From shocks to cycles - an examination of Euro area economic cycles

From Shocks to Cycles - An Examination of Euro area Economic Cycles

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[1] This chapter was presented at the All China Economics Conference, City University of Hong Kong, in 2006.

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[2] A shortend paper based on this chapter has been accepted for the Royal Economic Society (RES) conference, University of Warwick, in 2008.

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Abstract

It is often the case that the key stumbling block for policy formation is limited knowledge of the way the macroeconomy works. Along with the introduction of a common currency, the interest and need for business cycle analysis at the Euro area level has increased. For this reason, at the present time business cycle research for the Euro area has an added significance, given current efforts to understand the workings of the Euro area economy, in terms of the impulse - real, monetary and international - and propagation mechanisms that drive the cycle, so as to design Euro-wide policies.

The Euro area's internal mechanisms are explored by using various shock-based models to investigate, first, how much of the Euro area business cycle is due to various shocks - be they real or nominal - and second, whether these shocks explain the dampening in the Euro area business cycle over the last two decades. This so-called 'great moderation' - the decline in volatility for the Euro area is measured to be just over 40 percent during the past two decades - has only recently motivated economists to ask why business cycles over the past decade are now less volatile across the developed world than was the case in the 1970s and 1980s. These lines of enquiry are extended to investigate the role the Euro area economy plays in the wider global economy by examining the importance of international shocks on the Euro area economy. Linking in with the moderation literature, the study explores whether international shocks have been a key contributing factor behind the decline in business cycle volatility. Little, if any, work examining these issues for the Euro area have been yet undertaken.

Allowing for caveats, the results show permanent productivity shocks - modelled using the balanced growth assumptions - to have had a significant role in driving output fluctuations for the Euro area, though they are not quite as important as claimed by real-business-cycle theory. The results also go on to show that permanent shocks explain a larger proportion of the decline in output volatility than is the case with monetary shocks. The estimation undertaken in chapters 4 and 5 show that despite the moderation in business cycle volatility being associated with structural change in the early 1990s, benign business cycles in the Euro area have been more down to 'good luck' than good policies, such as changes in the priority of monetary policy. Finally, consistent with the good luck hypothesis, the results show output growth to have become more forecastable - as measured by the mean-squared-forecast-error - over the last two decades. Although, this improvement is constrained mainly to asset price variables, with little improvement in the forecasting power of monetary aggregates.

Part I

Literature Review

Chapter 1

Measuring the Business Cycle

Studying business cycles is of interest for both economic theory and policy alike. Economic policy is often adjusted to the state of the business cycle. However, policy is sometimes constrained by some measures of the business cycle. For example, a central bank may lower interest rates if the country is perceived to be plunging into a recession in the classical business cycle definition sense, but not if growth is lower due to structural reasons - a growth recession. Hence, before any analysis of the Euro area business cycle can take place, it is important to define what is meant by the term 'business cycle'. There remains controversy over what are suitable measures of economic activity, and how these should be calculated. It is desirable to know the facts before attempting to explain them, hence the attractiveness of organising business-cycle regularities within a model-free framework. This chapter investigates some of the difficulties faced by economists in trying to define what constitutes a business cycle, along with discussing ways of trying to extract a business cycle series that can accurately capture the state of the Euro area economy over the last two-and-a-half decades. An attempt at an accurate compilation of stylised facts for the Euro area business cycle is important for two reasons. First, it provides a summary of the complex comovements existing among aggregates in the economy, thus allowing a rough calculation of the magnitude of the fluctuations in economic variables, which in turn may guide researchers in choosing leading indicators of economic activity. Second, it provides a set of regularities which macroeconomists can use as benchmarks to examine the validity of empirical versions of theoretical models.

A key aspect of the analysis is to obtain a quantifiable definition of a business cycle. There is a long intellectual history of the empirical analysis of business cycles. Burns and Mitchell (1946) offer the following definition of the business cycle:

"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 in recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own" (Burns and Mitchell, 1946, p.3).

An issue surrounding this definition involves whether one should look at fluctuations in the level of economic activity or fluctuations around some trend; which measure constitutes the most accurate description of economic activity? Some researchers examine *classical* cycles, which concern turning points in the level of real economic activity. Other researchers study *growth* cycles, in which expansions and recessions refer to periods of increasing and decreasing growth, typically defined after detrending the output series. Hence, empirical examination of the business cycle involves the delicate and controversial issue of detrending. There are two problems connected with detrending. The first concerns the lack of a consensus on what constitutes business cycle fluctuations. Singleton (1988) observed that the stylised facts motivating recent specifications of various business cycle models may be distorted by prefiltering procedures. Documenting the properties of different types of business cycles may therefore help, on the one hand, to provide a more exhaustive description of the data and, on the other, to highlight the sense in which they are economically different.

Industrial production is one of the most cyclical macroeconomic time series, and is best used to illustrate the cyclical fluctuations that characterise the Euro area economy. Figure 1.1 plots the natural logarithm of an index of industrial production for the Euro area from 1980 to 2005. Over the last 20 years, the index has increased by almost 50 percent. This reflects the growth in the Euro area labour force and of the productivity of European workers over the last 20 years. Also evident in Figure 1.1 are the periods of increase and decline that constitute Euro area business cycles. These fluctuations coincide with some of the signal events of the Euro area economy over the last two and half decades; for example, the collapse of the Exchange Rate Mechanism (ERM) and the bursting of the dotcom bubble at the turn of the millennium. To bring these fluctuations into sharper focus, Figure 1.2 illustrates an estimate of the cyclical component of industrial production. This estimate was obtained by passing the series through a bandpass filter that isolates fluctuations at business cycle periodicities. The vertical lines indicate the cyclical peaks and troughs in the classical cycle definition sense, measured by the Bry and Boschan (1971) algorithm. Evidently, the business cycle is an enduring feature of the Euro area economy. A very pertinent final impression that can be gleaned from the plot in Figure 1.2 is the finding that peaks and troughs of the growth cycles, as measured by the Baxter and King (1999) filter, correspond quite closely with the estimated peaks and troughs, where troughs are defined as periods of absolute falls in output. This has important implications for the discussion.

Figure 1.1 Industrial Production Index, Levels

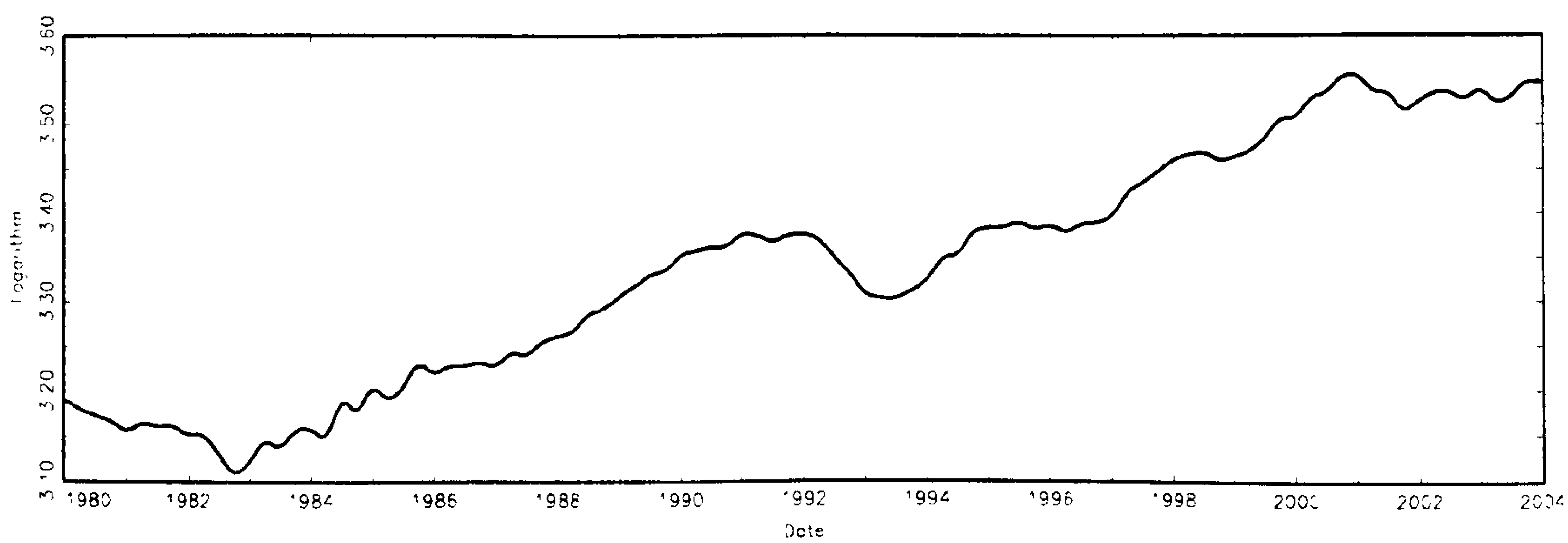
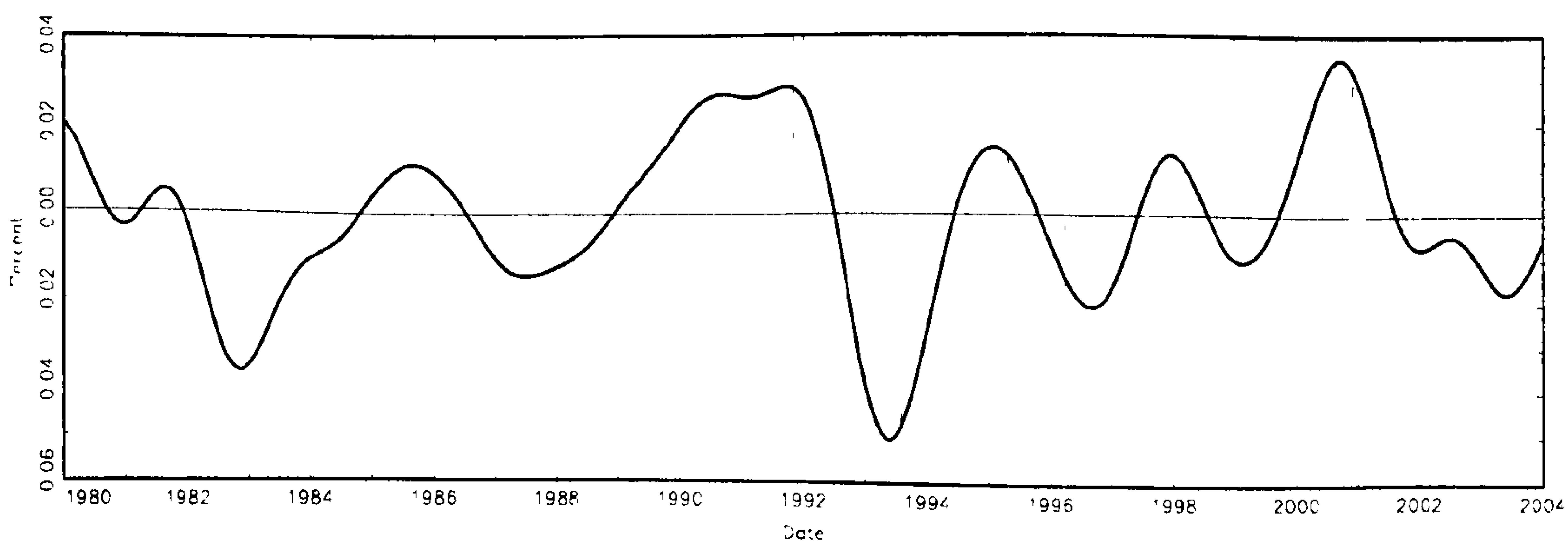


Figure 1.2 Business Cycle Components



Looking at the graphs for the first time would incline one to identify a repeated sequence of ups and downs. Although one's eye is sympathetic to the claim that the series displays a recurrent pattern, it does not appear to be cyclical in the sense of exhibiting strict periodicity. For example, the two consecutive industrial production peaks in 1991:4 and 1994:4 are separated by less than three years, whereas those of 1994:4 and 2001:1 are separated by six years. Whether the cycle presented in Figure 1.2 represents an accurate picture of the state of the Euro area economy over the last two and a half decades has been debated extensively.

The classical business cycle, which is what researchers often implicitly try to analyse, refers to absolute declines in output and other measures. From this description comes the definition of a recession, which emphasises the "three D's"; it should be sufficiently long (duration), it should involve a substantial decline in economic activity (depth), and it should involve all the sectors of the economy rather than simply reflecting an isolated decline in a single sector or region (diffusion). Alternative definitions have been examined in order to obtain a more accurate picture and definition of the business cycle. One alternative is to examine cyclical fluctuations in economic time series that are deviations from their long-run trends. Zarnowitz (1992) refers to the resulting cycles as growth cycles. Whereas classical cycles tends to have recessions that are considerably shorter than expansions because of underlying trend growth, growth recessions and expansions have approximately the same duration. The study of growth cycles is consistent with modern macroeconomic models from Real-Business-Cycle (RBC) theory. The study of growth cycles refrains from separating trend and cyclical activity. Such assumptions assume that productivity shocks determine both long-run economic growth and the fluctuations around that growth trend. This implies that the trend-cycle dichotomy is only justified if the factors determining long-run growth and those determining cyclical fluctuations are largely distinct. It has been noted that growth cycle chronologies are, by construction, less sensitive to the underlying trend growth rate of the economy. Some countries which have experienced very high growth rates, such as Japan in the 1980s or the UK since the mid-1990s, exhibit growth cycles since they have few absolute declines in real output, and thus have fewer classical business cycles.

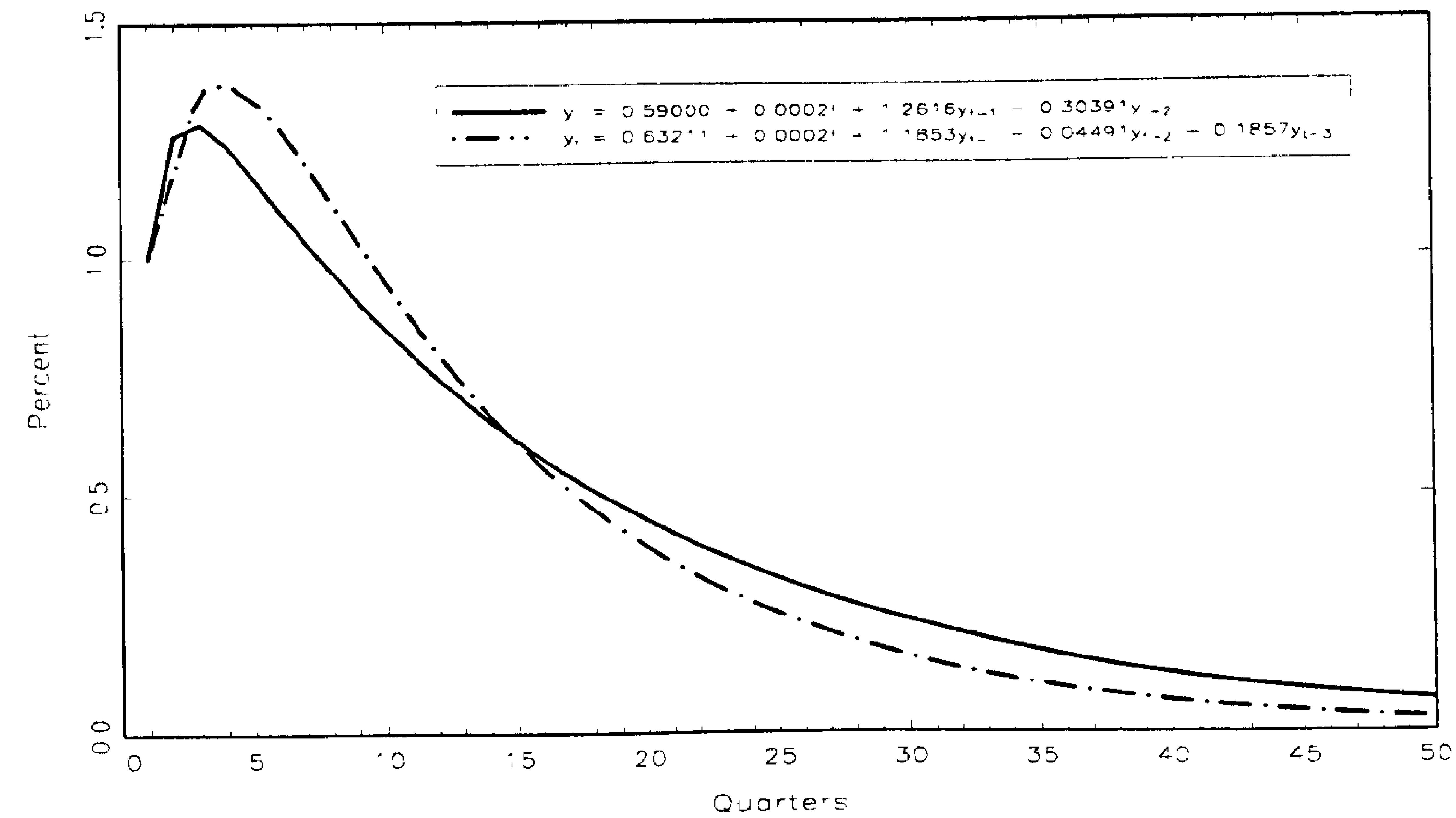
The issue of whether real GDP should be separated into transitory and cyclical components, however, runs to the heart of major business cycle theories. In addition, whether fluctuations in output are dominated by temporary deviations from the natural rate implies profound methodological concerns. The separation of the trend and cycle is consistent with traditional monetary and Keynesian theories of economic fluctuations. For example, it would imply that an innovation to output should not substantially change one's forecast of output in, say, five or ten years. Over the long horizon, the economy should return to its natural rate - the time series for output should be trend-reverting. Both traditional Keynesian and monetarist theories held the view that business cycle fluctuations in output represented temporary deviations from trend. However, traditional monetary and Keynesian theories suffered in the early 1980s from a combination of factors - notably stagflation and theoretical internal inconsistencies concerning expectations. These issues were first synthesised by Granger (1964), who showed that the 'typical spectral shape' of a macroeconomic variable is monotonically decreasing, meaning that the bulk of the variance is attributable to very low frequency components, such as long-run trends and, albeit to a lesser extent, to business cycle (or medium frequency) fluctuations. This neoclassical synthesis remains the standard workhorse assumption of macroeconomics, and is a prevalent view amongst politicians and journalists alike. The strong contribution of frequencies around zero is often held as the primary reason why business cycle analysis requires prior detrending of the original series.

1.0.1 Measurement of Business Cycles: Filtering Trends and Growth Cycles

Before proceeding it is important to identify two important classifications for the business cycle, since both definitions have important implications in extracting cyclical fluctuations from a real GDP time series. The first is the classical cycle. The demands of a classical cycle dating algorithm are relatively few: peaks are first defined by reference to an immediate subsequent downturn in the absolute level of output and troughs by immediate recovery in the level of output. Then, peaks and troughs are required to alternate. Finally, to qualify as a cycle, downturn and upturn phases are required to fulfil minimum duration requirements - usually six months. Second, the growth cycle, or 'deviation cycle', is defined to be where peaks and troughs are essentially marked by upward and downward inflections in the growth rate of the chosen measure of economic activity. The latter concept of the cycle involves some form of detrending. The issue of appropriate filtering is important when considering the welfare implications of business cycles. For example, a departure of output below its (rising) trend may imply relatively little lost income or under-utilised resources, whereas an absolute decline in output would almost surely entail significant welfare losses.

According to the traditional view, fluctuations in real GDP primarily reflect deviations of production from trend. Blanchard (1981) and Kydland and Prescott (1980) subscribed to the then uncontroversial suggestion that the logarithm of quarterly real GDP is well represented as a stationary second-order autoregressive ($AR(2)$) process around a deterministic time trend. The response of the model to a positive one percent innovation can be calculated by rearranging the AR process to arrive at a moving-average representation; $y_t = [1 - \varphi(L)]^{-1}\varepsilon_t$, where $\varphi(L)$ represents the lag polynomial of the estimated AR coefficients. This is shown in Figure 1.3, where an $AR(3)$ specification is also included as a comparison. The dynamic response from the $AR(2)$ process implies that the effect of a shock increases y_t, but dies out afterwards. These authors, along with many others, view this dynamic response of output to an innovation as a phenomenon to be explained by macroeconomic theory.

Figure 1.3 Impulse Response Functions



However, problems arise because dynamic economic theory does not indicate the type of economic trend that series may display nor the exact relationship between secular and cyclical components. Consequently, standard textbook treatments of macroeconomic fluctuations separate the high frequency business cycle fluctuations from low frequency growth fluctuations. This dichotomy lies at the heart of most Keynesian and rational expectations models. Sophisticated Keynesian macroeconometric models, such as the Fair model, incorporate a production function that determines output in the long-run. Rational expectations with misperception models of the cycle, such as Lucas (1973), also have monetary impulses moving output temporarily from a trend level. In these models, shocks to aggregate-demand temporarily move the economy away from some 'full employment', 'potential', or 'natural' level of output. The natural level of output is determined by the capital stock, the labour force and technology in long-run equilibrium. These supply-side factors are assumed to be independent of the business cycle phenomenon. This dichotomy is central to the neoclassical synthesis, superimposing business cycles as short-run disequilibrium phenomena on an economy in long-run equilibrium.

Models have been proposed where the long-run component may be either deterministic or stochastic and may or may not be related to the cyclical component, i.e. the trend and cycle interact in a non-trivial way. Popular methods of extracting the cyclical component include the following: the Beveridge and Nelson (1981) (BN) decomposition based on an unconstrained $ARIMA$ model (Cochrane, 1988, Campbell and Mankiw, 1987, Watson, 1986), Unobserved-Components (UC) models (Clark, 1987), the Hodrick and Prescott (1997) (HP) filter, and the Bandpass (BP) filter (Baxter and King, 1999). Note that the HP filter is not *per se* a trend-cycle decomposition since it also eliminates high-frequency components. Nevertheless, for the real GDP series analysed, high frequency movements are not important and, hence, it effectively acts as a trend removal procedure. A major problem faced by practitioners is that these methods usually lead to different trend-cycle decompositions and the differences are often substantial, leading to quite different 'stylised facts' about the business cycle to be used when confronting models with the data. In addition, employing detrending techniques sometimes presupposes certain conditions upon the data, which can significantly bias the data against certain business cycle theories.

These concerns are succinctly described in Figures 1.4 - 1.6, which plot cyclical fluctuations of quarterly Euro area real GDP from 1980 till 2005. As with the fluctuations illustrated in Figure 1.1, such cyclical fluctuations are evident in real GDP. Figures 1.5 and 1.6 show that there are some fluctuations in the series that occur over periods shorter than a business cycle, arising from temporary factors such as industrial strikes or measurement error. Intuition would suggest that, if the long-run growth component of GDP is a linear time trend, a natural way to eliminate this trend component is to regress the logarithm of real GDP against time. The trend, in general, is represented by a deterministic linear function of time, assumed to be independent of the cyclical component and extracted using simple regression methods. The trend is estimated by fitting y_t to a constant and to scaled polynomial functions of time using standard regression methods, and by taking the predicted value of the regression. The cyclical component is the residual, which if plotted results in a 'linear detrended GDP' series if just a linear trend is used. Figure 1.5 plots this simplest and oldest procedure for filtering real GDP. The fluctuations of output in Figure 1.5 are more pronounced than in Figure 1.4. However, Figure 1.5 still appears to contain fluctuations of a short duration that are arguably not related to business cycles. In addition, this procedure is statistically valid only if the long-run growth component is indeed a linear time trend, i.e., if GDP is trend-stationary. This assumption has been questioned however.

Figure 1.4 Level of GDP

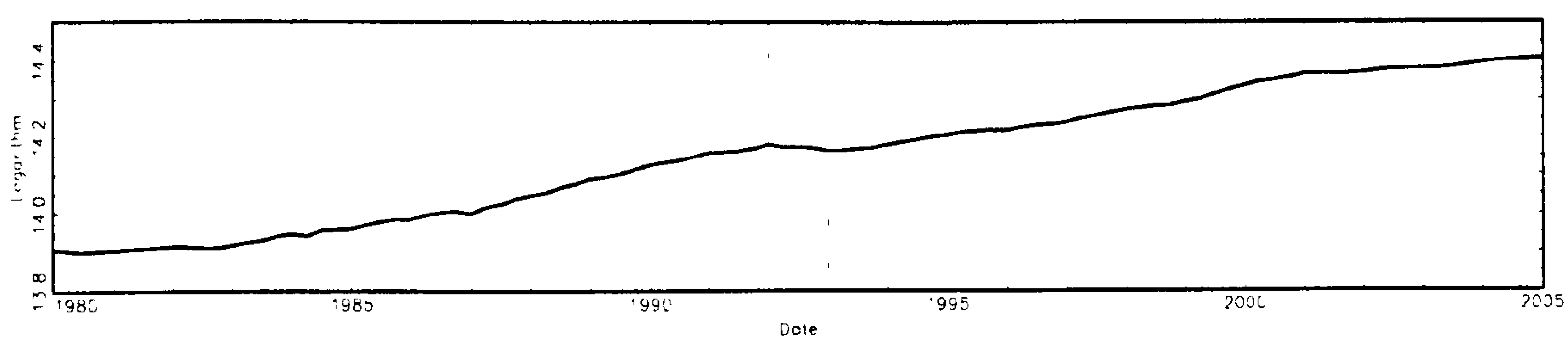


Figure 1.5 Linearly Detrended GDP

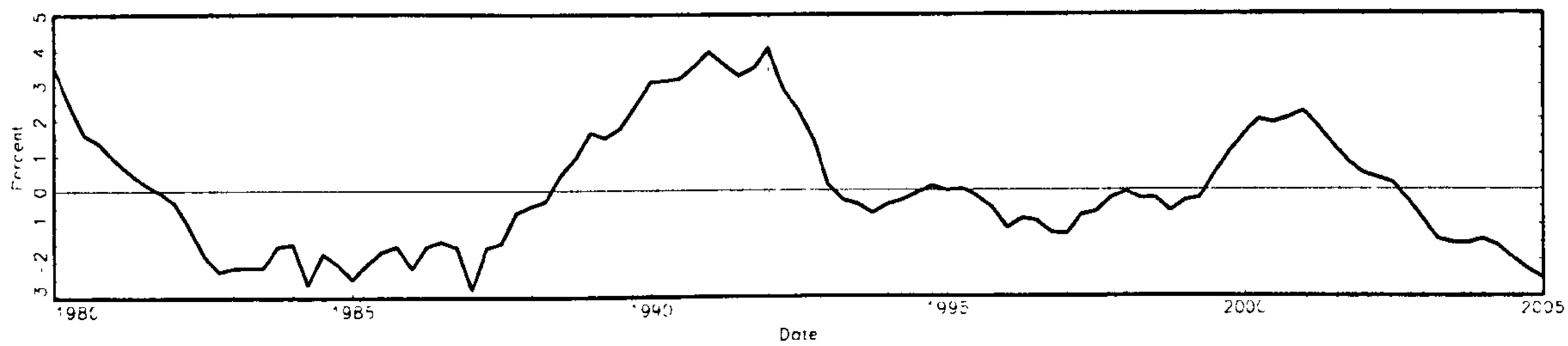
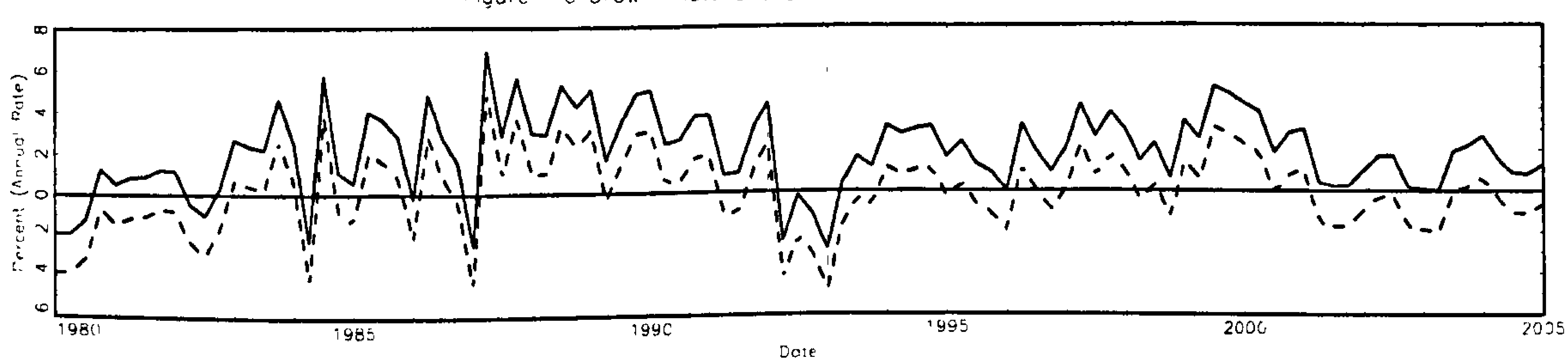


Figure 1.6 Growth Rate and Demeaned Growth Rate of GDP



Note: In Figure 1.6 the demeaned growth rate is represented by the dashed line, whilst the standard growth rate measure is represented by the solid line.

In the 1980s, a sequence of influential papers reported favourably on the hypothesis of a single unit root in the autoregressive representation of real GDP. Before the work of Nelson and Plosser (1982), it was commonplace to assume that the trend was linear. Nelson and Plosser (1982) challenged the orthodox assumption of trend stationarity by providing evidence, that for many widely used aggregate macroeconomic time series, the trend could be characterised as a random walk. That is, instead of being a fixed trend to which the time series would revert over the business cycle, the trend would be moved by random shocks, and then would stay at the new level until disturbed by another shock. This study was followed up by, amongst many others, Rudebusch (1993), Diebold and Senhadji (1996) and Nelson and Murray (2000). Much of the literature supports the view that real GDP is best modelled as difference stationary with a caveat that it is impossible to distinguish large stationary autoregressive roots from unit autoregressive roots, and that there might be nonlinear trends. Linear detrending also has a second unintended consequence. Detrending forces the resulting series to be trend-reverting, so that today's innovation has no ultimate effect on output, hence presupposing that output fluctuations are transitory at an infinite horizon. Nelson and Kang (1981) showed that by detrending a series and then estimating an $AR(1)$ process $\tilde{y}_t = \alpha + \theta\tilde{y}_{t-1} + \varepsilon_t$, for the detrended $\tilde{y}_t$, where α is a constant term representing long-term growth, leads to an estimate of α that is severely biased towards zero, preventing the presence of any long-term growth component. This implicitly rejects the conclusions drawn by Nelson and Plosser (1982), who showed that for a number of macroeconomic time series, measured annually over periods of 60 to 120 years, one cannot reject that some fraction of an innovation in real GDP is permanent. Similar results were found by Mankiw and Shapiro (1985).

It is very unlikely, however, that any given type of linear deterministic trend would persist over long stretches of time, surviving major structural and technical changes, wars, business expansions and contractions, financial crises, rising and falling inflation etc. In a sense, such a detrending technique presupposes no role for textbook RBC theory, in which the common explanation is that technology/productivity shocks are mostly responsible for movements in aggregate production, with such shocks having a permanent effect. Of course, it could still be the case that at large, but finite, horizons of five or ten years the detrended series displays a considerable effect of today's innovation. However, in samples of typical size, detrending could provide a seriously biased answer.

Auxiliary assumptions concerning the covariation of the trend and cyclical components of the data are necessary. Once covariation of the trend and cyclical component is allowed for, the rationale for detrending loses much of its appeal. Nelson and Plosser (1982) conclude that assigning a major portion of the variance in output to the innovation in a nonstationary component gives an important role for real factors in output fluctuations, whilst placing limits on the importance of monetary theories of the business cycle.[1]

Transforming log real GDP to a difference stationary process $(1 - L)y_t = \mu + \varepsilon_t$, where μ represents the mean growth rate, transforms the series into quarterly growth rates and eliminates the trend. The trend is defined as $\tau_t = y_{t-1} + \mu$, and an estimate of the cycle is obtained by $c_t = (1 - L)y_t - \mu$. This is plotted in Figure 1.6. The basic assumptions of a first-order differencing procedure is that the secular component of the series is a random walk, the cyclical component is stationary and that the two components are uncorrelated. In addition, it is assumed

[1] Campbell and Mankiw (1986) state that this analysis is inconsistent with many prominent theories in which output fluctuations are primarily caused by shocks to aggregate demand, including models based on long-term nominal contracts.

that real output has a unit root which is entirely due to the secular component of the series. First differencing evidently eradicates a visible trend, with recessions appearing as sustained periods of negative growth, concurring with the classical definition of the business cycle; contractions in economic activity are an essential ingredient of the classical definition of a business cycle. A consequence of first differencing, however, is that it exacerbates the difficulties presented by short run noise, which obscures the cyclical fluctuations of interest. Notwithstanding this, the advantage of differencing is that unlike detrending, first differencing does not presuppose that all output fluctuations are transitory. This can be illustrated with an $IMA(1,1)$ (integrated-moving-average); $(1-L)Y_t = \alpha + (1-\theta L)\varepsilon_t$, then a unit impulse in Y_t changes one's forecast of Y_{t+n} by $(1-\theta)$ regardless of n. Difference stationary processes have permanent components that show no such trend reversion, as they often reflect shocks which have long persistent effects. If GDP were a stochastic trend with no stationary component, then a one percent unit increase in GDP above its forecasted amount would change GDP by one percent, highlighting that a unit root is consistent with both great and little long-run persistence.

In the face of a strong theoretical argument in support of GDP being difference stationary, it would be misleading to say that there is stronger evidence for the stochastic trends hypothesis than for the traditional deterministic trends hypothesis. As shown by Perron (1989), the stochastic trends hypothesis may be rejected if one allows for shifts in the deterministic trend at turbulent times. The choice of whether to model a time series as following a stochastic or a deterministic but shifting trend[2] can thus not be made on empirical grounds only, but theoretical too, which is discussed in the following chapter. As a result of the difficulties faced by economists in trying to isolate an accurate measure of the business cycle, much work has been expended trying to find better methods that isolate cyclical components of real GDP associated with business cycles. Various filters have been developed over the past two decades, many of which have been based on the theoretical argument that measurement and analysis of cycles, as deviations from trend, constitute a very worthwhile subject for the light they may throw on the level of variability of growth and the sources of economic instability.

[2]Perron (1989) suggested three different characterizations of the break, or 'form of break' under the alternative, namely, (*a*) the crash model that allows for a break in the intercept alone, (*b*) the changing growth model that allows for a break in the slope with the two segments joined at the break-date, and (*c*) the mixed model that allows for a simultaneous break in the intercept and slope. Specifically, Perron (1989) examined the Nelson and Plosser (1982) macroeconomic series and U.S. Postwar quarterly Real GNP and found the changing growth model suitable for quarterly US real GNP, the mixed model suitable for common stock prices and real wages, and the crash model suitable for the remaining Nelson and Plosser (1982) series.

Filters

These considerations have spurred time series econometricians to find methods that better isolate the cyclical component of time series. Two important pieces of research undertaken in trying to acquire accurate measures of economic activity are due to Hodrick and Prescott (1997) and Baxter and King (1999). Both define the business cycle component on the basis of a decomposition of the series into permanent and transitory components.

The filter due to Hodrick and Prescott (1997) - HP filter - has been used by a large number of studies. The HP filter can be expressed as $y_t = y_t^{tr} + y_t^c$, where y_t^{tr} denotes the trend component, whilst y_t^c represents the cyclical component. Given the sample, the HP filter involves the estimation of the trend component from the solution to the following minimisation problem for fixed λ; $\min_{\{y_t^{tr}\}_{t=1}^T} \Sigma_{t=1}^T (y_t - y_t^{tr})^2 + \lambda((y_{t+1}^{tr} - y_t^{tr}) - (y_t^{tr} - y_{t-1}^{tr}))^2$. The first term in the objective function is a measure of the 'goodness-of-fit'. The second term penalises variations in the growth rate of the trend component. The parameter λ is key, since it determines the trade-off between 'goodness-of-fit' and the smoothness of the trend component. At the limit, $\lambda \longrightarrow \infty$, the trend becomes linear thereby allowing for large fluctuations in the cyclical component. When $\lambda \longrightarrow 0$ the trend component becomes equal to the data series y_t, and the cyclical component approaches zero. Many early studies fixed the smoothing parameter λ at 1600. The value is often based upon a prior about the variability of the cyclical part relative to the variability of the change in the trend component. This filter has the desirable property of removing the unit root trend component associated with stochastic trends.

The Baxter and King (1999) filter, a bandpass filter, draws on the theory of the spectral analysis of time series data. The height of the spectrum at a certain frequency corresponds to fluctuations of the periodicity. The filter removes higher or lower frequencies as 'noncyclical'. The cyclical component can be thought of as those movements in the series associated with periodicities within a certain range of business cycle durations. This is usually defined as a business cycle with periodicities of between six and 32 quarters. From a business cycle standpoint, the Baxter and King (1999) linear filter preserves these fluctuations but would eliminate all other fluctuations, both the high frequency fluctuations - periods less than six quarters - associated, for example with measurement error, and the low frequency fluctuations - exceeding 32 quarters - associated with trend growth. This filter has some advantages over the HP filter, in that it more readily separates the data into different frequency components, which have long been of interest to economists. Some economic hypotheses are naturally formulated in the frequency domain, for example. Friedman's hypothesis that the long-run Phillips curve is positively sloped, and the short-run Phillips curve is negatively sloped, is one example. A second example is the proposition that money growth and inflation are highly cyclical in the long-run but less correlated in the short-run. Perhaps the most prominent example is Friedman's permanent income hypothesis, with transitory income represented by the high frequency components, and permanent income explained by the low frequency part. Therefore, the theory of the spectral analysis of time series provides a foundation for the notion that there are different frequency components of the data. For the purposes of the research presented here, one may associate the frequency components with various cycles suggested as existing in economic series, such as 'Kondratieffs' long wave' (40 to 60 years), 'Kuznets' long wave' (20 to 30 years), the 'building cycle' (15 to 20 years), 'minor' or 'Kitchin cycles' (2 to 4 years), the 'business cycle' (1.5 to 6 years), and so forth.

The starting point is the spectral representation of a time series, according to which a sequence, y_t, can be approximated by an integral sum of mutually orthogonal random periodic components, with frequencies $\omega \in [-\pi, \pi]$; $y_t = \int_{-\pi}^{\pi} e^{i\omega t}\zeta(\omega)d\omega$. From this, the variance of y_t can be calculated as $var(y_t) = \int_{-\pi}^{\pi} f_y(\omega)d\omega$, where $f_y(\omega) = var(\zeta(\omega))$ is defined as the power spectrum of y_t. The latter provides information about the contribution of any periodic component to the total variance of y_t. If the data is filtered, such that $y_t^* = a(L)y_t$, where $a(L) = \Sigma_{j=-\infty}^{\infty} a_j L^j$ is a two-sided moving-average filter with infinite leads and lags expressed as a polynomial in the lag operator L, the spectral association can be written as $y_t^* = \int_{-\pi}^{\pi} e^{i\omega t}a(\omega)\zeta(\omega)d\omega$. The frequency response function, $a(\omega) = \Sigma_{j=-\infty}^{\infty} a_j e^{i\omega j}$, maps each frequency ω, altering the weight of the periodic component $\zeta(\omega)$ in the spectral decomposition. Accordingly, the variance of y_t^* is decomposed as $var(y_t^*) = \int_{-\pi}^{\pi} |a(\omega)|^2 f_y(\omega)d\omega$. As stated by Baxter and King (1999), the power transfer function of the ideal linear filter is unity for business cycle frequencies and zero elsewhere. For example, to isolate frequencies belonging to some interval $[\omega', \omega'']$, where $\omega' < \omega''$ (in business cycle research ω usually corresponds to $\omega' = 6$ and $\omega'' = 32$), the ideal filter must satisfy $a(\omega) = 1$ if $\omega' \leq |\omega| \leq \omega''$, with $a(\omega) = 0$ otherwise. The above equations allow a definition of the the outcome of any filtering procedure and, in turn, the filter required for that outcome to be achieved. In practice, however, the ideal bandpass filter cannot be used. It has to be replaced by an approximate bandpass filter, entailing finite leads and lags, k. For a given k, the associated frequency response function, denoted as $a_k(\omega)$, is chosen by minimising a loss function such as $Q = \int_{-\pi}^{\pi} |a(\omega) - a_k(\omega)|^2 d\omega$. In this criterion, the goodness of the approximation is measured by the integral sum of squared deviations between the approximate and ideal filters. As a result of this outcome, this minimization problem is sensitive to k. Of course, as k grows large it is possible to achieve better approximations, but because $2k$ observations are lost, there is a cost in terms of sample size. Moreover, cutting off the moving-average filter gives rise to two distortionary effects; leakage (overstating frequencies outside of the band of interest) and compression (under representing the frequencies of focus). The choice of k is normally chosen to account for this. The solution to these trade-off's is mainly an empirical matter. In sum, the application of a bandpass filter requires setting three parameters; two detrending, the breadth of the frequency band of interest (lower bound ω' and upper bound ω''), and a cut-off parameter k. Conditional on these choices, the bandpass filter yields a stationary series, with the variance (almost) completely attributable to frequencies between ω' and ω''.

The power transfer function of the bandpass filter and several candidate filters discussed so far are plotted in Figure 1.7. The spectral density of the time series y_t at frequency ω is $s_x = (2\pi)^{-1}\Sigma_{j=-\infty}^{\infty}\phi_y(j)e^{-\iota\omega j}$, where $\phi_y(j) = cov(y_t, y_{t-j})$. The power transfer functions of a linear filter $a(L)$ is $A(\omega) = ||\Sigma_{j=-\infty}^{\infty}a_j e^{i\omega j}||^2$, which represents the gain of the linear filter. The spectrum of a linearly filtered series, $y_t^* = a(L)y_t$, is $s_{y^*}(\omega) = A(\omega)s_y(\omega)$. Power transfer function of this ideal filter and several candidate feasible filters are plotted in Figure 1.7.

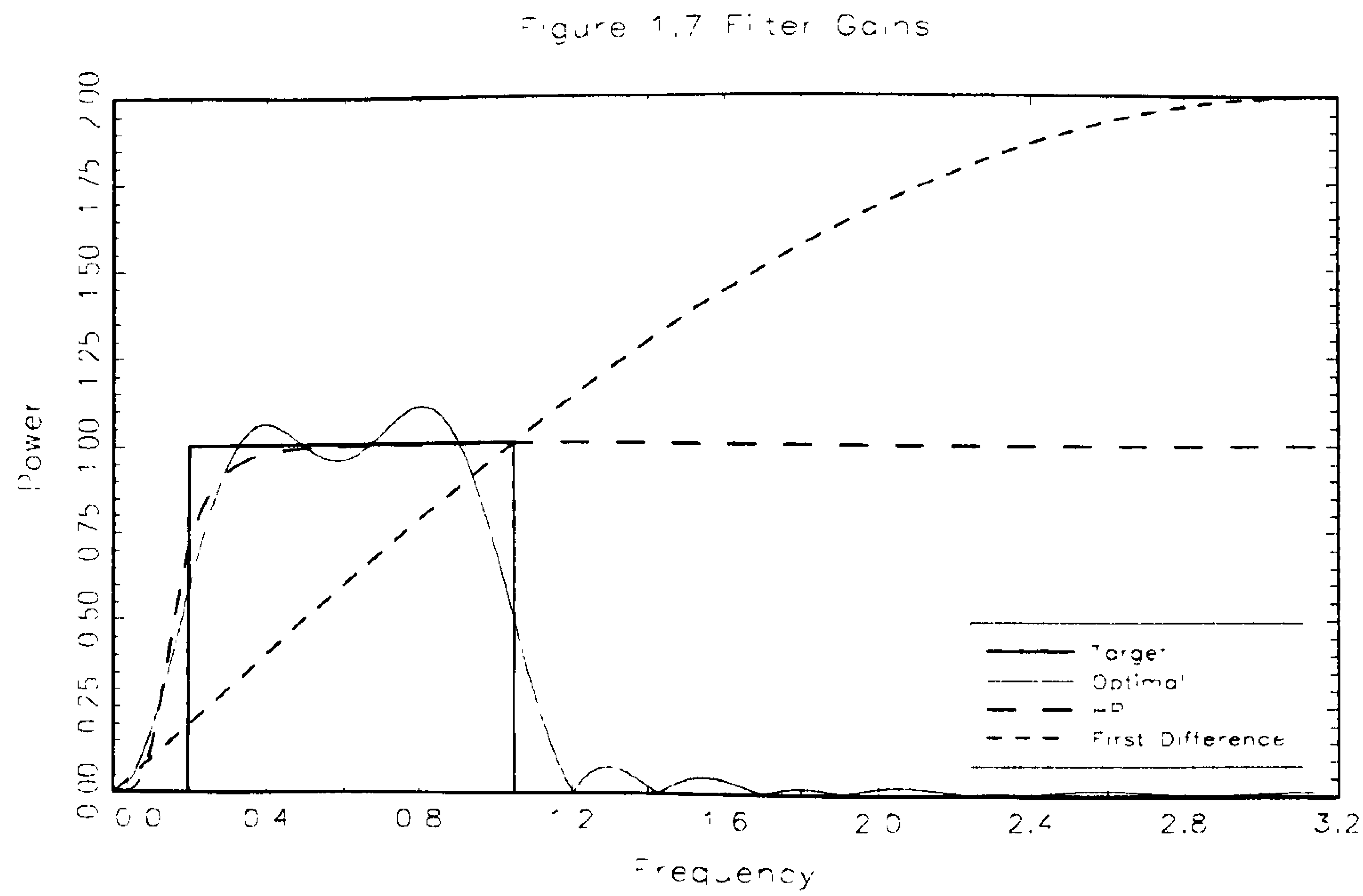


Figure 1.7 shows that the first differencing filter poorly estimates the trend component (low frequency parts), as argued by Nelson and Plosser (1982) and Campbell and Mankiw (1987), by exacerbating the effect of high frequency noise, as illustrated in Figure 1.6. The HP filter, which

is normally treated as a variant of the linear filter in which it is possible to allow for a flexible trend to appear by setting the smoothing parameter λ at an appropriate value, improves upon first differencing. It attenuates less of the cyclical component whilst not amplifying the high frequency noise. However, it still passes much of the high-frequency noise outside the business cycle frequency band. The filter adopted by Baxter and King (1999), however, is based on a twelve quarter centered moving average, where the weights are chosen to minimise the squared difference between the optimal and approximately optimal filters, Q. Because this is a finite approximation, its power transfer function is only approximately flat within the business cycle band and is nonzero for some frequencies outside this band (Stock and Watson, 1999).

Calculating the ideal bandpass filter to isolate the cyclical component of real GDP for the Euro area is illustrated in Figure 1.8. It must be noted that to obtain filtered values at the beginning and end of the sample, the series was augmented by twelve out-of-sample projected values at both ends of the sample, where projection were made using forecasts and backcasts from univariate fourth order autoregressive models. Figure 1.8 differs from linearly detrended real GDP plotted in Figure 1.5, in that the fluctuations are more closely centered around zero. This reflects the more flexible detrending method implicit in the bandpass filter. Second, the high frequency variations in the linearly detrended GDP have been eliminated and, finally, the number of identified cycles is larger than in the case of the classical cycle illustrated in Figure 1.6. Figure 1.8 also shows that the cycles that impact upon the economy are all different - in both amplitude and duration - providing support for the view that business cycles are caused by infrequent large shocks, as first suggested by Frisch (1933) and supported by Watson and Blanchard (1984). The bandpass filtering approach permits a decomposition of the series into trend, cycle and irregular components, which correspond to the low and high frequency parts of the spectrum. The trend and irregular components are plotted in Figures 1.9 and 1.10. The sum of the Figures in 1.8-1.10 sum to log real GDP. The cyclical fluctuations from the bandpass filtered data, viewed as deviations from a local trend, were negative in the 1980s. This corresponds to a growth recession even though there was not the absolute decline in Euro area output that characterises a classically dated business cycle recession. In conjunction with this point, it has been noted that the Baxter and King (1999) filter may well misdate if short periods of variation of indicators around their peaks and troughs are not taken into account properly. Hence, the elimination of high frequency variation from the data may affect the results adversely. Furthermore, it is doubtful that one can precisely identify the exclusively 'cyclical' frequencies and assume that the resulting bandpass filter remains valid and constant over time. In some very long phases, the expansions of the 1960s and 1970s in the Euro area being two notable examples, the relevant frequency mix may be rather different from that applying to some very short phases, such as the back-to-back recessions separated by the incomplete recovery in the late 1970s/early 1980s in the Euro area. However, studies have often filtered GDP to extract the cycle, using this as a proxy for the business cycle. Two prominent examples include Galì and Rabanal (2004) and Stock and Watson (2005). Finally, Figure 1.10 shows that the high frequency variation in real GDP has moderated significantly over time.

Trends and gaps are inherently two-sided concepts (Watson, 2007). For example, a trend estimate in 1998 depends on not only the observed value of GDP in 1998 compared to previous values, but also to future values, i.e., 1998 onwards. Hence, with the filters just presented, trends are estimated using both past and future data. As a result, it is more difficult to estimate their values at the beginning of the sample, where there is no past data, and at the end of the sample, where there is no future data, so creating significant sampling uncertainty.

As an extension, using the BP filter just described, it is possible to produce one-sided estimates of the business cycle in real time. These one-sided estimates are included as they clearly highlight the difficulties faced by policymakers and practitioners, whose job it is to devise macroeconomic policy in real time, but which is made difficult as real time estimates of the business cycle are often substantially inaccurate. Following the notation set out in previous paragraphs, Watson (2007) propose a one-sided bandpass filtered estimator defined using $\widehat{a}(L) = \Sigma_{j=-s}^{s} a_{|j|} L^{j}$, which represents a finite order filter, and is the best approximation to the ideal linear filter $(a(\omega))$. Defining, $X_t = \Sigma_{j=-r}^{s} a_j Y_{t-j}$, and assuming that data are available on a vector of random variables Z_τ from $1 \leq \tau \leq T$, Watson (2007) shows that the best minimum mean square error estimator of X_t is given by $E(X_t|\{Z_\tau\}_{\tau=1}^{T}) = \Sigma_{j=-r}^{s} a_j E(Y_{t-j}|\{Z_\tau\}_{\tau=1}^{T})$.

