A cross-sectional approach to business cycle analysis

Floris van Ruth

Discussion paper (10001)

Statistics Netherlands

The Hague/Heerlen, 2010

Explanation of symbols

.	= data not available
*	= provisional figure
**	= revised provisional figure
x	= publication prohibited (confidential figure)
–	= nil or less than half of unit concerned
–	= (between two figures) inclusive
0 (0,0)	= less than half of unit concerned
blank	= not applicable
2008–2009	= 2008 to 2009 inclusive
2008/2009	= average of 2008 up to and including 2009
2008/’09	= crop year, financial year, school year etc. beginning in 2008 and ending in 2009
2006/’07–2008/’09	= crop year, financial year, etc. 2006/’07 to 2008/’09 inclusive

Due to rounding, some totals may not correspond with the sum of the separate figures.

Publisher
Statistics Netherlands
Henri Faasdreef 312
2492 JP The Hague

Prepress
Statistics Netherlands - Grafimedia

Cover
TelDesign, Rotterdam

Information
Telephone +31 88 570 70 70
Telefax +31 70 337 59 94
Via contact form: www.cbs.nl/information

Where to order
E-mail: verkoop@cbs.nl
Telefax +31 45 570 62 68

Internet
www.cbs.nl

ISSN: 1572-0314

6008310001 X-10

A cross-sectional approach to business cycle analysis

Floris van Ruth[1]

Summary: The first and most important aim of this study is showing the validity of the so-called cross sectional approach to business cycle analysis. In this approach, the current stance of the business cycle is derived from a relatively small, diverse set of indicators. The mix consists of lagging, coincident, and leading indicators and is selected to reflect as many different aspects of the economy as possible. Using a number of different methods, the common cycle of this indicator set is derived. It is tested whether these are able to represent the business cycle and whether the cycles resulting from the different methods match. The exercise is performed both for the Netherlands and the USA. The results confirm that the aggregate common cycles of a mixed indicator set can accurately represent the current state of the business cycle, and that the different detrending methods yield very similar aggregate cycles. This indicates that the outcomes are not spurious or a chance outcome of one method. This offers support for the idea that the common cycle of a sufficiently diverse set of macro-economic indicators is the business cycle, the second aim of this study. Additional advantages of the cross sectional approach are the analytical possibilities offered by the diverse nature of the indicator set, the fact that the aggregate is robust to variations in the leading or lagging character of individual component series, and that the set can be constructed to yield a truly current picture of the state of the economy, i.e. even when accounting for publication lag..

Keywords: Business cycle analysis, detrending, business cycle indicators, common components

---

[1] The author would like to acknowledge that Gert Buiten, Symon Algera and Roberto Wekker of Statistics Netherlands played a crucial role in developing the ideas and concepts on which the Statistics Netherlands Business Cycle Tracer is based.

1. Introduction

There is an increasing variety of approaches and methods of measuring the business cycle; classical business cycles, growth cycles, using composite indicators or single indicators, or very large datasets, or using complex signalling models. Sometimes these methods are different ways of measuring the same phenomenon, and sometimes the underlying concepts are fundamentally different. Statistics Netherlands has further added to this abundance by introducing another approach to measuring the business cycle with its Business Cycle Tracer. Due to their potentially profound influence on society, there is much interest in business cycle developments. Internationally, there is a host of institutions which produce indicators for monitoring the business cycle of one or more countries, for example the Conference Board and the Economic Cycle Research Institute from the USA, the OECD and the centre for economic policy research. For the Netherlands, both the Dutch central bank and the centre for policy analysis produce a monthly business cycle indicator. Usually, the main focus is on forecasting business cycle developments via the construction of an composite index of leading indicators. An exception is CEPR's EUROCOIN index, which is constructed to reflect the current state of the Euro-zone business cycle [Altissimo et al. (2007) and Forni et al. (1999)]. The Statistics Netherlands Business Cycle Tracer has a similar aim, which is to provide a real time picture of the current state of the Dutch business cycle [Van Ruth et al. (2005)]. Its construction differs from most traditional business cycle indicators, both leading and coincident. It consists of a mixed set of lagging, coincident and leading indicators, selected to be representative of different aspects of the economy. The standard approach is to separate economic indicators into lagging, leading and coincident indicators, and construct separate composite indicators from the different sets. This mixed approach is termed here cross-sectional business cycle analysis. It is in fact a thorough application of the idea that the business cycle is the common factor in the economy. As such, it is related to the work of Harvey (1990, 1993, 2003), Stock and Watson(1998) and Forni et al (1999) who pioneered the formal derivation and estimation of common cycles.

This study has several aims. First and foremost the goal demonstrate the validity of the fundamental concept underlying the Statistics Netherlands business cycle tracer; the cross-sectional approach. This cross sectional approach to business cycle analysis states that it is possible to derive the current state of the business cycle from a diverse and mixed set of selected indicators, which individually do not have to reflect the current state of the business cycle. And that if done right, a small set is sufficient for achieving this. But in the process, further support will be provided that the common cycle as found by detrending economic data is a real phenomenon, and also towards the validity of the interpretation of the business cycle as the common cyclical component in the economy. The validity of the cross sectional approach proposed here depends of course on the existence of such a common cycle.

There is a long running debate concerning the nature and causes of the business cycle. Among those studying the business cycle, the only consensus seems to be on the general definition, the often cited original formulation of Burns and Mitchell (1946):

"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 in shorter cycles of similar character with amplitudes approximating their own."

Also informative is the NBER definition of a recession [Christiano and Fitzgerald (1998)]:

"… a recession is a persistent period of decline in total output, income, employment and trade, usually lasting from six months to a year, and marked by widespread contractions in many sectors of the economy."

These definitions are based on empirical observations, which have been replicated in most industrial countries [Klein and Moore (1982), Den Reijer (2002)]. The highlight two central points on which there is general agreement [Christiano and Fitzgerald (1998), Banjeri and Hiris (2001), Klein and Moore (1982), Stock and Watson (1988), Zarnowitz (1987)]: A business cycle concerns alternating periods of strengthening and weakening economic activity, where at first economic activity is not defined explicitly. And these fluctuations should have a broad presence in the economy. At first, co-movement between economic indicators was mainly used as a tool for identifying turning points, and some believe that this remains its main utility [Harding and Pagan (1999, 2002)]. But the very influential work of Stock and Watson [1998, 2002] showed that a common component or cycle is a fundamental and independent aspect of the dynamics of the economy. They developed a method which formally estimated the common dynamic component from the set of coincident indicators for the US. The plausibility of the common cycle concept was further confirmed by formal estimations using other methods, mainly Unobserved Components models [Harvey (1990, 2000, 2003] and large scale dynamic factor models[Forni et al (1999), Stock and Watson 2002]. This study focuses on deriving the common cycle from a very varied set of the most important macro-economic indicators, showing that it is not necessary

This study also wishes to contribute to the broadening of the concept of the business cycle. Purist maintain that the only relevant measure of the business cycle is output, i.e. GDP, and that only declines in the level of output signal a recession or decline in economic activity [Harding and Pagan (1999, 2002)]. But most studies concerning the business cycle start out talking about fluctuations in *economic activity,* a much broader and abstract concept than output. Economic activity is a multidimensional phenomenon, and is better measured using a multivariate approach [II, XIII]. This dovetails with the view of the business cycle as a unobserved, but common factor in the economy. There are also more practical reasons for choosing a multivariate approach. A change in the cycle does not appear all at once in the economy. It works its way through the economy via a phased process. Empirical research has shown that most economic indicators can be broadly classified as either leading, lagging or coincident with the business cycle. This classification may not always hold, but is true on average [Zarnowitz (1987)]. It is difficult to find a single indicator which provides a good measure of current economic conditions, and relying on individual indicators is dangerous as each recession and slowdown tends to have its own causes and characteristics [Marcellino (2004), Carriero and Marcellino (2007)]. Another fundamental reason for choosing a broad set of indicators to monitor the state of the business cycle, such as in the Statistics Netherlands Business Cycle Tracer, is the analytical possibilities it offers. Leading, coincident and lagging indicators each offer different and complementary information on business cycle developments. Tracking them together shows the evolution of the business cycle, and the interactions between the indicators [Klein and Moore (1982), Zarnowitz (1987)].

This study tests several methods for extracting the common cycle from a mixed set of macro-economic indicators. The resulting aggregate cycles are compared to reference chronologies and each other, to test their plausibility. The proposition is that broad similarity of common cycles resulting from such different methods proves the credibility and reliability of the computed aggregate cycles. The focus is on a general characterization of the businesses cycle, whether the economy is in a period of strengthening or weakening economic activity. Most relevant are then those moments when one phase switches to the other, the so-called turning points. The original work was done for the Dutch economy, but to improve the usefulness and to make reviewing the outcomes easier, the exercise was repeated for the US economy.

The first section of this study will give some brief background information on business cycle theory and concepts. The next section concerns practical methodological issues, describing the indicator selection process and the different methods used to find the cyclical component in the data. The first section with results concerns the US, the second the results for the Netherlands. The papers ends with a discussion of the outcomes.

2. Some background theory

Earlier theories of the business cycle tended to focus on cyclical processes in inventories or fixed capital formation as the underlying cause of medium-term economic fluctuations[Zarnowitz (1987)]. Later, non-linearity and feedback mechanisms were proposed as explanation, but these proved difficult to apply. Currently, the most influential theories are the so-called Real Business Cycle models. These state that business cycle fluctuations are caused by aggregate shocks to production technology. These models have received some serious criticism. For a start, the existence of *negative* shocks to production technology is required to create business cycle fluctuations in these models. No convincing explanation or proof of these has been offered. Furthermore, it has proven very difficult or impossible to reconcile the observed so-called stylised facts of the business cycle with the predictions of Real Business cycle models [Christiano and Fitzgerald (1998), Hamilton (2005)]. Currently, there is no generally accepted theory which explains the business cycle[Zarnowitz (1987), Prescott (1986), Cooper (1997), Fuhrer and Schuh (1998), Marcellino (2004)]. The main debate is to whether the business cycle is an intrinsic, probably non-linear, phenomenon or caused by exogenous shocks [Marcellino (2004)]. In the latter case, the development would be characterised by a random walk process. But this is at odds with the observed similarities between business cycles and countries, and the existence of more or less stable relationships between indicators in the course of the evolution of the business cycle [Klein and Moore (1987), Zarnowitz (1987)]. Experience also shows that the business cycle is not an instant affair, but developments spread from firm to firm, from industry to industry and from region to region [Banrji and Hiris (2001)]. This suggests a different mechanism than a single aggregate shock hitting the economy. It is unclear what form this should take, but there is some consensus that while the causes of individual business cycles differ, there exists a more or less constant mechanism by which the fluctuations propagate. This would explain both the observed similarities between business cycles, and the contrasting variation in duration and severity of individual cycles [McGuckin et all. (2007), Zarnowitz (1987), Hamilton (2005)]. There is no suggestion that the business cycle is fixed, either in length or other characteristics, each cycle is unique. It is accurately characterized as recurrent, but not periodic [Zarnowitz (1987), Den Rijer (2006)]. A practical consequence of this all is that is preferable to monitor a set of indicators to track business cycle movements than relying on a single indicator.

The debate on the causes of the business cycle is reflected in a long and inconclusive debate on how to measure them. There are three basic approaches to defining the business cycle, which though related can give very different outcomes. Each has its own advantages and disadvantages. The classical approach is based on the work of

Burns and Mitchell, who identified business cycles by analysing changes in the absolute level of important economic indicators. In their analysis, a business cycle downswing requires a decline in the absolute level of the indicator, meaning negative growth rates. According to Harding and Pagan (2001, 2002), this is still the only relevant method of analysing business cycles. They argue that only absolute growth and decline in output are relevant for policy makers and the wider public, and that other measures of business cycles are either too complex or ill-defined. However, the classical concept is less useful in periods of sustained high growth, such as experienced in the US and Europe in the 1950's and 60's, and currently in China [Klein and Moore (1987)]. Even during these high growth episodes, there will be slowdowns, periods of lower economic activity. These will be characterised by lower, but still positive growth rates. It seems arbitrary to classify all periods with above zero growth as strong economic conditions. The converse can be true for economies which have made a, possibly temporary transition to a condition of low structural growth rates. Here, a low or possibly even a small negative growth rate can be a favourable realisation. The classical approach to business cycle measurement offers no concepts to analyse situations like this. Even under normal conditions, the analysis offered by the classical approach is fairly crude. An economy is either in a recession, negative growth rates, or not. All further analysis is just interpretation.

In reaction to these issues, a different approach to business cycle measurement was developed. The business cycle was defined as the deviation of the economy from its potential, these are termed growth- or deviation cycles. In practice, this meant computing whether an economic indicator is developing above or below its trend. This approach has several attractive properties. The cycle gains economic content, as deviation from trend is a measure of the output gap, and whether an economy develops below or above its potential has real significance. As a result, a more refined analysis of the current state of the economy becomes possible, see for example Van Ruth et al.(2005). An added advantage is that it becomes easier to compare the evolution of different economic indicators, as trends tend to differ much more than the cyclical component of the dynamics. This approach has received a fair amount of criticism as well though. Two main sources of problems have been identified. The first is that the real-time measurement of growth cycles is very difficult because the trend estimation is unstable, especially for recent periods [II]. And perhaps more seriously doubts have been raised as to the plausibility of the estimated cycles. It has been stated that under certain conditions virtually all detrending techniques can yield spurious cycles [Den Rijer (2007), Harvey and Jäger (1993), Guay and St-Amant (1997), Schenk-Hoppé (2001), and Harvey and Trimbur (2003)]. This is probably less serious than it sounds, as it seems that this mainly concerns short, weak cycles [Van Ruth (2005), Bonenkamp (2003), Kranendonk et al (2003, 2004)]. Canova (1998) states that business cycle stylised facts are not robust under different detrending techniques, but other research indicate that overall the outcomes of different methods show great similarity, at least as far as approximate dates of turning points and number and identity of cycles is concerned [Klein and Moore (1982), Banrji and Hiris (2001), Zarnowitz and Ozyildirim

(2002), Kranendonk et al (2003, 2004)]. An earlier study for confirmed this for the Dutch economy, using a univariate analysis of cycles in industrial production and GDP [Van Ruth et all. (2005)]. This study differs from most others in that it tests the similarities of different aggregate cycles, i.e. a multivariate approach.

Still, these problems resulted in the proposition of an alternative approach: the analysis of cycles in growth *rates* [Banjrii and Hiris (2001)]. These are easier to compute, and much less sensitive to the calculations, while the cycle remains clearly visible in the outcomes. But a meaningful analysis of the outcomes for policy and professional use still requires an judgement as to whether the economy is in a high growth or low growth phase. This will usually result in a determination of the average, or *trend*, growth rate. It was stated above that while these three approaches to business cycle measurement differ significantly, they are related. It probably is useful to demonstrate how this relationship works. Consider an (seasonally adjusted) economic indicator y_t which can be described as consisting of a trend (T), a cycle (C) and an irregular component (ε). In a log linear formulation:

$$y_t = T_t + C_t + \varepsilon_t$$

Or in differences:

$$\Delta y_t = \Delta T_t + \Delta C_t + \Delta \varepsilon_t$$

Based on these formulas, it is possible to derive when recessions and turning points in the different business cycle concepts will occur, and how these relate to each other, see table 2.1.

Table 2.1; Conditions for occurrence of recession phases and business cycle turning points for the different business cycle concepts

approach	*Recession*	*Turning point*
classical	Δy<0 (=ΔC+ΔT<0)	Δy=0 (=ΔC+ΔT=0 → ΔC=-ΔT)
Growth (deviation) cycle	C<0	ΔC=0
Growth rate cycle	Δy<0 (=ΔC+ΔT<0) ?	Δy (=ΔC+ΔT) minimal or maximal → ΔC minimal or maximal

What becomes clear is that recessions and turning points occur under different circumstances in the different business cycle concepts, although there is a structural relationship between them. Classical and growth rate recessions will be rarer than growth/deviation cycle recessions, as the first require a very negative development of the cycle to overcome trend growth, whilst the latter only require the cycle to become negative. But all classical recessions will be growth cycle recessions as well. As far as turning points are concerned, these will occur at different moments, but with a predetermined order. Growth rate turning points will lead both classical cycle and growth/deviation cycle turning points. On the other hand, peaks in the deviation cycle will lead peaks in the classical cycle, but troughs in the classical cycle will lead the troughs in the deviation cycle.

3. methodology

The first part of this section describes how the individual component indicators were selected, the subsequent parts which techniques were used to extract the cyclical components from the individual time series.

3.1 Indicator selection

Most institutions and researchers use a more or less standard process when selecting indicators for constructing a business cycle indicator. This process can be characterised by the set of criteria for indicator selection as formulated by Marcelllino (2004) and Carriero and Marcellino (2007):

- Consistency in lagging/leading/coincident character
- Conformity to the general business cycle
- Economic significance
- Statistical reliability of data collection
- Prompt availability without major revisions
- Smooth development

Of course, this set of requirements reflects an ideal situation, to which not all relevant indicators will be able to conform. Indicator construction is partly the art of balancing the requirements. Using the cross sectional approach proposed here actually means that several of these requirement can be relaxed:

- Absolute consistency in leading/lagging character is no longer important. The whole indicator set is constructed to be on average coincident, and thus the aggregate will be relative insensitive to temporary fluctuations in the leading/lagging character of individual indicators.

