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The Statistics Netherlands' Business Cycle Tracer. Methodological aspects; concept, cycle computation and indicator selection

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THE STATISTICS NETHERLANDS' BUSINESS CYCLE TRACER. METHODOLOGICAL ASPECTS; CONCEPT, CYCLE COMPUTATION AND INDICATOR SELECTION

Summary: *This report describes the development and workings of the Statistics Netherlands Business Cycle Tracer, a system which acts as a coincident indicator of the Dutch business cycle. It maps real-time business cycle developments by tracking the cyclical development of a selected set of lagging, coincident and leading economic indicators. The disaggregated approach enables a detailed analysis of the state of the economy.*

The methodological section describes the selection of the component indicators and cycle extraction method (filter). We performed various ex-post and real time tests to asses the plausibility of the computed cycles and the practicality of the methods. It was found that although no method was perfect, the cycles in general showed much agreement and are a credible representation of the state of the Dutch business cycle. For practical use, several methods were rejected on theoretical or practical grounds, but three methods were deemed acceptable.

We believe that the Business Cycle Tracer is a useful tool for the description of the Dutch business cycle. It offers a reliable representation of the current state of the business cycle and is able to detect major tuning points in the cycle as they occur.

Keywords: *Business cycle analysis, lagging, coincident and leading indicators, real-time testing, turning point detection, filters, Unobserved Components models, Christiano-Fitzgerald filter, Hodrick-Prescott filter, Baxter-King filter, Beveridge-Nelson filter, Cycle computation, end-value problem, revisions*

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1. Introduction

Every month, Statistic Netherlands publishes a whole array of socio-economic statistics which aim to characterise economic conditions in the Netherlands. Short-term economic indicators are mainly used to track developments in the business cycle. This can be a difficult task, partly because of the volatile nature of many economic statistics and partly because of the wide range of available indicators which sometimes offer (seemingly) conflicting information.

The Statistics Netherlands Business Cycle Tracer is intended as a tool to facilitate the analysis of medium-term economic developments. It clarifies the state of the indicators by focusing on the business cycle component of their development, filtering out short-term and erratic components. The tool gives an easy to interpret graphical representation of the development of all selected indicators. Combining the indicators in one system has two important advantages. It is then possible to analyse the development of an indicator in context, confronting it with other relevant indicators. And by selecting a representative set of indicators, it is possible to obtain an overview of the current state of the economy.

The business cycle is the subject of much economic research, and also of much debate. There is no agreement in the theory on the causes and nature of business cycles. For an overview of current opinions, we refer to some of the extensive literature [Zarnowitz (1987), Prescott (1986), Cooper (1997), Fuhrer and Schuh (1998)]. Given this lack of unambiguous theoretical foundations, it is not surprising that measuring the state of an economy is a much debated issue. Partly, it is down to how one defines business cycles. However, most economists would still agree on the definition given by Burns and Mitchell in 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;”

Also informative is the current 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]. There are several ways to define and measure fluctuations, we will return to this topic in the next section.

The definitions introduce several crucial properties of business cycles on which there is general agreement [Christiano and Fitzgerald, Banjeri and Hiris, Klein and Moore, Stock and Watson 1988, Zarnowitz 1987]. For a start, business cycles are characterised by comovement among many important economic variables. The fluctuations should be visible in among other things production indicators as well as expenditure and labour market indicators. Related to this aspect is the requirement of pervasiveness: the fluctuation should be felt in many sectors of the economy, not just in one isolated industry. Furthermore, business cycles are recurrent, but not periodic. There should be a continuing interchange of expansions and contractions, but not necessarily at regular intervals. A last important aspect is that the fluctuations should be pronounced and persistent; small, short fluctuations do not qualify. Business cycle definitions emphasise that business cycle fluctuations will be visible in all or most of the important economic indicators, and conversely that for a fluctuation to be part of the business cycle, it should be present in a majority of these indicators.

Another important aspect of business cycle is that s needs to be mentioned. 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]. Usually the leading indicators are financial variables and indicators from business and consumer surveys. Real economic variables such as production, consumption and investment are roughly coincident with the cycle, while labour market variables tend to lag. Each of these types of indicators has its own role to play in the analysis. As their name implies, leading indicators give an early warning of coming developments, but these may be misleading as not all developments in the leading indicators are linked to the business cycle. The coincident indicators show what is currently going on, but with publication lags and lags introduced by the computations, these may be late in identifying developments. The lagging indicators are usually relatively stable, and can be used to distinguish between important changes and temporary fluctuations.

We have decided to make use of the useful properties of these various types of indicators by combining them into one, on average coincident, system instead of constructing separate lagging, coincident and leading indicators. By making a careful selection from the most important Dutch economic indicators, the whole will on average reflect of the state of the Dutch business cycle at a given point in time. These indicators will all to some extent *reflect* the business cycle, but this is quite different from causality.

We based our system for tracking the current state of the Dutch business cycle on these general principles and properties. It is important to stress here that the aim is neither to produce a model of the economy, nor to identify and show causes of business cycles. The Statistics Netherlands Business Cycle Tracer is meant to support short-term economic analysis and to make it easier to interpret the development of main economic indicators. Our aim was to construct a system that uses a simple graphical representation to show the direction of the development of the indicators and that elucidates business cycle patterns. It should be stable and reliable. This meant carefully choosing a method to extract the business cycle component (cycle) from the series, and selecting a well-balanced set of indicators.

The structure of this report is somewhat different than might be expected. First (Section 2), we explain the principles and ideas behind the Statistics Netherlands Business Cycle Tracer. In Section 3 we jump ahead and describe the workings of the finished tracer, i.e. the chosen methodology and indicator set. Then, in Section 4 we return to the selection of the cycle extraction methodology. The theoretical background of the different filters is briefly described, followed by an assessment of their theoretical validity. This section also contains an empirical investigation of the properties of the different cycle extraction methods. We first focus on the ex-post plausibility of the respective cycles and then on the real-time properties of the different methods. In Section 5 we turn to the selection of our indicator set. In a selection process of several stages, a long-list of potential indicators is whittled down to a set of 14 indicators with the desired properties. Section 6 presents our conclusions.

2. Tracer concepts

The Statistics Netherlands Business Cycle Tracer was developed with two goals in mind. Foremost, it is meant as a tool to support the analysis of the Dutch business cycle. By confronting the developments of a selection of the main economic indicators with each other, patterns and links between indicators become visible. Their common component is a reflection of the state of the economy. Next to this, the Tracer will aid in the analysis of the macro-economic indicators which Statistics Netherlands publishes every month. The emphasis is on making the dynamics of the indicators more clearly visible and easier to interpret. This is achieved by presenting their cyclical component, which is easier to interpret than normal mutations and focuses on medium-term developments. The disaggregated approach means that developments in different aspects of the economy (e.g. the labour market) can be studied individually, but also in relation to the rest of the economy.

Unlike most business cycle indicators, which are constructed to lead the business cycle, we aim for a coincident system: it should be able to pinpoint the current state of the business cycle as precisely as possible. As mentioned in the introduction, the business cycle is characterised by comovement among many economic indicators. The economic cycle will be visible in almost all main economic indicators. These indicators are usually classified as being leading, lagging or coincident with respect to the general business cycle, and are used to construct, leading, lagging and coincident aggregate indicators. We take a different approach, aiming to construct a system which shows at a glance all important aspects of the business cycle. This means combining leading, coincident and lagging indicators in one system. By using a balanced mix, the whole set can be made on average to be coincident with the cycle. The advantage is that the system gives information on many aspects of the economy and is less sensitive to variations in the leading or lagging character of the individual indicators.

Just as there is no agreement on the causes of business cycles, there is also much debate on how to measure these phenomena. There are basically three different concepts, and whichever one chooses, the choice will be open to criticism. The classical approach is based on the work of Burns and Mitchell (Harding, Pagan), 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 are relevant for policy makers and the wider public, and that other measures of business cycles are either too complex or ill-defined. One disadvantage of this approach is that it seems rather arbitrary to define a small decline as a slowdown or recession, but an almost zero, but still positive growth. – by definition -not This is especially so for countries characterised by high economic growth. Also, it means that as long as there is positive growth, this approach offers little to track and characterise business cycle developments. There are other theoretical objections to this approach: in much of the relevant economic theory, the emphasis is not on growth or shrinkage but on the development of an economy relative to its potential. Very different economic regimes are in place when an economy is above or below potential, each with its own characteristic developments. If an economy is exhibiting positive growth but is also growing (far) below its potential, phenomena associated with recession may still manifest themselves.

An alternative is therefore to define the business cycle by deviations of the economy from its potential. The cyclical component of an indicator is then found as the deviation from its long-term trend. These are called deviation or growth cycles. The concept of potential growth is well-grounded in economic theory, and determining whether an indicator is developing above or below trend gives important information. Therefore, the deviation from trend approach enables a more thorough characterisation of the dynamics of short-term economic indicators.

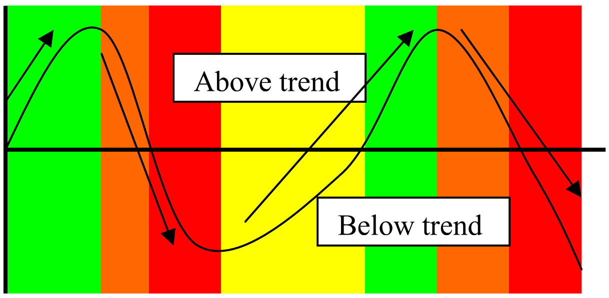
The deviation cycle approach has received much criticism for various reasons. One strand of criticism is fundamental, based on the Real Business Cycle theory. This states that changes in the economy are random, and therefore no long-term trend exists. However, this theory itself is controversial and unproven. Also, many institutional business cycle analysts use the cyclical approach, and it has proven itself in practice. Other criticism of deviation cycles is more practical, stating that as the trend cannot be observed directly, there will always be an element of arbitrariness in the computations [Canova 1998]. As a result, it will be unclear to what extent the computed cycles are real or an artefact of the filter used.

One way of dealing with these difficulties in determining the trend, is to analyse the cycles in the growth rates of the indicators instead. This is the third approach to business cycle analysis, the so-called growth-rate cycles. But other studies conclude that important business cycle facts are not very sensitive to the method used to determine trend and cycle [Klein and Moore 1982, Banerji and Hiris]. Using growth rates in the construction of a business cycle tracking system also just shifts the problem. As most economic time series are rather volatile, it will be necessary to filter the growth rates to separate the important developments from noise. Otherwise, the series will probably be too noisy to give a clear picture of its state. More importantly, for a thorough analysis of business cycle developments, it will also be necessary to decide whether a certain realisation is high or low. If this is to be done systematically, it will still be necessary to compute some benchmark or average growth rate, i.e. a trend growth rate.

Because of these considerations, we decided to base our analysis on deviation cycles. These have several advantages. The cyclical approach offers a ready and clear framework to classify the state of the indicators and the economy. It is easy to compare and combine the development of different indicators, as they are all translated to standardised cycles. The cyclical approach highlights the dynamics most relevant for business cycle analysis, and cycles are in general easier to interpret than the noisy unfiltered realisations.

The system should be easy and quick to interpret and give a clear representation of the current state of the business cycle. When considering a cycle, either the business cycle or the cycle of an individual indicator, several classifications are possible. The most basic one is by upswings and downswings, depending on whether the cycle is increasing or decreasing. Much more complex classifications are possible, for example dividing the contraction into several distinct stages [Burns and Mitchell 1946].

Statistics Netherlands' system is based on a systematic and objective classification of the cycle by four different states:

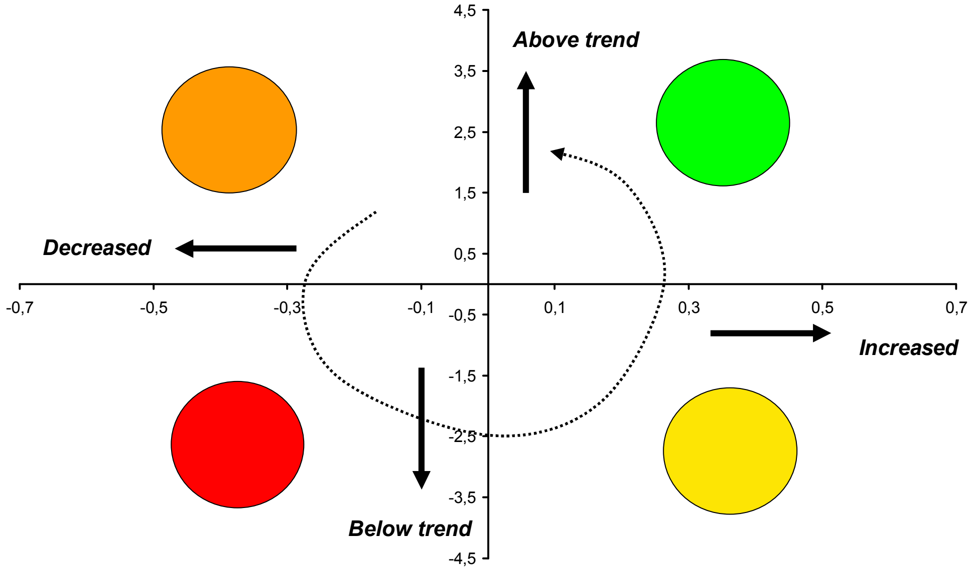


An indicator can be either above trend or below trend, and in each of these conditions it can be either increasing or decreasing. Thus, four possible classifications for the state of the indicators result.

Green	above trend	increasing
Orange	above trend	decreasing
Red	below trend	decreasing
Yellow	below trend	increasing

The emphasis is on analysing the dynamics (increasing vs. decreasing) of the indicators and on the identification of turning points in the business cycle. Each of the four possible states has a clear meaning in business cycle analysis. Moreover, a business cycle peak is a switch from above trend and increasing to above trend but decreasing, while a trough is a switch from below trend and decreasing to below trend but increasing. This division into four states is a robust and simple method to characterise the development of an indicator, or the economy as a whole. Another advantage of this simple classification method is that the precise values of the distance to trend and of the period on period change are less relevant. This reduces the sensitivity of the system to the method of cycle computation.

Now we can present the Business Cycle Tracer system. We have chosen a graphical representation, as this is easy to interpret and read. It is simply a coordinate system, with the horizontal axis representing the period-on-period change of an indicator and the vertical axis its distance to trend. Another way of interpreting this set-up is that the vertical axis gives the state of the indicator, and the horizontal axis its direction of change. The four phases of the cycles described earlier are now the four quadrants of this coordinate system.



The indicators are placed in the diagram according to the coordinates resulting from their cycle. As the cycle of an indicator develops, it will follow a counter-clockwise path through the Tracer diagram, moving from quadrant to quadrant as it moves through the phases of the cycle. Because we shall present all the indicators together in the tracer diagram, it is possible to confront their movements with each other. The common patterns will represent business cycle movements.

3. The Business Cycle Tracer Step-by-Step

In this section we jump ahead and present the finished Business Cycle Tracer. The details of the research which resulted in the chosen methodology and the indicator selection can be found in Sections 4 and 5. Here, we set out which computations are used for the Business Cycle Tracer, how the Tracer is constructed from the computed indicator cycles and how it can be read. First, we list the indicators selected for the Statistics Netherlands Business Cycle Tracer (graphs of their cycles and further details can be found in the appendices):

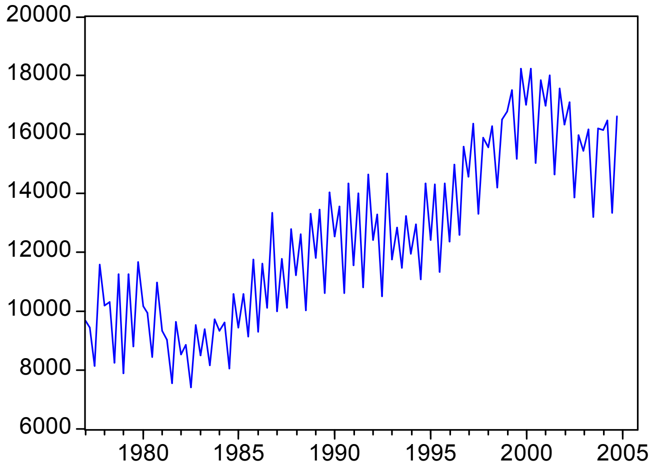
Producer confidence	
Unemployed labour force	(inverted)
Consumer confidence	
Jobs of employees	
Temp jobs	
Consumer Survey; Purchases of Durables (large purchases)	
Exports	
Fixed capital formation	
Business survey; Orders received	
GDP	
Total Household Consumption	
Index of Industrial Production	(manufacturing)
Vacancies	
10-year bond yield	(capital market rate)
Bankruptcies	(inverted)

The realisations of these series are translated into coordinates of the tracer diagram by first computing their cycle. When all indicators are combined in the diagram, the Business Cycle Tracer gives a reflection of the current state of the Dutch business cycle.

