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Detrending methods and stylized facts of business cycles in Norway – an international comparison

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Abstract. This paper analyses the stylized facts of business cycles in Norway, by comparing different detrending methods. As the choice of the appropriate data transformation depends on the nature of the underlying dynamic properties of the time series, a set of unit root tests are first applied to the data. The detrended data are analysed, both in the time domain and the frequency domain. The evidence suggests that whereas some variables (e.g. consumption and investment) behave consistently procyclically with GDP, for other variables (e.g. real wage and prices), the business cycle properties vary considerably with the detrending methods used. The results are evaluated from a real business cycle perspective, but overall, there is little evidence to support a (supply driven) real business cycle. Symmetries in business cycles are finally analysed by comparing the business cycles in Norway and selected countries.

Key words: Unit roots, trend-cycle estimation, stylized facts, real business cycles

JEL classifications: C20, E32

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1. Introduction

Following the recent success of the Real Business Cycle (RBC) approach to generate artificial data on business cycles (see e.g. Kydland and Prescott (1982) and Long and Plosser (1983)), several empirical studies have set out to present the *stylized facts* (or broad regularities) of business cycles. Recent empirical studies include the influential paper by Kydland and Prescott (1990) about the US, Blackburn and Ravn (1992) about the UK, Englund et al. (1992) about Sweden, Fiorito and Kollintzas (1994) about the G7 and Christodoulakis et al. (1995) about the EC.

In empirical studies of business cycles, the researcher is confronted with the statistical problem of how one should extract the cyclical component, as most time series are both fluctuating and growing. The traditional idea was to assume that the cyclical and the trend component could be studied separately, as the economic mechanisms underlying short and long run economic fluctuations were quite different. Output fluctuations were for instance seen as temporary deviations from a smooth deterministic trend, that represented potential GDP.

The failure of Nelson and Plosser (1982) to reject the hypothesis of a unit root in many macroeconomic time series, changed this traditional view. Instead of regarding output fluctuations as trend reverting, the existence of a unit root in the time series implied that a large fraction of stochastic shocks to output fluctuations would not die out. Each shock could have a permanent effect on the series, so for a pure unit root, all fluctuations would represent permanent changes in the trend. Only by taking first differences would stationary be obtained. Nelson and Kang (1981) brought further criticism to the traditional view of business cycles. They showed that if you detrend data that are actually generated by a random walk, one will infer spurious cycles in the data.

In the influential paper by Kydland and Prescott (1990), the cyclical component was isolated by using a filtering procedure that extracts a stochastic trend that moves smoothly over time (the Hodrick-Prescott filter). However, although the method is stochastic in nature, the smoothness of the stochastic trend component has to be determined a priori. Recently, the method has also been challenged, on the grounds that applying the filter to a non-stationary (random walk) process may create spurious cyclical behaviour (cf. Cogley and Nason (1995)). Hence, the methodology is essentially subject to the Nelson and Kang critique.

This paper analyses empirically the economic fluctuations of the quarterly national accounts in Norway, by comparing several detrending methods, including deterministic detrending, stochastic detrending, frequency filtering techniques and the structural time series approach. The stylized facts will thereafter be evaluated from a real business cycle perspective, by examining whether a simple model like that in Kydland and Prescott (1982), can match some of the sample moments in Norway. Throughout the paper I will focus specifically on the cyclical behaviour of prices and real wage, as both serve as powerful indicators of the driving force behind business cycles. Finally, symmetries in business cycles are analysed by comparing the business cycles in Norway and selected international countries.

That different detrending methods give very different cyclical behaviour in the time series, is well known by now (see e.g. Canova (1998)). However, the ultimate choice of the appropriate transformation of the data will essentially depend on the nature of the underlying dynamic properties of the time series. I therefore first analyse the stochastic properties of the series, by applying a set of unit root tests to the data. The remainder of the paper is organised as follows. In section two, the different detrending methods are presented. Section three presents tests for unit roots, and analyses the stylized facts in the time and the frequency domain, using the different detrending methods. The sample moments are thereafter evaluated from a real business cycle perspective. In section four, I compare business cycles in Norway and selected international countries. Section five summarises and concludes.

2. Trend-cycle decompositions

Five univariate methods will be used to extract cyclical components in the time series. In the first, the series are modelled as stationary cycles around a deterministic trend, which is allowed to have one structural break. The next two decompositions are stochastic in nature. One method is based on Nelson and Plosser (1982) notion of stochastic trends, and the trend is found by using the Beveridge-Nelson (1981) procedure. The other method uses the Hodrick-Prescott filter, which is an exponential smoothing procedure. A further method is based on frequency domain filtering, where it is not essential whether the trend is stochastic or deterministic. The final method uses the structural time series approach, which is set up in terms of different components that have direct interpretations, but are not observed directly (also referred to as the unobserved components method). For the respective first three decompositions, I assume that the logarithm of a variable y_t, can be decomposed as:

$$y_t = g_t + c_t \tag{1}$$

where g_t is the trend and c_t is the cycle. The data are seasonally adjusted prior to the trend-cycle transformation. In the above representation, any noise component left in the data after the trend is removed will be attributed to the cycle. Finally, for the frequency domain filtering method and the unobserved components method, I use the following decomposition:

$$y_t = g_t + c_t + s_t + \varepsilon_t \tag{2}$$

where g_t and c_t are defined as above, but now I use unadjusted data. Hence, I specify the seasonal component, s_t, and the noise component, ε_t, explicitly in the model.

As will be seen below, although different in nature, many of these detrending methods are in fact related. For instance, the Hodrick-Prescott filter with a high smoothing value, gives approximately a linear trend. Using the same filter, with a low smoothing value, gives values equivalent to the stochastic Beveridge and Nelson method. These techniques place particular restrictions on the unobserved components structure of the time series, which can be examined by using the structural time series approach (see Harvey and Jaeger, (1993)). Therefore, by including the unobserved components method in this analysis, I embed the various methods in a framework, so that the unobserved components method can be used as a basis for comparison. In the next sections I will briefly outline and evaluate the different methods that are used in this paper.[1]

[1] For all but the unobserved component and the frequency filtering method, I use RATS to compute the trend-cycle decompositions. For the unobserved component and the frequency filtering method, I use STAMP and GAUSS respectively.

2.1. Deterministic trends – a linear time trend with break

The traditional method used to estimate business cycles, was to define a smooth (natural) growth path for the economy, which was only perturbed by transitory cyclical fluctuations. The secular component would reflect the long term evolution of the economic series caused by e.g. productivity, which was assumed to grow constantly over time. However, historically, productivity growth has been far from smooth and may have experienced several structural breaks. These structural changes may for instance be due to an episode like the oil price shock in 1973/1974, which reduced output growth in many OECD countries permanently. To allow for a possible structural break, I have represented y_t with a determinist trend that has a break in the slope or the level of the trend:

$$
\begin{aligned}
y_t &= \alpha_0 + \alpha_1 t + \alpha_2 DS_t(k) + \alpha_3 DL_t(k) + \varepsilon_t \\
\hat{g}_t &= \hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 DS_t(k) + \hat{\alpha}_3 DL_t(k) \qquad (3) \\
\hat{c}_t &= y_t - \hat{g}_t
\end{aligned}
$$

where ε_t can be measured as a stationary ARMA process. $DS_t(k)$ and $DL_t(k)$ are dummy variables that capture the change in the slope or the level of the trend in period k, $(1 < k < T)$, respectively. Hence, $DS_t(k) = t - k$ and $DL_t(k) = 1$ if $t > k$, zero otherwise. To ensure there are no mis-specifications between the break in the level and the slope of the trend alternatives, I include both alternatives in the estimation and let the data determine the most significant break point. The relevant break dates will be taken from the sequential unit root tests reported in table 1 below.