Figure 1.8 Bandpass-Filtered GDP (Cycle)

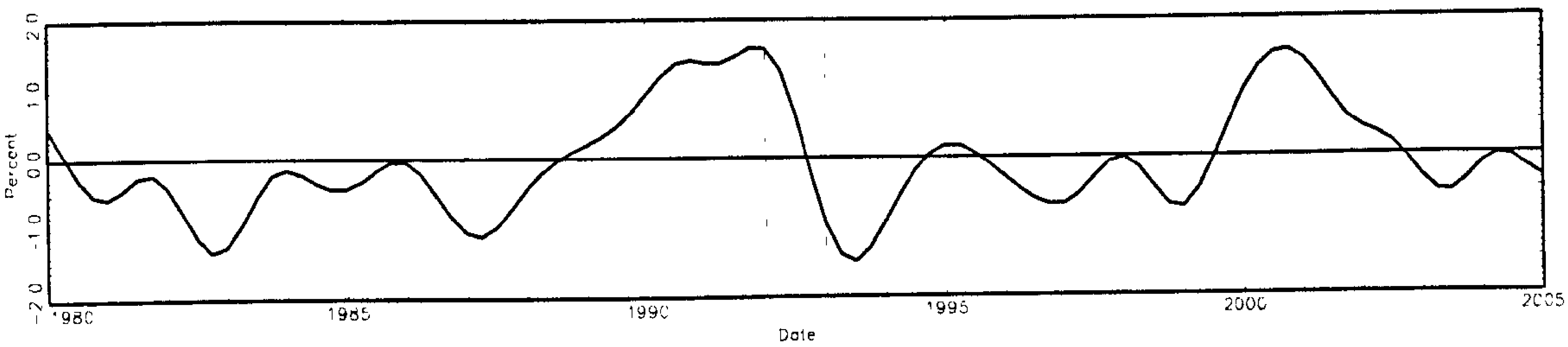


Figure 1.9 Bandpass-Filtered GDP (Trend)

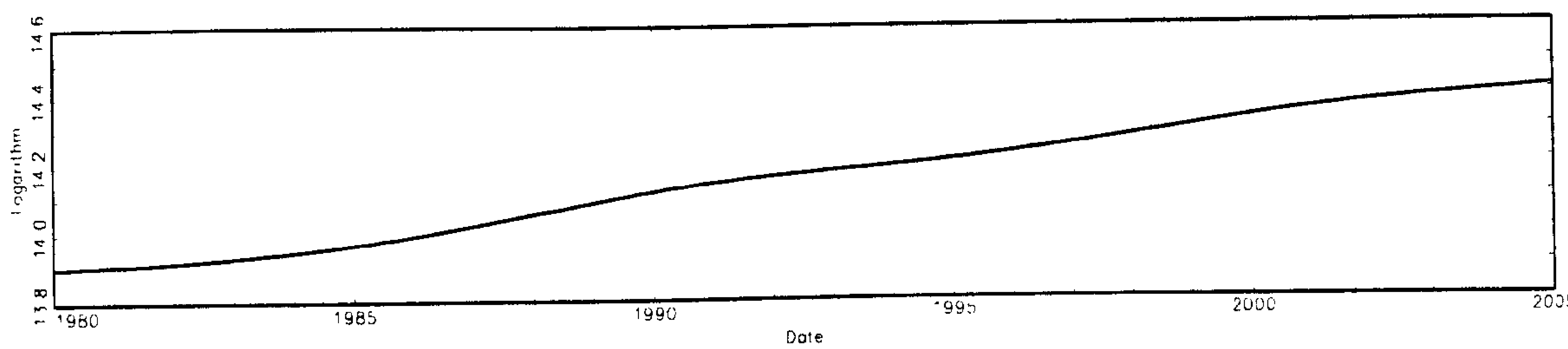


Figure 1.10 Bandpass-Filtered GDP (Irregular)

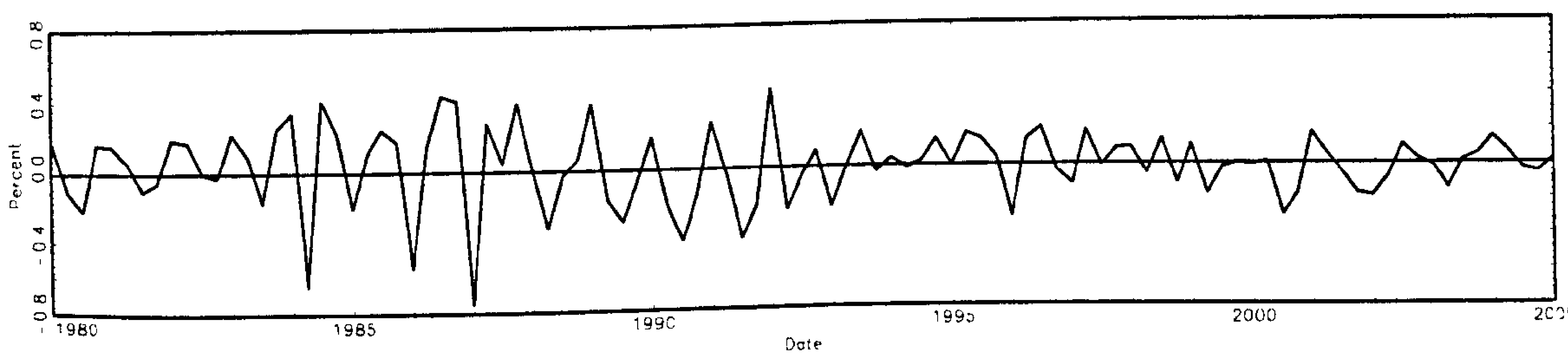


Figure 1.11 One-Sided Estimates (Trend)

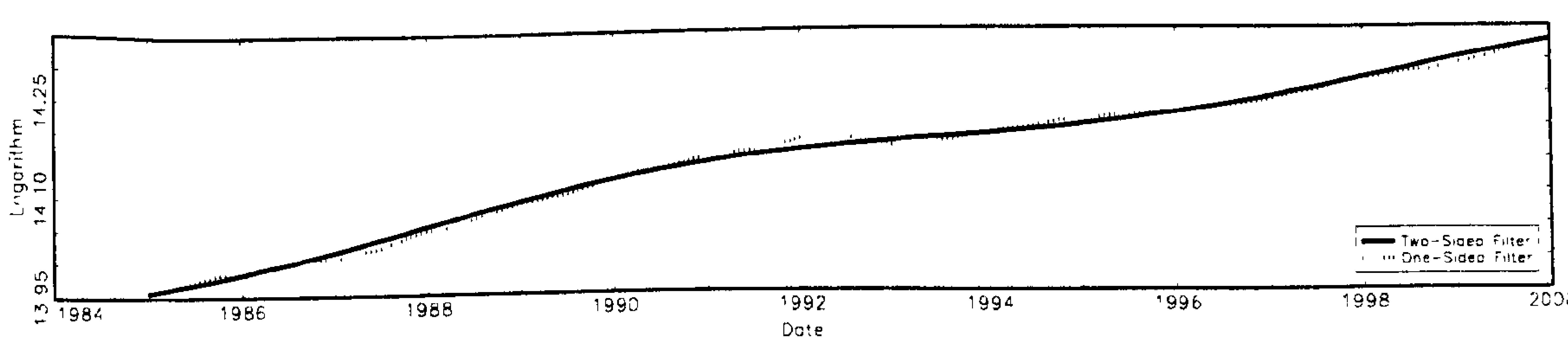
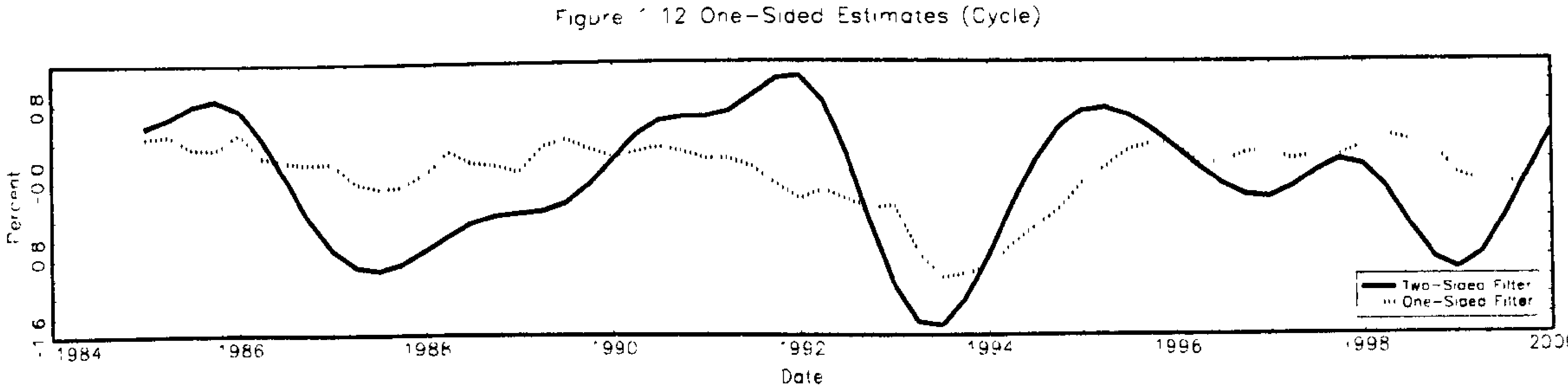


Figure 1.12 One-Sided Estimates (Cycle)



Watson (2007) suggests the following procedure for constructing real-time BP estimates of the trend and gap. First, approximate $\widehat{a}(L) = \Sigma_{j=-s}^{s} a_{|j|} L^j$ with filter weights given by $\omega' = 6$ and $\omega'' = 32$. Second, assume $\{Z_\tau\}_{\tau=1}^{T}$ denotes the sample observations of Z, construct $Y_{t|T}^{Trend} = \Sigma_{j=-r}^{s} a_{|j|} Y_{t/T}$, where $Y_{t/T} = E(Y_t | \{Y_\tau\}_{\tau=1}^{T})$. As a result, $Y_{t|T}^{Trend}$ is constructed using the ideal filter, truncated after a large number of terms and applied to the Y_t series padded into the future and past using forecasts and backcasts of the series. The error in the trend $Y_{t|T}^{Trend}$ can be calculated from $Y_{t|T}^{Trend} - Y_t^{Trend} = \sum_{j=-s}^{s} a_{|j|}(Y_{t-j|T} - Y_{t-j}) + \sum_{|j|>s} a_{|j|} Y_{t-j}$. Hence, to compute the one-sided estimate for 1998:1, the model estimates from 1980:1 till 1997:4.

In Figure 1.12 the solid lines are the two-sided estimates, as in Figure 1.8. The dashed lines are one-sided estimates that do not use data after the date shown on the horizontal axis. The results indicate that one-sided estimates are substantially less accurate than the two-sided estimates used for historical analysis. The error in the one-sided estimates arises from the use of forecasts of future values of Y_t in place of the true values. These forecasts were based on univariate informations sets; that is, future values of Y_t were forecast using current and lagged values of Y_t. It must be noted that improvements in the construction of the one-sided estimates could be achieved by using leading indicators to help forecast future values of Y_t (this is further explored in Chapter 6). It highlights the difficulty faced by practitioners and policymakers in gauging the state of an economy in real time. Estimates of the business cycle and trend are more accurate with the two-sided moving average BP filter, as shown in Figure 1.8, which takes into account both leads and lags, leading to an unsettling conclusion in which, assuming a random disturbance, policies that attempt to raise the welfare of its citizens, by reducing business cycle fluctuations from the shock, are very difficult to administer in real-time, causing possible under or over reaction to events.

In conclusion, there are a few notable concerns with the use of the HP and BP filters. In the case of the former, transitory and trend components are not correlated with each other. This implies that the growth and cyclical components of a time series are assumed to be generated by distinct economic forces, which is often incompatible with many business cycle models. In this sense, the HP filter rejects Stock and Watson's (1988a, b) notion that transitory fluctuations are a temporary aberration in movements toward a new level of trend growth, perhaps induced by productivity shocks. This would appear to eradicate the possibility of a neo-Keynesian channel of productivity shocks into output fluctuations. Second, the transitory component is white noise. This is also questionable, since it is not always the case that the stationary component of output is strictly white noise. To negate this issue, King and Rebelo (1993) show that this condition can be replaced by the following assumption; an identical dynamic mechanism which propagates changes in the trend component and innovations to the cyclical component. Third, the parameter controlling the smoothness of the trend component, λ, may be inappropriate. Note that it corresponds to the ratio of the variance of the irregular component to that of the trend component. Economic theory provides little or no guidance as to what this ratio should be. While attempts have been made to estimate this parameter using maximum-likelihood methods, as in Harvey and Jaeger (1993), it appears difficult to estimate with reasonable precision. Fourth, for the finite sample version of the HP filter, data points near the beginning or the end of the sample are susceptible to claims of inaccuracy. This is simply a consequence of the fact that the HP filter, being a two-sided filter, changes its nature and becomes closer to a one-sided filter as it approaches the beginning or the end of a time series. Indeed, after studying the properties of the HP filter at those extremities, Baxter and King (1999) recommend three years of data be dropped at both ends of a time series when the HP filter is applied to quarterly or annual data. Finally, both filters perform adequately when the spectrum of the original series has a peak at business-cycle frequencies. However, when the spectrum is dominated by low frequencies, the filters provide a distorted business cycle. Since it is assumed that most macroeconomic series have the typical Granger shape - the bulk of the variance is attributable to very long frequency components, such as long-run trends - the HP and BP filters perform poorly in terms of identifying the business cycles of these series. As a result, two consequences of applying the HP and BP filters are that they may induce spurious dynamic properties, extracting a cyclical component that fails to capture a significant fraction of the variance contained in business cycle frequencies.

The analysis now goes on to investigate two more widely-used decompositions of GDP that yield starkly different results. The Beveridge and Nelson (1981) (BN) decomposition implies that a stochastic trend accounts for most of the variation in output, while the unobserved components (UC) decomposition implies that cyclical variation is dominant. Which is correct has broad implications for the relative importance of real versus nominal shocks. Figures 1.13 and 1.14 illustrate an UC model based on Clark (1987), in which real GDP is decomposed into its transitory and permanent components. The model decomposes Y_t into a permanent, τ_t, and a transitory component, c_t. Depending on the assumptions about the variances of the error terms, different trends can be obtained from this framework. For example, if the variance of the cyclical component is zero, the model reduces to a deterministic linear trend. The advantage of this approach is that it reconciles two extremes. On the one hand many traditional theories of the business cycle maintain two fundamental premises. First, fluctuations in output are assumed to be driven primarily by shocks to aggregate demand, such as monetary policy, fiscal policy or animal spirits and, second, such shocks are deemed to have only a temporary effect on output. At the other extreme, Nelson and Plosser (1982) argue that the first premise, that fluctuations are driven by aggregate demand (in particular monetary disturbances), should be abandoned. They advocate, along with the theory that evolved partly from their work - RBC theory - that fluctuations are attributable to changes in aggregate supply such as shifts in the available production technology. Nonetheless, even assuming that real shocks dominate as a source of output fluctuations, these shocks need not always work through the mechanisms highlighted in RBC models. It is possible that economic fluctuations are driven by real shocks but that these affect the economy through some Keynesian channel, reconciling both monetarist and Keynesian theories on the one hand and RBC theory on the other. As highlighted by Hall (1986), this is especially true if technological innovation is determined by demand. As pointed out by Stock and Watson (1988b), real shocks tend to shift the long run path of output, so short term fluctuations will largely reflect adjustments toward a shifting trend if real shocks play a dominant role. It is possible to attribute a major role to supply shocks without completely abandoning a role for demand shocks, as shown by Campbell and Mankiw (1987).

The trend-cycle decomposition, developed by Harvey (1985) and Clark (1987), is motivated by the idea that the log of aggregate output is usefully thought of as the sum of a component that accounts for long-term growth and a stationary, transitory deviation from trend, consistent with the notion from Campbell and Mankiw (1987), thus helping to partially negate a conclusion as extreme as that of Nelson and Plosser (1982). The data generating process (DGP) is as follows,

$$Y_t = \tau_t + c_t \tag{1.1}$$

$$\tau_t = g_t + \tau_{t-1} + v_t \tag{1.2}$$

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + u_t \tag{1.3}$$

$$\text{where } v_t \sim i.i.d.(0, \sigma_v^2) \text{ and } u_t \sim i.i.d.(0, \sigma_u^2) \tag{1.4}$$

The UC model views real GDP as the sum of a deterministic trend, τ_t, and stochastic deviations treated as the residual cyclical component, c_t. The dynamics of the cyclical component are specified as a second order autoregressive process. The DGP assumes transitory and permanent components to be uncorrelated. The key identifying assumptions of this procedure are that the trend components follows a random walk with drift and that the cyclical component is a stationary finite order AR process. Data is generated from equations (1.1) – (1.3), which set $\phi_1 = 1.2$ and $\phi_2 = -0.28$; estimates from an $AR(2)$ model. Different values for ϕ_2 allows the possibility to control the location of the peak in the spectrum of the cyclical component. The long-term growth component g_t is set equal to 0.7.[3] Equation (1.2) can be interpreted as modelling the output gap. The standard-error ratio for the disturbances $\sigma_v^2 \backslash \sigma_u^2$, which changes the relative importance of the trend and cyclical component, is set equal to 1.[4] This framework is similar in principle to Watson's (1986) specification for US real GDP. The generated unobserved components model is shown in Figures 1.13 and 1.14.

Figure 1.13 Transitory Component – Unobserved Components

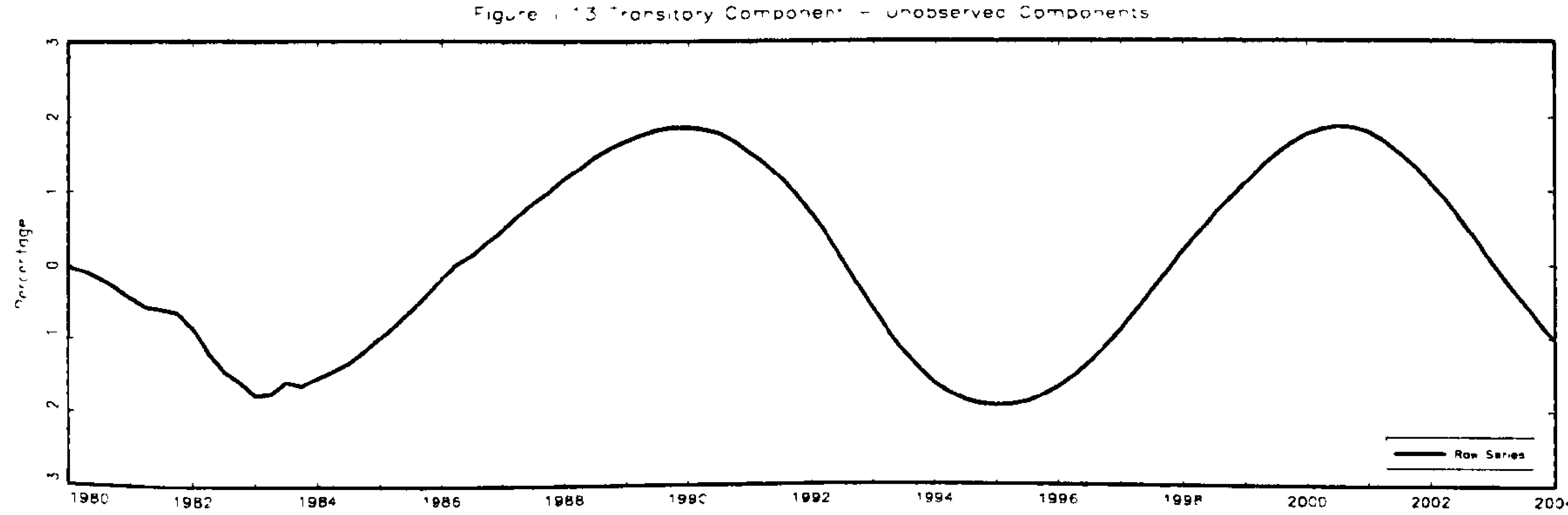
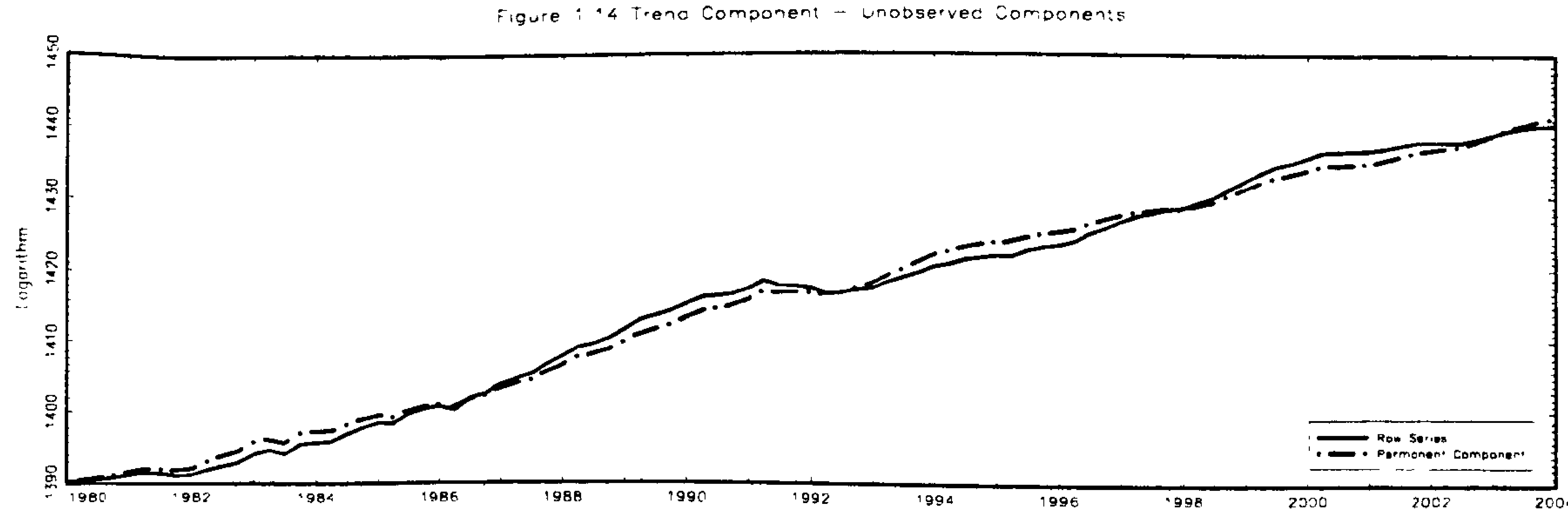


Figure 1.14 Trend Component – Unobserved Components



As with the other filters discussed, the UC model makes no distinction between business cycles and growth cycles. The UC approach, introduced by Harvey (1985) and Clark (1987), implies a very smooth trend and a cycle that is large in amplitude and highly persistent, in contrast to the BN decomposition, which implies that much of the variation in GDP is due to adjustments in the

[3] This figure is chosen since it allows the model to approach convergence more easily.
[4] This is sometimes referred to as the signal-to-noise ratio.

trend, while the cycle component is small and noisy. This contrast is apparent in Figures 1.13 and 1.15, where the two cyclical components are plotted respectively.

The BN decomposition provides a measure of the trend and cycle for an integrated time series. However, there are two ways to interpret the results from the decomposition. One interpretation is that the long-run forecast (minus any deterministic drift), calculated as the BN trend, corresponds to an estimate of an unobserved permanent component. The second is that the long-run forecast defines an observable permanent component. Morley (2007) argues in favour of the latter, since the BN decomposition can be applied to any forecasting model. In particular, the autoregressive and vector autoregressive models are easy to estimate and have well-identified parameters. In this case, the BN decomposition of y_t can be expressed as $BN = \lim_{i \to \infty} E[y_{t+i} - M\mu|\Omega]$. In this expression $\mu = E[\Delta y_t]$ is the deterministic drift and Ω is the information set used to calculate the conditional expectation. This implies that the BN trend is the long-horizon conditional point forecast of the time series process y_t, with any future drift removed. The BN cycle is simply the difference between the series and the BN trend. In practice, the BN trend is often calculated using an $ARMA$ model, which captures the autocovariance structure of y_t.

Let $w_t = [1 - L]y_t$ be an $ARMA$ process with moving average representation, so that the $ARIMA$ specification is $\phi(L)w_t = \theta_0 + \theta(L)\varepsilon_t$. The moving average is represented as $w_t = \mu + \gamma(L)\varepsilon_t$, where $\varepsilon_t \sim i.i.d.(0, \sigma^2)$, $\mu = \phi(L)^{-1}\theta_0$ and $\gamma(L) = \phi(L)^{-1}\theta(L)$ is a polynomial in the lag operator with the roots of $\phi(z) = 0$ outside the unit circle. Beveridge and Nelson (1981) demonstrated that the secular component of a series can be defined as the long-run forecast for its mean rate of change $k\mu$, $x_t \equiv y_t + \widehat{w}_t(1) + \ldots + \widehat{w}_t(k) - k\mu$, with $\widehat{w}_t(i) = E_t(w_{t+1}|y_t, y_{t-1}, \ldots) = \Sigma_{j=0}^{k-1}(\Sigma_{i+j+1}^{j+k}\gamma_i)\varepsilon_{t-j}$. As $k \to \infty$, x_t collapses to $x_t \equiv x_{t-1} + \mu + (\Sigma_{i=1}^{\infty}\gamma_i)\varepsilon_t$, which represents the long-run path of output. The cyclical component of the series is then $c_t = \widehat{w}_t(1) + \ldots + \widehat{w}_t(k) - k\mu = \chi(L)\varepsilon_t$. Two characteristics of this decomposition should be noted. First, unlike all of the procedures laid out, the BN decomposition of the trend and cycle are driven by the same shock. As a consequence, this decomposition has the property that the secular and the cyclical components are perfectly correlated. Second, since estimates of $\gamma's$ and forecasts $\widehat{w}_t(i)$ are obtained from an autoregressive-integrated-moving average ($ARIMA$) model, the problems inherent to $ARIMA$ specifications are carried over to this method. Christiano and Eichenbaum (1990) have shown that it is often the case that several $ARIMA$ models fit the sample autocorrelations of a data set fairly well. In addition, Maravall (1993) has argued, because $ARIMA$ models are designed to fit the short-run properties of the data they are ill-suited to capture their long-run features. Since the results may vary considerably with the choice of $\theta(L)$ and $\phi(L)$, both in terms of magnitude of the fluctuations and of the path properties of the data, Figures 1.15 and 1.16 are results obtained using a variety of $ARMA$ specifications.

The BN decomposition is illustrated in Figures 1.15 and 1.16. The most surprising conclusion that can be extracted from the UC and BN approaches is that the two decompositions are so different, given that both are model-based, each letting the data 'speak for themselves'. Neither imposes smoothness in trend *a priori* as does a polynomial or a smoother as in the HP filter. The BN decomposition shows that the time series, real GDP, will be a random walk with the same mean growth rate as the observed series, that the deviation from trend is a stationary process, and that the innovations of the BN decomposition are perfectly negatively correlated, since the trend and cycle are driven by the same shock. The advantage in the use of the BN decomposition is that it allows the cycle to be deciphered using the classical definition.

If it is accepted that innovations to trend are strongly negatively correlated with innovations to the cycle, then the case for the importance of real shocks in the macro economy is strengthened. For example, a positive productivity shock will immediately shift the long run path of output upward, leaving actual output below trend until it catches up. This implies a negative contemporaneous correlation since this positive trend shock is associated with a negative shock to the transitory component, supporting the theoretical assertions made by Campbell and Mankiw (1987). This would, however, imply that the trend and cyclical components are two indistinguishable elements. Conversely, it may be plausible that any productivity shock not only shifts the trend upwards, but has a similar effect on the cyclical component. For example, assuming a neo-Keynesian channel, a positive technology shock could lead to an increase in aggregate demand as economic agents anticipate a rise in incomes, propagating an upward shift in the transitory component also. As pointed out by Stock and Watson (1988b), real shocks tend to shift the long-run path of output, so short-term fluctuations will largely reflect adjustments towards a shifting trend. Hall (1986) also observed that technological change might be influenced by the level of demand. By contrast, a positive nominal shock, such as a shift by the monetary authorities towards stimulus, will be a positive innovation to the cycle without any impact on the trend.

Figure 1.15 Cyclical Component - Beveridge Nelson

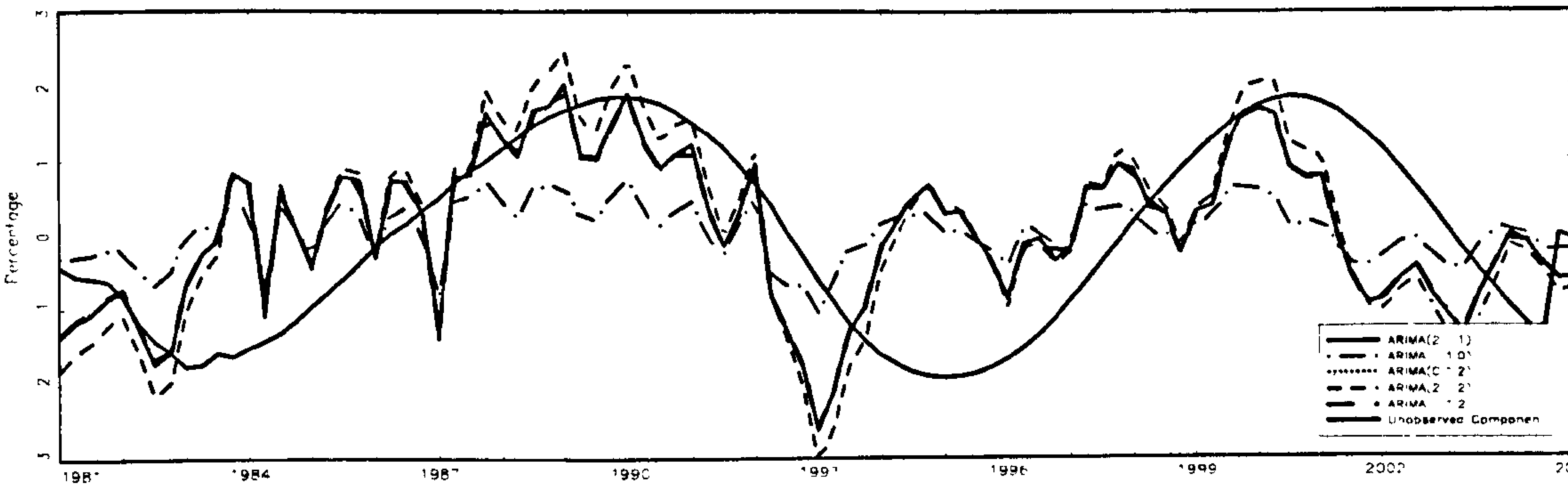
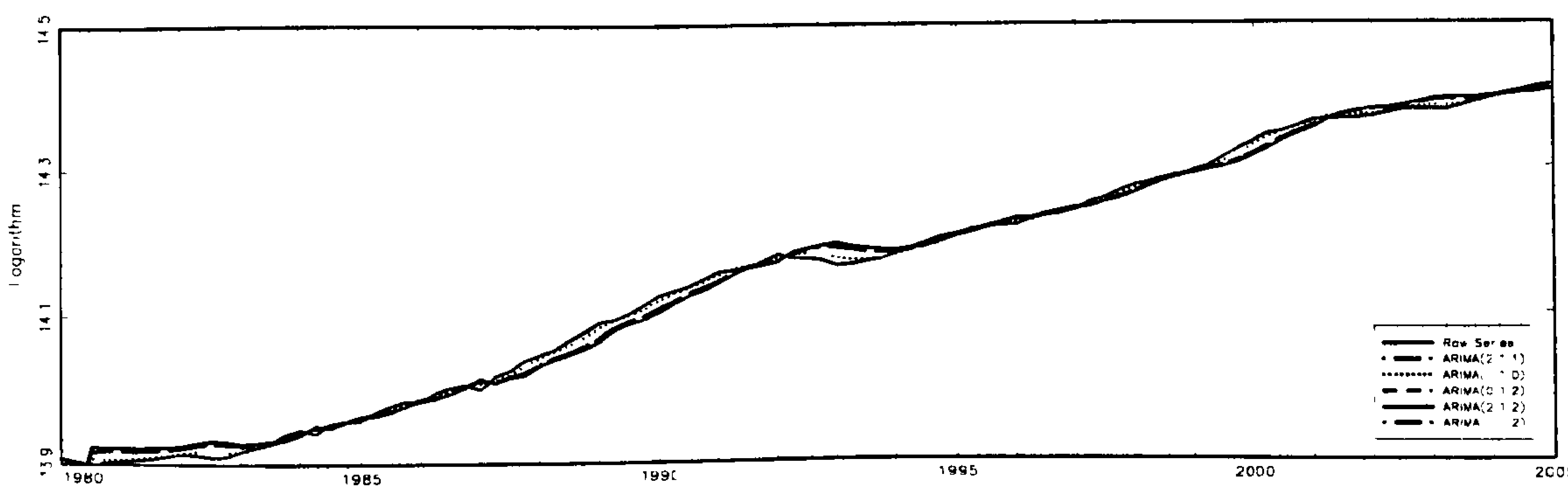


Figure 1.16 Trend Component - Beveridge Nelson



The fact that the two approaches have produced such different estimates of trend and cycle in practice implies that they must be based on conflicting representations of the data. Morley *et al.* (2002) have shown that trend-cycle decompositions based on UC models are at odds with the BN decomposition, not because they are different in principle, but because the underlying empirical models differ. In particular, when the restriction that the unobserved trend and cycle component are uncorrelated is relaxed, i.e., the UC model adopts the trend cycle correlation principle of the BN decomposition, then the two approaches, BN and UC, yield identical decompositions and identical univariate representations. Their results would seem to infer that, assuming the implication that innovations to trend are strongly negatively correlated with innovations to the cycle, the case for the importance of real shocks in the economy is strong.

A theoretical argument against the procedures just laid out is due to the increasing perceived importance of using growth theory as an explanation for business cycles. In fact, what is often implied by some of the different detrending methods, which yield various growth cycle estimates, is that growth cycles and business cycles are not distinguishable, with slowdowns treated like recessions, despite both growth and business cycles being distinct by definition. Despite this, trend-cycle decomposition attains a central role in business cycle analysis. Since accurate trend estimates are required to study economic growth empirically and to test related theories. This task cannot be accomplished without sufficiently long and reliable data series, and without confronting the question of how trends and cycles influence one another. This is a dominant point, due to the perceived importance of economic growth and its major sources, notably technological and productivity, for society's well being. Second, the first two post-World-War II decades in the Euro area, noting that it was an era of reconstruction, democratisation, foreign aid, and important monetary, fiscal and structural reforms, were characterised by very high real growth rates. These expansions were interrupted by temporary aberrations, rather than absolute declines in overall economic activity. In the absence of business cycle recessions, sequences of slowdowns and catch-ups of substantial size, amplitude and duration attracted considerable public attention in many advanced market-orientated economies.

Closing with a few caveats, it must be noted that all the decompositions considered here share a common restriction, that the cycle is symmetric. Keynes (1936) noted that 'the substitution of a downward for an upward tendency often takes place suddenly and violently, whereas there is, as a rule, no such sharp turning point when an upward is substituted for a downward tendency'. Recent business cycle research suggests asymmetry may be an important feature of business cycles across the industrialised world. Indeed, an important feature of post-war US business cycles appear to be that recessions are characterised as an occasional sharp drop followed by a more gradual recovery. Evidence for this has been found by Neftci (1984), Hamilton (1989, 1996), Sichel (1993, 1994), Beaudry and Koop (1993) and Kim and Nelson (1999). Friedman's (1992) plucking model of business cycle fluctuations also implied downturns to be steeper than expansions, as Keynes (1936) had observed. The inference that variation in real output is dominated by variation in trend may reflect primarily the long periods of expansion when actual output is relatively close to potential, with any cycle short lived and small in amplitude. In addition, Friedman's (1992) plucking model illustrated a second type of asymmetry, examined in Beaudry and Koop (1993), that may characterise output fluctuations. The distinguishing feature of the plucking model, for a purely real model of business cycle fluctuations, is the prediction that negative shocks are largely transitory, while positive shocks are largely permanent, implying that it is of no use predicting the onset of the next recession, or its severity. Finally, it must be noted that the decompositions considered here are univariate: hence only two sources of shocks - innovations in the cycle or trend - are considered. Additional information introduced in a multivariate setting may affect estimates of trend and cycle. This is further explored in Chapter 3, where trend output estimates are constructed using estimated productivity disturbances from the balanced growth hypothesis.

1.0.2 Dating the Cycle

Although an analysis of the various dating procedures sometimes used to calculate business cycle phases is beyond the scope of the work here, this subsection briefly highlights the most popular method, which is used in subsequent chapters of dating turning points of the business cycle. The Bry and Boschan (1971) method is the most commonly used dating algorithm, since it operates on the levels of a univariate time series that is free from seasonal and calendar variation, and is thus tailored to date recessions and expansions in the classical sense. As a matter of fact, the chronology arising from its application to US aggregate macroeconomic time series closely mimics the official NBER one and the turning points judgementally selected by Burns and Mitchell. The scope of a dating algorithm is to estimate the location of turning points, according to a particular notion of the business cycle: (1) Alternation of peaks and troughs; (2) Minimum duration times for the phases and the full cycle. Downturns and upturns have to be persistent to be qualified as cycle phases; thus, they need to fulfil minimum duration constraints, such as 5-6 months, or 2 quarters for each phase; moreover, to separate it from seasonality, a full cycle has to last longer than one year (e.g. 15 months or 5 quarters); (3) Depth restrictions, motivated by the fact that only major fluctuations qualify for the phases. This method utilises a set of *ad hoc* filters that locate local minima and maxima in a time series. At these minima and maxima the series is said to have transited from a contraction to an expansionary period, or vice versa.

The Bry and Boschan (1971) algorithm proceeds to the determination of turning points via a sequence of steps. The first step concerns the identification and replacement of outlying observations, based on the comparison of the observed value with the filtered series obtained using a Spencer 15 months moving average.[5] Steps II–IV identify and successively refine turning points on a sequence of three different filtered series, with a decreasing degree of smoothness: a 12 - term moving-average is first used, then a Spencer filter, then a 3-6 term moving average according to a measure of signal to noise ratio (months of cyclical dominance). The Spencer 15 months moving average is a cascade filter resulting from the successive applications of four simpler moving averages; it can be viewed as a local cubic polynomial smoother. The filter can be represented as $w_s(L) = L^{-3}w_1(L)w_2(L)w_3(L)$, with $w_1(L) = 1/4(1 + L + L^2 + L^3)$, $w_2(L) = 1/5(L^{-2}+L^{-1}+1+L+L^2+L^3)$ and $w_3(L) = -3/4L^{-2}+3/4L^{-1}+1+3/4L-3/4L^2$, where

[5] Spencer's weighted moving average is an approach to computing a moving average that will compensate for a cubic trend in the data. It consists of two averages, one for 15 periods and the other for 21 periods. Both have been used widely in many decomposition methods.

the factor L^{-3} centres the moving average.[6] This algorithm calculates moving averages of different lengths to narrow down the region where the turning points are likely to be located and then pinpoints the exact month where the peak or trough occurred using the original series. At each step the identification of turning points is done in two stages: in the first, turning points are tentatively identified as those values that are smaller (trough) or greater (peak) than the next and the previous 5 observations; then alternation of peaks and duration restrictions are enforced. Finally, the turning points are referred back to the original unsmoothed series (corrected for outliers).

Table 1.1 illustrates the differences in the classical and growth cycle, using a variation of the dating algorithm of Bry and Boschan (1971) from Watson (1994). In this case, the procedure interpolates GDP from quarterly into a monthly series, before calculating the turning points. Table 1.1 shows there to be more growth cycles than cycles of the classical definition. The main reason for this is that, in the classical definition, a full cycle has to move from a peak to a trough, where the trough has to be characterised by an absolute decline in real output for at least six months. This is in contrast to growth cycles, where a 'recession' is termed as output growth below the long-run average. Since the classical definition has only occurred once during the sample period, 1992:1 - 1993:1, it is not at all surprising to find the results in Table 1.1. Although it would appear that the Euro area pulled out of recession in 1993:1, from which point output was no longer contracting, the growth recession did not end until six months later. Clearly, all recessions involve slowdowns, but not all slowdowns involve recessions; hence growth cycles are more numerous than business cycles. The two sets of phenomena or processes are related, but they are distinct as defined. It it clear that growth cycles are generally shorter, more frequent, and more symmetrical than business cycles and they vary less by duration. This is because business cycle expansions are usually interrupted by significant slowdowns. These slowdowns give rise to additional declines in the detrended series when compared with the original decline in the levels of the same series. In addition, most postwar recessions in the Euro area were preceded by marked retardations of growth. It must be noted that the application of the Bry and Boschan (1971) algorithm to the dating of growth cycles is less well established, mostly because no independent reference chronology exists for a growth rate cycle, as is the case for the classical cycle in most industrialised economies.

[6] The exposition of the Spencer filter follows Kendall and Stuart (1976).

Table 1.1 Dating the Cycles

	peaks	*trough*	*Duration (qtrs.)*
Classical Cycle			
Real GDP	1992:1	1993:1	4
Growth Cycle			
Real GDP (bandpass filtered)	1984:1	1984:4	3
	1986:1	1987:2	5
	1991:4	1993:3	7
	1995:1	1996:4	7
	1998:1	1999:1	4
	2000:4	2003:3	11
	2004:2		
Real GDP (Linear Detrend)	1992:1	1993:4	7
	1994:4	1997:1	9
	1998:1	1998:4	3
	2001:1		

The concept of the classical cycle has recently reclaimed a degree of popularity. Dating the peak of the cycle by reference to a subsequent decline is no longer such a 'rare event', as was the case before the first oil price shock in 1973. As Zarnowitz (1998) notes, the period following the war was characterised more by growth cycles than classical business cycles. Following 1973, however, periods of absolute decline became more common. Moreover, the intervening popularity of the growth cycle has suffered from the realisation that detrending techniques may spuriously create cycles of their own and shift the timing of the turning points in an undesirable way. Singleton (1988) notes that the stylised facts motivating recent specifications of the business cycle models may have been distorted by prefiltering procedures. More recently, Marcet and Ravn (2001) have found this to be case for both the HP filter and the BP filter, along with suggesting a reformulated HP filter, which is explored in Chapter 5.

It is clear that different statistical representations for the trend embed different economic concepts of business cycle fluctuations. Hence, choosing one detrending method over another may at times imply, implicitly, that the practitioner is selecting one particular economic object or theory over another. It must be further noted that since the issue of what is an 'appropriate' statistical representation of the trend cannot be solved in small samples and, since the choice of the relationship between cyclical and secular components is arbitrary, statistical based approaches to detrending raise questions about the robustness of certain 'facts'.

The analysis so far has concentrated on a single measure of economic activity, real GDP. The following subsection explores a second important issue in measuring the economic cycle. Does real GDP accurately portray movements in economic activity?

1.1 Cyclical Behaviour of Selected Economic Time Series

"Analysing business cycles means neither more nor less than analysing the economic process of the capitalist era. Cycles are not like tonsils, separable things that might be treated by themselves, but are, like the beat of the heart, the essence of the organism that displays them" (Joseph Schumpeter, 1939, p.10[7])

The business cycle commonly refers to comovements in different forms of economic activity, not just fluctuations in GDP. If so, it would be incorrect to define specific phases of the business cycle, such as a recession, in terms of one variable, such as monthly industrial production. For example, suppose that a drought dramatically reduces agricultural output but that output in other sectors remains stable, so that aggregate unemployment remains steady. This scenario does not fit the traditional definition of a recession - the "three D's". Burns and Mitchell (1946, p. 4) wrote,

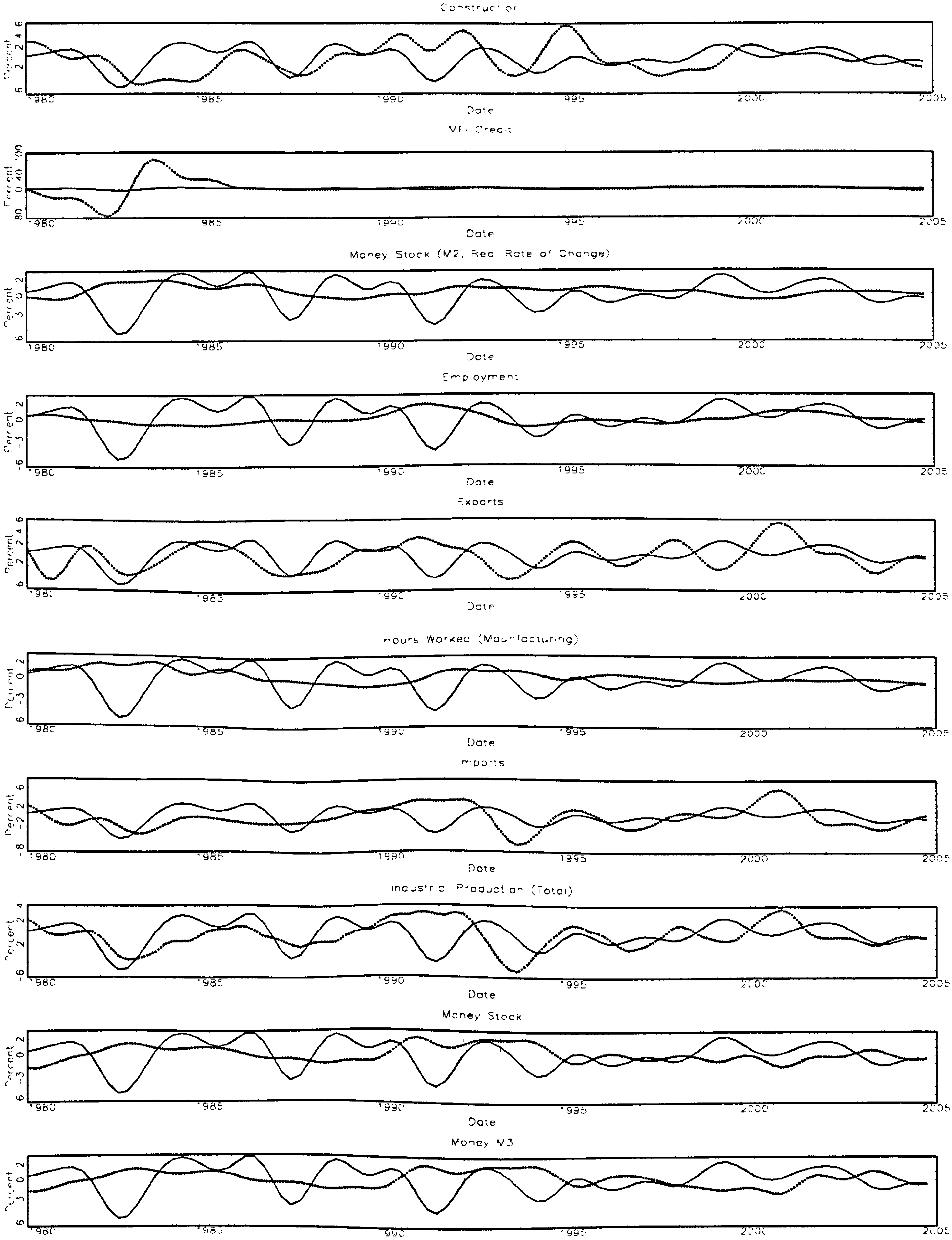
"Business Cycles are a type of fluctuation found in the aggregate economic activity of nations that organise their work mainly in business enterprises"

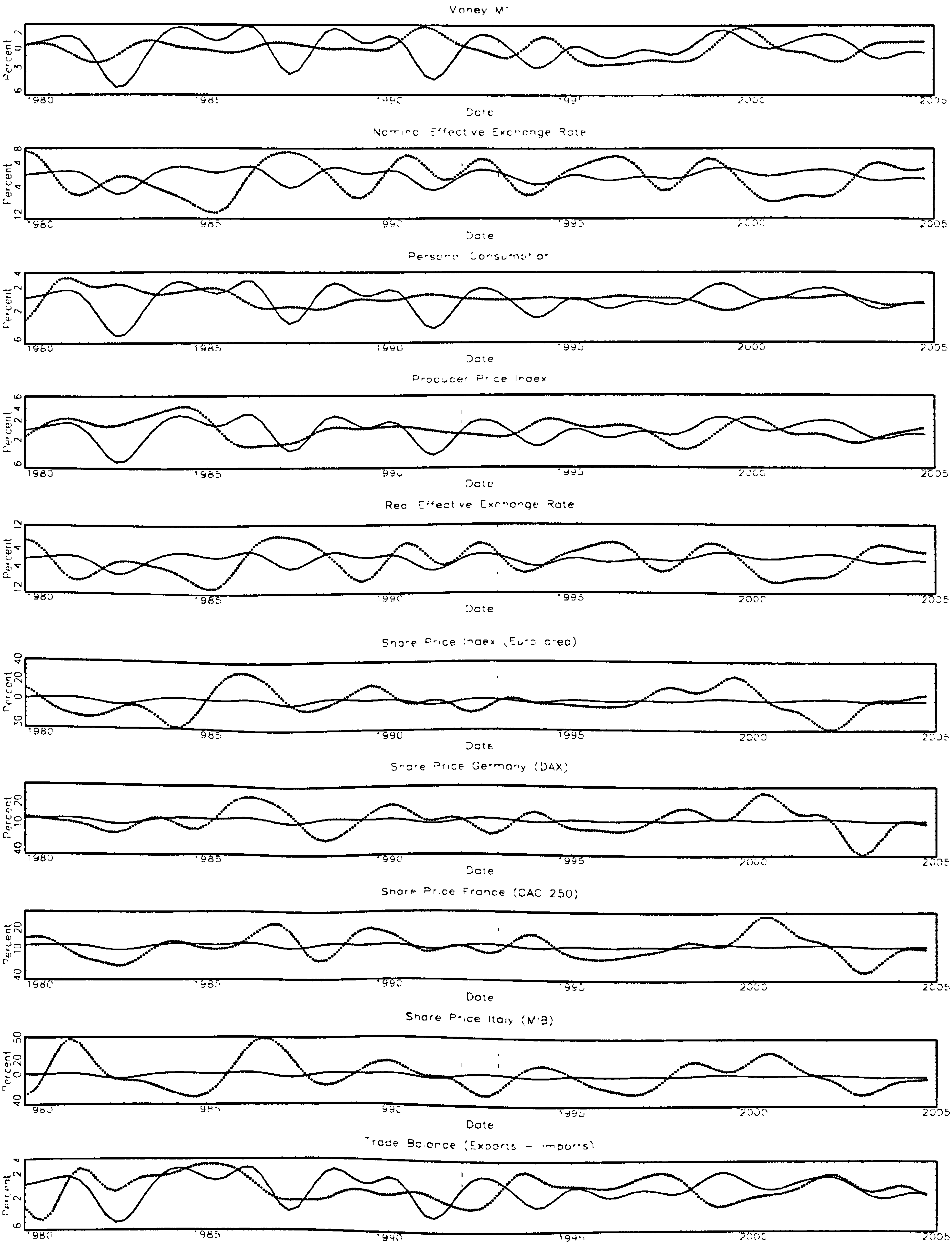
The use of the term business cycle, which is usually measured as real GDP, is generally accepted as a synthesised measure of the state of an economy. However, it has been argued that GDP represents an inaccurate measure of the state of an economy. For this reason numerous articles - Sims (1992) and Canova and Nicolo (2002) for example - prefer to use industrial production to measure the state of an economy. It must be noted that there are at least two problems with this. Industrial production is declining and, in the Euro area at least, a small proportion

[7] *Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process* (New York, 1939).

of overall economic activity and, secondly, the series is very noisy, making it sometimes difficult to turn the higher frequency of availability to good advantage. Authors occasionally use more than one variable to proxy business cycle fluctuations. For example, Leeper *et al.* (1996) analyse movements in both output and employment. The reason for caution in using real GDP to measure the state of the economy is reflected by the finding of a quite considerable idiosyncratic component in real output. It is generally assumed that macroeconomic time series have two components: a common component corresponding to the business cycle and an idiosyncratic component that is specific to each time series. It is the common component which is relevant for economic modelling and forecasting purposes. Consequently, if a macroeconomic variable contains a predominant idiosyncratic component, it may be only useful in explaining the dynamics of itself, rather than of other variables, and in turn the general state of the economy. In this sense time series used should be selected on the basis of economic judgement, and assumed to contain information about the current and/or future economic situation. Kose *et al.* (2003a, b) found, when analysing country-specific factors for the G7 economies, that using real GDP contains a sizeable idiosyncratic component. Consequently, it has become increasingly common to use factor models, as in Stock and Watson (2005b, 2002b,c) and Forni *et al.* (2001, 2000), to synthesise the state of an economy by pooling together information from an array of macroeconomic time series. The last two approaches are, in this respect, following in the footsteps of the NBER 'founding fathers' of business cycle analysis - Burns, Mitchell and Moore. Factor models are further explored and utilised in Chapters 4 and 5.

Figure 1.17. Bandpass Filtered Macroeconomic Time Series




Money M1
Producer Price Index
Share Price Germany (DAX)
Share Price France (CAC 250)
Share Price Italy (MIB)
Percent
Date
1980
1985
1990
1995
2000
2005

Burns and Mitchell's (1946) definition of the business cycle has a key feature. This is the comovement among individual economic variables, which is used to describe changes in 'economic activity'. Indeed, this comovement among series, taking into account possible leads and lags in timing, was the centrepiece of Burns and Mitchell (1946) methodology. In their analysis, the historical concordance of hundreds of series, including income, interest rates, and prices, were investigated. In support, Lucas (1976b) drew attention to a key business cycle observation that the output of broadly-defined sectors move together.

Table 1.2: Descriptive Statistics for Cyclical Components of Series 1980 - 2005

		Cross Autocorrelations With real Output ($Cor(x_t y_{t+k})$)								
Series	***Std Dev***	***-4***	***-3***	***-2***	***-1***	***0***	***1***	***2***	***3***	***4***
Gross Domestic Product	1 58	-0 23	0 11	0 53	0.87	1 00	0 87	0 53	0 11	-0 23
Construction	2 19	-0 21	-0.20	-0.10	0 03	0 11	0 11	0 01	-0 15	-0 29
MFI Credit	4 29	0 14	0 19	0.19	0 17	0 17	0 18	0 25	0 34	0 37
Money Stock (M2, Real Rate of Change)	0 50	-0 19	-0 18	-0 15	-0 13	-0 11	-0 14	-0 19	-0 26	-0 31
Employment	0 69	0 10	0 04	-0 01	-0 05	-0 08	-0 08	-0 08	-0 06	-0 02
Exports	2 26	-0.02	-0 04	-0 03	0 01	0 07	0 13	0 20	0 25	0 25
Hours Worked (Maunfacturing)	0 56	-0 16	-0 19	-0 21	-0.19	-0 15	-0 09	-0 01	0.05	0 05
Imports	2 52	-0 11	-0 14	-0 11	-0 04	0 05	0 15	0 23	0 27	0 27
Industrial Production (Total)	1 81	-0 04	-0 10	-0 11	-0 05	0 03	0 11	0 17	0 19	0 17
Money Stock	0 99	0 03	0 04	-0 02	-0 13	-0 26	-0 37	-0 41	-0 38	-0 32
Money M3	1.06	-0 04	-0 08	-0 16	-0 27	-0 37	-0 42	-0 41	-0.36	-0 30
Money M1	1 27	0.25	0 13	-0 02	-0 16	-0 26	-0 28	-0 22	-0 10	0 04
Nominal Effective Exchange Rate	4 59	-0 21	-0 23	-0 22	-0 22	-0 25	-0 30	-0 37	-0 40	-0 35
Personal Consumption	0 70	-0 01	-0 05	-0 12	-0 16	-0 15	-0 10	-0 01	0 07	0 07
Producer Price Index	1 34	-0 11	-0 12	-0 10	-0 08	-0 04	-0.04	-0 03	-0 01	0 00
Real Effective Exchange Rate	4 96	-0 21	-0 21	-0.18	-0 17	-0.20	-0.26	-0 34	-0 39	-0 35
Share Price Index (Euro area)	12 72	0 24	0 31	0 32	0 29	0 22	0 15	0 07	0 00	-0 05
Share Price Germany (DAX)	15 33	0 37	0 31	0.23	0 16	0 10	0 06	0 04	0 03	0 02
Share Price France (CAC 250)	13 98	0 47	0 44	0 33	0 20	0 08	0 02	0 01	0 05	0 11
Share Price Italy (MIB)	18 26	0 50	0 41	0 28	0 14	0 02	-0 05	-0 09	-0 08	-0 04
Trade Balance (Exports - Imports)	1 53	0 18	0 20	0 16	0 09	0 02	-0 05	-0 08	-0 08	-0 08
Wages (Manufacturing)	0 98	0 26	0 26	0 20	0 09	-0 03	-0 12	-0 19	-0 21	-0 22

Figures 1.17 examines comovements between each series and real GDP to highlight the issue of coherence amongst different sectors in the economy, as mentioned by Burns and Mitchell (1946) and Lucas (1976b). The cyclical component of each series - obtained using the bandpass filter - is plotted, along with the cyclical component of output, for the period 1980 till 2005. Note that the vertical scales of the plots differ. Relative amplitudes can be seen to be comparing the series to aggregate output (real GDP is presented with the solid line, whilst the dashed line represents the constituent variable). As in all the major industrialised economies, it would appear that comovements among business cycle indicators is undeniable for the Euro area.

