connected to minor cycles.

Table 5 **Results of selection leading indicators**

	NLD	BEL	FRA	DEU	ITA	ESP	JPN	GBR	USA
Consumer confidence			5 0.60	6 0.63			9 0.51	12 0.75	
Consumer price index*	8 0.54	17 0.72			9 0.79		16 0.53	14 0.83	
World market prices commodities*					18 0.61	15 0.55			14 0.84
M1*						22 0.78			
Equity price			14 0.62						9 0.52
Short term interest rate*	19 0.51	18 0.93		12 0.61	15 0.80		27 0.64	18 0.88	18 0.80
Long term interest rate*	18 0.53	16 0.57			12 0.68		25 0.53		15 0.71
IFO	5 0.74	7 0.63		5 0.91	9 0.60	6 0.60			
Expected business activity	6 0.84								
Expected future industrial production								8 0.94	
Storage final products*	6 0.59		5 0.61	5 0.90		6 0.70	13 0.70	10 0.92	9 0.77
Prospects total economy					10 0.72			11 0.95	
Judgement of order arrivals			5 0.70	6 0.85	15 0.73	6 0.70			
Level order position			5 0.82	5 0.91					
Hourly wage industry*	6 0.57	12 0.78		5 0.88	11 0.89		11 0.56		8 0.73
Domestic sales prices*		9 0.56			15 0.73		23 0.68	13 0.82	7 0.90
Producer confidence			5 0.74						
Consumption							10 0.67		
Total wages*								16 0.77	
Labour costs per unit product*		7 0.92	12 0.63						
Composite leading indicator	6 0.81	9 0.66	3 0.81	7 0.78	6 0.84	7 0.77	7 0.68	5 0.87	9 0.83

Table 5 **Results of selection leading indicators (continued)**

Notes:	The first number in each cell is the optimal fine-tuned lead (9) and the second number is the maximum correlation (8) of the corresponding basic leading indicator variable with the deviation cycle indicator of the manufacturing industry, DCI .
	The variables marked with a '*' counter-cyclically lead the cycle instead of pro-cyclically. The statistics presented in this table are, except for the Netherlands, based on the cyclical motions of the variables filtered with a lower bound of 36 instead of 18 months and an upper bound of 120 months.
	The composite leading indicator, CLI , is the weighted average of the synchronized basic leading indicator variables. The lead of the CLI is adjusted such that its turning points match most closely with the corresponding ones of the DCI . The resulting optimal lead and the corresponding cross-correlation of the fine-tuned CLI with the DCI are presented in the last two rows.

The mean and the standard deviation of the differences in months between the timing of the corresponding turning points of the DCI and CLI are presented in the last rows of Table 6. The absolute value of the mean difference is by construction smaller than a half due to the fine tuning, which optimally matches the corresponding turning points of both indicators. While on average the match is optimal for each country, the standard deviation of the differences reveals the variation in the lead/lag time for the turning point dates. The standard deviation is for most countries of the same order of magnitude as the lead of the CLI . The lead time of the CLI lays therefore grosso modo just outside the one standard deviation confidence interval of the difference in months between the corresponding turning points of both indicators. Therefore, more or less 85% of all turning points are signalled by the CLI during its lead time, so before the DCI does. Only Italy is a special case, the lead of the CLI is larger than two times the standard deviation. The CLI is signalling almost all turning points before the DCI does. Moreover, the Italian CLI never missed a turning point or gave a false alarm.

6 Conclusion

The cycles in the manufacturing industry of nine OECD-countries are identified as deviations from trend. We use the Christiano-Fitzgerald band-pass filter to estimate the unobservable trend and the cyclical component of a time series. We adopt the convention that the business cycle frequencies consist of all cycles with duration longer than 18 months and shorter than 10 years. From the deviation cycle in the manufacturing industry, we derive the cyclical turning points, low- and high-growth periods and summary statistics describing features like amplitude, steepness and duration of the cycle for each country.

The manufacturing industries in the Netherlands and, to a lesser extent, Belgium stand out compared to the nine countries on stability by showing a relatively modest cyclical spread around the trend. Their cyclical motions are however the least moderate so that the manufacturing industries of both countries move quickly from low- to high-growth phases and vice versa. Japan acts as the mirror image by showing the largest cyclical swings. The U.S. reveals a pattern of smooth rounded peaks and pointed deep troughs. The hypothesis of no duration dependence is rejected for nearly all deviation cycles in the manufacturing industries for all countries in both high- and low-growth phases. The international linkage between the manufacturing industries is explored by calculating the fraction of time the two countries are both in the same phase. This statistic shows that manufacturing industry in the United Kingdom is more synchronised with the one in the United States than with the one in the euro area. Moreover, the average synchronisation between the United Kingdom and the euro area countries is lower than the average synchronisation of the euro area countries with one another.