Using a linear trend with a structural break gives an intuitive first approximation to the study of business cycles. The disadvantage of this method is that it is rather time consuming in terms of finding the exact break point. Further, if the series has more than one break date, or, it is integrated of first order, detrending with a deterministic trend with a one time structural break will infer spurious cycles. Hence the method is subject to the Nelson-Kang critique.

2.2. The Beveridge and Nelson Procedure

The obvious question, when a time series can be characterised by a non-stationary process, is how to decompose the series into a permanent and a transitory component. In one decomposition, that is due to Beveridge and Nelson (1981) (henceforth BN), the permanent component is shown to be a random walk with drift. The transitory component is a stationary process with zero mean, which is perfectly correlated with the permanent component.

Let y_t be integrated of first order, so that its first differences, Δy_t, are stationary. According to the Wold decomposition, then Δy_t can be written as an infinite moving average, $\Delta y_t = A(L)\varepsilon_t$, where ε_t are uncorrelated, mean zero, random disturbances with variance equal to σ^2 and $A(L)$ is the polynomial of moving average coefficients. The BN decomposition can be obtained from the

Wold decomposition as:

$$\Delta y_t = \Delta g_t + \Delta c_t$$
$$\Delta g_t = \alpha_1 + A(1)\varepsilon_t \tag{4}$$
$$\Delta c_t = (1 - L)A^*(L)\varepsilon_t$$

where $A(1)$ is the infinite sum of the moving average coefficients, and $A^*(L) = (1 - L)^{-1}(A(L) - A(1))$. Solving for (4), it follows that the trend is a random walk with drift, whereas the cyclical component is stationary:

$$g_t = g_0 + \alpha_1 t + A(1)\sum_{s=1}^{t} \varepsilon_s \tag{5}$$

$$c_t = A^*(L)\varepsilon_t \tag{6}$$

Cuddington and Winters (1987) have suggested that a quick way to identify the cyclical and trend components is to calculate g_t directly from the expression in (5), by estimating $A(1)$ from a truncated Wold representation of Δy_t. One obvious difficulty with this method is that the initial value, (g_0), is unknown, so the procedure is only correct up to an additive factor. A more precise computational procedure has been suggested by Newbold (1990), by noting that the stochastic trend can be calculated as the long-term forecast of the series adjusted for the mean rate of change. However, provided the error in estimating ε_t is small, it is still possible to use (5) to estimate the trend component, as long as g_0 is established by applying Newbold's method for one period only.

The approach I take in this paper is the following: I apply Newbold's method for one period to establish g_0, and thereafter use (5) and (6) to determine the remaining values for g_t and c_t. For comparison, in determining $A(1)$ I estimate two different ARIMA models. The first is a (best fit) low order ARIMA model (BN-low) based on the Schwarz and the Akaike criteria, whereas the second is a model using a high order ARI model (BN-high), chosen from the criteria by the Ljung-Box Q statistics. Details on the estimation of these models can be obtained from the author on request.

The advantage of the BN method is that it is an appropriate method to extract cycles when a series is integrated of first order. There are, however, several problems associated with this method. First, in many cases it may be difficult to distinguish between the different ARIMA models that can fit the short run properties of a series. However, the forecast functions from these models may differ substantially and hence the corresponding trend-cycle decompositions. Second, fitting low order ARIMA models seems to systematically overestimate the random walk component in the data (see also Cochrane, (1988)). Third, when the persistence in the series is estimated to be large, it may be difficult to interpret the cycles. In particular, as the variance of the innovations in the permanent component, $(\Sigma_{i=0}A_i)^2\sigma^2$, will be larger than the variance of the innovations in the observed data, (σ^2), if $(\Sigma_{i=0}A_i)^2$ is larger than one, then the cycles will be generated by an excessive moving trend that deviates around the series, rather than vice versa.

2.3. The Hodrick-Prescott filter

One commonly used approach to extract cycles in the real business cycle literature, is to use the Hodrick-Prescott (HP) filter (see Kydland and Prescott (1990)). This filter extracts a stochastic trend, (g_t^{HP}), which for a given value of λ, moves smoothly over time and is uncorrelated with the cycle:

$$\begin{aligned}&\min_{[g_t]_{t=1}^{T}}\left[\sum_{t=1}^{T}(y_t-g_t)^2+\lambda\sum_{t=3}^{T}((g_t-g_{t-1})-(g_{t-1}-g_{t-2}))^2\right]\\&\hat{c}_t=y_t-g_t^{\mathrm{HP}}\end{aligned} \tag{7}$$

where λ is the smoothing parameter, which penalises the variation in the growth rate of the trend. When λ approaches infinity, the lowest minimum is achieved when the variability in the trend is zero, and the trend is perfectly log linear. Since the smoothness of the secular component will be sensitive to the value of λ, a justification for the choice of λ should be made. Kydland and Prescott simply argued that $\lambda = 1600$ is a 'reasonable' choice for quarterly data, and many subsequent studies have used this value. Here I will use $\lambda =$ 1600, as a benchmark value. For comparison, I have chosen two other values for λ that reflect two other stories. First I choose $\lambda = 16$, which can account for relative more volatility in the trend.[2] On the other hand, to account for the fact that a small open economy like Norway (being dominated by the oil sector), may experience rather more cyclical volatility, I consider $\lambda = 160000$.

The HP-filter is easy to apply, and the broad use of it in many international studies makes it interesting to include here for comparisons. However, the method has recently come under severe criticism by among others Harvey and Jaeger (1993), King and Rebelo (1993) and Cogley and Nason (1995), on the grounds that when the HP filter is applied to an integrated series, it can generate business cycle periodicity, even if none is present in the original data. Hence, the HP filter is also subject to the Nelson-Kang critique.

2.4. Frequency filtering techniques

Applying a band-pass filter to the original data in the frequency domain can also identify cyclical and secular components. The band pass filter will be constructed to filter out all the components in a series, except those that correspond to the chosen frequency band. However, in designing the filter, one has to determine the periodicity of the business cycles one wants to extract. Burns and Mitchell (1946) first defined the duration of business cycles to vary between one and twelve years. More recently, the NBER classification has specified the US cycle to show up with an *average* periodicity of about 4–6 years, (see e.g. Zarnowitz and Moore (1986)). In the following I define business cycles as having a periodicity from 1.5 to 8 years, as the length of the cycles in the Norwegian economy may be somewhat different than the average

[2] Nelson and Plosser (1982) argued for a low value for λ, as the ratio between the standard deviations of the innovations in the growth component and the standard deviation in the cyclical component, should be with values between one and six rather than 1/40 as Kydland and Prescott (1990) chose.

American business cycle (being a smaller country and facing more idiosyncratic shocks). Cycles with a periodicity of more than 8 years I attribute to the trend and cycles with a periodicity less than 1.5 years, I allocate to the irregular component. As I use unadjusted data, the seasonal component will be wiped out and attributed to the noise component.

The computational procedure is as follows. I first apply a filter to the spectrum of the original series. Estimation of the spectrum is based on the fast Fourier transform (FFT) $f(\omega)$. Whereas an ideal filter in an infinite sample eliminates all frequencies other than the chosen business cycle frequencies, applying the filter to a finite sample will lead to some 'leakages' outside the band. The FFT will treat the series as periodic and assume that the last observation corresponds to the observation preceding the first observation. This effect of having a linear time trend in the data can distort the time series and create spurious cycles in the data. To eliminate this distortion, I allow each series to be linearly detrended before I apply the filter (for a discussion of this issue, see Stock and Watson (1990) and Hassler et al. (1992)). To use the FFT I further pad the data with zeros up to four times its length, until the number of elements are equal to a power of two. The Fourier transform of the cyclical component is then found as:

$$f_c(\omega) = |B_c(\omega)|^2 f_y(\omega) \tag{8}$$

where $f_c(\omega)$ and $f_y(\omega)$ are the Fourier transforms of the cyclical component and the original series respectively. The transfer function to the band pass filter $B_c(\omega)$, is defined as:

$$\begin{aligned} B_c(\omega) &= 1 \text{ if } \frac{2\pi}{32} \leq \omega \leq \frac{2\pi}{6} \wedge 2\pi\left(1 - \frac{1}{6}\right) \leq \omega \leq 2\pi\left(1 - \frac{1}{32}\right) \\ &= 0 \text{ otherwise} \end{aligned} \tag{9}$$

With ω_j defined over $0, 2\pi/T, \ldots, 2\pi(T-1)/T$, the spectrum is periodic with a period of 2π, and the values for $\pi \leq \omega_j \leq 2\pi$ equals $-\pi \leq \omega_j \leq 0$. I therefore construct a two-sided symmetric filter over the whole period 2π. Finally, the filtered cyclical component is found in the time domain by calculating the inverse FFT.