- Prompt availability also becomes less important, as the set can be balanced to be coincident by taking publication lags into account in the indicator selection process, as a modulation of the leading/lagging character. A sufficiently broad indicator set will mean that later revisions in some indicators can be absorbed.
- Smooth development is desirable, but can be achieved by using appropriate filtering techniques.

The single most important criterium is conformity to the general business cycle, usually made operational by analysing correlation and conformity in turning point dating with some suitable reference series, usually GDP, or by testing conformity to a reference business cycle chronology. The cross-sectional approach as implemented here, with a limited dataset, introduces two new requirements [see also Van Ruth et al. (2005)].

- The total number of component indicators should neither be too small, to ensure representativeness and averaging out of idiosyncratic movements, or too big, because calculations may become infeasible and the indicator set becomes difficult to analyse. As a guide, the set should contain between 10 and 15 indicators
- The indicator set should be representative of all aspects of the economy, to ensure representativeness and to prevent a development peculiar to one aspect of the economy dominating the outcome. This also ensures that the aggregate is only the development common to all important economic indicators, as everything else averages out.

3.2 Hodrick-Prescott filter

The Hodrick-Prescott filter was first described in Hodrick and Prescott (1997) and is widely used for trend cycle decompositions. It is not a filter in the traditional sense, as no upper or lower limits are defined for the frequencies to be extracted. The filter contains only one parameter, which controls the smoothness of the filtered series.

Hodrick and Prescott use the following model:

$$y_t = \mu_t + c_t ,$$

According to this model the series contains only a trend and a cycle. The ratio of the variances of c_t and μ_t is assumed to be equal to the chosen parameter λ. For a larger λ, a smoother trend will be obtained. As measure of the smoothness of the trend, Hodrick and Prescott take the sum of squares of the second order differences. Furthermore, they pose that the cycle is the deviation from the trend, and its long-term average should be zero. This results in the following minimisation problem:

$$\min_{\{\mu_t\}}\left\{\sum_{t=1}^{T} c_t^2 + \lambda\sum_{t=1}^{T}\left[(\mu_t-\mu_{t-1})-(\mu_{t-1}-\mu_{t-2})\right]^2\right\}.$$

According to the literature, the optimal values are $\lambda = 1600$ and $\lambda = 14400$ for quarterly and monthly data respectively. Here however, a variant was chosen based on earlier research [Van Ruth et al. (2005)]. It uses a large value of λ, typically 1000000 for monthly series and 50000 for quarterly ones, to extract a relatively inflexible trend from a pre-smoothed series. This pre-smoothed series can be the Henderson trend as can be computed in the Census-X12 program. The deviation of this pre-smoothed series from the Hodrick-Prescott trend then constitutes the cycle. The advantages of this approach are that it yields less minor cycles and is relatively insensitive to new observations.

3.3 Christiano-Fitzgerald filter

Christiano and Fitzgerald (1999) propose a band-pass filter similar to the Baxter-King filter. However, they assume the time series to be a random walk:

$$y_t = y_{t-1} + \varepsilon_t,$$

Where the ε_t are again i.d.d. Under these assumptions, the Christiano-Fitzgerald filter minimises the expected squared deviations from the ideal weights. Their solution for the end value problem encountered by the Baxter-King filter is to use an asymmetrical weighting scheme, where the final observation receives the weights of all the missing (future) observations.

$$\begin{array}{lll}
For & t=1 & w=(\frac{1}{2}B_0, B_1, \ldots, B_{T-2}, -\frac{1}{2}B_0 - \sum_{k=1}^{T-2} B_k) \\
For & t=2 & w=(-\frac{1}{2}B_0, B_0, B_1, \ldots, B_{T-3}, -\frac{1}{2}B_0 - \sum_{k=1}^{T-3} B_k) \\
For & 3 \le t \le T-2 & w=(-\frac{1}{2}B_0 - \sum_{k=1}^{t-2} B_k, B_{t-2}, \ldots, B_1, B_0, B_1, \ldots, B_{T-t-1}, -\frac{1}{2}B_0 - \sum_{k=1}^{T-t-1} B_k) \\
For & t=T-1 & w=(-\frac{1}{2}B_0 - \sum_{k=1}^{T-3} B_k, B_{T-3}, \ldots, B_1, B_0, -\frac{1}{2}B_0) \\
For & t=T & w=(-\frac{1}{2}B_0 - \sum_{k=1}^{T-2} B_k, B_{T-2}, \ldots, B_1, \frac{1}{2}B_0),
\end{array}$$

where $B_0 = \frac{2}{p_l} - \frac{2}{p_u}$ en $B_k = \frac{\sin(\frac{2\pi k}{p_l}) - \sin(\frac{2\pi k}{p_u})}{\pi k}$ and p_l and p as in the Baxter-King filter.

Low-pass and high-pass filters can be constructed by taking, $p_u = \infty$ or $p_l = 2$ respectively. The computations in this study were performed using the eviews-package, where the low and high pass were set on respectively 11 and 3 years.

3.4 Stock and Watson methodology

The approach of Stock and Watson, as set out in their 1988 paper was the source of much innovation in business cycle measurement. Central to their approach is taking as a starting point the definition of the business cycle as the movement common to the majority of macroeconomic indicators, and then making this concept operational by using appropriate econometric methods. In effect, they turn this argument around, by stating that if one finds the strongest stationary common component of a group of relevant economic indicators, this will almost by definition be the business cycle. Because their aim is to extract the business cycle itself, they use the coincident indicators, then of the department of commerce, as the relevant variables. The central feature of their approach is to use dynamic factor analysis to extract from these economic indicators the unobserved "state of the economy". This is done by formulating the following model:

$$X_t = \beta + \gamma * C_t + v_t$$
$$\Phi(L) \cdot C_t = \delta + \eta_t$$
$$D(L) \cdot v_t = \varepsilon_t$$

Where: X_t = a vector of n observations for n indicators at time t

β = a n-dimensional vector of constants

γ = a n-dimensional coefficient vector

v_t = a n-dimensional component representing measurement error

$\Phi(L)$, $D(L)$ are lag polynomials

δ = a constant

η_t = an innovation term

ε_t = an innovation term

The essential aspect of this model is the description of the dynamics of the economic indicators as consisting of two stochastic components; a scalar time series C_t representing the common, unobserved component and an n-dimensional component v_t which contains the idiosyncratic movement of the indicator series and the measurement error. By using appropriate econometric techniques, this separation can be performed and the unobserved series C_t, which represents the business cycle, can be extracted. This can be done by using the Kalman filter, for which the model has to be cast in the state space form. In order for this to work here, the input series need to be stationary, which usually means for economic time series that a form of differencing is required to remove stochastic trends. Stock and Watson apply first differencing, in this study year on year growth rates will be used as this removes seasonal effects as well. A state space model consists of a measurement equation, which links the observed realisations to the unobserved state variables, and of a transition equation which describes the dynamics of the state variables and therefore of the model. In general form:

Measurement equation: $y_t = \beta + Z\alpha_t + R\xi_t$

Transition equation: $\alpha_t = T\alpha_{t-1} + \zeta_t$

I will not describe here the state space model used in detail, it suffices to focus on the central variable, the state vector α_t which in the Stock and Watson model takes the form:

$$\alpha_t = \begin{bmatrix} C_t \\ C_{t-1} \\ C_{t-2} \\ . \\ . \\ . \\ \\ C_{t-p} \end{bmatrix}$$

Where C_t now is the difference of the unobserved coincident index of economic activity. The p lagged values of C_t present in the state vector are not just entered to obtain a better fitting model, but are necessary for modelling a cyclical component. Stock and Watson set p=2, whilst in this study using 4 quarterly lags yielded the best common components.

3.5 Unobserved Components models

The so-called Unobserved Components (UC) models were developed in the 1980´s and 1990´s, e.g. Watson (1986), Harvey (1990), Harvey and Jäger (1993) and Harvey and Koopman (2000). A time series is assumed to consist of a number of (unobserved) components, which are explicitly modelled. This allows their presence to be formally tested. The most general model contains trend, cyclical, seasonal and irregular components. It is also possible to introduce external innovations into the model.

Thus the most general form of the model is:

$$y_t = \mu_t + c_t + s_t + \varepsilon_t \,.$$

Each term can be specified in different ways. Here, the trend is modelled as a so-called "local linear trend" model (UC-LLT)

$$\begin{aligned} \mu_t &= \mu_{t-1} + \nu_{t-1} + \xi_t \\ \nu_t &= \nu_{t-1} + \eta_t \,, \end{aligned}$$

where ξ_t and η_t are independent, normally distributed error terms.

If the unknown variances of ξ_t and η_t are represented by σ_ξ and σ_η, two basic variations on the local linear trend-model de can be obtained:

smooth trend (UC-ST), $\sigma_\xi = 0$

local linear trend with fixed slope (UC-LLTF), $\sigma_\eta = 0$.

The total cycle is modelled in trigonometric form as the sum K cycles

$$c_t = \sum_{k=1}^{K} c_{k,t} \,,$$

where

$$\begin{bmatrix} c_{k,t} \\ c_{k,t}^* \end{bmatrix} = \rho_k \begin{bmatrix} \cos(\lambda_k) & \sin(\lambda_k) \\ -\sin(\lambda_k) & \cos(\lambda_k) \end{bmatrix} \begin{bmatrix} c_{k,t-1} \\ c_{k,t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix},$$

κ_t and κ_t^* are independent, normally distributed variables, , λ_k is the wavelength to be determined of the k^{th} cycle, and ρ_k is the unknown damping factor of the k^{th} cycle.

The seasonal component is modelled either in a similar fashion to the cyclical component, by 12 (4) underlying cycles, one for each month(quarter), or - more simply - by using seasonal dummies

4. Results USA

4.1 A reference chronology for the USA

A difficult issue is how to evaluate the credibility of the cycles found in a business cycle analysis. As mentioned in the theory section, different concepts of what constitutes a business cycle exist, which result in different business cycle chronologies. In the US, there is of course the NBER business cycle dating committee. This determines the begin (Peaks) and end (Troughs) dates of US recessions using data on industrial production, personal income, consumer sales and hours worked. This is the reference chronology for the US and a useful benchmark. However, the NBER uses a variant of the classical concept of a recession, based on an absolute decline in the level of economic activity. This differs markedly from the concept of the deviation (or growth) cycle, as employed by among others the OECD and Statistics Netherlands. Therefore, we will compare several chronologies for the US business cycle to see whether there exists a common denominator. As the main focus in this study is on deviation cycles, it would be useful to have a deviation cycle based variant of the NBER business cycle chronology. This was achieved here by constructing a composite coincident cyclical indicator from the four indicators on which the NBER bases its business cycle analysis. The CF-filter was used to compute the cycles of the individual series, after which the average of these cycles was taken to represent the business cycle. Other chronologies were obtained from the Conference Board and the OECD.

Table 4.1; Business cycle chronologies for the USA, as defined by dates of peaks and troughs.

	NBER (recessions)	*NBER cyclical composite*	*Conference board (recessions)*	*OECD (business cycle chronology)*
Trough	**1970 IV**	**1971-5**	**1970-11**	**1970-11**
Peak	**1973 IV**	**1973-7**	**1973-11**	**1973-10**
Trough	**1975 I**	**1975-10**	**1975-3**	**1975-3**
Peak	**1980 I**	**1979-5**	**1980-1**	**1978-12**
(Trough)	1980 III		1980-7	
(Peak)	1981-7		1981-7	
Trough	**1982-9**	**1983-2**	**1982-11**	**1982-12**
(Peak)		1984-11		1984-6
(trough)		1986-6		1986-9
Peak	**1990-7**	**1989-9**	**1990-7**	**1989-1**
Trough	**1991-3**	**1991-10**	**1991-3**	**1991-3**
(Peak)		1995-1		1995-1
(Trough)		1996-10		1996-1
Peak	**2001-3**	**2000-5**	**2001-3**	**2000-6**
Trough	**2001-11**	**2002-6**	**2001-11**	**2001-12**

Bold; good correspondence between GDP/IP date and reference, italicized; good correspondence between different GDP&IP turning points, less with reference turning points. Minor cycles between brackets.

If we focus on the similarities between these chronologies, we find that all methods identify major turning points at roughly the same time. The agreement is far from absolute, individual datings can deviate more than 12 months, a significant amount. Also, the chronologies do not agree on the number of cycles which have occurred in the period considered here. However, the additional cycles are minor ones, smaller fluctuations of economic activity, and none of the chronologies shows a completely different business cycle chronology. Though we will show the NBER-recession dates in the graphs, a rough business cycle chronology can be found when focussing on the major turning points on which, broadly speaking, there is agreement.

Table 4.2; "Average" business cycle chronology for the USA, as defined by dates of peaks and troughs.

Trough	*Peak*	*Trough*	*Peak*	*Trough*	*Peak*	*Trough*	*Peak*	*Trough*
1970	1973	1975	1980	1982/1983	1990	1991	2000/2001	2001

Having thus obtained a picture of the US business cycle, it is possible to proceed to the first step of constructing a business cycle indicator; selecting the reference series. As mentioned before, the most used reference is GDP. As this is only available with a quarterly frequency, industrial production will be used for the analyses on a monthly basis. For both series, deviation cycles were computed using both the Christiano-Fitzgerald-filter (CF) and the Hodrick-Prescott (HP) variant. The major turning points of the cycles obtained for both series are compared in table 4.3.

Table 4.3; Business cycle chronologies (dates of peaks and troughs) for the USA based on GDP and industrial production deviation cycles compared with average reference chronology. Cycles computed using Christiano-Fitzgerald filter and HP-method.

	reference	*GDP HP-method*	*GDP CF-filter*	*IP HP-method*	*IP CF-filter*
Trough	1970	*1971 III*	**1971 I**	**1971-1**	**1971-2**
Peak	1973	**1973 II**	**1973 III**	**1973-10**	**1973-10**
Trough	1975	**1975 II**	**1975 II**	**1975-5**	**1975-9**
Peak	1980	*1978 IV*	*1979 I*	*1979-2*	*1979-3*
Trough	1982/1983	**1982 IV**	**1982 IV**	**1982-12**	**1982-12**
Peak	1990	**1989 I**	**1989 IV**	1988-11	1988-6
Trough	1991	1995 IV	**1991 III**	1993-9	**1991-8**
Peak	2000/2001	**2000 I**	**2000 I**	**2000-5**	**2000-4**
Trough	2001	*2003 I*	*2003 I*	*2003-6*	*2003-6*

Bold; good correspondence between GDP/IP date and reference, italicized; good correspondence between different GDP&IP turning points, less with reference turning points.

There is reasonably good correspondence between the turning point dates found by the different filters and between the GDP- and IP-cycle turning points. With the exception of 1980 and 2001, there is good correspondence with the external reference turning points as well. The difference in 1980 and 2001 is probably due to the difference between classical and deviation cycles.

The selection process of the business cycle indicators for the United States differed from that used for the Netherlands. In stead of rigorously testing all economic indicators deemed suitable, only those used for business cycle analysis by the conference board, OECD, ECRI, and NBER were considered. The sheer number of economic indicators available for the USA made this a sensible approach. For each candidate indicator, cycles were computed using both the HP-method and CF-filter. These individual cycles were compared to the reference cycles (IP and GDP), and classified as leading/coincident/lagging. From those indicators which most clearly reflected business cycle developments, several sets were formed and their aggregate performance tested. It turned out that the exact composition of the indicator set did not matter very much for the resulting aggregate cycle. This is strong support for the thesis that the business cycle can be defined and found as the common component of the development of core macro-economic indicators. According to this view, the common component should be relatively insensitive to the exact composition of a broad enough set of indicators. The final indicator selection is shown in the table below.

Table 4.4; Cross sectional indicator set for the US, with lead and lags relative to reference series (IP cycle computed both with Hodrick-Prescott variant and Christiano-Fitzgerald filter).

Indicator	*Correlation with IP-cycle* *CF-cycles*	*Lead(-) /lag(+) (months)*	*classification*	*Correlation with IP-cycle* *HP-cycles*	*Lead(-) /lag(+) (months)*	*classification*
Total retail trade	0,75	-1	leading	0,83	-3	leading
Weekly Hours (Manuf.)	0,68	-5	leading	0,68	-5	leading
new orders (durables)	0,89	0	coincident	0,9	-1	leading
Exports	0,63	+6	lagging	0,39	+11	lagging
Personal income	0,68	+6	lagging	0,44	+11	lagging
NYSE Composite	0,57	0	coincident	0,58	-5	leading
PPI Finished goods	0,51	+17	lagging	-0.62	-12	leading
Capacity utilisation (industry)	0,82	-2	leading	0,81	-2	leading
Civilian employment	0,84	+3	lagging	0,84	+3	lagging
Bank credit (loans)	0,68	+7	lagging	0,63	+9	lagging

As intended, this set is a mix of leading, coincident, and lagging indicators, and of different types of economic indicators. Unfortunately, in a few cases the leading or lagging character of the indicator depends on the method used to extract the cycle, a phenomenon well known from literature [Canova (1998,1999)]. However, on average the difference in lead/lag is only couple of months. But for an indicator with only a small lead or lag, this difference can result in a change in classification. This is a phenomenon which will recur in other results. Though the different methods for extracting and analysing the cycle tend to show good overall agreement, important differences can occur concerning specific details, such as certain correlation patterns or the dating of turning points.