In addition to measuring cycles we constructed for each country a single composite leading indicator, which replicates and predicts the deviation cycle in the manufacturing industry. The composite leading indicator is based on economic, financial and survey variables possessing leading properties. These variables are selected from a set of candidate variables for each country. The variables that have been selected for five or more countries are the short term and long term interest rates, the storage of final products, the hourly wages, the domestic sales prices, the IFO-indicator for Germany and the consumption price index. The lead of the composite leading indicator is determined such that the dates of the turning points match most closely with the corresponding turning point dates of the deviation cycle indicator of the manufacturing industry. Moreover, the majority of the turning points are signalled by the composite leading indicator within its lead time.

Table 6 **Dating of turning points**

	NLD		BEL		FRA		DEU		ITA	
	DCI	*CLI*	*DCI*	*CLI*	*DCI*	*CLI*	*DCI*	*CLI*	*DCI*	*CLI*
Trough	67m6		67m5		68m4		67m6		69m11	
Peak	70m1		69m8		69m6		69m12		70m8	
Trough	72m4		71m11		71m9		72m1		71m7	71m10
Peak	74m3	74m4	74m4	73m12	74m2		73m11		74m1	73m12
Trough	75m7	75m12	75m7	76m4	75m7		75m6	75m8	75m8	75m9
Peak	76m8		76m9		76m10	76m10		77m1	76m11	76m10
Trough	77m7		77m8		77m9	77m10		78m2	77m12	77m11
Peak	79m11	79m11	79m11	80m7	79m11	79m12	79m12	80m1	80m3	79m12
Trough			81m2							
Peak			81m12							
Trough	83m1	83m4	82m11			80m4	82m12	83m1	83m3	83m5
Peak	84m11	84m9	84m1			82m6	85m9	84m7		
Trough	87m8	86m12	86m12	86m3	85m4	85m6	87m11	88m3		
Peak	90m7	90m1	89m5	89m6	89m6	89m8	91m9	91m1	89m7	89m6
Trough	93m8	93m11	93m1	92m4	93m7	93m8	93m8	93m10	93m6	93m7
Peak	95m1	95m7	95m7	95m7	95m2	95m3		95m7	95m8	95m3
Trough	97m1	96m9	96m6	96m6	96m9	96m10		96m11	96m11	96m12
Peak	98m1	98m5	98m1	98m4	97m12	98m6	98m4	98m8	97m12	98m6
Trough	99m2	99m9	99m4			99m7	99m5	99m11	99m3	99m7
Peak	00m8	00m11	00m8			00m9	00m10	01m1	00m12	00m8
Trough	03m9	02m5		02m4	03m5	02m3		02m6		02m5
False signals		0		0		4		4		0
Missed turnings		2		8		0		0		0
MEAN		-4/14		-1/9*		1/10		-2/10*		3/14*
STDV		6.4		6.5		5.2		7		3

Table 6 **Dating of turning points (continued)**

	ESP		JPN		GBR		USA	
	DCI	*CLI*	*DCI*	*CLI*	*DCI*	*CLI*	*DCI*	*CLI*
Trough	68m03				68m07		67m07	
Peak	69m07	70m03	70m03		69m08		69m07	
Trough	71m07	71m11	71m12		72m01		70m11	
Peak	74m02	73m07	73m10	74m5	73m05		74m01	73m04
Trough	75m10	75m10	75m06	76m4	75m10		75m07	75m11
Peak		77m06						
Trough		78m07						
Peak	79m12	79m10	80m01	80m6	79m09	79m09	79m05	79m05
Trough					81m02	81m04	80m08	
Peak							81m04	
Trough	82m05	81m04	83m01	82m5			82m11	83m03
Peak	83m05	83m01	84m12		85m02	84m06	84m06	84m08
Trough	85m05	85m07	87m02		86m06	86m10	86m08	85m12
Peak	89m09	89m09	91m02	89m6	89m01	88m12	88m07	88m02
Trough	93m04	93m10	93m11	93m4	91m10	91m09	91m07	91m12
Peak	95m03	95m06			95m01	95m06	95m01	95m01
Trough	96m06	96m11				96m09	96m04	
Peak	98m04	98m06	97m06	97m9		98m01		
Trough		99m09	98m11		99m03	99m06		98m04
Peak		00m08	00m10		00m12	00m08	00m05	00m03
Trough	02m02	02m02	02m01	02m9	02m07	02m05	01m12	01m12
False signals		4		0		2		0
Missed turnings		0		4		0		2
MEAN		-4/14		-2/8		-2/10		-3/11
STDV		5.3		10.4		3.9		4

Notes: DCI is the abbreviation for the deviation cycle indicator of the manufacturing industry. CLI is the abbreviation for the composite leading indicator. The mean (MEAN) and standard deviation (STDV) of the differences in timing of turning points refer to the differences in months between the timing of the corresponding turning points of the DCI and the CLI . A false signal occurs if the CLI shows a cycle and the DCI does not. A missed turning point occurs of the DCI shows a cycle and the CLI does not. Due to data availability, the CLI starts at a later date and therefore no turning points corresponding to the ones of the DCI exists at the beginning of the sample.

* For Belgium, Germany and Italy, the most recent turning point is not reported and not taken into account in the calculations. As shown in Figure A1, a competitive turning point date might become the relevant one as the estimates of the DCI get revised with the arrival of new data observations.