Given that my intention is to establish comovements between the business cycle component in the main economic variables, this method has an intuitive appeal. Here I will be able to extract the frequency components I am interested in directly, without having knowledge of the statistical properties of the data. However, some consideration has to be given to how one shall remove the low frequency component before filtering in the frequency domain.

2.5. Unobserved components

A structural time series model is specified in terms of components that have a direct interpretation. These components are not directly observable, but are assumed to have ARIMA representations, (see Harvey (1989)). Structural time series models for quarterly data will typically consist of a trend, cycle, seasonal and irregular component as defined in (2). All four components are stochastic, and the disturbances driving them are mutually uncorrelated. In this framework, the stochastic trend evolves as:

$$g_t = g_{t-1} + \beta_{t-1} + \eta_t \tag{10}$$

$$\beta_t = \beta_{t-1} + \zeta_t \tag{11}$$

where β is the slope of the trend, and η and ζ are normal, independent, white noise disturbances, with variances σ_η^2 and σ_ζ^2 respectively. The cyclical component is defined as:

$$\begin{aligned} c_t &= \rho \cos \lambda_c c_{t-1} + \rho \sin \lambda_c c^*_{t-1} + v_t \\ c^*_t &= -\rho \sin \lambda_c c_{t-1} + \rho \cos \lambda_c c^*_{t-1} + v^*_{t-1} \end{aligned} \tag{12}$$

where ρ is the damping factor such that $0 \leq \rho \leq 1$, λ_c is the frequency of the cycle in radians, and v_t and v^*_t are independent white noise disturbances, with variances σ_v^2. Finally, the irregular component is assumed to be white noise, and the seasonal component will be estimated as a trigonometric function.

Estimation of the whole model will be carried out by maximum likelihood with the Kalman filter in the STAMP package. An important issue to determine prior to estimation, is whether both the slope and the level of the trend shall be stochastic. In the general specification, the trend will be an ARIMA $(0, 2, 1)$ process. The restriction that $\sigma_\zeta^2 = 0$, reduces the trend to a random walk with drift. One the other hand, if $\sigma_\eta^2 = 0$, the trend remains an I(2) process, but a trend with this feature will be relatively smooth. Finally, if $\sigma_\eta^2 = \sigma_\zeta^2 = 0$, the stochastic trend collapses to a deterministic trend; $g_t = g_0 + \beta t$. Harvey and Jaeger (1993) argued that if one feels that the underlying trend in a series should be relatively smooth, then one should apply the restriction $\sigma_\eta^2 = 0$ a priori. However, as emphasised by the same authors, whereas this may be a reasonable argument for a real series like GDP, a nominal series like prices may not display this feature.

The approach I take in this paper is therefore the following. For all series, I start by using the general model, where both the level and the slope of the trend are stochastic. Judging the results, I found that for all series except consumption, productivity and export, I could not reject this general model. For these three variables, the cyclical component virtually vanished using the general model. In order to obtain a cyclical component at all, I therefore restricted the level of the trend for consumption, productivity and export to be fixed, but allowed the slope of the trend to be stochastic.

The unobserved components model has the advantage that non-stationarity can be handled directly, without having to difference the data explicitly. It has the clear advantage over the Hodrick-Prescott filter in that the smoothness of the trend will be intrinsic in the estimation, rather than having to be determined a priori. Some judgement must nevertheless be applied so as to specify the type of trend in the series.

3. Stylized facts of business cycles in Norway

The methods used in this chapter are: A linear trend with a break (LTB), the Hodrick-Prescott filter with $\lambda = 16$ (HP-16), $\lambda = 1600$ (HP-1600), $\lambda = 160000$

Table 1. ADF and Sequential unit root tests[1]

Series:	ADF	Break in the slope in the trend			Break in the level in the trend		
	t_{ADF}	k^*	$F_{DU\text{-}k^*}$	$t_{ADF\text{-}k^*}$	k^*	$F_{DU\text{-}k^*}$	$t_{ADF\text{-}k^*}$
GDP	−1.36	1986Q1	6.09	−2.84	1988Q1	11.59	−3.38
C	−2.20	1986Q1	9.07	−3.78	1988Q2	14.04	−4.34
I	−1.77	1986Q3	18.34[b]	−4.68[b]	1988Q2	22.78[a]	−4.40
X	−2.50	1982Q4	9.30	−3.89	1974Q2	16.33[c]	−3.97
M	−3.04	1986Q1	2.04	−3.31	1988Q2	8.11	−4.23
PR	−1.57	1984Q4	6.00	−2.93	1986Q2	5.03	−2.60
U	−2.30	1986Q2	6.23	−3.40	1988Q2	19.36[b]	−4.87[b]
RWG	−1.06	1976Q4	34.30[a]	−5.30[a]	1973Q2	19.76[b]	−3.79
CPI	0.42	1987Q2	19.25[a]	−3.65	1988Q2	6.01	−0.83
M2	1.57	1987Q4	16.29[c]	−3.10	1988Q2	18.78[b]	−0.81

[1] k^* indicates the break date suggested by $F_{DU\text{-}k^*}$.
a) Rejection of the unit root hypothesis at the 2.5 pct. level, b) Rejection of the unit root hypothesis at the 5 pct. level, c) Rejection of the unit root hypothesis at the 10 pct. level.

(HP-160000), the Beveridge-Nelson decomposition with a high order ARI specification (BN-high) and a low order ARIMA specification (BN-low), the frequency domain technique (FRE), and the unobserved component method (UCM).

The data used in this analysis are taken from the quarterly national accounts in Norway. They are real gross domestic product (GDP), private consumption (C), investment (I), export (E), import (M), productivity (PR), real wage (RWG), unemployment rate (U), consumer prices (P) and money (M2), (see appendix A for further definitions and their sources). To analyse the stochastic properties of the series, I start by pre-testing for unit roots.

3.1. Deterministic trends and stochastic trends

To analyse whether there is a unit root in the time series, I use the traditional augmented Dickey-Fuller (ADF) test for unit roots. In the ADF test, the alternative hypothesis assumes a (trend-) stationary process. More recently, Perron (1989) has argued that the traditional ADF test may be severely biased in favour of the unit root hypothesis, if there has been an important structural break during the period examined. Mis-specifying a trend-stationary model with a structural break as an integrated process, would mean that one would attribute more persistence to innovations in the economic variables than might be the true case. To correct for this bias, I also use a sequential unit root test suggested by Banerjee et al. (1992), that treat the break point as unknown prior to testing. The break will be in the form of a shift in the slope or the level of the trend.