The choice of economic activity variable is not straightforward. The standard measure, as illustrated previously, is GDP. However, a concern raised with the use of GDP is its lagged publication, which makes it unsuitable for gaining a timely insight into the state of an economy. An alternative to economic activity is to measure the business cycle according to a statistical model which identifies underlying shocks that drive the business cycle. Dynamic factors are part of this line of thinking, and provide a more formal way to select relevant cyclical variables. Factor models have a long history of use in cross-sectional settings, and their generalisation to dynamic environments is due to Sargent and Sims (1977), Geweke (1977), Watson and Engle (1983), and more recently, Forni *et al.* (2000, 2001) and Stock and Watson (2005b, 2002b). The most prominent recent examples include the Stock and Watson (1989, 1991, 1993a) composite leading index (CLI), which is based on the notion that the comovements in many macroeconomic variables have common elements that can be captured by a single underlying, unobserved variable. This variable is taken to represent the state of an economy. Estimates of this unobserved index provide an alternative index of coincident indicators. This approach also implicitly agrees with Long and Plosser (1987), in that economic fluctuations are best explained by aggregated shocks rather than disaggregated shocks. The early emphasis on the consistent pattern of comovement among various variables over the business cycle, as demonstrated in Figure 1.17, led directly to the creation of composite indexes. A model based on Stock and Watson's (1989, 1991, 1993a) CLI has the following structure;

$$\Delta Y_{it} = \lambda_i(L)\Delta C_t + D_i + e_{it} \quad i = 1, 2, 3, 4 \text{ and } t = 1, 2..., T \tag{1.5}$$

ΔY_{it} represents the first difference of the log of the i^{th} indicator, $i = 1, ..., 4 : \lambda_i(L)$ is the polynomial in the lag operator; ΔC_t is the growth rate of the composite index; D_i is the intercept for the i^{th} indictor; and e_t is a process with AR representation,

$$\psi_i(L)e_{it} = \varepsilon_{it} \quad \text{where } \varepsilon_{it} \sim i.i.d.(0, \sigma_i^2) \tag{1.6}$$

Thus each indicator ΔY_{it}, $i = 1, 2, 3, 4$, consists of an individual component $(D + e_{it})$ and a linear combination of current and lagged values of the common factor, or index, ΔC_t. The index is assumed to be generated by an AR process

$$\phi(L)(\Delta C_t - \mu_{s_t} - \delta) = v_t \quad \text{where } v_t \sim i.i.d.(0, 1) \tag{1.7}$$

where v_t and ε_{it} are independent of one another for all t and i, while the variance of v_t is taken to be unity for identification of the model. The parameters δ and μ_{s_t} are constant over time. In a slight variation of the model, Kim and Nelson (1998) allow μ_{s_t}, to depend on whether the economy is in recession or boom. In their model, $\mu_{s_t} = \mu_0 + \mu_1 S_t$, where S_t represents the state of the economy. However, in Stock and Watson's (1989, 1991, 1993a) factor model, the mean growth rate of the coincident index $(\mu_{s_t} + \delta)$ does not switch between regimes. Hence, in this case μ_{s_t} is set equal to zero, implying that long-run growth is determined by δ. The weights $\lambda_i(L)$ indicate the extent to which each series is affected by the common component, C_t, which arises from a single source. The main identifying assuming in the model is that e_{it} and C_t are mutually uncorrelated at all leads and lags.

The model can be cast into state space form

$$\Delta Y_t = H\zeta_t + \widetilde{D} \quad \text{where} \quad \zeta_t = \widetilde{M}_t + \widetilde{\delta} + F\zeta_{t-1} + u_t \tag{1.8}$$

where $\Delta Y_t = [\Delta Y_{1t}, \Delta Y_{2t}, \Delta Y_{3t}, \Delta Y_{4t}]$, $\widetilde{D} = [D_1, D_2, D_3, D_4]$, with the other terms defined appropriately, according to the specifications of $\phi(L)$, $\psi_i(L)$ and $\lambda_i(L)$. For example, assuming an $AR(1)$ common component and $AR(1)$ individual components and $\lambda_i(L)$, $i = 1, 2, 3, 4$, then

$$H = \begin{bmatrix} \lambda_1 & 1 & 0 & 0 & 0 \\ \lambda_2 & 0 & 1 & 0 & 0 \\ \lambda_3 & 0 & 0 & 1 & 0 \\ \lambda_4 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad F = \begin{bmatrix} \phi_1 & 0 & 0 & 0 & 0 \\ 0 & \psi_{11} & 0 & 0 & 0 \\ 0 & 0 & \psi_{21} & 0 & 0 \\ 0 & 0 & 0 & \psi_{31} & 0 \\ 0 & 0 & 0 & 0 & \psi_{41} \end{bmatrix}, \quad \zeta = \begin{bmatrix} \Delta C_t \\ e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{bmatrix}$$

$$u_t = \begin{bmatrix} v_t \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}, \quad \widetilde{M}_t = \begin{bmatrix} (1-\phi(L)) \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad \widetilde{\delta} = \begin{bmatrix} (1-0)\delta \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

When the data are expressed as deviations from means, $\Delta y_{it} = \Delta Y_{it} - \Delta \overline{Y}_i$, equations (1.5) – (1.7) truncate to $\Delta y_{it} = \lambda_i(L)\Delta c_t + e_{it}$ and $\phi(L)(\Delta c_t - u_{s_t}) = v_t$, where, as stated previously, u_{s_t} is set equal to zero. In this case $\Delta c_t = \Delta C_t - \delta$. Since the model does not assume regime switching as in Kim and Nelson (1998), the model is a linear Gaussian model and the procedures described in Stock and Watson (1991), based on the likelihood function, could be applied to; (1) estimate the parameters of the model based on the state space representation; (2) recover D_i and δ from $\Delta \overline{Y} = [\Delta \overline{Y}_1, \Delta \overline{Y}_2, \Delta \overline{Y}_3, \Delta \overline{Y}_4]$; and (3) calculate the composite coincident index C_t. The estimated specification follows that of Kim and Nelson (1998) and Stock and Watson (1991) . A second-order autoregressive specification is adopted for the error processes of both the common component and the four idiosyncratic components in equations (1.5) and (1.6). Similarly, three lags of Δc_t are included on the employment index, due to the arguments set out in Kim and Nelson (1998) and Stock and Watson (1991), in which it was pointed out that employment may not be exactly coincident, lagging slightly the unobserved common component. The measurement and transition equations can be represented as,

$$\begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{2t} \\ \Delta y_{2t} \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \lambda_2 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \lambda_4 & \lambda_{41} & \lambda_{42} & \lambda_{43} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \Delta c_t \\ \Delta c_{t-2} \\ \Delta c_{t-2} \\ \Delta c_{t-3} \\ e_{1t} \\ e_{1,t-1} \\ e_{2t} \\ e_{2,t-1} \\ e_{3t} \\ e_{3,t-1} \\ e_{4t} \\ e_{4,t-1} \end{bmatrix}$$

Measurement Equation

$$\begin{bmatrix} \Delta c_t \\ \Delta c_{t-2} \\ \Delta c_{t-2} \\ \Delta c_{t-3} \\ e_{1t} \\ e_{1,t-1} \\ e_{2t} \\ e_{2,t-1} \\ e_{3t} \\ e_{3,t-1} \\ e_{4t} \\ e_{4,t-1} \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \psi_{11} & \psi_{21} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \psi_{21} & \psi_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \psi_{31} & \psi_{32} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \psi_{41} & \psi_{42} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \Delta c_{t-1} \\ \Delta c_{t-2} \\ \Delta c_{t-2} \\ \Delta c_{t-4} \\ e_{1t-1} \\ e_{1,t-2} \\ e_{2,t-1} \\ e_{2,t-1} \\ e_{3,t-1} \\ e_{3,t-2} \\ e_{4t-1} \\ e_{4,t-2} \end{bmatrix} + \begin{bmatrix} v_t \\ 0 \\ 0 \\ 0 \\ \varepsilon_{1t} \\ 0 \\ \varepsilon_{2t} \\ 0 \\ \varepsilon_{3t} \\ 0 \\ \varepsilon_{4t} \\ 0 \end{bmatrix}$$

Transition Equation

This approach warrants the choosing of important economic time series that are of interest in subsequent analysis and forecasting. The choice of the variables depends for a large part on the judgement of the practitioner. The variables chosen in Figure 1.18 were sales of manufacturing goods, industrial production, employment and a share price index based on the largest stock market in the Euro area, the German DAX. The variables are monthly and span 1989:10 till 2006:12. Although it is usual to include a measure of personal income, such measures are unavailable for the Euro area. Consequently, the variables chosen were based on their availability, as well as their widespread use in various coincident index measures.

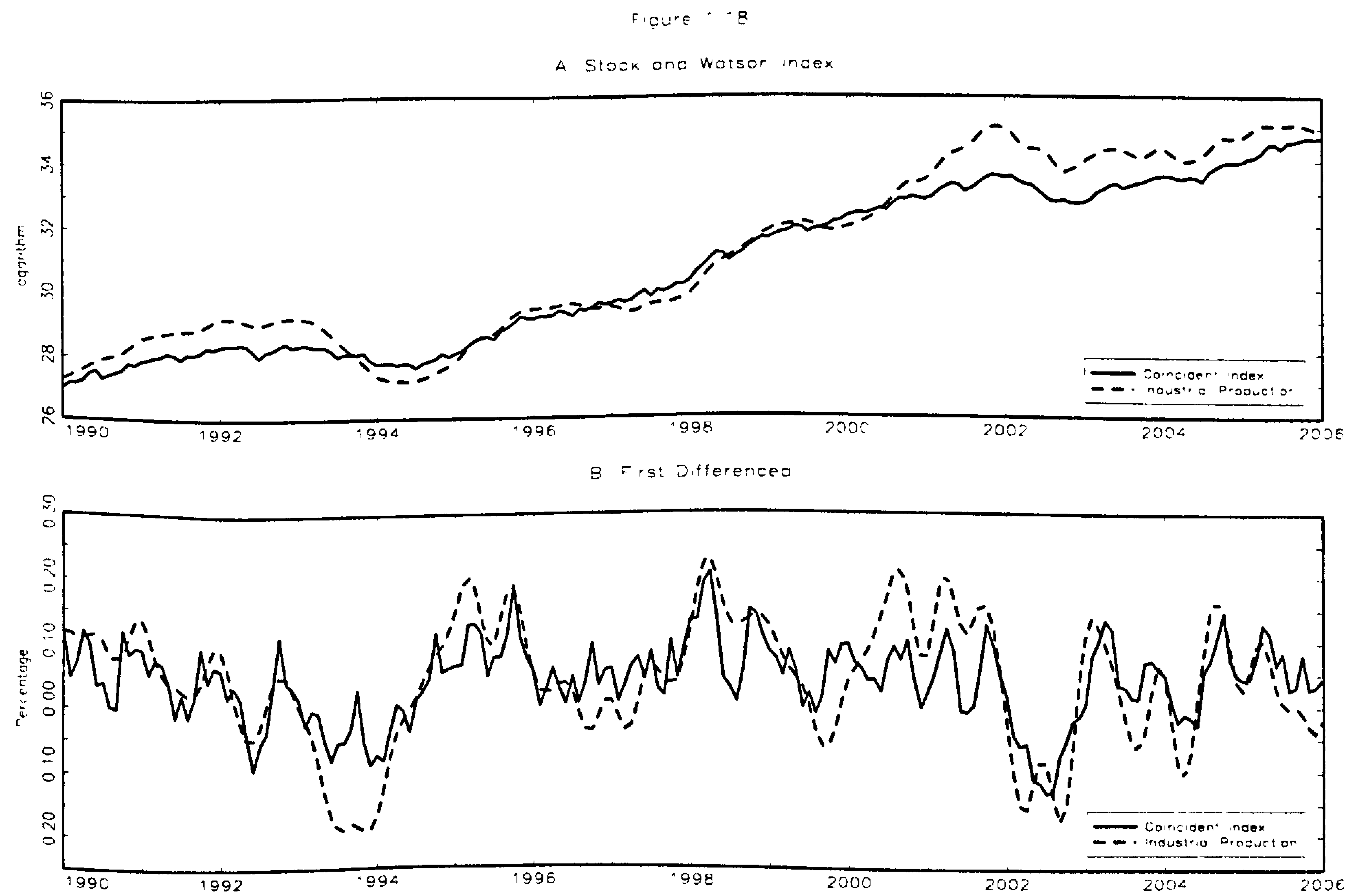


Figure 1.18 illustrates estimates of the coincident index based on Stock and Watson's (1989, 1991, 1993a) factor model. Figure 1.18 part A synthesises the information from the variables into a single index called a coincident index, conforming to Burns and Mitchell (1946), in which business cycles should be viewed in terms of fluctuations in a number of time series. This result is compared to a standard measure of economic activity - industrial production. The first aspect to notice in Figure 1.18 part B is the increase in noise over the standard economic activity measure, industrial production. The results support the underlying assertion in common factor modelling that the

behaviour of the set of n variables is qualitatively similar to the behaviour of just *one* variable. However, the drawback of increased noise is a noticeable one. Models like the dynamic factor model estimated in Figure 1.18 are, more often than not, used for forecasting purposes rather than determining what are the driving factors behind business cycles. This is because the variables often contained in leading indicator and coincident indices, such as stock prices or monetary aggregates, are used as exogenous shock variables to decipher how the economy reacts to changes in these variables.

Finally, business cycle fluctuations are sometimes modelled as a set of integrated stochastic trends between the major macroeconomic time series. There is a large body of evidence that macroeconomic variables behave as if they contain stochastic trends. Multivariate empirical analysis suggests that trend variations and business cycle movements appear to be related. One interpretation of this link is that business cycle fluctuations might be caused by innovations in growth. This can be investigated by a set of long-run relations - the so-called balanced growth relations among consumption, investment and output. Simple stochastic equilibrium models of the business cycle that incorporate growth imply that, even though these aggregate variables can contain trends, including stochastic trends, their ratios should be stationary. King *et al.* (1988a,b) deduce that macroeconomic fluctuations are best modelled as stochastic growth trends. The most prominent stochastic trend dictates movements in output, consumption and investment, which together constitute close to 80 percent of Euro area economic activity. The finding of a stochastic trend running through output, consumption and investment has been well documented for the US economy by King *et al.* (1991). This issue also raises the question of a 'statistical versus an economic based decomposition', which arises from the 'measurement without theory' concern first raised by Koopmans (1947). In support, Canova (1998) has noted that, before variables can be selected and facts reported, a theory explaining the mechanism generating economic fluctuations is needed. This point of view has been advocated by those who use economic theory to choose an economic-based decomposition of the actual time series in deriving business cycle regularities, as in Singleton (1988), King *et al.* (1988a,b), King *et al.* (1991), Attfield (2003), Whelan (2005) and Attfield and Temple (2006), to name but a few.

Figure 1.19 Time Series of Output, Consumption and Investment

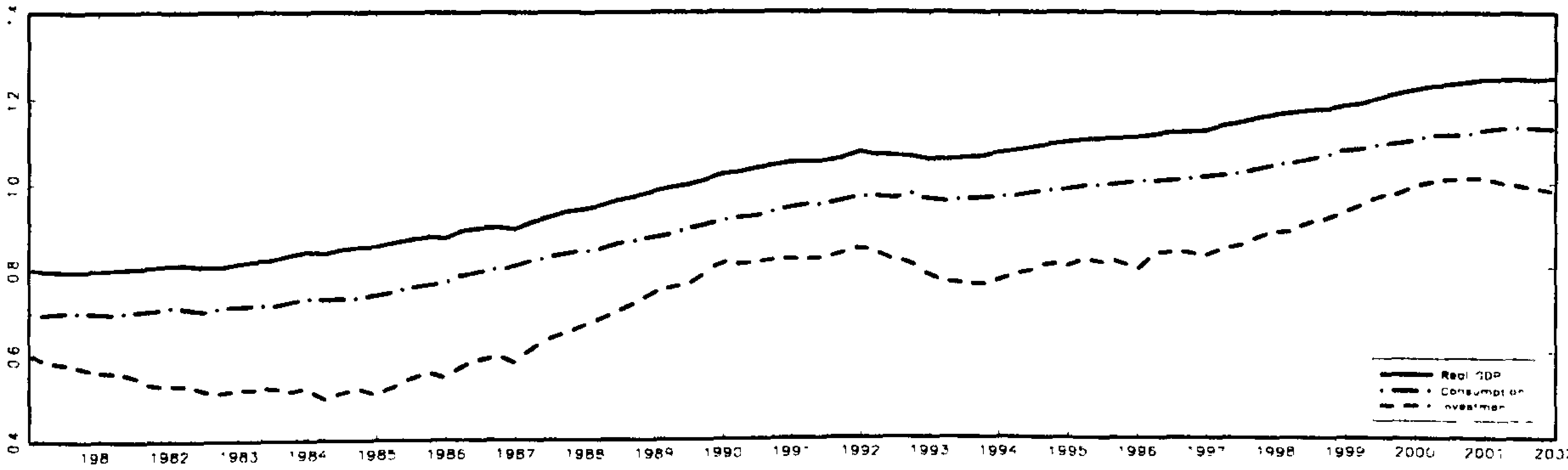


Figure 1.20 Great Ratios

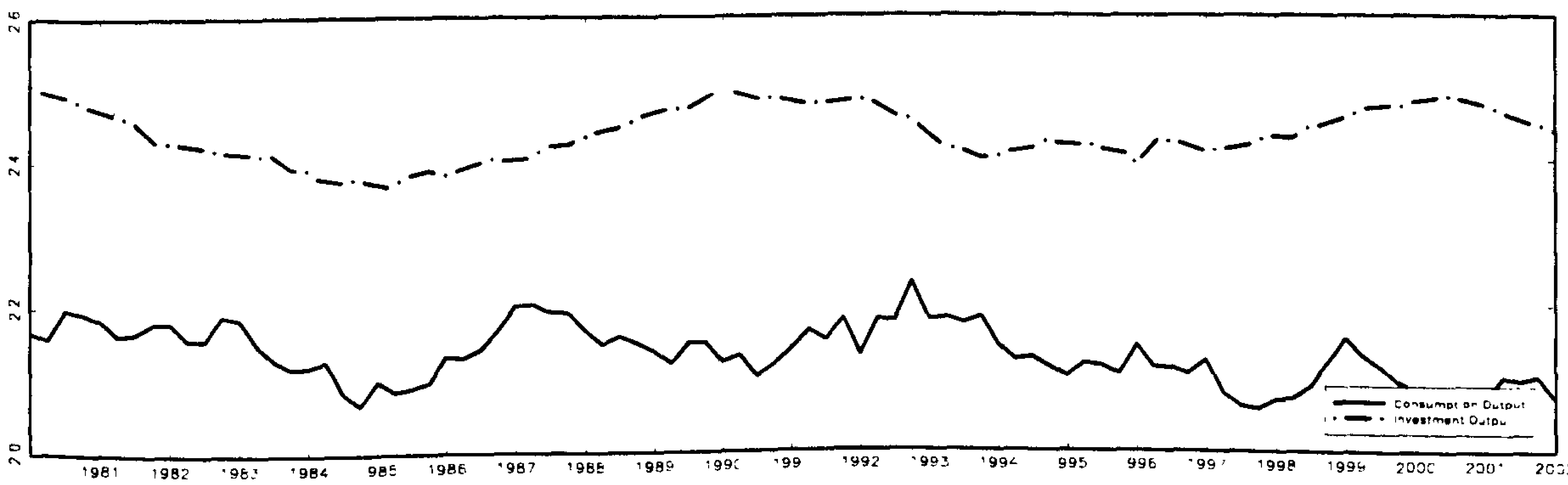


Figure 1.20 plots the consumption-output and investment-output ratios, which are considerably more mean reverting than the aggregate series shown in Figure 1.19. These relations have proven remarkably stable over the past two decades, providing important benchmarks for assessing theoretical macroeconomic models and for guiding macroeconomic policy. The relationships illustrated in Figure 1.20, which implies that economic fluctuations could potentially be modelled as a cointegrating relationship between output, consumption and investment. In such a scenario, fluctuations in economic activity could be framed on growth theory based on the RBC theory approach of King *et al.* (1988a,b).

In conclusion, although the business cycle is technically defined by comovements across many sectors and series, fluctuations in aggregate output are at the core of the business cycle, so that the cyclical component of real GDP is a useful proxy for the overall business cycle and is thus a useful benchmark for comparisons across series. In fact, RBC theorists, such as Hodrick and Prescott (1997) and Burnside *et al.* (1996), often justify the use of GDP as the overall measure of economic activity because of the strong coherence of different sectors of the economy. Here we will tend to concentrate, where applicable, on the most widely accepted measure of economic activity, real GDP, since it is generally assumed that the measure takes adequate account of the 'pervasiveness' that is required in the definition of the cycle.

1.2 Summary

This discussion illustrates some of the controversies and difficulties surrounding, first, what constitutes a business cycle and, second, how best to extract the cyclical component of an economy. A trend denotes a long-run tendency in an economic time series, for example, an upward inclination reflecting real growth or price inflation. There is much variability in the intermediate and short-run component (the business cycle) of many macroeconomic time series that evolve rather slowly, without sudden disturbances, that are difficult to explain. Economies grow through cycles of expansions and contractions that vary widely in amplitude and duration The results from the different decomposition methods used to isolate an accurate series that reflects postwar fluctuations in economic activity show that the most difficult problem for time-series decomposition in the present context arises because trends and business cycles interact. However, by using the classical definition of the business cycle, it is possible to negate this issue, since the cycle has to include a duration of absolute decline in economic activity regardless of trend growth, removing the possible usefulness of many filters. On the other hand, using the growth cycle definition can lead to periods of supposed 'higher' growth being quickly followed by a growth recession, induced by a sudden upward shift in trend growth, formulating very different policy conclusions. In this case, the perceived slowdown in economic activity may not be due to a 'true' slowdown in economic activity, as in the classical business cycle definition used by the NBER and the founding fathers of business cycles research - Burns and Mitchell (1946) - but because productivity/technological change has meant output falling below trend, lending to misleading conclusions being drawn about the state of an economy.

Deriving a series that represents the business cycle ultimately involves discretion and judgement on behalf of the practitioner, with few written down rules on the correct way to proceed. In Canova (1998), an exhaustive study of various business cycle extraction methods, the argument is made in favour of passing data through a variety of detrending filters which emphasise different business cycle concepts, in order to check the implications of theoretical models over a wide range of cyclical frequencies. Ultimately, theory should indicate which concept of the cycle is the object of research, classical or growth cycles, and therefore implicitly dictate a class of detrending procedures, and empirical practice should indicate whether this choice leaves out important features of the data or produces distortions of various kinds.

Chapter 2

Business Cycles: Continuity and Change

2.1 Introduction

Ever since Koopmans (1947) criticised Burns and Mitchell (1946) as being 'measurement without theory', the reporting of business cycle facts has tended to concentrate upon small, and more recently large, scale models. The postwar period witnessed a large increase in the theoretical discussion of business cycles, since undertaking any empirical work requires the selection of variables based on some notion of the theory that generates economic fluctuations. The importance of understanding the causes of economic volatility in output is due to the many undesirable effects it has on economic welfare; some of which include increases in risk premia associated with risk in the economy, which are likely to reduce equilibrium output and lower capital stock, as well as creating a more uncertain and unpredictable future by making it difficult for households and firms to plan ahead with any degree of certainty. Hence, policies that reduce anticipated and unanticipated volatility will therefore raise output and welfare in the long-run.

What shocks are responsible for economic fluctuations? Despite at least two hundred years in which economists have observed fluctuations in economic activity, it still remains unclear. The main goal of this chapter is to appraise the role played by different theories of the business cycle, and the periods in which they came to prominence, whilst also illustrating the basic concepts of each theory using simple plotted data of the main macroeconomic time series for the Euro area. This section also highlights the difficulties and controversies found in trying to estimate the most prominent theories of the business cycle over the last three decades.

Up until recently - the early millennium slowdown being the turning point - the business cycle had been considered, in some quarters, to be 'dead'. This conclusion was largely drawn at the height of the dotcom boom of the mid to late 1990s, a period characterised by so-called 'irrational exuberance'. Similar claims, were also made in the 1980s, when the US witnessed one of the longest peacetime economic expansions, and its second longest ever. As this expansion evolved, many economists views also changed. In both expansionary periods, the idea emerged that the business cycle was an artifact of history, with the belief that 'things are different this time'. In addition, it had been argued that 'baby boomers', who in earlier years had caused large swings in aggregate demand, were now maturing and shifting their focus to saving, leading to lower inflation, lower interest rates, and sustained steady long-term economic growth; in other words, stable economic growth without cycles. In hindsight, however, rumours of the death of the business cycle were premature.

Several factors in the 1980s expansionary period supported the belief that the cycle was dead. During the first half of the decade, a strong dollar made US products uncompetitive in world markets and led to the deindustrialisation of the US economy. A similar scenario was witnessed in the UK, as well as Euro area economies. In addition, the US stock market crash in 1987 did not dent expansion in economic activity. When economic collapse failed to follow the stock market crash, a consensus view emerged which argued that the Federal Reserve had 'mastered' monetary policy to prevent future recessions. Given the lack of private incentive to restrain the stimulative effects of this 'oldest business cycle mechanism', it would only be the Federal Reserve that could engineer a recession, but since the Federal Reserve had mastered monetary policy this seemed unlikely. This hypothesis has recently re-emerged again, as in Cogley and Sargent (2005) and Stock and Watson (2002a, 2003b), who investigate whether improvements in counter-cyclical monetary policy is a possible explanation for the moderation witnessed in the business cycles of the industrialised economies and whether, because of improved policy, the business cycle is permanently damped. In fact, Samuelson (1998) noted that 'when the next recession arrives you will find written on its bottom - Made in Washington'. A similar case was also made for the expansionary period of the dotcom era, where not even the Asian financial crisis stopped most industrial economies from continuing their economic expansion. Dornbusch (1997) argued that 'none of the US expansions of the past 40 years died in bed of old age; every one was murdered by the Federal Reserve'. Hence, as long as the Federal Reserve allowed growth to continue, there was not much to go wrong. Such equanimity was also taking hold in other major industrialised economies in the Euro area, such as Germany and France. Yet it was clear to those who were reasonably informed in the history of economic fluctuations that they were predicting a radical shift from the historical trend-cycle patterns of economic change.

In both periods, the end of the 1980s and the start of the early millennium, proof that the business cycle was alive and well arrived with a recession in 1992 and a major economic slowdown in 2001 in the Euro area. In both cases the recession was a surprise to those who believed the cycle was dead. The early 1990s slowdown in most of the industrialised economies is attributed, by some, to oil shocks due to the first Gulf war. However, with regards to the Euro area, monetary policy shocks were probably the central protagonist, with interest rates rising across the economies of the Euro area in an effort to maintain their fixed exchange rate regimes. Perhaps the fallacy in thinking that the business cycle was 'dead' can be explained by Frisch (1933), a view rejected by Lucas (1977), who forcefully restated Slutsky's (1937) view that the accumulation of small shocks could generate data which mimicked the actual behaviour of the main macroeconomic time series. The former view, however, clearly underlies many descriptions and policy discussions in the business cycle literature today. This view is that there are infrequent, large, identifiable shocks which dominate all others. Particular economic fluctuations can be ascribed to particular large shocks, followed by periods during which the economy returned to equilibrium. Such a view is implicit in the description of specific periods. The behaviour of economists during times of economic prosperity, with no slowdown in economic activity, reveals the belief that economic expansion will continue as long as there are no 'large' shocks that impinge upon the economy - in this case the belief was of monetary shocks - implicitly revealing, without perhaps realising, that business cycle fluctuations (as in the classical definition) are caused by 'shocks'. This can be illustrated using two examples from the US economy. First, the early millennium slowdown, which was examined by Stock and Watson (2003c) and Peersman (2005). As late as early 2001, economic forecasters were predicting confidently that there would be no recession, only a slowdown. However, the 11th of September and the consequent military response caused a precipitous drop in consumer confidence. The second illustration concerns the recession of the early 1990s. As of mid till late 1990, economic forecasters were predicting confidently there would be no recession, at worst a slowdown. However, Iraq's invasion of Kuwait, and the US military response, caused a drop in economic activity, with resultant high oil prices. As such, it could be argued that policy actions to help tame economic fluctuations, such as monetary policy, are irrelevant because shocks are inherently unpredictable. Instead, policy should aim to minimise vulnerability of the economy. However, policy can only be at its most effective if policymakers have a degree of confidence as to how far shocks are propagated through the economy, and whether they are real or nominal shocks. This analysis would suggest that the business cycle may remain a vital characteristic of economies around the world, perhaps for ever! Indeed, Fuhrer and Schuh (1998) argued that previous ideas of the business cycle being 'dead' were ideas without merit. As such, the view that the business cycle had vanished, as was prevalent in the 1980s and 1990s, was perhaps a little vacuous in thinking that it might be so. Indeed, work by Hamilton (2005a) has explored whether 19^{th} century economists were right to focus on the underlying assumption of all business cycle research, one that modern day economists may have forgotten. Is there really a business cycle, or is it an expression from a less informed era? Hamilton (2005a) concludes that there is a recurring pattern in the level of economic activity that needs to be explained. In agreement, Samuelson (1998) notes that economic instability has always been with us, and will continue to remain.

Recently, the literature has moved on to question not whether the business cycle is 'dead', but whether the business cycle has moderated, and whether this shift is permanent. There have been important changes in the developed economies in the post-war era, including changes in the composition of production and of the labour force, in the technology of inventory management, and in the importance and behaviour of government. Hence, it would not be too surprising if the empirical characteristics of business cycles varied secularly over time. More importantly, with regards to the literature, the null hypothesis is that there has been a decline in the importance of shocks, and this has led to a dampening in business cycle fluctuations. The most prominent studies are Zarnowitz (1992), Kim and Nelson (1999), McConnell and Perez (2000), Blanchard and Simon (2001), Stock and Watson (2002a, 2003a) and Ahmed *et al.* (2004). All studies found business cycle fluctuations to have moderated for the US economy.[1] However, very little work has been undertaken on other industrialised economies. Has the business cycle dampened in the Euro area? Is this down to less frequent shocks hitting the economy? What have been the effects of monetary policy changes with regard to the dampening in economic fluctuations? Finally, what role have 'imported' business cycles played in regard to this. All these questions remain unanswered for the Euro area. This issue, along with its corresponding international dimension is fully explored in Chapters 4 and 5.

[1]The results differ slightly, in that Blanchard and Simon (2001) estimate a prolonged moderation starting in the 1960s, whereas Kim and Nelson (1999), McConnell and Perez (2000) and Stock and Watson (2002a) attribute the moderation to a break in 1984. In addition, Stock and Watson (2002a) conclude that the moderation in the US cycle is unlikely to continue, with the past decade being unique in that fewer shocks have impinged upon the US economy relative to the three decades following the end of world war two.

2.2 Shock Based Theories

Early analysts of the business cycle, such as Mitchell (1913), believed that each cyclical phase of the economy carries within it the seed that generates the next cyclical phase. A boom generates the next recession, with the recession generating the next boom and so on; in essence, cycles are endogenously determined and, in this sense, self-sustaining. A new way of thinking about economic fluctuations, however, started off with Frisch (1933) and Slutsky (1937), in which business cycles were attributed to cyclical fluctuations and the cumulative effects of shocks and disturbances that continually buffet the economy. These irregular fluctuations - impulses - are troublesome, since they seem to make prediction of the movements of the system impossible. But if there are a sufficient number of independent shocks and if the number of large shocks is small, Frisch (1933) argued that the average period of fluctuation of the system should be left unaffected by these shocks. This result, if it applies sufficiently generally, was of great importance, in as much as it enabled practitioners to predict movements of the system merely by studying its 'natural tendencies'. Indeed, it became the underlying principal of Beveridge and Nelson's (1981) decomposition. However, there is general agreement that the 'natural tendencies' are more relevant when focusing on a longer term horizon than the short term fluctuations more relevant for business cycle analysis.

The propagation-impulse framework, which was introduced into economics by Frisch (1933) and Slutsky (1937), has come to dominate the analysis of economic fluctuations. Fluctuations in economic activity are seen as the result of small, white noise, shocks which affect the economy through a complex dynamic propagation system. Frisch's (1933) model implies that, if some transient random event raised output above the economy's normal level, all macroeconomic variances - output, investment and consumer spending - would return to normal in a cyclical fashion. These swings in economic activity would gradually diminish in strength and eventually die. This methodology was first applied to macroeconometric models developed by Keynesian economists. The most cited example is the Klein and Goldberger (1952) model. It was from this model that Adelman and Adelman (1959) simulated the US economy and showed that the model, in the absence of outside shocks, produced damped oscillations. Gordon (1985) argued that, within the history of business cycle theory, Adelman and Adelman (1959) shifted the attention of economists from propagation mechanisms to the sources of impulses.

Since the work of Adelman and Adelman (1959), proponents of the importance of the propagation mechanism and of impulses have fused, in so far as the literature now observes the business cycle as resulting from irregular impulses whose effect on economic activity is transmitted by a complex propagation mechanism. This view is sometimes referred to as the 'exogenous view'. It must be noted, that self-sustaining cycles are making a slow comeback. Many papers examine models that display multiple rational expectations equilibria. In multiple equilibria models, the seeds of the next downturn are sown in the boom period through changes in expectations: examples include Wen (1998) and Benhabib and Wen (2003). An important difficulty with multiple equilibria models is that they require beliefs to be volatile but coordinated across agents. Such models are sometimes characterised as the 'endogenous view' of output fluctuations.

The exogenous view of the business cycle emphasises the role of independent shocks as the main source of business cycles. These conceptual differences translate into important implications for business cycle predictions, because of the different role business cycle phases play in the joint data generating process for economic activity under the two views. In the endogenous view, expansions and recessions play an intrinsic role in determining economic outputs. Knowing the state of the business cycle may help to explain the likely direction of the economy. In contrast, the exogenous view puts weight on the extrinsic nature of cycles; that is, business cycle fluctuations produce patterns that exhibit features consistent with a definition of expansions and recessions, as seen in the previous section, but the denotations are simply labels rather than an intrinsic part of the data generating process. It is the latter that economists have often attempted to use, and offer a mixture of shocks in a spirit of compromise, so that recessions are either sums of many small negative impulses, or that different shocks cause different historical episodes. Two examples are Blanchard (1991), who investigated the early 1990s economic slowdown in the US, and Gert and Peersman (2005), who explored which shocks were responsible for the early millennium slowdown in both the US and the Euro area. Cochrane (1994a) notes that there are good reasons to try and limit the analysis to a small number of recurring shocks. Business cycles are 'all alike' in many ways, as opined by Lucas (1977). Investment and durables fall by more than output, hours fall about as much as output, nondurable consumption by much less than output. Different shocks are unlikely to produce similar responses. For example, if a shock, such as a credit crunch, is temporary, it should cause a small reduction in consumption, and a big decline in investment. If it is permanent, like a tax increase, it should cause a much larger decline in consumption, and may not change investment at all. The need to produce roughly similar dynamics severely constrains the dynamic structure of the shocks and, hence, argues for a common source. In explicitly dynamic models, it is no longer true that any source of aggregate demand decline is as good as another and kicks off the same dynamic pattern (Cochrane, 1994a).[2]

There are technical limitations to examining the question 'what exogenous shocks account for output fluctuations?' Assume that oil prices have small direct effects on the economy, but they induce monetary policy makers to cause recessions. In this case, oil prices are the exogenous shock, with the monetary authorities playing the part of the propagation mechanism. However, to conclude from this that oil shocks account for fluctuations would be a misleading description; monetary policy caused the recession. In such a scenario it often becomes difficult to disentangle shocks. Zarnowitz (1998) argues that oil price boosts and monetary policy shifts have triggered some recent cyclical downturns, but even in these particular episodes, other more regularly observed developments played major roles. Consequently, the insistence on single shocks as the cause of recessions is erroneous. This criticism, along with the idea that, if business cycles are caused by random shocks then how is it possible to determine the business cycle if its main determinants are driven by a twist of fate, have cast a cynical shadow on business cycle analysis.

In spite of these limitations, it would be a falsification to suggest that it remains unimportant which factors drive the cycle. Adherents to the Keynesian tradition of emphasising fluctuations in aggregate demand as a primary contributor of the business cycle, for example, differ substantially from those of the RBC persuasion. Since these two views of the sources of the business cycle lead to radically different macroeconomic models and prescriptions for government policy, resolution of this debate remains important. In addition, the issue of shocks raises the concept of 'vulnerability' - an issue that is central to policymakers. This issue bears on the distinction between shocks and systematic economic behaviour. Fuhrer and Schuh (1998) use the following example. Consider the collapse of a building during an earthquake. While the proximate cause of the collapse was the earthquake, the underlying cause may better be attributed to poor construction techniques. Due to the structural defects, the building was probably going to fall when the 'right shock' came along. This analogy can be used to highlight any deficiencies in the economy or the monetary policy regime. Macroeconomists tend to focus primarily on the overall health of the economy, as measured by aggregate demand or by the unemployment rate. They may be able to improve their economic models by incorporating vulnerability, such as various financial variable measures.

[2] For the purposes of Chapters 3, 4 and 5, the preceding literature focuses solely on shock based studies. This and subsequent chapters interpret 'cause' to mean the shocks that initiate the movements in the cycle, trying to identify the source of instability rather than policy responses that may have aggravated the movements.

2.2.1 Fall of Monetarist Theories of the Business Cycle

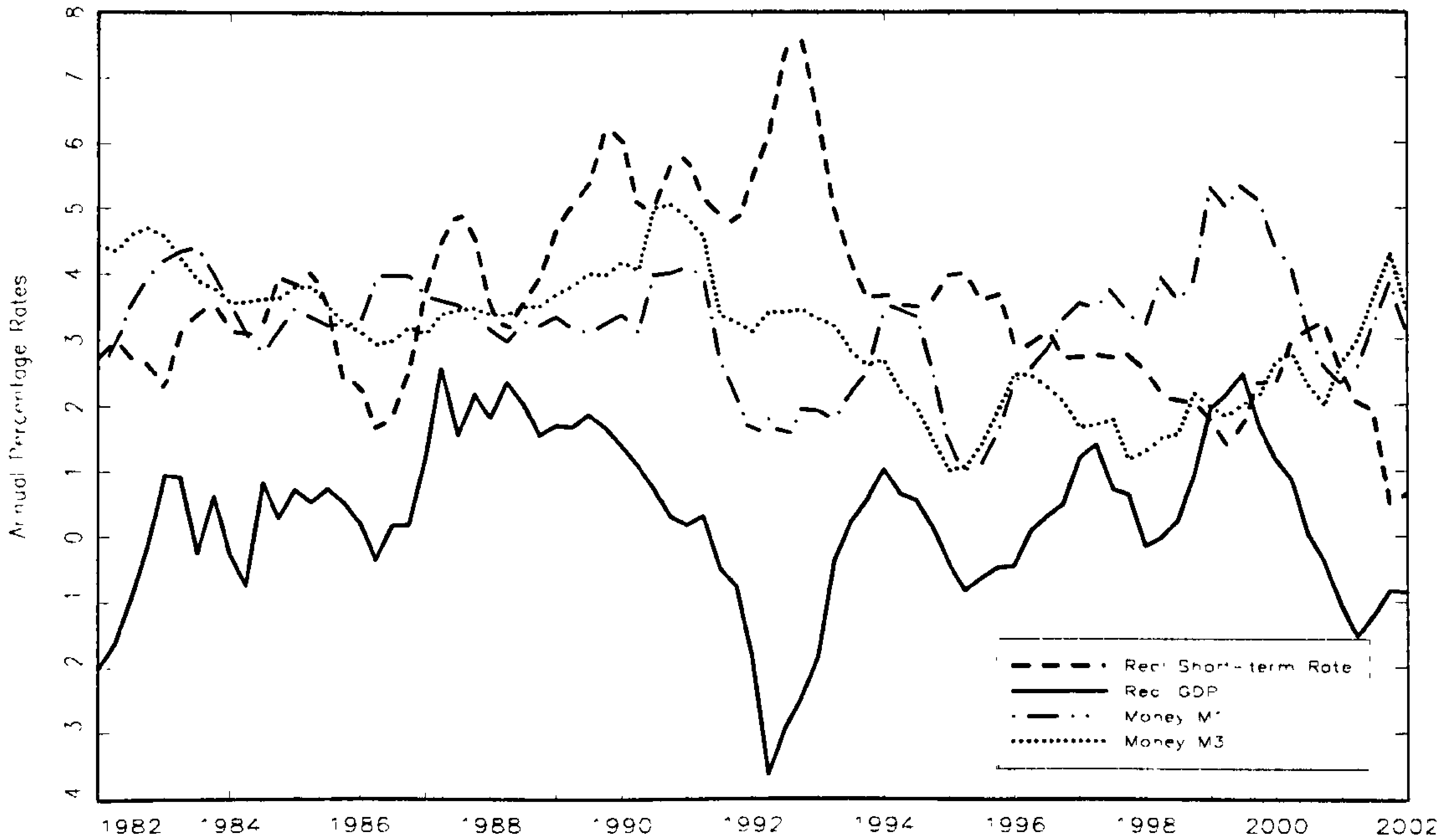
Implicit in the discussion so far is that, if shocks are unpredictable, then it may be impossible to prevent fluctuations in economic activity at business cycle frequencies. This hypothesis falls apart, however, if one assumes that the shocks impinging upon the economy are policy induced, specifically from monetary policy. Friedman and Schwartz (1963), in analysing the monetary history of the US economy by tracking down several important events, discovered that income expansions/contractions were always preceded by expansions/contractions in the money supply. They observed that in many episodes the actions of the monetary authorities, despite possibly good intentions, actively destabilised the economy. Indeed, Friedman's (1992) plucking model of the business cycle maintains a central role for monetary disturbances, leading output fluctuations to 'pluck' downwards below the trend of output. Friedman and Schwartz (1963) documented the strong time series correlations of monetary aggregates with both output and prices, and then went further to argue that these correlations did not primarily represent passive responses of monetary aggregates to developments in the private sector, but instead mainly the effects of monetary policy shifts on the private sector. They buttressed these claims by showing that the correlations persisted even when attention was focused on changes in monetary aggregates that could not have been predicted from current or immediately preceding developments in the private sector. This amounted to an informal argument that innovations in the monetary aggregates - unforecastable movements in them - were a good approximate measure of monetary policy disturbances. The importance of Monetarist ideas reached their zenith in the early 1980s. However, a setback for Monetarist ideas arrived, firstly, from Sims (1980), who concluded that there is probably no Monetarist business cycle, with the caveat that this does not mean the same thing as saying there is no influence of monetary policy on the business cycle. Secondly, Friedman and Kuttner (1992) found that, post-1982, the results did not indicate a close or reliable relationship between money and output, especially when nominal interest rates were controlled for.

The difficulty in trying to empirically capture the relationship between monetary policy and output is due to the many monetary models, which do not give any explicit dynamic predictions. Empirical researchers typically search for vector autoregression (VAR) specifications to produce impulse-responses that capture qualitative monetary dynamics, as described in Friedman (1968). Other shocks, such as oil, credit, etc., are not associated with well articulated dynamic theories of their effects on the economy, so identification and evaluation is often tenuous. For this reason, shock identification is often based on simplified stylised features rather than the predictions of explicit models; 'demand' shocks have no long-run effect on output, 'monetary' shocks are represented by unforecastable movements in the monetary policy instrument, and so forth. The best recent example is Uhlig (2005), which estimated a Bayesian VAR, in which sign restrictions were placed on nominal interest rates, prices and money. These restrictions were based on so-called 'general consensus view' on the effects of monetary policy, i.e., interest rates rise, money and prices fall, rather than on any model specification. Similarly, earlier work by Christiano *et al.* (1996) and Bernanke and Mihov (1998), among others, attempted to restrict VAR models, using informal arguments to justify the restrictions, in such a way as to arrive at estimated responses to monetary policy shifts that have interest rates declining, monetary stock expanding and prices rising following an expansionary monetary policy shock. Kim (1999) extended this line of work to open economies. Much of this research, which is a continuation of the 'Sims agenda', attempts to avoid unreasonable identification restrictions.

In a related criticism, the role of the propagation mechanism provides added constraints on deciphering the effects of monetary policy on output. Most of the literature focusing on monetary shocks on business cycle fluctuations use a broad class of propagation mechanism, making it difficult to find answers to questions pertaining to the use of sticky price noncompetitive models. It remains difficult to come up with some behaviour that a whole class of models, as yet not investigated, is incapable of producing. For example, monetary shocks could account for fluctuations through an intertemporal market clearing mechanism - a RBC model with a cash-in-advance constraint - as well as through a sticky price mechanism. A good illustration of this is Christiano *et al.* (1998), who survey monetary shocks. They are particularly interested in the response of the economy to exogenous shocks, but recognise that the very identification of these shocks is specific to their model. Thus monetary shock accounting has not been very successful in saying anything about the plausibility of broad classes of economic models.

Such failures have been used by Fuhrer and Schuh (1998) to argue that these theories are an unsatisfying answer, since the framework assumes that the macroeconomy usually obeys simple behavioural relationships but is occasionally disrupted by large 'shocks', which force output away from these relationships. In this sense, RBC explanations of business cycle fluctuations are an improvement over monetarist theories since, broadly speaking, as examined and identified by Cogley and Nason (1995), RBC models rely on three kinds of propagation mechanism; capital accumulation, intertemporal substitution of labour, and various kinds of adjustments lags or costs, as exploited by Burnside *et al.* (1993).

Figure 2.1 Monetary Variables and Real GDP



The rise of monetary theories of the business cycle owed much to simple 'eyeball' interpretations of the data, from which it was deduced that a rise in interest rates precedes each postwar recession. Plotted data series for the Euro area appear to show that cyclical movements in real interest rates tend to coincide with cyclical movements in real GDP, and in some cases precede movements in real GDP. It would be foolish, however, to suggest that movements in interest rates alone capture the behaviour of the monetary authorities. In addition, the observation that a rise in interest rates preceded each slowdown in real output does not necessarily imply that policy induced interest rate movements caused the recession. If, for example, rapid expansion of private demand for credit systematically causes all interest rates to rise near the end of an expansion, this rise in interest rates should not be interpreted as the cause of the subsequent slowdown; it is a consequence of previous strong demand.

Research looking at the effects of monetary policy on output has tended to take a shock based approach. This is mainly due to Lucas (1977), who concluded that anticipated monetary policy has little effect on output, as individuals are endowed with rational expectations - the 'Lucas Critique'. Consequently, to gauge the effect of monetary policy on output, the model needs to capture the actions of monetary authorities when the monetary policy changes are unanticipated - in other words, a 'shock' - leaving little or no time for households and firms to adjust in advance. Indeed, most of the literature has focused on unanticipated policy shocks. This is not because they are quantitatively important - indeed, the conclusion of most of the literature is that policy shocks are too small to account for much of the overall variation in output - but because it is argued that causes and effect can be cleanly disentangled only in the case of exogenous, or random, changes in policy. Although this is the most prominent approach in trying to identify the effects of monetary policy on output, the issue of identifying monetary shocks in this way is problematic. The majority of work on the effect of monetary policy on business cycles and on whether much of the business cycle can be primarily explained by monetary policy disturbances has been undertaken using VARs, as pioneered by Sims (1980). Examples include Bernanke and Blinder (1992), Christiano and Eichenbaum (1992), Sims (1992, 1996), Strongin (1995), Leeper *et al.* (1996), Bernanke *et al.* (1997), Bernanke and Mihov (1998), Uhlig (2005) and Sims and Zha (2006). Although there appears to be little agreement on the correct way of identifying policy shocks, alternative identification assumptions seem to deliver very similar conclusions: 1) short-term interest rates rise; 2) output, employment and money aggregates decline; 3) prices decline with the impact occurring after a delay of at least six quarters; 4) monetary policy shocks account for, at most, a modest portion of output and price volatility. Kim (1999) and Canova and Nicolò (2001) have shown that monetary shocks play, at most, a modest role in driving output fluctuations in the G7 economies. It must be noted, however, that earlier work, conducted mainly on the US economy, by Romer and Romer (1989) found that monetary policy does play a large role in driving output fluctuations if no distinction is made between anticipated and unanticipated policy changes. Romer and Romer (1989), using Federal Reserve records, identify a series of dates at which, in response to high inflation, the Fed changed policy in sharply contractionary directions. Romer and Romer (1989) find that their dates were typically followed by large declines in real activity and conclude that monetary policy plays an important role in fluctuations. However, critiques have pointed out that this approach to the study of the effects of monetary policy on output blurs the distinction between anticipated and unanticipated policies and, consequently, suffers from precisely the identification problem that the VAR literature has attempted to avoid; namely, that it is not obvious how to distinguish the effects of anticipated policies from the effects of the shocks to which the policies are responding.

It was Friedman and Schwartz (1989) who argued in favour of separating autonomous movements in policy from movements in policy induced by business conditions. This has potentially important implications for any work that focuses on the effects of monetary policy and real output for the Euro area, since a number of the most significant tightening periods of monetary policy in the Euro area economies have followed on the heels of major increases in the price of imported oil - 1973 and 1979 being the most prominent examples. Cochrane (1996) has emphasised that even identification of the effect of unanticipated policy changes may hinge on distinguishing between anticipated and unanticipated changes, since an innovation in policy typically also changes the anticipated future path of policy. This leaves the practitioner facing the uncertainty of determining how much of the economy's response to a policy shock is due to the shock *per se*, and how much is due to the change in policy anticipations engendered by the shock. It must be noted that, from a theoretical viewpoint, the argument made by Lucas (1977) regarding the distinction between unanticipated and anticipated policy rests on a number of key propositions that rarely hold in modern economies, for example perfect competition and perfectly flexible wages and prices.

Debate has also raged on the most suitable variables to capture monetary shocks. Since the seminal work of Poole (1970), it is well known that in a frictionless certainty equivalent economy, money supply and interest rate policies to stabilise business cycle fluctuations would be identical. In such a scenario only money demand innovations would lead to large uncertainties and real nominal rigidities. However, due to the presence of real and nominal rigidities, the use of different variables can give vastly contrasting results. Christiano *et al.* (1996) find that the estimates of monetary policy shocks for output fluctuations remain very sensitive to the way monetary policy is measured. For example, using the US Fed Funds Rate, they find monetary policy shocks account for around 21 percent of the four quarter forecast error variance for real GDP, which rises to 30 percent for the 24 quarter forecast error variance. In contrast, much smaller effects were found when using policy measures based on monetary aggregates. It is now generally agreed that only the most extreme monetarist would choose money as the sole indicator of monetary policy. This highlights the importance of the monetary policy rule (the reaction function) in estimating the effects of monetary policy on output. Of course, it is perfectly possible that neither short-term interest rate innovations nor money stock innovations are good measures of policy shifts. Indeed, it is routine to expect this result if the monetary authorities smoothed short-term interest rate fluctuations.

Accordingly, the vast literature trying to identify monetary policy shocks has recognised that the identified monetary policy shocks in previous studies are not exogenous. Identifying monetary policy shocks with innovations to broad money led to the liquidity puzzle, i.e., monetary expansions appear to be associated with rising interest rates. Consequently, work by Sims (1992) uncovered that innovations in broad monetary aggregates reflect other structural shocks, in particular money demand shocks, and so are not exogenous. The problem with trying to capture the influence of monetary shocks lies in the difficulty of disentangling monetary shocks from other types of real shocks. The 1973 oil crisis is often cited to demonstrate this problem. Did the oil shock cause the recession or was it the over-reaction of the monetary authorities to the oil shock that caused the recession, thereby categorising the recession as a monetary phenomena? Similarly, if the monetary authorities simply moves interest rates in response to prior observed inflation, any subsequent effect on real output could just as well be attributed to inflation itself as to the consequent movement in interest rates. It must be noted that an appealing feature of the use of VAR models in this context is that they focus only on those monetary policy actions determined to be unsystematic, in the sense that the VAR cannot explain them in terms of prior movements in other variables. As a result, trying to extract exogenous monetary policy shocks depends on the model. If the econometric model regards the actions of the monetary authorities as exogenous, perhaps searching for policies that can insulate the economy from external shocks, then the monetary authority is the appropriate cause. Models that endogenise the actions of the monetary authorities to explore the sources of instability in the Euro area economy often use oil shocks, which is the obvious candidate. Causes, in other words, do not have independent existences, they are just functions of the models being used and the questions being asked.

With regards to studies conducted on the Euro area, it is not clear to what extent monetary policy shocks have contributed to real output fluctuations. Indeed, work by Smets (1997), Mojon and Peersman (2001), Mihov (2001), van Els *et al.* (2003), Angeloni *et al.* (2003), Peersman and Straub (2005) and Rafiq and Mallick (2008) all confirm the ambiguity of the effects of monetary policy on output for the Euro area. While Smets (1997), Mojon and Peersman (2001), van Els *et al.* (2003) and Angeloni *et al.* (2003) relied on reduced form VAR technology, Peersman and Straub (2004) compared the results from a Bayesian VAR, based on a procedure due to Uhlig (2005), with a simple RBC model with sticky prices. The studies all seem to have one commonality that monetary shocks play, at most, a modest role in driving output fluctuations in the Euro area. However, and more generally, the results comparing the effects of interest rate shocks across countries of the Euro area have not shown a high degree of consistency across studies, casting some doubts on their robustness.

Much of the literature just cited for the Euro area has attempted to examine monetary policy using parsimoniously restricted multivariate time series models. This has tended to concentrate upon the VAR framework. In addition to the problems raised with using VAR models to investigate monetary policy shocks, the use of VAR technology in the analysis of monetary policy on real output raises a series of questions that has only become relevant over the past decade. It is generally accepted that output fluctuations in the 1990s are more stable than earlier fluctuations in output. Indeed, for the Euro area output is 40 percent less volatile now than was the case in the 1980s. Some authors have put this down to the fact that monetary authorities learned to systematically offset real shocks through countercyclical monetary policy. Of course, this example presumes that systematic or anticipated monetary policy can have real effects. Output may have been more volatile if the monetary authorities had stopped, accommodating such shocks.[3] As a result, a negative fraction of output variance is due to monetary policy. But the variance decompositions derived from the VAR methodology are poorly suited to addressing these issues, since variance decompositions cannot be negative. The use of VARs may, implicitly, discount the whole issue of whether monetary policy has led to more stabilised output cycles.