The selected set contains financial indicators, business survey indicators, labour market indicators and indicators of the real economy. As mentioned before this has two important consequences; no single aspect of the economy, or developments limited to one specific sector can dominate the development of the set, and in disaggregate form the indicator set yields rich and diverse information on developments in the economy. Now we arrive at the central theme of this study; the derivation of the stance of the business cycle from this indicator set. This serves two complementary goals; firstly to prove that this cross sectional approach, using a mix of very different leading, coincident and lagging indicators, can be used to track the current stance of the business cycle. But the aim is also to supply further proof for interpreting the business cycle as the common cyclical component in the economy. The common cycle of the macro-economic indicators, which in our interpretation represents the stance of the business cycle, will be extracted using several different direct and indirect methods, as described in the methodology section. Indirect means that first the cycles of the individual indicators will be computed, and subsequently the stance of the overall cycle will be deduced from this collection of individual cycles. In the case of direct methods, the common component is extracted in a single step from the whole set of indicators. The outcomes of these very different methods of arriving at the common aggregate cycle will be compared, and the hypothesis is that they will be very similar.

4.2 Results USA common cycle computation using indirect methods

First, the results of computing the common cycle using indirect methods will be reported. The basis of these methods is the extraction of the individual cycles for the separate indicators. The cycles were extracted using the Christiano-Fitzgerald (CF) filter and a variant on the Hodrick-Prescott (HP) method, as described in the methodology section. After the individual cycles were extracted, three different methods were used to find the overall stance of the business cycle. These are all based on the idea that all the indicators next to idiosyncratic components also contain the business cycle . This means that the strongest common component of the individual cycles is the business cycle, while the individual idiosyncratic components will average out.

There is of course the problem that indicators will lead or lag the general business cycle. But one can use the same principle as used for dealing with the idiosyncratic nature of the individual cycles; by combining a approximately balanced set of leading, coincident and lagging indicators. The expectation is then that on average such a set will be coincident with the business cycle. The standard approach to constructing a coincident indicator of the business cycle is to limit the set to indicators which are deemed to be coincident with this cycle. We will show that this is not necessary, but that a more or less balanced, broad set of macro-economic indicators will also yield a coincident indicator of the business cycle. A broad set of indicators yields more information and reduces the risk of misleading results. To test this concept, additional aggregate business cycle indicators were constructed for which the component indicators were shifted in time according to their measured lag or lead of the business cycle (as approximated by the cycle of the manufacturing industry). This exercise was performed both for the CF-filter cycles and the HP-filter cycles, and for the direct Stock and Watson (SW) and Unobserved Components (UC) common cycles. If the assumption above is correct, there should be little difference between the resulting business cycles of the non-shifted and shifted indicator sets. Note that it is of course impossible to construct a time-shifted aggregate indicator in real time as the relevant realisations of lagging indicators will not yet be available.

A obvious basic approach for filtering out the business cycle is to simply take the average of the individual cycles. The idiosyncratic components of the series should average out, leaving only the common component; the business cycle. A somewhat more advanced approach is to use a form of factor analysis. We used principal components analysis, which extracts from the series orthogonal common components by maximizing the fraction of the series' variance explained by these components. This method is thus specifically constructed to find what the individual cycles have in common. The first principal component is the strongest, which means that it represents most of the common variance of the series. When applied to the cycles extracted from our indicators, it should yield the business cycle as the first principal component, as this should be the strongest common component. The results of the factor analysis of the CF-cycles can be found in table 4.5, those of the HP-cycles in table 4.6.

Table 4.5; Results principal components analysis cross sectional indicator set for the US, individual cycles computed using Christiano-Fitzgerald filter. Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles.

Principal component extraction CF-cycles	Extraction	Loading (variance explained 1st component 57,2%)	Lead/lag (months, + = shifted back in time, - = shifted forward	Extraction	Loading (variance explained 1st component 64,7%)
Manufacturing Production	0,921	0,911	-	0,916	0,945
Total retail trade	0,769	0,815	+1	0,742	0,826
Weekly Hours (Manuf.)	0,74	0,385	+5	0,804	0,625
new orders (durables)	0,914	0,942	-	0,943	0,971
Exports	0,894	0,808	-6	0,843	0,819
Personal income	0,894	0,801	-6	0,914	0,8
NYSE Composite	0,661	0,716	-	0,676	0,591
PPI Finished goods	0,867	0,302	-17	0,442	0,624
Capacity utilisation (industry)	0,934	0,69	+2	0,907	0,758
Civilian employment	0,829	0,857	-3	0,929	0,897
Bank credit (loans)	0,878	0,812	-7	0,87	0,885

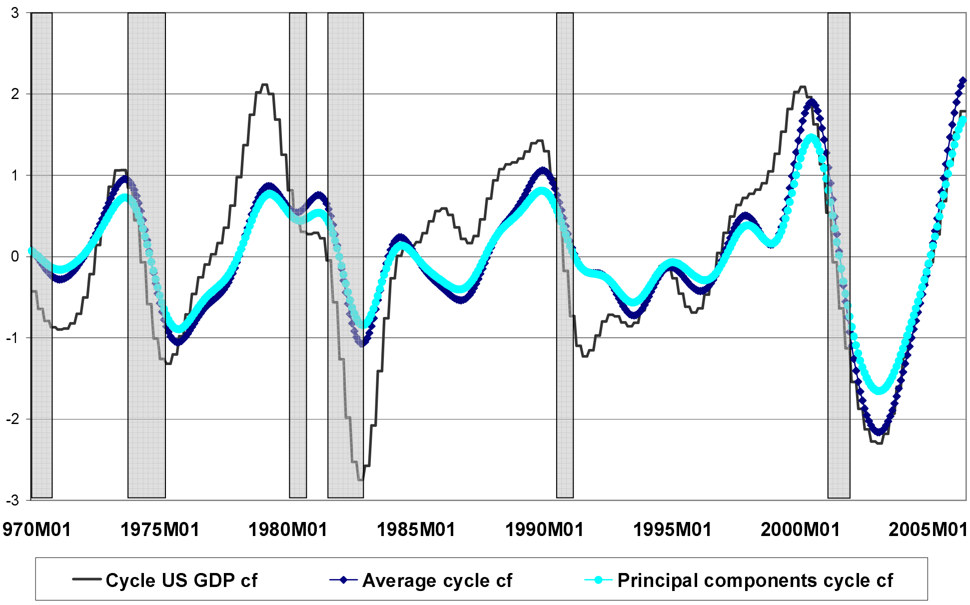
The first two columns give respectively the extraction of the different indicators and the loading on the first principal component. The extraction is a measure of how well the variance of a specific indicator is captured by the computed principal components. The measure of extraction is generally quite high, 0.8-0.9, both for the HP- and CF-cycles. This indicates that a large fraction of the variation of the individual cycles is due to common components. The factorloadings in the third and fifth columns indicate how strong the cycle of an indicator is connected to the first principal component. These tend to be quite high for most indicators, especially for the CF-cycles, which is not surprising as the Christiano-Fitzgerald filter is of superior construction. Also, the first principal component explains about half of the total cyclical variance. These results indicate that the first principal component can be considered to represent the business cycle, as it has a strong connection to all indicators and is responsible for the larger part of the cyclical variability.

Table 4.6; Results principal components analysis cross sectional indicator set for the US, individual cycles computed using Hodrick-Prescott variant. Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles.

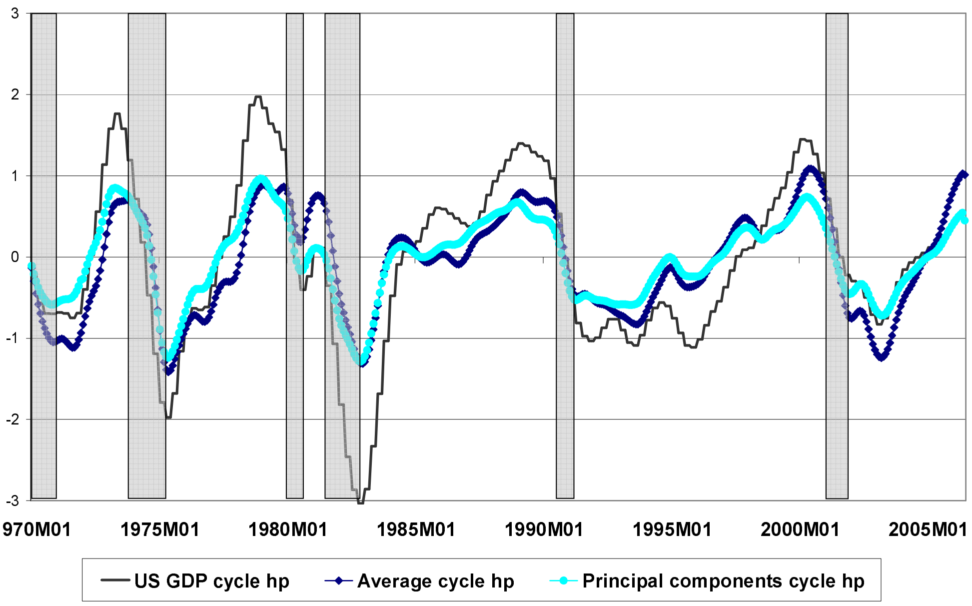
Principal component extraction HP-cycles	Extraction	Loading (variance explained 1st component 49,1%)	Lead/lag (months, + = shifted back in time, - = shifted forward	Extraction	Loading (variance explained 1st component 50,4%)
Manufacturing Production	0,932	0,964	-	0,905	0,873
Total retail trade	0,879	0,855	+3	0,882	0,874
Weekly Hours (Manuf.)	0,676	0,706	+5	0,662	0,596
new orders (durables)	0,917	0,904	+1	0,898	0,839
Exports	0,859	0,108	-11	0,69	-0,605
Personal income	0,8	0,304	-11	0,76	-0,482
NYSE Composite	0,731	0,519	+5	0,674	0,381
PPI Finished goods	0,856	-0,459	+12	0,769	-0,182
Capacity utilisation (industry)	0,933	0,899	+2	0,947	0,92
Civilian employment	0,856	0,892	-3	0,891	0,872
Bank credit (loans)	0,546	0,488	-9	0,697	0,758

In graphs 4.1 and 4.2, the resulting aggregate cycles from respectively the CF-filter and the HP-method are shown. On the whole, these do a good job in representing the business cycle. All major turning points are identified, the cyclical peaks occurring, as they should, although sometime before the onset of recession as identified by the NBER (shaded areas). Also, correlation with the relevant GDP-cycle tends to be high (0.8-0.9) and coincident, see table 4.12. There is little difference between the aggregate cycles as computed by taking a simple unweighted average and via principal components analysis. Table 4.10 shows that the correlations between the aggregate HP- and CF-cycles is high as well, around 0.8, and broadly coincident. So these two methods of finding the aggregate business cycle yield a comparable business cycle chronology. This is conformed by the dating of the major turning points, which for both methods tend to be within a few months of each other (table 4.7). There are of course a few disparities. In two cases, the dating of a major turning point differs more than six months between HP and CF, and both methods identify a trough in 2003, whilst according to the NBER dating that recession ended in 2001. Both the HP-method and the CF-filters yield minor cycles which are not present in the general business cycle chronology. But as stated, these are minor cycles.

Graph 4.1; Common cycle representing US business cycle based on cross-sectional data set. Individual deviation cycles computed using Christiano-Fitzgerald filter (CF), composite cycle computed using both simple average and principal component analysis. Compared with reference cycle based on US GDP. Shaded areas represent NBER recession periods.

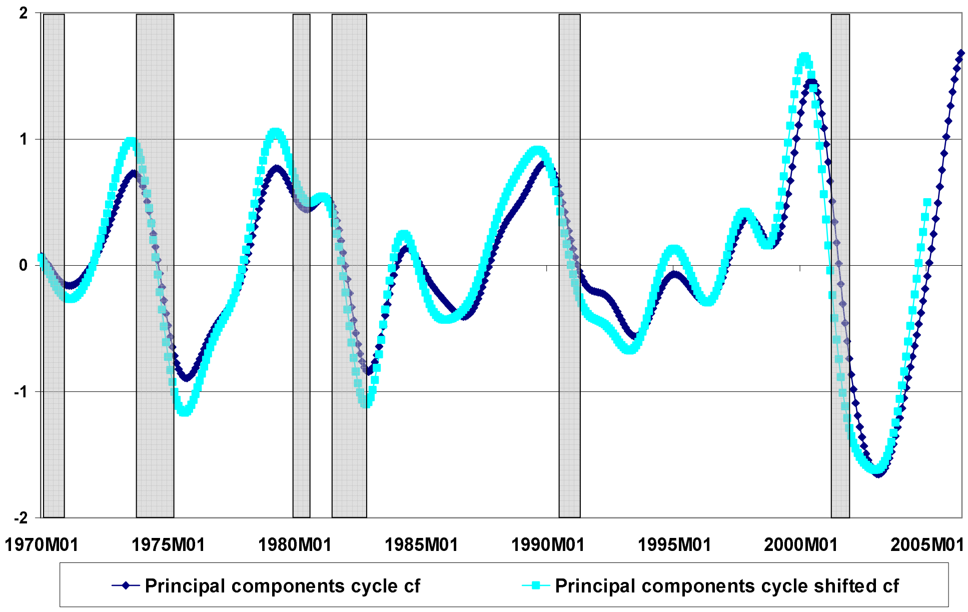


Graph 4.2; Common cycle representing US business cycle based on cross-sectional data set. Individual deviation cycles computed using Hodrick-Prescott variant (HP), composite cycle computed using both simple average and principal component analysis. Compared with reference cycle based on US GDP. Shaded areas represent NBER recession periods.



Analysing the results of the computations based on the time-shifted component indicators is somewhat complex. For the HP-cycles, the results are slightly confusing. All factor loadings change, but most actually decrease. On the other hand, the percentage of variance explained by the first principal component does increase marginally. For the CF-cycles the result is much more clear, most loadings increase somewhat, as does the percentage of variation explained by the first principal component. This means that this set has a stronger common cycle, indicating that it better represents the business cycle. The aggregate results reported later will confirm this, but also show that the improvement is relatively small.

Graph 4.3; Common cycle representing US business cycle based on cross-sectional data set. Individual deviation cycles computed using Christiano-Fitzgerald filter (CF), composite cycle computed using principal component analysis. Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles. Shaded areas represent NBER recession periods.



Correlations and leads and lags with the reference series differ little between the original and time-shifted aggregates. The dating of the major turning points does not differ much between the original and time-shifted indicator sets, see table 4.7. The time-shifted aggregate indicator of the HP-cycles actually performs worse that the original one, perhaps indicating that the time-shifts employed were not the correct ones. Overall, the conclusion here is that shifting the component indicators in time to make them all coincident with the business cycle does not result in a more plausible or even much different aggregate business cycle indicator. This is important as it shows is that when using a broad, diverse set of relevant component indicators, it is possible to directly obtain a reliable coincident representation of the business cycle. It is not necessary to select only coincident indicators or to correct for leads and lags.

Table 4.7; Business cycle chronologies (dates of peaks and troughs) for the USA according to composite indicators computed by principal component analysis of individual cycles computed using Christiano-Fitzgerald filter and HP-method. Time shifted means that individual indicators were shifted in time to compensate for their respective leads and lags compared to the reference business cycles.

	reference	*HP-method Principal component*	*HP-method Principal component Time-shifted*	*CF-filter Principal component*	*CF-filter Principal component Time-shifted*
Trough	**1970**	**1970-10**	**1970-9**	1971-2	1971-3
Peak	**1973**	**1973-4**	**1973-2**	**1973-9**	**1973-8**
Trough	**1975**	**1975-5**	**1975-3**	**1975-11**	**1975-9**
Peak	1980	*1978-12*	*1978-10*	*1979-4*	*1979-4*
Trough	**1982/83**	**1982-11**	**1982-8**	**1982-12**	**1983-11**
Peak	1990	1988-12	1988-9	1989-12	1989-8
Trough	1991	*1993-6*	*1992-8*	*1993-7*	*1993-4*
Peak	**2000/01**	**2000-5**	**2000-1**	**2000-7**	**2000-3**
Trough	2001	*2003-3*	*2002-12*	*2003-2*	*2002-12*

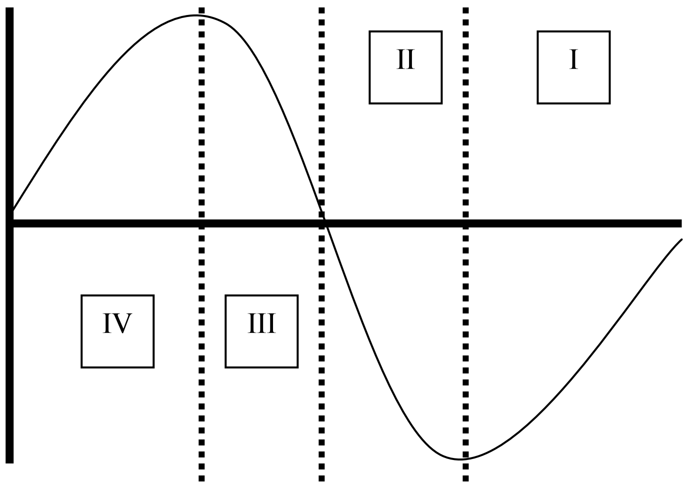
Bold; good correspondence between GDP/IP date and reference, italicized; good correspondence between different GDP&IP turning points, less with reference turning points.