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Appendix

A technical note on testing for duration dependence

This appendix derives a regression based test statistic for duration. The state variable S_t is obtained by applying the dating rules (1) to the indicators of the deviation cycle. Moreover, let d_i be the duration of the i^{th} phase in number of months. Consider the random sample of n observations $(D_1, D_2, ..., D_n)$ of durations from a discrete distribution with density function $f(d)$. Then the hazard rate function is defined as,

$$h(d) = \frac{f(d)}{1 - F(d)}$$

For a small Δ, $h(d)\Delta$ is the probability that the phase will terminate during the interval $(d, d + \Delta)$. If there is to be no duration dependence, then the termination probability must be constant, regardless of the duration of time spent in the phase and so does not depend on d, that is

$$H_0 : h(d) = \theta \text{, for some } \theta > 0 \text{ and all } d > 0. \qquad \text{(A.1)}$$

In the discrete case, the null hypothesis of no duration dependence (A.1.) can only be satisfied by the geometric distribution. The geometric density of D with termination probability p reads as

$$P(D = d) = (1 - p)^d \, p \text{ for } 0 \le d < \infty,$$

and its constant hazard function can be derived as:

$$h(d) = \frac{P(D = d)}{1 - P(D \le d)} = \frac{(1 - p)^d \, p}{(1 - p)^d} = p.$$

Moreover, it holds in the geometric case that $E(D) = (1 - p)/p$, $Var(D) = (1 - p)/p^2$ and so

$$Var(D) - [E(D)]^2 - E(D) = 0.$$

So, the null hypothesis (A.1) of no duration dependence implies a testable moment condition.

However, in this study a minimum duration on the complete cycle of 18 months is imposed by the parameter settings of the CF-filter. So, effectively the distribution of D becomes a delayed geometric one $P(D^{delayed} = D - c)$, or equivalently :

$$P\left(D^{delayed}=k\right)=\begin{cases}0 & \text{otherwise}\\ p\left(1-p\right)^{k-c} & \text{for } k=c,c+1,...\end{cases}.$$

And it holds that

$$E\left(D^{delayed}\right)=\frac{(1-p)}{p}+c=E(D)+c\ ,\ Var\left(D^{delayed}\right)=\frac{(1-p)}{p}=Var\left(D\right)$$

and the testable moment restriction for the delayed geometric distribution reads as:

$$\operatorname{var}(D)-[E(D)]^2-(2c+1)E(D)-c(c+1)=0\,. \tag{A.2}$$

A regression based test statistic for duration dependence, which is of delayed geometrically distributed durations (A.2), can be constructed as a variable -addition test in a regression equation. The test is a modification of Ohn *et al.* (2004) to allow durations to be delayed in addition to be geometrically distributed.

Consider the following regression:

$$S_t=\beta_0+\beta_1 S_{t-1}+\beta_2 S_{t-1}X_{t-1}+error \tag{A.3}$$

where the number of consecutive months spent in a high-growth phase up and through time *t* is given by:

$$X_t=1+\left(1-S_t\left(1-S_{t-1}\right)\right)\left(1-S_{t-1}\left(1-S_t\right)\right)X_{t-1}\,.$$

It is possible to derive an analytic form for the estimate of β_2 which is identical to the moment restriction (A.2).

Consider:

$$\frac{1}{T}\sum_{t=1}^{T}S_{t-1}S_t=\overline{S}-\frac{n}{T}$$

where $\overline{S}$ is the sample mean of S_t, T is the sample size and n is the number of TP-phases. Moreover,

$$\begin{aligned}\overline{SX}&=\frac{1}{T}\sum_{t=1}^{T}S_tX_t=\frac{1}{T}\sum_{i=1}^{n}\frac{\left(d_i^{delayed}+1\right)d_i^{delayed}}{2}\\&=\frac{1}{T}\sum_{i=1}^{n}\frac{\left(d_i+1+c_m\right)\left(d_i+c_m\right)}{2}=\frac{n}{2T}\left[\overline{d^2}+\left(2c_m+1\right)\overline{d}+\left(c_m^2+c_m\right)\right]\end{aligned}$$

where d_i is the duration of the i^{th} high-growth phase[10] minus the minimum of c_m periods.

Finally,

$$\frac{1}{T}\sum_{t=1}^{T} S_t S_{t-1} X_{t-1} = \frac{1}{T}\sum_{i=1}^{n} \frac{(d_i - 1 + c_m)(d_i + c_m)}{2} = \overline{SX} - \overline{S}\ .$$