The cycles of the indicators are computed from the original series as follows (exact parameter settings for each of the series can be found in appendix 2):

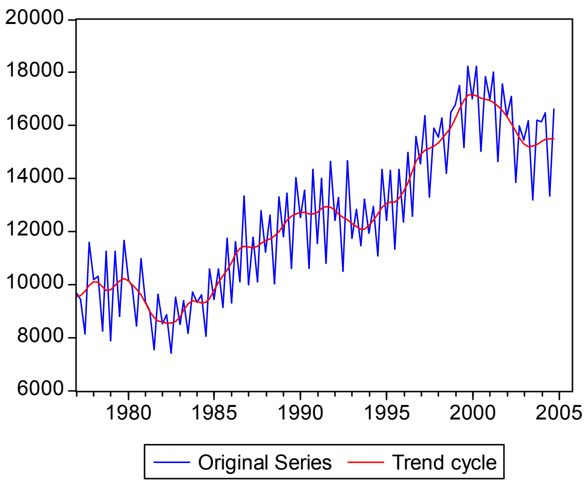
1. If necessary, correct for trading day effects

Graph 3.1; Fixed capital formation



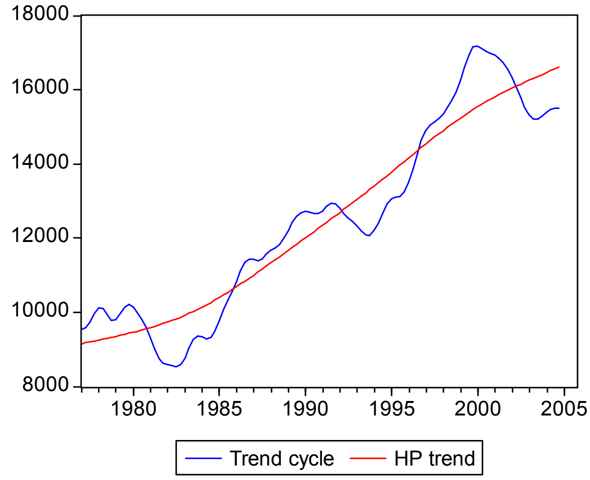
2. Compute the Henderson trend cycle using the Census X12 program to filter out noise and seasonal fluctuations

Graph 3.2; Fixed capital formation and its trend cycle



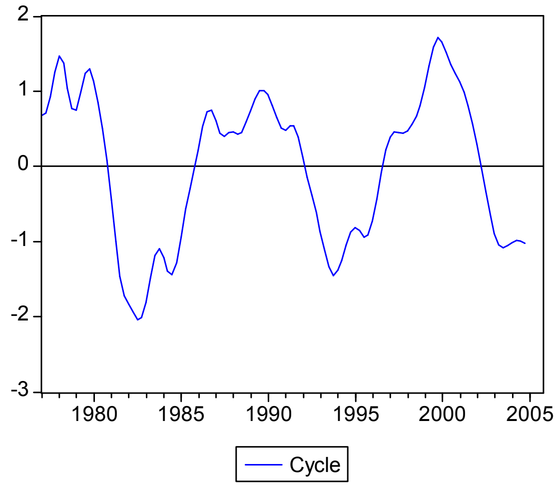
3. Using the trend cycle, compute the Hodrick-Prescott (inflexible) trend

Graph 3.3; Fixed Capital formation, trend cycle and Hodrick-Prescott trend



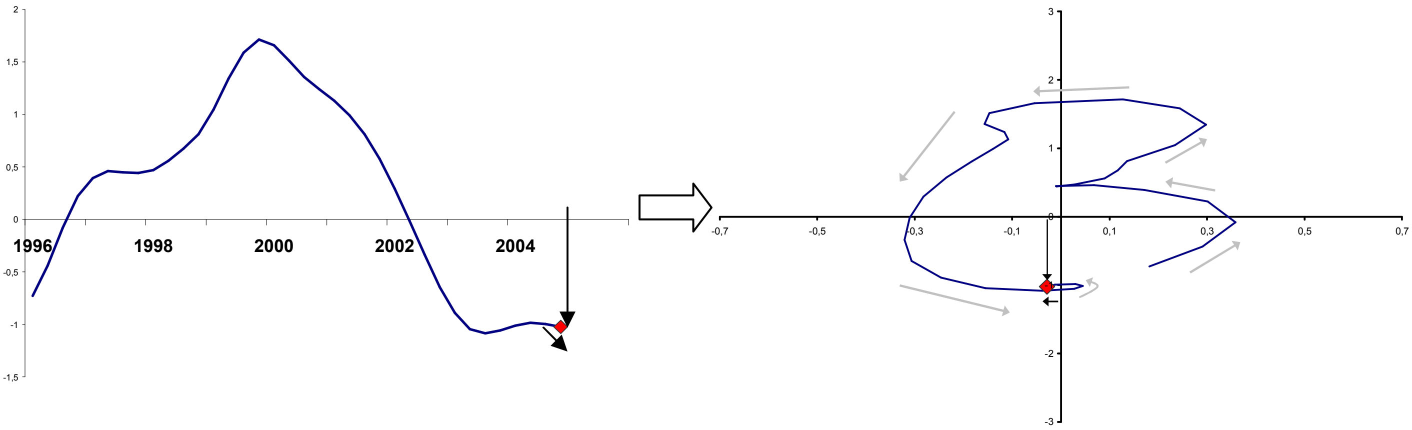
4. Compute the deviation from the Hodrick-Prescott trend and standardise by subtracting the mean and dividing by the standard deviation

Graph 3.4; Cycle fixed capital formation



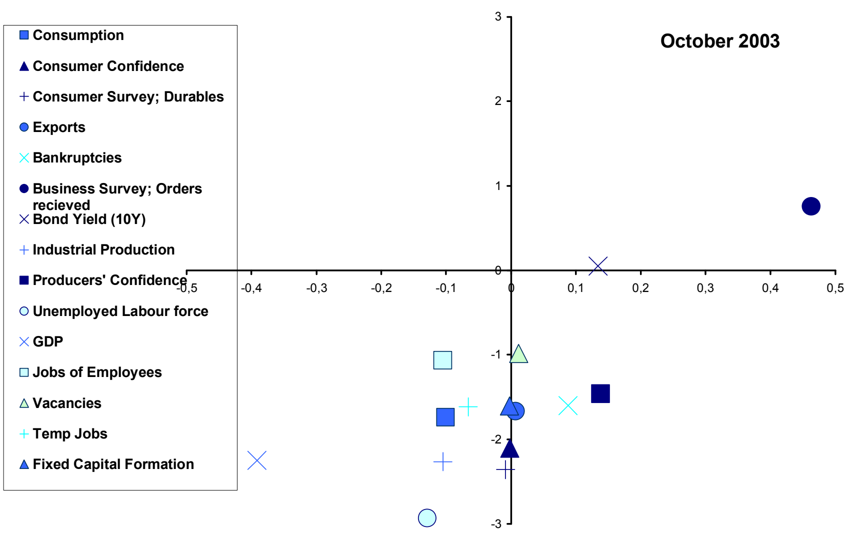
5. Compute the coordinates of each indicator in the Business Cycle Tracer by taking the deviation from trend (=the cycle) as the y-coordinate and the period-on-period change in the cycle as x-coordinate

Translation of fixed capital formation cycle to tracer coordinates



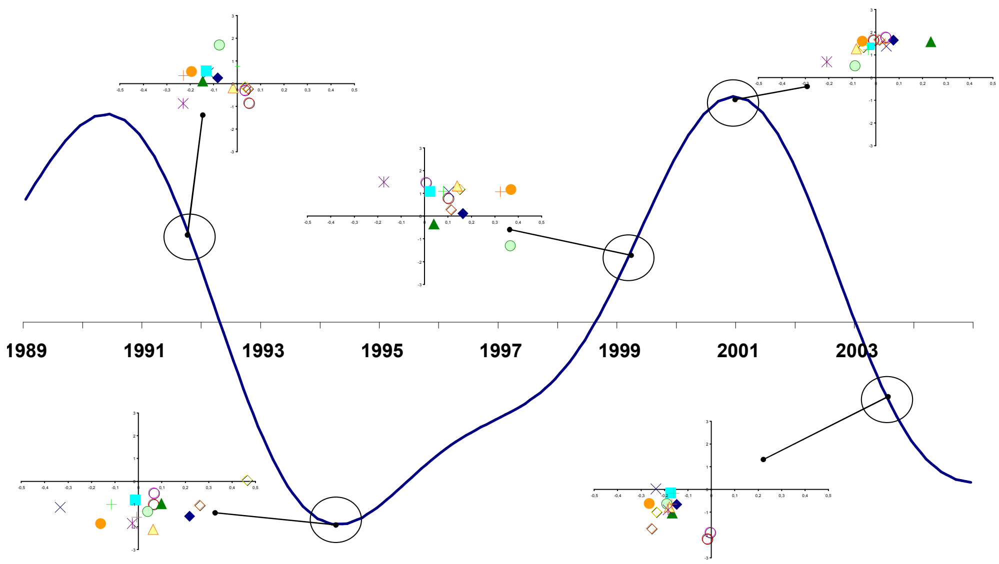
When the coordinates for all the indicators have all been computed in this way, they are plotted together in the tracer diagram. The result is a monthly cross-section view of the Dutch business cycle. The clustering and general movement of the indicators reflects the state of the business cycle. By way of example the tracer for October 2003, around a business cycle trough is shown below. In the diagram, a movement from the lower left quadrant, to the lower right quadrant can be seen. This means that although most indicators are still below trend, some are starting to increase again, a sign of a beginning recovery.

Graph 3.6; Business Cycle Tracer of October 2003.



Graph 3.7 shows how the patterns in the tracer diagram are connected to the phase of the business cycle. There are distinct patterns for peaks, troughs, upswings and downswings. The component indicators will cluster in the quadrants representing the state of the business cycle at that specific moment.

Graph 3.7; Dutch business cycle based on GDP cycle and corresponding patterns in the Business Cycle Tracer



4. Cycle extraction methods

A crucial part of the business cycle tracing system is the computation of the cycles. We made a selection of the most frequently used cycle extraction methods, or filters. The two most important properties of these methods are whether the cycles they yield are real, i.e. present in the series filtered, and whether a filter performs well in normal practice, the real-time properties. These properties determine whether a cycle extraction method will be able to give an accurate monthly picture of business cycle developments. In this section we evaluate the candidate methods on these two properties. First, we briefly review the literature on the theoretical properties of the different methods. Then each method is used to calculate the ex-post cycles for GDP and industrial production so that the plausibility of the computed cycles can be assessed. Finally, to test the real-time performance of the filters, a simulation exercise is performed, making it possible to quantify how much the real-time cycles deviate from the final ex-post cycles, and thus how reliable each method will be in practice.

4.1 Theoretical Background

Our initial selection of cycle extraction methods, or filters, is:

1. Constant (logarithmic) linear trend
2. Hodrick-Prescott filter
3. Beveridge-Nelson method
4. Baxter-King filter
5. Christiano-Fitzgerald filter
6. Unobserved Components-models

Some techniques often featured in the literature were not selected, mostly for practical reasons. These include non-linear trend methods, first order differences, Phase Average Trend [Boschan en Ebanks 1978], Markov-switching models [Hamilton 1989], exponential smoothing [Gardner 1985] and the Rotemberg decomposition [Rotemberg 1999].

The National Bureau for Economic Research (NBER) in the United States uses the Phase Average Trend (PAT). This method consists of two steps. First, a preliminary trend is computed, which is used to determine turning points in the cycle. Using these turning points, the definite trend is determined in an iterative procedure. Until recently, the PAT method was used at the Netherlands Bureau for Economic Policy

Analysis However, the this Bureau has decided to start using the Christiano-Fitzgerald filter, as the PAT method was deemed to be too cumbersome, and the determination of the turning points introduced a measure of arbitrariness into the process [Bonenkamp (2003)].

Furthermore, our study is limited to univariate techniques, in which each series is evaluated separately. Multivariate techniques model common trends and cycles in a collection of series, which leads to different interpretations of the extracted cycles.

The following notation will be used below:

$$\begin{aligned} y_t &= \text{original time series} \\ c_t &= \text{cycle} \\ s_t &= \text{seasonal component} \\ \mu_t &= \text{trend} \\ \varepsilon_t &= \text{residuals} \end{aligned}$$

the index *t* represents either months or quarters..

4.1.1 Constant, (log) linear trend

In the case of log-transformed series, the determination of the constant trend is a simple linear regression of the series on a time variable:

$$y_t = \alpha + \beta t + c_t,$$

in which α and β are unknown parameters. Thus the cycle is contained in the residuals and is not modelled explicitly. To obtain a good extraction of the cycle, it is therefore necessary to pre-filter the series to remove noise and seasonal fluctuations. This is done using a long-term moving average, the Henderson trend-cycle from the census X12 package. One disadvantage is that the stiffness of the trend increases as the time series lengthens.

4.1.2 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.

4.1.3 Beveridge-Nelson decomposition

Beveridge and Nelson (1981) show that every ARIMA(p,1,q)-process can be decomposed into a permanent and a transitory or cyclical component. The permanent component is a "random walk" with drift and the cyclical component is a stationary stochastic process of mean zero. Also, both components are driven by the same innovations. This separation of a time series into two components is called the Beveridge-Nelson decomposition.

the model is

$$\begin{aligned} y_t &= \mu_t + c_t \\ \mu_t &= \mu_{t-1}+\alpha+\varepsilon_t, \end{aligned}$$

where α is the unknown drift parameter and ε_t the i.d.d. innovations.

The so-called Beveridge-Nelson filter yields a prediction for the trend using a weighted combination of the current observation and past observations. Proietti and Harvey (2000) developed a Beveridge-Nelson "smoother", which estimates the trend using a weighted average of all observations. In this study we shall use the less cumbersome approach of Cuddington and Winters (1987). Their algorithm is:

1. Compute the series′ first differences $\Delta y_t = y_t - y_{t-1}$.
2. Apply an ARMA(p,q) model with drift to Δy_t.
3. Estimate the drift α, the ARMA parameters $\phi=(\phi_1,\ldots,\phi_p)$ and $\theta=(\theta_1,\ldots,\theta_q)$, and determine the residuals $\hat{\varepsilon}_t$ of the "best" fitting model.
4. Estimate the growth $\Delta\mu_t$ of the permanent (trend) component by: $\Delta\hat{\mu}_t=\dfrac{\hat{\alpha}}{1-\hat{\phi}_1-\ldots-\hat{\phi}_p}+\dfrac{1-\hat{\theta}_1-\ldots-\hat{\theta}_q}{1-\hat{\phi}_1-\ldots-\hat{\phi}_p}\hat{\varepsilon}_t$, where $2\le t\le T$.
5. Estimate the growth Δc_t of the cyclical component by detracting the estimated growth of the trend component from Δy_t.
6. Determine the trend and cycle by requiring the cycle to have an average of zero.