Table 1 reports the ADF test, (t_{ADF}), together with the sequential F-test ($F_{DU\text{-}k^*}$) and t-test ($t_{ADF\text{-}k^*}$) suggested by Banerjee et al. (1992). Using the ADF test, for none of the variables can I reject the hypothesis of a unit root in favour of the deterministic trend alternative. When allowing the trend alternative to have a break, for many variables (investment, export, unem-

Table 2. Autocorrelations of the cyclical component of GDP

	LTB	HP-16	HP-1600	HP-160000	BN-high	BN-low	FRE	UCM
1	0.61	−0.21	0.33	0.69	0.40	−0.41	0.89	0.98
2	0.58	−0.09	0.30	0.67	0.54	−0.13	0.62	0.92
3	0.53	0.02	0.24	0.61	0.58	0.14	0.33	0.84
4	0.37	−0.27	−0.01	0.46	0.42	−0.17	0.11	0.73
5	0.37	−0.02	0.02	0.43	0.45	0.05	−0.02	0.62

ployment, real wage, prices and money), there is evidence that there has been a trend-break during the estimation period. However, based on the sequential *t*-test, only in a few cases are these breaks significant enough to reject the unit root hypothesis. In the end, only for unemployment, real wage and investment is there substantial evidence against the null hypothesis of a unit root in favour of a deterministic trend with a break. The break occurred in 1976 for real wage, 1986 for investment and in 1988 for unemployment.[3]

3.2. Cyclical properties in the time-and the frequency domain

To illustrate the differences in the business cycle components using the different detrending methods, the cyclical components are analysed both in the time domain and the frequency domain. In the time domain I focus on autocovariances, whereas in the frequency domain I interpret the power spectrum.

In table 2, the first five autocorrelations of GDP that each method generates are reported. This tells us something about the duration (or persistence) of the business cycles. Clearly, the autocorrelation pattern for GDP varies with the method used. Generally, I can divide the methods into two groups with regard to what type of serial correlation they generate in the business cycle. The first group generates slowly decaying positive autocorrelations, indicating a ‘persistent’ pattern for the cycle. Here I find the deterministic trend together with the “smoothest” HP trend (HP-160000), FRE and UCM. Of these, the cycle generated by FRE decays most quickly.

The other group indicates a shifting pattern of negative and positive autocorrelations, giving a noisy pattern for the cycle. Here I find the cycles generated by the most volatile stochastic trends; HP16, and BN-low. Both methods generate negative first order autocorrelations, and behave essentially as random walks. The autocorrelation patterns generated by HP-1600 and BN-high somewhere in between the two groups, although their first order autocorrelations are positive. The cycle generated by HP-1600 decays most quickly, whereas the BN-high method generates a more oscillating pattern for the cycle. Given that HP-16 and BN-low behaved very similarly (as random walks), to limit space in the remaining discussion I will focus only on HP-16,

[3] Zivot and Andrews (1992) have also developed a sequential unit root test that is quite similar to that of Banerjee et al. (1992). In addition, they allow for a third alternative, namely that of both a break in the level and the slope of the trend at the *same* time. Applying their test to the data nevertheless confirms the results found above (see Bjørnland (1999)).

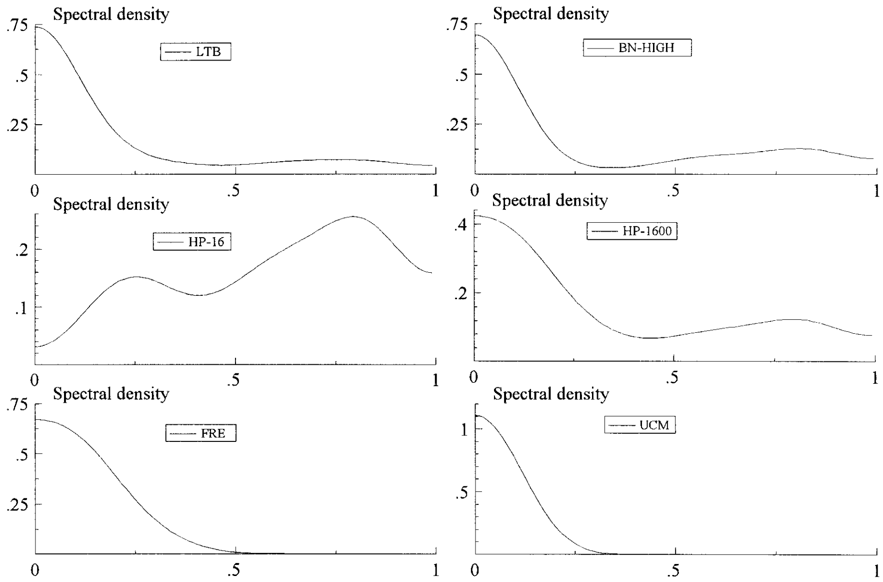

Fig. 1. Spectrum of detrended GDP

but will refer to BN-low if the results deviates significantly from those obtained using HP-16.

In figures 1–3, I compare the spectra for the three variables GDP, real wage and prices respectively, using LTB, BN-high, HP-16, HP-1600, FRE and UCM.[4]

The spectra show that using LTB, the power at zero frequency is not totally removed for neither of the variables, although for real wage (for which I rejected the hypothesis of a unit root in favour of a deterministic trend with break), more of the power at the low frequencies is removed than for prices.

The spectra for BN-high all have a peak at the zero and intermediate frequencies, indicating an important cyclical component at the low frequencies. This emphasises that even after the unit root process has been removed from the series, a large amount of persistence still remains. This is again, in particular, the case for prices.[5]

Using HP-16, almost all of the power at the zero frequency is removed and high frequency cycles are instead emphasised. For GDP, the spectrum emphasises essentially only white noise. For real wage and prices, HP-16 emphasises cycles of approximately 1.5 and 2.5 years respectively. Increasing λ to 1600, more of the power at the high frequencies is removed, and a narrower band of intermediate (business cycle) to low frequencies is emphasised instead. This becomes particularly evident using HP-1600 for GDP.

[4] The spectra are estimated using PC-FIML9, and I use the modified Bartlett lag widows.

[5] However, as suggested above, the results depends crucially on the ARIMA model specified in the Beveridge and Nelson decomposition, and using a less parsimonious specification like BN-low, mostly high frequency noise would be recognised in the spectra.