Now, the standard linear regression of $S_t - \overline{S}$ on $S_{t-1} - \overline{S}$ and $S_{t-1}X_{t-1} - \overline{SX}$, with Δ the determinant of the scaled (by $1/T$) cross product matrix of the two regressors, results in:

$$\Delta\hat{\beta}_2 = \overline{S}\left(1-\overline{S}\right)\left(\overline{SX} - \overline{S} + \frac{n}{T}c_m - \overline{SX}\,\overline{S}\right) - \overline{SX}\left(1-\overline{S}\right)\left(\overline{S}\left(1-\overline{S}\right) - \frac{n}{T}\right)$$

$$\Leftrightarrow \frac{T\Delta\hat{\beta}_2}{n\left(1-\overline{S}\right)} = \overline{SX} + \overline{S}\left(c_m - \frac{T}{n}\overline{S}\right)$$

$$= \frac{1}{T}\sum_{i=1}^{n} \frac{(d_i + 1 + c_m)(d_i + c_m)}{2} + \frac{n\left(\overline{d} + c_m\right)}{T}\left(c_m - \frac{n}{T}\frac{T}{n}\left(\overline{d} + c_m\right)\right)$$

$$\Leftrightarrow \frac{2T^2\Delta\hat{\beta}_2}{n^2\left(1-\overline{S}\right)} = \overline{d^2} - 2\overline{d}^2 - (2c_m - 1)\overline{d} - c_m(c_m - 1)$$

$$= \operatorname{var}(D) - [E(D)]^2 - (2c_m - 1)E(D) - c_m(c_m - 1). \qquad \text{(A.4)}$$

Note that for $c_m := c+1$ equations (A.2) and (A.4) are equivalent. The variable addition test statistic $H_0 : \beta_2 = 0$ for equation (A.3) is therefore also effectively testing for no delayed duration dependence. Because of the binary nature of the variables involved one needs to consider the heteroskedastic and autocorrelation consistent t-statistic.

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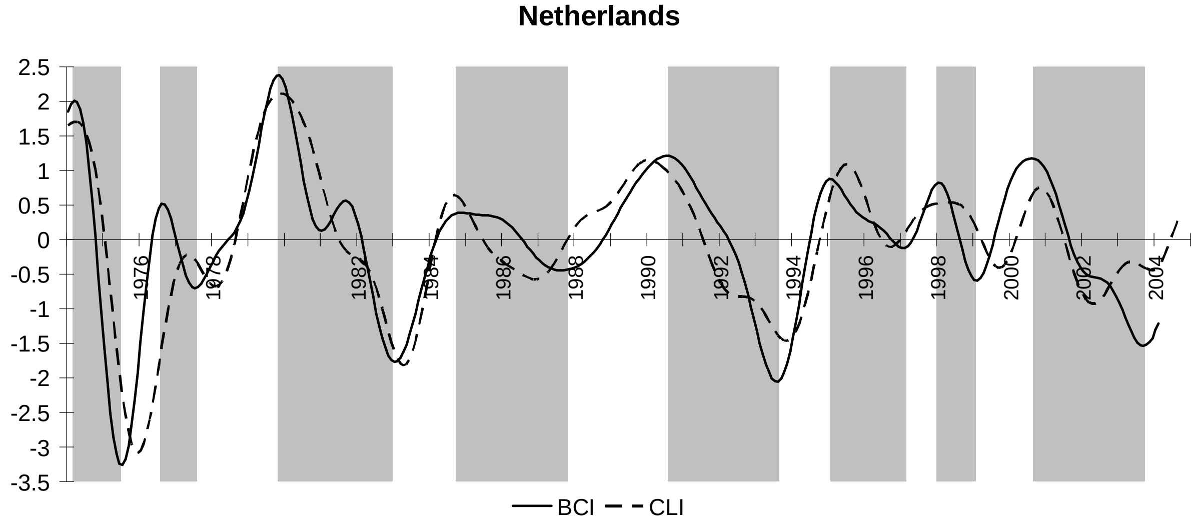
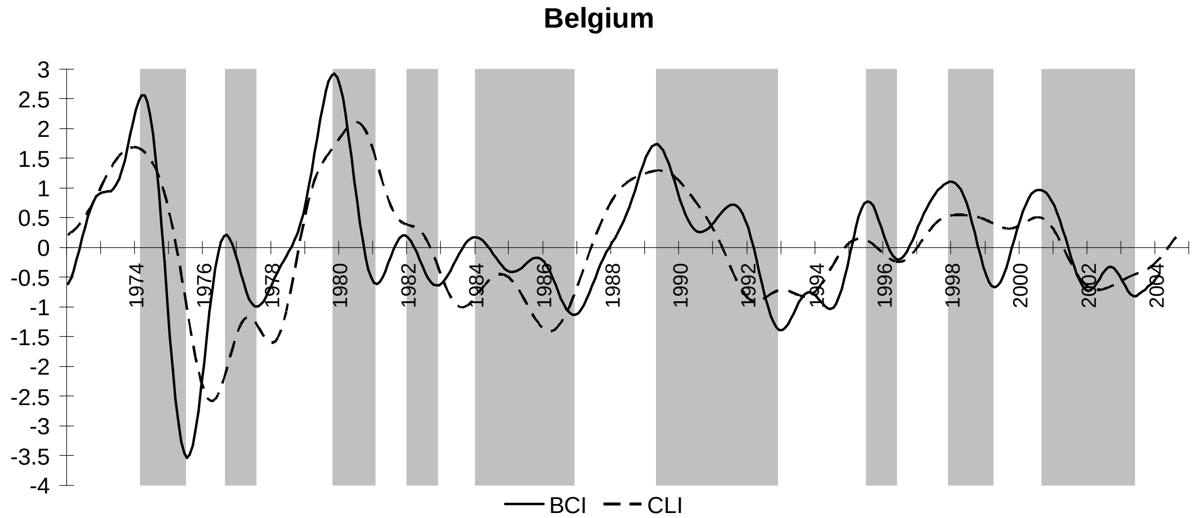
10 The analysis can be performed for low-growth (PT-) phases as well by defining $S^{low-growth\ phase} = 1 - S^{high-growth\ phase}$.