In summation, though many economists have a firm view on this subject, the state of the empirical literature attempting to identify the effects of monetary policy leaves the issue far short of resolution.

2.2.2 Real-Business-Cycle Theory

The oil crises of 1973 and 1979 gave credence to the idea that a recession could be caused by aggregate supply shocks, with aggregate demand explanations began to give way to supply-orientated interpretations. However, if the 1970s and 1980s were popularised by monetarism, the 1990s, as well as being characterised by debate and discussion as to whether the business cycle was 'dead', was a period during which RBC theory was the reigning paradigm. The ideas underlying RBC theories contrasted sharply with the traditional macroeconomic notion that changes in aggregate demand cause most of the fluctuations in business cycles. RBC theory was developed by Kydland and Prescott (1982), who built upon the work of Lucas (1977) by introducing microfoundations to macroeconomic modelling. RBC models view aggregate economic variables as the outcomes of the decisions made by many individual agents acting to maximise their utility subject to production possibilities and resource constraints. Such models find that technology shocks are the main source of fluctuations. Demand shocks, like the actions of central banks, do not figure in these models. Prescott (1986) found that technology shocks account for more than half of the output fluctuations

[3]Such studies, include Cogley and Sargent (2001, 2005), Stock and Watson (2002a, 2003a) and Ahmed *et al.* (2004).

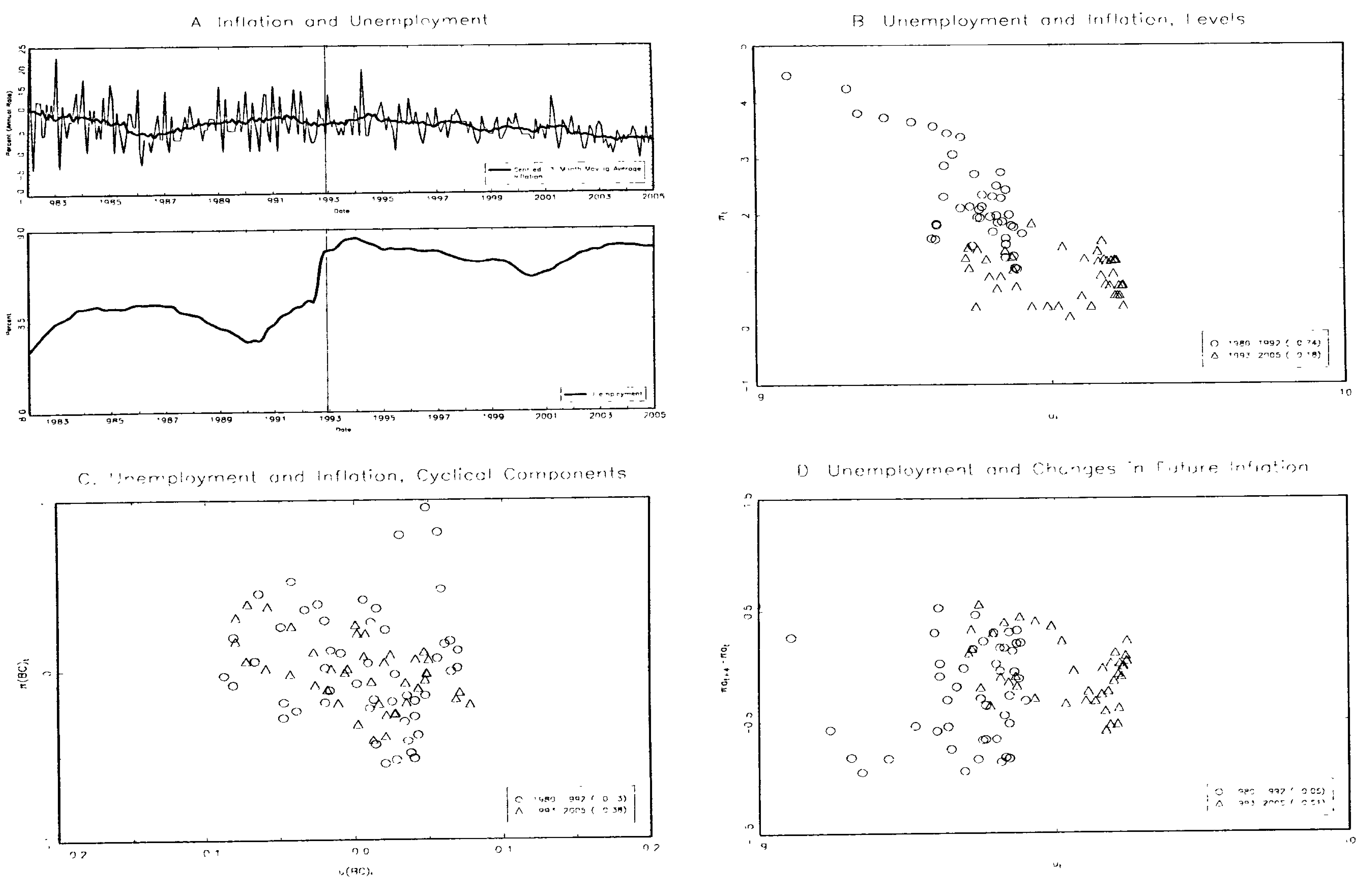
in the postwar period, with a best point estimate near 75 percent for the US economy. Hence, if shocks due to technological change are frequent and random then the random walk path of output will exhibit features resembling a business cycle. Assigning a role for permanent shocks would appear to be fully justified based upon the time series properties of real output which, as discussed in Chapter 1, is generally agreed to contain a significant integrated component. As such, RBC theory attempted to end the dichotomy between the short-run and long-run, since RBC models assume fluctuations at all frequencies are accounted for by the same shocks (shocks that move real output at business cycle frequencies also affect the economy in the long-run).

RBC models generally reject the Keynesian and Monetarist notion that monetary factors can affect output fluctuations in the short-run, thereby denying a tenet that was accepted by almost all macroeconomists before the 1980s. By assuming a Walrasian economy, RBC theory hypothesises that movements in the economy represent an optimal response by firms and households to exogenous shocks. RBC perceives business cycle fluctuations as optimal moving equilibria. In this sense, both Keynesian and monetarists are at one in that they recognise that output fluctuations (at business cycle frequencies) are predominantly a demand-side phenomenon.

RBC theory also highlighted one of the essential flaws in Keynesian thinking. A central feature of the Keynesian system of the 1960s was the trade-off between inflation and some measure of real output. The statistical artifact of the Phillips curve also plays a key role in underpinning Monetarist theories of the business cycle, as well as the principals of the NAIRU forming an important underlying pillar in RBC theory. In addition, as demonstrated by Phelps (1967), Friedman (1968), Lucas (1972) and Taylor (1980), the Phillips curve can describe the simultaneous adjustments of both real activity and prices to changes in aggregate demand. As noted by King and Watson (1994), during the 1980s business cycle research was basically conducted by two groups. The first did not study the Phillips correlation, since it was perceived to be highly improbable, almost fanciful. In a pure RBC framework there would be no room for a Phillips curve. The second group viewed the Phillips curve as an essentially intact structural relationship. Conventional Phillips curves continued to be a much used tool for medium term forecasting and policy analysis. The importance of the Phillips curve, and the vertical Phillips curve put forward by Friedman (1968), are briefly explored with some simple scatterplots. Figure 2.2 part A plots the monthly inflation rate, π_t, which is the annualised percentage rate of change in the consumer price index for the Euro area. Since the monthly inflation series is very volatile, also included is the annual average inflation rate. Annual average inflation is presented as the bold solid line in Figure 2.2

part A, calculated as the centred moving average; $\pi_t = (\Sigma_{i=-6}^{6}\pi_{t-i})/13$. The vertical line in the panel represents the collapse of the Exchange Rate Mechanism. Using the data in Figure 2.2 part A, it is possible to illustrate the Phillips curve, highlighting the case made by RBC theorists against a central Keynesian proposition, the trade-off between inflation and unemployment. Figures 2.2 part B - 2.2 part D illustrate the relationship between different measures of unemployment and inflation for the Euro area. Figure 2.2 part B is a scatterplot of the unemployment rate and the inflation rate, plotted for two different subperiods 1980-1992 and 1993-2005. There appears to be a strong relationship between the two series in the first subperiod (circles, with a correlation of -0.74), but this relationships appears to break down, with the second subperiod (triangles, correlation -0.18) showing no discernible relationship. A scatter plot of the cyclical components of unemployment and inflation using the bandpass filter, eliminating the long-run (zero frequency) movements in these series, is shown Figure 2.2 part C. This figure provides conclusions that differ starkly from those from Figure 2.2 part B. In contrast with Figure 2.2 part B - in which the correlations imply that inflation and unemployment over long horizons, i.e. using the levels of inflation and unemployment, are stronger in the first rather than second subsample - under business cycle frequencies the reverse is true, with a correlation of -0.13 and -0.38 respectively. Finally, Figure 2.2 part D is a scatterplot of the annual change in the annual inflation rate over the next year; $100 \times [\ln(CPI_{t+4}/CPI_t) - \ln(CPI_t/CPI_{t-4})]$. This is plotted against the current level of unemployment. Similar to Figure 2.2 part C, and in contrast to Figure 2.2 part B, the plot illustrates a stronger relationship between inflation and unemployment in the second period than the first. The second period inflation- unemployment relationship in Figure 2.2 part D is stronger than in Figure 2.2 part C.

Figure 2.2. Phillips Curve Analysis



It must be noted, however, that these scatterplots fail to account for possible lengthy dynamic adjustment of prices and unemployment to macroeconomic shocks. In addition, the scatterplots show that this relationship is not stable in the second subsample. The marginal R^2 from adding four lags of unemployment to a regression predicting inflation over the next k quarters using four quarterly lags of inflation is 0.08 for predicting inflation $k = 1$ quarter ahead, 0.13 for two quarters ahead, 0.18 for four quarters ahead, and 0.24 for eight quarters ahead. It would appear that these regressions are stable; the QLR statistic for the one-step ahead forecasting regression has a p-value of 40 percent.[4] The apparent relative stability of the scatterplot in Figure 2.2 has led some to treat the non-accelerating inflation rate of unemployment (NAIRU), as an empirical expression of Friedman's (1968) notion of a natural rate of unemployment (or output). Accordingly, this version of the Phillips curve has come to provide a guidepost for monetary policy; if unemployment persists too long below NAIRU, inflation is predicted to increase.

A controversial aspect of RBC models is the role of technology shocks in generating recessions. Typically a recession is defined as a significant decline in economic activity spread across the economy, normally visible in real GDP, employment, industrial production and wholesale retail sales. The distribution shows that, in absolute terms, output fell in around 30 percent of the quarters between 1980 and 2005.

RBC theory describes economic fluctuations as a changing Walrasian equilibrium, implicitly implying that all fluctuations are efficient. Attempts by government policy to alter the allocations of the private markets, such as policies to stabilise employment, at best are ineffective and at worst can do harm by impeding the 'invisible hand'. This is because, given consumer preferences and the production possibility frontier, determined by the technology possibilities facing an economy, the levels of employment, output and consumption cannot be improved upon. However, this particular strand of RBC thinking has been heavily criticised, since it implies that recession/slowdown is an optimal condition, consequentially implying that there are no welfare reducing effects from a recession/slowdown.

[4] The QLR statistic is computed as follows. First a break date is posited, τ. The likelihood ratio statistic, $F(\tau)$, testing the null hypothesis of constant regression coefficients, against the alternative hypothesis that the regression coefficients changed at the break date τ, is computed by comparing the value of the Gaussian likelihood of the full sample regression to the two relevant subsample regressions. The QLR statistic is $\max_{k_0 \leq \tau \leq T-k_0} F_\tau$, where k_0 is a trimming value, taken to be 15 percent of the sample size. Although this test was originally developed to detect a single break, it also has good power against alternatives with multiple breaks and slowly evolving coefficients.

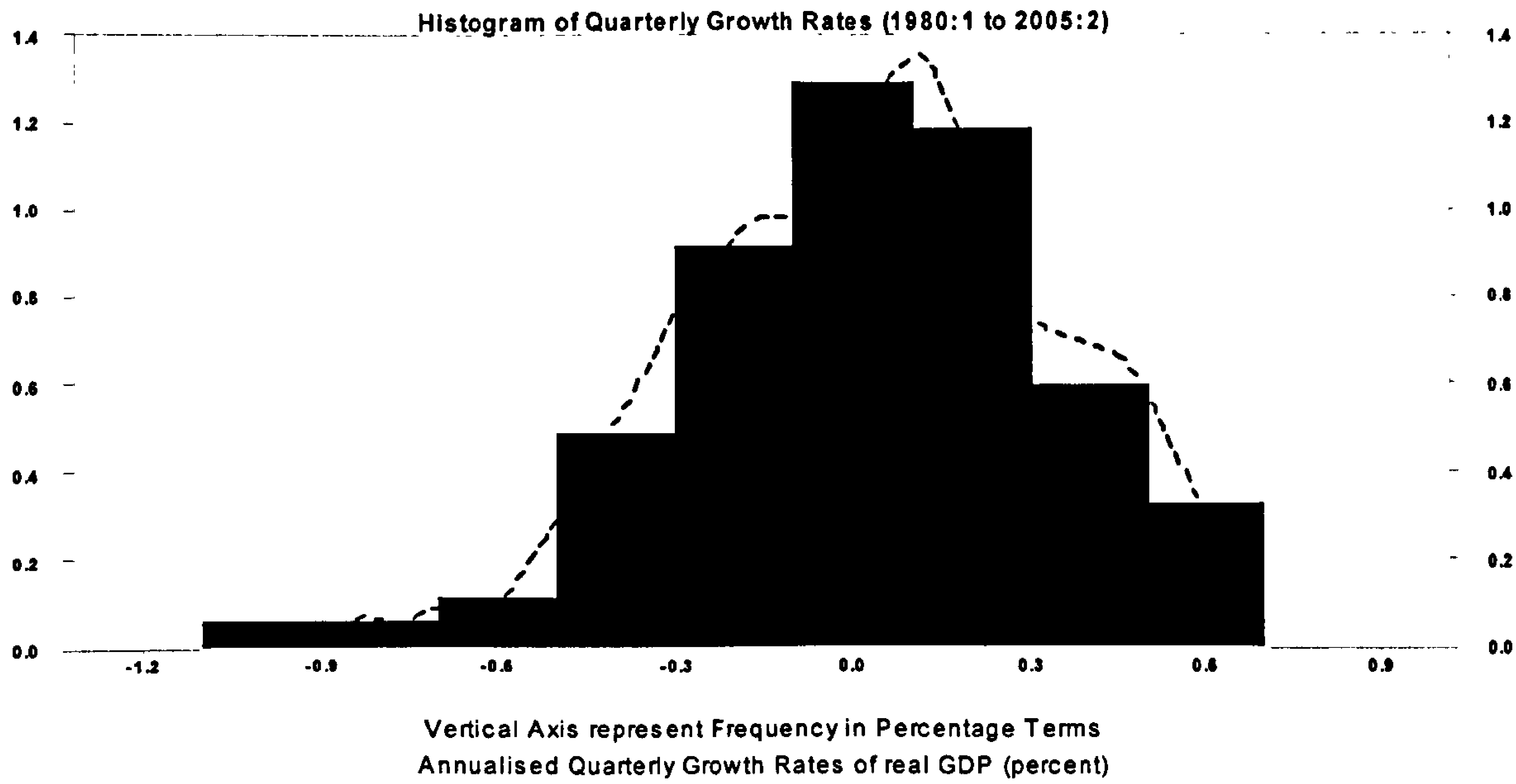


Figure 2.3

However, it would appear undeniable that the level of welfare is lower in a recession than in the boom that preceded it. Traditional Keynesian theory explains the reduction in welfare by a failure in economic coordination; because wages and prices do not adjust instantaneously to equate supply and demand in all markets, some gains from trade go unrealised. In contrast, RBC theory allows no unrealised gains from trade, since the reason welfare is lower in a recession is that the technological capability of society has declined.

Central Role of Technological Disturbances

Adelman and Adelman (1959) were the first to treat residuals as random shocks. In this case the residuals were acquired from the Klein and Goldberger (1952) model of the US economy. Adelman and Adelman (1959) found that the behaviour of macroeconomic variables, treating the residuals as random shocks, resembled actual US business cycles. This explicitly implied that residuals were prime sources of cyclical volatility. Using this hypothesis in the theory of economic growth, positive Solow residuals are seen as a major cause of economic growth. Consequently, most RBC models require a decline in the Solow residual[5] in order to replicate the declines in output observed

[5] The Solow residuals is sometimes referred to as total factor productivity (TFP), as the residual measures the deviation of labour productivity from its model predicted value.

in the data, in effect implying that there are large and sudden changes in the production function. For example, when the Solow residual rises above its trend path, indicating better than average growth in the economy's technological capability, firms are motivated to invest in new plant and equipment at a faster than average rate. To meet the increased demand for investment goods, businesses hire more than the average number of workers. Above average employment growth leads, in turn, to faster than average growth in consumer spending. Thus, a rise in the Solow residual above its trend path makes investment, employment, and consumer spending rise above their respective trend path as well. This comovement of key macroeconomic variables is a central feature of business cycles, as first spelt out by Burns and Mitchell (1946).

Despite the logic of the Solow residual, the notion that recessions are caused by TFP declines usually meets with substantial scepticism since, interpreted literally, implies that recessions are times of technological regress. An example that could be used to pour scorn on the hypothesis of technological regress comes from unfolding the events of the Great Depression of the 1930s. Despite it being the worst slump of the last 100 years, Field (2003) showed that the period of the Great Depression was the most technologically progressive decade of the century, despite the large contraction in output across the industrialised economies. Similar results, using long-run restrictions in a VAR framework, were found by Francis and Ramey (2004). In addition, the idea that fluctuations in economic activity are caused by supply-side shocks has received mixed empirical support. Cochrane (1994a) started from an unstructured position, employing a sequence of progressively more tightly specified VARs to indicate what kinds of shocks cause business cycles. He concluded that technology shocks were not an important source of variation in output. This is less ideological than it seems, as Cochrane (1994a) concluded that no single class of exogenous shock - from either demand or supply - was the main source of business cycles. Galí (1999, 2004) has further fueled the debate on the importance of technology shocks as a business cycle impulse, using a structural VAR which is identified by assuming that technology shocks are the only source of long-run changes in labour productivity. Galí (1999) uncovers a negative response of employment to a positive technology shock in all G7 countries, with the exception of Japan. Galí (1999) also points out some differences in those estimates relative to those obtained for the US; in particular, the negative employment response to a positive technology shock in Germany, the UK and Italy, which also appears to be larger and more persistent than the results for the US. This final result from Galí (1999) could be interpreted as evidence of 'hysteresis' in European labour markets. Very similar qualitative results for the Euro area as a whole were found in Galí (2004), which applied the same empirical framework as Galí (1999). In particular, technology shocks are found to account for only five and nine percent of the variance of the business cycle component of Euro area employment and output respectively, with the corresponding correlation between their technology driven components being -0.67. Indeed, more recent work by Galí and Rabanal (2004) finds the bulk of the evidence raises serious doubts about the importance of changes in aggregate technology as a significant (or, even more, a dominant) force behind business cycles. Instead, it points to demand factors as the main force behind the strong positive comovement of output and labour input measures that is the hallmark of the business cycle. In addition, Burnside *et al.* (1996) construct a time series for technological change, and apply it to Swedish two-digit manufacturing industries. They find that positive shocks to technology have a non-expansionary effect on output. Similarly, Francis *et al.* (2003), using long-term UK time series data that tracks back to the nineteenth century, find that technology shocks play little role in the UK. The implications of this evidence suggests that a key finding of the standard RBC paradigm is rejected, namely, the positive comovement of output in response to technology shocks. That positive comovement is the single main feature of RBC models, and accounts for their ability to generate fluctuations that resemble business cycles. Galí (1999) argues that standard RBC models shed little light on whatever small role technology shocks play because they imply that hours worked rise after a positive technology shock. Recent work by Hamilton (2005a) also casts some doubt on the claim that the business cycle is 'real'. Hamilton (2005a) finds that, over the course of the business cycle, forces that cause fluctuations to rise may be quite different from those that cause than to fall, implying that not all fluctuations are due to technological disturbances but perhaps to a combination of demand and supply shocks.

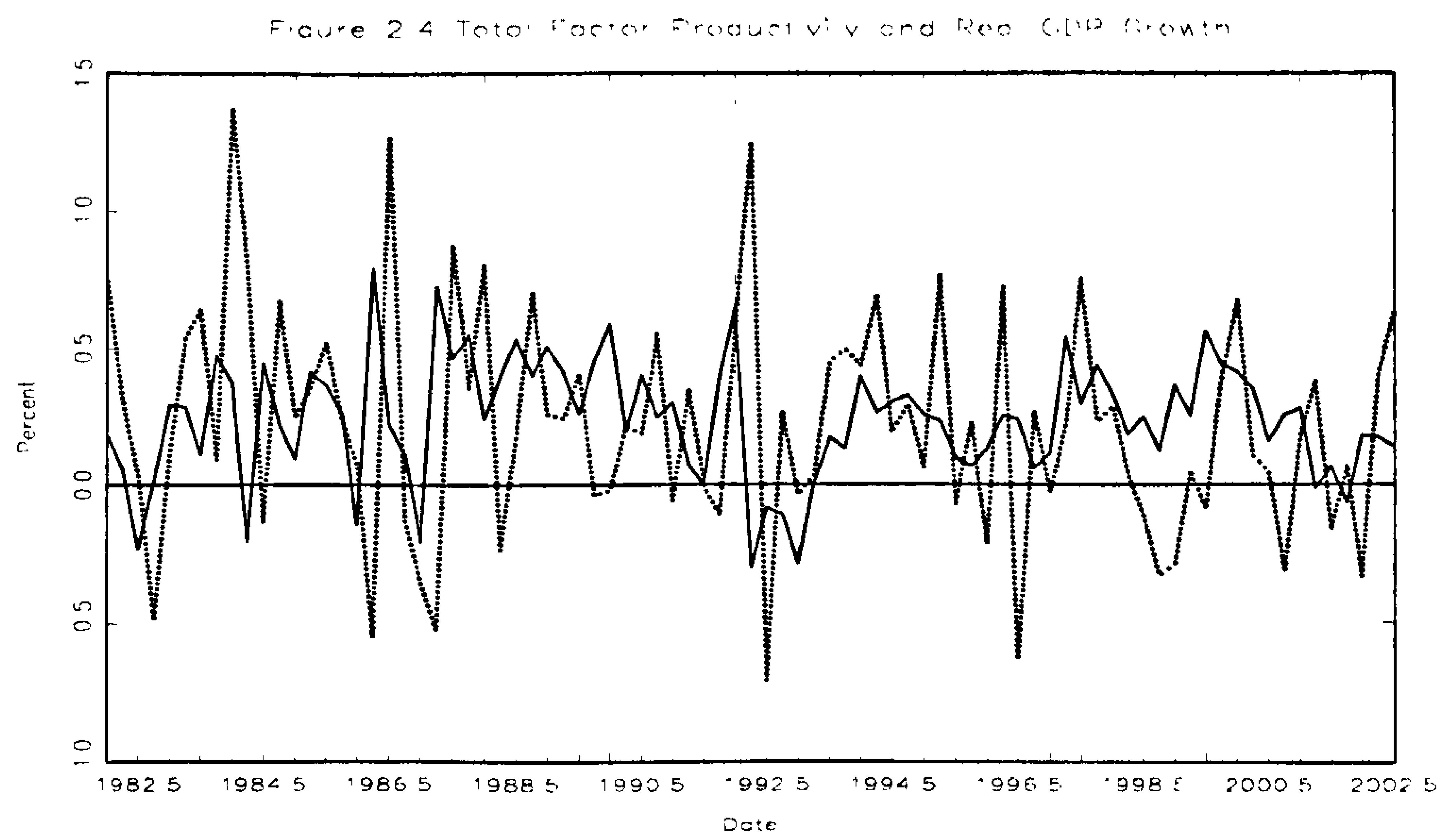
Figure 2.4 plots TFP, which was calculated in a fashion similar to that of Prescott (1986) - as the percent change in output less the percentage change in inputs, where the inputs are weighted by their factor share of 0.6 and 0.4 for labour and capital respectively (the factor shares are based on calculations from Musso and Westermann, 2005) - show that movements in real output do, in general, follow general trends in TFP. Early RBC models computed TFP and treated it as a measure of exogenous technology shocks. However, there are reasons to distrust TFP as a measure of true technology shocks. The evidence suggests that TFP is not a pure exogenous shock, but contains some endogenous components. Variable capital utilisation, considered by Basu (1996) and Burnside *et al.* (1996), variability in labour efforts, explored by Burnside *et al.* (1993), and changes in the markup rates, considered by Jaimovich (2004), drive important wedges between TFP and true technology shocks. These wedges imply that the magnitude of true technology shocks is likely to be much smaller than that of TFP shocks.

Like the original results presented by Prescott (1986) for the US economy, as well as Shapiro (1987), plots of TFP for the Euro area show that measured productivity is strongly procyclical. In practically every year in which output fell, TFP also fell. The strict RBC interpretation would hold that some factor caused a decline in the productive capacity of the economy and led to a downturn. In some cases, such an interpretation seems plausible; the energy crisis of 1973/74 would be one example. In spite of some isolated incidents, most macroeconomists find declines in the Solow residual during downturns puzzling. If the Solow residual is a valid measure of the change in the available production technology, then recessions are periods of technological regress.

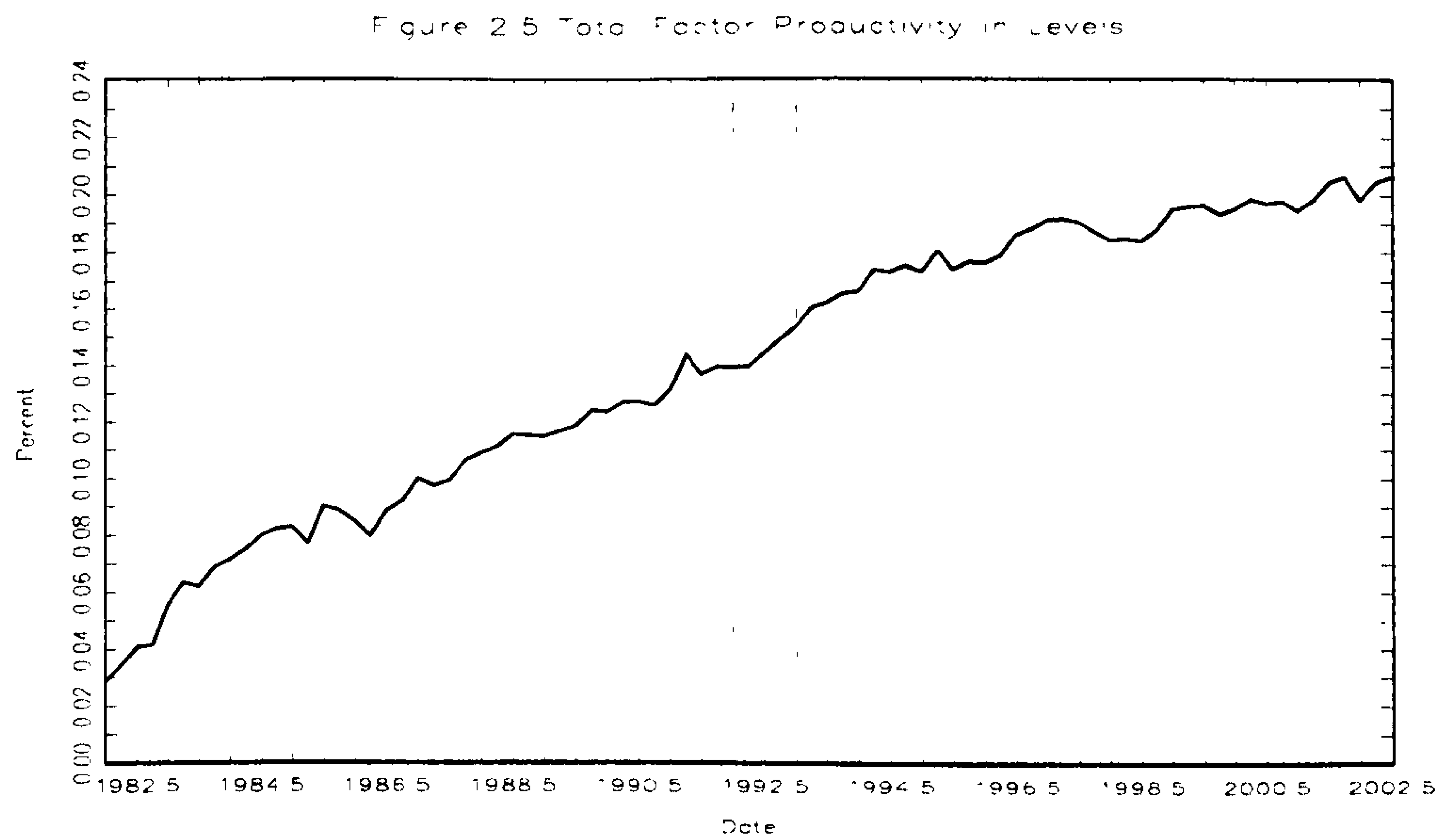
Hall (1987) offers an alternative explanation for the strongly procyclical TFP measure in Figure 2.4. The Solow residual could reflect endogenous changes in technology due to demand shocks. Such endogeneity may arise if, for example, learning-by-doing is important. Hall (1987) offers a second interpretation, which relies upon a traditional Keynesian interpretation of economic fluctuations. If a demand shock can lead to an increase in output with little increase in input, then marginal cost must be low. Competitive firms with the ability to increase output with little increase in inputs would cut prices. Demand would increase and hence attenuate the procyclicality of measured productivity. Hence, Hall (1987) interprets the procyclicality of productivity as evidence that firms behave monopolistically and that they have consistent excess capacity; in other words, firms hoard labour: such behaviour also provides part of the theoretical underpinnings of Okun's Law. As such Hall's (1987) suggestion asserts that there is a considerable demand component in the Solow residual, allowing it to accentuate the strong procyclicality demonstrated in Figure 2.4. Perhaps a more appealing interpretation is that the Solow residual is not a good measure of changes in the economy's technological abilities over short horizons. Basu (1996) argues that the Solow residual was only intended to estimate the long-run impact of technology on the economy, not the cyclical impact. In partial agreement, Christiano *et al.* (2003) find that permanent technology shocks play a very small role in business cycle fluctuations. However, they are quantitatively important at frequencies that hypotheses from traditional growth models might anticipate.

The importance of understanding the empirical, as well as theoretical, support for RBC theory is due to the considerable policy differences between Keynesian and Monetarist, models on the one hand, and RBC theory on the other. Mankiw (1989) notes that RBC theory is potentially dangerous, due to its perceived trivialisation of the social cost of observed business cycle fluctuations. The danger is that those who advise policymakers might attempt to use the theory to evaluate the effect of alternative macroeconomic policies or to conclude that macroeconomic policies are unnecessary. Much of the controversy surrounding RBC models stems from the belief of RBC models to interpret declines in economic activity, as due to technological regress. A second, potentially large flaw, in standard RBC frameworks that use stochastic growth remains their inability to forecast future output. Consequently, drawing policy implications from such models becomes difficult. Technology shocks are often assumed to have a permanent effect, with little, if any, mean reversion. Cochrane (1994a) has noted that the concept of technology shocks has more of less disappeared. Its interpretation is now very broad, standing essentially for any distortion that causes a measured Solow residual. With this interpretation, it is perhaps inappropriate to state that technology shocks cause output fluctuations. Therefore, the cyclical movements in TFP witnessed for the Euro area need not be interpreted as evidence of exogenous technological disturbances. The standard explanations of cyclical productivity may apply, such as reflecting labour hoarding and other 'off the production function' behaviour. Productivity may fall in a recession because firms keep unnecessary and underutilised labour. In a boom the hoarded labourers begin to put out greater efforts, i.e., output increases without a large increase in measured labour input. With all these arguments stacked up against the Solow residual, a better interpretation may be that the Solow residual indicates not the amount that can be explained by technology, but the amount of what any specific model does not observe.

Hansen and Prescott (1993) offer an unorthodox explanation for what the Solow residual actually captures. They argue that, since every nation has regulations that govern business, which can alter the incentives to adopt more advanced technology as well as the resources to operate existing machinery, mechanisms that divert businesses from improving technology to rent-seeking activities, in addition to changing the regulatory system often induce negative as well as positive changes in technology. This implies that technology shocks are changes in the inefficiencies induced by policy. They liken technology shocks to small perturbations in all factors that alter the relative competitiveness between nations. Vijselaar and Albers (2002) have found partial support for the role of technology in driving output fluctuations.



Note: Solid Line is real GDP growth, with the dashed line representing TFP.



On the basis of available data for the Euro area, evidence is found that there has been an increased contribution of information and communication technologies to economic activity. Furthermore, work by Peersman and Straub (2004) using Euro area aggregated data and a Bayesian VAR sign restriction procedure, which allows an alternative identification strategy to that used by Galì (1999, 2004), has found that technology shocks play an important role in driving output fluctuations in the Euro area. Similarly, Peersman (2005) found that supply-side shocks played a central role in the early millennium slowdown in the Euro area. Similarly, Temin (1998) has shown that over the period 1890 - 1990 for the US economy, business cycles have been instigated more by real, rather than monetary, innovations, particularly over the past 40 years. In earlier work, Shapiro (1987) has shown that the Solow residual strongly covaries with a function of factor prices, which suggests the Solow residual is a useful measure of technology shocks that impact upon the US economy.

Although unifying growth and business cycle theory holds tremendous aesthetic appeal, since it will simplify the issues raised in Chapter 1, this particular solution is not without its detractors. Indeed, the reasons that Fisher (1932) gave in rejecting such an approach have, in the opinion of many yet to receive a satisfying response from modern RBC theorists, '*In times of depression, is the soil less fertile? Not at all. Does it lack rain? Not at all. Are the mines exhausted? No, they can perhaps pour out even more than the old volume of ore, if anyone will buy. Are the factories, then, lamed in some way - down at the heel? No; machinery and invention may be at the very peak*' (Fisher, 1932, p. 5).

2.2.3 Alternatives to Technology Shocks

The debate on the role of technology and monetary shocks in business cycle fluctuations has influenced and inspired research on models in which technology shocks are either less important or play no role at all. The two most prominent types of shock, beyond the usual demand, monetary and technology shocks, are oil price shocks and shocks emanating from international business cycle linkages.

Oil Shocks

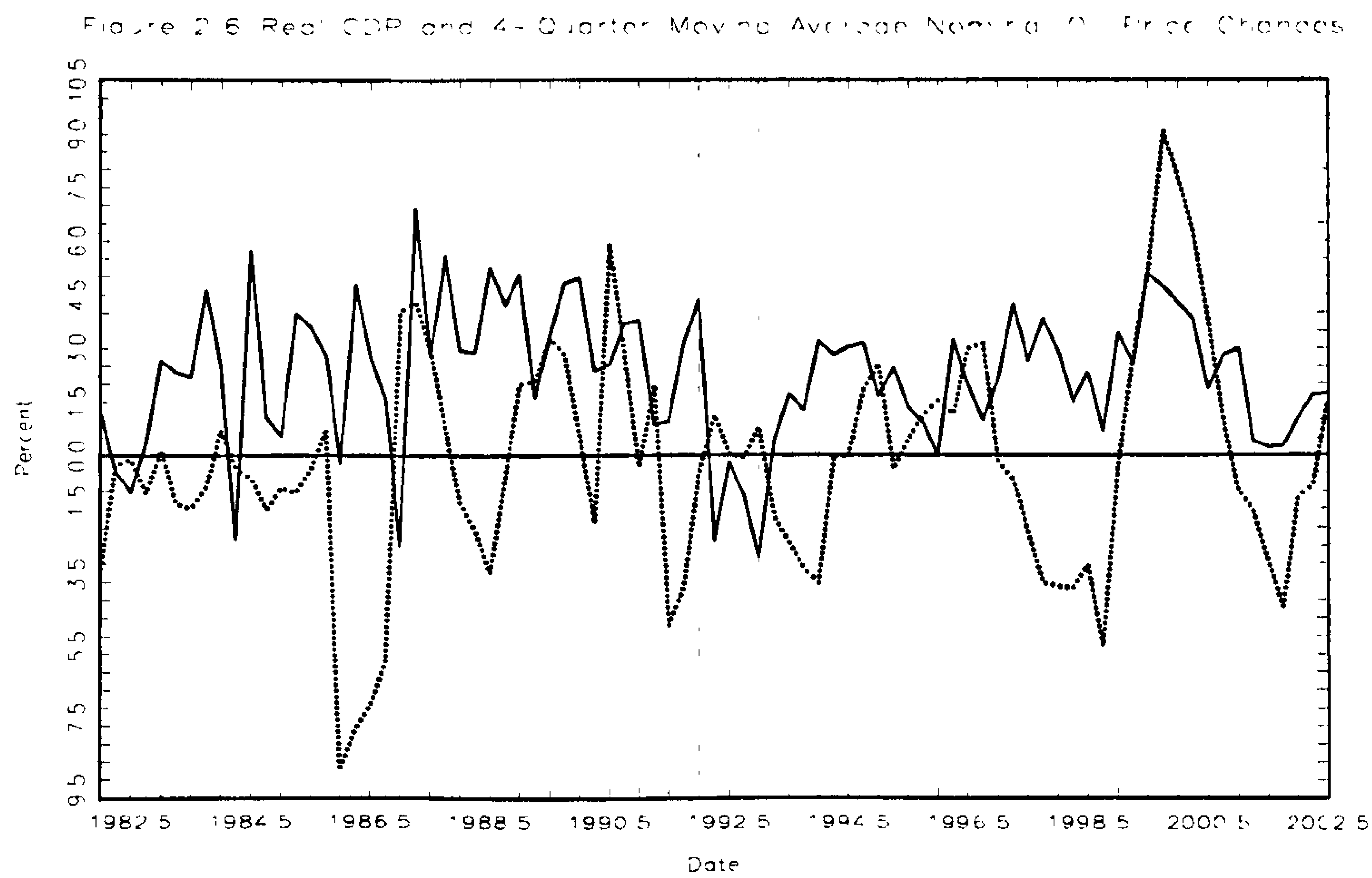
Movements in oil and energy prices are loosely associated with slowdowns and recessions in the industrialised world. Nine out of ten of the US recessions since World War II were preceded by a spike up in oil prices (Hamilton, 2005b). One way to inquire whether this might be just a coincidence is with a statistical regression of real GDP growth rates (quoted at a quarterly rate) on lagged changes in GDP growth rates and lagged logarithmic changes in nominal oil prices. The results from an OLS estimation of this relation for t = 1980:2 to 2005:4 are as follows (standard errors in parentheses);

$$\begin{aligned} y_t = \; & \underset{(0.087)}{0.253} + \underset{(0.104)}{0.190} y_{t-1} - \underset{(0.105)}{0.086} y_{t-2} + \underset{(0.105)}{0.125} y_{t-3} - \underset{(0.102)}{0.120} y_{t-4} \\ & - \underset{(0.287)}{0.212} o_{t-1} + \underset{(0.288)}{0.043} o_{t-2} - \underset{(0.286)}{0.333} o_{t-3} + \underset{(0.288)}{0.202} o_{t-4} \end{aligned}$$

The coefficient on the fourth lag of oil prices (o_{t-4}) is positive and statistically insignificant (t-statistic = 0.70), and an F-test leads to a non-rejection of the null hypothesis that the coefficients on lagged oil prices are all zero with a p-value of 0.67. The results suggest a weak relationship between nominal oil prices and real GDP for the Euro area. In contrast, Hamilton (1983, 2005b) found particularly strong evidence for the US economy.

Figure 2.6 plots movements in real GDP along with a moving-average oil price measure. A moving-average oil price is used to reduce the noise present in any first differenced oil price series. From simple eyeballing, nominal oil prices appear to be procyclical. Investigations by Rache and Tatom (1977, 1981), Hamilton (1983), Burbridge and Harrison (1984), Santini (1985, 1994), Gisser and Goodwin (1986), Rotemberg and Woodford (1996), Daniel (1997), Raymond and Rich (1997), Carruth *et al.* (1998) and Hamilton (2003) have all rejected the hypothesis that the relationship between oil prices and real output is just statistical coincidence. Hamilton (1983) showed that increases in the nominal price of oil Granger-causes downturns in economic activity.

Economic theory infers that it would be the real oil price rather than the nominal price that should matter for economic decisions. However, it probably does not make much difference in summarising the size of any given shock whether one uses the nominal price or the real price of oil, since in most of these shocks the move in nominal prices is an order of magnitude larger than the changes in overall prices during that quarter. As noted by Hamilton (1983, 1985, 2005b), the nominal price normally stays frozen for years then suddenly adjusts. The procyclical nature of oil prices and output may be a result of the common dependence on some third factor, or factors, that are the true cause of both the increase in oil prices as well as the subsequent recession. For example, something about the last stages of an economic expansion often produces a surge in oil prices. Hamilton (1996) has argued that the correct measure of oil shocks depends very much upon the precise mechanisms by which changes in the price of oil are supposed to affect the economy. Possibilities include aggregate supply effects operating through costs of production and the indirect effects of wage rigidity, aggregate demand effects arising from the interaction of uncertainty of future energy prices and the irreversibility of investment, and asymmetric sectoral impacts that force costly reallocations of resources.



Note: Oil Prices are represented as the dashed line.

Another possible way in which oil prices might affect the economy could be the role oil prices play in monetary policy. Barsky and Kilian (2002, 2004) have argued that, for the US economy, a monetary expansion was the cause of much of the 1973-74 oil price increase, and that the monetary expansion also led to the subsequent decline in output. Bernanke *et al.* (1997) compared historical and alternative hypothesised responses of monetary policy to economic disturbances. In their model monetary policy responds to oil price shocks. In other words, the Federal Reserve responds to an oil price shock by raising interest rates in order to control inflation, with the monetary contraction itself the principal cause of the downturn. Work by Kim and Loungani (1992), Rotemberg and Woodford (1996) and Finn (2000) studied the effects of energy prices in RBC models. These shocks improve the performance of RBC models, but they find that oil price changes are not the major cause of output fluctuations. It could be the case that, although energy prices are highly volatile, energy costs are too small as a fraction of value added for changes in energy prices to have a major impact on economic activity.

International Output

Business cycles exhibit a great deal of regularity across countries. As discussed in Chapter 1, studies of closed economies suggest that a stochastic growth model with a single aggregate technology shock can account for, among other things, the magnitude of fluctuations relative to output in consumption and investment, and the correlation of these fluctuations with output. In the analogous world economy, countries experience imperfectly correlated shocks to their technologies, as well as other shocks such as monetary ones. The interaction between these shocks and the ability to borrow and lend internationally can, in principle, have a substantial influence on the magnitude and character of aggregate fluctuations. In open economies, a country's consumption and investment decisions are no longer constrained by its own production. With respect to technology, it is possible that capital be allocated to the country with the more favourable technology shock and this generates greater variability in domestic investment. Perhaps the distinguishing feature of an open economy is that it can borrow and lend in international markets by running trade surpluses and deficits. The trade balance, which measures the difference between domestic production and absorption, can vary systematically over the cycle. The cyclical properties are determined by the balance of two forces; the desire and ability of agents to smooth consumption using international capital markets and the additional cyclical variability of investment that international capital flows permit. These phenomena are reflected in the correlation between saving and investment rates, as demonstrated by Dooley *et al.* (1987) and Tesar (1991). Backus *et al.* (1992) argues, theoretically, that with an open-economy perspective, consumption should be highly correlated across countries. This has been shown by King and Plosser (1989), Kydland and Prescott (1990) and Backus and Kehoe (1992) to hold across countries. With complete markets, the ability to share risk internationally should produce a large correlation of consumption across economies. Since, in most industrialised economies, consumption contributes the largest share of economic activity, it is reasonable to assume that business cycles across economies should also be fairly highly correlated. As such, shocks that impinge upon one economy are more likely to diffuse to other economies if they are closely correlated, perpetuating the idea that it is possible that a significant proportion of the shocks that drive output fluctuations in the Euro area originate from abroad.

In view of the fact that the economies of various countries are increasingly closely integrated through trade in goods and services, financial markets and technology diffusion, the literature is increasingly moving to forecasting domestic business cycles with variables from foreign economies. Sensier *et al.* (2004), for example, forecast turning points in Germany, France, Italy and the UK by using a range of leading indicators from all four countries. A similar approach, using a Markov switching framework, was undertaken by Artis and Zhang (1999). These studies have found that using variables from another economy can, in some cases, improve the performance of forecasting models. Indeed, the saying 'When the United States sneezes, the world economy gets a cold' is symptomatic of the prevalent view that disturbances in foreign economies may directly, or indirectly, impact upon the domestic economy. Work by Bergman *et al.* (1998) found that cyclical patterns in the industrialised economies are stable across time, regime and countries. They conclude that the business cycle is always and everywhere apparent in a broad sense and could forecast no foreseeable factor that might prevent this from being so. Backus *et al.* (1992), by allowing for technology diffusion between economies, found that openness substantially alters the nature of some of the closed-economy comovements, highlighting that in open economies additional sources of shocks may be more important than is the case in closed economies. Evidence from Stock and Watson (2005a), using a factor structural VAR with two common factors, has shown the importance of international business cycles on the domestic cycles of the G7 economies. In addition, recent work by Doyle and Faust (2005) found the relative stability experienced by the industrialised economies may be due to shifts in international growth. Similar results were uncovered by Backus and Kehoe (1992). Work by Temin (2003), studying the monetary history of the US economy, made a distinct separation between domestic shocks and shocks that originate from abroad, using the open economy Mundell-Fleming IS-LM framework. As Temin (1998) notes, the shock of the Great Depression of the 1930s needs to be put into context. This context revolves around the international arena; mainly the strains on the international economy that derived from the first world war. Temin (1998) found that during the period 1890 - 1990, five cycles in the US economy were due to foreign monetary policy shocks. In addition, 26 months of production were lost to foreign monetary shocks. The analogous results for domestic US monetary policy were 5.5 and 18.5 respectively, highlighting the importance of shocks from abroad. Furthermore, Cooper (1988) finds that the recessions of the US were accompanied by recessions elsewhere in the world. Cooper (1988) notes, however, that the greater coherence may be attributed to the importance of the oil price shocks in these recessions.

Increasing trade and financial integration have made it possible for economies that are a long distance apart to be affected by one another through 'contagion', as well as through the dissemination of information from advancements in information technology, suggesting the need to consider global factors when studying business cycles. This is undertaken in Chapter 5.

2.3 Summary

The perfect markets of economic theory do not exist in the real world and, hence, diminish the credibility of RBC theory. The economic outcomes against which the predictions of RBC theory are compared have resulted from an interplay of imperfect markets and a vast array of laws, regulations, policies, and customs that help or hinder the workings of these markets. Lucas (1994) attempted to provide a reconciliation between monetarist and RBC theories of the business cycle. Whilst accepting that RBC theory's central finding that TFP shocks can lead to output variability, Lucas (1994) reconciles this finding with the lessons of monetarist theories of the business cycle, noting that it is possible to think of RBC theory as providing a good approximation to events when monetary policy is conducted well, and a bad approximation when it is not. Controversially, Lucas (1994) argued that, viewed in this way, the RBC theory's relative success in accounting for the postwar experience can be interpreted simply as evidence that postwar monetary policy has resulted in near-efficient behaviour, not as evidence that money does not matter, as claimed by proponents of RBC theory. This implicitly implies that, since RBC theory claims no role for monetary or financial influences on the cycle, monetary policy must be better than in the prewar period studied by Friedman and Schwartz (1963). In essence, postwar economies mimic a perfect market economy, in part, because postwar monetary policy and other countercyclical policies allowed the economy to attain its near optimal business cycle behaviour. This view is plausible, but finds little empirical support. As described in Stock and Watson (2002a, 2003a), Basistha and Startz (2004) and Ahmed *et al.* (2004), although business cycles have moderated in the US, very little of this moderation is down to improved monetary policy. Consequently, instead of guiding the US economy towards optimal behaviour, such policies may have resulted in a discrepancy between actual and optimal behaviour.

It is probably true that fluctuations arise from a mixture of shocks, as demonstrated by Cochrane (1994a) and Shapiro and Watson (1987). The role of economic models should therefore aim to disentangle these shocks. Indeed, the general consensus now is that policymakers in a world continually subject to business cycles should adopt certain goals to improve their ability to deal with fluctuations. Policymakers need to learn how to recognise and address the economy's vulnerability to disruption and unanticipated events. Finally, and more importantly, policymakers should understand that they cannot prevent every downturn, but they should concentrate their efforts on averting the 'big ones', like the ERM crisis.

The discussion in this chapter has attempted to highlight the problems of estimating and interpreting various shocks, which have important implications for the work presented in subsequent chapters. Chapters 3, 4 and 5 use these various shock based theories in an attempt to highlight and explain key business cycle episodes that have characterised economic fluctuations in the Euro area over the last two and a half decades. As such, setting out beforehand the difficulties faced with estimation and interpretation of these various shock innovations may help bring some balance to the results presented in subsequent chapters. The exploration of whether monetary or technology shocks are primarily responsible for fluctuations in real output for the Euro area is examined in the following Chapter 3. The results from this analysis have important implications. If productivity shocks are found to be an important driver of real output fluctuations in the Euro area, does it then follow that productivity shocks have been a source for the dampening of business cycle fluctuations in the Euro area, assuming, of course, that the cycle has moderated as suggested by the literature.

Part II

An Extrinsic Examination of the Causes of Euro area Output Fluctuations

Chapter 3

Great Ratios, Balanced Growth and Stochastic Trends: Evidence for the Euro Area[1]

3.1 Introduction

The prevalent view in both the empirical and theoretical literature remains that macroeconomic fluctuations arise from shocks to fundamental variables such as economic policy, preferences and technology. These shocks are then propagated through the economy and result in systematic patterns of persistence and comovements among macroeconomic aggregates, which make it possible to examine linkages between growth related shocks and transient fluctuations by incorporating stochastic rather than deterministic trends. This line of literature is followed by investigating the stochastic trend properties of postwar Euro area macroeconomic data to evaluate the empirical relevance of standard RBC models with permanent productivity shocks. This is achieved by presenting evidence on the 'traditional' great ratio balanced growth hypothesis in the determination of Euro area macroeconomic fluctuations by using a long-run restriction to examine whether, as claimed by RBC theory, a common stochastic trend underlies the bulk of economic fluctuations for the Euro area - an assumption satisfied by a large class of standard business cycle models - or whether other forces, namely the monetary and price level shocks stressed in traditional macroeconomic analysis, have been important over historical business cycles.

As with all RBC analysis, this research solicits the question, 'What role does economic growth play in the study of economic fluctuations?'. Proponents of RBC theory claim a central role for exogenous variations in technology as a source of economic fluctuations in industrialised economies,

[1]This chapter was presented at the All China Economics Conference, City University of Hong Kong, in 2006.

implying that permanent shifts in productivity will induce long-run equiproportionate shifts in the paths of output, consumption and investment. Does it matter whether the time path of the Euro area economy is characterised by balanced growth? Yes. Observed empirical regularities are important for developing an understanding of how the economy works, and a breakdown in one of these empirical regularities might be viewed as a setback. Such an analysis of the Euro area economy as a whole would be useful for the design of Euro-wide policies.[2]

The traditional approach to analysing macroeconomic fluctuations viewed secular growth as a deterministic process and has focused upon fluctuations around the trend as the 'business cycle'. However, following Beveridge and Nelson (1981), the trend component of many time-series can be characterised as a random walk with drift, i.e., a stochastic process. This allows the balanced growth hypothesis to imply that log consumption (c) and log investment (i) are cointegrated with log output (y), so that there is a common stochastic trend. If technology grows at a constant rate, then the model's solution is that y, c and i grow at the same average rate in the long-run. Thus the ratios of any of the real aggregates will be stationary stochastic processes.[3] The stationarity of the great ratios has been a stylised fact of macroeconomics as far back as the well-known contributions by Kaldor (1957) and Kosobud and Klein (1961).[4] However, studies have shown evidence for the balanced growth hypothesis is far from uniform. Rejection of stationary great ratios, as in Serletis (1994, 1996), has been used as evidence against the use of exogenous growth models in the study of real output fluctuations. Very little, if any, analysis of this important stylised fact has been undertaken for the Euro area.

By adopting the idea of Frisch (1933) and Slutzky (1937) - that business cycles may be seen as the result of an interplay between a set of stochastic impulses and certain propagation mechanisms - utilising a common trends model will allow the joint study of exogenous growth innovations and business cycle phenomena by tracing out the cyclical behaviour of output, consumption and investment to a permanent productivity innovation. This chapter also makes a number of contributions to the existing literature. Firstly, the use of a common trends model attempting to interlink exogenous productivity innovations and real output fluctuations has only been detailed for the US

[2] The introduction of a common currency has increased the interest and need for business cycle analysis at the level of the Euro zone.

[3] Furthermore, given diminishing marginal returns to capital accumulation, a temporary rise in savings will only allow capital to grow faster than output for a temporary period. Hence, the ratios involving any of the variables capital, investment, consumption and output must be stationary.