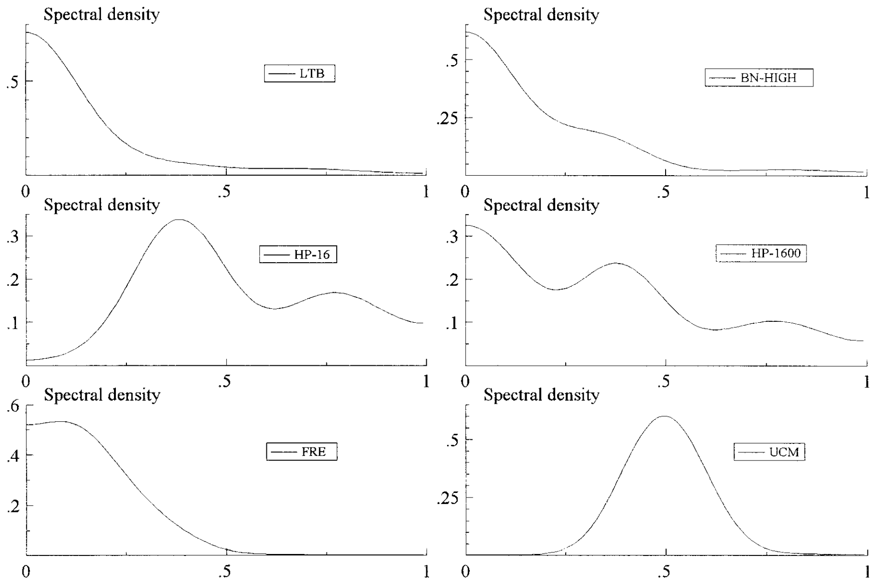

Fig. 2. Spectrum of detrended real wage

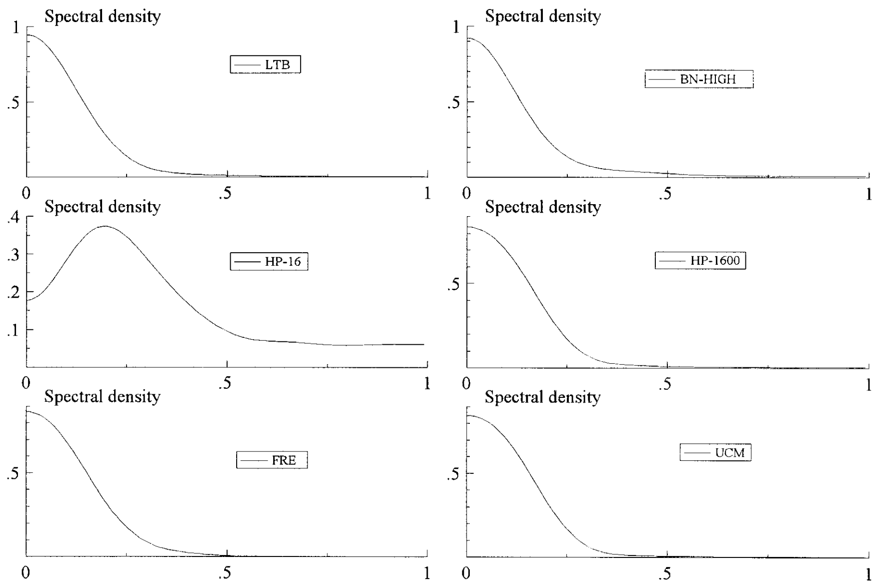

Fig. 3. Spectrum of detrended CPI

The spectra for FRE show that more of the power at the zero frequency is removed, emphasising instead more of the intermediate frequencies. For real wage, in particular, the spectrum has a distinct peak corresponding approximately to a cycle of four years. Note also that consistent with how it has been specified, the filter removes most of the high frequency noise.

Table 3. Standard deviations of the cyclical component, in percentage[1]

	LTB	HP-16	HP-1600	HP-160000	BN-high	FRE	UCM
GDP	2.78	1.51	2.13	3.13	1.45	1.66	1.93
C	2.75	1.26	2.32	3.45	1.82	1.95	2.71
I	6.89	2.30	5.12	9.37	4.94	4.49	6.78
X	5.61	2.60	4.30	5.93	2.85	3.91	2.23
M	6.36	2.81	5.49	7.31	4.43	5.07	6.60
PR	2.61	1.63	2.01	2.52	1.33	1.40	1.00
U	0.52	0.18	0.44	0.62	0.33	0.42	0.39
RWG	2.81	1.34	2.05	2.96	1.41	1.63	0.70
CPI	2.98	0.51	1.54	4.55	3.28	2.59	1.40
M2	2.29	0.78	1.68	4.35	4.95	2.03	1.16

[1] For all variables except the unemployment rate (U), I report the percentage standard deviation. For U, I report the percentage point change.

Finally, the UCM emphasises different cycles for the different variables. For GDP and prices, the low (and intermediate) frequencies are emphasised, whereas for real wage, the spectrum has a distinct peak, at a frequency corresponding to a cycle of one year. Note that as emphasised for FRE, high frequency noise is filtered out.

3.3. Stylized facts of business cycles

The stylized facts of Norwegian business cycles are presented following Lucas (1977) definition of business cycles, as the *comovements* between the deviations from trend (the business cycle) of GDP and the business cycles in various aggregate time series. I further specify a business cycle as *procyclical* (*countercyclical*) if the cross correlation with GDP is positive (negative). If the highest correlation between a variable and GDP occurs when the variable is shifted backwards (forwards) relative to GDP, then I define the variable to be *leading* (*lagging*) GDP. If, on the other hand, the correlation coefficient is close to zero, the series is said to be uncorrelated with the cycle, or *acyclical*.[6] Below, the facts are first presented in terms of volatility, before I establish the correlation coefficients.

In table 3, the absolute standard deviations of the cyclical components are reported. Obviously, the less volatile the trend, the more volatility is attributed to the cycle (plus noise) in the series. Hence, standard deviations are largest for three of the methods in the first group mentioned above, (LTB, HP-160000, FRE) and HP-1600, whereas volatility is lowest for HP-16. BN-high and UCM display volatility in line with the first group, except for some variables; export, productivity and real wage, where both behave more in line with HP-16.

[6] The large sample standard deviations indicate that if the data are generated by Gaussian white noise, the sample autocorrelation shall lie between ± 0.2 about 95% of the time. Obviously, as the data may not be generated by Gaussian white noise, the "true" standard deviations may be larger than those indicated. Hence, a standard deviation of 0.2 serves only as a lower boundary.

The ranking of the variables, according to their percentage standard deviations, varies somewhat between the methods used. Nevertheless, (disregarding the unemployment rate that is not measured in logarithms), all methods except the UCM and the BN method, rank investment, export and import as the three most volatile series. UCM considers consumption in addition to investment and import as the three most volatile series, whereas BN-high considers money in addition to investment and import as the three most volatile series.[7] Finally, consumption, productivity and real wage are essentially as volatile as GDP using all methods except the UCM, where consumption is clearly more volatile than GDP (recall that I used a smooth trend version for consumption) and real wage is far less volatile than GDP.

The cross correlations of the cyclical components are reported in table 4. For most variables, the stylized facts of cross correlations are suggestive, although the absolute value of the correlation coefficients may differ (widely) between the methods used. For a few variables, the results are more difficult to interpret, as the correlation coefficients vary substantially with the different detrending methods.

Consumption, *investment*, *import* and *productivity* are clearly procyclical, although the range of correlations vary, with the lowest correlation coefficient usually generated by the stochastic methods; HP-16 and BN-high. There is some evidence that investment is leading GDP, whereas import and productivity might be lagging. *Unemployment* shows a countercyclical behaviour, where all the methods except BN-high, indicate that unemployment leads the cycle by one quarter.

One of the stylized facts of the Norwegian business cycles by the end of the 1970s, was the fact that *export* was procyclical and leading the cycle (cf. Wettergreen (1978)). Extending the data to 1994, the results are more difficult to interpret. When export is modelled using a smooth trend like HP-160000 or HP-1600, it displays a countercyclical pattern leading the cycle by a year. Adjusting for a (possible) structural break (LTB) (recall that based on the sequential F-test, I found some evidence that export had a break in the level of the trend in 1974), or using FRE or HP-16, export displays a procyclical pattern, especially if it is lagging the cycle. Finally, BN-high and UCM find export to be acyclical. Hence, using a more stochastic trend or allowing for a break in the deterministic trend, I conclude that export is procyclical, but now lagging the cycle. However, the less volatile is the cyclical component, the less pronounced is the procyclicality (c.f. the low standard deviations using BN-high and UCM reported in table 3). These results essentially emphasise that when the time series may be on the borderline of being difference-stationary or trend-stationary (with a structural break), using the HP-filter with a high smoothing value may create spurious cyclical behaviour.

Real wage displays a similar conflicting pattern. Using a smooth trend like HP-160000, HP-1600 or a very noisy stochastic trend like HP-16, real wage is procyclical. Using LTB, BN-high and FRE, real wage is countercyclical and lagging the cycle. UCM reports real wage to be acyclical. Given that I believe I have captured the business cycle component with FRE, and that LTB seems

[7] One reason why the BN method ranks money as the most volatile series, is due to the fact that the cyclical component is generated by excess volatility in the trend, as the variance of the innovations in the permanent component is much larger than the variance of the innovations in the observed data (cf. the discussion in section 2.2).