Figure A1 **International deviation cycles in the manufacturing industry and composite leading indicators**





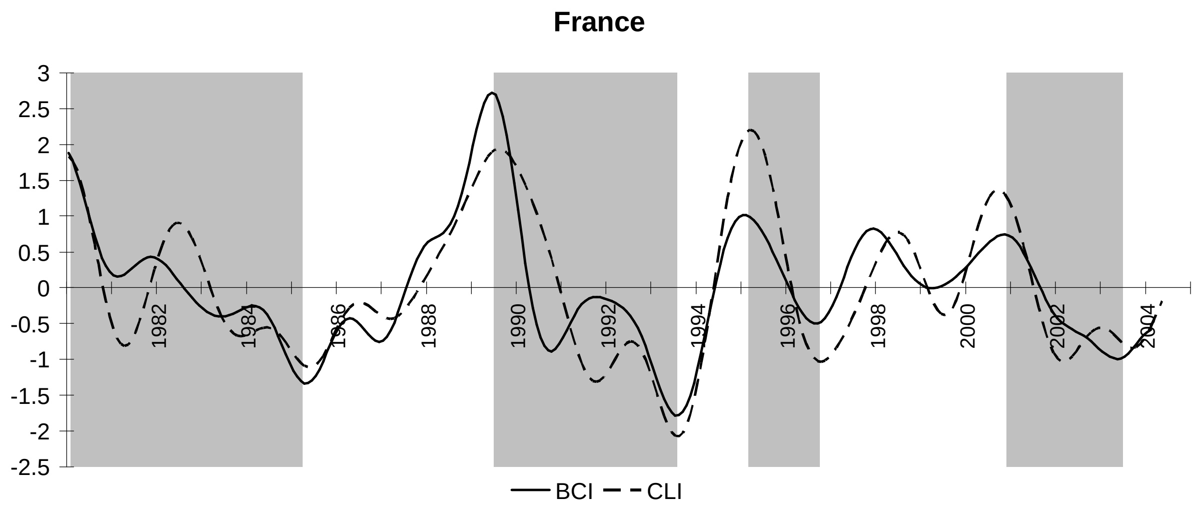
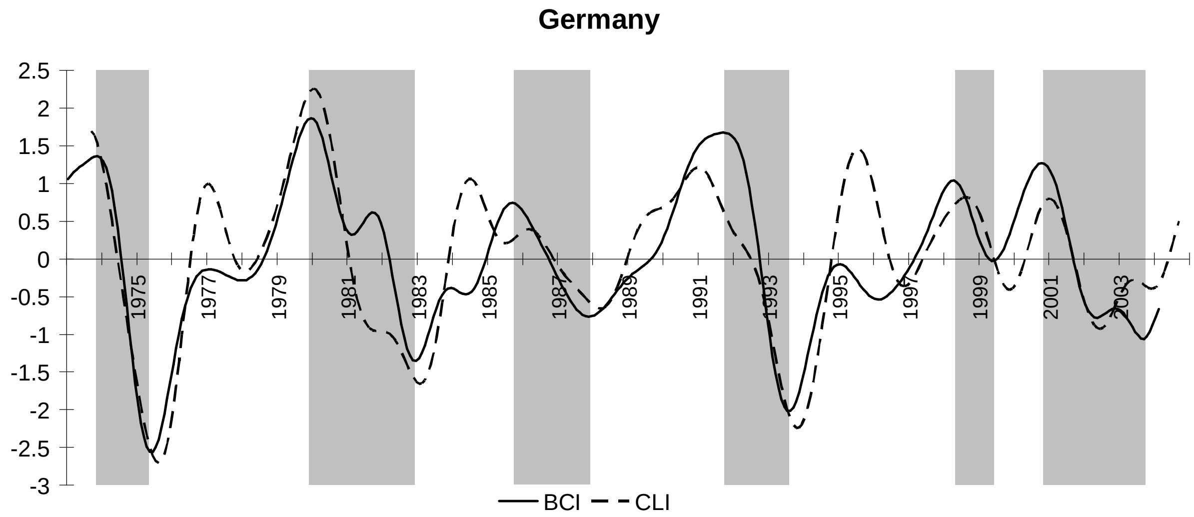
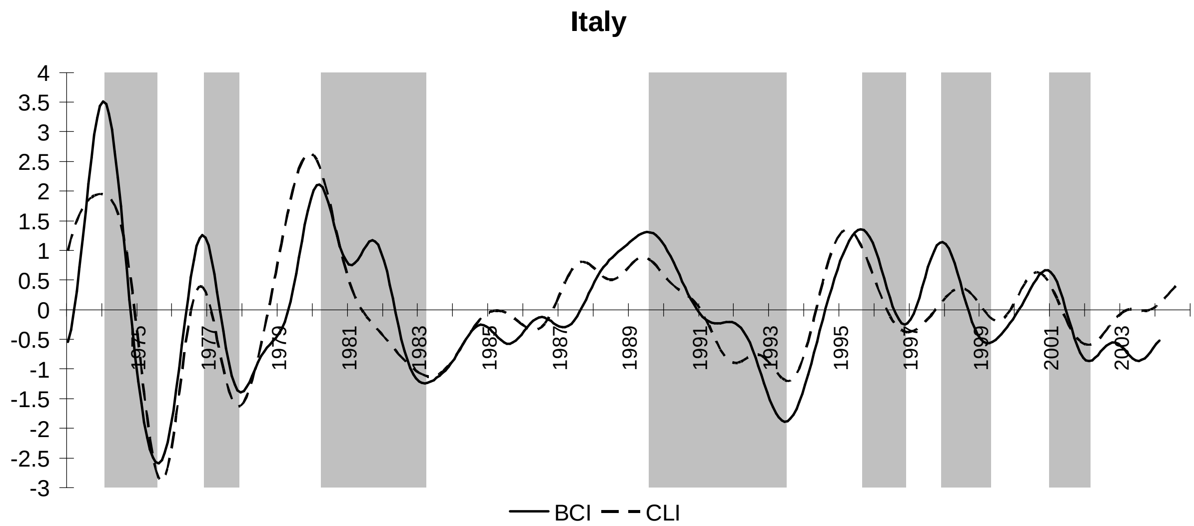