[4] Cochrane (1994) and Rotemberg and Woodford (1996) both relied on stationary ratios of consumption to output in an econometric estimate of the transitory cyclical components of consumption, investment and output. Furthermore, endogenous growth models, such as those from Romer (1986), also imply stationary great ratios.

economy (and more recently the UK).[5] By concentrating on the Euro area, the analysis in this chapter provides a useful robustness check for evaluating a wide class of RBC models using common trend restrictions. Since the properties of the Euro area as a single economy are less well known than those of the individual countries making up the Euro area, the model will help determine how applicable neoclassical growth assumptions are to the study of real output fluctuations for the Euro area, particularly when the results are compared to Galí (2004), who also investigated the role of exogenous technology shocks on real GDP for the Euro area using more standard VAR techniques. The model is then utilised to analyse the historical explanatory power of exogenous productivity shocks in explaining specific business cycle episodes for the Euro area. Finally, using the assumptions of the great ratios, this chapter attempts to measure trend output for the Euro area to gauge whether sensible trend output estimates can be derived using the assumptions of a standard neoclassical growth model.[6]

Several findings of this chapter are consistent with the predictions of RBC models and much of the received wisdom that has been previously outlined in the literature. First, output, consumption and investment appear to share a common stochastic trend and, second, real permanent shocks do play some role as a driver of output fluctuations. The chapter is structured as follows. The basic model is outlined with a brief discussion of the theory in the second section, with the econometric methodology discussed in the third section. The fourth section demonstrates Euro area data to produce results that are broadly supportive of the balanced growth hypothesis, with the dynamic responses of y, c and i due to the balanced growth innovations being discussed in section 5, including the extension of the model to include nominal variables, namely money balances and inflation. The results are summarised in the last section.

3.2 Great Ratios, Growth and Fluctuations

Interest in growth theory and the associated 'great ratios' of macroeconomics has undergone a considerable resurgence since the 1990s, as the implications of the neoclassical stochastic growth model under uncertainty have been married with those emanating from the econometric literature, such as in King *et al.* (1991), Neusser (1991) and Mills (2001). Ever since Koopmans (1947)

[5] Mellander *et al.* (1992) estimate a common trends model for a small open economy. Other studies, such as Attfield and Temple (2006), have used some of the assumptions from the King *et al.* (1991) model to construct output trend estimates for the UK and US economies. Also see Serletis (1996), Koray *et al.* (1996) and Mills (2001), who all have investigated the properties of the one-sector neoclassical growth model on the UK and US economies.

[6] A similar exercise has recently been undertaken by Attfield and Temple (2006) for the UK and US economies.

'measurement without theory' concern, it has been common place for models to focus on theoretical predictions that are general to wide classes of models. Hence, theoretical dissimilarities can be partially negated if predictions are made about the long-run outcomes, since models that differ sharply in their short-run predictions will often be in much closer agreement about the nature of the long-run equilibrium.

Analysis of long-term movements in the great ratios are usually based on the neoclassical growth model. The starting point for this model is an aggregate resource constraint of the form $C_t + I_t = Y_t = F(K_t, A_t L_t)$, where the production function displays diminishing marginal productivity with respect to capital accumulation. The model presented below simplifies the ideas first put forward by Kydland and Prescott (1982) and detailed in King *et al.* (1988a,b). In this basic neoclassical model, output, Y_t, can be described by a constant returns to scale Cobb-Douglas production function,

$$Y_t = \gamma_t K_t^{1-\alpha} N_t^{\alpha} \tag{3.1}$$

where K_t is capital input, N_t is labour input and γ_t is total factor productivity. Assuming a deterministic trend for γ_t of the form $\log(\gamma_t) = \mu_\gamma + \log(\gamma_{t-1})$ leads to per capita output, consumption and investment sharing a common growth rate μ_γ/α - a deterministic trend, as in Solow (1970). This implies that the great ratios of investment and consumption to output are constant along the steady state growth path, μ_γ/α. Assuming a deterministic trend for γ_t thus leads, under suitable assumptions concerning preferences, capital accumulation and resource constraints, to a steady state growth path. This follows from the economy's commodity resource constraint, $Y_t = C_t + I_t$, with investment technology defined as $K_{t+1} = [1-\delta]K_t + I_t$, with δ representing the rate of depreciation. The economy's allocation of time between work and leisure must also be constant in the steady state.[7]

When uncertainty, ζ_t, is added, realisations of ζ_t change the forecast of trend productivity equally at all future dates. Adapting the deterministic system to include uncertainty leads to a logarithmic random walk $E_t \log(\gamma_{t+s}) = E_{t-1}\log(\gamma_{t+s}) + \zeta_t$, where the innovations $\{\zeta_t\}$ are $i.i.d(0, \sigma^2)$ (the deterministic system was adapted by Brock and Mirman, 1972, and Donaldson and Mehra, 1983, to form the neoclassical stochastic growth model under uncertainty). A productivity shock raises long-run growth expectations, which sets off transitional dynamics. As capital is accu-

[7] This supports the intuition, in terms of its generality, behind the use of the one-sector growth model, which holds across a wide range of specifications for preferences and technology and in which long-run growth is exogenously determined by the specified rate of labour augmenting technical change, as in King *et al.* (1988b).

mulated, the economy moves towards a new steady state with the great ratios changing temporarily before returning to their steady state. From this basic neoclassical framework, balanced growth follows the common growth rate $(\mu_\gamma + \zeta_t)/\alpha$, with the stochastic trend represented by $\log(\gamma_t)/\alpha$. With common stochastic trends, the logarithms of output, consumption and investment, c_t, y_t and i_t, are integrated of order one, i.e., they share a common stochastic trend, and the great ratios $c_t - y_t$ and $i_t - y_t$ become stationary stochastic processes. When there is a stochastic steady state, the great ratios will be stationary stochastic processes.[8] Clearly c_t and i_t are respectively cointegrated with y_t in this framework. As King *et al.* (1991) point out, the property of a deterministic trend has a natural analogue in a model where technical progress is stochastic. When there is a stochastic steady state, the great ratios will be stochastic processes.

A central implication in such models is that the growth of the economy is driven solely by a single integrated stochastic process (of order one), representing exogenous labour augmenting technological progress which, if it occurs at a constant rate, will lead to a balanced growth path along which output, consumption, capital and investment all grow at the same constant rate.

Furthermore, the analysis presented here will also focus upon the two other great ratio type relations, given their importance in RBC modelling. The first is the money-demand equation,

$$m_t - p_t = \beta_y y_t - \beta_R R_t + v_t \tag{3.2}$$

where $m_t - p_t$ is the logarithm of real money balances, R_t is the nominal interest rate, and v_t is the money-demand disturbance. The final equation is the conventional Fisher relation

$$R_t = r_t + E_t \Delta p_{t+1} \tag{3.3}$$

where r_t is the *ex ante* real rate of interest, p_t is the logarithm of the price level, and $E_t\Delta p_{t+1}$ denotes the expected rate of inflation between t and $t+1$. If real money balances, output and the nominal rate of interest are $I(1)$, with the money-demand disturbance being $I(0)$, then real balances, output and the interest rate are cointegrated. If the real rate is $I(0)$ and the inflation rate is $I(1)$, then (3.3) implies that nominal interest rates and inflation are cointegrated. Thus the empirical model investigates the possible cointegrating relations and isolates the common stochastic

[8] In the one sector world examined here, there is no role for changing relative prices of capital goods. There is no substantive distinction between the share of nominal investment and the ratio of real investment to real output. By contrast, in a two sector world in which the relative price of capital goods can change, the distinction between nominal and real is more valid. Despite this, unit root tests are undertaken on the nominal ratios as well.

trends that they may imply.

3.3 Econometric Methodology

Structural VAR modelling, using long-run restrictions to capture productivity shocks, has often been utilised to impose some theoretical structure without being unduly restrictive. The most notable examples include Shapiro and Watson (1988), Blanchard and Quah (1989) and Galí (1999, 2004). In line with such modelling techniques, the econometric procedure followed here uses the model's long-run balanced growth implication to isolate the permanent productivity shocks and then trace out the short-run effect of these shocks. The long-run restrictions imposed are, in structural form, similar to Stock and Watson (1988a), who developed a common trends representation that was shown to be equivalent to a VECM representation. Such common trends models have provided a useful tool for studying growth and business cycle phenomena in a joint framework. The basic idea is to extract a reduced number of linear stochastic trends that feed the system, implying that there exists certain linear combinations of the level series which ensure that the trends average out, i.e., the residuals from the linear combinations are stationary stochastic processes.

The methodology starts from an unrestricted VAR(p) representation of a vector X_t of n $I(1)$ variables. Constant terms are omitted for ease of exposition. Written in levels form and in error-correction (VECM) form, the model can be represented as,

$$\begin{aligned} X_t &= \Pi(L)X_{t-1} + e_t \\ \Delta X_t &= \Pi^*(L)\Delta X_{t-1} + \Pi(1)X_{t-1} + e_t \end{aligned}$$

where e_t is a vector of $i.i.d.$ serially uncorrelated disturbances with zero mean and covariance matrix Σ, $\Pi(L) = \Pi_1 + \Pi_2 L + ... + \Pi_p L^{p-1}$, $\Pi(1) = \Sigma_{i=1}^{p}\Pi_i$ and $\Pi_i^* = -I + \Sigma_{i=1}^{p}\Pi_i$. If there are $0 < r < n$ cointegration relations among the variables, $\Pi(1)$ is of reduced rank r and can be expressed as the product of two $n \times r$ matrices, $\Pi(1) = a'\beta$, where β contains the cointegrating vectors, such that $\beta' X_t$ are stationary linear combinations of $I(1)$ variables, and a is a matrix of factor loadings. The resulting cointegrated VAR is then,

$$\Delta X_t = \Pi^*(L)\Delta X_{t-1} + a\beta' X_{t-1} + e_t$$

The cointegrated VAR is inverted to yield the following stationary Wold representation of ΔX_t,

$$\Delta X_t = C(L)e_t \tag{3.4}$$

where $C(L) = I_n + \Sigma_{i=1}^{\infty} C_i L^i$ with $\Sigma_{j=0}^{\infty}|C_j| < \infty$. The common trends representation can be arrived at by adding and subtracting $C(1)e_t$ to the right hand side of equation (3.4), which yields $\Delta X_t = C(1)e_t + [C(L) - C(1)]e_t$. Recursive substitution into $X_t = C(1)e_t + [C(L) - C(1)]e_t + X_{t-1}$ gives the following expression for X_t in levels form,

$$X_t = X_0 + C(1) \sum_{j=0}^{t-1} e_{t-j} + C^*(L)e_t$$

where $C^*(L) = \Sigma_{j=0}^{\infty} C_j^* L^j$ with $C_j^* = -\Sigma_{i=j+1}^{\infty} C_i$. The matrix $C(1)$ captures the long-run effect of the reduced form disturbances e_t on the variables X_t. The existence of r cointegrating vectors implies that the long-run matrix $C(1)$ has rank $k \equiv n - r$ and $\beta' C(1) = 0$.

In order to obtain an economically meaningful interpretation of the dynamics of the variables in X_t from the reduced form representations, the vector of reduced form disturbances e_t must be transformed into a vector of underlying 'structural' shocks, with both permanent and transitory effects on the level of X_t. The structural form in first differences of X_t is represented as

$$\Delta X_t = \Gamma(L)\varepsilon_t \tag{3.5}$$

where the vector of structural disturbances is partitioned into permanent and transitory components $\varepsilon_t \equiv (\varepsilon_t^1, \varepsilon_t^2)'$, where ε_t^1 and ε_t^2 are subvectors of k and r elements respectively, $\Gamma(L) = \Gamma_0 + \Gamma_1(L)$, and ε_t is *i.i.d.*, with zero mean and an identity covariance matrix. The relationship between the reduced form and the structural shocks is given by $e_t = \Gamma_0 \varepsilon_t$, where Γ_0 is an invertible matrix. Hence, a comparison of equations (3.4) and (3.5) shows that

$$C(L)\Gamma_0 = \Gamma(L)$$

implying that $C_i\Gamma_0 = \Gamma_i, \forall\, i > 0$, and $C(1)\Gamma_0 = \Gamma(1)$. In order to identify the elements of ε_t^1 as the permanent shocks and the elements of ε_t^2 as the transitory disturbances, the following restriction on the long-run matrix of $\Gamma(1)$ must be imposed,

$$\sum_{i=1}^{\infty} \Gamma_i = \Gamma(1) = [A \quad 0]$$

where A is an $n \times k$ submatrix. The disturbances in ε_t^1 are then allowed to have long-run effects on specific variables in X_t, whereas the shocks in ε_t^2 are restricted to have only transitory effects. The matrix of long-run multipliers is determined by the condition that its columns are orthogonal to the cointegrating vectors, and $A\varepsilon_t^1$ represents the long-run components of X_t (King *et al.*, 1991). Hence, the model traces out the permanent components necessary for any RBC analysis.

The structural form representation for the endogenous variables in levels can be shown to be,

$$\begin{aligned} X_t &= X_0 + \Gamma(1)\sum_{j=0}^{t-1}\varepsilon_{t-j} + \Gamma^*(L)\varepsilon_t \\ &= X_0 + A\sum_{j=0}^{t-1}\varepsilon_{t-j}^1 + \Gamma^*(L)\varepsilon_t \end{aligned} \tag{3.6}$$

where the partition of ε_t and the restrictions have been used and $\Gamma^*(L)$ is defined in a similar fashion to $C^*(L)$. The permanent component from the above, $\Sigma_{j=0}^{t-1}\varepsilon_{t-j}^1$, may be expressed as a k-vector random walk with innovations ε_{t-j}^1,

$$\tau_t = \tau_{t-1} + \varepsilon_t^1 = \Sigma_{j=0}^{t-1}\varepsilon_{t-j}^1. \tag{3.7}$$

Using equations (3.6) and (3.7), the common trend representation for X_t can be arrived at

$$X_t = X_0 + A\tau_t + \Gamma^*(L)\varepsilon_t \tag{3.8}$$

The identification of the model is undertaken by specifying separate permanent shocks on the long-run impact matrix A in the common trend model. The structural permanent shocks are constructed using the VAR residuals, $C(1)e_t = A\varepsilon_t^1$, from which $\varepsilon_t^1 = (AA')^{-1}A'C(1)e_t$. Hence, the dynamics of the variables in X_t due to the permanent disturbances may be interpreted as the long-run forecast of X_t, computed as $X_0 + A\Sigma_{j=0}^{t-1}\varepsilon_{t-j}^1$. This is expanded upon in later subsections of this chapter.

The only restrictions that the structural model places on the reduced form are the cointegrating restrictions. This implies efficient estimates of the structural model if i) the reduced form is estimated imposing only cointegration restrictions and ii) the estimated reduced form is transformed into the structural model using the relations given above.

3.4 Properties of the Data

3.4.1 Data

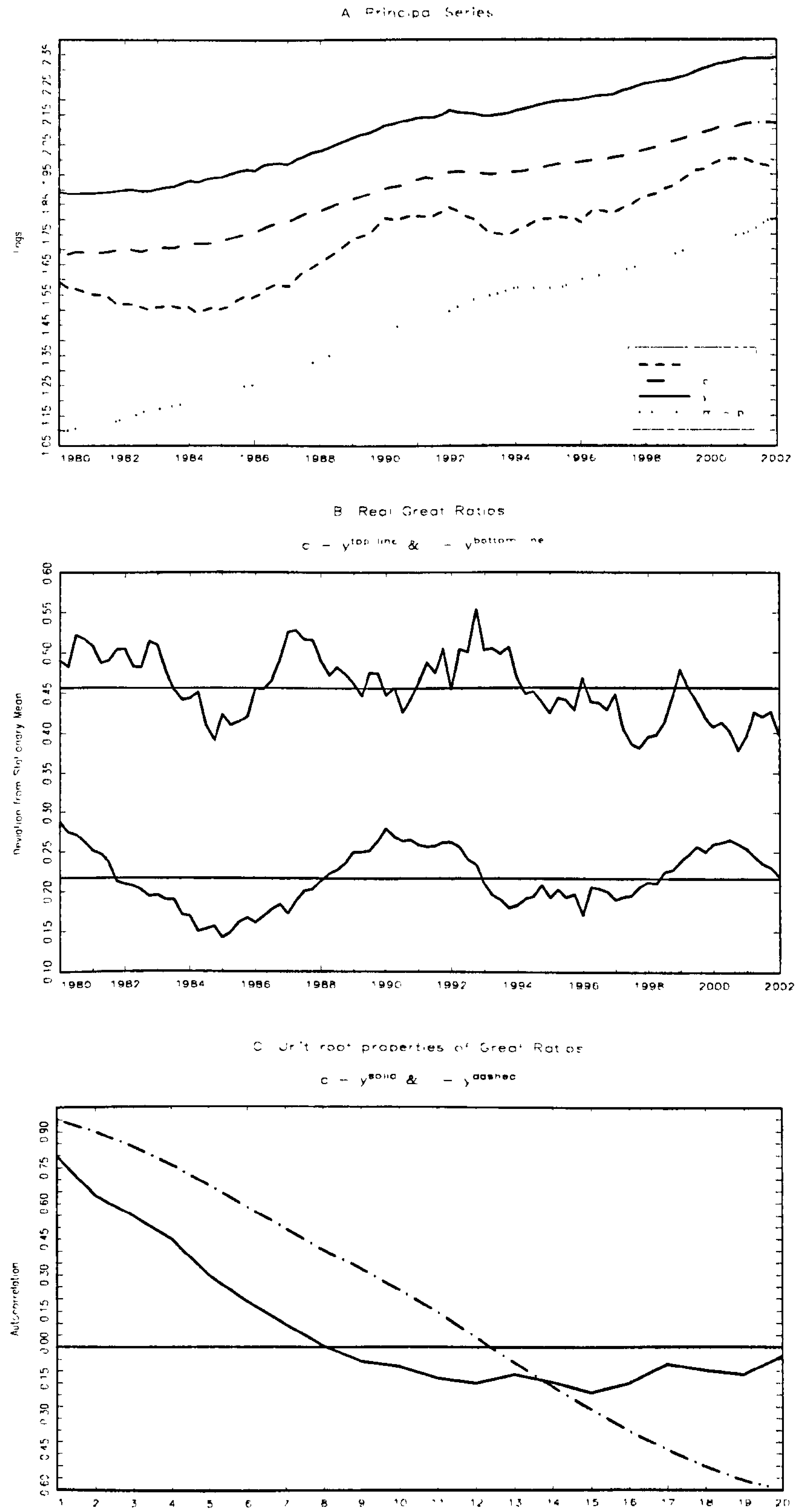
All data are taken from the area-wide model (AWM) of Fagan *et al.* (2005), also used by, amongst many others, Galí (2004), Peersman and Straub (2004) and Peersman (2005). The GDP deflator is used as a proxy for prices. The data set spans 1980:1 till 2002:4, giving a total of 92 *logged* observations. The common Euro currency has only existed since the beginning of 1999.

The construction of the data is based on a constant set of weights for each of the twelve current Euro area member countries, with a weighted aggregate formed by applying these weights to the national (log) levels data for each variable. In all cases, except inflation, the aggregation weights are based on 2001 real GDP weights adjustment for purchasing power parity (PPP): that is the weighting system depends on constant real exchange rate weights. By aggregating using constant weights, the AWM method preserves the growth rates of the overall variables.

The methods used in creating a Euro area data series long enough for meaningful macroeconomic analysis has come under criticism however. Beyer et al. (2001), for example, aggregate variables in growth rates to avoid problems associated with exchange rate fluctuations which arise in levels aggregation, such as the AWM dataset in real exchange rates. In addition, there is disagreement over the appropriate weights (see Anderson *et al.* (2006). An OECD dataset for the Euro area, for example, is compiled using fixed weights adjusted for PPP. Furthermore, it has been suggested that the use of synthetic Euro area data prior to the common currency is inappropriate, since the data process is not representative of any sort of meaningful economic process. Indeed, because of the problems associated with aggregated European data the use of German data has been advocated, since Germany is the economy most representative of the Euro area. Additionally, Germany had the least adjustment to the convergence criteria of the Maastricht Treaty so that its data process is undistorted by policies designed to result in meeting those conditions.

Despite these limitations, as mentioned by Anderson *et al.* (2006), the AWM is perceived as the benchmark Euro area dataset in the empirical literature. However, it is important to acknowledge that due to the way the AWM Euro area dataset is constructed, the results may offer a distorted view of the nature of the economic relationships between the variables.

Figure 3.1. Time Series Plots of Principal Series



Note: To facilitate graphing, constant terms were added to the logarithms of the variables.

3.4.2 Unit Root Tests

To test for stationary great ratios, the analysis here goes one step further than Serletis (1994), Attfield (2003), Whelan (2005) and Attfield and Temple (2006) by also considering public sector activities. As mentioned by Neusser (1991) and Serletis (1996), the stationarity properties of the great ratios can be affected by how government expenditures are handled.[9] Consequently, government consumption expenditure (GE) and government investment expenditure (GI) are also included.[10]

If economies converge towards a balanced growth path, the great ratios of consumption to output and investment to output will demonstrate properties associated with stationarity. Figure 3.1 part A graphs the logarithms of the real variables $(y, c, i, m - p)$. All variables demonstrate the familiar growth and cyclical characteristics of macroeconomic time series. Output, consumption and investment display strong upward trends. Investment is the most volatile, followed by output. Figure 3.1 part B displays the real great ratios: consumption-output $(c - y)$ and investment-output $(i - y)$. Over the period in question the $c - y$ ratio displays stability. It is easy to view the $c - y$ ratio as fluctuations around a constant mean. The most striking feature of the investment-output ratio $i - y$ is, at first glance, it would appear to be nonstationary. The $i - y$ ratio drifts through time, leaving one with the impression of random walk behaviour. The plots clearly indicate long swings in the ratios over many years, and indicate that mean reversion is occurring slowly (this is highlighted more clearly in the appendix, where the moving averages clearly indicate long swings in the great ratios over many years).[11]

Why does mean reversion appear to be so slow? One possible explanation may be that the great ratios have been subject to periodic mean shifts, or structural breaks. As Attfield and Temple (2006) point out, even if the majority of shocks to the great ratios are temporary, there may be occasional permanent shocks that reflect changes in the underlying parameters. Finally, the graphs also highlight a contradiction in the volatility of the plots of the great ratios. The log investment-output ratio should be more volatile since reallocating one percent of y to c and i should have a greater proportional effect on the $i - y$ ratio, given that investment accounts for a smaller share of y than c. The graphs in Figure 3.1 part B would appear to suggest the opposite.

[9] Neusser (1991) points out that 'the proper way of dealing with government activities and with the openness of the economy are problems still to be faced'. Hence, this chapter also plays a role in partially filling this gap.

[10] Cochrane (1994b) has shown that consumption less government purchases is more strongly related to business cycle movements.

[11] The slow mean reversion may bias the results towards nonrejection of the null of unit root for both ratios.

Part C of Figure 3.1 illustrates the autocorrelations of the great ratios. The $c - y$ autocorrelations appear to decay more quickly than those for $i - y$. However, both $c - y$ and $i - y$ autocorrelations decay quicker than those for y, c and i, which all demonstrate characteristics associated with nonstationarity. Both autocorrelation series decay slower than their first difference equivalents (not shown). These interesting first impressions are examined formally by unit root tests.

The ADF, KPSS and the DF-GLS unit root tests are performed on the great ratios, with results given in Table 3.1.[12] A constant term is included in the regressions for all tests but trend terms are omitted since the possibility of trend stationary great ratios is not a sensible inference to admit. The results show that the findings are robust across tests and to alternative ways of handling government expenditure. The unit root test results partially confirm the impressions gained from the time series plots in Figure 3.1. There is evidence for stationarity concerning the $c - y$ ratio. Both the ADF and DF-GLS statistics reject the presence of a unit root at the 10 percent significance level for the $c - y$ ratio. The DF-GLS unit root test for the $i - y$ ratio indicates a unit root. The KPSS statistic, however, does support stationary behaviour as the null of stationarity cannot be rejected.

In summary, there is more evidence of the data being consistent with the balanced growth conditions than against, implying that models of exogenous growth could potentially be utilised to study the joint occurrence of growth and business cycles for the Euro area. Finally, real money balances, inflation and the interest rate are nonstationary. From these results, it may be assumed that, if real balances, output and interest rates are $I(1)$, while the money-demand disturbance is $I(0)$, then real balances, output and nominal interest rates are cointegrated.

[12]The unit root tests are actually tests for cointegration, but with restricted short-run dynamics, which may bias the results toward non-rejection of the null of unit root.

Table 3.1: Unit Root Tests

A. Unit Root Statistics

	ADF+	KPSS^	DF-GLS
Great Ratios			
$c - y$	-2.62*	0.64**	-2.23**
$(C + GE) - y$	-3.60**	0.07**	-2.68
$i - y$	-3.20**	0.07*	-0.67
$(C + GI) - y$	-3.51**	0.12*	-1.27
Nominal Ratios			
$c - y$	-1.96	0.58**	-1.93
$i - y$	-2.25	0.73**	-0.24*
$(R - \Delta p)$	-2.44	0.58**	-2.03**
$(m - p)$	-0.27	1.12	1.52
Δp	-1.78	0.98*	-0.28

B. Largest Median Unbiased Autoregressive Root[b]

	Largest Root			
	Growth	OLS	MUB	90% Conf. Int.
Log Levels				
y_t	0.30	1.00	1.02	(0.86, 1.06)
c_t	0.20	1.00	1.03	(0.89, 1.07)
i_t	-0.30	1.00	1.03	(0.80, 1.07)
Log Ratios				
$c - y$	-0.10	0.53	0.82	(0.63, 1.04)
$(C + GE) - y$	-0.20	0.08	0.75	(0.55, 1.04)
$i - y$	-0.60	0.84	0.90	(0.78, 1.06)
$(C + GI) - y$	-0.40	0.64	0.79	(0.40, 1.04)

Notes: *, ** denotes rejection of the null at the 10 and 5 percent significance levels. + - a constant term is included in the regression but trend terms omitted since the possibility of trend stationary great ratios is not a sensible inference to admit. ^- a constant is included, with the * indicating that it is not possible to reject the null of stationarity b - The mean growth rate of each series was estimated using the Prais - Winston method as described in Canjels and Watson (1997). The median unbiased estimates and the 90 percent confidence intervals are computed by inverting the Dickey-Fuller (1979) unit root test statistic. Upper bounds rather than point values are reported for the median unbiased estimate.

Panel B shows estimates of persistence, as measured by the value of the largest autoregressive root of each series. Due to the ordinary least squares (OLS) estimator of the largest autoregressive root being biased towards zero, a median unbiased estimator of this largest root is reported in Table 3.1. The median unbiased estimator is constructed following Stock (1991).[13] The hypothesis of a unit autoregressive root is not rejected in favour of trend stationarity at the five percent level for output, consumption and investment. Although a unit root cannot be rejected for the consumption-output ratio, the estimates of the largest root for the two balanced growth ratios are small. Although these statistics do not line up perfectly with the simple balanced growth predictions, they do indicate that these ratios are considerably more mean reverting than the aggregate series themselves.

3.4.3 Integration and Cointegration Properties

The balanced growth conditions imply that, if the logarithms of output, consumption and investment are $I(1)$ then, for the great ratios $c_t - y_t$ and $i_t - y_t$ to be stationary, log consumption and log investment must respectively be cointegrated with log output. Hence, the analysis proceeds to test for the presence of a common trend, since the identification of a common stochastic trend reveals whether the system is driven by shocks to a single variable (a technology shock), or if the common trend is a linear combination of (permanent) shocks to more than one variable.

Since balanced growth forms the central hypothesis of this chapter, it is important to ensure its legitimacy. The analysis reported in Table 3.2 uses a variety of tests to check whether the notion of stationary great ratios is robust to various permutations. Panel A of Table 3.2 reports the largest eigenvalues from the companion matrix of an estimated VAR(6).[14] Evidence of a common stochastic trend (balanced growth) would imply that the companion matrix has one unit eigenvalue, corresponding to the common trend, with all other eigenvalues less than 1 in modulus. The point estimates are consistent with one common trend. Estimating a VAR(2), in accord with the AIC and BIC statistics, does not change this conclusion.

The standard Johansen (1996) maximum likelihood procedure for estimating the cointegration rank is reported in Panel B, which also reports the Stock and Watson (1988a) test for common

[13] The estimates presented in Table 3.1 represent γ_1 from the regression $\Delta X_t = a + \gamma_1 X_{t-1} + \Sigma_{i=1}^{p} \Delta X_{t-i} + \varepsilon_t$.

[14] The largest non-unit eigenvalue of the companion matrix is determined by rewriting a VAR model with k lags as a VAR model with one lag by stacking vectors and using equivalence relations, thus obtaining the so-called companion form. The eigenvalues of the matrix on the first lag in this representation are equal to the inverse of the roots of the lag polynomial for the original VAR model. The modulus of each such eigenvalue is computed and the largest non-unit value among these is presented. Values below unity are expected for stationary processes.

trends.[15] Support for the balanced growth hypothesis would be reflected by the finding of two cointegrating relations. The cointegration test results reported in Table 3.2 were examined using both a VAR(2) and VAR(3). The results from panel B provide partial support for the balanced growth hypothesis.[16] Some degree of cointegration is detected by the trace test statistic, with the results showing at least one cointegrating vector at the five percent significance level. The Stock and Watson (1988a) statistic, which illustrates whether the series are integrated (not cointegrated), by examining if there are three unit roots in the companion matrix, is consistent with the one-unit root (one common trend) specification. As a note of caution, due to the relatively small dataset used and because these tests for cointegration rely on the correct lag order and trend specification and on critical values from limiting distributions, they have been shown to have rather unreliable finite sample performance.[17]

Part C of Table 3.2 follows the principle of Pesaran and Smith (1998), in which preference is given for imposing the great ratio restrictions, as such an approach is consistent with the 'structural cointegration approach', which emphasises the important role of long-run restrictions placed by economic theory.[18] The one-sector growth model provides a powerful intuition about the convergent forces that make it unsustainable for c_t and i_t to have different long-run trends from output. The finding of unrestricted coefficient estimates that are close to unity in part C is consistent with the hypothesised balanced growth values. Although the estimate of the output coefficient in the output vector for both specifications is not far from the predicted value of -1, the standard errors are very small, making deviation from the predicted value significant at conventional levels. Based on economic significance, however, it could reasonably be claimed that the output restrictions are satisfied. As a robustness check, running a bootstrap simulation on the balanced growth coefficients further strengthens the case for unit coefficients (see Appendix). Single vector cointegration tests

[15]Stock and Watson (1988) show that if the $n \times 1$ vector X_t of $I(1)$ variables has r cointegrating vectors then this is equivalent to a representation of X_t that has $k = n - r$ common stochastic trends. The common trends representation can be obtained from the moving-average representation of the VECM of equation (3.4). The common trends representation of X_t is obtained by decomposing the $C(L)$ matrix polynomial as $C(1) + (1 - L)C^*(L)$, where $C^*(L) = [C(L) - C(1)]/(1 - L)$. This yields the reduced form common trends representation for X_t as $X_t = C(1)(1-L)^{-1}e_t + C^*(L)e_t$, where $(1-L)^{-1}e_t$ is a pure random walk, while the total impact matrix $C(1)$ must have reduced rank of $k = n-r$. The reduced form common trend representation shows that the common stochastic trends are formed by the accumulation of reduced form errors e_t.

[16]Notes: *(**) significance at the 10 (5) percent level. Finally, + critical values taken from Stock and Watson (1988). The stock and Watson (1988) test in part B are for models that include a constant and linear time trend. a normalised.

[17]See Horvath and Watson (1995) and Mills (2001).

[18]Mills (2001) noted that cointegration tests that rely upon imposing the great ratio restrictions *only* as a test for the balanced growth hypothesis are significantly more powerful than tests for cointegration which do not impose any theoretical structure.

for $c-y$ and $i-y$ in part C provide support for the balanced growth hypothesis, with the Wald test statistic indicating the great ratio restrictions cannot be individually rejected, both with p-values of 0.14. Finally, the balanced growth hypothesis is tested more directly by testing the joint significance of stationary great ratio restrictions on both $c-y$ and $i-y$. Without any loss of generality, panel C reports maximum likelihood estimates of the cointegrating vectors conditional on the presence of one unit root in the VAR. At conventional levels, the Wald test statistic shows the unity restrictions imposed jointly on the cointegrating vectors are consistent with the balanced growth proposition at the one and five percent significance level. Hence, the results for the Euro area imply, with a single technology process, that a unit shock to that process would result in almost a one percent increase in consumption and investment.[19]

As a further robustness check, part D of Table 3.2 reports a second test of the balanced growth hypothesis, testing whether consumption and investment share a common trend.[20] In general, the null hypothesis of no cointegration between i and c can be rejected based on the Wald test statistic, if a normalising coefficient on i is set equal to -1, as implied by the one-sector model balanced growth hypothesis. The point estimate of -0.88 is derived from maximum likelihood estimation in an unrestricted VECM. The fact that the null hypothesis of cointegration between the logs of consumption and investment cannot be rejected implies that, technically, one cannot reject the idea that there still exists a single common trend representation for these two series. However, it is hard to imagine what the economic basis for such a single trend representation would be. For example, in an economy with a single technology process, why would a unit shock to that process result in a one percent increase in consumption but only a 0.88 increase in investment. In other words, why would this long-run relationship always have to take the form $a_1 = (1,-0.88)$? The one sector growth model provides a powerful intuition about the convergent forces that make it unsustainable for the levels of consumption and investment to have different long-term trends. This provides a theoretical case for $a_1 = (1,-1)$ as a cointegrating vector, which is more dubious for the vector $a_1 = (1,-0.88)$, or any other vector $a_1 = (1,-b)$, where b is especially far from 1.

[19]The sensitivity of this result is tested, firstly, by including a trend term, which is restricted to the cointegrating vector; $\Pi(L)\Delta X_t = \mu_0 + \alpha\mu_1 t + \alpha\beta' X_{t-1} + e_t$. This leads to the cointegrating vectors $c_t - 1.399y_t + 0.002t$ and $i_t - 2.524y_t + 0.007t$, both of which have coefficients on y_t that are significantly greater than unity. The trend term in the first cointegrating vector is significant at the five percent level, whilst it is insignificant in the second. As found by Mills (2001) for the UK economy, it would appear that there is a trade-off between including a trend term and the imposition of the great ratio unit coefficients.

[20]Whelan (2005) suggested testing for cointegration between c and i as a more direct test of the balanced growth hypothesis.

Table 3.2: Three Variables Model (y, c, i)

A. Largest Eigenvalues of Estimated Companion Matrix

VAR(6) with constant			*VAR(6) with constant & trend*		
Real	Imaginary	Modulus	Real	Imaginary	Modulus
1.00	0.00	1.00	0.91	-0.16	0.92
0.91	0.15	0.93	0.91	0.16	0.92
0.91	-0.15	0.93	-0.17	0.77	0.79
0.81	-0.23	0.84	-0.14	0.77	0.79
Log Likelihood: 1063.73			Log Likelihood: 1980.57		

B. Multivariate Unit-Root Statistics

Johansen Statistic	H_0: $r \leq 0^{**}$	H_0: $r \leq 1^{*}$	H_0: $r \leq 2$
Trace	30.40	13.44	2.552
Stock and Watson	*Test Statistic*	*Critical Value*$^{+}$	*Null/alternative*
$q_T(3,0)$	-5.40	-12.1	3 unit roots / 0 roots
$q_T(3,1)$	-24.0	-22.1	3 unit roots / 1 root

C. Estimated Cointegrating Vector

Variable	*Null Hypothesis*		*Estimates*	
	α_1	α_2	α_1	α_2
c	1	0	1.00^a	0.00^a
i	0	1	0.00^a	1.00^a
y	-1	-1	-0.975 (0.015)	-1.108 (0.086)
Wald Test of Balanced Growth Restrictions: $X^2_{[2]} = 5.40 (p = 0.07)$				
c	1			
i	0			
y	-1			
Wald Test of consumption:output ratio: $X^2_{[1]} = 3.93 (p = 0.14)$				
c	0			
i	1			
y	-1			
Wald Test of investment:output ratio: $X^2_{[1]} = 3.81 (p = 0.14)$				

D. Consumption - Investment Cointegration

c	1	1.00^a
i	-1	-0.882 (0.067)

Notes: *, ** denote 10(5) percent significance level; Stock and Watson test includes trend + constant: a - normalised.

This section also explores a possible explanation for the slow mean reverting behaviour of the great ratios. As found by Attfield and Temple (2006) for the UK and US economies, the slow mean reversion in Figure 3.1 part A could be due to the fact that the great ratios might have been subject to periodic mean shifts, or structural breaks. Since the equilibrium great ratios depend on structural parameters, tests for stationarity of the great ratios are ultimately testing a joint hypothesis of not only convergence towards a balanced growth path, but also the auxiliary assumption of parameter constancy. Attfield and Temple (2006) mention the need for strong auxiliary assumptions, such as parameter constancy, for stationary great ratios to hold. This is examined using parameter constancy tests from Hansen and Johansen (1999).

In models without parameter restrictions and without exogenous variables the eigenvalues from a reduced rank regression can be computed recursively. Let $\lambda_i^{(\tau)}$ be the i^{th} largest eigenvalue for consecutive sample sizes $\tau = t, ..., T$. The recursive estimates of the eigenvalues, as in Hansen and Johansen (1999), are illustrated in Figure 3.2.

The recursive eigenvalues can also be used as the basis for formal tests of parameter constancy, which are shown in Figure 3.3. Defining

$$\zeta_i^{(\tau)} = \log\left(\frac{\lambda_i^{(\tau)}}{1-\lambda_i^{(\tau)}}\right)$$

and

$$\mathcal{T}(\zeta_i^{(\tau)}) = \frac{\tau}{T}\frac{|(\zeta_i^{(\tau)} - \zeta_i^{(T)})|}{\widehat{\sigma}_{ii}^2}$$

Hansen and Johansen (1999) derive the limiting distribution of

$$\sup_{t<\tau<T} \mathcal{T}(\zeta_i^{(\tau)})$$

Critical values for the limiting null distribution are tabulated by Ploberger *et al.* (1989). If the difference between the eigenvalues based on the subsamples and the full sample gets too large so that $\mathcal{T}(\zeta_i^{(\tau)})$ exceeds the critical value, then parameter constancy is rejected. A second test statistic is based on the sum of the r largest recursive eigenvalues,

$$\mathcal{T}\left(\sum_{i=1}^{r}\zeta_i^{(\tau)}\right) = \frac{\tau}{T}\frac{\left|\left[\sum_{i=1}^{r}\zeta_i^{(\tau)} - \zeta_i^{(T)}\right]\right|}{\widehat{\sigma}_{1-r}}$$

Here $\widehat{\sigma}_{1-r}$ is an estimator of the standard deviation of the difference $\Sigma_{i=1}^{r}\zeta_i^{(\tau)} - \zeta_i^{(T)}$. Again, Hansen and Johansen (1999) show that

$$\sup_{t<\tau<T} \mathcal{T}\left(\sum_{i=1}^{r} \zeta_i^{(\tau)}\right)$$

can be used for checking model stability, with critical values again taken from Ploberger *et al.* (1989). This is reported in Figure 3.3.

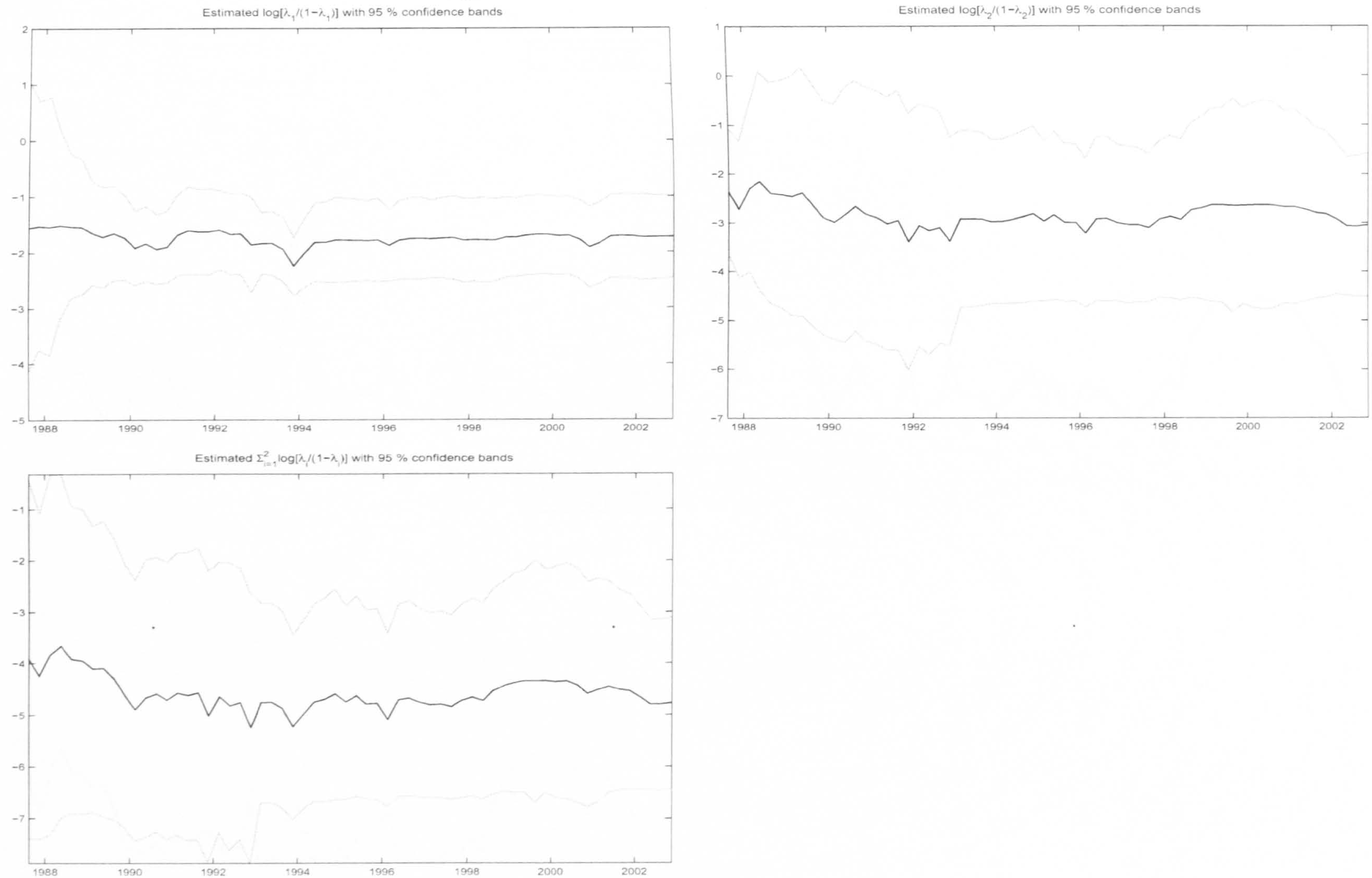
Figure 3.2 shows that there does not appear to be any large changes in $\widehat{\lambda}_1$ or $\widehat{\lambda}_2$. Besides, the point estimates decrease during the sample period. It is possible to evaluate the constancy of the eigenvalues jointly, by looking at the sample path of $\Sigma_{i=1}^{2}\zeta_i = \Sigma_{i=1}^{2}\log(\widehat{\lambda}_i/1-\widehat{\lambda}_i)$. When evaluated jointly, the changes in the estimated parameters do not appear to be any more pronounced as when λ_i are evaluated separately. It must be noted that, although this is not a formal test of parameter constancy, it does support a hypothesis suggesting constant parameters.

Figure 3.3 illustrates whether there has been a break in the two cointegrating relations, $\mathcal{T}(\Sigma_{i=1}^{2}\zeta_i^{(\tau)})$. There appears little evidence for the structural shift hypothesis of Attfield and Temple (2006). Figure 3.3 infers that, in all cases, the null hypothesis of parameter constancy cannot be rejected at the 95 percent significance level.

Overall, the evidence is reasonably supportive of the balanced growth proposition. The unit root tests are more favourable of stationary $c-y$ and $i-y$, than against. Second, the estimated unrestricted coefficients for $c-y$ and $i-y$ are close to the unit coefficients hypothesised by the balanced growth hypothesis. A result further strengthened by the bootstrap simulation. Third, the Wald test cannot reject the unit coefficient restrictions imposed on the individual cointegrating vectors of $c-y$ and $i-y$, as well their joint tests of significance. These results suggest that consumption and investment are cointegrated with real output, which is confirmed by Stock and Watson (1988a) test statistic result of one common trend between y, c and i. However, despite the Johansen test indicating the presence of cointegration, the results are not supportive of two cointegrating vectors at the five percent significance level.[21] In general, the evidence presented appears much more favourable for the balanced growth hypothesis than contrary to. Hence, y, c and i are modelled as cointegrated of great ratio form.

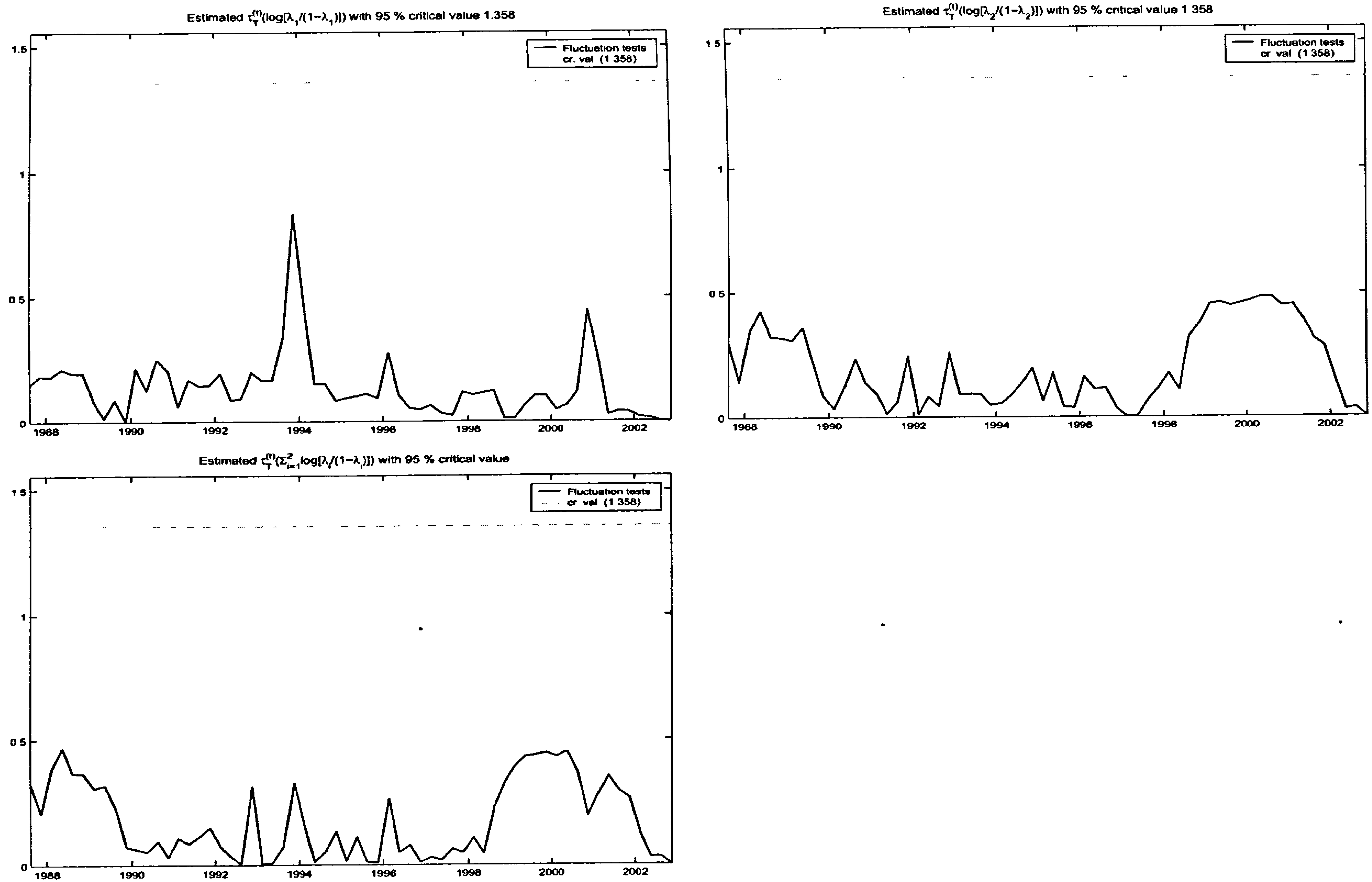
[21] Attfield and Temple (2006) contend that there are reasons to be sceptical that the great ratios will revert to constant means, since the equilibrium ratios are a function of parameters that may vary over time (including the trend growth rate).

Figure 3.2. Estimates of Recursive Eigenvalues



Notes: Panel A and B are the eigenvalues for the first and second cointegrating vectors. Panel C evaluates constancy of both eigenvalues jointly. $\Sigma_{i=1}^{2}\zeta_i = \Sigma_{i=1}^{2} \log(\widehat{\lambda}_i/1-\widehat{\lambda}_i)$.

Figure 3.3. Recursive Eigenvalue Break Test



Notes: Panel A and B are the eigenvalues for the first and second cointegrating vectors, $\tau(\zeta_i^{(\tau)}) = \frac{\tau}{T}|(\zeta_i^{(\tau)} - \zeta_i^{(T)})|/\widehat{\sigma}_{ii}^2$

Panel C evaluates constancy of both eigenvalues jointly, $\tau\left(\sum_{i=1}^2 \zeta_i^{(\tau)}\right) = \frac{\tau}{T}\left|\left[\sum_{i=1}^2 \zeta_i^{(\tau)} - \zeta_i^{(T)}\right]\right|/\widehat{\sigma}_{1-r}$

3.5 Baseline Model

Using the results from Table 3.2, the basic idea here is that there is a reduced number of linear stochastic trends feeding the system. This implies that there exist certain linear combinations of the level series which ensure that the trends average out, implying that the residuals from the linear combinations are stationary stochastic processes. With three time series and two independent stochastic trends, algebra points towards the construction of one independent vector in $\Gamma(1)$ that eliminates the trends, i.e., there is one cointegrating vector which describes the steady state in the system. In the common trends framework, the existence of two cointegrating relationships among the three variables implies the presence of one distinct source of shock having permanent effects on the variables in X_t.

Two identification assumptions are imposed. First, the permanent shock is uncorrelated with their transitory counterparts and, second, the cointegrating restrictions impose constraints on the matrix of long-run multipliers, $\Gamma(1)$, which help identify the permanent components. The balanced growth hypothesis is analysed using the common trends model derived in equation (3.9),

$$\begin{bmatrix} y_t \\ c_t \\ i_t \end{bmatrix} = \mu + \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} [\tau_t] + \Gamma^*(L) \begin{bmatrix} \varepsilon_t^1 \\ \varepsilon_t^{2,1} \\ \varepsilon_t^{2,2} \end{bmatrix} \tag{3.9}$$

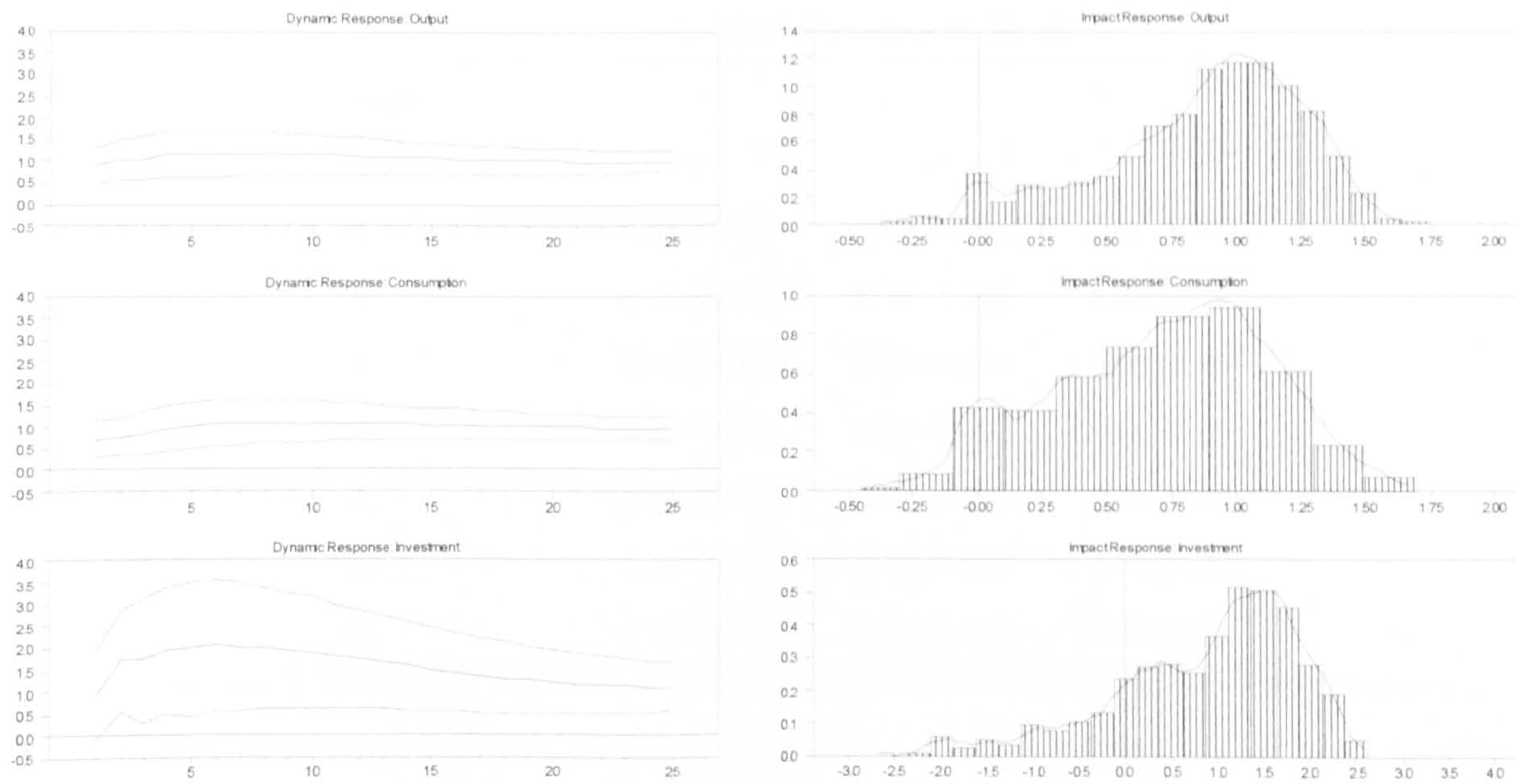
The restrictions imposed in (3.9) identify the balanced growth shock as a common long-run component in X_t, where $\mu = [\mu_y, \mu_c, \mu_i]'$ represents a vector of constant drift terms. The permanent part of (3.9) is the common trends representation, which is assumed to follow a random walk, $\tau_t = \mu + \tau_{t-1} + \varepsilon_t^1$. The final restriction imposed to capture the effects of a permanent productivity shock corresponds to ε_t^1 being uncorrelated with $\varepsilon_t^{2,1}$ and $\varepsilon_t^{2,2}$, which helps determine the dynamic effect of the permanent innovation, ε_t^1, on X_t. The innovations $\varepsilon_t^{2,1}$ and $\varepsilon_t^{2,2}$ are purely transitory disturbances, to which, given the main focus of the analysis, are not attributed any structural economic interpretation. One possible description of $\varepsilon_t^{2,1}$ and $\varepsilon_t^{2,2}$ is that they represent the transitory component of the business cycle, illustrating the temporary adjustment of the business cycle to a new higher trend following a balanced growth innovation.[22]

The dynamic response functions of c, i and y to a one standard deviation innovation in the common trend are presented in the left panel of Figure 3.4. The corresponding graphs on the right

[22] Such an interpretation would be consistent with Stock and Watson (1988a).

show the simulated distribution of each variable's response on *impact*.