Table 4. Contemporaneous and maximum cross-correlation of GDP with[1]

	LTB	HP-16	HP-1600	HP-160000	BN-high	FRE	UCM
C	0.57	0.45	0.56	0.72	0.50	0.64	0.71
	–	–	–	–	0.57	–	–
					(+4)		
I	0.65	0.28	0.52	0.74	0.64	0.65	0.84
	–	–	–	0.76	0.66	0.72	0.88
				(−2)	(+1)	(−1)	(−2)
X	0.31	0.00	−0.08	−0.11	0.12	0.00	−0.08
	0.44	0.28	−0.28	−0.25	–	0.30	−0.16
	(+2)	(+2)	(−4)	(−4)		(+4)	(−4)
M	0.51	0.31	0.57	0.67	0.13	0.68	0.77
	–	–	–	–	0.33	–	0.79
					(+5)		(+1)
PR	0.78	0.83	0.68	0.71	0.63	0.65	0.50
	–	–	–	–	–	0.68	0.59
						(+1)	(+3)
U	−0.52	−0.23	−0.53	−0.72	−0.43	−0.72	−0.80
	−0.59	−0.33	−0.57	−0.74	−0.61	−0.74	−0.81
	(−1)	(−1)	(−1)	(−1)	(+5)	(−1)	(−1)
RWG	−0.09	0.35	0.14	0.21	−0.14	−0.14	0.01
	−0.30	–	0.20	0.30	−0.27	−0.21	–
	(+4)		(−5)	(+2)	(+4)	(+2)	
CPI	−0.53	−0.29	−0.19	0.23	−0.35	−0.14	−0.17
	−0.62	–	−0.32	0.45	−0.44	−0.51	−0.36
	(+5)		(+5)	(−4)	(+4)	(+5)	(+4)
M2	0.02	0.13	0.26	0.45	−0.49	0.37	0.10
	0.10	–	0.28	0.55	–	0.46	0.11
	(−5)		(−2)	(−3)		(−1)	(−1)

[1] Each cell contains in the first row the contemporaneous cross correlation between GDP and the individual series. The second row contains the maximum correlation, (if different from the contemporaneous correlations), between GDP(t) and the individual series($t-k$), ($k = -5, -4, \dots, 0, \dots, 4, 5$), with the chosen number of lead (−)/lag (+) in parenthesis below. Hence, a value −5/(+5) in parenthesis, implies that the series leads/(lags) GDP by 5 quarters.

appropriate (I could reject the unit root hypothesis in favour of a deterministic trend with break), then it is reasonable to suggest that the business cycle behaviour of real wage relative to GDP is countercyclical. This behaviour may also have been appropriately captured by the stochastic trend (BN-high). On the other hand, the procyclical behaviour suggested by the two smooth HP trends, may reflect spurious cyclical behaviour, by misrepresenting the structural break in the data, whereas the procyclical or acyclical behaviour captured by HP-16 and UCM respectively, is most likely due to high frequency "white noise" correlation, (c.f. the peak in the spectra for real wage in figure 2).

For *prices*, HP-160000 displays a procyclical leading pattern, whereas the other methods suggest that prices are countercyclical and mostly lagging GDP. Again, given that I cannot reject the unit root hypothesis for prices, the smooth trend that shows a procyclical pattern seems inappropriate for capturing the business cycle component. Hence, it seems reasonable to suggest that the correlation (at the business cycle component) is countercyclical, lagging the cycle by about a year.

Money is procyclical and mostly leading the cycle using all but the BN-high method, when it is countercyclical. However, as I could not reject the unit root hypothesis in favour of a deterministic trend (c.f. table 1), using a smooth trend like HP-160000 (and maybe also HP-1600) which give the highest correlations, may create spurious cycles. On the other hand, the reason that the BN method suggests money to be countercyclical, may be due to the fact that the cycle is created by an excessive moving trend, as the variance in the permanent component is larger than the variance in the innovations in the observed data, (c.f. the large standard deviation reported in table 3). Hence, I conclude that money is at the most weakly procyclical and leading the cycle.

Using information about the cyclical and the secular properties of the variables above, I have been able to establish some stylized facts of business cycles in Norway.[8] However, for some variables like prices and real wage, the correlation coefficients were quite low, suggesting that the sample moments may have changed over time. Typically, there may have been different shocks (with different effects on the variables) hitting the economy at different times. Lucas (1977) definition of stylized facts of business cycles requires that although they may not have an uniform periodicity or amplitude, the co-movements reported must be regular over time. I therefore finally analyse the behaviour of prices and real wage relative to GDP, by investigating the cross correlations in different sub-periods.

3.4. Principal regularities and stability analysis

Below I study the sample moments (of the cross correlations) over time, when they are computed as a fixed fraction of the full sample, which is shifted over time. The fraction used to calculate the "rolling" correlations corresponds to 8 years, the maximum expected length of a business cycle. The first observation in the rolling correlation, will be placed in the mid point in the first eight year sample. The correlations of GDP with prices and real wage are analysed below in figures 4 and 5 respectively.

Both figures demonstrate that the correlation coefficients have not been stable over time. Figure 4 shows that the countercyclical behaviour of prices suggested in table 4 by HP-1600, FRE and UCM, stems mainly from the 1980s, whereas during the early 1970s (and middle 1970s for UCM), prices were procyclical. The rolling correlation coefficient generated by BN-high behaves somewhat different. Until the middle of the 1980s, BN-high indicates that prices are procyclical, but thereafter, the rolling correlation becomes negative, making prices overall countercyclical in table 4.

In figure 5, LTB, BN-high and FRE suggest that real wage went from a countercyclical behaviour in the early 1970s, to a procyclical behaviour by the 1980s. This is consistent with the fact that prices became more countercyclical during the 1980s (c.f. figure 4). However, the procyclical behaviour of real

[8] Analysis of the relationship between two cyclical variables were also performed in the frequency domain, by investigating the coherence function. However, the results are not reported here as the coherence functions had few distinct peaks that dominated, and therefore did not add much to the conclusions already drawn above.

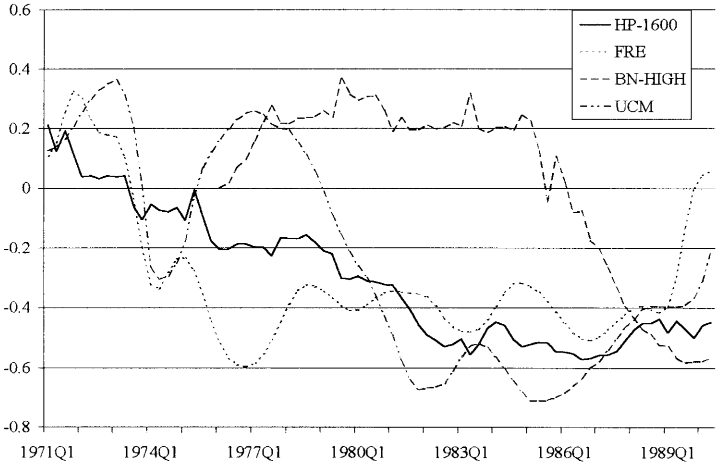

Fig. 4. Rolling correlation coefficients between detrended GDP and CPI

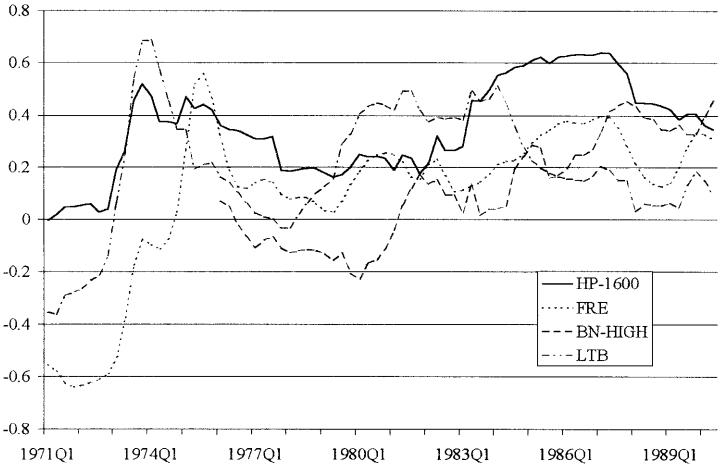

Fig. 5. Rolling correlation coefficients between detrended GDP and real wage

wage from the 1980s is fluctuating and quite low in periods. HP-1600 finds real wage to be procyclical over the whole period, although more so at the end, than at the beginning of the sample. Overall then, the countercyclical behaviour indicated by LTB, BN-high and FRE in table 4, seems basically to stem from the 1970s.