Figure A1 **continued**





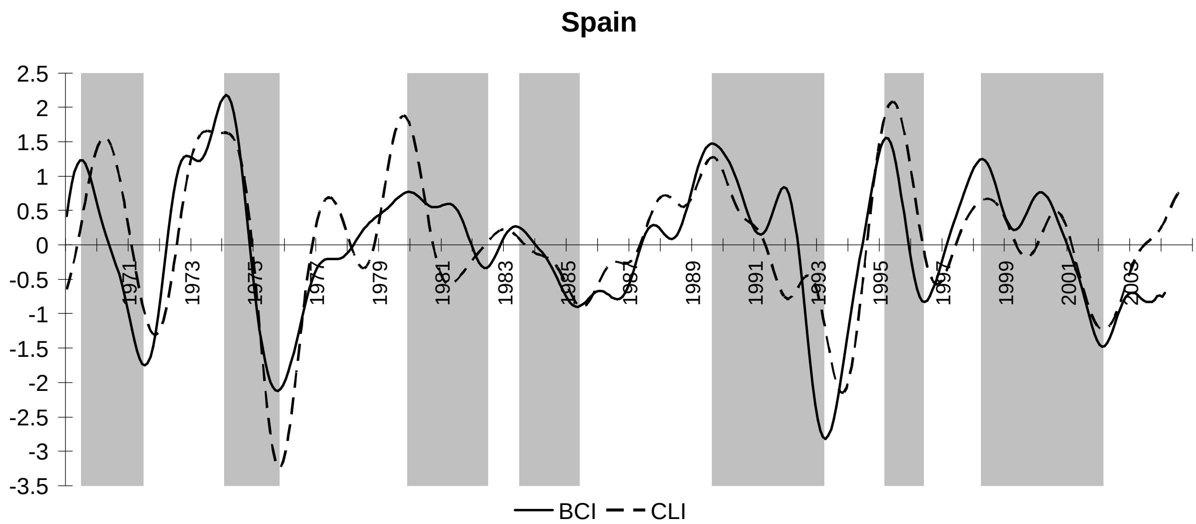
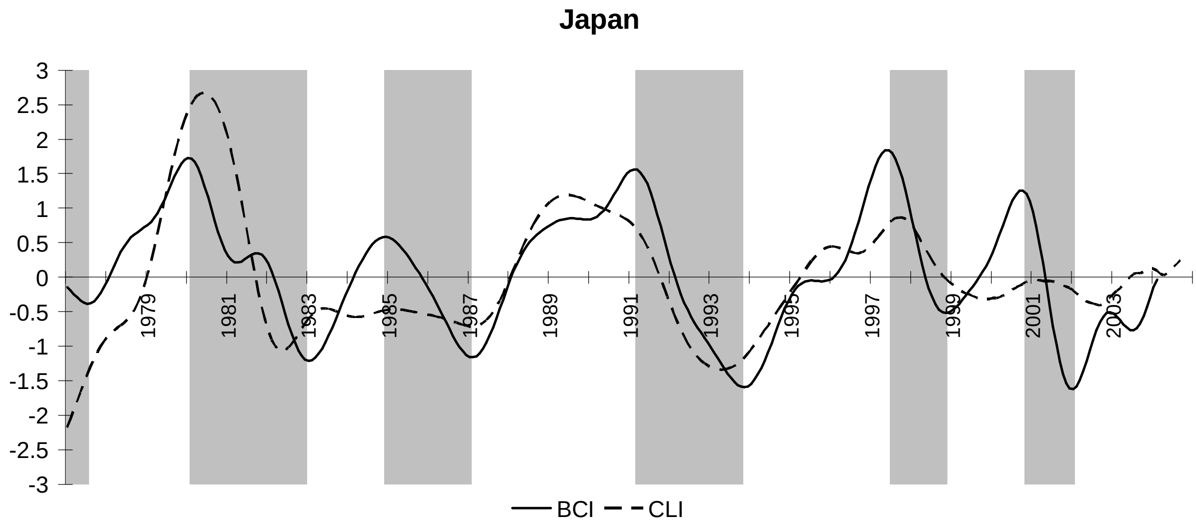
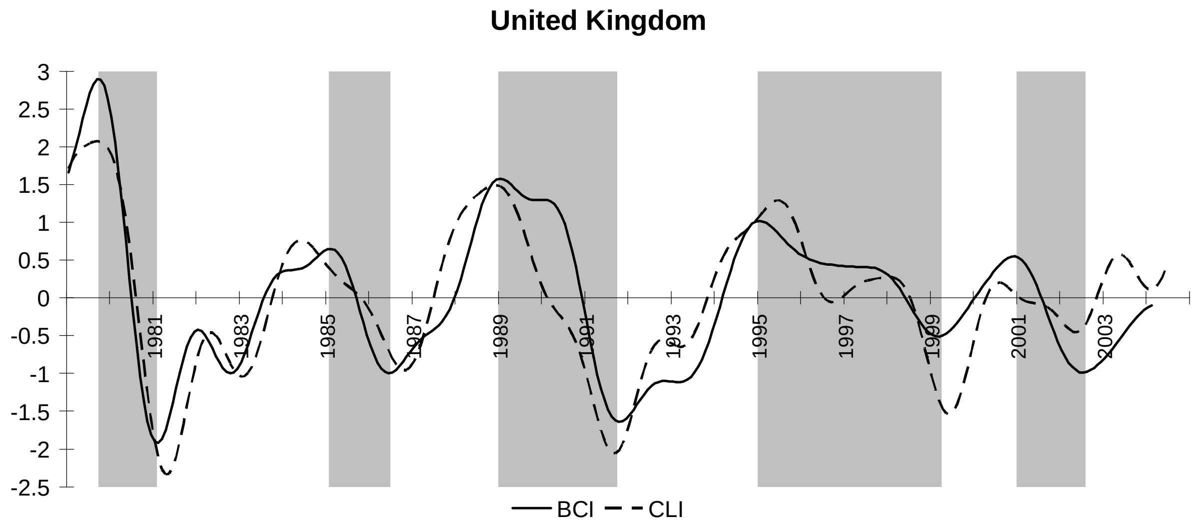