The third and final indirect approach of business cycle analysis tested here is a type of diffusion index. Generally speaking, a diffusion index counts how many of the component indicators exhibit a certain behaviour, for example is increasing or decreasing. Here, it is applied to our classification of the business cycle in four distinct phases:

- Below trend and decreasing
- Below trend and increasing
- Above trend and increasing
- Above trend and decreasing

This is a logical and clear way to give a general characterization of economic developments. Its simple nature also means that this classification is quite robust, misclassifications are rare. Obviously, this is a long way from the output-gap interpretation of the business cycle. As stated before, the aim here is to track and analyse the current stance of the business cycle, which means that the absolute level of the cycle is less important than the general phase of the cycle.

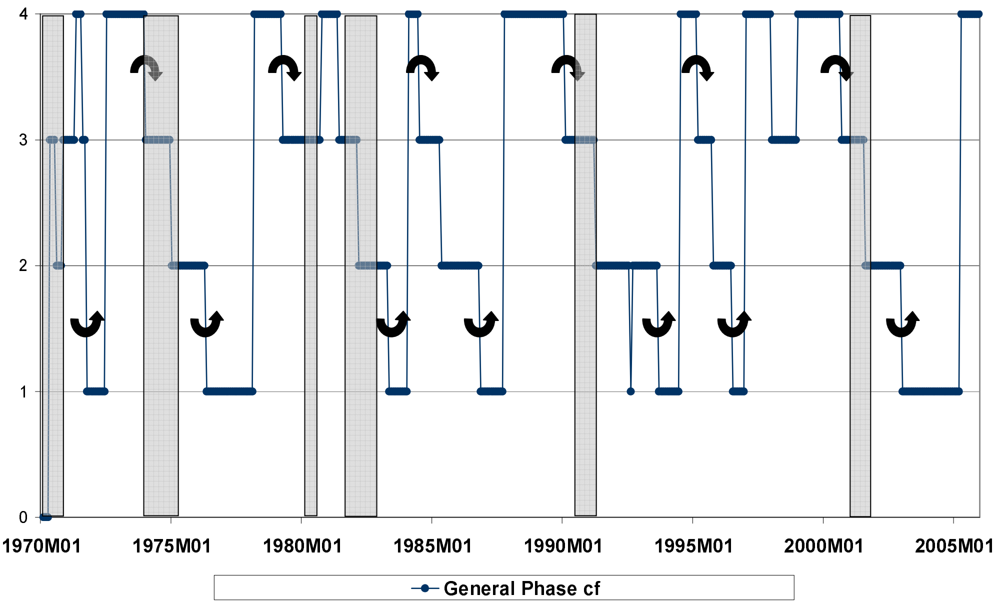
Figure 4.1; Different phases of the business cycle according to Statistics Netherlands business cycle tracer method.



This classification of the overall cycle can also be applied to the cycles of the individual indicators. By counting how many indicators are in each phase, a diffusion-type indicator can be constructed. The overall business cycle is deemed to be in the phase in which the majority of the indicators can be found.

The somewhat complicated diagram below (4.4) gives the results of this approach of business cycle analysis. It depicts the phase chronology of the business cycle for the CF-filtered indicator set. At each point in time, the **symbol** indicates in which of the four phases the business cycle is according to the majority of the indicators. A change from 4 (above trend and increasing) to 3 (above trend and decreasing) constitutes a cyclical peak, while a cyclical trough is identified by a change from phase 2 (below trend and decreasing) to 1 (below trend and increasing).

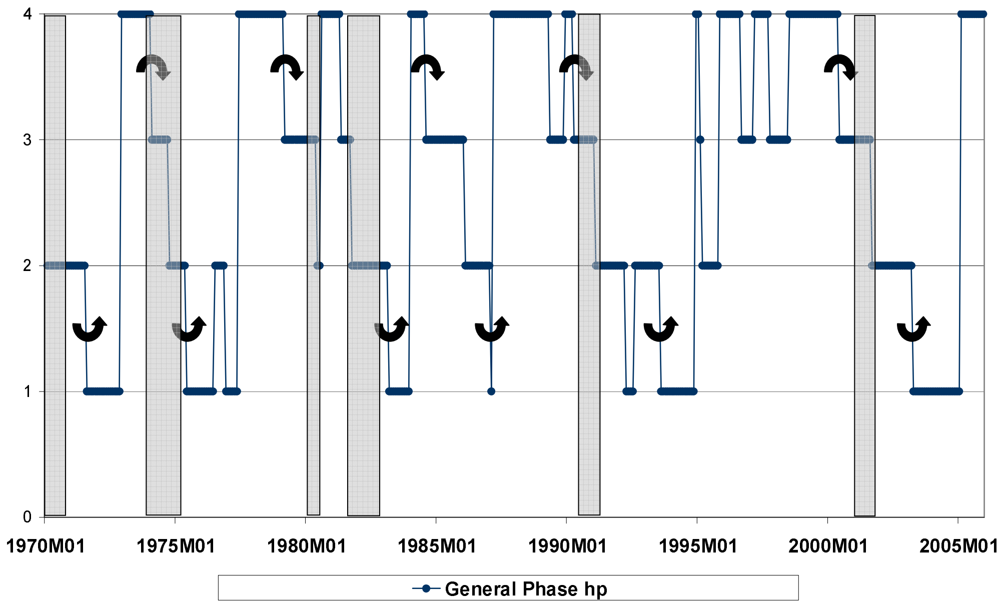
Graph 4.4; US business cycle chronology according to diffusion method, based on cross-sectional data set. Individual deviation cycles computed using Christiano-Fitzgerald filter (CF). Levels represent different business cycle phases 1=below trend and increasing, 2=below trend and decreasing, 3= above trend and decreasing, 4= above trend and increasing. Phase of majority of individual indicators determines aggregate phase. Shaded areas represent NBER recession periods.



curved arrows indicate turning points.

The results are comparable with those of the aggregate business cycle indicators; all major turning points/recessions are identified, with some qualifications. As expected, cyclical peaks occur sometime before the onset of recession, cyclical troughs sometime after the classical recession has ended. Conspicuous is that the recession phases (2) seems to last relatively long in this analysis. Also, several additional, mostly minor, cycles are identified, and sometimes the indicators flicker between phases. This is unfortunate, because for the Netherlands, this analysis method yielded more stable outcomes than traditional aggregate indicators, identifying almost exclusively the major cycles. This could be an indication that the selected indicator set is not optimal for the US. The results for the HP-method indicator set were largely similar, though somewhat more volatile, see graph 4.5.

Graph 4.5; US business cycle chronology according to diffusion method, based on cross-sectional data set. Individual deviation cycles computed using Hodrick-Prescott variatnt (HP). Levels represent different business cycle phases 1=below trend and increasing, 2=below trend and decreasing, 3= above trend and decreasing, 4= above trend and increasing. Phase of majority of individual indicators determines aggregate phase. Shaded areas represent NBER recession periods.



curved arrows indicate turning points.

A further positive result is that the dating of the major turning points in the cycle does not differ much here between the CF- and HP-sets, and from the dating by the standard aggregate indicators, see table 4.8. This is another confirmation that different methods of identifying the business cycle from a cross-sectional indicator set yield consistent and credible results. The similarities in business cycle chronology resulting from the different indirect methods of finding the aggregate business cycle tested here, lend credibility to the thesis that it is actually the business cycle which results from the indicator set.

Table 4.8; Business cycle chronologies (dates of peaks and troughs) for the USA according to diffusion index method. Individual cycles computed using Christiano-Fitzgerald filter and HP-method.

	reference	*HP-method diffusion index*	*CF-filter diffusion index*
Trough	1970	*1971-M8*	*1971-M5*
Peak	1973	*1974- M2*	*1974-M1*
Trough	1975	*1975-M6*	*1976-M5*
Peak	1980	*1979-M3*	*1979-M4*
Trough	1982/83	*1983-M3*	*1983-M5*
Peak	1990	1989-M5	1990-M2
Trough	1991	*1993-M8*	*1993-M9*
Peak	2000/01	*2000-M6*	*2000-M9*
Trough	2001	*2003-M4*	*2003-M1*

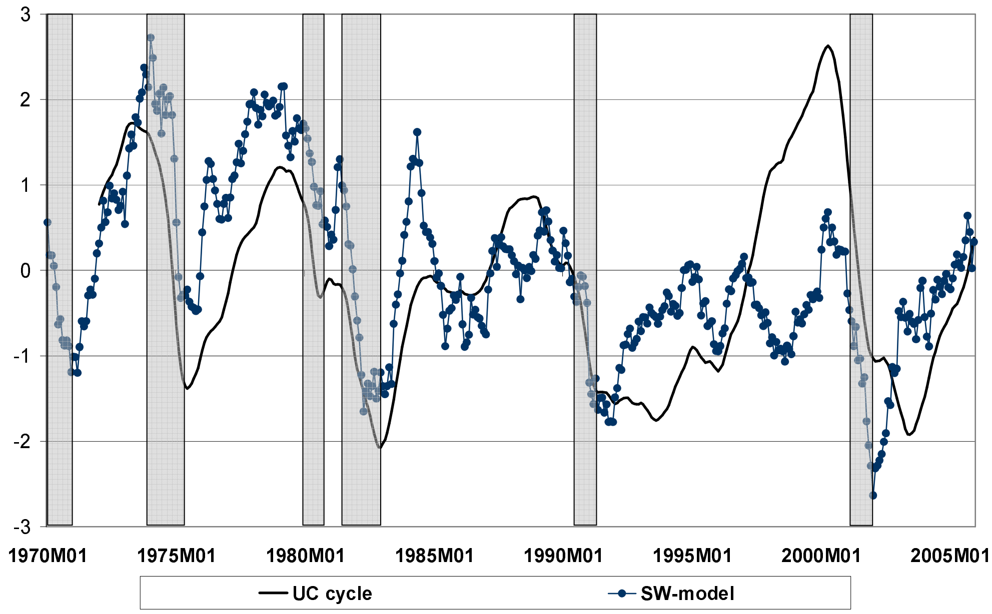
Bold; good correspondence between GDP/IP date and reference, italicized; good correspondence between different GDP&IP turning points, less with reference turning points.

4.3 Results USA common cycle computation using direct methods

Now we turn to the outcomes of what we have termed direct methods of business cycle extractions. For the Stock-Watson method (SW) and Unobserved Components approach (UC) used here do not first extract individual cycles, but immediately yield the common cyclical component, the business cycle. Graph 4.6 shows the outcomes together with the recession periods as identified by the NBER.

The direct methods of extracting the business cycle from the indicator sets, the SW-method and UC-method have been discussed in the methodological section. Here, it suffices to say that these methods do not require the cycles of the individual indicators to be computed separately. It is important to note that the cycle of the SW-method is computed from the growth rates of the indicators, resulting in a growth rate cycle. This is a somewhat different concept of the business cycle than deviation/growth-cycles, but the most relevant consequence here is that *growth rate* cycles will **lead** *growth* cycles. They should identify the same peaks and troughs, only somewhat earlier.

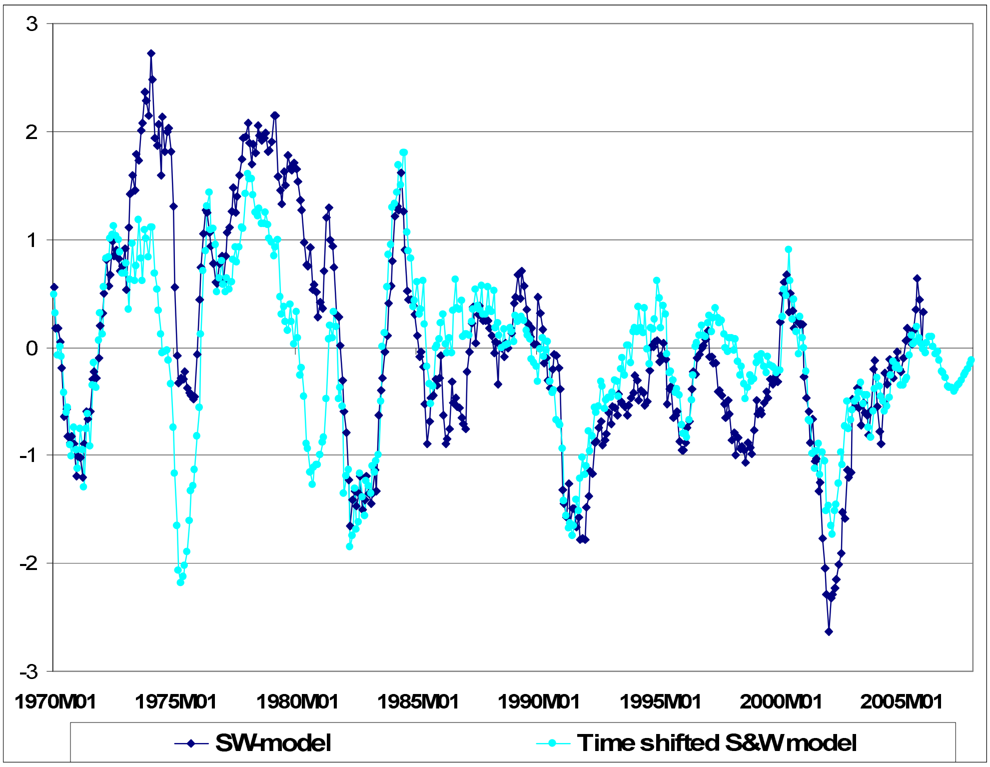
Graph 4.6; Common cycles representing US business cycle based on cross-sectional data set, computed via direct methods; Stock and Watson method (SW) and Unobserved components model (UC). Shaded areas represent NBER recession periods.



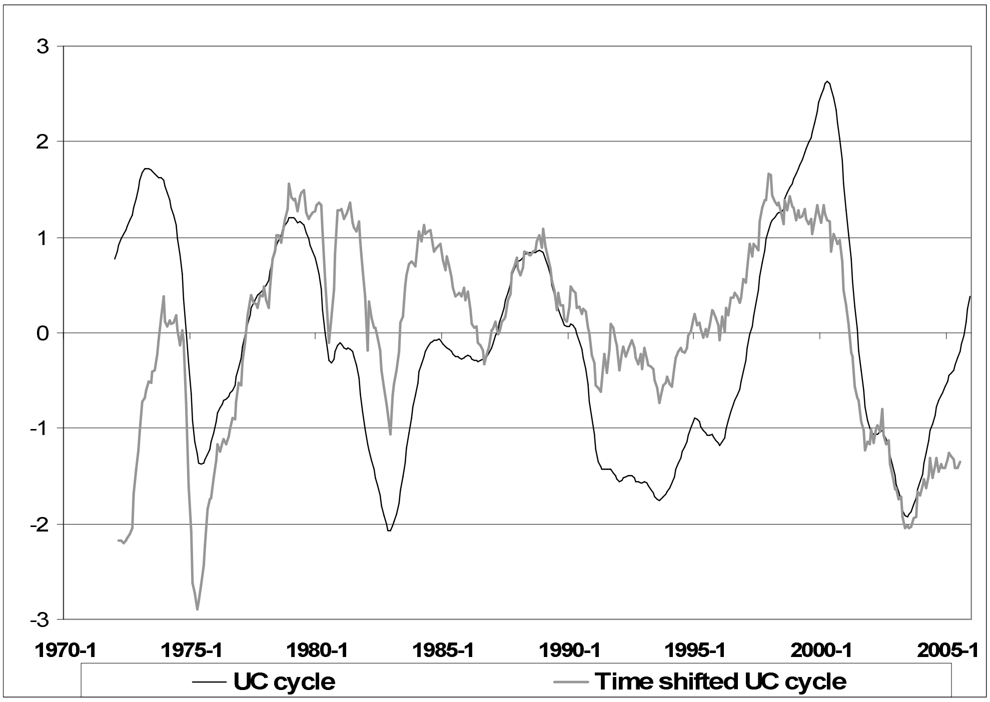
The results from the SW-method as found here are somewhat volatile. No efforts were made to produce more smooth results, as the aim here is to test whether different methods yield a roughly equivalent business cycle. For this, it is enough to be able to compute correlations and identify the major turning points. Also, the SW-method is based on extracting the common component from the growth rates, which are inherently more volatile than levels. Cycles based on growth rates will also lead the deviation cycles which result from the other methods discussed in this paper. But by keeping these considerations in mind, the SW-method is a very usefull benchmark with which to compare the other results, because just as the UC method, it formally estimates the hypothesised common cycle . The UC-method yields a very clear cycle, which exhibits strong correspondence with the SW-cycle. The UC model is the only method yielding a direct estimate of the duration of the business cycle. For the period considered and based on this data set, the average duration of the US business cycle was estimated at 8.3 years. Significantly, both methods are able to identify the NBER-recession periods clearly and timely, with the UC-cycle even lacking real minor cycles. The significance of these results lies again in the fact that they show that when an common cyclical component is extracted from this mixed set of leading, lagging and coincident indicators, it clearly represents the business cycle. This supports both the approach of using a cross-sectional indicator set for business cycle analysis and thinking of the business cycle as the common cyclical factor of the development of major economic indicators.