Akaike's Information Criterion (AIC), is used to determine the ARIMA model, *4.1.4 Baxter-King filter*

Baxter and King (1999) introduced a band-pass filter which is an approximation of the ideal filter for series which are integrated of order one or two and contain a deterministic trend. For an ideal filter, an infinite series is required. Baxter and King construct a filter which is optimal for series of the form:

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

where $\theta < 1$ and ε_t's i.d.d.. [Christiano en Fitzgerald (1999)]. Here, optimal is defined as minimal expected quadratic deviation between the ideal filter and the approximation for a finite series.

The Baxter-King filter is actually based on combining two low-pass filters. It is the difference between a low-pass filter with as boundary the upper frequency of the band and a low-pass filter with the lower frequency as boundary. The Baxter-King band-pass filter is symmetrical and uses the following weights:

$$w_k = \begin{cases} \dfrac{\sin(\frac{2\pi k}{p_l}) - \sin(\frac{2\pi k}{p_u})}{\pi k} - \dfrac{C}{1+2K} & \textit{for} \quad 1 \le k \le K \\ \dfrac{2}{p_l} - \dfrac{2}{p_u} - \dfrac{C}{1+2K} & \textit{for} \quad k = 0, \end{cases}$$

where

$$C = \frac{2}{p_l} - \frac{2}{p_u} + 2\sum_{k=1}^{K}\left(\sin(\frac{2\pi k}{p_l}) - \sin(\frac{2\pi k}{p_u}) \right),$$

with p_l and p_u the lower and upper boundary for the wavelength in months or quarters. For example, the band-pass filter for cycles between 2 and 10 years uses $p_l = 24$ en $p_u = 120$ for monthly data. Baxter and King recommend $K = 12$ for quarterly data and $K = 36$ for monthly data. This means that the filter uses data from three years in the past and three years into the future when determining the cycle for a certain month.

By construction, this filter runs into trouble at the last K observations. For a monthly series, it takes 36 months until the filter is able to compute a value. For practical purposes, such a lag is of course unacceptable. Two solutions have been proposed in the literature; extrapolation of the original series into the future and an adaptation of the weighting scheme. Extrapolation requires a statistical model to estimate the expected future observations. This can be done using a procedure similar to the one for the Henderson trend cycle in the Census X12 [e.g. Vollebregt (2002) and Doherty (2001)].

4.1.5 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_u 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.

4.1.6 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)

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

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

A UC model can be represented by an ARIMA process. Apart from the seasonal component, the difference with the Beveridge-Nelson decomposition is in the correlations between the innovations to the trend and cyclical components. In the Beveridge-Nelson decomposition, the estimated components are completely negatively correlated, whilst in the UC-models it is assumed that all correlations between the innovations are zero. For a comparison of the models, see Morley, Nelson and Zivot (2003). They indicate that in the case of the Beveridge-Nelson decomposition, the variance of the series is mostly attributed to the stochastic trend, whilst in the UC-decomposition it ends up in the cyclical component.

4.2 Theoretical Plausibility

Only a few examples of studies comparing multiple cycle extraction methods can be found in the literature. Most authors focus on the advantages and disadvantages of a single technique. Examples of studies comparing different methods are Canova (1998 and 1999), Zarnowitz en Ozyildirim (2002) and Bonenkamp (2003).

Canova (1998) uses both quantitative and qualitative properties to support his analysis. Quantitative properties are standard deviations, skewness, kurtosis, correlations with the reference cycle and the reaction to cyclical shocks using the impulse-response function. The qualitative, so-called stylised facts are based on economic theory. For example, consumption should be less volatile than GDP. Canova concludes that the properties of the cycles differ greatly for the different techniques. However, he immediately remarks that every technique uses different assumptions concerning the cyclical component and that these assumptions correspond to different economic concepts. Qualitative properties are very sensitive to these differences.

In another study (1999), the same author focuses on the correct detection of turning points in the GDP of the USA. He uses as reference the turning points identified by the National Bureau of Economic Research (NBER) and the Department of Commerce (DOC). Apart from the turning points, he uses several other characteristics of the cycles, such as amplitude length. Two filters, the Hodrick-Prescott and the Baxter-King filters, prove to be superior in detecting the NBER and DOC turning points.

Zarnowitz and Ozyildirim (2002) did a qualitative comparison between the NBER's PAT method and several other techniques. They conclude that the Hodrick-Prescott and Baxter-King filters give results comparable to those of PAT, but that the PAT method is superior on details. The authors have a somewhat subjective view of what the business cycle should be like, and as the PAT method contains a subjective element, it is no surprise that they judge it favourably

The Netherlands bureau for economic policy analysis) recently switched from PAT to the Christiano-Fitzgerald filter [Bonenkamp (2003), Kranendonk, Bonenkamp and Verbruggen (2003) and Bouwman (2003)]. Their choice was mainly based on the end value problem and the statistical coherence with GDP. Their analysis shows that the Christiano-Fitzgerald filter possesses the lowest sensitivity to new observations, while the cross correlation with GDP and the phase shift are comparable to those of the Baxter-King and the Hodrick-Prescott filters.

The constant trend method is in effect a linear regression of the series on time. Nelson and Kang (1981) show that such a trend suffers from spurious cycles if the series in question is a random walk. They also point out that de typical spectra of economic time series, the so-called Granger-Shape, closely resemble that of a corrected random walk.

The Hodrick-Prescott filter has been much criticised in the literature (Harvey and Jäger (1993), Guay and St-Amant (1997) and Schenk-Hoppé (2001)). The most important criticisms are the presence of spurious cycles and the sensitivity to new observations. Guay and St-Amant (1997) and Schenk-Hoppé (2001) point out that the Baxter-King filter suffers from the same problems. They conclude that both filters perform well if the spectrum of the series contains a peak which falls within the range of the cycle. However, untransformed economic time series are usually dominated by low frequencies in which case the filters will yield distorted cycles. A study by the Dutch Central Bank (DNB, De Haan and Vijselaar 1998) states that using a high λ ($1*10^6$ for monthly series) results in a cycle more representative of the business cycle as the number of cycles is reduced. An additional advantage of this much more inflexible trend is that the end value problem is reduced.

Harvey and Trimbur (2003) show that filters based on so-called Unobserved Components models belong to a class of generalised Butterworth filters, of which the Hodrick-Prescott filter is a special form. This generalisation allows filters to be compared directly and makes it possible to derive in which circumstances which filter should be preferred. They find that simple, under certain conditions ideal filters can result in spurious cycles when applied to non-stationary time series. The broad class of generalised Butterworth filters can partly resolve this by explicitly modelling the trend. Possibly because of their large variety, the Unobserved Components models are as far as we know the only method not criticised for producing spurious cycles. .

The Christiano-Fitzgerald filter mentioned earlier has not been thoroughly reviewed. It is known that asymmetric filters like the Christiano-Fitzgerald can lead to phase shifts. Furthermore, the filter uses a weighting-scheme comparable to that of the Baxter-King filter, and can therefore also be expected to produce spurious cycles when applied to a series which does not confirm to the assumptions of the filter.

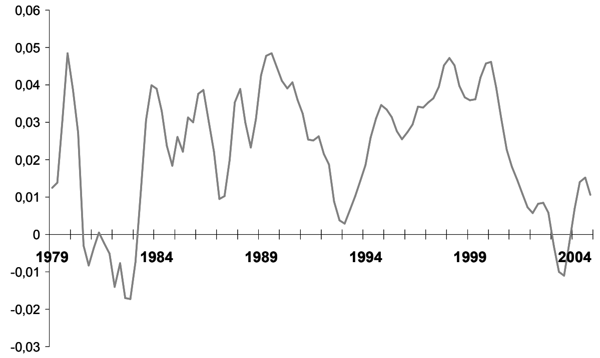
4.3 Empirical tests of cycle extraction methods

The literature reviewed in the previous section indicated that almost all cycle extraction methods, except for the Unobserved Components models, may result in so-called spurious cycles. These are cycles introduced by the filter, and not present in the original series. A few qualifying remarks are in order here. Most studies only show that spurious cycles will occur under certain specific circumstances. And even if spurious cycles are present, this does not mean that all cycles found are false. Another problem is that for certain series some filters may yield cycles which are correctly filtered out, but which are not connected to business cycle developments. Usually these cycles will be relatively short and are called mini-cycles here. For these reasons, it is necessary to experiment and test the filters on actual data and then evaluate the cycles. We shall do this by calculating the ex-post cycles for GDP and industrial production and then evaluating the resulting cycle chronology by dating and number of turning points and other business cycle characteristics. The results can be found in Section 4.3.1.

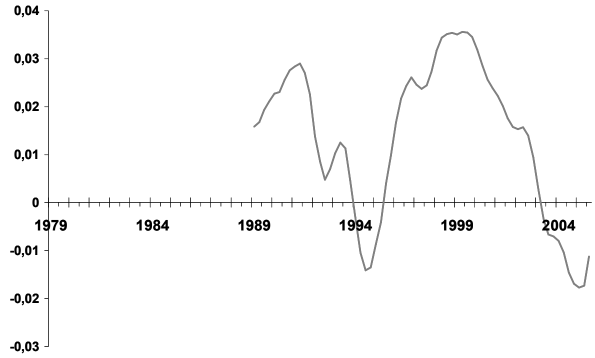
As stated before, we are trying to construct an instrument to assist in the day to day analysis of business cycle developments. This means that aspects such as clarity, stability and timeliness of the representation of the state of the business cycle are very important. In our computations, we favour parameter settings which minimise short-term small fluctuations, and thus. yield smoother cycles. However, all methods yield an approximation of the cycles as the analyses are based on a finite time series. This is especially problematic for the last few data points, as all relevant future observations are still missing. Therefore, the different filters use different methods to approximate the cycle for the most recent observations. As more 'future' data become available, the computed cycle for a certain point in time will change; this is the end value problem. Thus, the ex-post cycle at a certain point in time will usually differ significantly from the moment when this point in time was the most recent observation. This is especially relevant at turning points in the cycle, as fluctuations in the computed cycle can make analysis here very difficult. The question is how fast a certain filter identifies the turning point, and how stable this identification is. A timely identification is not very useful if the turning point has vanished again the following month. These aspects of filter performance will be evaluated in a real-time simulation in Section 4.3.2.

It is necessary, though difficult, to assess the plausibility of the extracted cycles. Here, we shall attempt to construct a rough independent benchmark for this. One possibility is to use the chronologies of other institutions, such as the OECD, as a reference. Unfortunately, these are also based on deviation cycles and are therefore unsuitable to function as independent benchmarks. Another approach is to compare deviation cycles with a different approach to business cycle analyses, the growth rates. Deviation cycles and growth rate cycles cannot be compared directly. They are different concepts which measure business cycle developments in a very different manner. However, they are linked. Sustained periods of above trend growth should be accompanied by relatively high growth rates, the reverse for below trend development. Therefore, the business cycle chronology resulting from the deviation cycles can be compared to that of the growth rates, and there should be a rough correspondence. It is important to note that growth rates will lead the deviation cycles. As mentioned in the introduction, a multi-dimensional approach to business cycle analysis is to be preferred. This means combining production data with among other things expenditure and labour market data to get a better picture of the development of the economy. The graphs below depict the year-on-year growth rates (3 period moving averages) for industrial production, household consumption, GDP, fixed capital formation and jobs of employees. These graphs give an indication of business cycle conditions in the Netherlands over time.

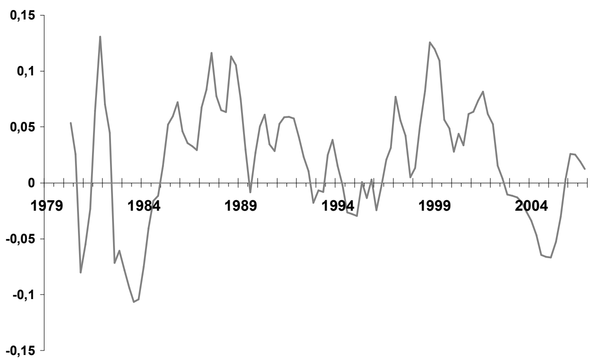
Graph 4.1; GDP



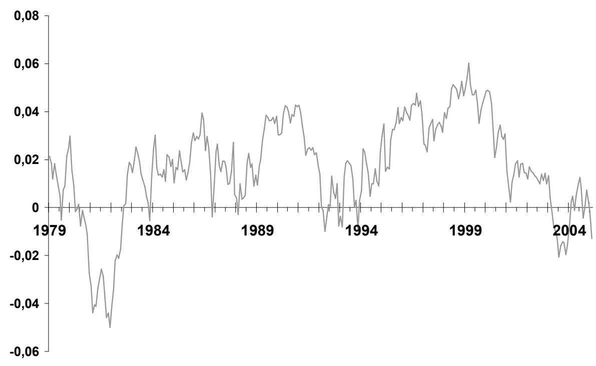
Graph 4.2; Jobs of employees



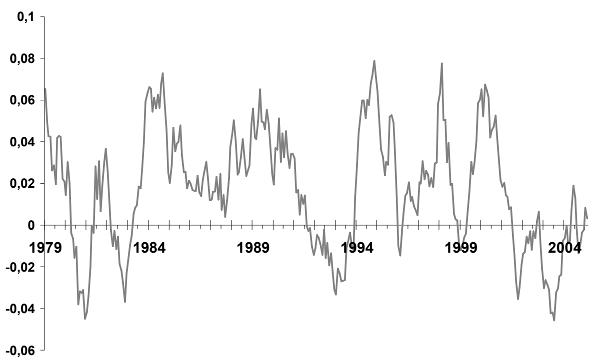
Graph 4.3; Private fixed investment



Graph 4.4; Household consumption



Graph 4.5; Industrial production



Quantities such as consumption and manufacturingindustrial production, but also to a degree fixed capital formation, are much more volatile than GDP and total hours worked. These more volatile series will probably exhibit more cycles in our analysis as well. The slower moving quantities can thus be used as a check to assess the importance of the individual cycles in series such as industrial production. When the developments in all these series are taken into account, a general pattern emerges. In the beginning of the 1980's all indicators exhibit negative growth rates. By about 1984, these are positive again. By the end of the 1980's there is a dip in growth rates, but it is shorter and GDP and industrial production growth remain positive.. For the 1990's, we can use the development in jobs as well. Industrial Production and fixed capital formation show quite a few peaks and troughs in this period. However, when considering GDP and Total Hours Worked, the picture becomes much simpler. There is an upswing until about 1990, and then a downswing lasting until 1993. This is followed by a period of varying but sustained growth until 2000. Then, a new downswing starts. The other indicators confirm this analysis, but possess some additional cycles. In this case, the lowest common denominator should be chosen, i.e. only cycles visible in all indicators should be considered. According to this analysis, very broadly the chronology of the Dutch economy in the past 25 years is as follows:

1979-1983	recession
1984-1988	recovery, higher growth
1988	short period of stagnation
1989-1992	boom
1992-1994	recession
1995-2002	boom

The business cycle chronology of the deviation cycles should not conflict with this one.

4.3.1 Empirical test of ex-post plausibility cycles

We start by computing the cycles for GDP (constant prices) and industrial production (volume index, corrected for trading days) using the different cycle extraction methods. GDP is at constant prices and for industrial production the volume index corrected for trading days is used. We chose these two series as test-subjects because they are the individual series most representative of the business cycle. Therefore, their cycles represent a basis for a business cycle chronology. The first approach we use to test the plausibility of our extracted cycles is to compare the cycles found by the various filtering methods with each other. As filtering methods based on very different principles are used, clear similarities between the resulting cycles offer support for their authenticity.

In table 4.1 the cycle extraction methods used in these tests are listed, together with the most relevant parameters.