3.5. Stylized facts of business cycles from a real business cycle perspective

One of the main objectives in Kydland and Prescott (1990), was to discard of the “myths” that prices were procyclical, whereas the real wage was at the most countercyclical, (arguments which are supported by traditional models that rely on a sticky wage and aggregate demand shocks). Instead they showed that prices in US were countercyclical and real wage was procyclical. In addition, money was found not to be leading output, the major output components in US moved together, and whereas investment was much more volatile than GDP, the volatility in consumption was much lower than that of GDP. These "new facts" could easily be accounted for by a real business cycle model like that of Kydland and Prescott (1982), which is a stochastic dynamic general equilibrium model, subject to persistent technological shocks. Subsequently, studies like Fiorito and Kollintzas (1994) about the G7 and Christodoulakis et. al. (1995) about the EC, have also reported stylized facts that can be accounted for by a real business cycle model. In particular, it seems to be uniformly agreed that there is a strong countercyclical relationship between prices and output in all countries.

The conflicting pattern of the stylized facts of prices and real wage in Norway presented above, give very little conclusive evidence about the driving force behind the business cycles. With overall countercyclical behaviour of prices and real wage, there seems to be neither enough support for the real business cycle models, nor the sticky wage, demand driven models. Instead, the instability of the results point in the directions that there are many shocks hitting the economy, some more important than others at certain times. For instance, demand shocks may have been most important during the 1970s (when prices were procyclical and real wage countercyclical), whereas later in the 1980s, supply shocks may have dominated (giving way to a countercyclical behaviour of prices and a procyclical behaviour for real wage). However, to give more causal statements than these, requires the use of a multivariate model that carefully distinguishes between the different shocks to be analysed. In contrast to Kydland and Prescott (1990), I also found monetary disturbances to lead the cycle, although the procyclical behaviour is weak, suggesting that money is not a good leading indicator for the Norwegian business cycle.

That most of the components of GDP in Norway were procyclical, can be accounted for by a RBC model, as well as demand driven (Keynesian) model. However to judge whether the magnitude of the correlations and volatility are consistent with a RBC model, I simulate the "time to build" model in Kydland and Prescott (1982), to see if it can generate artificial data that match the Norwegian sample moments. The model is calibrated to the Norwegian economy by specifying the permanent and transitory technological shocks, so that the volatility in the simulated cyclical component of GDP matches the volatility of the cyclical component of actual GDP. As the cyclical components of the simulated data in the RBC model are found using the HP filter with $\lambda = 1600$, I compare the results using HP-1600 in table 3. Some of the sample moments of the Kydland and Prescott model are presented in table 5. Clearly, the low volatility of consumption and the highly procyclical nature of consumption, investment and productivity generated by the RBC model, are not consistent with the Norwegian data.[9]

[9] A dynamic RBC model that is more consistent with the empirical regularities of a small open economy has been developed in Correia et al. (1995). However, the model still implies much lower volatility of consumption and higher procyclical pattern for consumption, investment and productivity, than can be observed in the data for Norway.

Table 5. Sample moments from an artificial real business cycle model[1]
Standard deviation and cross correlation with GDP

	Std. dev pct.	Cross correlations (leads and lags)				
		−2	−1	0	+1	+2
GDP	2.13	0.24	0.39	1.00	0.39	0.24
Consumption	0.62	0.13	0.32	0.89	0.62	0.47
Investment	6.50	0.28	0.40	0.84	0.45	0.21
Productivity	0.82	0.17	0.34	0.92	0.59	0.44

[1] The sample moments are calculated using the Kydland and Prescott (1982) model, where the cyclical components are found by applying the Hodrick-Prescott filter with $\lambda = 1600$. The model is calibrated by specifying the standard deviation of the permanent and transitory shocks so that the standard deviation of artificial GDP is equal to standard deviation of actual GDP (using HP-1600 in table 3). Generally, the standard deviation of the permanent shocks had to be very high to be able to obtain the same volatility in artificial GDP as in the actual data. In addition, the parameters of the inventory/GDP ratio and the labour share of GDP were calibrated to the Norwegian National Accounts (1994).

4. International business cycles

Symmetries in economic fluctuations across countries are particularly important when these countries are to coordinate their economic policies. To examine whether business cycles in Norway are in phase with European or American business cycles, I analyse business cycles in GDP across seven selected countries; United States, United Kingdom, Germany, Denmark, Sweden, Finland and Norway. The cyclical component is extracted using the frequency filtering method. This seems appropriate, as I want to analyse the correlations at the "business cycle" frequency components, without having to say anything about the underlying process. The sample varies somewhat, (see appendix A for definitions).

In table 6, I report the bivariate correlations of output between these seven countries, with the shortest sample used in each correlation. In Norway, (non-oil) output behaves procyclically with output in all the other countries, but the correlation coefficients are relative low. The business cycle in Norway is highest correlated with the business cycle in Denmark, Germany and the US when Norway is leading the cycle.

Whereas the correlation between Sweden and Norway is relative low, the cycles in Sweden and Finland behave highly procyclically. Both Finland and Sweden are also highly correlated with UK when Finland and Sweden lead the cycle. Among the other countries, Denmark and Germany behave procyclically, and UK behaves procyclically with US. None of these countries are leading the cycle. Whereas UK and US behave procyclically, UK and Germany behave countercyclically, when Germany is lagging the cycle with a year. However, (although not reported here) Germany and UK behave procyclically, when Germany is leading the cycle with five quarters (the correlation coefficient is 0.37). Germany and US are also procyclical, if Germany is leading the cycle with two quarters.

Hence, there seems to be three groups of countries, where the cycles are most synchronised. In the first group, I find Germany, Denmark and Norway. In the second group, Sweden and Finland are situated, whereas in the third

Table 6. Cross correlations in output between

	Finland	Germany	Norway	Sweden	UK	US
Denmark	−0.19	0.64	0.28	0.13	0.27	0.35
	−0.23	–	0.49	0.18	–	0.45
	(−2)		(+3)	(+1)		(−3)
Finland	1	−0.11	0.12	0.79	0.37	−0.09
		−0.50	–	–	0.66	−0.31
		(−5)			(−3)	(+5)
Germany		1	0.22	0.29	−0.11	0.30
			0.40	0.34	−0.55	0.39
			(+5)	(−1)	(+4)	(−2)
Norway			1	0.17	0.04	0.02
				0.18	0.15	0.43
				(−1)	(−4)	(−5)
Sweden				1	0.29	0.02
					0.70	0.42
					(−5)	(−5)
UK					1	0.67

[1] Each cell contains in the first row the contemporaneous cross correlation between GDP in both countries. The second row contains the maximum correlation, (if different from the contemporaneous correlations), between GDP(t) in the country reported in the column on the left hand side of the table, and GDP($t-k$), ($k = -5, -4, \ldots, 0, \ldots, 4, 5$) in the countries reported in the top row in the table, with the chosen number of leads (−)/lags (+) in parenthesis below. For instance, the value 0.49 (+3) in the cell between Denmark and Norway, indicate that the maximum correlation between Denmark and Norway is 0.49, and that Denmark is lagging Norway with three quarters.