As a further test of the validity the outcomes and thus of using a cross sectional approach to extract the current stance of the business cycle, an analysis was performed using time shifted versions of the indicators. Thus their respective leads and lags were compensated for, as it is possible that these distort the estimation of the common component. For the cross sectional approach to be valid, there should be not too much effect on the resulting UC and S&W aggregate cycles. In graphs 4.7 and 4.8, it can be seen that although the effect is larger than in for the indirect methods, the resulting business cycles are broadly similar.

Graph 4.7; Common cycle representing US business cycle based on cross-sectional data set. Common cycle computed using Stock and Watson model (SW). Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles.



Graph 4.8; Common cycle representing US business cycle based on cross-sectional data set. Common cycle computed using Unobserved components model (UC). Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles.



This is confirmed by analyzing the correlations between the original and time shifted aggregate cycles. For the S&W-method cycles the maximum correlation is 0.732 at zero lag or lead, for the UC-cycles this is 0.527 at lag 0 as well. Thus, on average the original and time shifted aggregate cycles move in step. Correlation in the UC is relatively low because the time shifted common cycle is somewhat noisy. The similarities in outcomes are confirmed when comparing the dating of cyclical peaks and troughs, these are usually within a few months of each other for the original cycles and the time-shifted outcomes, see table 4.9.

Table 4.9; Business cycle chronologies (dates of peaks and troughs) for the USA according to common cycles computed using S&W-method and UC-model. Time shifted means that individual indicators were shifted in time to compensate for their respective leads and lags compared to the reference business cycles.

	reference	*UC-model*	*UC-model Time-shifted*	*S&W-method*	*S$W-method Time-shifted*
Trough	**1970**	na	na	*1971-3*	*1971-4*
Peak	**1973**	**1973-5**	**1973-12**	**1974 -1**	**1973 -7**
Trough	**1975**	**1975-7**	**1975-4**	**1975-10**	**1975-4**
Peak	1980	*1979-1*	*1978-12*	1979-3	1978-1
Trough	**1982/83**	**1983-1**	**1982-12**	**1982-4**	**1982-4**
Peak	1990	*1988-11*	*1989-1*	*1989-5*	*1989-2*
Trough	1991	*1993-8*	*1993-8*	1991-12	1991-6
Peak	**2000/01**	**2000-4**	1998-1	**2000-4**	**2000-5**
Trough	2001	*2003-6*	*2003-8*	*2002-1*	*2002-3*

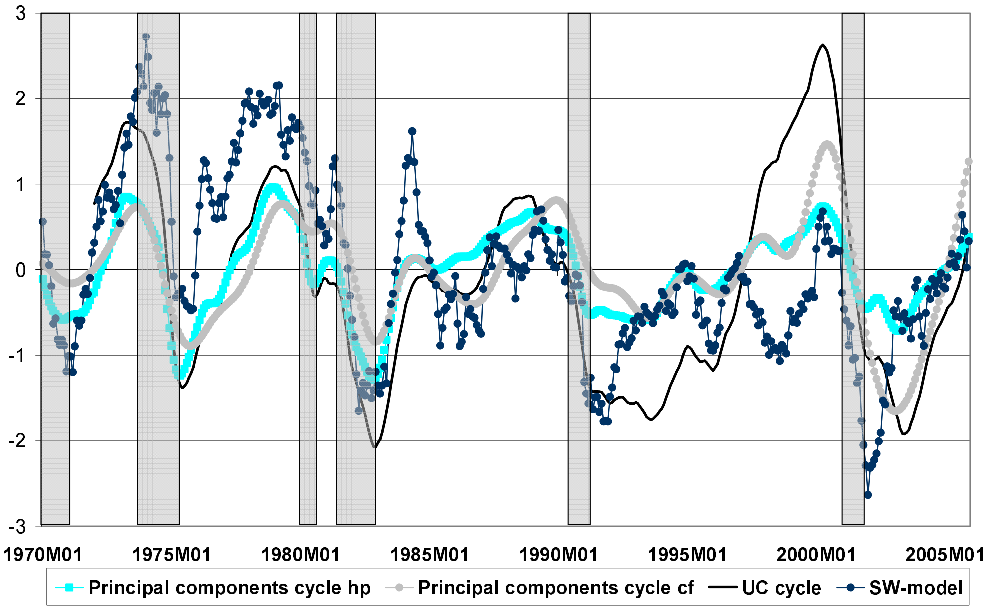
Bold; good correspondence between turning point date and reference, italicized; good correspondence between original and time shifted turning point date, less with reference turning points.

This means that direct estimation of the common cycle from a mixed, cross-sectional indicator set is a valid approach, it is not necessary to correct for leads and lags in the component series.

4.4 Overall comparison results common cycle computation for the USA

The final step is to compare the results of all methods used and see in how far the common cycles overlap. In graph 4.9 the computed aggregate cycles of the most relevant direct and indirect methods are shown, yielding a somewhat confusing picture. But it does show that though the match is far from 100%, the cycles broadly agree on the major busines cycle movements.

Graph 4.9; Common cycles representing US business cycle based on cross-sectional data set, computed via both direct and indirect methods; Stock and Watson method (SW), Unobserved components model (UC), Hodrick-Prescott variant (HP) followed by principal component analysis, Christiano-Fitzgerald filter (CF) followed by principal component analysis. Shaded areas represent NBER recession periods.



The correlations between the different cycles, in table 4.10, support this conclusion. Correlations are mostly high, around 0.8 and show the cycles being roughly coincident. Only the correlations with the SW-cycle are lower, but this is as expected given its more volatile nature. The dating of the major turning points confirms the correspondence between the different aggregate cycles, see table 4.11. In general, these lie within a few months of each other (note again that the S&W indicator will by construction lead the others). As observed before, in a few cases the turning point dates deviate from that of the reference chronology, especially so in 1991/1993. But these deviations are consistent across the different methods used here, and therefore probably mainly due to the broader indicator set used here.

Table 4.10; Correlations between common cycles for the US economy resulting from the different detrending methods.

	HP-method simple average	HP-method Principal component	CF-filter simple average	CF-filter Principal component	UC-model	SW-method
HP-method simple average						
HP-method Principal component	**0,926 (-1)**					
CF-filter simple average	**0,885 (0)**	**0,762 (+2)**				
CF-filter Principal component	**0,894 (0)**	**0,785 (+3)**	**0,998 (0)**			
UC-model	**0,81 (0)**	**0,869 (+1)**	**0,762 (-1)**	**0,774 (-1)**		
SW-method	**0,506 (-1)**	**0,576 (+1)**	**0,493 (-4)**	**0,499 (-4)**	**0,541 (0)**	

Leads and lags concern the indicator in the leftmost column

Table 4.11; Business cycle chronologies (dates of peaks and troughs) for the USA according to common cycles computed using Hodrick-Prescott variant, Christiano-Fitzgerald filter (both simple average and principal component), S&W-method, and UC-model.

	reference	*SW-method*	*UC-model*	*HP-method simple average*	*HP-method Principal component*	*CF-filter simple average*	*CF-filter Principal component*
Trough	1970	1971-3	na	1971-9	1970-10	1970-12	1971-2
Peak	**1973**	**1974 -1**	**1973-5**	**1973-5**	**1973-4**	**1973-9**	**1973-9**
Trough	**1975**	**1975-10**	**1975-7**	**1975-6**	**1975-5**	**1975-9**	**1975-11**
Peak	1980	*1979-3*	*1979-1*	*1979-11*	*1978-12*	*1979-5*	*1979-4*
Trough	**1982/83**	**1982-4**	**1983-1**	**1982-12**	**1982-11**	**1982-12**	**1982-12**
Peak	1990	*1989-5*	*1988-11*	*1990-1*	*1988-12*	*1990-2*	*1989-12*
Trough	1991	1991-12	1993-8	1993-9	1993-6	1993-9	1993-7
Peak	**2000/01**	**2000-4**	**2000-4**	**2000-7**	**2000-5**	**2000-6**	**2000-7**
Trough	2001	*2002-1*	*2003-6*	*2003-3*	*2003-3*	*2003-2*	*2003-2*

Bold; good correspondence between GDP/IP date and reference, italicized; good correspondence between different GDP&IP turning points, less with reference turning points.

A second approach to testing the in how far the aggregate cycles represent the business cycle is by evaluating the overall correspondence with the reference cycles, being either the IP- and GDP-cycles or the constructed NBER-composite On average, the computed cycles match the reference cycles quite well, see table 4.12.

Table 4.12; Correlations between common cycles for the US economy resulting from the different detrending methods and several reference series based on deviation cycles of industrial production, GDP and NBER coincident composite..

	IP-HP cycle	*GDP-HP cycle*	*IP-CF cycle*	*GDP-CF cycle*	*NBER-based reference cycle (HP)*	*NBER-based reference cycle (CF)*
HP-method simple average	0,906 (0)	0.847 (+1)			0.920 (0)	
HP-method Principal component	0,969 (-1)	0.941 (0)			0.975 (-1)	
CF-filter simple average			0,898 (+2)	0.843 (+2)		0.781 (+1)
CF-filter Principal component			0,91 (+2)	0.860 (+2)		0.804 (+1)
UC-model	0.912 (0)	0.824 (0)	0.819 (0)	0.846 (0)	0.873 (-1)	0.708 (-2)
SW-method	0.561 (0)	0.505 (0)	0.559 (-1)	0.542 (-1)	0.540 (-1)	0.576 (-2)

Leads and lags in months, + means that the indicator lags the reference, - means a lead.

Again with the exception of the SW-cycle, all aggregate cycles possess high correlations with the relevant reference cycles, around 0.8-0.9, with generally only minor leads or lags. This analysis compares the common cycles found here with several other common representations of the bussiness cycle, finding good correspondence between these and between the aggregate indicators themselves, both when considering average correlation and turning points. In appendix II, another method is used to assess the similarities of the different cycles. It is the degree of concordance of Harding and Pagan[2002], which measures in how far the cycles are in the same business cycle phase, and compares this to the expectation under independence. The outcomes show that the cycles are much more synchronised than they would be in the case of no relationship between the cycles.

These results offer a final support to the interpretation of the common cycle of the cross-sectional indicator sets as representing the business cycle. The fact that such different methods arrive at a very similar aggregate cycle makes it unlikely that these are purely an artefact of the detrending methods used. It also shows that the properties of the *aggregate* cycles are not that sensitive to the method used for computing the common cycle. This stands in contrast with the observed sensitivity of business cycle properties of *individual* indicators to the detrending method used. The general conclusion from these results for the USA is that it is possible to find the current state of the business cycle via a cross sectional approach, where a relatively small, mixed set of macro-economic indicators is used to track developments in the economy.

5. Results for the Netherlands

Here the results for the Netherlands of the same exercises as in the previous section will be reported. Because of this overlap, analysis will be much shorter. It will become clear that the results for the Netherlands support the cross-sectional approach to business cycle analysis even more. Possibly because the economic structure of the Netherlands differs somewhat from that of the USA, but also possibly because the indicator set for the Netherlands originates from a earlier, exhaustive business cycle indicator construction program.

5.1 A reference business cycle chronology for the Netherlands

As reference business cycle chronology the standard Statistics Netherlands chronology will be used, which is quite similar to the one of the Dutch Central Bank (DNB), see table 5.1 [Den Rijer (2006)].

Table 5.1; Business cycle chronologies for the Netherlands, as defined by dates of peaks and troughs.

	Statistics Netherlands	*Central bank (DNB)*
Peak	1979-Q3	1979-Q4
Trough	1983-Q3	1982-Q4
(Peak)	(1986-Q1)	1985-Q4
(Trough)	(1986-Q4)	1987-Q4
Peak	1990-Q3	1990-Q4
Trough	1993-Q4	1993-Q3
Peak	2000-Q2	2000-Q3
Trough	2003-Q3	2003-Q4

The Statistics Netherlands chronology It is mainly based on the GDP-cycle but as table 5.6 shows, there is much agreement on the dates of the major turning points in the Dutch business cycle, both between the IP- and GDP-cycles and between different cycle extraction methods.

Table 5.2; Business cycle chronologies (dates of peaks and troughs) for the Netherlands based on GDP and industrial production deviation cycles compared with average reference chronology. Cycles computed using Christiano-Fitzgerald filter and HP-method.

	reference	*GDP HP-method*	*GDP CF-filter*	*IP HP-method*	*IP CF-filter*
Peak	1979-Q3	**1979-Q3**	**1980-Q1**	**1979-M10**	**1979-M5**
Trough	1983-Q3	*1982-Q3*	*1982-Q4*	*1982-M11*	*1983-M1*
Peak	1990-Q3	**1990-Q3**	**1990-Q3**	**1990-M5**	**1990-M8**
Trough	1993-Q4	**1993-Q4**	**1993-Q3**	**1993-M7**	**1993-M2**
Peak	2000-Q2	**2000-Q2**	**2000-Q2**	**2000-M11**	**2000-M7**
Trough	2003-Q3	**2003-Q3**	**2003-Q2**	**2003-M7**	**2003-M10**

Bold; good correspondence between GDP/IP date and reference, italicized; good correspondence between different GDP&IP turning points, less with reference turning points.

5.2 Results for the Netherlands common cycle computation using indirect methods

The indicators used are those selected for the Statistics Netherlands business cycle tracer, as described in Van Ruth et al. (2005). The selected set and their relation to the Dutch business cycle can be found in table 5.3. Just as before, the classification of an individual indicator as either leading, coincident or lagging can depend on the type of filter used. But the differences in lead or lag are generally small here, a few months. Both the HP- and CF-set tend somewhat towards a leading character, but due to publication lags and lags induced by computational effects, slightly leading indicators will in practice be more or less coincident. In addition to the indicators presented in the table, industrial production is part of the indicator set as well.

Table 5.3; Cross sectional indicator set for the Netherlands, with lead and lags relative to reference series (IP cycle computed both with Hodrick-Prescott variant and Christiano-Fitzgerald filter).

Indicator	*Correlation with IP-cycle* *CF-cycles*	*Lead (-) /lag(+) (months)*	*classification*	*Correlation with IP-cycle* *HP-cycles*	*Lead(-) /lag(+) (months)*	*classification*
Consumer confidence	0.742	-3	leading	0.589	-5	leading
CS-durables	0.664	-5	leading	0.515	-5	leading
Producer confidence	0.627	-3	leading	0.627	-4	leading
BS-new orders	0.756	-8	leading	0.561	-7	leading
Consumption	0.523	-1	leading	0.661	+5	lagging
Exports	0.726	-4	leading	0.811	-1	leading
Bankruptcies	0.698	-3	leading	0.804	-1	leading
Unemployment	0.624	+8	lagging	0.675	+9	lagging
10-year bond yield	0.828	0	coincident	0.546	0	coincident
Job vacancies	0.686	-3	leading	0.819	0	coincident
Private fixed capital formation	0.512	0	coincident	0.686	-3	leading
Temporary employment	0.343	-12	leading	0.553	-12	leading
Total hours worked	0.616	+9	lagging	0.766	+10	lagging

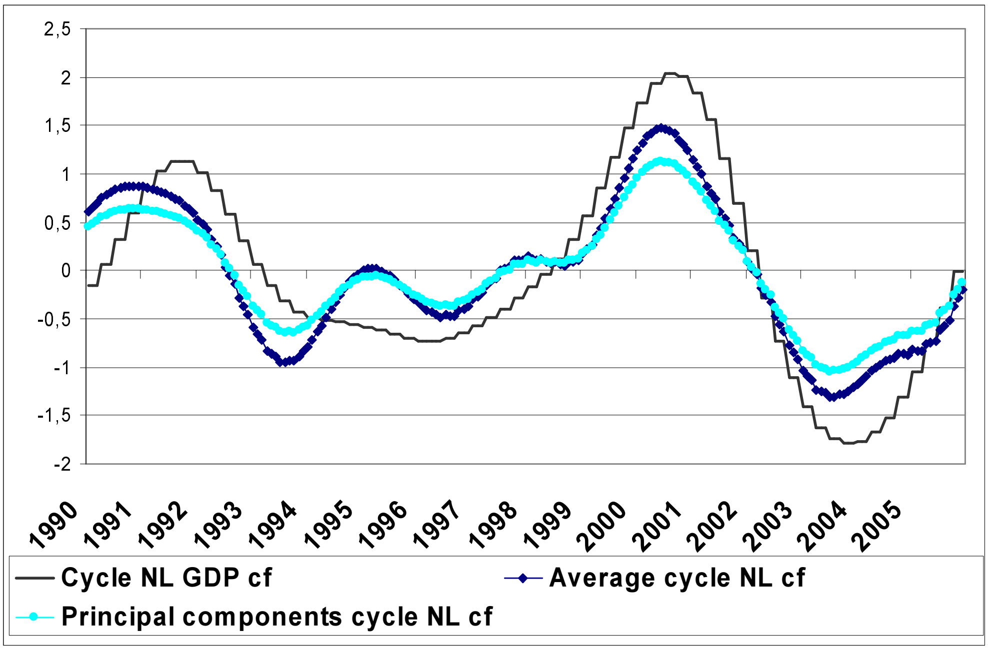
The discussion of the results of the indirect methods of extracting the business cycle from the indicator set will being with the results of the CF-filtered cycles. Principal component analysis (table 5.4) shows that the individual indicators generally have a strong relationship with the common cycle, as the factorloadings on the first principal component are generally high. Conversely this again indicates the presence of a clear common cycle, which can be interpreted as being the business cycle.