Table 4.1; Set-ups for different cycle extraction methods

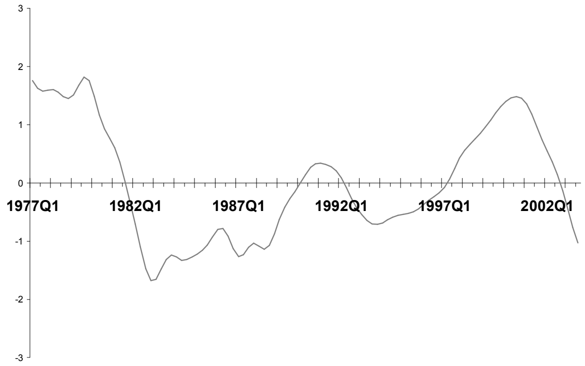
Filter	*parameters*
Christiano-Fitzgerald	Bandwidth 2-11 years, integrated series
Hodrick-Prescott	λ=1600/14400 quarterly/monthly, prefiltered = preliminary smoothing by Henderson trend cycle.
Hodrick-Prescott inflexible	λ=50000/1000000 quarterly/monthly, prefiltered = preliminary smoothing by Henderson trend cycle.
Constant logarithmic trend	Trend determination by Linear regression on logarithm of Henderson trend cycle
Baxter-King	Trend=24
Beveridge-Nelson	Model=(2,1,2)
Unobserved components	Local linear trend, fixed slope with seasonal component and two cycles

What we have termed the Hodrick-Prescott inflexible variant, or quasi-constant trend method, was included as a study of the Dutch Central Bank. De Haan and Vijselaar (1998) state that it has desirable properties. The high value of λ results in a trend which changes only slowly. This is probably a more realistic reflection of economic reality than a very flexible trend. It results in fewer cycles and a reduced end value problem.

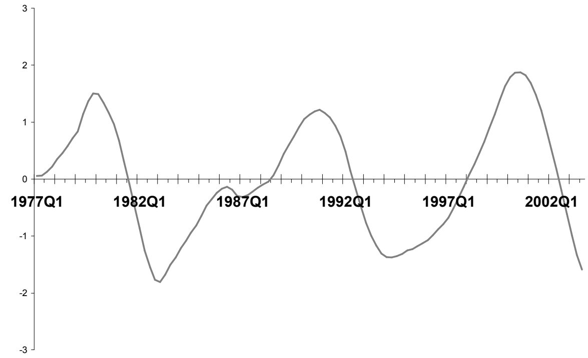
To estimate the unobserved components models, we used the STAMP package (5.0). (Koopman, Harvey, Doornik and Shephard (1995), Koopman, Doornik and Shephard (1997)).The package optimises the log-likelihood function using a quasi-Newton method, and we used the Kalman smoother to reconstruct the components. The specific UC-model and the number of cycles and cycle length were selected using log-likelihood and prediction error variance.

The cycles found by the various methods for GDP and industrial production are depicted below. Graphs 4.8 and 4.9 show all the different cycles together. Although they may seem confusing at first, they are instructive in that they show to what extent the cycles are similar, and to what extent they differ.

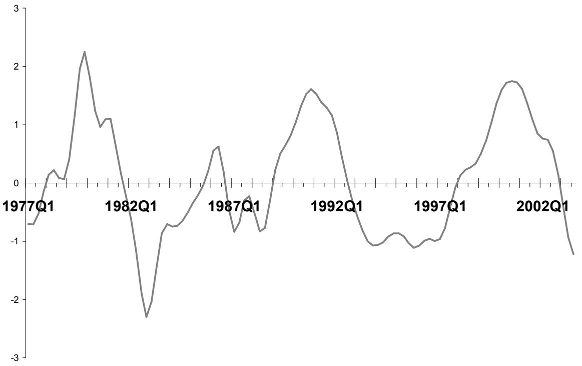
Graph 4.6a; GDP cycle Constant logarithmic trend



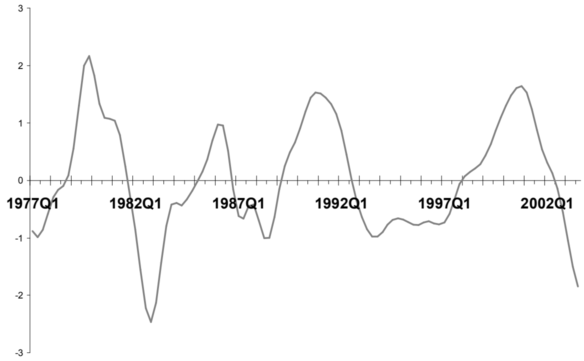
Graph 4.6b; GDP cycle Unobserved Components (LLT-FS, 2 cycle)



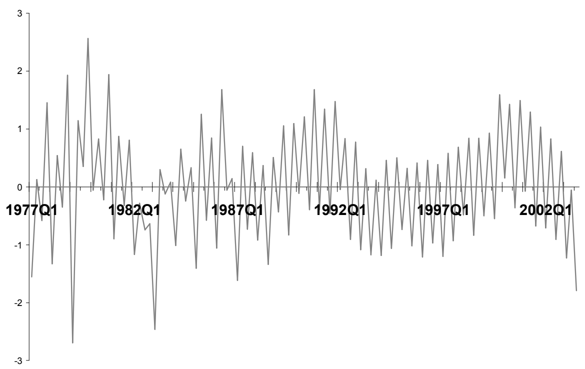
Graph 4.6c; GDP cycle Hodrick-Prescott inflexible(50000)



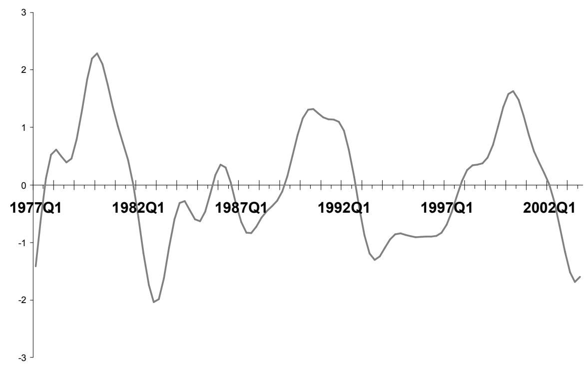
Graph 4.6d; GDP cycle Hodrick-Prescott (1600, pre-filtered)



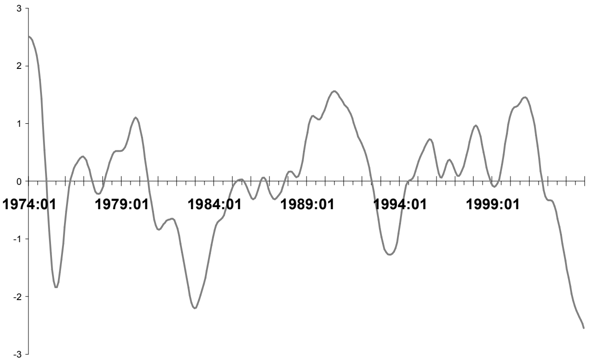
Graph 4.6e; GDP cycle Hodrick-Prescott (standard, 1600)



Graph 4.6f; GDP cycle Christiano-Fitzgerald

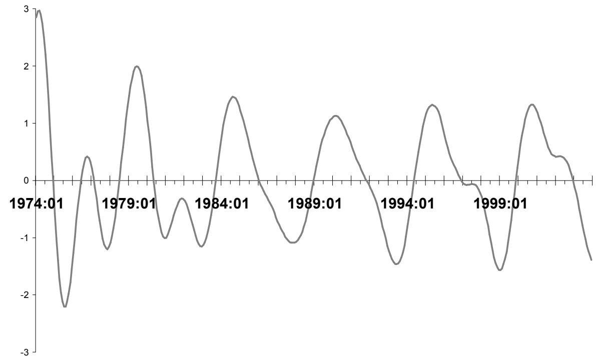


Graph 4.7a; Cycle Industrial Production Constant logarithmic trend

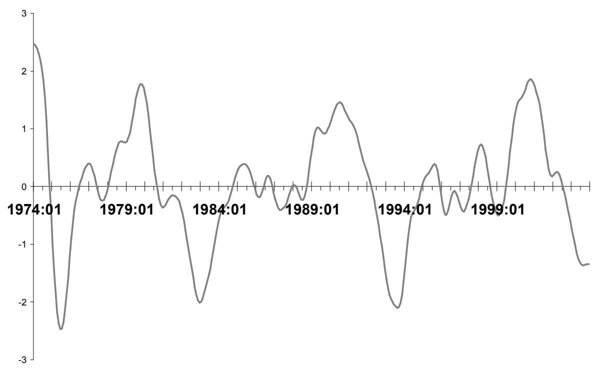


Graph 4.7a; Cycle Industrial Production Unobserved Components

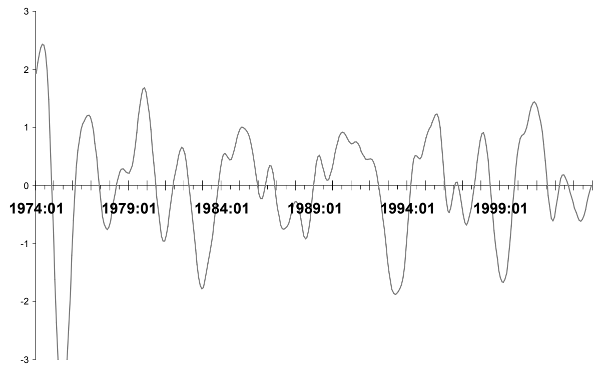
(LLT-FS, 2 cycles)



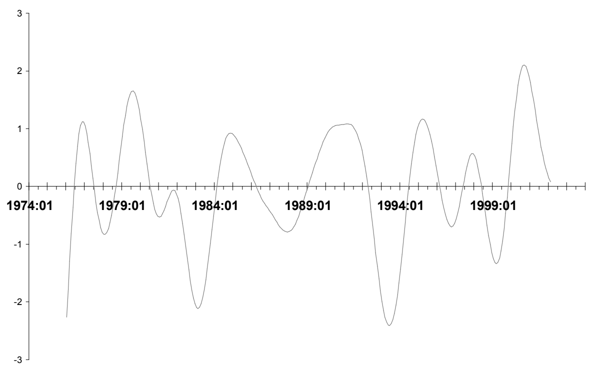
Graph 4.7c; Cycle Industrial Production Hodrick-Prescott inflexible (1M)



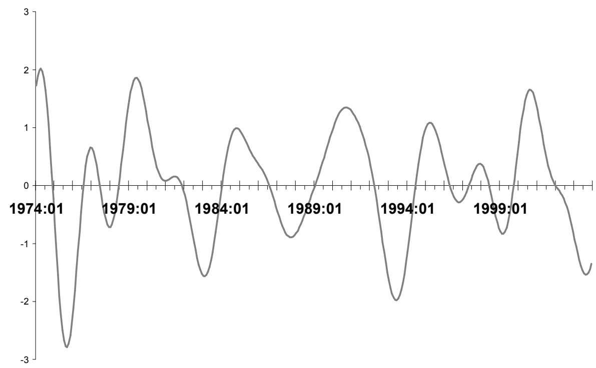
Graph 4.7d; Cycle Industrial Production Hodrick-Prescott (14400)



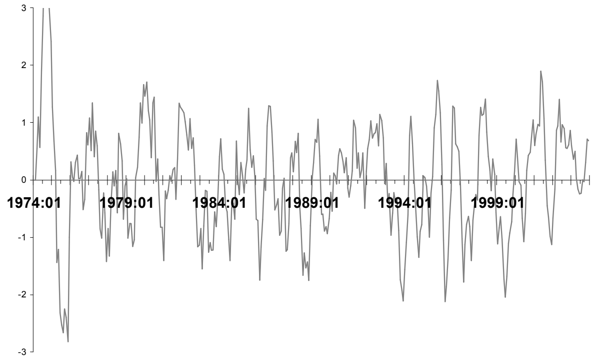
Graph 4.7e; Cycle Industrial Production Baxter-King filter



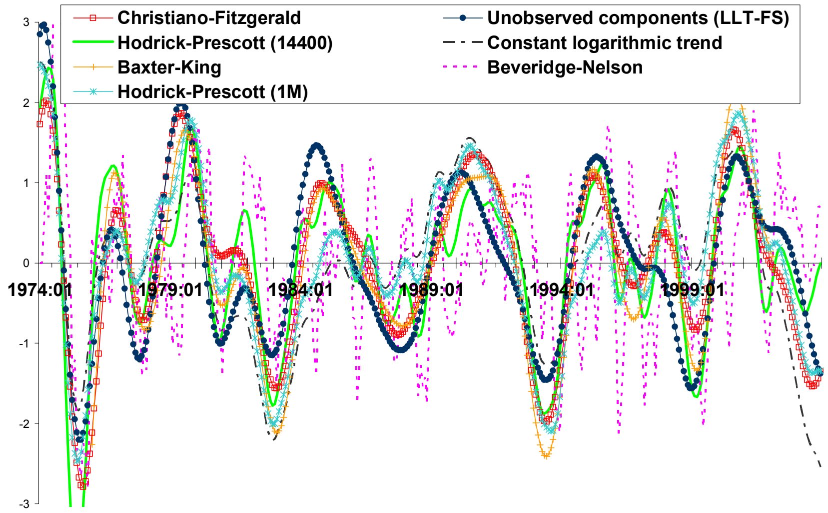
Graph 4.7f; Cycle Industrial Production Christiano-Fitzgerald



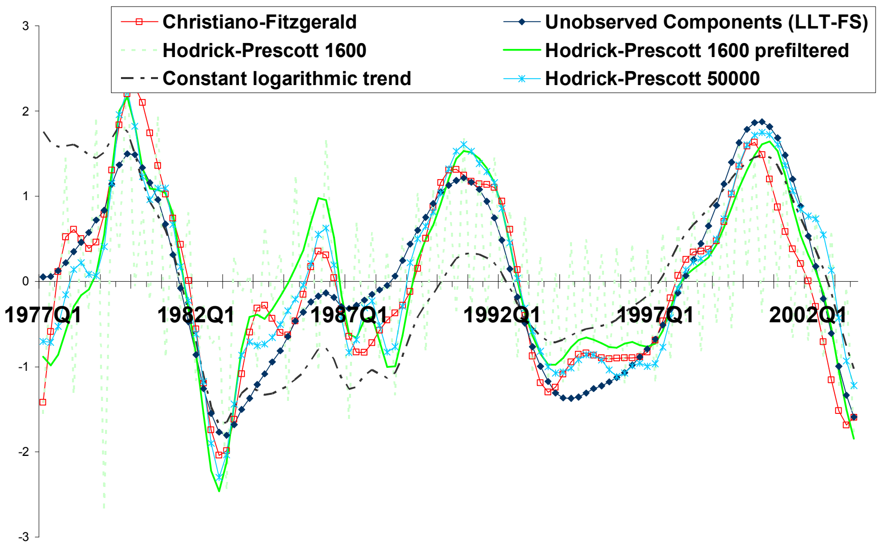
Graph 4.7g; Cycle Industrial Production Beveridge-Nelson



Graph 4.8; Cycles for the index of industrial production resulting from the different extraction methods.



Graph 4.9; Cycles for GDP resulting from the different extraction methods.



The results differ somewhat between GDP and Industrial production. For GDP, apart from one deviating case (Hodrick-Prescott without pre-filtering), the different methods yield cycles of very similar shape and periodicity. The cycles computed for industrial production differ more. Some filters show one or two additional small cycles and there are clear differences in amplitude at various moments. The more volatile nature of Industrial production clearly brings out the differences between the cycle extraction methods. The main difference is in the treatment of the weaker cycles in Industrial production. The constant trend method and the inflexible Hodrick-Prescott largely suppress these, while they are much stronger in the results from the Christiano-Fitzgerald, Baxter-King and standard Hodrick-Prescott filters. The cycle of the unobserved components model is somewhere in between. Some of these weaker cycles in Industrial production should be classified as mini-cycles, as they are absent or much weaker in other important indicators.

Overall, however, for example in turning points and as far as periods of increase or decrease are concerned, there is marked overall agreement. The cycles are rather similar, especially for GDP, but also for the major cycles in Industrial production. To support this analysis, we analysed several properties of the cycles to elucidate differences and similarities. The first are the cross-correlations of the GDP cycles (table 4.2), which confirm the overall similarities. The correlations are generally high, without leads or lags, i.e. the cycles are on average not shifted in time relative to each other.