Figure A1 **continued**





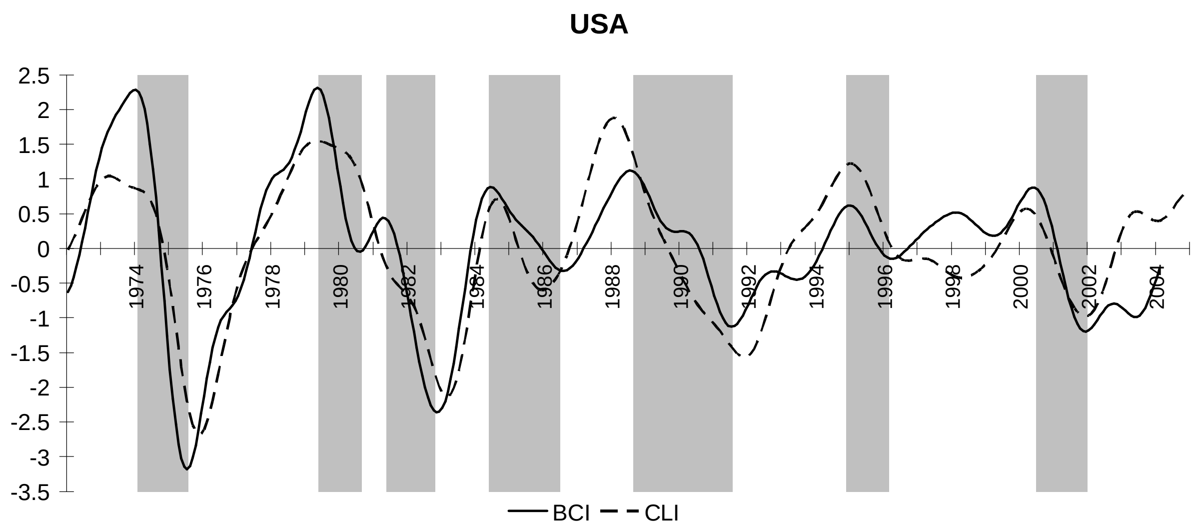


Table A1 **Data source**

Description	Code	Source*
The Netherlands		
Industrial production	IRAA04MB	CBS
Consumer price index	IRDE31MA	CBS
Short term interest rate	IKGB01MA	Prebon/Yamane IKGB11MA, from 1999 DNB-FM IKGB01MA
Long term interest rate	IKGE11MA	DS
IFO, expected business situation	IJDEFDMA	DS
Hourly wage industry	IRDK11MA	CBS
Storage final products	IJNLFAMA	DS
Expected business activity	IRAD41MA	CBS
Belgium		
Industrial production	IIBEAXMB	BIS
Consumer price index	IIBEBAMA	BIS
Short term interest rate	IKGB01MA	BIS IIBELBMA, from 1999 DNB-FM IKGB01MA
Long term interest rate	IIBELDMA	DS
IFO, expected business situation	IJDEFDMA	DS
Hourly wage industry	IJBEFEMA	DNB S&I*
Domestic sales prices	IIBEBCMA	BIS
Labour costs per unit product	IJBEFFMA	DNB S&I*
France		
Industrial production	IJFRFLMH	DS
Consumer confidence	IIFRAMMB	DS
Producer confidence	IIFRAQMB	DS
Equity price	IIFRLXMA	BIS
Labour costs per unit product	IJFRFFMA	DNB S&I IIFRAGKA*
Judgement of order arrivals	IJFRFBMA	DS *
Storage final products	IJFRFAMA	DS
Level order position	IJFRFCMA	DS
Germany		
Industrial production	IJDEFLMH	DNB S&I (ECB, BIS)
Consumer confidence	IIDEAMMB	DS
Short term interest rate	IKGB01MA	DNB-FM IKGB41MA, from 1999 DNB-FM IKGB01MA
IFO, expected business situation	IJDEFDMA	DS
Hourly wage industry	IIDEADMB	BIS
Judgement of order arrivals	IJDEFBMA	DS
Storage final products	IJDEFAMA	DS
Level order position	IJDEFCMA	DS

Notes: * Quarterly to Monthly

BIS = Bank of International Settlements, *CBS* = Statistics Netherlands,
DNB-FM = De Nederlandsche Bank - division Financial Markets,
DNB S&I = De Nederlandsche Bank - division Statistics & Information,
DS = Datastream, *ECB* = European Central Bank

Table A1 **Data source (continued)**

Description	Code	Source*
Italy		
Industrial production	IJITFLMH	DNB S&I (ECB, BIS)
Consumer price index	IIITBAMA	DS
Short term interest rate	IKGB01MA	BIS IIITLBMA, from 1999 DNB-FM IKGB01MA
Long term interest rate	IIITLDMA	DS
IFO, expected business situation	IJDEFDMA	DS