Table 5.4; Results principal components analysis cross sectional indicator set for the Netherlands, individual cycles computed using Christiano-Fitzgerald filter. Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles.

Principal component extraction CF-cycles	*Extraction*	*Loading (variance explained 1st component 56.6%)*	*Lead/lag (months, + = shifted back in time, - = shifted forward*	*Extraction*	*Loading (variance explained 1st component 66.2%)*
Consumer confidence	0.854	0.833	-3	0.806	0.830
CS-durables	0.808	0.896	-5	0.769	0.877
Producer confidence	0.901	0.618	-3	0.805	0.576
BS-new orders	0.762	0.386	-8	0.763	0.530
Consumption	0.906	0.818	-1	0.898	0.823
Exports	0.768	0.864	-4	0.779	0.863
Bankruptcies	0.894	0.933	-3	0.888	0.940
Unemployment	0.974	0.667	+8	0.929	0.927
Industrial production	0.920	0.775	-	0.888	0.788
10-year bond yield	0.870	0.470	-	0.684	0.457
Job vacancies	0.979	0.966	-3	0.974	0.972
Private fixed capital formation	0.955	0.861	-	0.966	0.895
Temporary employment	0.793	0.547	-12	0.864	0.793
Total hours worked	0.949	0.605	+9	0.934	0.912

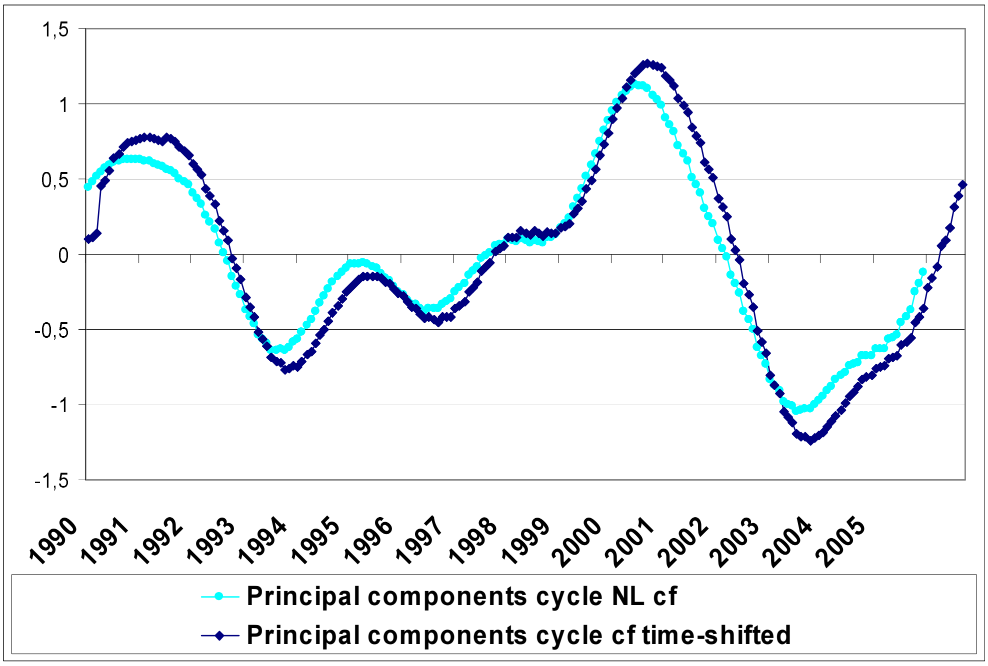
On the whole there is not much difference in outcomes between determining the common cycle by principal component extraction or by simply taking the average of the 14 series, see graph 5.1. The correlations of these two types of common cycle with the GDP- and IP-cycles are high in both cases, with both being virtually coincident.

Graph 5.1; Common cycle representing Dutch business cycle based on cross-sectional data set. Individual deviation cycles computed using Christiano-Fitzgerald filter (CF), composite cycle computed using both simple average and principal component analysis. Compared with reference cycle based on Dutch GDP.



When the individual indicators are shifted in time to reflect their lags/leads with the IP-cycle, as proxy for the business cycle, the common cycle becomes even stronger. The variance explained by the first principal component rises from 56.6% to 66.2%, and also important, previously relatively low factor loadings increase. This indicates that in this case the pure cross-sectional approach, using the contemporaneous realisations of the indicators, results in a somewhat suboptimal business cycle extraction.

Graph 5.2; Common cycle representing Dutch business cycle based on cross-sectional data set. Individual deviation cycles computed using Christiano-Fitzgerald filter (CF), composite cycle computed using principal component analysis. Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycle.



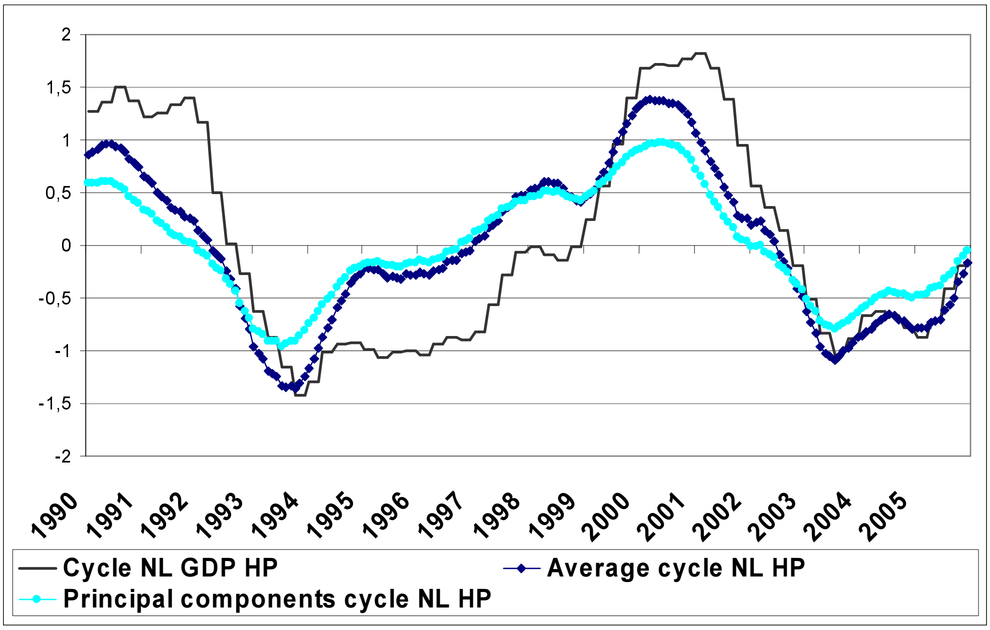
Correlations with the GDP- and IP-cycles are somewhat higher (table 5.12) and the already small lead is reduced by a month or so. But overall the differences are slight, as also can be seen in graph 5.2. The general shape of the two cycles is the same, though there seems to be a small shift present. A comparison of the dates of the major turning points, see table 5.6, shows that this amounts to about two months. Therefore, shifting the component indicators in time to cancel their leads and lags results in only a minor change in the aggregate cycle. This confirms that it is possible to extract a coincident indicator from an uncorrected, mixed set of indicators.

The same conclusions go for the cycles extracted by the HP-method. Communality is strong, and increases somewhat when the indicators are shifted in time. Both the aggregate cycles resulting from principal component analysis and from simple averaging perform well in capturing the business cycle, see table 5.6 and graph 5.3.

Table 5.5; Results principal components analysis cross sectional indicator set for the Netherlands, individual cycles computed using Hodrick-Prescott variant. Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles.

Principal component extraction HP-cycles	*Extraction*	*Loading (variance explained 1st component 55,5%)*	*Lead/lag (months, + = shifted back in time, - = shifted forward*	*Extraction*	*Loading (variance explained 1st component 68,6%)*
Consumer confidence	0.866	0.781	-3	0.862	0.856
CS-durables	0.726	0.742	-6	0.725	0.775
Producer confidence	0.943	0.663	-4	0.959	0.758
BS-new orders	0.859	0.452	-7	0.936	0.635
Consumption	0.865	0.703	+7	0.831	0.834
Exports	0.811	0.836	0	0.838	0.849
Bankruptcies	0.886	0.939	-1	0.905	0.951
Unemployment	0.913	0.700	+11	0.924	0.922
10-year bond yield	0.835	0.272	0	0.859	0.234
Industrial production	0.860	0.839	-	0.917	0.854
Job vacancies	0.914	0.924	0	0.938	0.923
Private fixed capital formation	0.950	0.947	0	0.942	0.918
Temporary employment	0.871	0.708	-9	0.922	0.857
Total hours worked	0.960	0.607	+10	0.955	0.929

Graph 5.3; Common cycle representing Dutch business cycle based on cross-sectional data set. Individual deviation cycles computed using Hodrick-Prescott variant (HP), composite cycle computed using both simple average and principal component analysis. Compared with reference cycle based on Dutch GDP.



A minor point is that the lead of the aggregate cycles on the GDP-cycle seems to be somewhat large, at around six months. This is a minor point as, as has been mentioned, real time circumstances induce a lagging effect. For the HP-cycles time shifting the indicators also somewhat reduces this lead and increases correlations. But again, differences are small, and turning point dates (table 5.6) do not differ much.

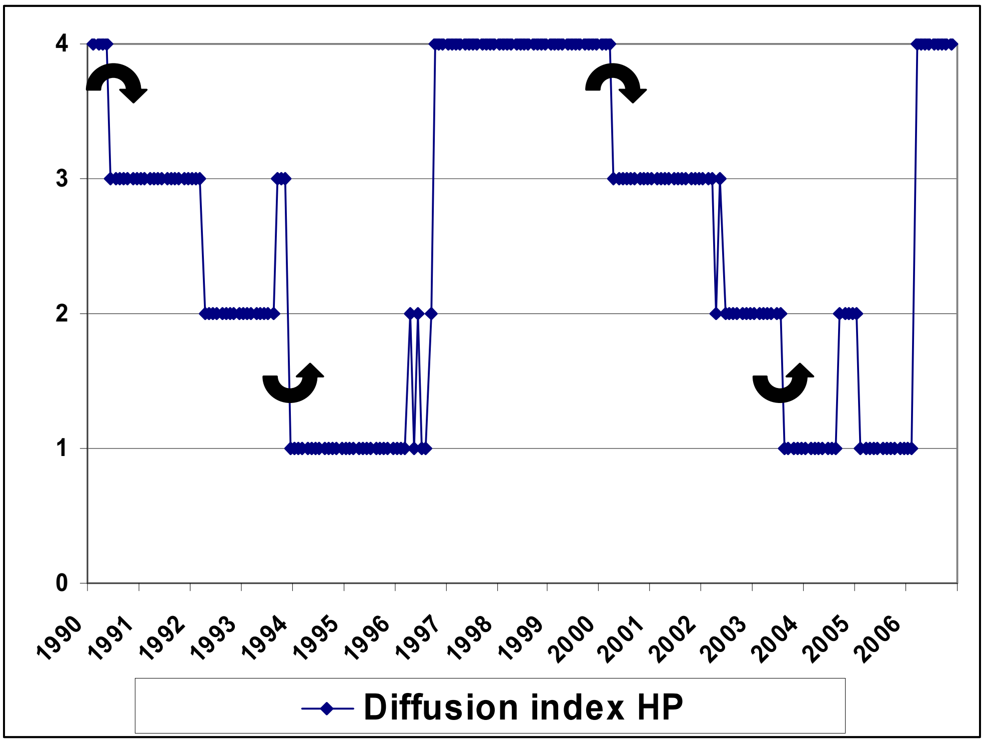
Table 5.6; Business cycle chronologies (dates of peaks and troughs) for the Netherlands according to composite indicators computed by principal component analysis of individual cycles computed using Christiano-Fitzgerald filter and Hodrick-Prescott variant. Time shifted means that individual indicators were shifted in time to compensate for their respective leads and lags compared to the reference business cycles.

	reference	*HP-method Principal component*	*HP-method Principal component Time-shifted*	*CF-filter Principal component*	*CF-filter Principal component Time-shifted*
P	1990-Q3	1990-6	1990-2	1990-11	1991-2
T	**1993-Q4**	**1993-7**	**1993-10**	**1993-10**	**1993-10**
P	**2000-Q2**	**2000-6**	**2000-10**	**2000-6**	**2000-9**
T	**2003-Q3**	**2003-7**	**2003-8**	**2003-8**	**2003-10**

Bold; good correspondence between GDP/IP date and reference, italicized; good correspondence between different GDP&IP turning points, less with reference turning points.

Now we come again to the somewhat complex diagrams representing the outcomes of the diffusion index style analysis. Remember that the expected sequence of business cycle phases is: - 4 (boom) – 3 – 2 (recession) – 1 – 4 -. This form of analysis is more successful with the Dutch indicator set than it for the USA, especially for the HP-cycles. The picture they paint of the state of the business cycle is generally stable and consistent, with few(er) minor cycles, see graphs 5.4 and 5.5.

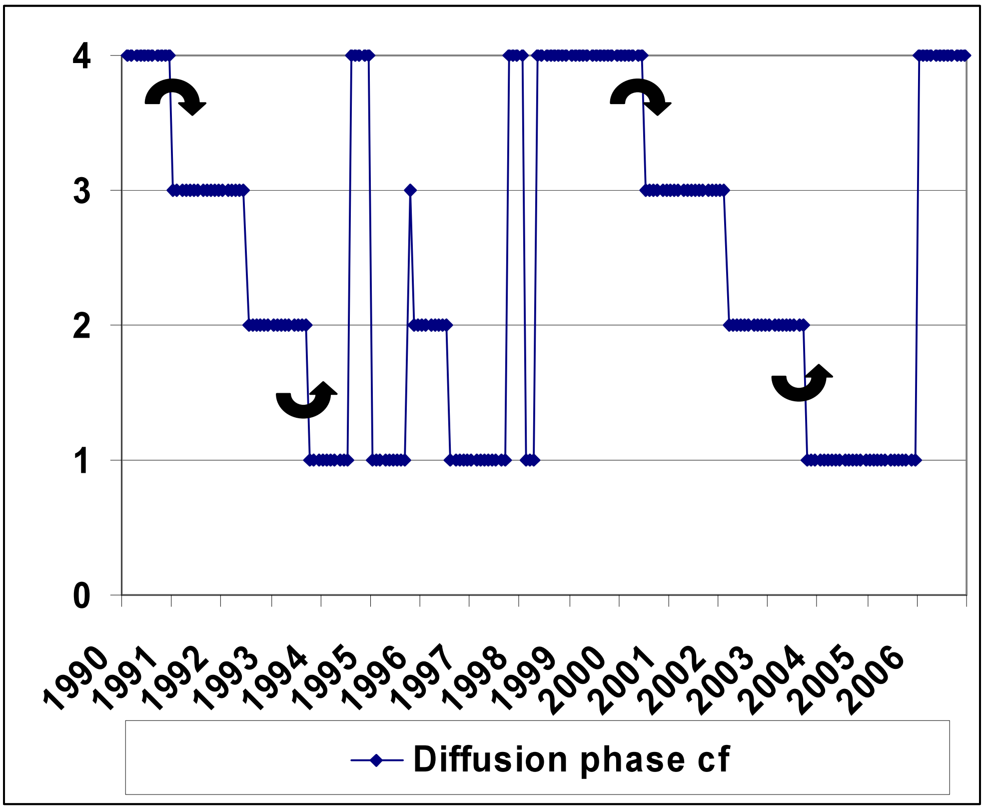
Graph 5.4; Dutch business cycle chronology according to diffusion method, based on cross-sectional data set. Individual deviation cycles computed using Hodrick-Prescott variant (HP). Levels represent different business cycle phases 1=below trend and increasing, 2=below trend and decreasing, 3= above trend and decreasing, 4= above trend and increasing. Phase of majority of individual indicators determines aggregate phase.



curved arrows indicate turning points.

The CF-cycles diffusion index has a few periods of instability, where the phase changes do not follow the expected chronology (4-1-2-3-4), but overall this is a robust way identifying the general state of business cycle. Turning point detection is central in this approach, and the identification of the major turning points is as expected, see table 5.7.

Graph 5.5; Dutch business cycle chronology according to diffusion method, based on cross-sectional data set. Individual deviation cycles computed using Christiano-Fitzgerald filter (CF). Levels represent different business cycle phases 1=below trend and increasing, 2=below trend and decreasing, 3= above trend and decreasing, 4= above trend and increasing. Phase of majority of individual indicators determines aggregate phase.



curved arrows indicate turning points.