Table 4.2; Cross-correlations cycles GDP for different cycle extraction methods.

Filter	*CF*	*CT*	*HP1600*	*HP50000*	*UC*
CF	-				
CT	**0.7(0)**	-			
HP1600	**0.9(0)**	**0.6(0)**	-		
HP50000	**0.9(0)**	**0.7(0)**	**0.96(0)**	-	
UC	**0.9(0)**	**0.8(0)**	**0.9(0)**	**0.9(0)**	-

CF= Christiano-Fitzgerald filter, CT= Constant logarithmic trend, HP1600=standard Hodrick-Prescott filter, HP50000 = inflexible Hodrick-Prescott filter, UC= unobserved components model

Correlations are long-term, average properties. It is therefore also important to compare the cycles at specific moments in time. The most important individual moments in business cycle analysis are turning points, i.e. the peaks and troughs in the cycle. Strong disagreement on the dates of these turning points would indicate that some or all of the cycles lack credibility. The number of turning points is important as well, as it is linked to the number of individual cycles a filtering method yields. Here, we define a turning point as a maximum or minimum of the cycle, but only if the trend has been passed since the last maximum/minimum. With some arbitrariness, cycles of relatively small amplitude are classified as minor or sub-cycles. Very small fluctuations around the trend were ignored.

Table 4.3; Peaks and troughs in GDP for different cycle extraction methods. Minor-cycles in parentheses.

Filter	*Peaks*	*No. of peaks*	*Troughs*	*No. of troughs*
CF	**1980Q1**, (1986Q1,) **1990Q3, 2000Q2**	**3**(4)	**1982Q4**, (1987Q3,) **1993Q3, 2003Q2**	**3**(4)
CT	**1979Q3, 1991Q1, 2000Q3**	**3**	**1982Q4, 1993Q4**	**2**
HP1600	**1979Q4, 1986Q1, 1990Q4, 2000Q4**	**4**	**1977Q2, 1982Q4, 1987Q2, 1993Q4,**	**4**
HP50000	**1979Q3,** (1986Q1,) **1990Q3, 2000Q2**	**3**(4)	**1982Q3,** (1986Q4,) **1993Q4**	**2**(3)
UC	**1979Q4, 1990Q4, 2000Q3**	**3**	**1983Q1, 1994Q2**	**2**

CF= Christiano-Fitzgerald filter, CT= Constant logarithmic trend, HP1600=standard Hodrick-Prescott filter, HP50000 = inflexible Hodrick-Prescott filter, UC= unobserved components model

For the GDP-cycle, most filter extraction methods yield the same number of (major) cycles, about three in the period considered. The turning points are usually within one quarter of each other, as can be seen in table 4.4.

Table 4.4; Dating of most important turning points in GDP by cycle extraction method.

Filter	*Peak 1979*	*Trough 1983*	*Peak 1990*	*Trough 1993*	*Peak 2000*
CF	**1980Q1**	**1983Q3**	**1990Q3**	**1993Q3**	**2000Q2**
CT	**1979Q3**	**1983Q3**	**1991Q1**	**1993Q4**	**2000Q3**
HP1600	**1979Q4**	**1983Q3**	**1990Q4**	**1993Q4**	**2000Q4**
HP50000	**1979Q3**	**1982Q3**	**1990Q3**	**1993Q4**	**2000Q2**
UC	**1979Q4**	**1983Q1**	**1990Q4**	**1994Q2**	**2000Q3**

From these turning point dates, two interesting characteristics of the business cycle can be computed; the average length of the business cycle (peak-peak or trough-

trough) and the average length of the upswing (trough-peak) and the downswing (peak-trough). As expected from the turning point dates, there is not much difference between the filters in the average cycle length.

Table 4.5; Average cycle length and duration of upswings and downswings in GDP for different cycle extraction methods.

Filter	*Cycle length peak-peak*	*Cycle length trough-trough*	*Length peak-trough (downswing)*	*Length trough-peak (upswing)*	*Ratio downswing/ upswing*
CF	**10Y**	**10Y**	**3Y**	**7.5Y**	**0.41**
CT	**10.5Y**	**10Y**	**3Y**	**7.5Y**	**0.4**
HP1600	**10.5Y**	**10Y**	**3Y**	**3.5Y**	**0.79**
HP50000	**10Y**	**11Y**	**3Y**	**7Y**	**0.43**
UC	**10.5Y**	**11Y**	**3.5Y**	**7Y**	**0.48**

According to these results, the length of the business cycle in the Netherlands over the past thirty years is on average a little over ten years. In a cycle, the downswing takes less than half the time of the upswing, confirming the well-known phenomenon that contractions are usually sharper than expansions. The ratio of the duration of the downswing to that of the upswing is a little over 0.4 for all filters, except the standard Hodrick-Prescott filter. Therefore on several important cyclical characteristics, there is clear agreement between most methods.

The situation is slightly more complex for the index of production, as this indicator is more volatile and results in more cycles, as is clearly visible in tables 4.6 and 4.7.

Table 4.6; Peaks and troughs in Index of industrial production for different cycle extraction methods. Mini cycles in parentheses.

Filter	*Peaks*	*No. of peaks*	*Troughs*	*No. of troughs*
CF	**74/3,** (76/11)**, 79/5, 84/10, 90/8, 95/3,** (97/11), **00/7**	**6**(8)	**75/8,** (77/11)**, 83/1, 87/9, 93/5,** (96/10), **93/2, 99/1, 03/7**	**7**(9)
CT	**73/12**, (76/11), **79/9, 90/6**, (98/1), **00/9**	**4**(6)	**75/6,** (77/9), **82/11, 93/7,** (99/1),	**3**(5)
HP14400	**74/5, 76/10, 79/10**, (81/10), **85/2,** (86/7), **90/7, 95/7, 98/1, 00/10,**	**8**(10)	**75/5, 77/10,** (80/11)**, 82/11,** (86/1), **88/6, 93/4, 97/3, 99/1,** (01/10,) (03/04)	**7**(11)
HP1M	**73/12,** (77/8), **79/10,** (85/3), (86/7), (87/12), **90/5**,(95/7,) (98/1), **00/9**	**4**(10)	**75/5**, (77/8), **82/11,** (86/2,) (87/3,) (88/6), **93/7,** (96/2), (99/1), **03/8**	**4**(10)
UC	**74/2,** (76/8), **79/5, 84/7, 90/3, 95/4, 00/8**	**6**(7)	**75/7,** (77/10), **83/1, 87/10, 93/5, 98/12**	**5**(6)
BK	**76/10, 79/7, 84/10, 91/2, 95/2**, (97/11), **00/8**	**6**(7)	**78/1, 83/1, 87/11, 93/5,** (96/9), **99/2**	**4**(6)

CF= Christiano-Fitzgerald filter, CT= Constant logarithmic trend, HP14400=standard Hodrick-Prescott filter, HP1M = inflexible Hodrick-Prescott filter, UC= unobserved components model, BK = Baxter-King filter

Table 4.7; Dating of most important turning points in Industrial production by cycle extraction method. (Major turning points in bold)

Filter	***P74***	***T75***	***P79***	***T83***	*P84*	*T87*	***P90***	***T93***	*P95*	*T99*	***P00***
CF	**74/3**	**75/8**	**79/5**	**83/1**	84/10	87/ 9	**90/8**	**93/2**	95/3	99/1	**00/7**
CT	**73/12**	**75/6**	**79/ 9**	**82/11**	-	-	**90/6**	**93/7**	-	-	**00/ 9**
HP14400	**74/5**	**75/5**	**79/10**	**82/11**	85/ 2	88/6	**90/7**	**93/4**	95/7	99/1	**00/10**
HP1M	**73/12**	**75/5**	**79/10**	**82/11**	85/3	87/3	**90/5**	**93/7**	95/7	99/1	**00/11**
BK	**76/ 10**	**78/1**	**79/7**	**83/1**	84/10	87/11	**91/2**	**93/5**	95/2	99/2	**00/8**
UC	**74/2**	**75/7**	**79/7**	**83/1**	84/7	87/10	**90/3**	**93/5**	95/4	98/12	**00/8**

CF= Christiano-Fitzgerald filter, CT= Constant logarithmic trend, HP14400=standard Hodrick-Prescott filter, HP1M = inflexible Hodrick-Prescott filter, UC= unobserved components model, BK = Baxter-King filter

For this indicator, there is more discrepancy in the number of cycles identified in the period 1974-2003. The Christiano-Fitzgerald and Hodrick-Prescott filters in particular tend to identify more turning points, though for the latter method this is reduced by using a much larger value for λ (the inflexible variant). But as with GDP, all filters identify the same major turning points, usually within three months of each other. The main differences are in the dating of the weaker cycles.

If we consider only those peaks and troughs we classify as part of the major cycle, the different cycle extraction methods yield very similar results, both in average cycle length and in turning point dating. If we consider all the cycles, cycle length decreases sharply and the similarities between the different filters diminish. This is not surprising given the fact that the additional cycles are weaker, and therefore harder to detect, than what we consider to be the major cycles. But even for these cycles there is much similarity. The same conclusions hold for the analysis of upswing and downswing durations. If we only consider the major cycle, the results for the different methods are similar. The same ratio between downswing and upswing duration is found, the former lasting less than half the time of the latter. When the mini cycles are included in the analysis, the results vary much more.

Table 4.8; Average cycle length of Industrial production cycle according to the different cycle extraction methods. Both for major cycles only and if all observed cycles are included.

Average cycle length (Years)	***Peak-peak only major cycle***	***Trough-trough only major cycle***	***Peak-peak major and minor cycles***	***Trough-trough major and minor cycles***	***Peak-trough (upswing) only major cycle***	***Trough - peak (down-swing) only major cycle***	***Ratio down-swing/ upswing***	***Peak-trough (upswing) major and minor cycles***	***Trough - peak (down-swing) major and minor cycles***	***Ratio length down-swing/ upswing***
CF	**8.7Y**	**8.8Y**	**5.4Y**	**5.9Y**	**2.5Y**	**6.3Y**	**0.4**	**2.8Y**	**2.4Y**	**1.2**
CT	**8.9Y**	**9.0Y**	**8.0Y**	**9.0Y**	**2.6Y**	**6.3Y**	**0.41**	**2.6Y**	**6.3Y**	**0.41**
HP14400	**8.8Y**	**9.0Y**	**5.3Y**	**5.9Y**	**2.3Y**	**6.5Y**	**0.35**	**2.6Y**	**2.7Y**	**0.97**
HP1M	**8.9Y**	**9.1Y**	**5.3Y**	**5.9Y**	**2.6Y**	**6.3Y**	**0.41**	**2.7Y**	**2.5Y**	**1.1**
BK	**7.9Y**	**7.7Y**	**4.8Y**	**5.3Y**	**2.3Y**	**5.6Y**	**0.42**	**2.8Y**	**2Y**	**1.48**
UC	**8.8Y**	**8.9Y**	**5.5Y**	**5.9Y**	**2.8Y**	**6.1Y**	**0.45**	**3Y**	**2.3Y**	**1.33**

CF= Christiano-Fitzgerald filter, CT= Constant logarithmic trend, HP14400=standard Hodrick-Prescott filter, HP1M = inflexible Hodrick-Prescott filter, UC= unobserved components model, BK = Baxter-King filter

For industrial production by itself, the division into major- and mini-cycles is somewhat arbitrary. The distinction was made by taking into consideration the amplitude of the peaks and troughs and by considering the cycles observed in indicators such as GDP and Total Hours Worked. It seems that Industrial production is more cyclical than the economy as a whole.

The correspondence between the cycles identified for GDP and production and the approximate business cycle chronology constructed before based on growth rates is quite good. Periods of high overall growth can be matched with periods of above trend development, and conversely, periods of low growth match periods of below trend development. All GDP turning points can be placed in the middle of relevant periods of business cycle development. The same goes for the corresponding turning points in Industrial production, although this indicator possesses some additional cycles.

	Growth rate classification	Corresponding turning point from cycles
1979-1983	recession	peak 1979, trough 1983
1984-1988	recovery, higher growth	trough 1983
1988	short period of stagnation	peak 1987 (IP)
1989-1992	boom	peak 1990
1992-1994	recession	trough 1993
1995-2002	boom	peak 2000

The chronologies are sufficiently similar to offer additional credibility to the cycles found.

It is now possible to come to several important conclusions. Broadly speaking there is substantial similarity between the cycles resulting from the different extraction methods. The correlations are generally high, without leads or lags. Also, there is approximately broad consensus on the dating of the major turning points and several cycle characteristics such as cycle length and duration of upswings and downswings. As the cycle extraction methods considered here are based on very different principles, this makes it very unlikely that the turning points are purely an artefact of the filters. One problem is still the fact that certain filters yield cycles which are either absent or unimportant in other methods; the Christiano-Fitzgerald and the standard Hodrick-Prescott filters suffer most from this. But given the differences in methods and concepts, this was to be expected. As mentioned in the literature, using a very large value for λ reduces this problem for the Hodrick-Prescott method. We consider it premature to discard these filters based on these grounds. This is different for the Beveridge-Nelson and Baxter-King methods. The Beveridge-Nelson method did not give a satisfactory decomposition, and the missing observations problem of the Baxter-King filter makes it unsuitable for practical use. It is also clear that the Hodrick-Prescott filter needs a preliminary filtering step to remove erratic and seasonal fluctuations. For this, the Henderson trend cycle from the Census X12 program was used.

4.3.2 Real-time performance of cycle extraction methods

In this section we shall evaluate how much uncertainty there is in the real-time cycle computations of the different cycle extraction methods. As mentioned before, all methods suffer from the end value problem. For an accurate computation of the cycles of the last observations, future observations are necessary, and as these are unavailable, an approximation is needed. This will lead to revisions as more data become available. In this section we shall quantify how sensitive each method is to this problem.

To test this important aspect of filter performance, we performed a quasi real-time simulation of the identification of two major turning points in the cycle; the peak in 1990 and the trough in 1993., Revisions have their potentially greatest impact at major turning points in the cycle, and timely and reliable identification is important. The exercise was performed on the index of industrial production using the remaining five cycle extraction methods; the Christiano-Fitzgerald filter (2 to 11 years), the standard Hodrick-Prescott filter (λ=144000), the inflexible Hodrick-Prescott filter (λ=1000000), the unobserved components model (local linear trend with fixed slope, seasonal effects and two cycles (2.6 and 5.9 years)), and lastly the constant logarithmic trend. Starting at respectively 1990:1 and 1993:1, for each method, the cycle was computed, the series lengthened by one month and the cycle computed again. This process was repeated twelve times. The Hodrick-Prescott and constant trend methods use data pre-filtered using the Henderson trend cycle from Census X-12 (h=17). This was also computed month by month. This approach is quasi real-time as we use final data (without revisions), which were of course not available at the time itself.

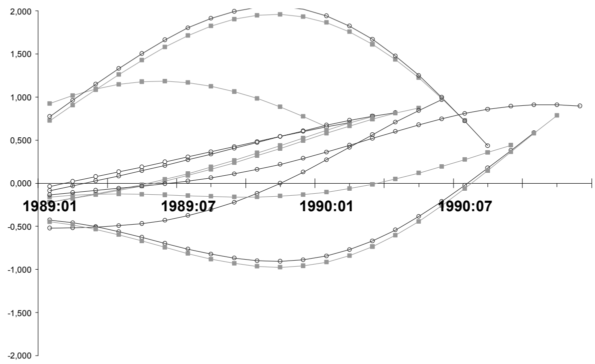
For each method, the average absolute revision for each month in the simulation range was computed.

$$\mathrm{Re}\,vision = \frac{\sum_{i=0}^{n} \left| Cycle_{t|t+i} - Cycle_{t|t+i-1} \right|}{n}$$

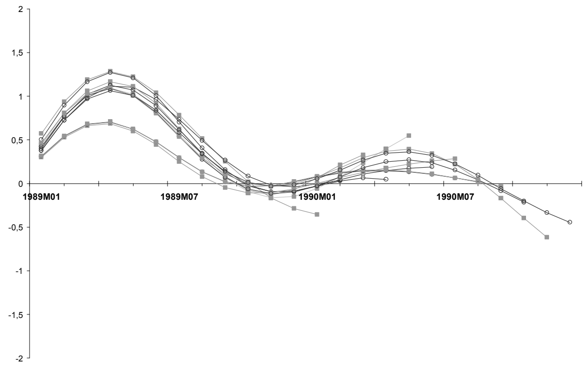
This is a measure for how sensitive a cycle extraction method is for new data. A larger average revision means a noisier representation of the business cycle. Also, it was determined when the turning points were securely identified, compared to the ex-post dating. The results are presented in table 4.9, and the graphs of the simulated cycles are shown below.