Figure 3.4 - Responses to Shock in Real Permanent Component



Response in a Three-Variable Model to a One-Standard-Deviation Shock in the Real Permanent Component

The x-axis represents the horizon in quarters. One standard deviation confidence bands are also reported. A shock of one-standard deviation in size in the permanent component leads to a greater than one percent permanent increase in y, c and i. The increase in investment is significantly greater than one percent, while the response for consumption and output is about half as strong as that for investment.

Table 3.3 - Forecast Error Variance
of Three Variable Model

Horizon	*Fraction of Forecast Error Variance attributed to Real Permanent Shock*		
	y	c	i
1	0.52 (0.30)	0.34 (0.28)	0.27 (0.27)
4	0.54 (0.30)	0.40 (0.29)	0.34 (0.30)
8	0.59 (0.30)	0.48 (0.29)	0.38 (0.30)
12	0.69 (0.29)	0.55 (0.28)	0.41 (0.30)
16	0.66 (0.28)	0.60 (0.27)	0.43 (0.30)
20	0.69 (0.21)	0.64 (0.22)	0.45 (0.23)
24	0.72 (0.20)	0.67 (0.21)	0.47 (0.21)

Note: Standard errors are shown in the parentheses, which were computed by Monte Carlo simulation using 500 replications

Investment adjustment is fully complete by the end of the second year. Consumption adjustment appears more languid, with half a percent response in the first year of the shock. Consumption peaks at the end of the third year. This result is consistent with the theoretical model discussed earlier. Growth in investment and consumption appears to have taken turns, with investment taking the lead.

Table 3.3 examines the fraction of the forecast-error variance attributed to innovations in the common stochastic trend at horizons of 1-24 quarters. Table 3.3 shows that innovations in the permanent component play a dominant role in the variation of output. At the 1-4 quarter horizon, the point estimates suggest that 54 percent of the fluctuations in output can be attributed to the permanent component. This result provides strong support for RBC theory. This increases to 72 percent at the six-year horizon. The permanent component explains a much smaller fraction of the movements in consumption and investment at the 1-4 horizon period; 34-40 and 27-34 percent, respectively.

3.5.1 Six Variable Model

The three variables y, c and i are now augmented by variables that represent real balances, the nominal interest rate and inflation, yielding a six-variable system. However, identification of the individual elements of ε_t^1 (permanent innovations) become more complicated when there is more than one permanent innovation, as the unique influence of each permanent component needs to be isolated. As before, the vector of structural disturbances ε_t is partitioned into two components $\varepsilon_t = (\varepsilon_t^1, \varepsilon_t^2)'$, where ε_t^1 contains the innovations that have permanent effects on the variables in the vector X_t, and ε_t^2 contains the disturbances that have only transitory effects on the variables in the vector X_t. Both ε_t^1 and ε_t^2 are uncorrelated, with ε_t^1 assumed to be internally uncorrelated.

Table 3.4 investigates the validity of a variety of models that incorporate both real and nominal trends. The analysis assesses the relationship between nominal and real factors, whilst also investigating the two other great ratio relationships central to RBC modelling: the money-demand equation and the Fisher-relationship, equations (3.2) and (3.3). Because of the importance of monetary policy in standard macroeconomic frameworks, the estimated model allows for an estimation of the effects of real rate shifts on consumption and investment.[23] Before any estimation is undertaken, the variables are checked to ensure they are $I(1)$. The unit root tests in Table 3.2 show $y_t, c_t, i_t, m_t - p_t, R_t$ and Δp_t to be $I(1)$ and, hence, suitable candidates for the cointegration test. The vector of endogenous variables is specified as $X_t = [y_t, c_t, i_t, m_t - p_t, R_t, \Delta p_t]'$, with a constant term and no linear trend.[24] Cointegration tests were undertaken, with the maximal eigenvalue and the trace test statistics indicating the presence of cointegration, with at least two/three cointegrating vectors.[25]

The Wald tests in Table 3.4 part C investigate various hypotheses about the cointegrating vectors, under the maintained hypothesis that the number of cointegrating vectors is correctly specified. The first hypothesis (model 1) is that the cointegrating vectors are balanced growth, without permitting cointegration between the great ratios and real rates, and money demand cointegrating vectors. This hypothesis is rejected. The remaining lines of Table 3.4 part C investigate alternative cointegration restrictions. There is strong evidence against a fourth cointegrating vector implying stationary real rates (model 4). The Stock and Watson (1988a) $q_r(6,3)$ statistic, reported in Table 3.4 part B, provides some evidence for a three-trend specification, rejecting six unit roots in favour of three. At conventional levels, the evidence is weakest against the set of

[23] As touched upon by De Grauwe and Storti (2005), this issue has been an important talking point in recent years with regards to the Euro area.

[24] The AIC and BIC test statistics indicated six and one lag respectively. The Doornik and Hansen (1994) test indicates that three lags is sufficient for the eradication of serial correlation in the errors.

[25] Both $r = 0$ and $r = 1$ were rejected at the five percent significance level according to the trace test statistics. However, the lamda-max statistic indicates the presence of three cointegrating relationships, with $r = 0$, $r = 1$ rejected at the one percent level and $r = 2$ rejected at the five percent significance level.

cointegrating restrictions for Model 3 - coefficient estimates are shown in Table 3.4 part B - which hypothesises that the stationary velocity model - $m_t - p_t - y_t - \beta_R R_t$, $c_t - y_t - \phi_1(R_t - \Delta p_t)$ and $(i_t - y_t) - \varphi_2(R_t - \Delta p_t)$ - is supported by the the Wald statistic at the one and five percent significance level.[26] The unrestricted coefficients of this model are presented in panel A. Suffice to say, the unrestricted coefficient estimates are only partially supportive of the balanced growth hypothesis with $c_t - 0.951y_t$ and $i_t - 1.491y_t$, which is quite far from the unit value hypothesised by the balanced growth hypothesis. The y_t coefficient for the money balances function is also relatively large, with a value of -1.45, which deviates from the consensus value in the theoretical literature of being in the locality of one.[27] Taken together, the analysis suggests that a money-demand cointegrating relation is consistent with the observed behaviour of the time-series. There is also evidence that the shares of consumption and investment move with permanent shifts in the real rate, and the hypothesis of balanced growth also appears to be generally consistent with the data.

With three cointegrating vectors and six variables, the common trends model is represented by three stochastic trends, $k = n - r = 6 - 3 = 3$. The theoretical model, thus, contains three stochastic trends that make a stationary system. The long-run equations from Table 3.4 are $c_t - y_t = 0.007(R_t - \Delta p_t)$, $i_t - y_t = -0.017(R_t - \Delta p_t)$ and $m_t - p_t = y_t - 0.030R_t$. The signs for the coefficient estimates ϕ_1 and ϕ_2 are as predicted by the long-run theory of the growth model.[28] For example, a higher real interest rate lowers the share of product going into investment and, symmetrically, raises the share of consumption. However, the long-run effects are small; a permanent increase in the annual real rate of one percentage point is associated with an increase in the $c - y$ ratio of 0.7 percentage points.

The common trends model incorporates the cointegrating relations $(c_t - y_t) - \varphi_1(R_t - \Delta p_t)$, $(i_t - y_t) - \varphi_2(R_t - \Delta p_t)$ and $m_t - p_t - y_t - \beta_R R_t$ by imposing restrictions on the matrix of long-run multipliers, $\Gamma(1)$. The first two relations link variations in the real ratios to shifts in the real interest rate, with the final restriction implying that money demand disturbances are $I(0)$. The vector of variables reads $X_t = [y_t, c_t, i_t, m_t - p_t, R_t, \Delta p_t]'$. The matrix A is of rank 3, i.e., six variables

[26]The cointegrating residuals from each vector were checked for stationarity to ensure cointegration. The DF-GLS unit root test reveals that residuals from the $c-y$, $i-y$ and money-demand cointegrating vectors can reject the null of unit root at the five percent level. The DF-GLS unit root test generally has higher power than the standard ADF unit root test. These results suggest that the vectors provide a good qualitative description of the cointegrating vectors for the system.

[27]This is close to the value found by Bruggeman *et al.* (2003) of -1.38.

[28]In contrast King *et al.* (1991) use Stock and Watson's (1993b) dynamic ordinary least squares (DOLS) procedure.

are explained by three cointegrating vectors. One can think of this model as incorporating three stochastic trends - two nominal (price, τ_p, and monetary, τ_R) and a real trend (balanced growth, τ_b). The common trends model is expressed in the form of equation (3.10)

$$\begin{bmatrix} y_t \\ c_t \\ i_t \\ m_t - p_t \\ R_t \\ \Delta p_t \end{bmatrix} = \mu + \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & \varphi_1 \\ 1 & 0 & \varphi_2 \\ 1 & -\beta_R & -\beta_R \\ 0 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_b \\ \tau_p \\ \tau_R \end{bmatrix} + \Gamma^*(L) \begin{bmatrix} \varepsilon^1_{t,b} \\ \varepsilon^1_{t,p} \\ \varepsilon^1_{t,R} \\ \varepsilon^{2,1}_t \\ \varepsilon^{2,2}_t \\ \varepsilon^{2,3}_t \end{bmatrix} \tag{3.10}$$

where the $\varepsilon_t^{2,i}$'s $(i = 1, 2, 3)$ are purely transitory disturbances, uncorrelated with the permanent shocks, to which no structural economic interpretation is attributed, and $\mu = [\mu_y, \mu_c, \mu_i, \mu_{m-p}, \mu_R, \mu_{\Delta p}]'$ represents a vector of constant drift terms.

The first column of A represents the balanced growth shock, which is modelled as a unit increase in y, c and i leading to an unit increase in real balances through the money demand relationship. The second column represents a neutral inflation shock, which is restricted to have no long-run effect on y, c and i but have a unit increase on inflation and nominal interest rates, while having a negative impact on real balances through $-\beta_R$.[29] The shock is neutral on real interest rates as a unit increase in Δp_t leads to a unit increase in the nominal rate, R_t, hence leaving the real rate of interest unchanged; the Fisher hypothesis.

[29]This identification differs from Ahmed and Rogers (2000) who allow the inflation trend to have real effects. Therefore, it could be argued that the model is more realistic than Ahmed and Rogers (2000) since it is not assumed that the unit root in inflation and productivity are independent.

Table 3.4 - Cointegration: Six Variable Model

A. Unrestricted Parameter Estimates

Variable	$\widehat{a}_1$	$\widehat{a}_2$	$\widehat{a}_3$
c_t	1.00	0.00	0.00
i_t	0.00	1.00	0.00
$m_t - p_t$	0.00	0.00	1.00
y_t	-0.951 (0.003)	-1.492 (0.077)	-1.449 (0.043)
R_t	-0.004 (0.001)	-0.017 (0.004)	-0.000 (0.008)
Δp_t	0.007 (0.002)	-0.004 (0.005)	0.009 (0.002)

B. Estimated Cointegrating Vectors

Variable	$\widehat{a}_1$	$\widehat{a}_2$	$\widehat{a}_3$
c_t	1.00[a]	0.00[a]	0.00[a]
i_t	0.00[a]	1.00[a]	0.00[a]
$m_t - p_t$	0.00[a]	0.00[a]	1.00[a]
y_t	-1.00[a]	-1.00[a]	-1.00[a]
R_t	-0.007 (0.002)	0.017 (0.006)	0.031 (0.002)
Δp_t	0.007 (0.002)	-0.017 (0.006)	0.00[a]

$q_T^f(6,3) = -62.6$ (95% critical value: -30.2)

C. Tests of Restrictions on Cointegrating Vectors

Null Hypothesis	Wald Test
Model 1: $(c-y), (i-y), m-p-y$	28.9(0.01)
Model 2: $(c-y) - \varphi_1(R-\Delta p_t), (i-y) - \varphi_2(R-\Delta p)$	10.9(0.03)
Model 3: $(c-y) - \varphi_1(R-\Delta p_t), (i-y) - \varphi_2(R-\Delta p_t)$	
$m-p-\beta_y y + \beta_R R$	11.5(0.08)
Model 4: $(c-y), (i-y), m-p-\beta_y y + \beta_R R, R-\Delta p$	29.5(0.01)
Model 5: $(c-y), (i-y), m-p-\beta_y y + \beta_R R$	13.7(0.01)

Notes: Values in parentheses are p-values values (for the test statistics) or standard errors (for estimators); a - normalised.

Figure 3.5 illustrates the response of the variables to a one-standard-deviation impulse in the balanced growth, inflation and real interest rate stochastic trends over 6 years.[30] The graphs on the left show the dynamic responses of y, c and i together with ($\pm$) two standard error bands. The corresponding graphs on the right show the simulated distribution of each variable's response on *impact*.[31] As expected, the response of output, consumption and investment to the balanced-growth shock is positive. The probability density functions are all heavily skewed positive, illustrating that the effects of a balanced growth shock is initially more than likely to be positive. Interestingly y, c and i all plateau within a few quarters of one another; output peaks before consumption followed by investment, providing some evidence for the view that growth occurs in a manner that is balanced. Both y and c recede back to equilibrium at roughly the same rate, with investment adjusting slightly more quickly. While these responses are smaller than those in the three-variable model, they are consistent with RBC predictions, conforming to how one might think a system would respond to news about technological developments.

Output and investment demonstrate small long-term declines in response to a positive change in the real rate. However, consumption (less so for investment) shows an unorthodox response to rising real interest rates by illustrating an initial rise before turning negative, making it difficult to find an explanation for such behaviour from standard macroeconomic models. Investment suffers from the largest fall following a one-percent rise in the real rate, with consumption affected least. The responses for all three variables are statistically significant.

Finally, the inflation shock shows a 'reverse-Tobin effect' for output and consumption, in contrast to the 'Tobin-type effect' found in Ahmed and Rogers (2000) for the US.[32] However, the results for output and investment are difficult to quantify, with the error bands showing the response could be both negative and positive. Although, the simulated distribution for y and i suggests that the initial response to a neutral inflation shock is, more than likely, negative.

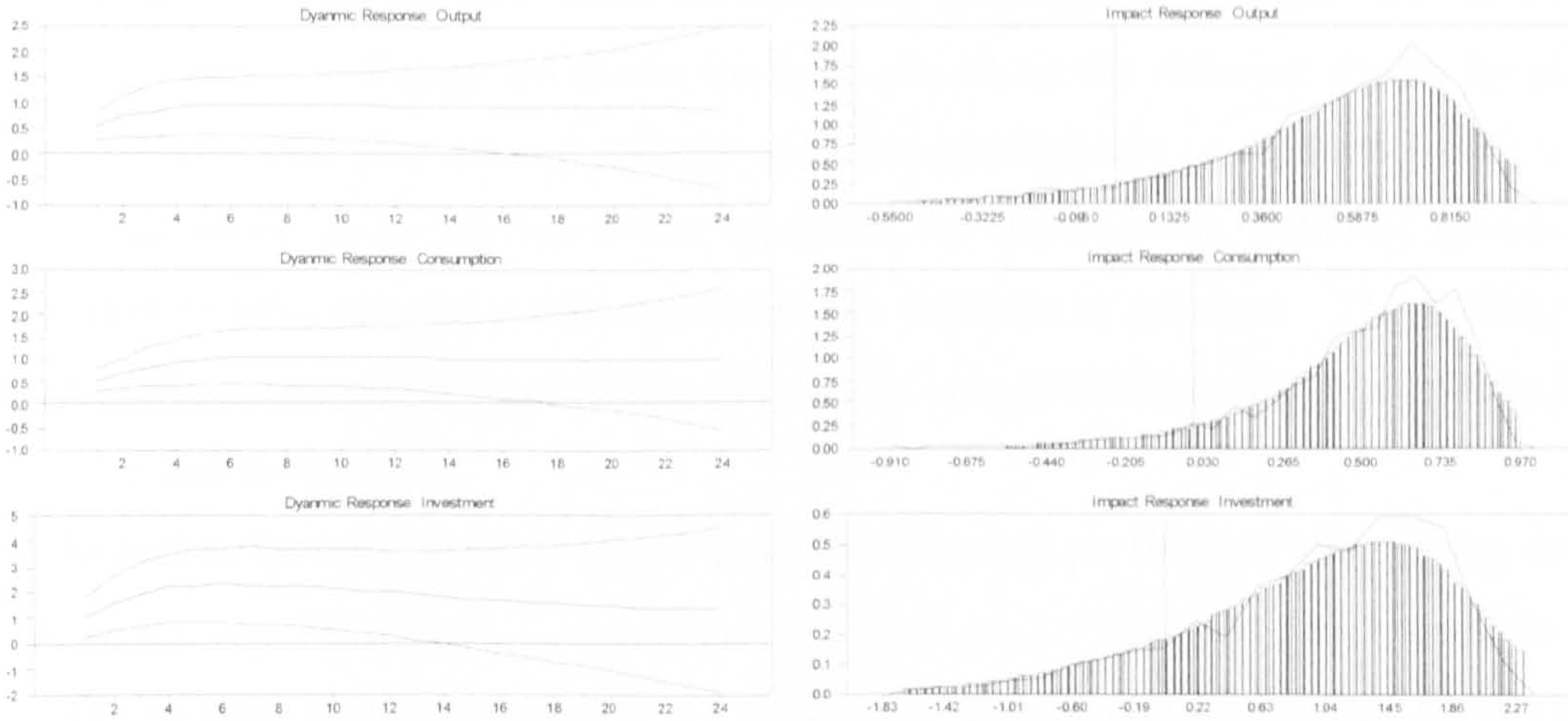
[30]The response of a series is normalised by dividing by its innovation variance.

[31]The distribution is obtained by means of a Montecarlo simulation based on 1000 drawings from the distribution of the stochastic trend VAR distribution.

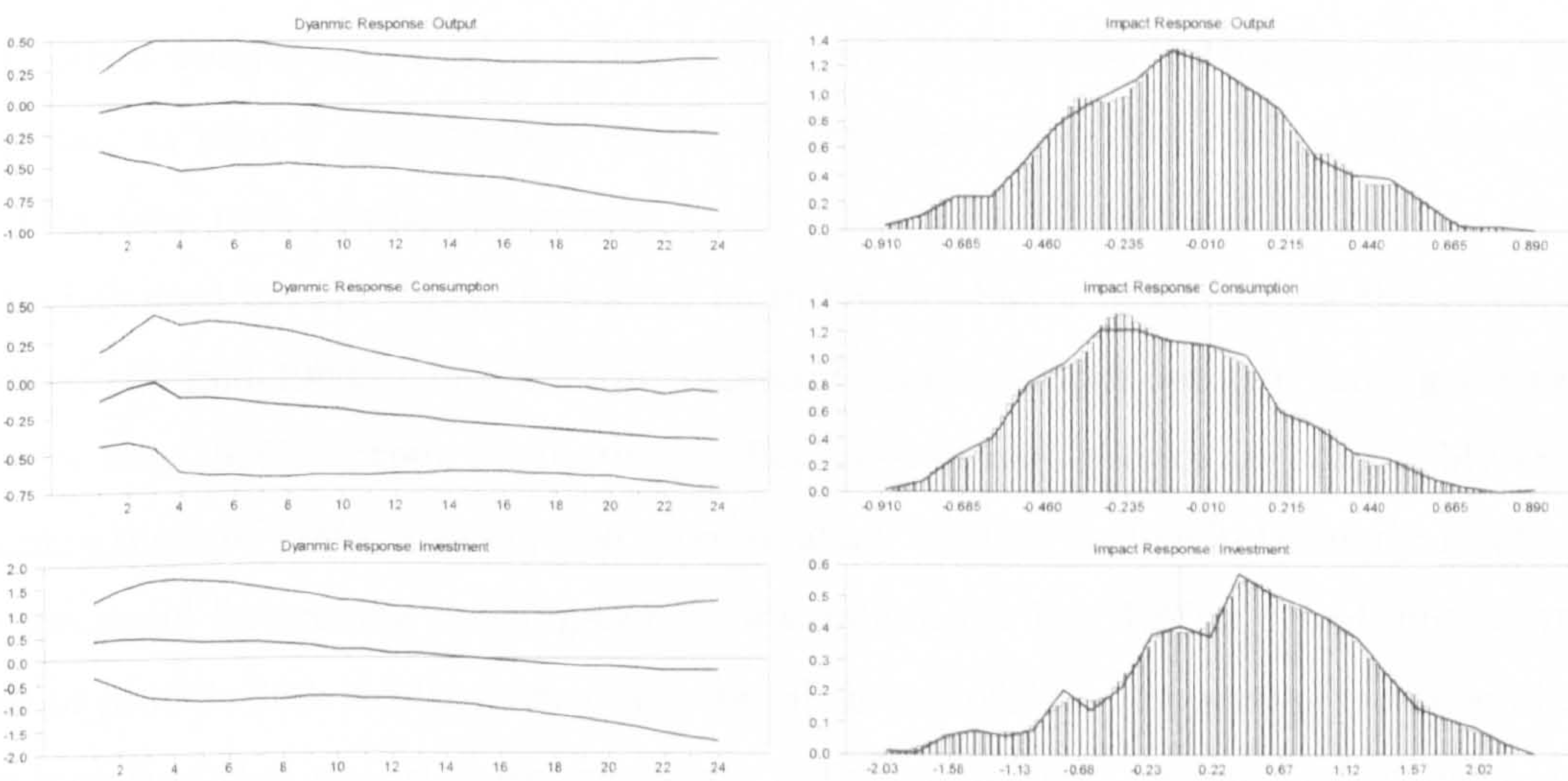
[32]Barro (1991) and Levine and Renelt (1992) find a negative impact of inflation on output growth. Similarly, Cooley and Hansen (1989) cash-in-advance consumption model shows that inflation acts as a tax on market activities and induces households to switch from market to non-market activity (leisure).

Figure 3.5

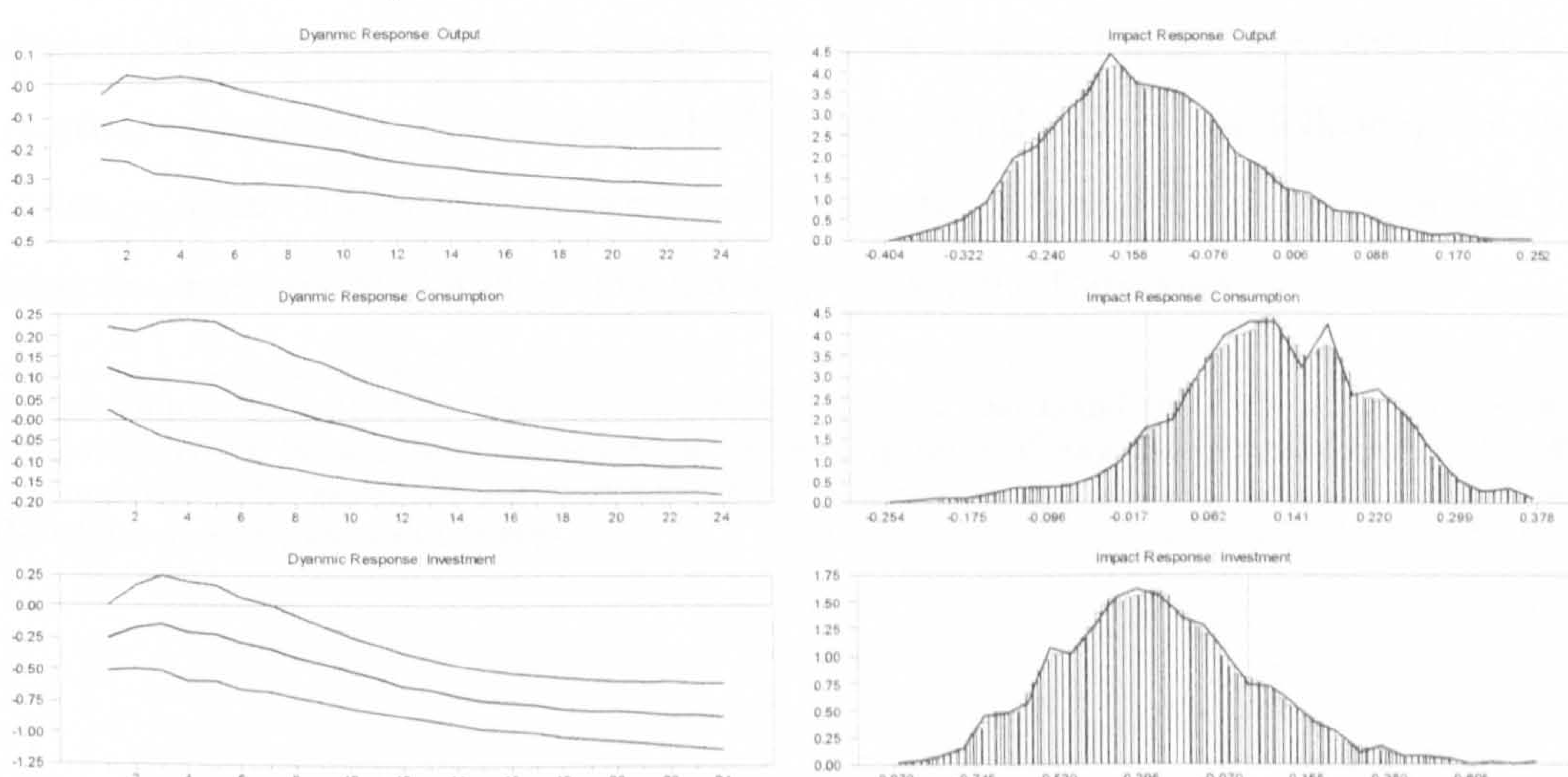
Responses to Innovations in the Balanced Growth Trend



Responses to Innovations in the Neutral Inflation Trend



Responses to Innovations in the Real Interest Rate Trend



Historical Significance of Balanced Growth, Monetary Policy and Price Level shocks

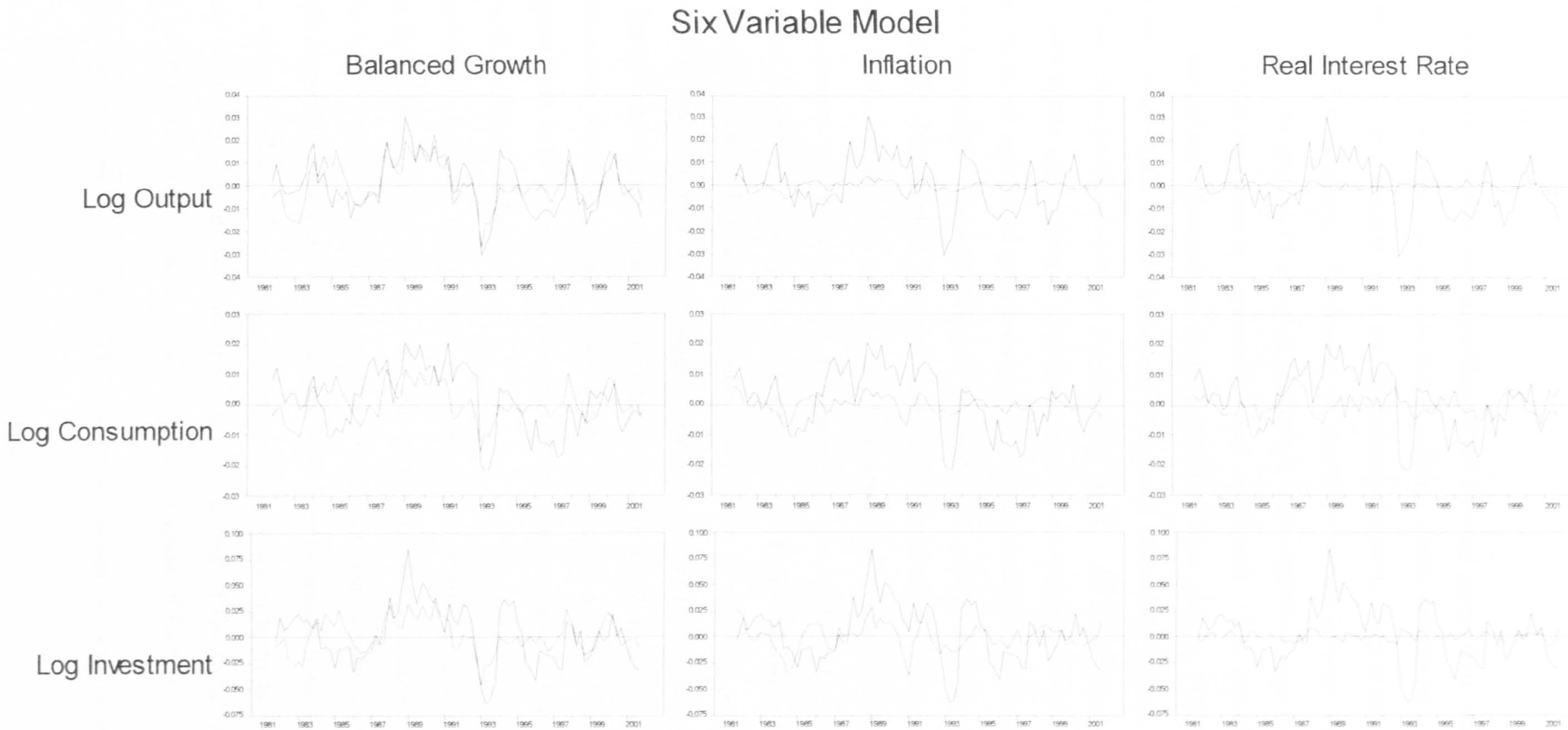
RBC theory has been used to determine the statistical properties of aggregate fluctuations induced by technology shocks. Figure 3.6 shows the roles played by the different shocks by plotting the forecast error at a two year horizon and the variation attributable to each stochastic trend for y, c and i. The labels along the top *x-axis* represent the three shocks, balanced growth, inflation and real interest rate, and the *y-axis* represents the variables in question. The findings in Figure 3.6 illustrate that the balanced growth shock provides only partially explanatory power for output, consumption and investment.

The historical decomposition is based upon the following partition of the moving average representation; $y_{T+j} = \Sigma_{s=0}^{j-1}\psi_s\varepsilon_{T+j-s} + [X_{T+j}\beta + \Sigma_{s=j}^{\infty}\varepsilon_{T+j-s}]$. The first sum represents that part of y_{T+j} due to innovations in period $T+1$ to $T+j$. The second component on the right hand side is the forecast of y_{T+j} based on information available at time T. If ε_t has N components, the historical decomposition of y_{T+j} has $N+1$ parts; in this case the forecast of y_{T+j} based upon information at time T and, for each of the N component of ε_t, the part of the first term that is due to the time path of that component.

The balanced growth shock does seem an important factor in explaining the sustained output growth of the mid-1980s. In addition, balanced growth shocks seem to have good explanatory power for late 1990's output fluctuations. Balanced growth shocks are reasonably successful in explaining the mid-1980s consumption growth, along with its decline in the early 1990s, appearing more successful forecasting consumption movements in the late 1990's. Real interest rate shocks appear to provide little explanatory power for all three variables, supporting the general conclusion in the literature that unanticipated monetary policy innovations have played, at most, a relatively modest role in driving business cycle fluctuations in the Euro area.[33] Looking at specific episodes for inflation, the explanatory power seems to be at its greatest for the very early 1980's decline in consumption and investment; a period of high inflation in the Euro area following the 1979 energy price crisis. From this period onwards the stochastic inflation trend becomes less important, signifying the move towards a 'new 'low inflation era for the Euro area.

[33] Results are also supportive of Peersman and Straub (2004), who found the early millennium slowdown to be caused by supply-side factors, with monetary policy playing little, if any, role in perpetrating the slowdown in economic activity. The model also correctly identifies a monetary policy shock in the early 1990s, which coincides with the exchange rate mechanism crisis.

Figure 3.6 - Historical Forecast Error Decomposition



The forecast errors are shown as percentages, on a decimal basis, forecasted using Monte Carlo simulation

Variance Decomposition

Table 3.5 presents the variance decomposition of the forecast errors from the six variable model.[34] Upper and lower bounds for the variance decomposition results are shown in the appendix. In the six variable model with nominal variables, the balanced-growth shock is less important for output, consumption and investment. Permanent productivity shocks account for close to half of the movements in y. At around 12 quarters exogenous technological change contributes to just over 48 percent of the fluctuations in consumption and investment. The results are more supportive of exogenous technology disturbances than Galí (2004) who, using a SVAR modelling procedure with long-run restrictions, found exogenous permanent technology shocks to explain around 10 percent of the fluctuations in output for the Euro area. At 20 quarters, close to one-quarter of output movements are explained by permanent real rate changes. However, the upper limit shows that up to 40 percent of the movements in output could be explained by real interest rate changes (see Appendix). These findings are partially consistent with monetary theories of business cycle fluctuations. Nonetheless, the main substantive implication of the real interest rate result is that most of the variation in the real rate represents the systematic response of policy to the state of the economy, i.e., unanticipated changes in monetary policy play, at most, a modest role, supporting the general consensus in the literature. As is often confused in the literature however, this result does not mean that monetary policy has little or no effect on real economic activity. In summation, the results for real output suggest that a significant proportion of the underlying cause of output fluctuations are due transitory innovations ($\varepsilon_t^{2,i}, i = 1, 2, 3$, in equation 3.10). In contrast, the importance of permanent shocks in explaining consumption (over 50 percent at 20 quarters, with an upper limit of 80 percent) is consistent with predictions of the life-cycle permanent-income hypotheses of consumption behaviour.

Changes in the real rate explain just over one-quarter of the movements in the nominal rate, suggesting that changes in the real rate are only partly driven by changes in the monetary policy instrument, which is consistent with the general literature, in which interest rate shocks have played a small role in perpetuating output fluctuations. It must be noted, however, there are difficulties associated with providing a fundamental interpretation to an exogenous real interest rate trend, particularly when the real interest rate trend is independent of the inflation trend. Finally, the stochastic trend in inflation shocks are not a significant driver of fluctuations in y, c and i.

[34] Standard errors are shown in parenthesis. The variance error results weer constructed from 1000 Monte Carlo simulations.

Table 3.5 - Forecast Error Variance Decomposition: $(y_t, c_t, i_t, m_t - p_t, R_t, \Delta p_t)$

A. Fraction of the forecast-error variance attributed to the real permanent shock

Horizon	y	c	i	$m-p$	R	Δp
1	0.37 (0.24)	0.34 (0.22)	0.27 (0.22)	0.20 (0.19)	0.10 (0.12)	0.22 (0.21)
4	0.42 (0.26)	0.46 (0.26)	0.39 (0.26)	0.30 (0.23)	0.19 (0.18)	0.20 (0.18)
8	0.46 (0.26)	0.57 (0.26)	0.44 (0.26)	0.36 (0.26)	0.36 (0.22)	0.26 (0.21)
12	0.48 (0.25)	0.57 (0.26)	0.45 (0.25)	0.39 (0.27)	0.31 (0.24)	0.31 (0.23)
16	0.48 (0.24)	0.58 (0.25)	0.44 (0.24)	0.42 (0.27)	0.34 (0.14)	0.35 (0.25)
20	0.47 (0.24)	0.58 (0.24)	0.43 (0.24)	0.43 (0.28)	0.37 (0.26)	0.38 (0.26)

B. Fraction of the forecast-error variance attributed to inflation shock

Horizon	y	c	i	$m-p$	R	Δp
1	0.10 (0.13)	0.11 (0.14)	0.13 (0.15)	0.12 (0.13)	0.16 (0.16	0.40 (0.25)
4	0.10 (0.13)	0.11 (0.14)	0.12 (0.15)	0.17 (0.17)	0.18 (0.17)	0.42 (0.22)
8	0.10 (0.13)	0.12 (0.14)	0.11 (0.14)	0.17 (0.17)	0.22 (0.18)	0.42 (0.23)
12	0.09 (0.12)	0.12 (0.14)	0.11 (0.13)	0.18 (0.18)	0.23 (0.19)	0.44 (0.24)
16	0.09 (0.12)	0.12 (0.14)	0.10 (0.12)	0.18 (0.18)	0.23 (0.19)	0.44 (0.24)
20	0.10 (0.12)	0.13 (0.14)	0.10 (0.12)	0.18 (0.19)	0.22 (0.22)	0.45 (0.24)

C. Fraction of the forecast-error variance attributed to real-interest-rate shock

Horizon	y	c	i	$m-p$	R	Δp
1	0.17 (0.16)	0.14 (0.14)	0.13 (0.15)	0.06 (0.08)	0.12 (0.13)	0.07 (0.09)
4	0.13 (0.13)	0.10 (0.11)	0.09 (0.11)	0.07 (0.10)	0.16 (0.15)	0.07 (0.07)
8	0.14 (0.13)	0.08 (0.10)	0.10 (0.11)	0.07 (0.10)	0.22 (0.16)	0.06 (0.07)
12	0.16 (0.14)	0.07 (0.08)	0.14 (0.12)	0.07 (0.10)	0.26 (0.17)	0.05 (0.06)
16	0.20 (0.14)	0.07 (0.08)	0.20 (0.14)	0.07 (0.10)	0.27 (0.17)	0.05 (0.05)
20	0.23 (0.15)	0.07 (0.07)	0.25 (0.14)	0.06 (0.10)	0.28 (0.18)	0.04 (0.05)

In conclusion, the results in Table 3.5 suggest that permanent productivity shocks play a significant role in short-to-medium term output fluctuations, supporting the view that growth and business cycles are to some degree interlinked. The balanced growth factor retains a significant role in the explanation of movements at horizons greater than two years for both the three and six variable models. The impulse response functions also appear consistent with the interpretation of the first shock as a real or balanced growth shock. Nonetheless, RBC theory maintains that permanent productivity innovations is the single *largest* factor driving output fluctuations. The forecast-error results imply that, although permanent innovations play an important role, they are not the single biggest contributor. The econometric tests do indicate, however, that the common stochastic trend/cointegration implication is consistent with postwar Euro area data.

The real interest rate results are not very supportive of monetary theories of the business cycle. In addition, consumption illustrates an orthodox response to rising interest rates, by showing an initial rise. Furthermore, contradictory to RBC theory, a rise in real interest rates leads to a fall in output and not the hypothesised rise.

Finally, the stochastic inflation trend results supports the empirical view in the literature that an inflation shock leads to a fall in real economic activity - Barro (1991) and Levine and Renelt (1992) - as well as simple theoretical models that generate reverse-Tobin effects - cash-in-advance models as in De Gregorio (1993) and Ahmed and Rogers (2000) - models that at the present time seem slightly more favoured in the inflation growth literature. In general, however, the effect of inflation on real output is small. From a future modelling perspective, this suggests that RBC models without money might be useful approximation when analysing historical Euro area data on real variables.

Sensitivity Analysis

Table 3.6 examines the performance of the results from the baseline model in (3.10). This is achieved by estimating a variety of six variable models. Compared to the three variable model, the inclusion of nominal variables leads to a fall in the fraction of the forecast errors in output, consumption and investment that are explained by balanced growth innovations. Balanced growth innovations do become significantly more consistent with RBC predictions when φ_1 and φ_2 are set equal to zero.

Table 3.6 - Three-Year-Ahead Forecast-Error Variance Decomposition: Summary of Results from Various Models

	Test of restriction on cointegrating vectors			*Fraction of forecast-error-variance attributed to the permanent real shock*					
Model	d.f.	Wald Test	Log Likelihood	y	c	i	$m-p$	R	Δp
R.1	2	5.40(0.07)	1,037.36	0.63	0.55	0.41	-	-	-
M.1	6	11.5(0.08)	1,265.68	0.48	0.57	0.45	0.39	0.31	0.31
M.2	8	28.9(<0.01)	1,257.04	0.56	0.64	0.53	0.45	0.41	0.16
M.3		———same as M.1———		0.29	0.30	0.19	0.32	0.07	0.09
M.4	4	29.5(<0.01)	1,263.89	0.37	0.36	0.43	0.16	0.59	0.74
M.5	4	13.7(0.01)	1,352.66	0.52	0.54	0.43	0.56	0.16	-

Model R.1: Three Variables $X_t = (y_t, c_t, i_t)$ model with cointegrating relations $c - y$ and $i - y$.

Model M.1: Six Variable $X_t = (y_t, c_t, i_t, m_t - p_t, R_t, \Delta p_t)$ baseline model of Table 3.5.

Model M.2: Identical to the baseline model, except that the coefficients φ_1 and φ_2 are set to zero in the cointergating vectors and the A matrix (i.e. the cointegration of shares and $R_t - \Delta p_t$ are dropped)

Model M.3: Identical to M.1, except the stochastic trend innovations are reordered to place the inflation shock first, the real-interest-rate shock second, and the balanced-growth trend third.

Model M.4: A two stochastic trend model for $X_t = (y_t, c_t, i_t, m_t - p_t, R_t, \Delta p_t)$, obtained by assuming the real-interest-rate is stationary. The cointegrating relations are $c - y, i - y$ and $m - p - \beta_y y + \beta_R R$ and $R - \Delta p$; $\widehat{A} = [\widehat{A}_1, \widehat{A}_2]$, where $\widehat{A}_1 = (1, 1, 1, \beta_y y_t, 0, 0)'$ (balanced growth shock) and $\widehat{A}_2 = (0, 0, 0, -\beta_R R_t, 1, 1)'$ (neutral inflation shock).

Model M.5: A five variable system $X_t = (y_t, c_t, i_t, m_t - p_t, R_t)$, with cointegrating relations $c - y$, $i - y$ and $m - p - \beta_y y + \beta_R R$ where $\widehat{A} = [\widehat{A}_3, \widehat{A}_4]$ $\widehat{A}_3 = (1, 1, 1, \beta_y y_t, 0)'$ (balanced growth shock) and $\widehat{A}_5 = (0, 0, 0, -\beta_R R_t, 1)'$ (neutral interest-rate shock).

In the case of where the stochastic trends are reordered, which involves putting the balanced growth shock last in the Wold causal ordering, balanced growth innovations become a less significant driver of output fluctuations. However, the main qualitative features are unchanged despite the ordering. The final five variable model strengthens the case for balanced growth innovations being the single largest contributor to output fluctuations. In summary, the sensitivity analysis indicates that the principal result for the six variable model are reasonably robust to a wide variety of changes in the identifying restrictions, with balanced growth innovations playing a comparatively significant role in the short-to-medium term fluctuations of y, c and i.

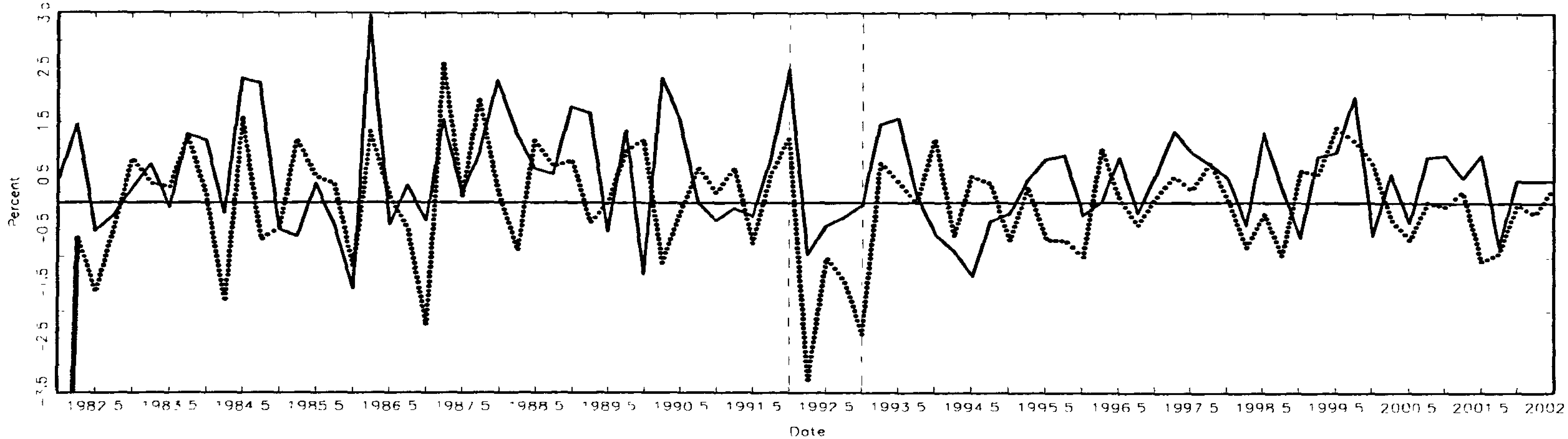
3.5.2 The Permanent Component in Output Fluctuations

The corresponding statistical common trend representation, developed in Stock and Watson (1988a), implies that all the endogenous variables have a common trend. This approach produces, as a by-product, a decomposition into secular (nonstationary) and cyclical (stationary) components, which can be thought of as the multivariate counterpart of the Beveridge and Nelson (1981) decomposition. In this subsection, the investigation tries to break down the neoclassical growth framework by investigating whether there is any evidence that productivity movements are related to innovations in the balanced-growth component of y_t, since common long-run movements in aggregate variables arise from changes in productivity. In the neoclassical growth model, the economy is described in terms of a Cobb-Douglas production function, which gives ζ_t the usual indicator of the Solow (1957) residual. The finding of stationary great ratios suggests that it is possible to draw on the joint behaviour of consumption, investment and output, while imposing relatively little theoretical structure. Therefore, as in Attfield and Temple (2006) and Garratt *et al.* (2006), the multivariate permanent-transitory decomposition in Figure 3.7 is based on those underlying processes that are identified as stationary by economic theory.

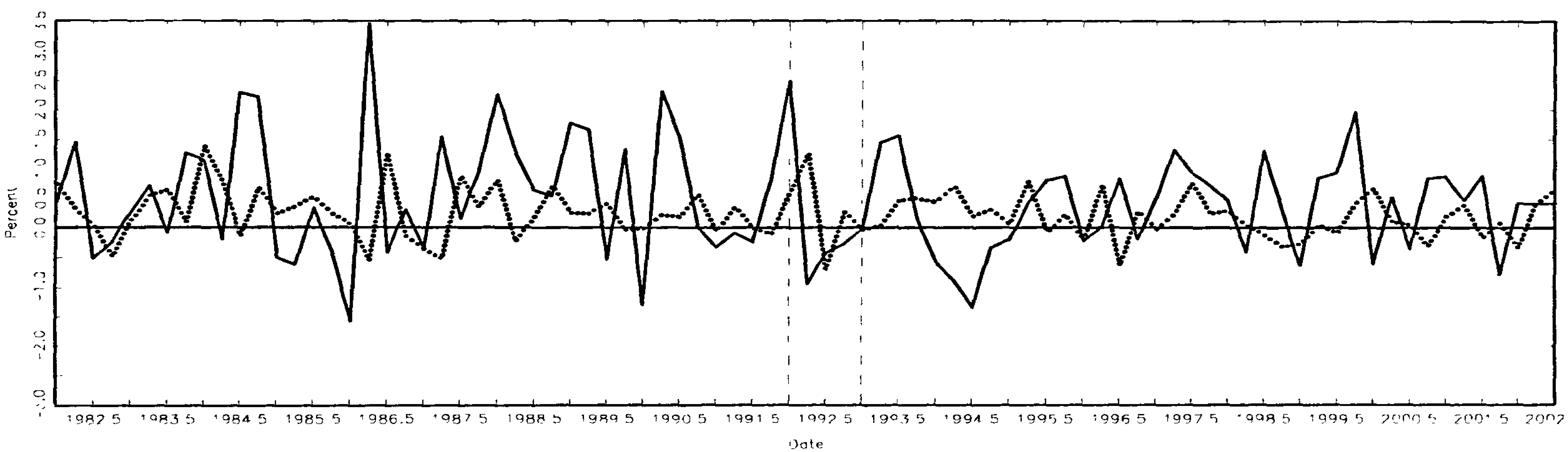
This section utilises the principal of Beveridge and Nelson (1981), which defines the trend in GDP as the level GDP will reach after all transitory dynamics have worked themselves out. The structural form can be expressed as $X_t = \mu t + \Gamma(1)\Sigma_{s=1}^{t}\varepsilon_s^t + \Gamma^*(L)\varepsilon_t$, where $\Gamma_j^*(L) = -\Sigma_{i=j+1}^{\infty}\Gamma_i$. Letting $\tau_t = \Sigma_{s=1}^{t}\varepsilon_s^1$, write $X_t = X_t^p + X_t^s$, where $X_t^s = \Gamma^*(L)\varepsilon_t$ is the stationary component of X_t and $X_t^p = \mu t + \Gamma(1)\Sigma_{s=1}^{t}\varepsilon_s^1 = \mu t + A\tau_t$ is the permanent component of X_t. By construction, X_t^p satisfies the natural notion of a trend as an infinitely long-run forecast of X, based on information through time t.

Figure 3.7. Estimated Balanced Growth Shock and Trend

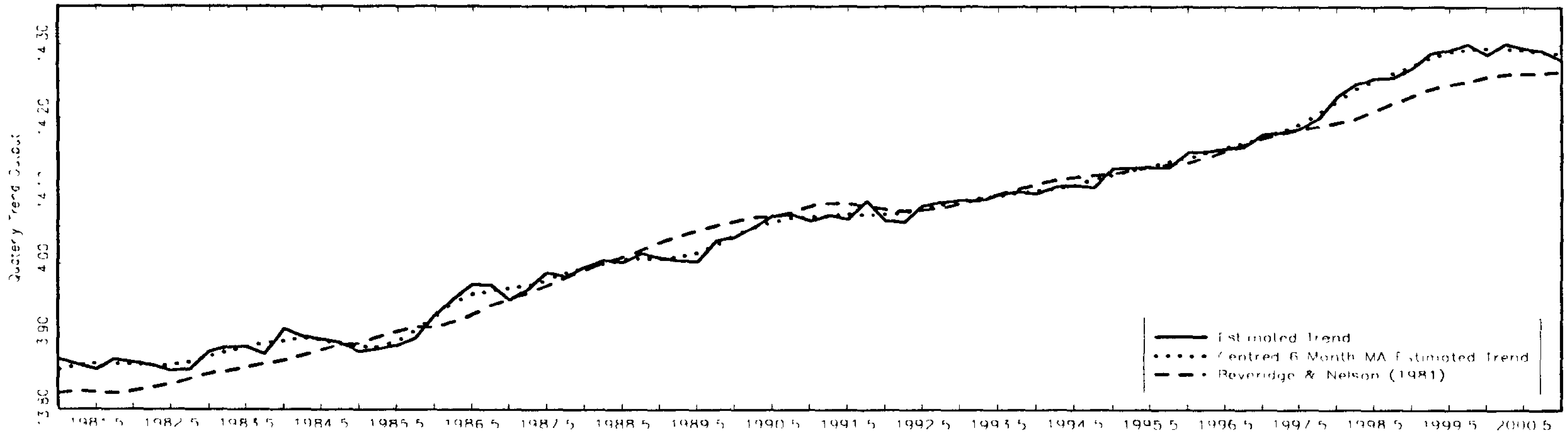
A. Estimated Balanced Growth Shock$^{\text{solid line}}$ and Gali (1999,2004) Productivity Shock$^{\text{dashed line}}$



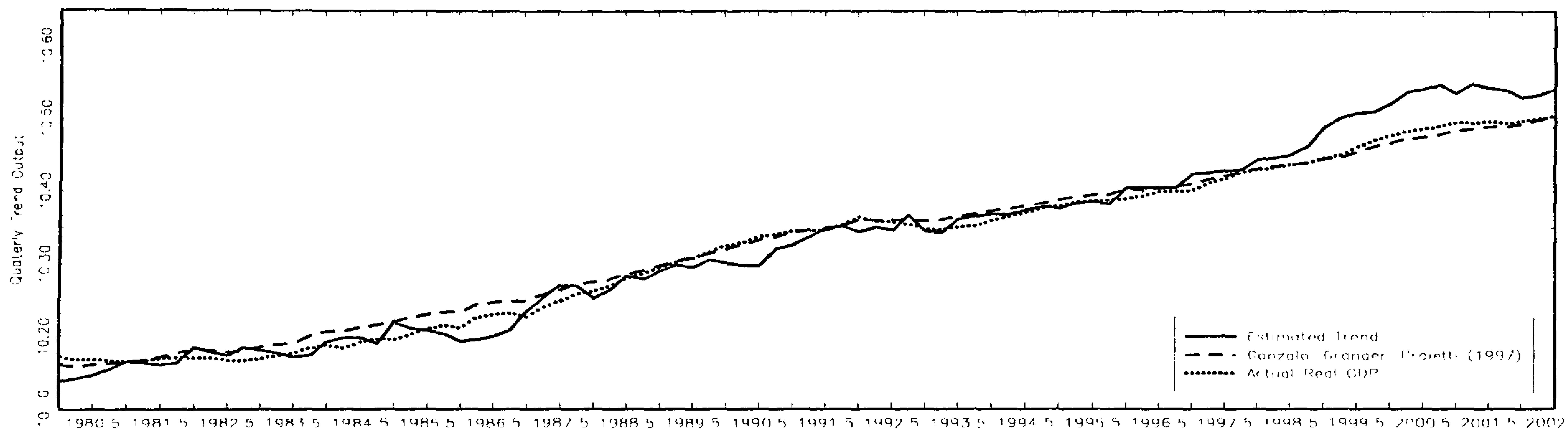
B. Estimated Balanced Growth Shock$^{\text{solid line}}$ and Solow Residual$^{\text{dashed line}}$



C. Comparison Estimated Trend & Beveridge & Nelson Decomposition



D. Comparison Estimated Trend & Gonzalo Granger Proietti Trend



Notes: Estimated Trend and Balanced Growth Shock is estimated from the Six Variable Model. Panels A and B illustrates estimates of the Balanced Growth Shock (solid line) and Galí's productivity and Solow Residual shocks (dashed line). Vertical lines represent the Bry and Boschan (1971) dated recession for Euro area real GDP. Finally, in the case of Panel C and D constant terms were included to facilitate graphing.