Table 5.7; Business cycle chronologies (dates of peaks and troughs) for the Netherlands according to diffusion index method. Individual cycles computed using Christiano-Fitzgerald filter and HP-method.

	reference	*HP-method diffusion index*	*CF-filter diffusion index*
P	1990-Q3	1990-6	1990-1
T	**1993-Q4**	**1993-12**	**1993-10**
P	**2000-Q2**	**2000-4**	**2000-7**
T	**2003-Q3**	**2003-8**	**2003-10**

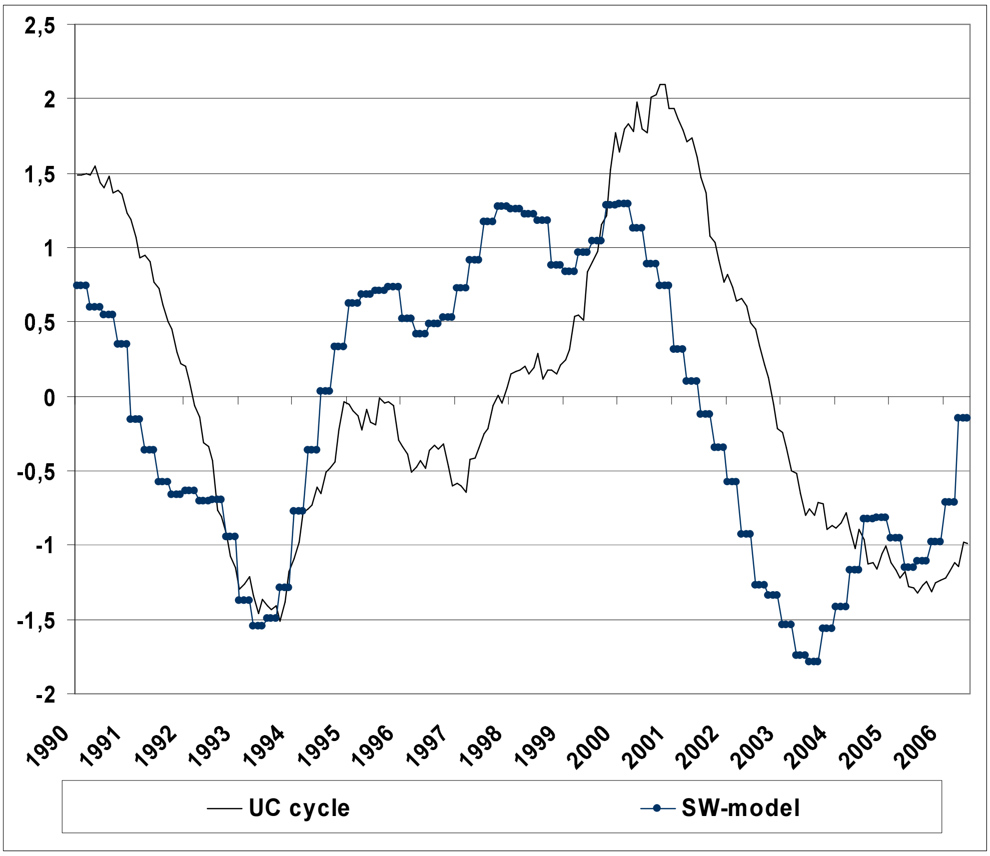
Bold; good correspondence between GDP/IP date and reference,
italicized; good correspondence between different GDP&IP turning points, less with reference turning points.

The conclusion is that the cross-sectional approach is able to reliably capture the business cycle for the Netherlands as well. The resulting aggregate cycles identify the major turning points, and correlations with the reference cycles are high (table 5.12). Also, shifting the component series in time to correct for leads and lags has little effect on the aggregate cycle, conforming the validity of the straightforward approach using uncorrected component indicators.

5.3 Results for the Netherlands common cycle computation using direct methods

The direct methods of extracting the business cycle from the indicator set were successful as well, see graph 5.6. The Unobserved Components cycle is somewhat noisy, but both methods yielded a credible cycle compared to the reference cycles, confirming the presence of a common cycle.

Graph 5.6; Common cycles representing Dutch business cycle based on cross-sectional data set, computed via direct methods; Stock and Watson method (SW) and Unobserved components model (UC). Shaded areas represent NBER recession periods.



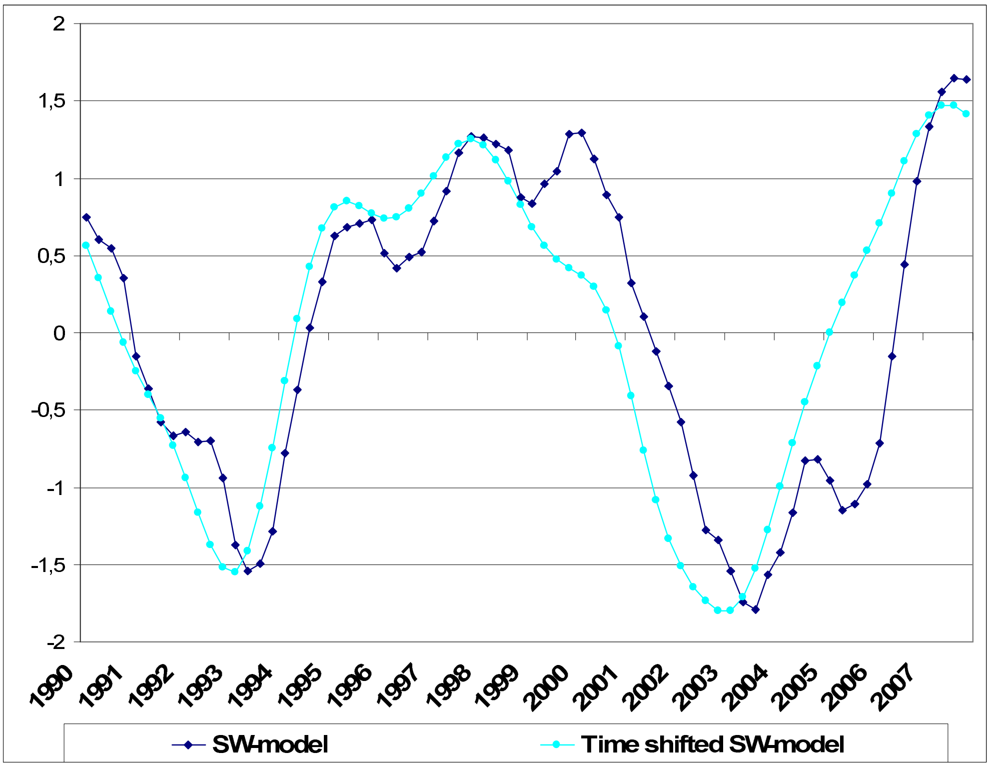
Both common cycles match the Dutch business cycle, as can be determined among others by comparing the dating of major turning points in table 5.9. Both common cycles found here concentrate on the major business cycle movements, with some influence of minor cycles. The only problem is with the dating of the 2003 trough by the UC model, which seems to be delayed to 2005. This is not a major problem, as the technique of finding the common component directly by UC is only used here as an alternative way of finding the business cycle, and on the whole the UC-cycle is credible. For the Netherlands, the estimated duration of the business cycle in this period was 8 years. The essential features of these two cycles are similar to those of the aggregate common cycles resulting from the indirect methods, as will be analysed further in the next section.

Table 5.9; Business cycle chronologies (dates of peaks and troughs) for the Netherlands according to common cycles computed using S&W-method and UC-model. Time shifted means that individual indicators were shifted in time to compensate for their respective leads and lags compared to the reference business cycles.

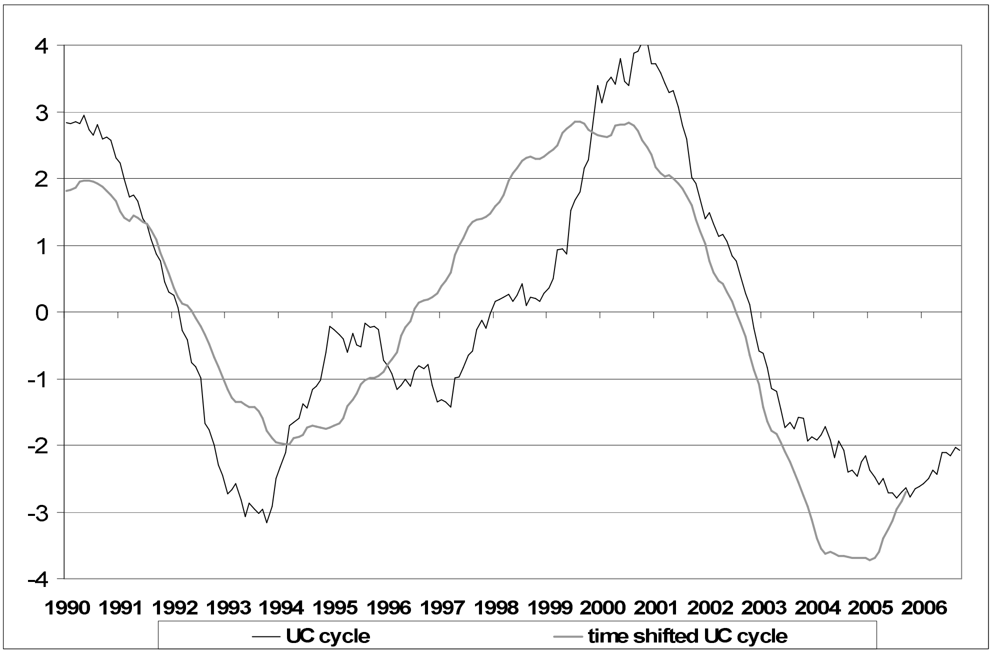
	reference	*SW-method*	*Time shifted SW-method*	*UC-model*	*Time shifted UC-model*
Peak	**1990-q3**	na	na	1990-3	1990-5
Trough	**1993-q4**	**1993-q2**	**1993-q1**	**1993-10**	**1994-1**
Peak	**2000-q2**	**2000-q1**	**1997-q4**	**2000-11**	1998-8
Trough	**2003-q3**	**2003-q3**	**2003-q1**	2005-7	2005-1

To see whether the estimation process suffered because a mix of lagging, coincident and leading indicators was used, again an additional cycle computation using a corrected indicator set was performed. The resulting common cycles do differ somewhat from the original cycles, but the business cycle chronologies and general course of the business cycle are sufficiently similar, see table 5.9 and graphs 5.7 and 5.8. This is confirmed by high correlations between the original common cycles and the common cycles resulting from the time shifted indicator set. For the UC-models, this amounted to 0.833 at lag zero, while for the SW-method correlation was 0.911 but with a lead of six months for the time-shifted indicator set. Overall, as was the case for the USA indicators, the use of a mixed dataset does not seem to have unduly distorted the cycle estimation.

Graph 5.7; Common cycle representing Dutch business cycle based on cross-sectional data set. Common cycle computed using Stock and Watson model (SW). Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles.



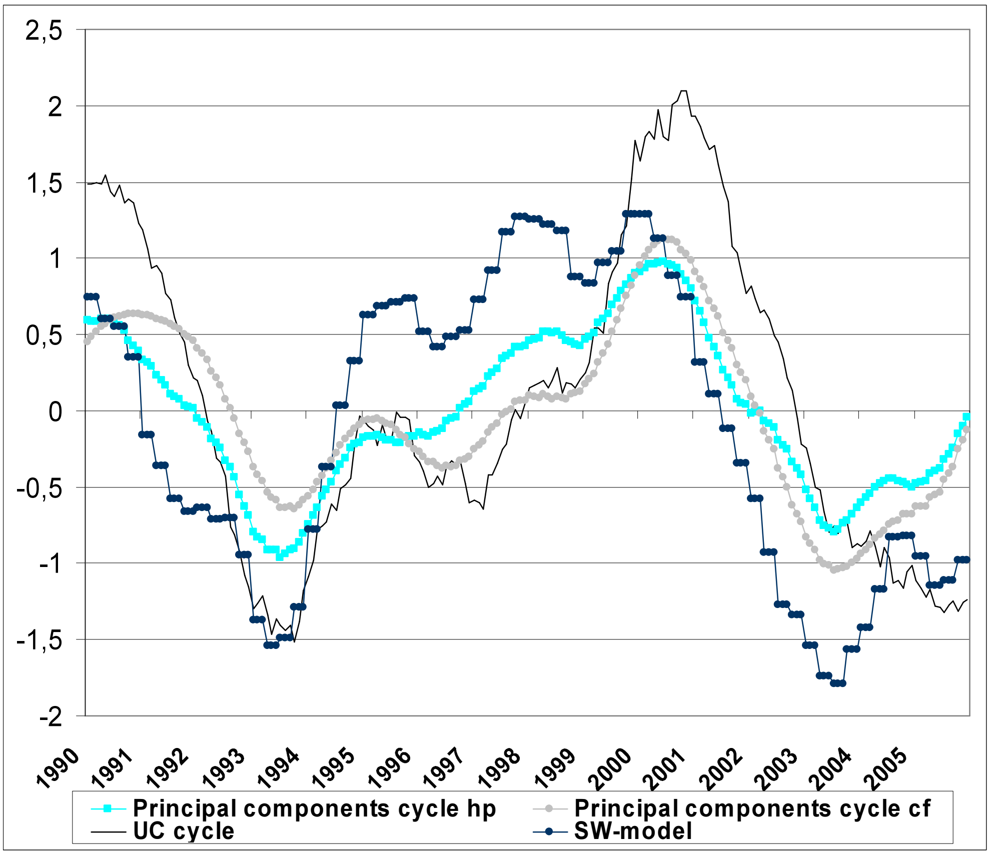
Graph 5.8; Common cycle representing Dutch business cycle based on cross-sectional data set. Common cycle computed using Unobserved components model (UC). Analysis both performed using original data and corrected data set with individual indicators shifted in time to compensate for their respective leads and lags compared to the reference business cycles.



5.4 Overall comparison results common cycle computation for the Netherlands

As for the USA, when comparing the business cycles yielded for the Netherlands by the different methods, there is clear averall similarity. In graph 5.9, the cycles of the HP, CF, UC and SW methods are shown together, and the patterns of the different aggregate/common cycles are all but equal.

Graph 5.9; Common cycles representing Dutch business cycle based on cross-sectional data set, computed via both direct and indirect methods; Stock and Watson method (SW), Unobserved components model (UC), Hodrick-Prescott variant (HP) followed by principal component analysis, Christiano-Fitzgerald filter (CF) followed by principal component analysis.



This concordance is confirmed by the cross-correlations between the different cycles in table 5.10. These are high, on average almost 0.9 and in general leads or lags are not more than a few months. Only exception is again the SW-cycle, but as explained this difference is expected as this cycle is based on growth rates.

Table 5.10; Correlations between common cycles for the Dutch economy resulting from the different detrending methods.

	HP-method simple average	HP-method Principal component	CF-filter simple average	CF-filter Principal component	UC-model	SW-method
HP-method simple average						
HP-method Principal component	**0.986 (-1)**					
CF-filter simple average	**0.930 (0)**	**0.899 (+2)**				
CF-filter Principal component	**0.921 (0)**	**0.890 (+2)**	**0.998 (0)**			
UC-model	**0.879 (+3)**	**0.856 (+5)**	**0.837 (+3)**	**0.826 (+3)**		
SW-method	**0.786 (-3)**	**0.828 (-1)**	**0.698 (-3)**	**0.695 (-5)**	**0.721 (-10)**	

Leads and lags concern the indicator in the leftmost column

The identification of the major turning points in the business cycle according to the different methods is shown in table 5.11. As indicated before, all methods reliably and timely identify these when compared with the reference chronology. This automatically means that there is also strong concordance in turning point dating between the different methods, give or take a few months.

Table 5.11; Business cycle chronologies (dates of peaks and troughs) for the Netherlands according to common cycles computed using Hodrick-Prescott variant, Christiano-Fitzgerald filter (both simple average and principal component), S&W-method, and UC-model.

	reference	*SW-method*	*UC-model*	*HP-method simple average*	*HP-method Principal component*	*CF-filter simple average*	*CF-filter Principal component*
P	**1990-q3**	na	1990-3	**1990-6**	**1990-6**	**1990-11**	**1990-11**
T	**1993-q4**	**1993-q2**	**1993-10**	**1993-10**	**1993-7**	**1993-7**	**1993-10**
P	**2000-q2**	**2000-q1**	**2000-11**	**2000-5**	**2000-6**	**2000-6**	**2000-6**
T	**2003-q3**	**2003-q3**	2005-7	**2000-8**	**2000-7**	**2000-7**	**2003-8**

This agreement on major turning points is reflected in correspondence of the respective common cycles with standard proxies for the business cycle. In table 5.12 the correlations of the common cycles with the HP- or CF-cycles of IP and GDP are shown. IP and GDP are considered to be the best individual proxies of the business cycle. Correlations are high, typically between 0.8 and 0.9 (with exception again for the SW-cycle), generally with small or no leads, thus almost coincident.

Table 5.12; Correlations between common cycles for the Dutch economy resulting from the different detrending methods and reference series based on deviation cycles of industrial production and GDP.

	IP-HP cycle	*GDP-HP cycle*	*IP-CF cycle*	*GDP-CF cycle*
HP-method simple average	0.862 (-1)	0.879 (-3)		
HP-method Principal component	0.824 (-2)	0.849 (-6)		
HP-method Principal component time-shifted indicators	0.846 (0)	0.887 (-5)		
CF-filter simple average			0.908 (-2)	0.920 (-3)
CF-filter Principal component			0.930 (-1)	0.939 (-3)
CF-filter Principal component time-shifted indicators			0.807 (-1)	0.943 (0)
UC-model	0.898 (0)	0.887 (-1)	0.836 (-1)	0.747 (0)
SW-method	0.593 (-5)	0.585 (-12)	0.552 (-5)	0.672 (-12)

Leads and lags in months, + means that the indicator lags the reference, - means a lead.

All the computed common cycles are able to identify the major business cycle turning points in a reliable and timely fashion, and have strong, coincident correlations with proxies for the business cycle. Also, the different common cycles are very similar, so there is agreement between the different methods on the nature of the business cycle. It is especially noteworthy that methods which explicitly estimate a common cycle arrive at very similar cycles as result from aggregating the cycles of the individual indicators (the indirect approaches). This supports the notion that the (un)weighted average of the individual cycles is a common cycle.