Graph 4.10; Real time behaviour of different cycle extraction methods at 1990peak in Industrial production.

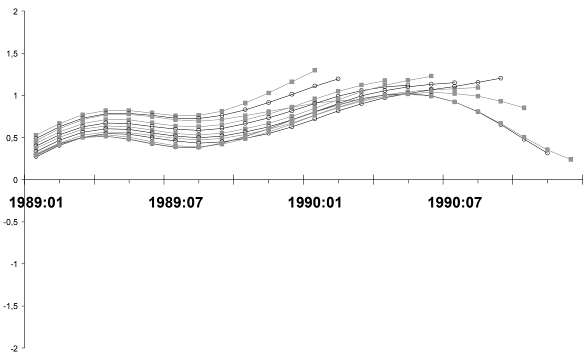
Graph 4.10a; Christiano-Fitzgerald filter



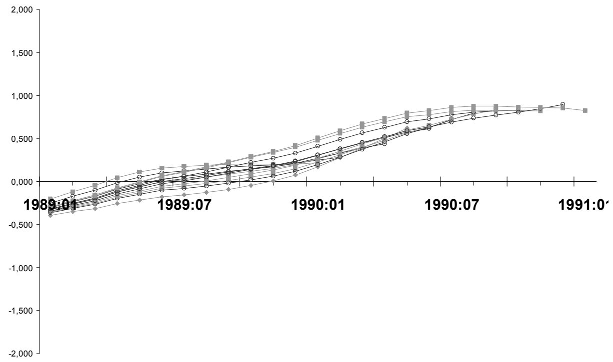
Graph 4.10b Hodrick-Prescott filter (pre-filtered, 14400)



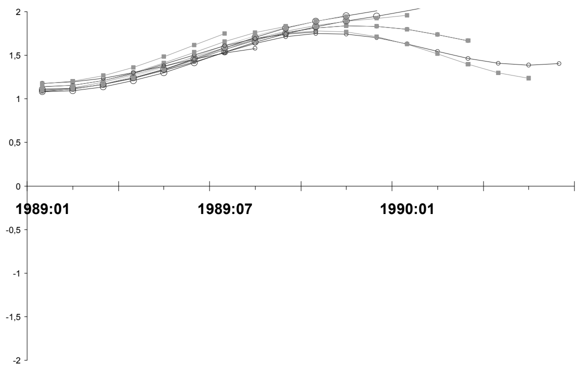
Graph 4.10c; Hodrick-Prescott filter (pre-filtered, 1M)



Graph 4.10d; Unobserved components (LLT-FS, 2 cycles)

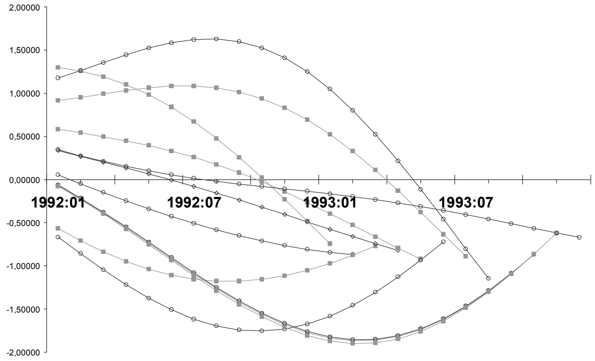


Graph 4.10e; Constant logarithmic trend

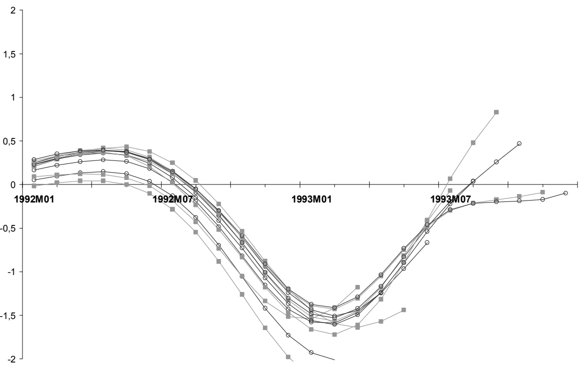


Graph 4.11; Real time behaviour of different cycle extraction methods at 1993 trough in Industrial production.

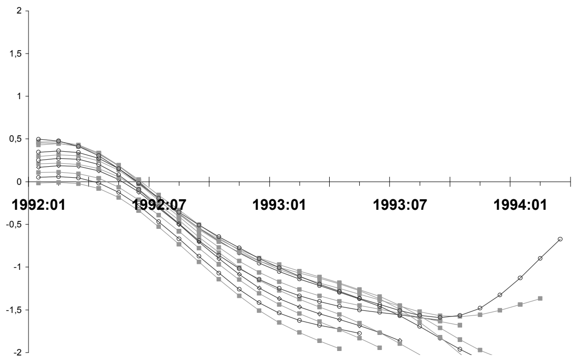
Graph 4.11a; Christiano-Fitzgerald filter



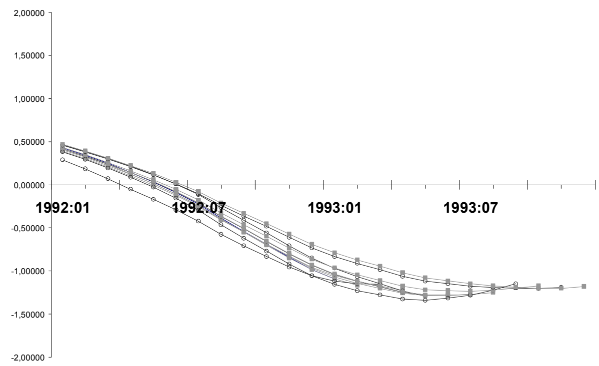
Graph 4.11b Hodrick-Prescott filter (pre-filtered, 14400)



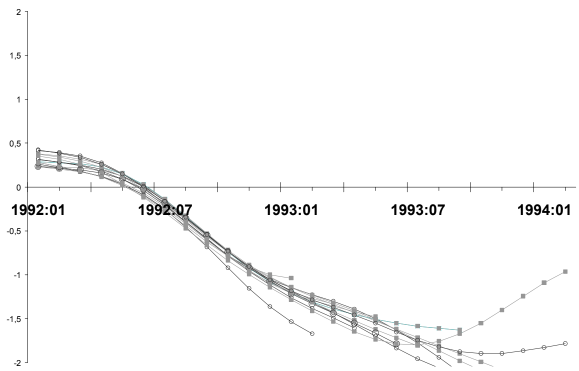
Graph 4.11c; Hodrick-Prescott filter (pre-filtered, 1M)



Graph 4.11d; Unobserved components (LLT-FS, 2 cycles)



Graph 4.10e; Constant logarithmic trend



The graphs show that end value revisions can have a serious impact. The average revisions are not negligible. These effects are quantified in table 4.9. The unobserved components, inflexible Hodrick-Prescott and the constant logarithmic trend scored best on this aspect. They give the most stable results. On the other hand, more flexible techniques like Christiano-Fitzgerald and standard Hodrick-Prescott seem at times to be able to identify turning points faster. But their stronger sensitivity to new data can at times result in a wildly fluctuating view on the state of the cycle.

Table 4.9; Results of tests for end value problem of different cycle extraction methods: average revisions and turning point detection

Cycle Extraction Method	*Average revisions peak 1990*	*Date of stable identification of turning point (ex-post date)*	*Average revisions trough 1993*	*Date of stable identification of turning point (ex-post date)*
CF	**0.461**	**1990:12** (1990:9)	**0.602**	**1993:12** (1993:3)
HP 14400	**0.090**	**1990:9** (1990:8)	**0.157**	**1993:3** (1993:5)
HP 1M	**0.066**	**1990:10** (1990:6)	**0.108**	**1994:2** (1993:8)
UC	**0.071**	**1991:1** (1990:2)	**0.084**	**1993:6** (1993:8)
CT	**0.052**	**1990:10** (1990:7)	**0.104**	**1994:2** (1993:8)

CF= Christiano-Fitzgerald filter, CT= Constant logarithmic trend, HP14400=standard Hodrick-Prescott filter, HP1M = inflexible Hodrick-Prescott filter, UC= unobserved components model

4.4 Summary and conclusions of cycle extraction methods

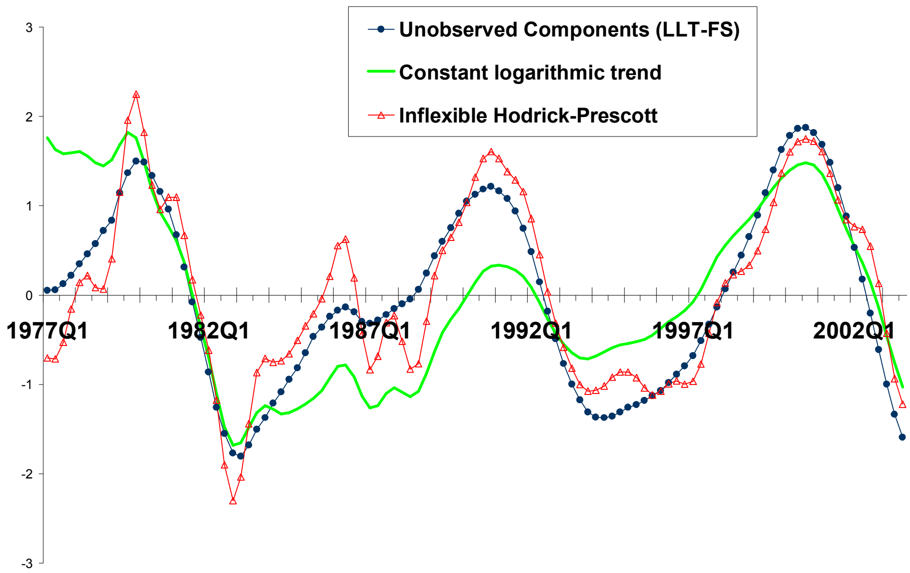
The theoretical literature shows that almost all cycle extraction methods may yield spurious cycles under certain circumstances. Whether this is a problem in practice is unclear, but not unlikely. A notable exception is the unobserved components model, of which no theoretical drawbacks are known in this respect. It is based on different principles from the other methods, fully formalising the cycle determination process, and therefore preferable from a theoretical point of view.

It is therefore interesting that the majority of the methods yield very similar ex-post cycles, both for GDP and Industrial production. There is broad agreement on the dates of the major turning points and on the average length of the business cycle. The cross-correlations between the different GDP cycles were generally high. Some filters, notably the standard Hodrick-Prescott, exhibited excess cycles, but overall there was good agreement on the cycle chronology. An exception was the Beveridge-Nelson method, which produced very aberrant results and was therefore dropped. At this point in the study, we decided to drop the Baxter-King filter as well, as it loses too many observations for practical use.

The next stage was to test the real-time behaviour of the filters, focusing on revisions due to the end value problem and real-time turning point detection. In our view the somewhat erratic behaviour of the Christiano-Fitzgerald filter renders it unfit for practical, day-to-day business cycle analysis. The verdict on the standard Hodrick-Prescott method is not so straightforward. Although it does suffer from relatively large revisions, it is very good in identifying turning points in real-time. However, combined with its theoretical drawbacks, i.e. the tendency to yield excess cycles, there are enough reasons to reject this method as well.

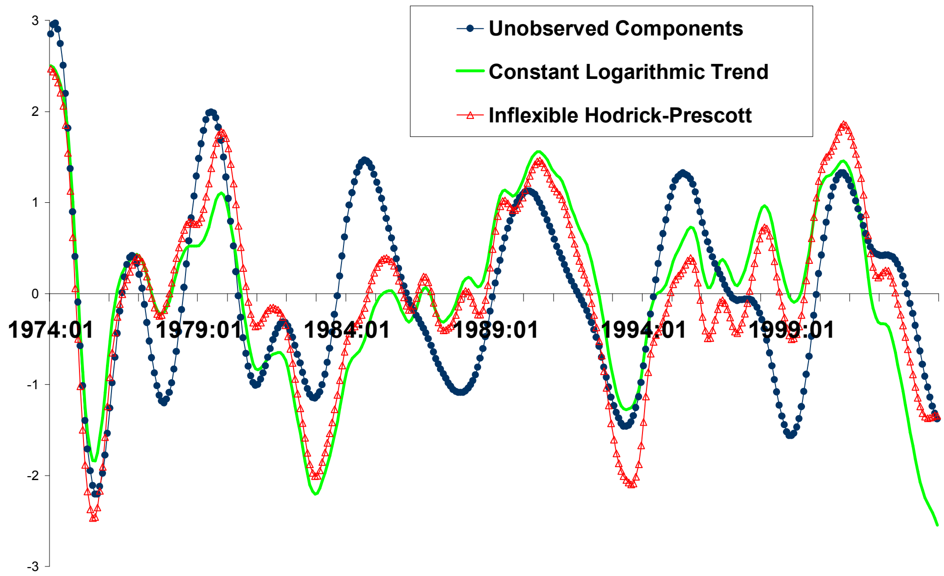
Therefore, we are left with the unobserved components method, the inflexible Hodrick-Prescott and the constant logarithmic trend. As discussed above, there are theoretical objections against the two latter methods. As far as we know, the unobserved components method does not suffer from this problem. Therefore it is important that broadly speaking, the cycles from these three methods are rather similar (graphs 4.12 and 4.11), although the Hodrick-Prescott method does yield somewhat more cycles than the others. Additional evidence for the general similarities of the cycles can be found in Appendix III: statistics measuring the average concordance between cycles of several additional characteristics.

Graph 4.12; GDP-cycle according to unobserved components model, constant logarithmic trend, and inflexible Hodrick-Prescott filter.



One drawback of the constant trend method is that it is constant. Over periods of several decennia, a constant trend is economically speaking very unlikely. It also tends to deform the cycles somewhat. However, the unobserved components method is difficult to implement in a practical production system and more research is needed to decide whether a univariate or multivariate set-up is preferable. Therefore, we feel that for now the inflexible Hodrick-Prescott method has the most attractive combination of properties. Its real-time behaviour is good, and its cycles possess strong similarities to the UC cycles. Its trend does change slowly over time, which is plausible from a theoretical standpoint.

Graph 4.13; Industrial production cycle according to unobserved components model, constant logarithmic trend, and inflexible Hodrick-Prescott filter.



5. Indicator Selection

The Statistics Netherlands Business Cycle Tracer has to be able to present an accurate reflection of the current state of the economy at any point in time. This requires a balanced set of indicators which gives an undistorted and timely picture of the state of the business cycle. To achieve this, we formulated a number of criteria for the selection of the indicators. These are very similar to standard approaches from the literature, such as Marcellino (2004), Boehm (2001) and Phillips (2003). We dropped the rather strict requirement that indicators should not be subject to revisions, as this would exclude a number of very important indicators. Our criteria can be divided into criteria for the individual indicators and criteria for the set as a whole.