Figure 3.7 part A compares the evolution of the balanced growth shock from the one-sector RBC framework with Galí's (1999, 2004) two-sector RBC model.[35] Figure 3.7 part B investigates the similarities between the balanced growth innovation and one of the earliest methods of calculating technological innovations - the Solow residual - which was calculated in a similar manner to Prescott (1986); as the percent change in output less the percent change in inputs, where the different inputs are weighted by their factor share of 0.6 and 0.4 for labour and capital respectively (the factor shares are based on calculations from Musso and Westermann, 2005). The relationship between the estimated balanced growth innovations and the change in the Solow residual is mixed. The early 1990s recession is picked up by both measures. However, in general there appears little relation between the two.

In contrast, the comovement between the Gali (1999, 2004) shock and the balanced growth innovations appear more synchronised, with a correlation coefficient of 0.35. Both measures of productivity innovations are negative during the early 1990s recession, supporting RBC assertions that downturns in economic activity are associated with negative technological disturbances.

The implied trend is illustrated in Figures 3.7 part C and D. Figure 3.7 part C includes a comparison with a univariate Beveridge and Nelson (1981) output trend, since it acts as a natural counterpart to the multivariate decomposition offering a different insight into the evolution of the permanent component. Interest in the Beveridge and Nelson (1981) decomposition has grown significantly since the work of Morley *et al.* (2003). Figure 3.7 part D compares the estimated trend with the Gonzalo-Granger-Proietti decomposition, which was developed by Proietti (1997), who built upon Gonzalo and Granger (1995) by showing that the Gonzalo and Granger (1995) decomposition could be obtained as a relatively simple extension of the Beveridge and Nelson (1981) decomposition.[36] It's inclusion is based on the idea that the Gonzalo-Granger-Proietti trend estimate allows changes in both the permanent and transitory components to affect changes in the

[35] Computation is as follows. First, total employee hours worked is subtracted from real GDP, providing a measure of productivity, which is then first differenced. Next, first and second differences are taken of total employee hours worked. Finally, to uncover the productivity shock, a regression is run on the second differences of total hours worked and the growth rate of the productivity measure, with two lags on the regressor, whilst using the first differences of total hours worked and the first differences of the measure of productivity as instruments. The 'structural residual' is then retrieved and used as a proxy for Gali's (1999, 2004) productivity disturbance.

[36] The Beveridge & Nelson (1981) decomposition has been criticised as a measure of the structural trend in output, since the permanent component does not contain any dynamics in the permanent and transitory shocks, as pointed out by Blanchard and Quah (1989). To address this problem, Gonzalo and Granger (1995) suggest a new permanent/ transitory decomposition in which the permanent component incorporates some dynamics. The Proietti (1997) decomposition is $X_t = X_t^p + X^s = C(1)\Gamma(1)X_t + (I - C(1)(\Gamma(1))X_t$, where $C(1)$ is the long-run response of the moving average representation of ΔX_t, where $X_t = [y_t, c_t, i_t]'$. Proietti (1997) shows $C(1) = \beta_\perp[\alpha'_\perp\Gamma(1)\beta'_\perp]^{-1}\alpha'_\perp$, where $\alpha_\perp$ and $\beta_\perp$ are the orthogonal components of α and β.

permanent component of the series. Hence, the approach is more general than in the Beveridge and Nelson (1981) decomposition where the permanent component is a random walk.

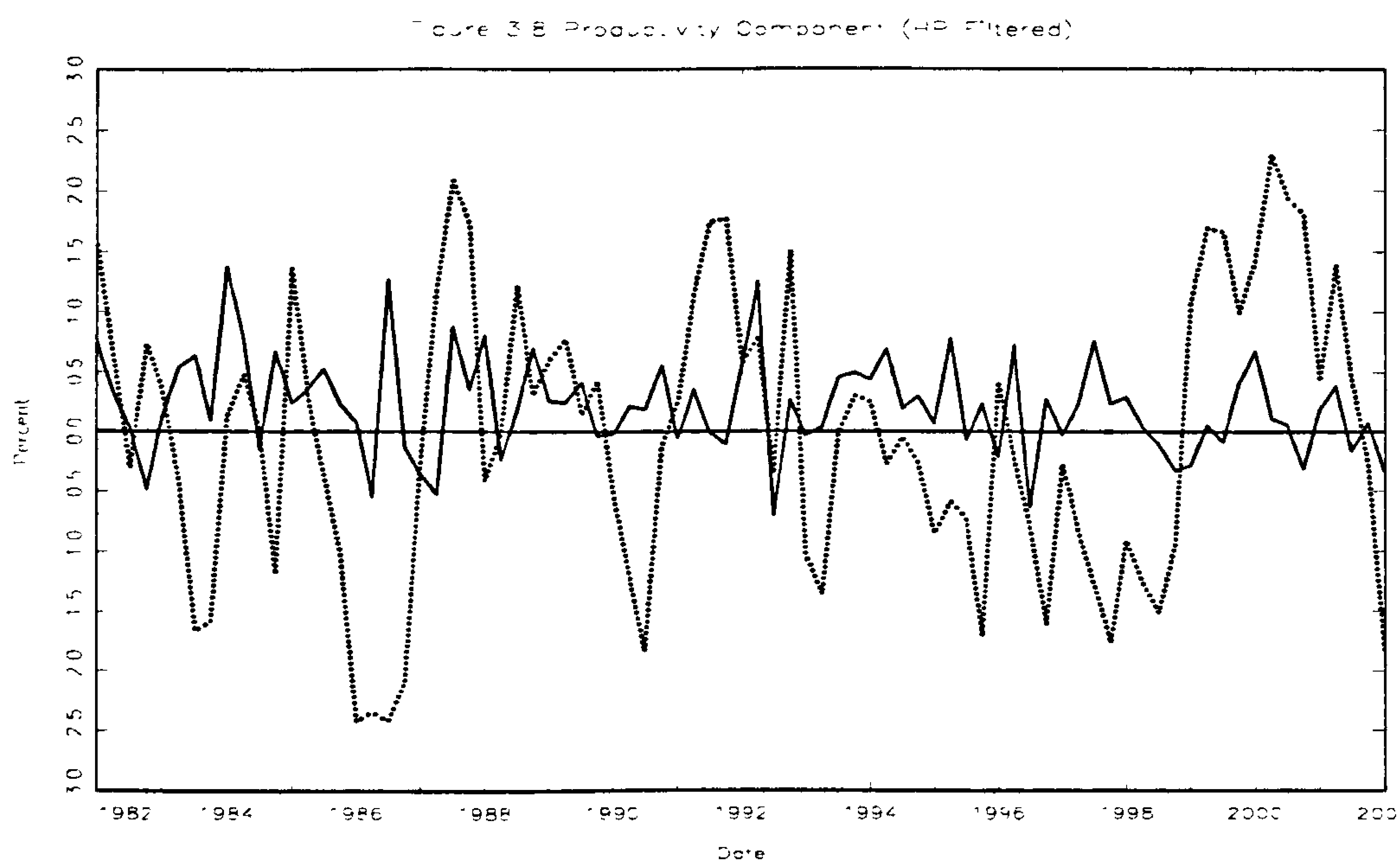
Apart from a brief period in the late 1980's and early 1990s, the estimated trend has, in general, estimated slightly higher output trend growth than the Beveridge and Nelson (1981) decomposition for the Euro area. Indeed, following the period of the introduction of the Euro area the trend estimates differ significantly. Consistent with this finding, the results illustrated in Figure 3.7 part D show the estimated trend and the Gonzalo-Granger-Proietti trend to demonstrate a difference in the evolution of trend economic activity post-Euro. It must be noted that the six variable model may be poorly suited to measuring potential output since, for example, it makes no use of demographic data, changes in which affect the productive capacity of an economy. However, the estimated trend is more wide-ranging than standard univariate decomposition methods, since the estimated trend includes inflation and the short-term interest rate. Consequently, the estimated trend approach may nevertheless by quite informative about long-term shifts in the behaviour of the permanent component and, hence, more suited than either the Gonzalo-Granger-Proietti or Beveridge and Nelson (1981) trend to picking up any structural changes that may have taken place post-ERM.[37] Perhaps due to this, the late 1980s early 1990s slowdown in the Euro area is more accurately reflected by the estimated trend than either the Beveridge and Nelson (1981) and Gonzalo-Granger-Proietti trend estimates. The results show that trend output estimates constructed from the great ratios are quite informative about the long-term shifts in the behaviour of the permanent component, with a correlation between the trend and the decomposed output trend using the Beveridge and Nelson (1981) procedure of 0.83.

To finish, the analysis explores a well-known anomaly associated with the basic RBC model, namely, its prediction of a high positive correlation between hours and labour productivity. This relationship underpins macroeconomics fluctuations in standard RBC frameworks, reflecting the shifts in the labour demand schedule caused by technology shocks, and to a lesser extent induced capital accumulation, combined with an upward-sloping labour supply. As noted by Galí (1999, 2004), a strong positive comovement between real output and labour-input (which is captured here by using hours worked from the Fagan *et al.*, 2005, data set) is a central feature of business cycles in industrialised economies. Consequently, any theory or econometric model which fails to capture

[37] Actual GDP is not plotted in Figure 3.7 part D, since it is often found that the permanent component identified by the univariate Beveridge and Nelson (1981) decomposition is almost indistinguishable from actual output, implying that most of the variation in output is driven by permanent shocks: innovations to trend.

this particular facet could be judged as empirically irrelevant. Hence, it is perhaps not unexpected that a high positive correlation of output and hours is a key prediction of the basic RBC model driven by technology shocks. This prediction, however, stands in contrast to the near-zero (and sometimes negative) correlation found in the data.

This has led to a considerable amount of research that augments RBC models with non-technology shocks (Christiano and Eichenbaum, 1992, added additional driving forces which included government spending); in particular, shocks that act predominantly as labour supply shifters, inducing a negative comovement between productivity and hours which may offset the positive correlation resulting from technology shocks. Alternatively, Galí (1999, 2004) developed a monopolistic competition model with sticky prices that reproduces the near-zero correlation between productivity and hours.



Notes: Constant terms were included to facilitate graphing. Vertical lines represent the Bry and Boschan (1971) dates recession for Euro area real GDP. Estimated Productivity disturbances (solid line) and Hours Worked (dashed line).

Figure 3.8 displays hours and the estimated trend from Figure 3.7, after being detrended, *ex post*, using a HP filter with a smoothing parameter set at 1600 in order to emphasise fluctuations at business cycle frequencies. The patterns displayed by the two series follow each other modestly well in the early 1980s and, more prominently, after the early 1990s recession. The middle-1980s to the early 1990s are characterised by the two series hardly matching one another. The strong positive comovement of real output and employment, which is generally viewed as a central characteristic of business cycles, is captured reasonably well with a correlation of 0.36.

Although this correlation is perhaps not as strong as that claimed by traditional RBC theory, it is nonetheless more successful in explaining movements in labour input than that found by Galí (1999, 2004) for the US and Euro area economies.

3.6 Conclusion

This chapter analyses the stochastic trend properties of postwar Euro area macroeconomic data to evaluate the empirical relevance of a wide class of RBC models with permanent productivity shocks. Several aspects are consistent with the central proposition of RBC models, namely, output, consumption and investment appear to share a common stochastic trend. The cointegration results are consistent with the balanced growth assumptions. In addition, there is reasonable evidence that money, prices, output and interest rates lead to an $I(0)$ long-run money demand cointegrating relationship.

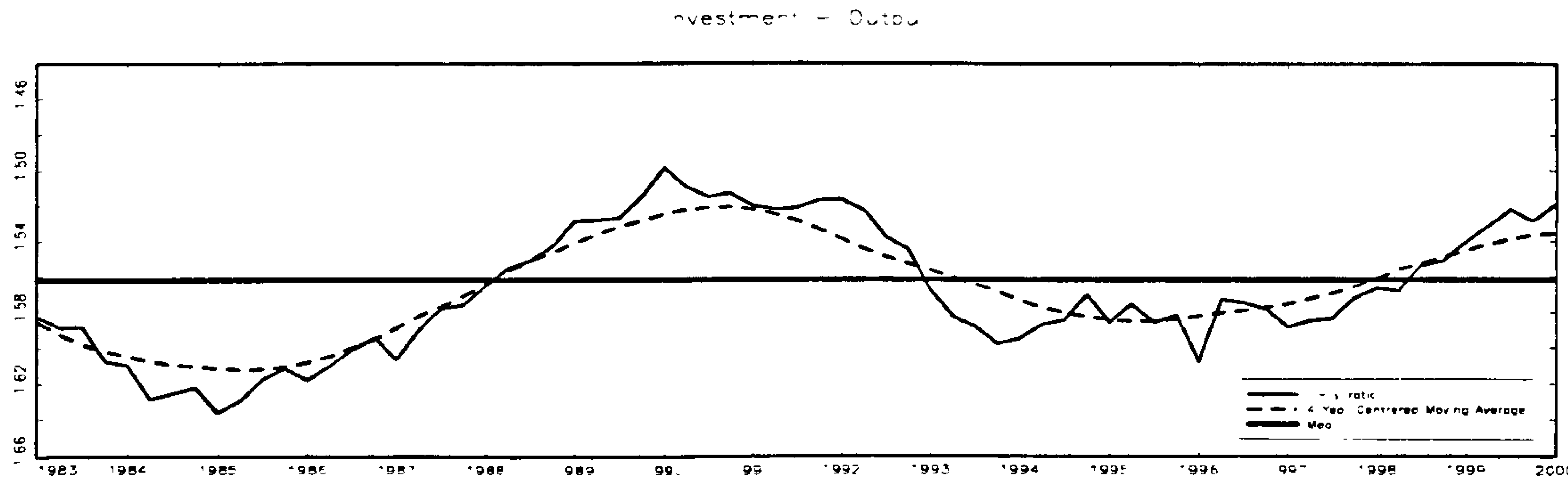
In the three variable real model, innovations in the balanced growth component account for more than 70 percent of the unpredictable variation in output over the forecast horizon. Even with regards to consumption and investment, balanced growth shocks are a determining factor. The explanatory power of the balanced-growth innovation for output is reduced with the introduction of nominal variables to just over 45 percent. Moreover, the power arises notably from the growth fluctuations of the mid to late-1980s.

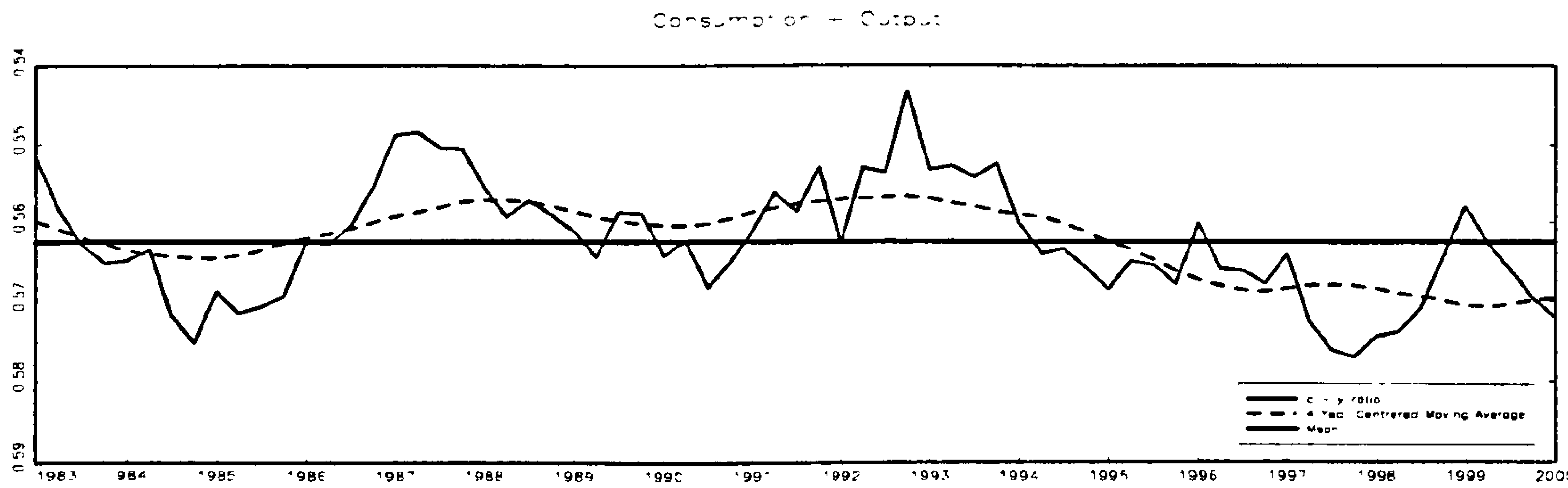
Within this context, the great ratios can also be used to construct reasonable measures of trend output. The model finds that the Beveridge and Nelson (1981) decomposition may be underestimating trend output growth for the Euro area since the introduction of the euro currency. The balanced growth restrictions also appear slightly more successful than univariate detrending techniques in highlighting the economic slowdown of the early 1990s.

What are the omitted sources of the business cycle? From a monetarist perspective, a small role is played by the inflation shock. Accelerations and decelerations in money growth and inflation, which are assumed to have no long-run effect on real flow variables and real interest rates, explain a trivial fraction of the variability in output and investment. The results from the real interest rate innovations show that the central bank has played a minor role in contributing to output fluctuations, with stochastic real interest rate changes have little effect on the real economy. As mentioned previously, it is difficult to ascribe any realistic interpretation to an exogenous real interest rate trend which is independent of inflation.

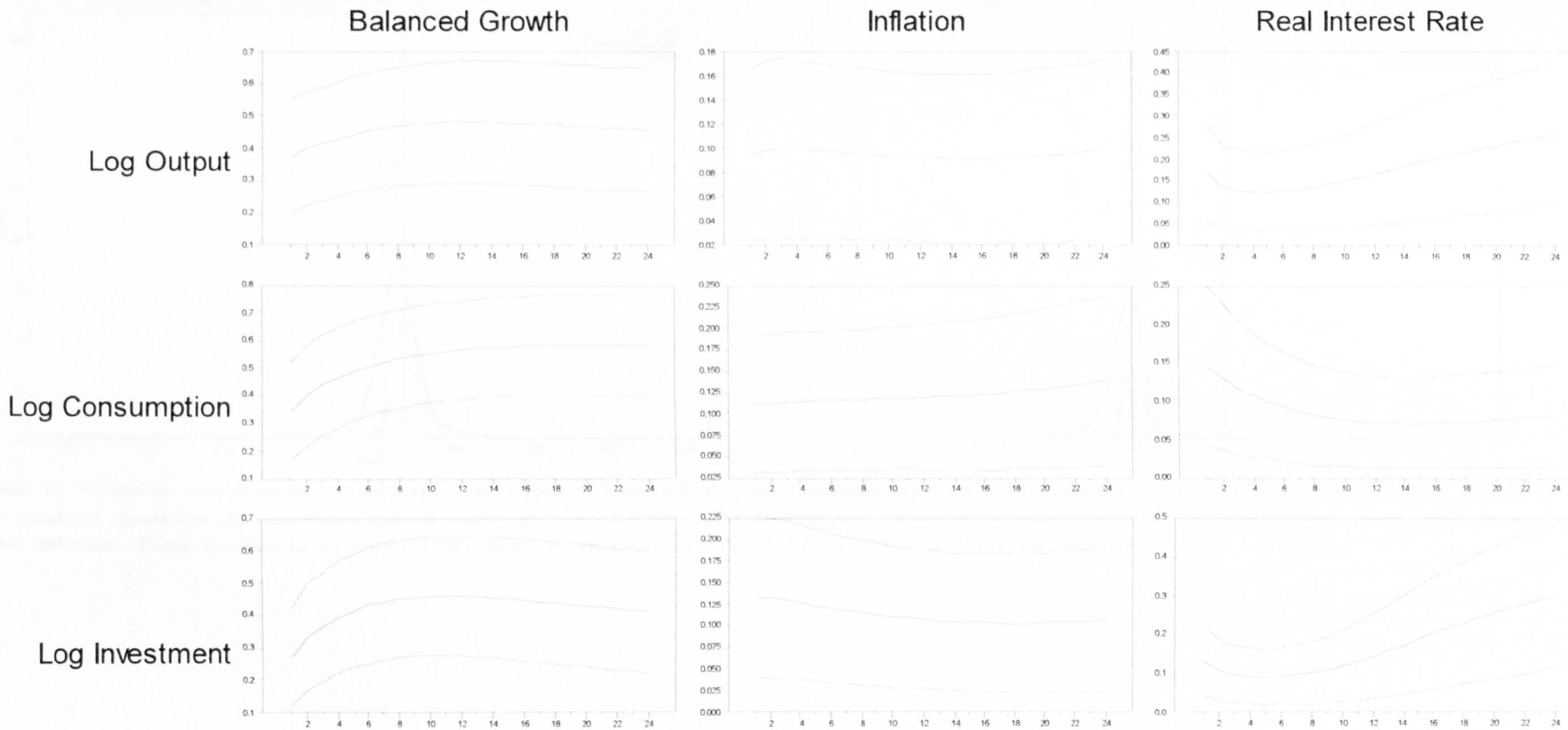
The results presented would seem to support the assertion that estimates of the stochastic trend include not only the long-term growth but also some of the major up-and-down movements. The latter are due to the random component of the trend, drawing the conclusion that permanent innovations account for a moderate proportion of short-to-medium term economic fluctuations. Subsequent chapters follow up the analysis by investigating the hypothesis that if permanent shocks are an important driver of output fluctuations in the Euro area, as suggested by the three variable model, does it necessarily imply that a reduction in permanent shocks has delivered a more stable business cycle over the last one and a half decades?

Appendix for Chapter 3



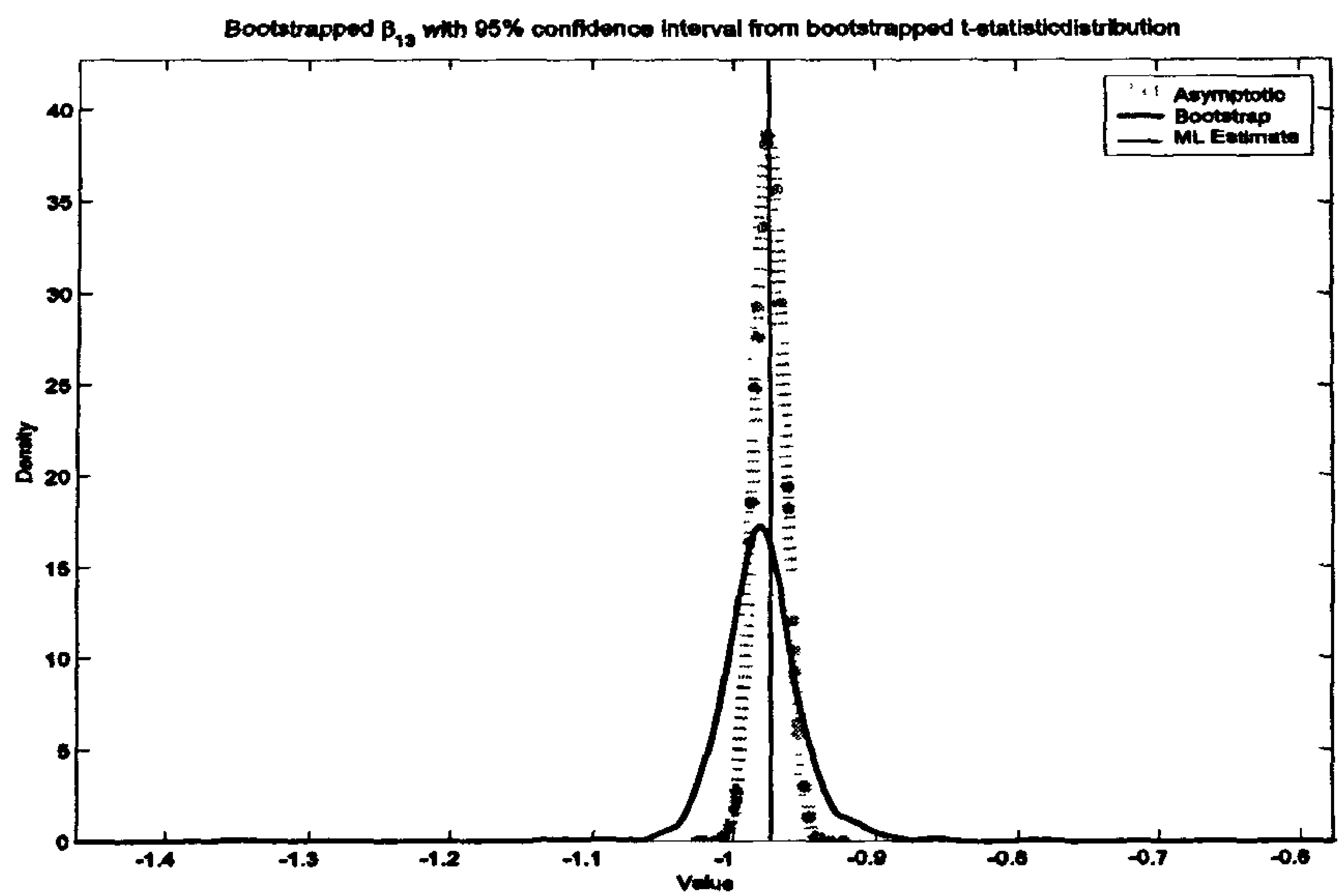


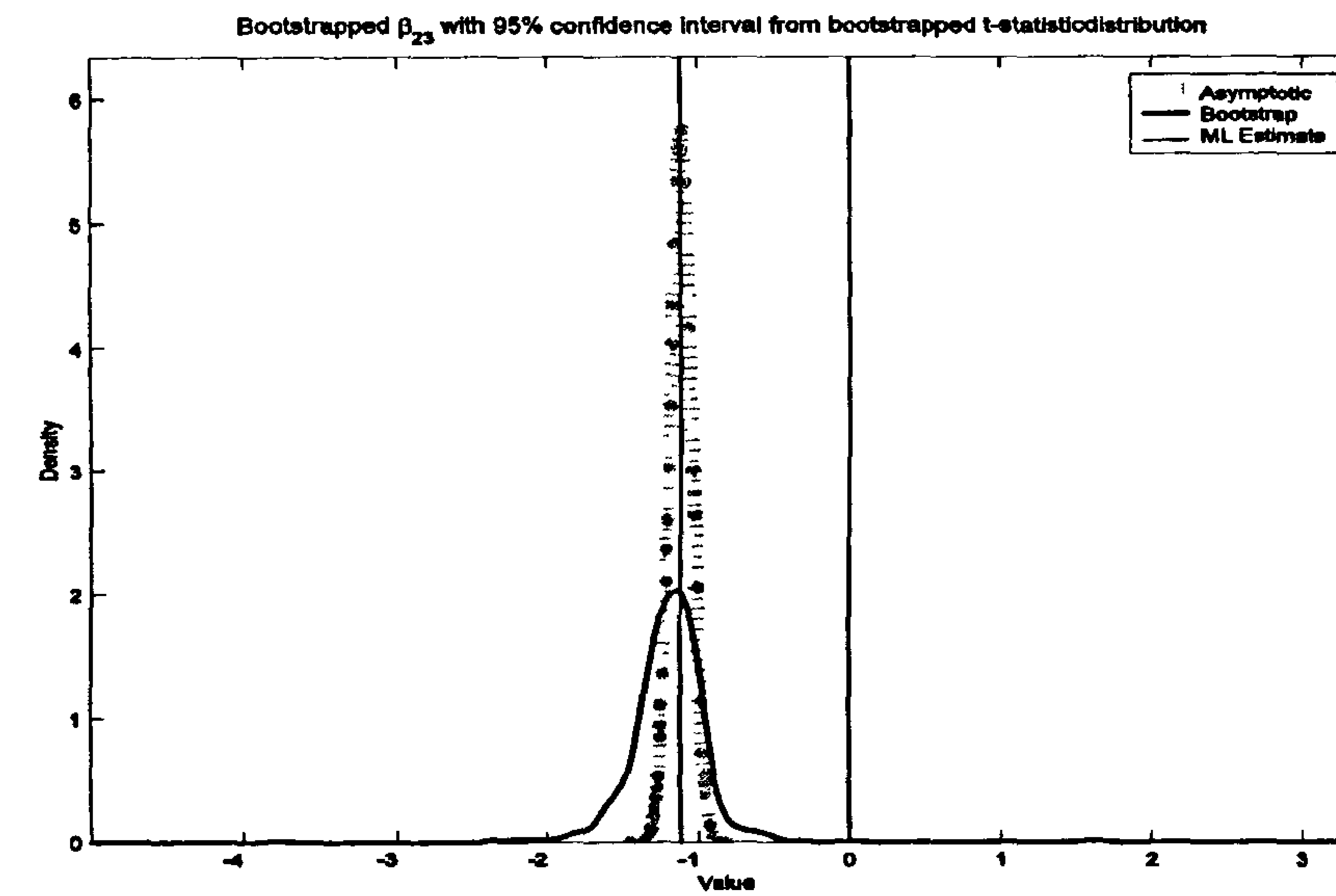
Variance Decompositions: Mean, Upper and Lower Bounds



The error bands are constructed from 1000 Monte Carlo simulations

Bootstrap Simulation for Unity Coefficients
Robustness test for unity β_{13} and β_{23} coefficients on $c_t - \beta_{13}y_t$ and $i_t - \beta_{23}y_t$





Note: The distributions were estimated using parametric bootstrapping. It is known that maximum likelihood estimators are asymptotically normally distributed. The bootstrap is undertaken by sampling n observations with replacements from the original data, where n is the number of observations. Second, fit the regression model by maximum likelihood. Steps 1 and 2 are repeated 1000 times. Finally, the sampling distribution of the estimates is used as an approximation of the 'true' population sampling distribution.

Chapter 4

Business Cycle Moderation - Good Policies or Good Luck?: Evidence and Explanations for the Euro Area[1]

4.1 Introduction

Is the business cycle dead, or at least permanently dampened? The history of business cycles can be conveniently summarised by measuring the volatility of economic growth. Using this measure, the past 30 years has witnessed a considerable decline in the volatility of economic activity in most industrialised economies. The reduction in volatility has been widespread across sectors within the G7. It was Kim and Nelson (1999) who coined the phrase the 'great moderation' to describe the increasing stability seen in business cycle fluctuations over the past three decades. Much has been written about the possible causes of this great moderation.

Although declining business cycle volatility is common wisdom, there is much less agreement about the causes of improved macroeconomic stability, especially with regards to improved output stability and whether this will endure. Much of the early literature focused upon the US experience, as in Kim and Nelson (1999), McConnell and Perez Quiros (2000), Stock and Watson (2002a, 2003a) and Ahmed *et al.* (2004). These studies assert that economies have become more self-stabilising as a result of a shift in economic activity from the secondary to the tertiary sector, better inventories management by firms, and greater integration of financial markets. Whilst improved credit markets have allowed households to smooth their spending, automatic stabilisers have also meant that incomes have varied less than production. Other economists, such as Taylor (1998) and Cogley and Sargent (2005), have put forward the claim that institutional change, such as central bank independence, along with more transparent monetary policy and inflation targeting,

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[1] **A shortend paper based on this chapter has been accepted for the Royal Economic Society (RES) conference, University of Warwick, in 2008.**

has led to improved economic stability. Consequently, Blanchard and Simon (2001) and Cogley and Sargent (2005) emphasise the role of inflation volatility in the decline of output growth volatility. In contrast to such theories, Stock and Watson (2002a, 2003a) put the stabilisation down to unadorned 'good luck', which allows them to draw the conclusion that the quiescence of the past fifteen years could well be a hiatus before a return to more turbulent economic times. In support, Martin and Rowthorn (2005) contend that the record of recent years is an exception and is unlikely to continue.[2]

This chapter provides a comprehensive characterisation of the decline in volatility using a large number of Euro area economic time series and a variety of methods designed to describe time-varying time series processes. Apart from the US economy, there has been little work undertaken on other industrialised economies examining why output growth has stabilised over the past two decades. Hence, the primary objective of this chapter is to provide new evidence on the quantitative importance of various explanations for the moderation witnessed in the Euro area cycle. The introduction of a common currency has increased the interest and need for business cycle analysis at the Euro area level. Such analysis acts as a reference for economic agents due to its influence on monetary policy decisions. Understanding the causes of the moderation of business cycles remains a crucial issue (Diebold and Rudebusch, 2001). Increasing instability in output increases risk associated with uncertainty in the economy. Increases in risk are likely to reduce the level of equilibrium output, possibly leading to both higher saving and a lower capital stock, which may in turn lead to greater capital outflows in an open economy. Policies that reduce anticipated and unanticipated volatility will therefore raise output and welfare in the longer run.

As in Stock and Watson (2002a, 2003a), the investigation here falls into five main categories. The first category will examine the evidence for structural change, helping to provide an answer to the question that underlies the bulk of the literature on this topic; has there been a structural break in post-war real output growth towards stabilisation? For the US, Kim and Nelson (1999), McConnell and Quiros (2000), Stock and Watson (2002a) and Sensier and van Dijk (2004) have documented a structural break in the volatility of output growth, finding a dramatic reduction in output volatility in the most recent two decades relative to the previous three.[3] This is investigated for the Euro area using a stochastic volatility model, which allows for the conditional mean and

[2] In contrast, Bernanke (2004) paints a more optimistic future.

[3] McConnell and Quiros (2000) suggest that the decline in US output volatiltiy can be traced to a break in the volatility of durable goods production, whose timing corresponds to a reduction in the proportion of durables accounted for by inventories.

the conditional variance to break (or not) at potentially different dates. The second category, first analysed by Moore and Zarnowtiz (1986), and later by McConnell and Quiros (2000), will focus upon changes in the structure of the economy, which include the shift in output from goods to services and financial market deregulation. Consistent with a shock based approach, the third category examines the impulse and propagation mechanisms for the Euro area in order to investigate signs of structural shifts in either the impulse or propagation mechanisms. The fourth category will examine whether improved monetary policy has led to a decline in output volatility, as suggested by Taylor (1998) for the US economy, and more recently by Cogley and Sargent (2001, 2005), Boivin and Giannoni (2002), Stock and Watson (2002a, 2003a), Ahmed *et al.* (2004), Basistha and Startz (2004) and Giannone *et al.* (2004). This category also extends to a shock based analysis of a variety of different variables to examine whether such disturbances have become more benign, i.e., a 'good luck' category. The fifth, and final, category develops a business cycle model which allows for business cycle comovements. This comovements analysis examines the role played by common factors between an array of macroeconomic shocks in the formation of business cycles, since standard small-scale VAR models have been criticised by Bernanke *et al.* (2005) and Stock and Watson (2005b) for lacking the necessary information to accurately capture structural disturbances that may impact upon the economy. Hence, this subsection allows for a greater detailed analysis of the role and contribution of structural shocks to the increased stability of the Euro area business cycle.

4.2 Economy-wide Reductions in Volatility

This section documents the widespread reduction in volatility and provides descriptive estimates of this reduction for major economic time series. There is a lack of a long time series data set for the Euro area that decomposes GDP into various major economic components, as with the NIPA[4] dataset for the US economy. The data used in this chapter thus represents a wide range of macroeconomic activity, and is taken from a variety of sources to help ensure a data set that is long enough for meaningful economic analysis. Most data series used in this paper are available from Datastream. Exceptions are the crude oil price and the raw materials index, both of which are taken from the 2005 International Financial Statistics (IFS) series from the World Bank, and average hours worked, short-term interest rate, long-term interest rate, total consumption and investment, all of which come from the Fagan *et al.* (2005) Euro-wide dataset. Finally, the

[4]National Income Public Accounts

composite leading indicator is an OECD measure (2005). Seasonally adjusted series were used when available. All of the analysis uses quarterly observations, which are transformed to eliminate trends and nonstationarity (full data descriptions are provided in the Appendix).

4.2.1 Volatility Measures

Table 4.2 reports the sample standard deviations of 27 leading macroeconomic time series. Each subsample standard deviation is presented relative to the complete sample standard deviation, so a value less than one indicates a period of relatively low volatility. The key demand and production variables illustrate a decline in volatility, with standard deviation ratios all less than one. All measures of inflation reflect a decline in volatility. The external sectors show a slight rise. Other key indicators of economic activity such as employment, construction, unit labour costs and capital goods production, all show a fall in volatility over the sample period. The results in Table 4.2 for the Euro area as a whole differ from the results of Blanchard and Simon (2001), who found the relative standard deviation of industrial production to be lower in the 1980s than in the 1990s.

Examining the monetary sector, one finds that the interest rate volatility is similar to that found for the US by Stock and Watson (2002a, 2003a). The Euro area experienced a decrease in the variance of interest rates both at the long and short end, but this decrease in volatility is slightly more marked for the long-term interest rate. In contrast, the money stock and money M1 show a slight rise in volatility. However, as touched upon by Kim *et al.* (2001), Stock and Watson (2002a) and Basistha and Startz (2004), the situation regarding different monetary indicators is somewhat complex. Finally, Table 4.1 shows the relative standard deviations of different sectors in the total labour market. Employment volatility has fallen in the highly volatile industrial and construction sectors. This decline is reflected by a volatility decline in total market conditions.

Table 4.1: Employment Volatility

	Agriculture	*Industry*	*Construction*	*Self-Employed*	*Employees*	*Total*
1981-1987	0.85	1.15	1.90	0.94	0.83	0.91
1988-1994	1.05	2.59	1.83	0.99	1.63	1.44
1995-2005	1.03	0.97	1.40	0.78	0.86	0.70

Note: Results represent percentages.

Table 4.2: Standard Deviation of Annual Growth Rates Macroeconomic Time-Series

		Std. Dev. relative to 1980 - 2005			Cor. with $\Delta^4 y_t$	
Series	1980-2005 *Std. Dev*	*1980 - 1987*	*1988 - 1994*	*1995 - 2005*	*80-92*	*93-05*
GDP	0.013	1.06	1.05	0.88	1.00	1.00
Consumption	0.039	1.24	1.04	0.62	0.97	0.97
Private cons.†	0.001	1.02	1.06	0.84	0.95	0.93
Gov't cons	0.008	1.02	1.06	0.84	0.09	0.03
Investment	0.001	0.73	1.20	1.08	0.71	0.65
GFCF	0.035	1.10	1.08	0.77	0.88	0.89
Residential	0.025	.	1.10	0.91	0.31	-0.36
Non-Resident	0.048	.	1.22	0.77	0.88	0.95
Export	0.035	0.98	0.97	1.05	0.66	0.52
Import	0.040	0.98	1.07	0.96	0.84	0.83
Production						
Goods (total)	0.028	0.93	1.21	0.83	0.87	0.85
Non-Durables	0.019	0.61	1.41	0.58	0.70	0.69
Capital Goods	0.046	0.61	1.30	0.80	0.76	0.59
Construction	0.048	1.17	1.17	0.47	0.66	0.76
PPI	0.025	1.40	0.46	0.91	0.05	-0.18
CPI	0.779	1.35	0.54	0.82	-0.24	-0.40
Deflator	0.024	1.36	0.55	0.86	-0.25	-0.38
Employment	0.011	0.92	1.18	0.88	0.75	0.76
Unit Labour	0.026	0.89	1.33	0.67	-0.49	-0.41
Av. Hours	0.004	0.78	1.17	1.03	-0.11	-0.25
Composite	0.026	0.96	0.94	1.10	0.56	0.35
Money M1	0.023	0.51	1.14	1.23	0.14	0.15
Money M3	0.022	0.88	1.24	0.85	-0.15	0.00
Mon. Stock	0.025	0.43	0.58	1.41	-0.07	0.04
Short $i_t^\dagger$	1.504	1.09	0.59	1.17	0.36	0.20
Long $i_t^\dagger$	1.246	1.19	0.38	1.16	0.27	0.09

Notes: Production non-durables begins in 1985, non-residential and residential data series start in 1991. The final two columns report the contemporaneous correlation between the row series and the four quarter growth rate of GDP.

† 1980 - 2002

4.2.2 Estimates of Time-Varying Standard Deviations

This section attempts to provide a graphical explanation of the decline in the volatility of real output for the Euro area, using two time series models. Before preceding, Figure 4.1 part A and 4.1 part B illustrates real GDP in first differenced form and run through a bandpass filter, with lower and higher frequencies set at 6 and 32 quarters. Figure 4.1 part A illustrates four quarter output growth to have slowed since early 2000. In addition, 1992 is the only year in which there was an absolute decline in economic output over the past 25 years. Finally, the bandpass filtered estimates of real GDP show that from the mid-1990s onwards, volatility in real output in the three other main economic zones of the world, Japan, the UK and US, have on average closely mirrored output movements in the Euro area.

The use of time varying standard deviations has advantages over the static estimates presented in Table 4.2, which might confound changes in the trend growth rate of output with changes in business cycle fluctuations. The Euro area grew more rapidly in the 1980s, partly because postwar reconstruction was still under way in Europe. Consequently, the standard deviations reported in Table 4.2 may contain the effects of changing cyclical fluctuations and decadal changes in the mean growth rate. It is therefore desirable to obtain alternative estimates of the time path of volatility which are robust to movements in the long-term growth rate of output. Accordingly, Figure 4.2 plots estimates of the instantaneous standard deviation of four-quarter GDP growth. These estimates are based on an autoregressive model with time-varying coefficients that allow for a long-run GDP growth rate that varies over time.

In Figure 4.2 part A the unbroken line shows the instantaneous time-varying standard deviation of the series, based on an $AR(4)$ model with time varying parameters and stochastic volatility. Specifically, y_t follows the time-varying AR process, $y_t = \alpha_0 + \Sigma_{j=1}^{p} \alpha_{jt} y_{t-j} + \sigma_t \epsilon_t$, where $\alpha_{jt} = \alpha_{jt-1} + c_j \eta_{jt}$ and $\ln \sigma_t^2 = \ln \sigma_{t-1}^2 + \varsigma_t$. The error terms are assumed as $\epsilon_t \sim i.i.d.(0,1)$ and $\eta_{1t}, ..., \eta_{pt} \sim i.i.d.(0,1)$. The parameter c_j controls for any parameter drift in the autoregressions. The model allows for large jumps in σ_t^2, thereby capturing a possible break in the variance, by using a mixture of normal models for the error term ς_t, which is distributed $N(0, \tau_1^2)$ with probability q and $N(0, \tau_2^2)$ with probability $1 - q$. The model is estimated with $p = 4$, to ensure sufficient dynamics. For these calculations the calibration parameters used are those in Stock and Watson (2002a); hence $\tau_1 = 0.04$, $\tau_2 = 0.2$ and $q = 0.95$.[5] Sticking to their notation, the model simulates

[5]Trying different calilbration parameters has little overall bearing on Figure 2.A. The parameter settings are based

a random vector (Y, A, S), where $Y = (y_1, ..., y_T)$ represents real output; $A = (a_{jt}, j = 1, ..., p)$, the AR parameters; $S = (\sigma_1, ..., \sigma_T)$, the instantaneous innovation variance. The procedure iterates between three conditional distributions of $Y|A, S$; of $A|Y, S$; and $S|A, Y$. From these, given the smoothed parameter values, the estimated instantaneous autocovariances of y_t are computed using $\sigma^2_{t|T}$ and $a_{jt|T}$, with the conditional means of σ^2_t and α_{jt} given by $y_1, ..., y_T$. Figure 4.2 part A plots the square root of the estimated σ^2_t.

Figure 4.2 part A illustrates output following a more stable path after the late 1980s/early 1990s recession in the Euro area, whilst the bandpass filtered real output data (dashed line) shows a less pronounced decline. The decline in output volatility is very similar to that found by Stock and Watson (2005) for Germany, for which volatility follows a linear trend decline. Splitting the sample in half, 1980:1-1992:4 and 1993:1-2005:2, suggests the second sample period to be just under 35 percent less volatile than the first. Similarly, the variance of real output has fallen by 68 percent. The time path of the decline in volatility illustrated in Figure 4.2 would certainly lend support to the view that technology may have played a role in the moderation witnessed in the Euro area, as there is a steady decline apart from the sudden drop in the early 1990s, similar to technology diffusing gradually. Figure 4.2 part B graphically shows the implied standard error from a rolling autoregressive model. Figure 4.2 part B illustrates a decline in the standard error, $\widehat{\sigma}_\varepsilon$, implying output has become more forecastable, i.e., the mean-squared-forecast-errror has fallen. Graphical evidence on the decline in volatility for the principal economic series of the Euro area is provided in Appendix A. There are a few notable exceptions to the declining volatility witnessed in the main indicators of the economy. The short and long-term interest rates have seen a slight rise in levels of volatility. A point worthy of note is that volatility in short-term interest rates began to rise from 1985 onwards. This period was characterised by a stronger commitment from central banks across the Euro area to keeping their currencies within the Exchange Rate Mechanism (ERM) than was the case at the launch of the ERM in 1979.

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on Stock and Watson's (2005) calibrated parameters for French, German and Italian real GDP. The three economies constitute over 75 percent of Euro area output. The same calibration parameters were also used for Japan, UK and the US. In fact, these parameter settings were generalised to a huge array of macroeconomic time series for the US economy.

Figure 4.1. Euro area Real GDP Time Series

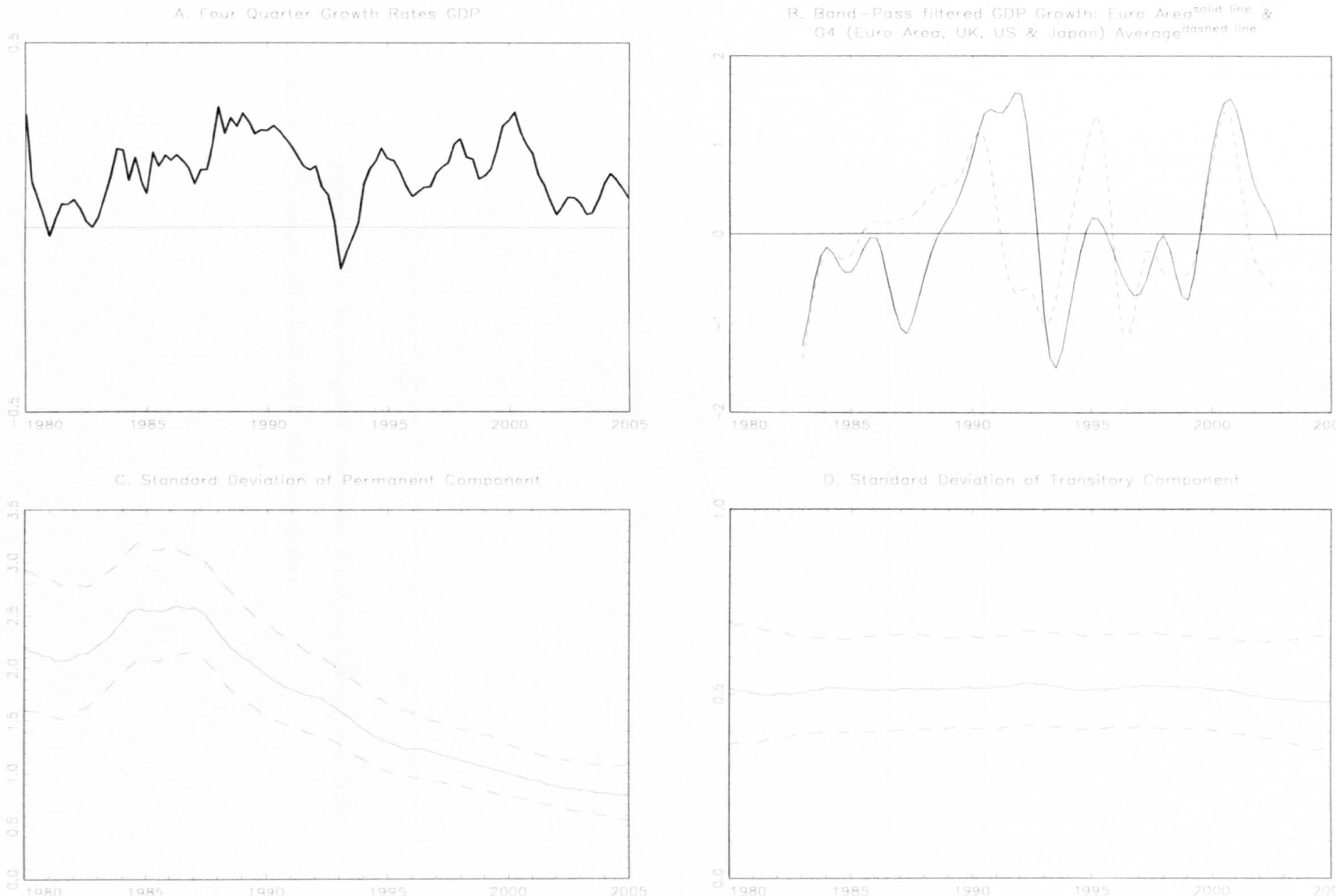
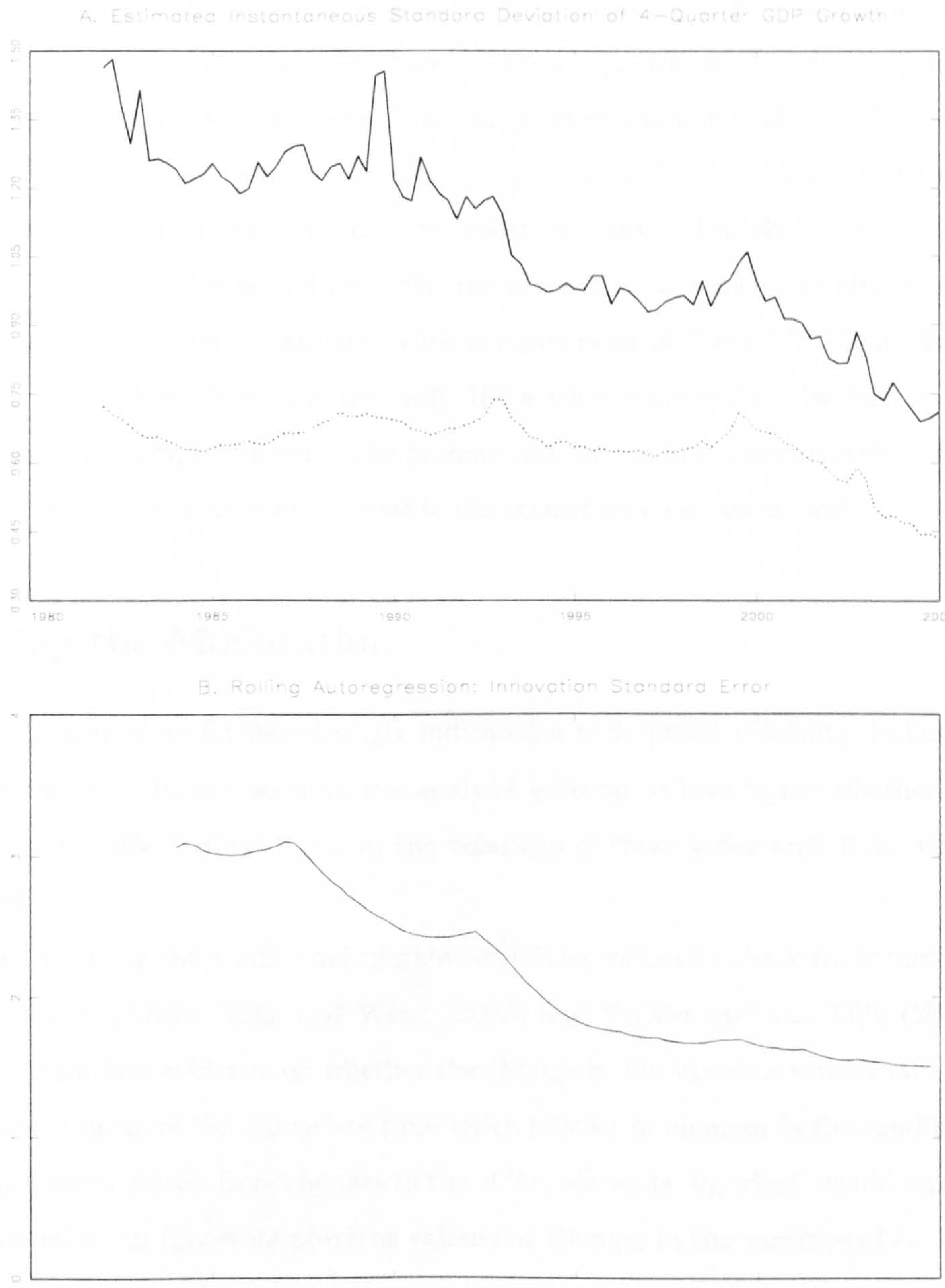


Figure 4.2. Time Path of Volatility in Real GDP



Note: The dashed line in the top panel represents bandpass filtered real GDP, calculated with frequencies between 6 and 32 quarters.