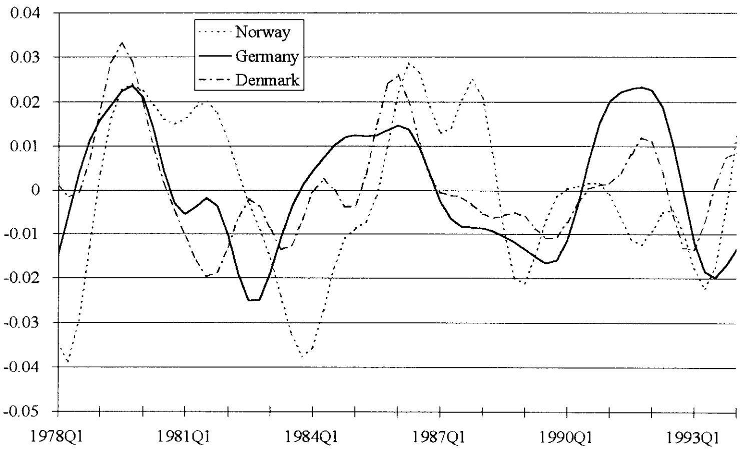

Fig. 6. Business cycles in GDP: Germany, Denmark and Norway

group, I find the UK and the US. These are plotted in figures 6, 7 and 8 respectively. Clearly, in figure 6, the cycles in Denmark and Germany have been very much synchronised, (except maybe for the early 1990s, when Germany experienced a boom due to the unification). Although Norway behaves somewhat procyclically with both Denmark and Germany, the amplitude of the cycles in Norway have generally been larger. These results essentially empha-

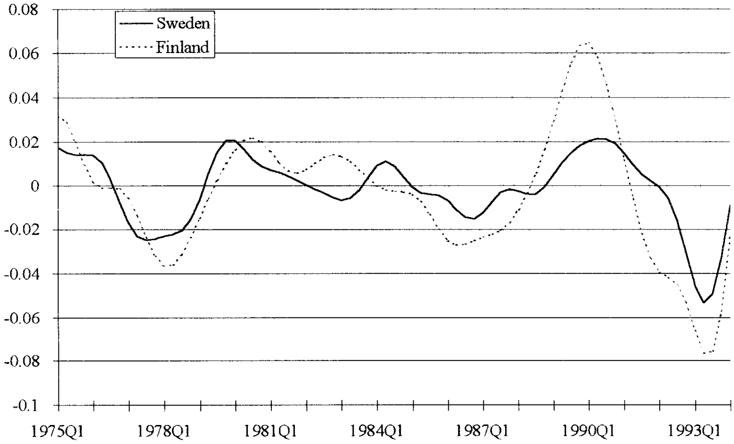

Fig. 7. Business cycles in GDP: Sweden and Finland

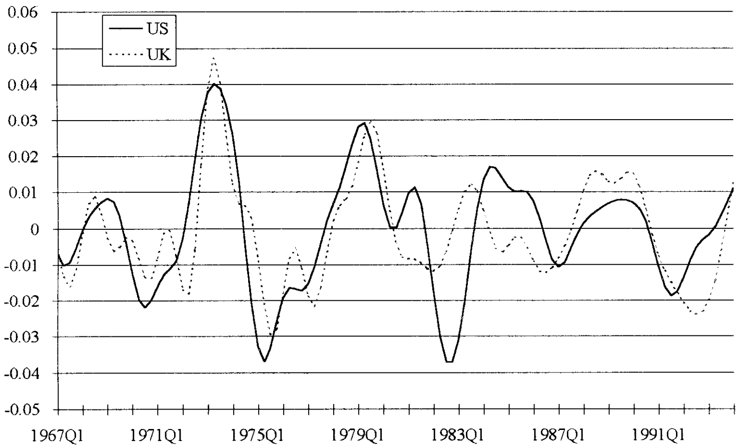

Fig. 8. Business cycles in GDP: US and UK

sise how Norway, being a small oil dominant country, may have experienced more idiosyncratic shocks than other OECD countries.

Sweden and Finland behave very similar during the periods examined, with a recession in the late 1970s, a huge boom by the end of the 1980s, and a long lasting recession thereafter (c.f. figure 7). In figure 8, the US and the UK have very synchronised peaks and troughs, with the most severe recessions in the middle 1970s and early 1980s, coinciding, with the timing of the two world wide oil price shocks.

5. Summary and conclusions

This paper set out to present the stylized facts of business cycles in Norway, by using a set of different detrending methods, including deterministic detrending, stochastic detrending, frequency filtering techniques and the structural time series approach. For many variables, the different detrending methods gave very different cyclical behaviour in the time series. To be able to evaluate the findings, the stochastic properties of the time series have to be analysed prior to the trend/cycle decompositions, for instance, by testing for unit roots.

Generally, I found that for some of the variables that experienced a structural break in the trend, "detrending" without appropriately adjusting for this break, could severely distort the results. This was clearly emphasised using the Hodrick-Prescott filter (with a smooth trend) for real wage and export.

Although the different methods may suggest somewhat different cyclical behaviour, I claim that I have come across some stylized facts. As in many other international studies, I find the cyclical components of investment and import in Norway to be among the most volatile series, whereas the volatility of consumption and productivity is much lower, being about as volatile as that of GDP. The behaviour of productivity and the components of GDP are also clearly procyclical, whereas unemployment displays a persistent countercyclical behaviour. However, the correlation coefficients in Norway are generally much lower than those in the other OECD countries and what a simple real business cycle model like that of Kydland and Prescott (1982) would predict.

For some variables like real wage and prices, the different detrending methods suggested very different cyclical behaviour. However, analysis in sub samples suggested that prices most likely went from a procyclical behaviour in the 1970s towards a countercyclical pattern in the 1980s, whereas real wage went from a countercyclical behaviour in the 1970s towards a procyclical pattern in the 1980s. This suggests a role for both demand shocks (in a traditional Keynesian model) and supply shocks (in the real business cycle models), acting in different periods.

Finally, output in Norway behaves procyclically with output in many other industrialised countries, but the correlation coefficients are small compared to that for instance between UK and US. One of the reasons why the Norwegian business cycle behaves very differently, may be the fact that Norway is a small oil producing country, which has experienced much more idiosyncratic shocks than many other OECD countries.

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Appendix A: Data sources and definitions

(A) NORWAY

All series used in the analysis except those used for the frequency filtering techniques and the unobserved components method are quarterly seasonally adjusted data from *KVARTS Database*, *Statistics Norway*. The seasonal adjustment used is X-11 ARIMA. The frequency filtering technique and the unobserved components method use unadjusted quarterly data from the

KVARTS Database. Throughout the analysis, the list of variables below refers to the seasonally adjusted and unadjusted data interchangeably. The periodicity is from 1967Q1–1994Q1. All variables are measured in natural logarithms except for the unemployment rate that is measured in levels.

GDP Gross Domestic Product in *mainland* Norway at constant 1991 prices
C Private consumption expenditure at constant prices
I Gross Fixed Capital formation in *mainland* Norway at constant prices
X Export of goods and services at constant prices
M Import of goods and services at constant prices
PR Productivity in *mainland* Norway; GDP/H
(H) Total hours worked in *mainland* Norway
RWG Real wage in *mainland* Norway; W/PY
(W) Nominal wage pr. employee (pr. hours.) – *mainland* Norway
(PY) Implicit deflator of Gross Domestic Product – *mainland* Norway
U Unemployment rate
CPI Consumer Price Index
M2 Money supply M2 at current prices

(B) INTERNATIONAL ECONOMY

Denmark: GDP, constant prices, (n.s.a.), (1977Q1–1994Q1). Source: *Datastream*
Finland: GDP, constant prices, (n.s.a.), (1975Q1–1994Q1). Source: *Datastream*
West Germany: GDP, constant prices, (n.s.a.), (1978Q1–1994Q1). Source: *Datastream*
Sweden: GDP, constant prices, (n.s.a.), (1970Q1–1994Q1). Source: *Konjunkturinstitutet*
UK: GDP, constant prices, (n.s.a.), (1967Q1–1994Q1). Source: *Datastream*
US: GDP, constant prices (s.a.), (1967Q1–1994Q1). Source: *Datastream*