Criteria for individual indicators:

- Strong enough theoretical grounds for inclusion
- A sufficiently strong and timely relation with the business cycle

  This means it must possess a minimum correlation of ±0.5 with the reference GDP-cycle at a maximum lead or lag of about six months
- Timely detection of major turning points in the business cycle (within about six months, before or after)
- No or a very small number of cycles unrelated to the general business cycle (minor cycles)
- A sufficiently long time series should be available

Criteria for the indicator set as a whole

- All major aspects of the economy should be represented (i.e. production, consumption, trade, labour markets, confidence indicators)
- The set should be balanced, no one aspect of the economy or type of indicator should dominate the Business Cycle Tracer. This will prevent non-general developments distorting the analysis.
- The whole system should be roughly coincident with the business cycle
- Major turning points in the cycle should be detected timely and reliably

We use the GDP cycle as the reference cycle, assuming that it reflects the (unobservable) business cycle. This is an imperfect measure of the business cycle (Stock and Watson 1988). As the business cycle is unobservable, it is best to base its analysis on several indicators, but GDP is the best individual indicator of the business cycle. It is more practical to use in a study like this than a multi-dimensional approach. Note that we do not require the indicators to be lagging, leading or coincident. We aim for a mix of leading, coincident and lagging indicators, which should result in a stable representation of the business cycle, which is still sensitive enough to register important new developments.

As a first step the individual indicators are scored on the first set of criteria mentioned above. Thus, individual indicators eligible for inclusion in the system can be selected. For each indicator, the maximum correlation (including lag) of its cycle with the GDP cycle was computed. Furthermore, it was determined whether and how fast the indicators detected the major turning points in 1990, 1994 and 2000. Lastly, the indicators were checked for the presence of idiosyncratic cycles or minor cycles.

Indicator	Correlation GDP cycle (lag)	Minor cycles/ idiosyncratic cycles	Lead/lag peak 1990	Lead/lag trough 1993	Lead/lag peak 2000	Classification
Jobs of employees	0.835(0Q)	No	0	+3Q	+3Q	Coincident
Total private sector jobs	0.97 (+1M)	Yes	+1Q	+2Q	+2Q	Lagging
Financial and services jobs	0.83 (-3Q)	Yes	-5Q	+2Q	-2Q	Leading
Savings	0.6//0.6 (?)	Yes	+4Q	+5Q	n.d.	?
Stock index	0.55 (-5M)	Yes	-6Q	-4Q	0	Leading
Stock index local companies	0.4 (-8M)	Yes	-3Q	-4Q	0	Leading
Consumption of durable goods	0.48 (-8M)	Yes	+8Q	+6Q	n.d	Lagging
Total Household Consumption	0.936 (0M)	No	0	0	-2Q	Coincident
Fixed Capital Formation	0.84 (0Q)	No	-4Q	-1Q	-3Q	Coincident
Business survey; production tendency	0.75(-2Q)	No	-2Q	-1Q	0	Leading
Business survey; capacity utilisation	-0.75 (-5Q)	No	-3Q	0	0	Leading
Business survey, orders received	0.47 (-10M)	Yes	-1Q	-2Q	-2Q	Leading
Business survey, demand constraints	-0.61 (+3Q)	Yes	n.d	-6Q	-4Q	?
Business survey, capacity assessment	0.75 (-2Q)	No	+1Q	0	-1Q	Leading
Business survey, capacity constraints	0.75 (-2Q)	No	+1Q	0	-1Q	Leading
Business survey, personnel constraints	0.75 (-2Q)	No	-2Q	-1Q	0	?
Business survey, total orders	-0.27 (-5M)	No	-2Q	-3Q	-1Q	Leading
Consumer price index	-0.66 (-11M)	Yes	?	?	?	?
Consumer confidence	0.61(-6M)	Yes	-4Q	-2Q	-1Q	Leading
Cons. Survey, Durables Purchases	0.97 (-4M)	Yes	-4Q	-1Q	0	Leading
Cons. survey, willingness to buy	0.95 (-4M)	Yes	-2Q	-1Q	0	Leading
Overnight interest rate	0.5 (+10M)	Yes	+4Q	n.d.	+1Q	Lagging
Retail sales	0.53(-2M)	Yes.	n.a.	n.a.	-2Q	?
Exports	0.5 (-1M)	No	-2Q	-4Q	0	Lead/Coin
Bankruptcies (excluding. one-man businesses)	-0.84 (-6M)	No	0	-2Q	-3Q	Leading
Unemployed labour force	-0.866 (+1M)	No	+1Q	+1Q	+2Q	Lagging
Catering industry turnover	?	Yes	n.d	n.d	n.d.	?
Wages	0.39 (+5Q)	~	+2Q	+1Q	n.d.	Lagging
New mortgages	-0.53 (+12M)	Yes	n.d.	-4Q	-6Q	?
Capital market rate (10-year bond yield)	0.2 (+5M)	Yes	-1Q	0	-1Q	Lead/Coin
Turnover manufacturing industry	0.76 (+1M)	Yes	+1Q	-1Q	+2Q	Coincident
Producer prices imports	-0.39 (-4)	Yes	-1Q	+2Q	n.a.	Coincident
Producer prices inputs	0.84 (0)	Yes	-1Q	0	+1Q	Coincident
Producer' confidence	0.7 (-6M)	No	-2Q	-3Q	0	Leading
Index of Industrial production	0.73 (-3M)	n.a.				Lead/Coin
Temp jobs	0.88 (-2Q)	No	-3Q	0	-9Q	Leading
Vacancies	-0.93 (-1Q)	No	-2Q	0	-1Q	Leading
New housing permits	-0.29 (-3Q)	no	n.a.	+4Q	-4Q	?
Yield curve	-0.63 (+14M)	Yes	n.d	-5Q	-3Q	Leading
Index of construction industry	0.85 (+3Q)	yes	n.a.	n.a.	+1Q	Lagging

Based on these results, we made a first selection. The criteria were not rigorously applied. If an indicator failed one criterion, but performed well on the others, it was not rejected out of hand. For example, most indicators exhibit minor cycles unrelated to the business cycle and strict application of this criterion would have left very few indicators. Truly deviating, idiosyncratic cycles were not tolerated, however. Among other indicators, the consumer price index and stock market index were excluded for this reason. Most indicators were rejected on a combination of possession of minor cycles and late or non-detection of turning points. A few series, like retail sales, were too short. A good balance between monthly and quarterly indicators is important as well. As the system is supposed to give a timely representation of the current state of the business cycle every month, an indicator set consisting mainly out of quarterly series would be no good. Thus, for each indicator the pros and cons were weighed against each other, resulting in the following preliminary selection (table 5.2).

Table 5.2; Potential indicators after first selection round.

Indicator	*Frequency*	*Leading/lagging*
Vacancies	Quarterly	Leading
Jobs financial services	Quarterly	Leading
Jobs private Sector	Quarterly	Lagging
Unemployed Labour Force	Monthly	Lagging
Consumer confidence	Monthly	Leading
Stock index local funds	Monthly	Leading
Bankruptcies	Monthly	Leading
Business survey; capacity constraints	Quarterly	Leading
Fixed capital formation	Quarterly	coincident
Business survey; demand constraints	Quarterly	Leading
Business survey; orders received	Monthly	leading
Index of Industrial production	Monthly	Leading/Coincident
Exports	Monthly	Leading/Coincident
Producer confidence	Monthly	Leading
Consumer survey; urchases of Durables	Monthly	Leading
Cons. survey; willingness to buy	Monthly	Leading
10-year bond yield	Monthly	Coincident
Temp jobs	Quarterly	Leading
Total Household Consumption	Monthly	coincident
Jobs of employees	Quarterly	coincident

This set is still too large, and there is significant overlap between different indicators (e.g. jobs, survey indicators). As a final test of the individual indicators, we performed a real-time simulation for the turning points in 1994 and 2000. We tested whether these indicators were able to detect the trough and peak within about six months. This left us with the list of indicators in table 5.3. Having arrived at this selection, the next stage was to look at the properties of the set as a whole. Several indicators are going to be included beforehand, because of their great relevance to the Dutch economy: Industrial production, exports, consumption, fixed capital formation and vacancies. As for the others, some labour market and confidence indicators will certainly be included, but the selection process will determine which ones.

This exercise brought to light another important fact. The computational process introduces a delay, because of the end value problem. New developments need some time to become fully visible. In practice, this means that the lead of most indicators was clearly reduced, sometimes disappearing altogether. On average, a two to three month delay is apparently introduced by these effects. One important consequence of this is that a system to track the business cycle has to be slightly leading ex-post to be coincident in real-time.

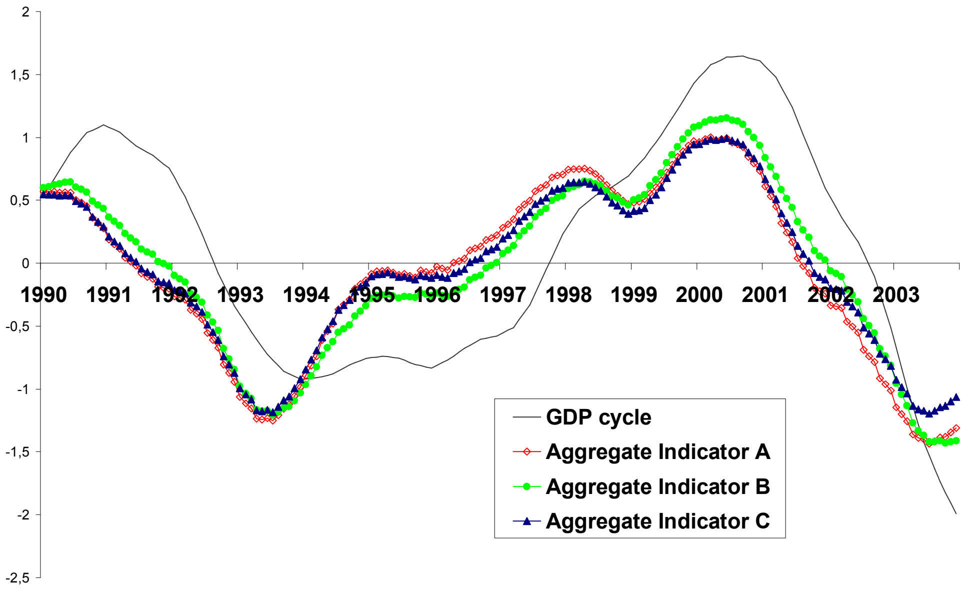
The different indicator sets are scored on two properties: turning point identification and overall agreement with the business cycle. The correspondence with the business cycle was tested by using factor analysis to create an aggregate indicator. Using Factor Analysis, it is possible to extract a common representation of the indicator set by computing which part of their development they have in common. The technique extracts common components in the variance of the series. The common factors are computed via the principal components methodology, and can be constructed from the individual series using the computed weights. Each series has a certain weight on each principal component, called the factor loading. The higher the factor loading, the more important the principal component is for that series. To what extent a principal component is representative for the set as a whole is measured by the percentage of variance it explains, the first principal component explaining the most. The first principal component of a set can be roughly described here as reflecting the average cycle of the indicators, thus summarising the state of the business cycle Tracer (Reijer 2002). Its development can be compared to the reference GDP cycle, and thus it is possible to test how well this principal component represents the business cycle. The results for our three preferred, slightly different sets of indicators are shown in table 5.3 (cycle graphs are in appendix III).

Table 5.3; Potential indicator Sets, indicator turning point detection at time of occurrence (●), factor loadings on aggregate indicators (principal components) of each set.

	Trough 1994 detection	*Peak 2000 detection*	***Aggregate A*** *Factor loading*	***Aggregate B*** *Factor loading*	***Aggregate C*** *Factor loading*
Vacancies	●		0.795	0.919	0.881
Unemployed Labour Force		●	X	0.719	0.665
Jobs of employees			X	0.719	0.643
Temp jobs		●	0.780	0.574	0.638
Consumer confidence	●	●	0.942	0.807	0.864
Cons. ; purchases of Durables	●	●	0.878	X	0.842
Business survey; orders received	●	●	0.616	X	0.522
Producer confidence	●	●	0.860	0.711	0.771
Bankruptcies	●	●	0.927	0.917	0.927
Fixed capital formation		●	0.840	0.942	0.918
Total Household Consumption		~	X	0.839	0.785
Index of Industrial production	●		0.907	0.900	0.909
Exports	●		0.702	0.738	0.742
10-year bond yield (Capital market rate)	●	●	0.031	0.056	0.035
Total jobs in financial services		●	0.876	X	X

Most indicators have rather high factor loadings (0.7-0.9) on the principal components (aggregate indicators). Two complementary conclusions can be drawn from this. First, the indicators have a strong common component. This supports our concept of using a mix of leading, coincident and lagging indicators for business cycle tracking and our indicator selection. The other way to look at this result is that these aggregate indicators/principal components are a good representation of the indicator sets. Thus it is possible to evaluate the performance of the tracer system in representing the business cycle using these aggregate indicators.

Graph 5.1; Aggregate indicator cycles of different indicator sets, compared to GDP cycle.



Two indicators, orders received from the business survey and especially the capital market rate,, have a low factor loading. This is because they lead the cycle and they possess additional cycles. However, apart from the useful informational content they have in themselves, there is another reason for deciding to include these indicators: they are very important turning point indicators. Reliable detection of turning points as they occur is an important function of a business cycle tracking system. In addition to the factor loadings, table 5.3 also indicates whether the indicators in a real-time simulation detect turning points at the moment of occurrence. This is an important additional test of the indicator sets, as the aggregate indicators only measure average correspondence to the business cycle. Graph 5.1. shows that there is not much difference in the average behaviour of the different sets. They all track the reference cycle quite well, possessing a quite high correlation with the reference cycle, though at different leads. Turning point detection is not done by analysing average behaviour, though. A turning point is detected if the majority of the indicators signal the occurrence of a peak or a trough, and this signal has the characteristics of a binary (yes/no) variable. As can be seen in table 5.4, turning point detection is much more dependent on the composition of the indicator set than the average relationship with the business cycle. The set with the highest correlation with the reference cycle, at the smallest lead, also fails to detect the turning points as they occur.

Table 5.4; Performance data for different indicator sets

	Aggregate A	***Aggregate B***	***Aggregate C***
% variance explained by principal component	**63.9%**	**59.6**	**57.6%**
Correlation with GDP cycle (lead, months)	**0.796 (-5)**	**0.912 (-1)**	**0.882 (-3)**
Detection of 1994 trough (no. of indicators in set signalling)	**9**	**7**	**9**
Detection of 2000 peak (no. of indicators in set signalling)	**9**	**6**	**8**

Indicator set C offers the best compromise between correspondence with the reference cycle and timely turning point detection. It has quite a high correlation of 0.883. The lead of three months might actually be an advantage, as tests have shown that in real-time the lead is reduced by several months because of end value effects. The indicator set is also able to detect both turning points in real time. For us these were for us strong reasons to choose this set. It also conforms to the important requirement of offering a well-balanced representation of the Dutch economy. All important aspects of the economy, in the business cycle sense, are present, Production, expenditure, labour market and confidence indicators. Lastly, GDP is added to this set. This can be viewed as a composite economic indicator in itself, and it is interesting to compare its development to the indicator set as a whole.

6. Conclusions

This study falls into two different parts. The main part is the construction and workings of the Statistics Netherlands Business Cycle Tracer system. Its concepts and workings, which are a kind of conclusion, can be found in Sections 2 and 3. Summarising, it can be said that it is possible to construct a system which is a coincident indicator of the Dutch business cycle from a disaggregated mix of lagging, coincident and leading indicators. A selection process tested the cycles of the different individual indicators on their relation with the overall business cycle. After that, different sets of indicators were tested on their overall performance to find the optimum composition. The result is a set of fourteen macro-economic indicators which offer information on all the relevant aspects of the Dutch economy. This system gives a reliable representation of the current state of the Dutch business cycle. The focus was on developing a practical system, which is able to offer in real-time a stable representation of the current state of the business cycle.