On the whole, all this shows that it is valid to state that the common cycle of the cross-sectional indicator sets represent the business cycle. The evidence in this study, the similarity in the common cycle resulting from the different detrending methods, suggests that cycles found are not spurious. This is also confirmed by the outcomes of the Harding and Pagan index of concordance, which can be found in appendix II. It would be rather unlikely that all the different methods tested here yielded the same business cycle chronology by chance. As concluded before, the aggregate cycle seems to be less sensitive to the detrending method used than cycles of individual indicators. It is also interesting to consider this argument in the reverse; stating that the business cycle can be defined as being the common cyclical component of a diverse set of relevant macro-economic indicators.

6. Discussion and conclusions

Each of the different approaches to measuring the business cycle has its advantages. The classical approach is very simple to understand and requires little computational effort. The growth rate approach to economic cycles is transparent and the methodology is robust. The growth or deviation cycle approach used here offers a more coherent and relevant way to analyse business cycle developments. It automatically classifies periods as exhibiting above or below trend development. This means that it defines an alternation between phases of weak or strong growth, which is a more fundamental and relevant distinction than between positive or negative growth. However, the main point here is that whatever business cycle concept is chosen, a multivariate approach is superior to relying on a single indicator to define the business cycle.

The concept demonstrated here is a cross sectional approach to business cycle analyses. This means that the current stance of the business cycle is derived from a mixed set of lagging, coincident and leading indicators. The results show that the aggregate or common cycle of a sufficiently diverse and representative set of macro-economic indicators successfully reflects the business cycle. Several different methods were used here to compute the common cycle. A distinction can be made between indirect methods and direct methods. In the case of the indirect methods, the cycles of the individual component indicators are computed first, here using both the Hodrick-Prescott and Christiano-Fitzgerald filters. Consequently the individual cycles were aggregated into a common cycle, via both unweighted averaging and principal component analysis. The direct methods give a direct, formal estimation of the common cyclical component. Here, the dynamic factor approach of Stock and Watson and the Unobserved Components methods were used. All these methods yielded aggregate common cycles which were very similar, and all gave a credible representation of the business cycle. The correspondence between the outcomes of the different methods is a well known fact from the literature [Klein and Moore (1982), Banrji and Hiris (2001), Valle e Azevedo et all. (2006), Zarnowitz and Ozyildirim (2002)], and it is very important. It means that it can be concluded that the computed common cycles are real, and not artefacts of a certain method. The cited studies confirm that most methods are able to reproduce the relevant standard business cycle chronologies. It is especially encouraging that the direct methods, with their formal estimation of the common cycle yield similar outcomes to the more informal indirect methods. The simplest approach, computing an unweighted average of individual cycles gives an outcome very similar to the most advanced methods, a result also found in earlier studies [Kranendonk et all. (2004), Den Rijer (2006)].

Using a cross sectional approach to identify the business cycle means that the emphasis in the analysis lies more on economic activity than on output. In this and in the use of a mixed indicator set, the cross sectional method is related to the large scale dynamic factor models as used for example in the Eurocoin indicator. The difference is that the approach presented here uses only a limited dataset and that the computations can be performed using different methods. Other studies have also shown that an indicator set of relatively limited size can be reliably used to track the business cycle [Valle e Azevedo et all. (2006), Inklaar et all. (2003)]. Economic activity is of course a rather abstract concept, but it can be equated with the common dynamic component in the economy, represented here by the common cycle. Economic activity is more relevant than output because it is a much broader concept. It also encompasses developments in the labour market, the financial markets and in economic confidence and expectations. It therefore is a more accurate reflection of current economic conditions.

One additional advantage of the cross sectional approach presented in this study are that this method is robust to transient idiosyncratic developments and (temporary) variations in the leading or lagging character of individual component indicators. These are averaged out. When relying a single indicator to track the business cycle, atypical or temporary developments can lead to misleading signals. Using a small, focused set of coincident indicators also means that one can be vulnerable to changes in behaviour. Also, the diverse character but manageable size of the indicator set allows for a more profound analysis of current economic developments. A final advantage is that the indicator set can be fine tuned to yield truly current monthly information on the state of the economy. With most coincident indicators this is difficult due to the presence of publication lags, which can vary between one and more than three months. By choosing the right mix of indicators, it is possible to construct a monitoring system which shows in real time the monthly current state of the business cycle.

Literature

Altissimo, F., Cristadoro, R., Forni, M., Lippi, M. and Veronese, G. (2007) "New EUROcoin: tracking economic growth in real time". CEPR discussion paper 5633

Banerji, A. and Hiris, L. "A multidimensional framework for measuring business cycles". Economic cycle research institute. www.businesscycle.com

Banrji, A and Hiris, L (2001) "A framework for measuring international business cycles". International journal of forecasting vol. 17, p.333-348

Bonenkamp, J. (2003), "Herziening van de CPB-conjunctuurindicator". (in Dutch) CPB Memorandum 71, Centraal Planbureau, Den Haag.

Bonenkamp, J., Krandendonk H. and Verbruggen, J. (2004) "A leading indicator for the Dutch economy". CPB discussion paper 32

Burns, A.F., and Mitchell W.C. (1946) "Measuring Business Cycles". NBER New York.

Canova, F. (1998), "Detrending and business cycle facts". Journal of Monetary Economics vol. 41,p. 475–512.

Canova, F. (1999), "Does detrending matter for the determination of the reference cycle and the selection of turning points?". The Economic Journal vol. 109, p. 126–150.

Carriero, A. and Marcellino, M. (2007) "Monitoring the economy of the Euro area: A comparison of composite coincident indexes". IGIER working paper no. 319

Carvalho, V.M. and Harvey, A.C. (2004) "Convergence and cycles in the Euro-zone". CEPR discussion paper 4726

Christiano, L.J. and Fitzgerald, T.J. (1998) "The Business Cycle: It's still a puzzle". Federal Reserve Bank of Chicago Economic Perspectives 4th quarter, p. 56-83

Christiano, L.J., Fitzgerald, T.J. (1999), ´The band pass filter". NBER Working paper 7257, National Bureau of Economic Research, Cambridge, USA.

Cooper, R. (1997) "Business cycles: Theory, evidence and implications". NBER working paper 5994.

Fuhrer, J.C. and Schuh, S.(1998) "Beyond Shocks: what causes business cycles? An overview". New England Economic Review November/December p.1-24.

Forni, M., Hallin, M., Lippi, M. and Reaichlin, L. (1999) "The generalized dynamic factor model: identification and estimation". CEPR discussion paper 2338

Guay, A., St-Amant, P. (1997), "Do the Hodrick-Prescott and Baxter-King filters provide a good approximation of business cycle?". Working Paper no. 53, Center for Research on Econometric Fluctuations and Employment, Université du Québec à Montréal, Canada.

Hamilton, J.D. (2005), "Whats real about the business cycle". NBER working paper 11161.

Harding, D. and Pagan, A. (1999) "Knowing the cycle". Melbourne institute working paper no. 12

Harding, D. and Pagan A, (2001) "Extracting, Analysing and Using Cyclical Information". Mimeo University of Melbourne

Harding, D. and Pagan, A. (2002) "Dissecting the cycle: A methodological investigation". Journal of Monetary Economics (49) p. 365-381.

Harvey, A.C. (1990), "Forecasting, Structural Time Series Models and the Kalman Filter". Cambridge University Press, Cambridge.

Harvey, A.C., Jäger, A. (1993), "Detrending, stylized facts and the business cycle". Journal of Applied Econometrics vol. 8, p. 231–247.

Harvey, A.C. and Koopman, S.J. (2000), "Signal extraction and the formulation of unobserved components models". Econometrics Journal vol. 3, p. 84–107.

Harvey, A.C. and Trimbur, T.M. (2003), "General model-based filters for extracting cycles and trends in economic time series". The Review of Economics and Statistics vol. 85, p. 244–255.

Hodrick, R.J. and Prescott, E.C. (1997), "Postwar U.S. business cycles: an empirical investigation". Journal of Money, Credit and Banking 29, 1–16.

Inklaar, R., Jacobs, J. and Romp, W. (2003) "Business cycle indexes: Does a heap of data help?" CCSO working papers 200312

Klein, P. en Moore, G. (1982) "The leading indicator approach to economic forecasting—retrospect and prospect. NBER Working paper 941.

Kranendonk, H., Bonenkamp, J., Verbruggen, J. (2003), "De CPB-conjunctuurindicator geactualiseerd en gereviseerd". CPB document, no 40, Centraal Planbureau, Den Haag.

Kranendonk, H., Bonenkamp, J. and Verbruggen J. (2004) "A leading indicator for the Dutch economy". CPB discussion paper no. 32

Luginbuhl, R. and Koopman, S. (2004) "Convergence in European GDP series". Journal of applied econometrics, vol. 19(5) p.611-636

Marcellino, M. (2004) "Leading indicators: What have we learned?" in Handbook of Economic Forecasting, Ellot, G., Granger, C., Timmermann, A. eds. Elsevier-North Holland

McGuckin, R.H., Ozylidirim, A. and Zarnowitz V. (2007) "A more timely and useful index of leading indicators". Journal of Business and economic statistics vol 25(1) p.110-120

Prescott, C.P. (1986) “Theory ahead of business cycle measurement”. Federal Reserve Bank of Minneapolis quarterly review 3rd quarter p.9-2.

Den Reijer, A.H.J., (2002) “International business cycle indicators, measurement and forecasting”. DNB research memorandum WO 689.

Den Rijer, A.H.J. (2006) “The Dutch business cycle: which indicators should we monitor?”. DNB working paper no. 100

Van Ruth, F., Schouten, B. and Wekker, R. (2005) “The Statistics Netherlands business cycle tracer. Methodological aspects; concept, cycle computation and indicator selection”. Statistics Netherlands discussion paper via www.cbs.nl

Schenk-Hoppé, K.R. (2001), “Economic growth and business cycles: A critical comment on detrending time series”. Working Paper no. 54, Institute for Empirical Research in Economics, University of Zurich, Switzerland.

Stock, J.H. and Watson, M.W. (1988), “A probability model of the coincident economic indicators”. NBER working paper 2772..

Stock, J.H. and Watson, M.W. (2002) “Macro economic forecasting using diffusion indexes”. Journal of business and economic statistics vol. 20 p. 147-162

Watson, M.W. (1986), “Univariate detrending methods with stochastic trends”. Journal of Monetary Economics vol. 18, p. 49–75.

Valle e Azevedo, J., Koopman, S. and Rua, A. (2006) “tracking the business cycle of the Euro area: a multivariate model-based band-pass filter”. Journal of business and economic statistics vol 24(3)

Zarnowitz, V., (1987) “The regularity of Business cycles”. NBER working paper 2381 .

Zarnowitz, V. and Ozyildirim, A. (2002), “Time series decomposition and measurement of business cycles, trends and growth cycles”. NBER Working paper 8736, National Bureau of Economic Research, Cambridge, USA.

Appendix I; Data

Table AI.1; Description data used for the Netherlands

Indicator	*Description*	*Source*
Consumer confidence	Composite consumer confidence indicator	CBS
CS-durables	Consumer survey; purchases of Durables	CBS
Producer confidence	Composite producers' confidence indicator from manufacturing industry survey	CBS
BS-new orders	Business survey manufacturing industry; orders received	CBS
Consumption	Total household consumption – volume (trading day corrected)	CBS
Exports	Total export of goods – volume (trading day corrected)	CBS
Bankruptcies	Business bankruptcies excluding one-man businesses	CBS
Unemployment	Total unemployed labour force	CBS
10-year bond yield	Capital market rate 10-year government bonds	CBS
Job vacancies	Existing job openings in private sector	CBS
Private fixed capital formation	Private sector fixed capital formation, constant prices	CBS
Temporary employment	Temp jobs (hours, phase A)	CBS
Total hours worked	Private and public sector, man-years	CBS
Industrial production	Volume index of production in manufacturing industry (trading day corrected)	CBS

Table AI.2; Description data used for US

Indicator	*Description*	*Source*
Total retail trade	Volume of total retail trade (sa)	OECD
Weekly Hours (Manufacturing)	Weekly hours of work in manufacturing (sa)	OECD
new orders (durables)	Net new orders for durable goods (sa)	OECD
Exports	Total exports (sa)	OECD
Personal income	Personal income (sa)	OECD
NYSE Composite	Share price; NYSE composite	OECD
PPI Finished goods	Producer price index – finished goods (sa)	OECD
Capacity utilisation (industry)	Rate of capacity utilisation in industry (%, sa)	OECD
Civilian employment	civilian employment – all persons (sa)	OECD
Bank credit (loans)	Commercial banks' credit (excl. interbank loans)	OECD

Appendix II; Degrees of Concordance of the different cycles

This analysis is a variant of the Harding and Pagan [2002] *degree of concordance*. They proposed this measure to give more depth to the concept of co-movement. The aim of their original formulation was to determine what fraction of time the cycles of two series y^r_t and y^j_t were both either in a state of contraction or of expansion. For each series a dummy S^i_t is created which has the value 1 if the cycle is in a state of expansion ($C_t > C_{t-1}$) and 0 if it is in state of contraction. The degree of concordance I_{rj} can than be calculated as:

$$I_{rj} = n^{-1}\left(\#\left\{S_t^r = 1 \wedge S_t^j = 1\right\}\right) + n^{-1}\left(\#\left\{S_t^r = 0 \wedge S_t^j = 0\right\}\right)$$
$$I_{rj} = n^{-1}\left(\sum \left(S_t^y S_t^r + \left(1 - S_t^r\right)\left(1 - S_t^j\right)\right)\right)$$

If the cycles of y^r_t and y^j_t are perfectly synchronised, $I_{rj}=1$, whilst if $I_{rj}=0$ the cycles are perfectly opposed. Any value between 0 and zero indicates a lesser degree of coherence, whilst if the cycles are completely independent then:

$$E\left[I_{rj}\right] = E\left[S_t^r\right]E\left[S_t^y\right] + \left(1 - E\left[S_t^r\right]\right)\left(1 - E\left[S_t^y\right]\right)$$
$$E\left[S_t^r\right] = prob\left(S_t^r = 1\right)$$

Where $E[S^r_t]=prob(S^r_t=1)$ is the fraction of time that the cycle of series y^r_t spends in expansion. Thus by calculating I_{rj} for each relevant pair of cycles, and comparing this to $E[I_{rj}]$ under the assumption of independence, a measure of to what extent the two cycles represent the same business cycle.

Table 1 shows the results for the United States. The degrees of concordance between the cycles resulting from the different cycle computation methods are compared to the expected values under an assumption of no independence. In all cases, the actual values of the index of concordance are larger than the expected values, indicating that the cycles are not unrelated, but more in phase. The outcomes of the Stock&Watson model are the exception, suggesting independence. This is probably due to the large presence of short-term fluctuations in the Stock&Watson cycles as computed here, a smoothed variant would exhibit much higher degrees of concordance. The results for the Netherlands are roughly the same. This is another confirmation of the similarity of the outcomes of the different business cycle computation methods.

Table A2-1; degrees of concordance I_{rj} of different US-business cycles, value of I_{rj} under assumption of no relation compared to actual value.

		average hp	*Factor hp*	*average cf*	*Factor cf*	*uc*	*sw*
average hp	expectation independence	0,64	0,66	0,62	0,61	0,65	0,57
average hp	actual	**1,00**	**0,88**	**0,84**	**0,84**	**0,81**	**0,60**
Factor hp	expectation independence		0,67	0,63	0,62	0,66	0,58
Factor hp	actual		**1,00**	**0,83**	**0,83**	**0,84**	**0,59**
average cf	expec indepent			0,59	0,58	0,62	0,55
average cf	actual			**1,00**	**0,98**	**0,79**	**0,59**
Factor cf	expec indepent				0,57	0,61	0,54
Factor cf	actual				**1,00**	**0,80**	**0,58**
uc	expec indepent					0,66	0,57
uc	actual					**1,00**	**0,57**
sw	expec indepent						0,50
sw	actual						**1,00**

Hp=Hodrick Prescott filter, cf=Christiano-Fitzgerald filter, sw=Stock&Watson model, uc=Unobserved Components model.

Table A2-2; degrees of concordance I_{rj} of different Dutch-business cycles, value of I_{rj} under assumption of no relation compared to actual value.

		average hp	*Factor hp*	*average cf*	*Factor cf*	*uc*	*sw*
average hp	expectation independence	0,47	0,52	0,48	0,49	0,42	0,45
average hp	actual	**1,00**	**0,95**	**0,85**	**0,85**	**0,71**	**0,75**
Factor hp	expectation independence		0,57	0,53	0,54	0,46	0,49
Factor hp	actual		**1,00**	**0,84**	**0,84**	**0,67**	**0,76**
average cf	expec indepent			0,48	0,50	0,43	0,45
average cf	actual			**1,00**	**0,97**	**0,67**	**0,75**
Factor cf	expec indepent				0,52	0,44	0,47
Factor cf	actual				**1,00**	**0,68**	**0,76**
uc	expec indepent					0,38	0,40
uc	actual					**1,00**	**0,63**
sw	expec indepent						0,42
sw	actual						**1,00**

Hp=Hodrick Prescott filter, cf=Christiano-Fitzgerald filter, sw=Stock&Watson model, uc=Unobserved Components model.