Hourly wage industry	IIITADMA	BIS
Domestic sales prices	IIITBCMA	BIS
Producer confidence	IIITAQMB	DS
Prospects total economy	IJITFEMA	DS
Judgement of order arrivals	IJITFBMA	DS
Level order position	IJITFCMA	DS
World market prices commodities	IRDF01MA	HWWA - Institut fur Wirtschaftsforschung
Spain		
Industrial production	IJESFLMH	DNB S&I (ECB, BIS)
M1	IJESFFMA	DNB S&I IIESHXMA + IIESTXME
IFO, expected business situation	IJDEFDMA	DS
Storage final products	IJESFAMA	DS
Level order position	IJESFCMA	DS
World market prices commodities	IRDF01MA	HWWA - Institut fur Wirtschaftsforschung
Japan		
Industrial production	IIJPAXMB	BIS
Consumer price index	IIJPBAMA	BIS
Short term interest rate	IIJPLBMA	BIS
Long term interest rate	IIJPLDMA	BIS
Consumer confidence	IJJPFBMA	DNB S&I IIJPAMKB*
Hourly wage industry	IIJPADMA	BIS
Domestic sales prices	IIJPBCMA	BIS
Storage final products	IJJPFAMA	DS *
Consumption	IJJPFCMA	DNB S&I IIJPCFKB*

Table A1 **Data source (continued)**

Description	Code	Source*
United Kingdom		
Industrial production	IIGBAXMB	DS
Consumer confidence	IIGBAMMB	DS
Producer confidence	IIGBAQMB	DS
Consumer price index	IIGBBAMA	DS
Short term interest rate	IIGBLBMA	Financial Times
Domestic sales prices	IIGBBCMA	BIS
Total wages	IJGBFFMA	OECD/QNA GBR.CQRSA.S1 Compensation of employees*
Expected future industrial production	IJGBFDMA	DS
Storage final products	IJGBFAMA	DS
Level order position	IJGBFCMA	DS
Prospects total economy	IJGBFEMA	DS
United States		
Industrial production	IIUSAXMB	BIS
World market prices commodities	IRDF01MA	HWWA - Institut fur Wirtschaftsforschung
Storage final products	IJUSFAMA	DS
Hourly wage industry	IIUSADMB	BIS
Equity price (S&P corporate 500)	IIUSLXMA	BIS
Short term interest rate	IIUSLBMA	BIS
Long term interest rate	IIUSLDMA	BIS
Domestic sales prices	IIUSBCMA	BIS

Notes: * Quarterly to Monthly

BIS = Bank of International Settlements, *CBS* = Statistics Netherlands,
DNB-FM = De Nederlandsche Bank - division Financial Markets,
DNB S&I = De Nederlandsche Bank - division Statistics & Information,
DS = Datastream, *ECB* = European Central Bank