The other part of this study was concerned with the technicalities of cycle computation. As we consider it to be the most informative concept for business cycle analysis, we based our system on deviation cycles. Methods for determining deviation cycles have been criticised in the literature for the potential presence of spurious cycles. Therefore, we tested a selection of the most used methods for cycle determination available today. Both the plausibility of the ex-post cycles and the real-time behaviour of the different methods were investigated. Our conclusion is that deviation cycles offer a credible representation of the state of the business cycle. When comparing the cycles for GDP and Industrial production as they result from different cycle extraction methods, or filters, we find broad, if not exact, agreement on major aspects of the business cycle: number of cycles, cycle length and dating of major turning points. Cross-correlations were high as well. Of course, this is not true for all filters. The Beveridge-Nelson filter did not work very well, and some filters, notably the standard Hodrick-Prescott filter, yield more cycles than others. From a practical point of view, we found that the Baxter-King filter is not of much use as it loses too many observations. A real-time simulation was performed to test the sensitivity of the different methods for new observations. In this case, the Christiano-Fitzgerald filter did not perform very well, exhibiting large revisions and wild swings at certain points. We were therefore left with the unobserved components method, the constant (logarithmic) trend method, and a quasi constant trend method based on an inflexible Hodrick-Prescott trend. These performed equally well on the practical tests, and there is strong agreement between their cycle chronologies. For practical reasons, it was decided to use the latter method for the Business Cycle Tracer. Because of its superior properties, further study of the possibility of using the unobserved components method in a practical business cycle analysis system is recommended.

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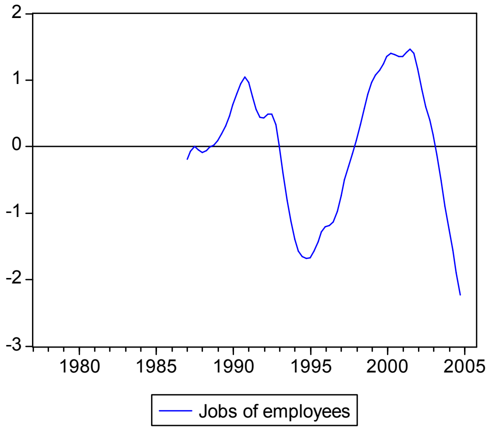
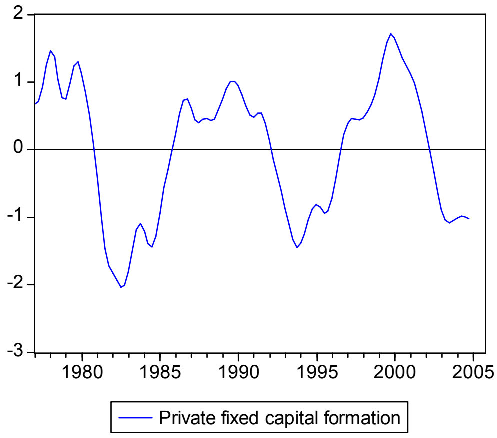
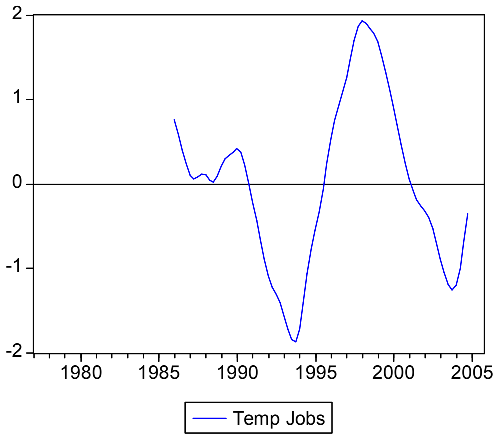
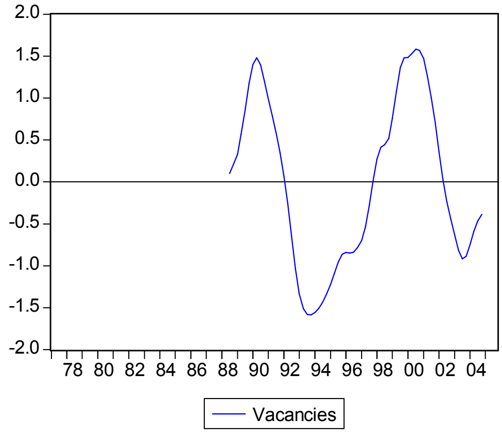
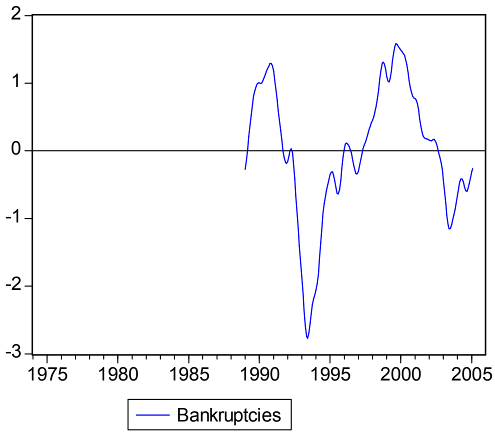
Appendix I; Cycles of individual indicators

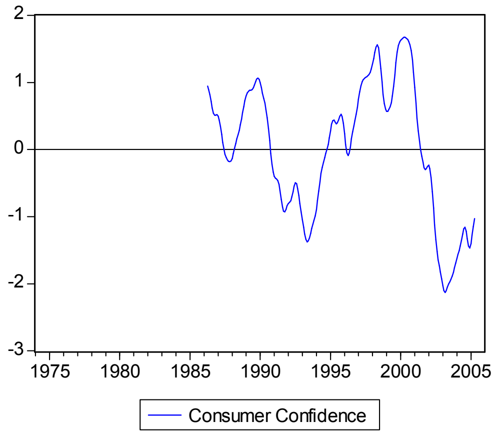


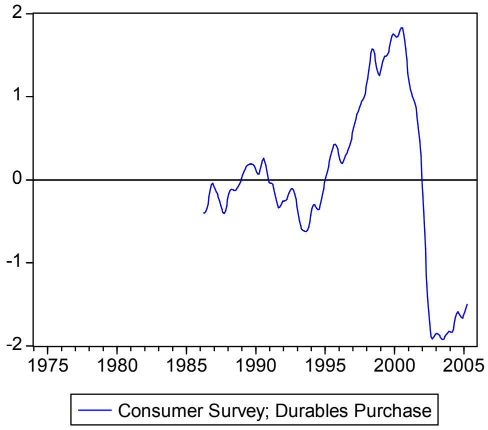








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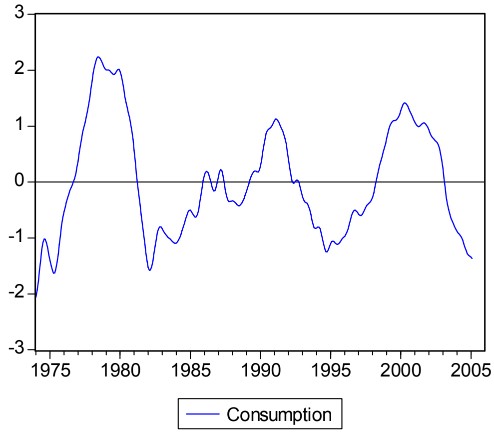
Consumer Survey; Durables Purchase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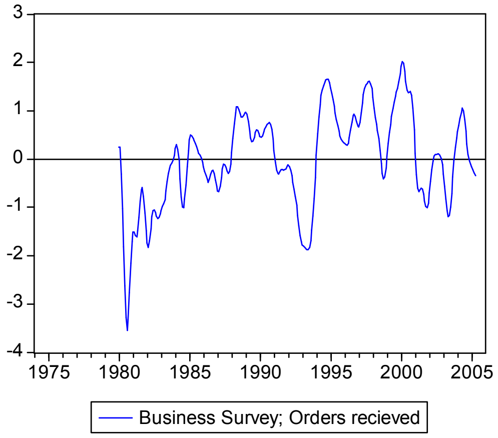
Consumption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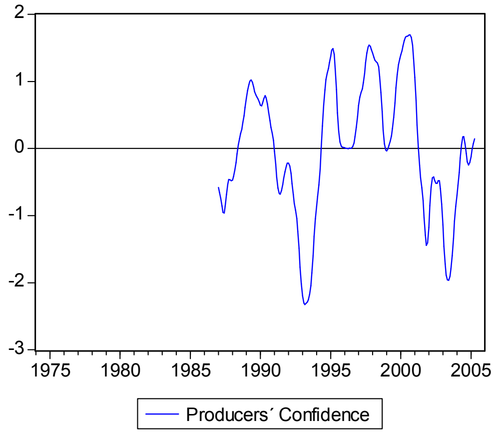
Business Survey; Orders recieved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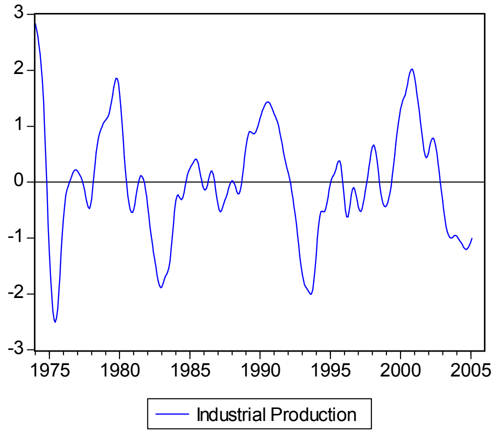
Producers´ Confidence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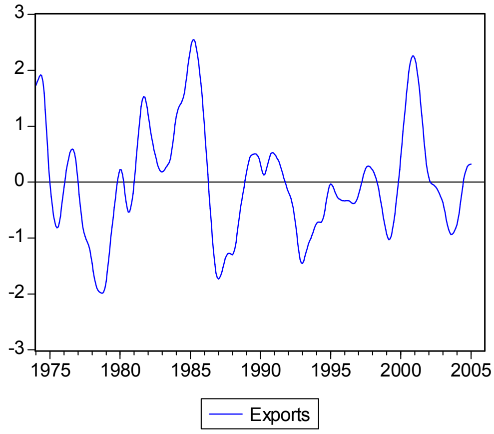
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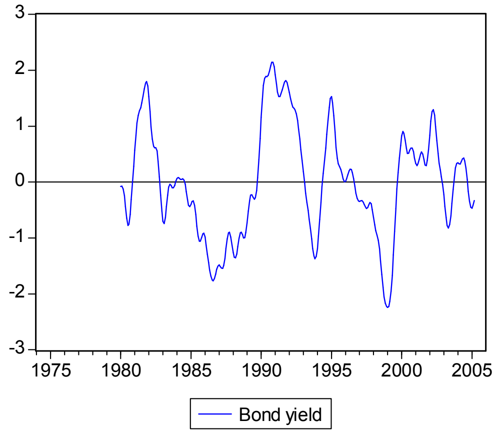
Unemployed labour force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Bond yield

Appendix II; Indicator details

Indicator	*Details (all non-s.a.)*	*Fre-quency*	*Cor-rections*	*Henderson Trend cycle parameter* **in this study**	*Hodrick-Prescott λ* **in this study**	*Henderson trend cycle parameter* monthly publication	*Hodrick-Prescott λ* monthly publication
Vacancies	private sector	Q		7	50000	7	50000
Unemployed Labour Force	total	M		15	1000000	15	500000
Job of employees	Total	Q		5	50000	5	3200
Temp jobs	hours, phase A	Q	Easter	7	50000	5	50000
Consumer confidence	balance	M		11	-	23	-
Consumer survey; purchases of Durables	balance	M		13	-	35	-
Business survey; orders received	balance	M		13	-	13	-
Producer' confidence	balance	M		11	-	13	-
Bankruptcies	Companies, excluding one-man business	M	Trading days,	15	1000000	23	1000000
Fixed capital formation	Private sector, constant prices	Q		9	50000	9	50000
Total houdehold Consumption	Volume index	M	Trading days, Easter	17	1000000	17	100000
Index of Industrial production	Volume index (manufacturing)	M	Trading days	17	1000000	17	1000000
Exports	Goods, volume index	M	Trading days	17	1000000	13	1000000
10-year bond yield	**Capital market rate 10-year government bonds**	M		11	1000000	11	1000000
GDP	constant prices	Q	Trading days, Easter	7	5000	5	5000

Appendix III; Measures of concordance between cycles for different cycle extraction methods.

CF= Christiano-Fitzgerald filter, CT= Constant logarithmic trend, HP14400=standard Hodrick-Prescott filter, HP1M = inflexible Hodrick-Prescott filter, UC= unobserved components model

Table AIII-1; Percentage of time (quarters) that cycles GDP for different cycle extraction methods both show period-on-period increases or decreases.

Method	*UC*	*CT*	*HP 1M*	*CF*	*HP 14400*
UC	-				
CT	87	-			
HP 1M	85.8	89.6	-		
CF	81	77	78.3	-	
HP 14400	85	85	89.6	81	-
Average overall agreement					84

Table AIII-2; Percentage of time (quarters) that cycles of GDP for different cycle extraction methods are both above or below trend

Method	*UC*	*CT*	*HP 1M*	*CF*	*HP 14400*
UC	-				
CT	87	-			
HP 1M	87	85	-		
CF	87	85	93	-	
HP 14400	83	79	93	91	-
Average overall agreement					86.8

Table AIII-3; Percentage of time (quarters) that cycles of GDP for different cycle extraction methods are both in the upswing (trough-peak) or downswing (peak-trough) phase.

Method	*UC*	*CT*	*HP 1M*	*CF*	*HP 14400*
UC	-				
CT	95.3	-			
HP 1M	97.2	98.1	-		
CF	92.5	91.5	93.4	-	
HP 14400	82.1	84.9	84.9	78,3	-
Average overall agreement					89.8

Table AIII-4; Percentage of time (months) that cycles of industrial production for different cycle extraction methods both show period-on-period increases or decreases.

Method	*UC*	*CT*	*HP 1M*	*CF*	*HP 14400*
UC	-				
CT	80.3	-			
HP 1M	78.1	94.5	-		
CF	87.5	80	79	-	
HP 14400	74.5	86	87.0	75	-
Average overall agreement					82

Table AIII-5; Percentage of time (months) that cycles of industrial production for different cycle extraction methods are both above or below trend

Method	*UC*	*CT*	*HP 1M*	*CF*	*HP 14400*
UC					
CT	69,3				
HP 1M	76,7	80,3			
CF	79,2	72	81		
HP 14400	80,3	75	80,9	83	
Average overall agreement					78

Table AIII-6; Percentage of time (months) that cycles of industrial production for different cycle extraction methods are both in the upswing (trough-peak) or downswing (peak-trough) phase.

Method	*UC*	*CT*	*HP 1M*	*CF*	*HP 14400*
UC	-				
CT	74.5	-			
HP 1M	91.7	81.2	-		
CF	94.5	72.9	89.5	-	
HP 14400	90.9	74.2	91.4	90.9	-
Average overall agreement					85

Appendix IV; Original plan for the development of Statistics Netherlands' Business Cycle Tracer.

By Gert Buiten

Goal:

Development of a representation of short-term economic indicators which will enable a quick analysis of the state of the business cycle via a disaggregate multivariate approach. The methodology should be scientifically sound and objective. The aim is analysis of the current state of the business cycle and not forecasting.

Basic principles:

The development of an indicator should be characterised by its business cycle component. It should be classified in one of four possible states:

The indicator is positive and increasing	green
The indicator is positive and decreasing -	orange
The indicator is negative and decreasing	red
The indicator is negative and increasing -	yellow

These four options should be translated into four quadrants of a graph, which will enable a quick analysis of the current state of the business cycle.

Tasks:

- Methodology:
    - Determination of current state: deviation from long-term average
    - Relation with business cycle theory
    - Determination of long-term average: trend or other method?
    - Determination of short-term development
    - Determination of business cycle component
- Indicator selection. By relation with reference series; turning-point identification, spectral analysis or other timing methods.
- Analysis of the diagram in different phases of the business cycle
    - Leading, lagging and coincident patterns.
    - Does a historical analysis of the diagram offer objective ways to characterise the state of the business cycle? The cycle of GDP is the normal measure of this (P72-T75-P79-T82-P90-T93-P00-T02?).