The analysis is taken one step further by decomposing output into its permanent and transitory components. Output is decomposed as $y_t = \tau_t + \eta_t$, where $\tau_t = \tau_{t-1} + \epsilon_t$ is a stochastic trend component. The errors are $\eta_t = \sigma_{n,t}\gamma_{n,t}$ and $\epsilon_t = \sigma_{s,t}\gamma_{s,t}$, where $\gamma_t = (\gamma_{n,t}, \gamma_{\epsilon,t}) \sim i.i.d.(0, I_2)$. The logarithms of the error variances evolve as independent random walks, $\ln\sigma^2_{n,t} = \ln\sigma^2_{n,t-1} + \psi_{n,t}$ and $\ln\sigma^2_{\epsilon,t} = \ln\sigma^2_{\epsilon,t-1} + \psi_{\epsilon,t}$, where $\psi_t = (\psi_{n,t}, \psi_{\epsilon,t}) \sim i.i.d.(0, \zeta I_2)$, with ζ being a scalar which controls the smoothness of the stochastic volatility process. Finally, γ_t and ψ_t are mutually independent. Note that this model has only one parameter, ζ, which can either be estimated or chosen *a priori*. The model is estimated with a vague prior of $\zeta = 0.2$.[6] Figure 4.1 part C plots $\sigma^2_{\epsilon,t}$ and $\sigma^2_{n,t}$. The results show that the early 1980s were characterised by high variations in the permanent component, τ_t, of output. The pronounced decline in the permanent component occurs from the late 1980s. This stands in contrast to the transitory component, which shows little decline in volatility.

4.3 Dating the Moderation

The evidence presented so far has strongly indicated a widespread volatility decline in the major economic time series. In this section, the analysis goes on to investigate whether this decline is associated with a single distinct break in the volatility of these series and, if so, when this might have occurred.

In contrast to using the traditional markov-switching model to check for structural breaks, as in Kim and Nelson (1999), Mills and Wang (2003) and Sensier and van Dijk (2004), Table 4.3 examines the univariate evidence on whether the change in the variance is associated with changes in the conditional mean of the univariate time series process or changes in the conditional variance. Variance changes could arise from changes in the AR coefficients, θ_t, which would represent changes in the conditional mean (given its previous values) or changes in the variance of ϵ_t. The change in the variance of a series can be associated with changes in its spectral shape, changes in the level of its spectrum,[7] or both (Stock and Watson, 2002). The attraction of the time-varying parameter model is that, by permitting the coefficients to evolve stochastically over time, it can be applied to models with parameter instability. The results in Table 4.3 are obtained from the following AR model,

[6]Changing the value of the prior, γ, has little overall effect on the shape of Figures 1.C and 1.D. The value is taken from Stock and Watson (2007).

[7]See Cogley and Sargent (2005), Seniser and Dijk (2001), Blanchard and Simon (2001) and Kim and Nelson (1999).

$$y_t = \alpha_t + \theta_t(L)y_{t-1} + \epsilon_t$$

where

$$\alpha_t + \theta_t(L) = \begin{matrix} \alpha_1 + \theta_1(L), & t \leq \kappa \\ \alpha_2 + \theta_2(L), & t > \kappa \end{matrix} \qquad \text{and } Var(\epsilon_t) = \begin{matrix} \sigma_1^2, t \leq \tau \\ \sigma_2^2, t > \tau \end{matrix}$$

$\theta_t(L)$ is a lag polynomial and κ and τ are break dates in the conditional mean and variance. The heteroskedasticity-robust Quandt (1960) likelihood ratio (QLR) statistic is used to test for a break in the conditional mean.[8] The QLR-test checks for the break date varying within 70 percent of the sample data; a 15 percent trimming. As mentioned by Stock and Watson (1998, 2002a, 2003a), the QLR test statistic has power over other forms of time variation such as drifting parameters. The conditional variance break is also calculated by the QLR statistic, which looks for a break in the mean of the absolute value of the residuals from the estimated AR model above, where the model allows for a break in the AR parameters at the estimated break date $\widehat{\kappa}$. The test for a break in the conditional variance is computed with the errors recovered from the above AR equation, which are denoted $\widehat{\epsilon}_t(\widehat{\kappa})$, where the AR coefficients break at date $\widehat{\kappa}$. Under the null hypothesis of no break in the variance, $E|\epsilon_t(\kappa)|$ is constant. By contrast, under the alternative hypothesis that there is a break date τ, $E\,|\epsilon_t(\kappa)| = \sigma_1 + \lambda 1(t \geq \tau)$, where σ_1 is the first-period standard deviation and λ is the difference between the standard deviations before and after the break. Therefore, the break test is undertaken by computing the QLR statistic in the regression of $|\widehat{\epsilon}_t(\widehat{\kappa})|$ against a binary variable $1(t \geq \tau)$ using homoskedastic standard errors, where $\widehat{\kappa}$ is the least squares estimator of the break date in the AR coefficients. Table 4.3 also reports a trend-augmented version of the test, in which $|\widehat{\epsilon}_t(\widehat{\kappa})|$ is regressed against a constant, $1(t \geq \tau)$ and a time trend t, as well as the p-value for the test that the coefficient on t is zero in the regression in which $\tau = \widehat{\tau}$. The confidence intervals for the conditional variance break date are also computed from the OLS regression of $|\widehat{\epsilon}_t(\widehat{\kappa})|$ against a constant and $1(t \geq \tau)$. Consequently, as noted by Stock and Watson (2002a), if there is a break

[8]The heteroskedasticity-robust QLR test is sometimes referred to as the sup-Wald test, from Andrews (1993). The maximum Wald statistic is defined as sup-Wald$= \sup_{\tau \in (\tau_{15}, 1-\tau_{15})} F_\tau(\kappa)$, the break date being endogenously determined. The $F_\tau(\kappa)$ statistic tests the null hypothesis that the parameters are constant against the alternative that they have a single break at a fraction τ through the sample. The break date, τ, is treated as unknown *a priori*, so that these tests involve computing the sequence $F_\tau(\kappa/T)$ for $\kappa = t_0..., t_1$, and then computing a functional of this sequence. Since κ appears under the alternative hypothesis only, in the case of an unknown break-point, a nuisance parameter problem arises. Hence, following Andrews (1993), a possible break (κ) is assumed to be between 0.15κ and 0.85κ for the sustainability of the model, i.e., the central 70 percent of the sample.

in the variance of the error term in this regression, the variance will differ before and after the break.[9]

The estimates from the stochastic volatility model have added significance for the Euro area. An often heard criticism of empirical research on the Euro area is that conclusions and policy implications are based on results obtained using historical pre-Euro area data (Mihov, 2001). The finding of a break date around the time of the Euro's introduction would validate this concern.

4.3.1 Results

The model is estimated as an $AR(4)$ to ensure sufficient dynamics.[10] In the event that the QLR statistic rejects the null at the five percent level, the reported OLS estimates of the break dates $\widehat{\kappa}$ (AR coefficients) and $\widehat{\tau}$ (innovation variance) are shown. The p-values test the null hypothesis of no break. Table 4.3 includes the main macroeconomic indices. Interest rates are included in levels and first differences, since there is little general consensus on the best way of modelling interest rate changes.

Table 4.3 presents the results of the QLR test of the null of no-break. Rejection of the null implies time variation, which may possibly not be of the single break form. The break date for real GDP is estimated to be 1992:2. The 67 percent confidence interval for the break date is 1991:4 - 1992:4. This break date coincides relatively closely with the reductions seen in the permanent component of output in Figure 4.1 part C. The test rejects the null of no break in the conditional variance of real GDP at the one percent significance level (the test also rejects the null of constant variance - Appendix F). The break date of 1989:1 in the conditional variance closely matches the sudden fall in the time-varying standard deviations in Figure 4.2.

[9] The confidence interval for the break date is obtained by inverting the test of the break date, which is based upon scaling the distribution differently on either side of the break by the estimated variance. For that reason, the estimated asymmetric confidence intervals estimated express greater uncertainty about the break date in the low volatility period than in the high volatility period.

[10] The results change little, however, if the model is estimated as an $AR(2)$.

Table 4.3: Estimates and Tests for Changes in the Autoregressive Parameters

$$y_t = \alpha + \theta_t(L)y_{t-1} + \varepsilon_t$$

		Conditional Mean			Condiational Variance: Break only			Conditional Variance: Trend and break		
	Transfor-mation	*P*-value	Break date	67% confidence interval	*P*-value	Break date	67% confidence interval	*P*-value trend	*P*-value break	Break date
GDP	Δ ln	0.00	1992.2	1991:4 – 1992:4	0.00	1989:1	1988:3 – 1990:4	0.98	0.59	.
Consumption	Δ ln	0.00	1987·2	1986:4 – 1987:4	0.00	1993:3	1992:2 – 1995:1	0.97	0.23	.
Private Consumption*	Δ ln	0.01	1985:4	1985:2 – 1986:2	0.80	.	-.	0.23	0.18	.
Gov't Consumption	Δ ln	0.00	1984:4	1984:2 – 1985:2	0.23	.	.-.	0.02	0.00	1988:4
Capital Consumption	Δ ln	0 00	1995:1	1994:3 – 1995:3	0 00	1994:4	1994:3 – 1995:2	0.50	0 00	1994:4
Investment*	Δ ln	0.00	1985:1	1984:3 – 1985:3	0.43	.	.-.	0.03	0.00	1993:1
GFCF Investment	Δ ln	0.01	1987:1	1987:1 – 1988:1	0.00	1998:3	1998:1 – 2000:2	0.00	0.08	.
Residential†	Δ ln	0.00	1999:1	1998:3 – 1999:3	0.00	1996:2	1995:4 – 1997·2	0.79	0.01	1996:2
Non-Residential	Δ ln	0.00	1995:1	1994:3 – 1995:3	0.15	.	.-.	0.20	0.74	.
Exports	Δ ln	0.00	2000:4	2000:2 – 2001:2	0.44	.	.-.	0.36	0.94	.
Imports	Δ ln	0.00	1992:2	1991:4 – 1992:4	0.17	.	.-.	0.58	0.22	.
Production										
Goods (total)	Δ ln	0.00	1984:2	1983:4 – 1984:4	0.00	1992:1	1986:4 – 1992:4	0.30	0.00	1992:1
Non-Durables†	Δ ln	0.00	1999:4	1999:2 – 2000:2	0.31	.	.-.	0.12	0.42	.
Capital Goods	Δ ln	0.00	2001:1	2000.3 – 2001:3	0.70	.	.-.	0.37	0.38	.
Construction	Δ ln	0.00	2000:1	1999:3 – 2000:3	0.01	1997:1	1996:4 – 1999:2	0.62	0.04	1997:1
Producer Price Index	Δ ln	0.00	1985:3	1985:1 – 1986:1	0.25	.	.-.	0.20	0.62	.
Inflation (CPI)	Δ ln	0.00	1999:1	1998:3 – 1999:3	0.73	.	.-.	0.39	0.75	.
GDP Deflator	Δ ln	0.00	1999:4	1999:2 – 2000:2	0.00	1991:3	1991:3 – 1993:2	0.94	0.22	.
Employment	Δ ln	0.00	2000:4	2000:2 – 2001:2	0.14	.	.-.	0 01	0.05	1988:4
Unit Labour Cost	Δ ln	0.00	1993:2	1992:4 – 1993:4	0.07	.	.-.	0.01	0.10	.
Average Hours Worked	level	0.01	1991:1	1990·3 – 1991:3	0.21	.	.-.	0.02	0.03	1994:2
Composite Leading Indicator	level	0.01	1992:1	1991:3 – 1992:3	0.19	.	.-.	0.86	0.31	.
Money Stock	Δ ln	0.00	1993:4	1993:2 – 1994:2	0.01	1990:1	1981:1 – 1990:2	0.98	0.53	.
Money M1	Δ ln	0.05	1996:3	1996:1 – 1997:1	0.07	.	.-.	0.05	0.85	.
Money M3	Δ ln	0.00	2000:4	2000:2 – 2001:2	0.14	.	.-	0.67	0.25	.
Short Interest Rate*	Δ	0.07	.	.-.	0.04	1993:3	1992:4 – 1996:1	0.02	0.21	.
Long Interest Rate*	Δ	0.50	.	.-.	0.88	.	.-.	0.67	0.98	.
Short Interest Rate*	level	0.00	1992:3	1992:1 – 1993:1	0.03	1984:1	1983:3 – 1985:4	0.05	0.79	.
Long Interest Rate*	level	0.00	1995:1	1994:3 – 1995:3	0.45	.	.-	0.78	0.63	.

Notes: *The p values are based on the QLR test for changes in the coefficients of an AR(4) model. The second column is the OLS estimate of the break date. The final column shows the 67% confidence interval for the break date. The 'Conditional Mean Coefficients' are represented by the parameters α and θ. The 'Conditional Variance' corresponds to ε_t, either with or without a time trend in the QLR regression.*

The Transformations are:

Level	$X_t = Q_t$
Δ	$X_t = (Q_t - Q_{t-1})\backslash Q_{t-1}$
Δ ln	$\ln X_t = \ln Q_t - \ln Q_{t-1}$

* 1980 - 2002

† 1985 - 2005

It is perhaps not surprising to find that the break confidence intervals for GDP, 1991:4 - 1992:4 for the conditional mean and 1988:3 - 1990:4 for the conditional variance, which are periods characterised by significant structural shifts in the Euro area. The main suspects are German reunification and the collapse of the ERM regime, which meant that the Bundesbank Bank no longer acted as the *de facto* anchor for other central banks in the Euro area, indicating a significant policy shift, with a resultant change in the expectations of economic agents.[11] Hence, the initial results for real output imply the moderation to be down to a combination of changes in the level and shape of the spectrum.

Most of the consumption components have breaks in the conditional mean in the mid-1980s. The results for both output and consumption suggest the that the 'break model' is appropriate, i.e., the decline in volatility is as a distinct break leading to a reduction in the variance. The results for the other series show widespread instability, especially in the conditional mean. A third of the series reject the null hypothesis of a constant variance. Inflation also provides another interesting result, with a break date in the conditional mean at 1999:1, the exact start date of the Euro currency. A similar break date is found for the GDP deflator, which is similar to the break date of the conditional variance for real GDP.

Trend or Break?

Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Mills and Wang (2003) and Sensier and van Dijk (2004) modelled volatility reduction using Markov switching models. The Markov switching models treat the moderation in the cycle as a discrete event in contrast to Blanchard and Simon (2001). Their study found, after estimating rolling standard deviations, that the moderation witnessed in the business cycle is better viewed as a longer term trend decline in which the 1980s were a temporary aberration. In investigating the evidence for both hypotheses, the results reported in the final three columns of Table 4.3 provides evidence on the 'trend vs. break' discussion.[12] The last three columns of Table 4.3 are calculated using the QLR test regression, $|\epsilon_t| = \phi_0 + \phi_1 t + \phi_2 d_t(\tau) + \eta_t$, where $d_t(\tau)$ is a binary variable that equals one if $t \geq \tau$ and equals zero otherwise, with η_t as an error term. Hence, the QLR test is modified so that the model for heteroskedasticity includes a time trend as well as a break, thus nesting both trend and break hypotheses. Hence, the final block of Table 4.3 tests an alternative specification in which the

[11] This result differs from Artis *et al.* (2004), who found a break point in the mid-1980s.

[12] A discussion which has been at the forefront since the work of Blanchard and Simon (2001) and Kim and Nelson (1999).

innovation variance is modelled as a linear function of time with a discrete jump at an unknown break date, thereby nesting the single break and linear time trend specifications.

The results assert that the null hypothesis of no break, which still allows the possibility of a time trend in the variance, cannot be rejected. The coefficient on the time trend is also not significantly different from zero. This finding, however, does not imply that the variance for Euro area output was constant, for the test of the conditional variance rejects the no break specification at the one percent level. In addition, the estimated instantaneous standard deviations in Table 4.2 and Figure 4.2 indicate a substantial reduction in volatility over this period. Rather, the nonrejections for the Euro area implies that neither the break nor the linear-decline model - as suggested by Blanchard and Simon (2001) - provide a good summary of the changing volatility of real output for the Euro area.[13] Interestingly, other popular measures of economic activity, such as industrial production and employment, indicate a break in the variance in the late 1980s/early 1990s. The break dates are similar to the confidence intervals for the conditional variance break date for real GDP, without the inclusion of a time trend. The decline in volatility, hence, may thus be only partly attributable to a continuing trend towards lower volatility, suggesting that explanations of the decline in output volatility for the Euro area are complex. This characterisation can also be made for consumption. However, in contrast to output and consumption, the decline in the volatility of total investment can be characterised by a discrete reduction in the variance, which distinguishes investment from it's sub-components. Finally, long-term interest rates do not seem to be well described by either model. However, short-term interest rate - both levels and in differences - indicate the their decline in volatility to be attributable to part of a longer term trend decline.

4.3.2 Multivariate Estimates of Break Dates

Following Hansen (2001), a more precise estimate of the break date can be obtained using multivariate methods. Hansen (2001), when estimating structural breaks in US productivity, found that individual measures of productivity provided poor results, whereas pooling together various variables which capture different facets of US productivity changes provided a more robust estimation. Bai *et al.* (1998) show that there can be substantial gains from using multivariate inference about the break dates.

The procedure used is the same as the OLS univariate stochastic coefficient regression break

[13] A very similar result was found by Stock and Watson (2005a) for Germany and France, the two largest Euro area economies.

date model estimated above, but extended to a VAR framework as in Stock and Watson (2002a). Potential break dates, κ, are calculated using the Wald QLR statistic.[14] This method allows the researcher to find endogenous break points for all of the parameters in a VAR system. Table 4.4 reports the OLS estimator of the break date in the mean absolute residuals, as well as the associated 67 percent confidence interval computed using the formulae due to Bai *et al.* (1998). In this case, Bai *et al.* (1998) denote $L(\kappa, \beta, \Sigma)$ as a pseudo-likelihood function, admitting a break at date κ, with parameters β and covariance matrix Σ, which are retrieved from the model estimated in Table 4.3 using OLS. Maximum likelihood is then used to maximise a function of several variables. For each given κ, denoted by $(\widehat{\beta}(\kappa), \widehat{\Sigma}(\kappa))$, the estimator maximises the likelihood function $\widehat{\kappa} = \arg\max_{1 \leqq k \leqq T} L(\kappa, \widehat{\beta}(\kappa), \widehat{\Sigma}(\kappa))$. The final estimator is defined as $(\widehat{\kappa}, \widehat{\beta}(\widehat{\kappa}), \widehat{\Sigma}(\widehat{\kappa}))$.

The null of no break is tested against the alternative of a common break in the system of equations using the QLR statistic, which is computed using the VAR residuals. Table 4.4 reports the OLS break date in the mean absolute residuals and the 67 percent confidence interval, as well as a QLR test statistic which tests the null of constant variance. The first VAR gathers the main components of real activity in the Euro area. The second VAR captures labour market changes, the third VAR focuses on monetary factors, while the fourth and fifth VARs capture consumption changes and price inflation. The final VAR was included because of the arguments, noted in Cogley and Sargent (2001), for the role of inflation in aiding business cycle moderation. All VARs are estimated with a lag length of four.[15] The model is insensitive to the ordering of the VAR. Finally, before estimation all $I(1)$ variables are transformed into $I(0)$ through first differencing.

The results from the VAR encompassing different measures of economic activity rejects the null of constant variance at close to the one percent significance level, with a break date in the early 1990s. The confidence interval bounds are relatively close together, suggesting the break date is a reasonably precise estimate. Similarly, the third VAR, designed to captures changes in the monetary side of the economy, rejects the null of constant variance. Whether this is policy induced or a consequence of monetary factors reacting the economic conditions will be explored in the following subsections. The break date for the third VAR is before the break date for the first VAR. The second, fourth and final VAR cannot reject the null hypothesis of constant variance.

[14]In contrast, Bai *et al.* (1998) use the Andrews and Ploberger (1994) mean and exponential Wald tests when estimating the break date confidence intervals in VAR models.

[15]The results change little when estimated as a VAR(2).

Table 4.4: Estimates of Common Break Dates of

Variances of VAR Residuals

Variables	# vbles	QLR p-value	$\widehat{k}$	67% Conf. Int.
GDP, Total Cons, Industrial Prod & Invest.	4	0.02	1993:1	1992:1 - 1994:1
Emp., Unit Labour Costs, Avg. Hours Worked	3	0.42	1987:2	1985:2 - 1989:2
Money Stock, M1, M3, Short i_t & long i_t	5	0.02	1989:3	1988:3 - 1990:3
Imports, Gov't Cons., Private Cons. & Construction	3	0.13	1993:1	1991:1 - 1994:3
GDP Deflator, CPI & PPI	3	0.30	1986:2	1984:3 - 1987:3

In summation, the results from Tables 4.3 and 4.4 suggest a break point that lies somewhere in the early 1990s, which coincides with an observed shift in the volatility of the permanent component of output. There is evidence that a trend model would also be suitable for the modelling of GDP volatility, since Figure 4.2 illustrates the decline to be part of a longer trend decline, in which the high volatility of the early 1980s was a temporary aberration. This is also the case for total investment (see Appendix A). This stands in contrast to the production side, where total goods production is best described by a discrete reduction in the variance. All confidence intervals are relatively small, indicating that the break dates are relatively accurate.

With the results showing part of the moderation to be down to changes in the AR coefficients, it is plausible that the moderation in real output is due, in part, to lower levels of output growth, and in part to a longer term trend decline in volatility.[16] This result has a precedent in Bai *et al.* (1998), who came to a similar conclusion when analysing the three largest economies of the Euro area - France, Germany and Italy. In general, the results for the Euro area imply that the decline in output volatility is complex and, therefore, cannot be easily categorised as part of a long-term trend decline, a break, or a discrete break. The truth probably lies somewhere in between.

4.4 Impulse or Propagation

The univariate analysis suggests that the moderation is perhaps due to breaks in the conditional mean and variance. Hence, this section uses multiple sources of information to compute the

[16]This results differs from that of Germany. Mills and Wang (2003) found no structural break in the mean for Germany, but rather a break in volatility. However, they found that stabilisation of Italian business cycles has been achieved at the expense of a lower growth rate, with similar evidence for France. The results for France and Italy are more closely aligned to that of the Euro area as a whole.

conditional mean of output growth, providing information on how much of the reduction in the variance of GDP is due to changes in the VAR coefficients and how much is due to changes in the innovation covariance matrix. This is achieved in a way similar to Boivin and Giannoni (2002), Stock and Watson (2002a) and Ahmed *et al.* (2004). This section asks if the observed reduction in volatility is associated with a change in the magnitude of the VAR forecast errors - the impulses - or in the lag dynamics modelled by the VAR - the propagation - or both. Many papers try to study shocks without specifying changes in the propagation mechanism, which may be a vital flaw in business cycle analysis, since the study of shocks and propagation mechanisms are not separate exercises. Shocks are only visible if there is a specification of how they propagate to observable variables.

Given that 1992 is characterised by the collapse of the ERM, signifying significant policy changes for the Euro area, in addition to the break test results in Tables 4.3 and 4.4, the sample is split pre and post-1992. Hence, the reduced form VAR is estimated over two separate time periods, 1980 - 1992 and 1993 - 2002. This will allow a calculation of how much of the reduction in mean output growth is due to changes in the VAR coefficients and the corresponding covariance matrix, and to see whether the amount of shocks hitting the economy in the second sample period has declined relative to the first. The VAR contains real output, y_t, GDP deflator inflation, π_t, real rate of interest, r_t, and a commodity price (crude oil) index, z_t; all are estimated in first differences. The ordering of the VAR is $X_t = [y_t, \pi_t, r_t, z_t]'$.[17] A constant term, μ, is included, with trend terms omitted. The reduced form VAR takes the form,

$$X_t = \mu_i + \Phi_i(L)X_{t-1} + u_{it}, \quad Var(u_{it}) = \Sigma_i \tag{4.1}$$

where μ_i and X_t are 4×1 vectors with the subscript i denoting the first and second period, $i = 1, 2$. The covariance matrix of the residuals is represented by Σ_i; the moving-average representation can be arrived at if $D_{i,j}$ is assumed to be the matrix of coefficients of the j^{th} lag in the matrix lag polynomial, hence, $D_i(L) = [I - \Phi_i(L)L]^{-1}$. This implies the variance of the k^{th} series in X_t in the i^{th} period is,

$$Var(X_{kt}) = \left(\sum_{j=0}^{\infty} D_{ij}\Sigma_i D'_{ij} \right)_{kk} = \sigma_k^2(\Phi_i, \Sigma_i) \tag{4.2}$$

Equation (4.2) shows $\sigma_k(\Phi_i, \Sigma_i)$ to be the standard deviation of X_{kt} in period i. From this it

[17] Rotemberg and Woodford (1997) call this three variable dataset the 'minimal set' needed for an analysis of the relationship between policy variables and macroeconomic time series.

is possible to calculate the counterfactual variance of X_{kt}. For example, $\sigma_k(\Phi_1, \Sigma_1)$ represents the standard deviation of X_{kt} in period 1. With this logic, $\sigma_k(\Phi_2, \Sigma_1)$ would be the standard deviation of X_{kt} if the lag dynamics had been those of the second period and the error covariance matrix been that of the first period. These expressions are based on the population parameters. The counterfactuals can be estimated by replacing the population parameters with sample estimates.[18]

The results for GDP suggest, had the shocks of the 1980s occurred in the second time period, 1993-2002, that the second period would have been as volatile as the first period. The counterfactual combination of second period dynamics and first period shocks, $\widehat{\sigma}(\widehat{\Phi}_2, \widehat{\Sigma}_1)$, produces an estimated standard deviation of 2.09, which is higher than the first period standard deviation. In contrast, first period dynamics with second period shocks, $\widehat{\sigma}(\widehat{\Phi}_1, \widehat{\Sigma}_2)$, produces a standard deviation of 0.64. These two findings are very supportive of the view that smaller shocks impinging upon the economy have played a significant role in moderating output. The results also show, had the shocks of the second period occurred in the first period, 1980 - 1992, the first period would have been as quiescent as the second period. The changes in the covariance matrix of the unforecastable components of the VARs - the impulses, Σ_i - would appear to account for a significant proportion of the reduction in the observed volatility of output. This result is supported by all the sensitivity analysis results in Table 4.5 part B, and is personified further when using the highly volatile industrial production series as the indicator of economic activity. These conclusions appear robust to different lag length permutations, as well as using other proxies of economic activity, such as consumption and different measures of inflation. The general results for real output are very similar to that found by Stock and Watson (2002a) for the US economy and supports those conclusions made by Ahmed *et al.* (2004) and Boivin and Giannoni (2002), in which they conclude that the reduction in variance stems from smaller shocks, with changes in the propagation mechanism playing a secondary role. The changes in the reduced-form VAR innovations could arise from reductions in the variance of certain structural innovations or from changes in the Euro area's economic ability to absorb such shocks, notably through changes in the priorities of monetary policy, all of which are tested in subsequent sections.

[18]The VAR is estimated with two lags, as selected from the standard AIC and BIC lag length criterion tests.

Table 4.5: **Impled Standard Deviation from GDP Growth from Subsample VAR**

	Sample Std. Dev.		*Standard of 4-Quarter GDP Growth*			
Variance of	1980 - 1992	1993 - 2002	$\sigma(\widehat{\Phi}_1, \widehat{\Sigma}_1)$	$\sigma(\widehat{\Phi}_2, \widehat{\Sigma}_2)$	$\sigma(\widehat{\Phi}_1, \widehat{\Sigma}_2)$	$\sigma(\widehat{\Phi}_2, \widehat{\Sigma}_1)$
y_t	1.33	1.01	1.32	1.03	0.64	2.09
π_t	1.10	0.69	1.17	0.89	0.93	1.36
r_t	1.55	1.38	1.58	1.23	0.91	2.38
Sensitivity Results						
VAR(4)			1.31	0.89	0.61	1.77
Levels Data			1.34	0.79	0.79	1.45
Using long-term rate for r_t			1.39	1.28	0.91	1.98
Using metals index for z_t			1.32	1.05	0.67	2.12
z_t dropped			1.32	1.05	0.67	2.12
GDP replaced with Ind. Prod.			7.08	5.45	5.88	7.14
Replacing y_t with consumption			0.09	0.07	0.05	0.14
Replacing CPI with PPI			1.39	1.25	0.77	1.98

Notes: The entries represent the square root of the variance of four-quarter GDP growth.

The results also demonstrate that along with a fall in shock volatility, monetary policy has in the second period with first period shocks is much more volatile, perhaps a sign that monetary policy has become more reactive to shocks that hit the economy. If the first period shocks had impacted upon the economy in the second period, monetary policy (r_t), would have been more volatile than was actually the case, $\widehat{\sigma}(\widehat{\Phi}_2, \widehat{\Sigma}_1) = 2.38$ instead of $\widehat{\sigma}(\widehat{\Phi}_1, \widehat{\Sigma}_1) = 1.58$. This result is perhaps not surprising given the break date of 1992 coincides closely with the collapse of the ERM, leading to the introduction of different priorities for monetary policy in many Euro area economies.

The results for inflation imply that shock reduction has played a significant role in reducing inflation volatility. Inflation volatility in the second period, using both the second period shocks and propagation mechanism, was 0.89. Substituting the second period shocks with those of the first period, $\widehat{\sigma}(\widehat{\Phi}_2, \widehat{\Sigma}_1)$, the standard deviation is hence 1.36; the ratio is 0.65. This has potentially important implications, since Blanchard and Simon (2001) and Cogley and Sargent (2001, 2005) cite the reduction in inflation volatility as being central to the dampening of real output fluctuations in the US economy.

Table 4.5 also shows the propagation mechanism has played a very small role in reducing the volatility of inflation. The results in Table 4.5 suggest that a significant proportion of the moderation in inflation has been due to changes in the impulses of the variance-covariance matrix of unforecastable errors, Σ. This finding leans toward the view that the high inflation during the early part of the 1980s in the Euro area was more down to inflationary shocks than to any structural economic issue.

4.5 Explanations for the Great Moderation

Inferences drawn from previous sections in this chapter are sympathetic to the hypothesis that there has been a significant fall in output volatility. This section considers four potential reasons. The first discusses the financial market deregulation hypothesis. As first pointed out by Moore and Zarnowitz (1986), and more recently by Blanchard and Simon (2001), financial market developments should reduce the cyclical volatility of aggregate production. Second, the reduced form VAR impulse and propagation results suggest that a significant proportion of the decline in the variance of real GDP was attributable to changes in the covariance of the VAR innovations. This category attempts to pinpoint the main types of shocks; money shocks, fiscal shocks, productivity/balanced growth shocks and oil/commodity price shocks. Financial market developments over the last two decades are also consistent with a shift in monetary policy over the period. Hence, the third section investigates the importance of improved monetary policy for the moderation in GDP growth. This is achieved through counterfactual monetary policy estimations. Finally, the section goes on to examine the role of common factor shocks by utilising a common trends Factor Structural VAR (FSVAR). This examines the idea first set out in Sargent and Sims (1977) that a few common factors are responsible for fluctuations in economic activity.

4.5.1 The Financial Market Deregulation Hypothesis

The opening up of capital markets in the industrialised economies has meant easier access to liquidity for firms who may require it. For firms, these changes include new ways to hedge risks and improved access to financing. For individuals, these changes include the development of increasingly widespread shareholding and easier access to credit in the form of credit card debt, mortgages and second mortgages; i.e., it has become easier for households to use various types of collateral, such as property, to secure credit. As Blanchard and Simon (2001) point out for the US economy, these financial market developments allow consumers to smooth shocks to their income, resulting in smoother consumption patterns at the individual level than would have been possible without the liberalisation of credit markets. Aggregated to the macro level, the increased access of consumers to credit should result in smaller changes in consumption for a given shock to income and, because consumption accounts for two thirds of real output, a moderation of the fluctuations in real output. Gordon (1985) found that consumption shocks can play a key role in driving instability in the business cycle. It must be noted, however, that changes in financial market developments would have had most of their effect on agents ability to smooth out transitory changes in income. If Friedman's permanent income hypothesis holds true - supported by Cochrane (1994b) - such transitory fluctuations are unlikely to have caused much of the volatility in consumption anyway, since consumption patterns are driven mainly by permanent income. Therefore, it may also be plausible that looser liquidity constraints have had very little effect on smoothing consumption patterns, for households in particular.

Although the net contribution of this deregulation to the moderation of output fluctuations has proved difficult to quantify, some evidence suggests that changes in financial markets might have played an important role. One representation of this is the volatility decline in the residential housing sector. Figure 4.3 part A presents estimates of the instantaneous standard deviations of the four-quarter growth of private residential and nonresidential construction put in place. Due to a lack of a historical time series spanning back till 1980, both series begin in 1991. Even starting from 1991, the residential measure shows a marked decline in volatility during the 1990s. This is even more pronounced for nonresidential construction. One explanation for the decreased volatility in residential and nonresidential construction is the increased ability of individuals to obtain both fixed and adjustable rate mortgages. One interesting observation from Figure 4.3 part A is that the decline in volatility is stronger for residential than nonresidential construction, which is in contrast to the results found for the US economy by Blanchard and Simon (2001) and Stock and Watson (2003a).

Figure 4.3A. Estimated instantaneous standard deviation of 4-quarter growth of residential and nonresidential construction

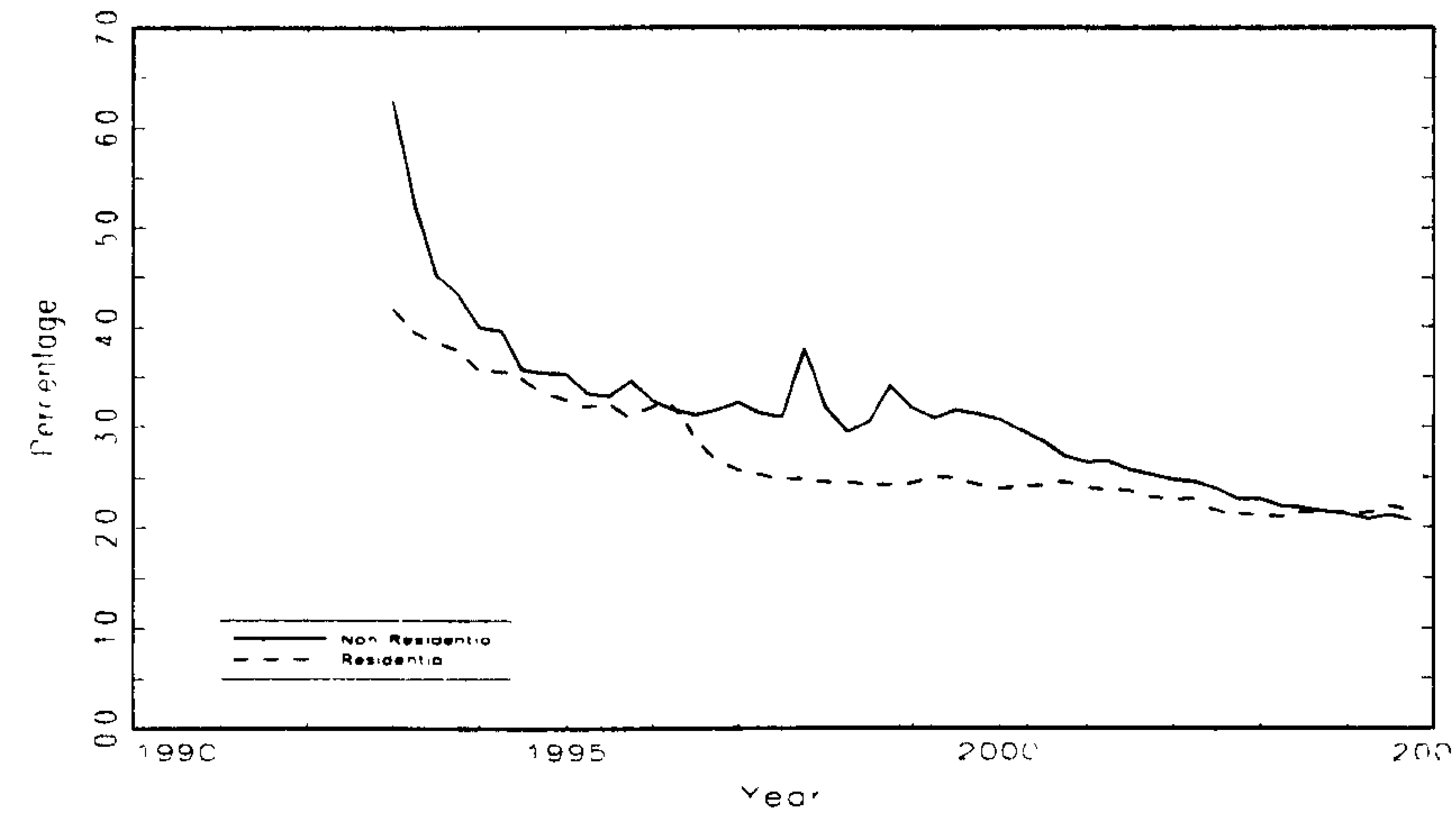
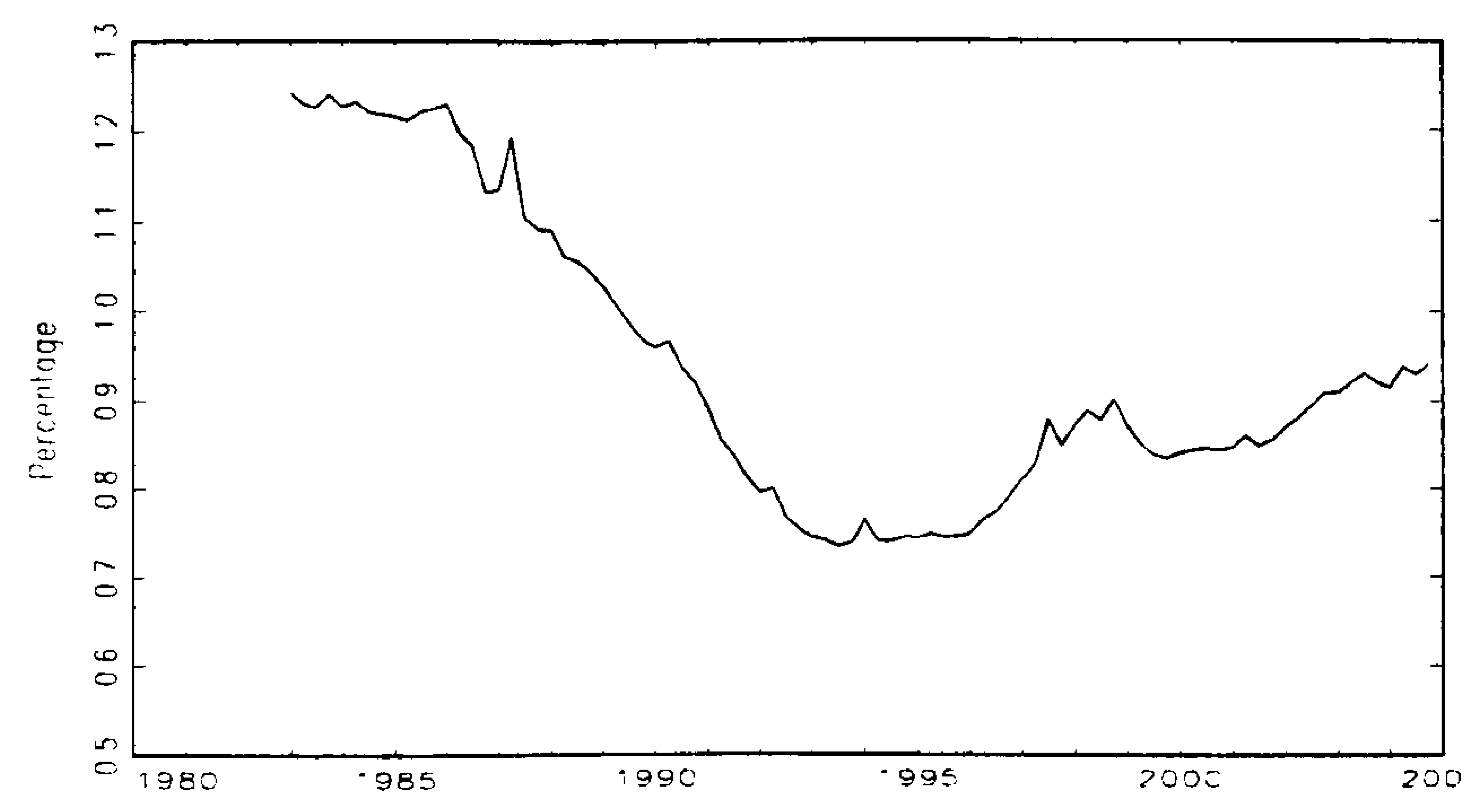


Figure 4.3B. Estimated instantaneous standard deviation of 4-quarter Consumption



Other evidence, however, raises questions about the 'financial market change' hypothesis. Easier access to liquidity should loosen constraints and, all else equal, resulted in firms and households planning smoother consumption paths. Figure 4.3 part B shows that over the past twenty five years personal consumption has become less volatile. Despite consumption volatility having been on the rise during the past decade, volatility has not reached the peak witnessed in the 1980s. However, the recent increase in the volatility of consumption might reflect the practical difficulty of using financial markets to smooth consumption, or it might simply be a consequence of greater volatility of individual income streams, as suggested by Moffitt and Gottschalk (2002). A second challenge for the financial market changes hypothesis is that the timing of these changes, which have been ongoing and gradual over the past two decades in the Euro area, does not match the continual gradual decline in volatility since the early 1980s evident in Figure 4.2. In short, although reductions in the volatility of housing construction suggest that financial market developments could have played a significant role in the great moderation, the problems of timing and the increased volatility of personal consumption suggest that there is more to the story of the great moderation than financial market developments.

4.5.2 Shocks and Surprises

The estimates from the previous section suggest that the decline in the variance of real GDP growth is partly attributable to changes in the covariance matrix of the VAR innovations, Σ. This has led many to claim that the volatility in output fluctuations in the 1970s and 1980s arose from misfortunes like the oil price crises. Conversely, less pronounced shocks over the past decade are deemed to have contributed to the decline in economic activity. This section attempts to pinpoint some of these shocks by investigating whether there is a dominant source of fluctuations that have contributed to the dampening of business cycles in the Euro area. To examine which fundamental disturbances are behind the decrease in reduced-form innovation variances, and whether the structural breaks in the coefficients are primarily in the policy rules being followed or by the structural output equation (perhaps emphasising business practices), this section moves from reduced-form VARs to structural VARs. This, of course, comes at the expense of making identification assumptions.[19] This subsection considers four types of shocks: money shocks, fiscal shocks, productivity shocks and oil/commodity price shocks.

Money Shocks

The idea that monetary policy is a major source of real fluctuations in the economy is an old one (Bernanke *et al.*, 1997). Its lasting appeal reflects the ongoing influence of monetarist ideas emanating from Friedman and Schwartz (1963). The vast amount of literature in this area has tested a variety of models in the hope of accurately capturing a monetary policy shock. However, obtaining credible measurements of monetary policy's contribution to business cycles has proved difficult. The disturbances presented in this section are often referred to as monetary policy shocks. Several authors like to think of these shocks as representing changes in monetary policy stance. However, Rudebusch (1998) criticises the use of VARs for the description of monetary policy effects,

[19] Also see Ahmed *et al.* (2004).

pointing out that monetary policy shocks obtained from VARs typically differ substantially from standard interpretations of past policy actions. In partial support, Sims (1996) insists that VARs may well provide a correct description of the economy's response to exogenous shocks, even though the interpretation of the residual shocks as historical monetary policy actions may be problematic. In addition, Christiano *et al.* (1999) suggest that monetary policy shocks may reflect exogenous shocks to preferences of the monetary authority, such as stochastic shifts in relative weights given to output versus inflation stabilisation.

To construct a historical time series of monetary shocks that have affected the Euro area economy, a Bayesian sign restriction VAR (SVAR) identification strategy due to Uhlig (2005) is performed, using the computational strategy of Mountford (2005).[20] With the sign-restricted VAR, the assumptions concern the directions of motion of several variables in response to a monetary policy shock and take the shocks satisfying those assumptions as monetary policy shocks. This seems to be a useful method, since it will reduce the likelihood of overlooking true monetary policy shocks by imposing minimum theoretical restrictions to identify monetary policy shocks.

The sign-restricted VAR belongs to the Monte Carlo simulation method, and builds upon the Bayesian VAR (BVAR) model in Uhlig (1994). Before proceeding, however, it is important to set out a few important theoretical concepts, whilst also formalising notation. Consider the following reduced-form VAR, $Y_t = B_1Y_{t-1} + B_2Y_{t-2} + \ldots + B_kY_{t-k} + u_t$. The data vector Y_t contains real GDP, the GDP deflator, the crude oil price index, a short-term real interest rate, money M1 and the real effective exchange rate (REER), making Y_t a 6×1 vector. However, to use VARs, a decomposition of the path of u_t into economically meaningful shocks or innovations is required. Let $\Sigma = E(u_t u_t')$ represent the variance-covariance matrix of the one-step ahead prediction error. Structural shocks should be uncorrelated. Let ε_t be a set of structural shocks or innovations with the identity matrix as their variance-covariance matrix. Supposing the one-step ahead prediction errors are related to the structural shocks as $u_t = A\varepsilon_t$. It then follows that $\Sigma = E(u_t u_t') = AE(\varepsilon_t \varepsilon_t')A' = AA'$. It is typically assumed that the dimension of ε_t is the same as that of u_t. Since Σ is symmetric, $\Sigma = AA'$ delivers $n(n+1)/2$ restrictions, i.e., the space of square matrices satisfying $\Sigma = AA'$ is of dimension $n(n-1)/2$, if the columns of Σ are all linearly independent (full rank). Hence, additional identifying restrictions are therefore needed to calculate A and thereby the mapping of $\varepsilon_t = A^{-1}u_t$ of the one-step ahead prediction errors into structural shocks.

Given A, the response of the vector of variables Y_{t+i} at date $t+i$ to a given structural shock

[20] A similar exercise has been undertaken by Rafiq and Mallick (2008).

j at date t, one standard deviation in size, is provided by the impulse response $r_{i,j}$, which can be calculated by recursive substitution into the reduced form VAR,

$$
\begin{aligned}
r_{0,j} &= A\mathrm{e_j} \\
r_{1,j} &= B_1 r_{0,j} \\
r_{2,j} &= B_1 r_{1,j} + B_2 r_{0,j} \\
&\vdots \\
r_{k,j} &= B_1 r_{k-1,j} + \cdots + B_k r_{0,j} \\
&\vdots \\
r_{i,j} &= B_1 r_{i-1,j} + \cdots + B_k r_{i-k,j} \\
&\vdots
\end{aligned}
$$

where $\mathrm{e_j}$ is a vector of zeros, except for a one at entry j. Consequently, the impulse responses provide a moving average representation of the data in terms of the structural shocks,

$$
\begin{aligned}
Y_t &= [I - B(L)]^{-1} A\varepsilon_t \\
&= \sum_{j=0}^{\infty} \sum_{i=0}^{n} r_{i,j}\varepsilon_{t-j,i}
\end{aligned}
$$

provided $[I - B(L)]$ is invertible.

Nonetheless, issues arise when discussing the identification of the matrix A. Should identification be achieved via Cholesky decomposition, as proposed in Sims (1980), or by structural identification, as in Sims (1986) and Bernanke (1986) and used in the second monetary model? Identification here is carried out using Uhlig's (2005) sign restriction methodology. Since the primary interest here is to estimate the response of economic variables to monetary policy shocks, there is no *a priori* reason to also identify the other $n-1$ fundamental innovations. As pointed out by Bernanke and Mihov (1998), if the central interest is in only identifying monetary policy shocks, identification need only concentrate on finding a column vector a from A that is associated with monetary policy shocks, and it is not necessary to specify all the elements of matrix A as is usual in traditional structural VAR modelling, when $n(n-1)/2$ restrictions are needed to acquire identification. Similarly, Christiano *et al.* (1999) recognise this, and use a block-recursive ordering to concentrate the identification exercise on only a limited set of variables which interact with the policy shock. In line with these studies, Uhlig's (2005) procedure amounts to identifying a single column $a \in \mathbb{R}^n$ of the matrix A in $\Sigma = AA'$, where a is called the 'impulse vector', and is the i^{th} column of A, associated with monetary innovations *only*.

To identify the impulse vector, a, corresponding to monetary policy shocks, the sign restrictions imposed are based on Mountford (2005). Hence,

Table 4.6: Sign Restrictions on Impulse Vector

Real GDP	GDP Deflator	Crude Oil Price	Real Interest	Money M1	Exchange Rate
	−		+	−	+

A contractionary monetary policy shock does not lead to an increase in prices (the price puzzle) or in money (liquidity puzzle) and does not lead to a decrease in the policy interest rate. In addition, a rise in interest rates leads to an appreciation of the exchange rate. Such assumptions are supported by the Mundell-Fleming-Dornbusch model.

Uhlig (2005) sets out two central definitions in the identification procedure of A.

Definition 1 *The vector $a \in \mathbb{R}^n$ is called an impulse vector, iif there is some matrix A, so that $AA' = \Sigma$ and so that a is a column of A.*

Given an impulse vector a, it is possible to calculate that part of the one-step ahead prediction error u_t which is attributable to the shocks and proportional to that vector. For example, as is the case in traditional structural VAR modelling, if the entire matrix A is available and a is the first column, it is enough to simply calculate $\varepsilon_t = A^{-1}u_t$ and use $\varepsilon_{t,1}$ (the first structural shock in $\varepsilon_t = [\varepsilon_{t1}, ..., \varepsilon_{tn}]'$) as the scale of the shock attributable to a. Motivated by this principal, Uhlig's (2005) second definition deals with this issue,

Definition 2 *With an impulse vector a and a one-step ahead prediction error $u_t \in \mathbb{R}^n$, then $\varepsilon_t^{(a)} \in \mathbb{R}^n$ is called the scale of a shock attributable to a, if there exists a matrix A with $A'A = \Sigma$, of which a is the j^{th} column for some j, so that $\varepsilon_t^{(a)} = (A^{-1}u)_j$.*

This ties down the scaling. In addition to these definitions, Uhlig (2005) sets out one important proposition central to the identification procedure,

Proposition 3 *With an impulse vector a and a one-step ahead prediction error u_t, the scale of the shock $\varepsilon_t^{(a)}$ attributable to a is unique and can be calculated by assuming as follows. Let $b \in \mathbb{R}^n$ solve the two equations,*

$$\begin{aligned} 0 &= (\Sigma - aa')b \\ 1 &= b'a \end{aligned}$$

The solution b exists and is unique, hence, $\varepsilon_t^{(a)} = b'u_t$ (Uhlig, 2005). Consequently, the part of the reduced form residuals, u_t, which is attributable to the shock and proportional to the impulse vector a is given by $u_t = \varepsilon_t^{(a)}a$, i.e., the appropriate column in A from $u_t = A\varepsilon_t$.

Thus, using this solution, Uhlig (2005) shows that any impulse vector a can be identified as follows. As before, let $AA' = \Sigma$ be the Cholesky decomposition of Σ. Then, a is an impulse vector if and only if there is an n-dimensional vector α of unit length so that,

$$a = A\alpha$$

The unit vector is of length one, geometrically, and only indicates the direction of the impulses but not the magnitude. Any vector of arbitrary length can be divided by its length to create a unit vector. Hence, the impulse vector a is normalised. As demonstrated by Uhlig (2005), given an impulse vector a, to calculate the appropriate impulse response, let $r_i(k) \in \mathbb{R}^n$ be the vector response at horizon k to the i^{th} shock in the Cholesky decomposition of Σ. The impulse response $r_a(k)$ for a is then given by

$$r_{(a)}(k) = \sum_{i=1}^{n} \alpha_i r_i(k)$$

Uhlig (2005) shows that, on finding a vector $b \neq 0$, such that, as previously, $0 = (\Sigma - aa')b$, and normalised so that $b'a = 1$, then,

$$\varepsilon_t^{(a)} = b' u_t$$

represents the scale of the shock at date t in the direction of the impulse vector a, and $\varepsilon_t^{(a)} a$ is the part of u_t which is attributable to that impulse vector. Essentially, b is the appropriate row of A^{-1} in $\varepsilon_t = A^{-1} u_t$. Hence, identification is achieved, and the structural disturbances can theoretically be retrieved. This method has many advantages over standard identification procedures, such as the Cholesky decomposition. The Cholesky method, however, lacks theoretical foundations. Thus, it is quite likely to overlook true monetary policy shocks. With the sign restricted VAR, however, assumptions are made concerning the directions of motion of several variables in response to a monetary policy shock and the shocks satisfying those assumptions are taken as monetary policy shocks. This seems to be a useful method, since it can reduce the likelihood of overlooking true monetary policy shocks by imposing minimum theoretical restrictions to identify such shocks.

As mentioned, the sign-restricted VAR belongs to the family of Monte Carlo simulation methods. Computation consists of the following three steps. First, a set of parameters for a reduced-form VAR is generated randomly. The Uhlig (2005) algorithm achieves this by using the data and forming a posterior distribution. The algorithm then takes a draw, (B, Σ), from the posterior, and calculates the Cholesky decomposition, $\Sigma = AA'$. Second, the impulse responses, a, are calculated. The latter is the key concept in using the sign-restricted VAR. For instance, a monetary policy impulse vector is defined as the innovations added to the VAR system in response to a unit monetary policy shock. Third, those impulse vectors whose impulse response functions satisfy the sign restrictions are kept, (B, Σ, a), whilst discarding the others. The estimation takes place with a lag length of two, selected from the AIC and BIC lag length selection tests, with the variables left in levels form. There is no inclusion of a time trend. The 'sign' methodology is robust to the presence of non-stationarity and, although it does not impose any cointegrating long-run relationship between the variables, it does not preclude their existence either. This procedure is sometimes referred to as an 'agnostic sign identification procedure', since the long-run effects are left open by the design of the identification procedure.

The final model uses a SVAR, which represents a more traditional identification procedure. The models used is often cited in the monetary policy literature, being held up as benchmark model from which to compare competitors.[21] The following describes the mechanics behind the SVAR

[21] This is also the case for the Bernanke and Mihov (1998) and Christiano and Eichenbaum (1999) models. But

model. The SVAR model starts with the structural form $B_0 Y_t = a + B(L)Y_{t-1} + \varepsilon_t$, where Y_t is a vector of n endogenous variables, $B(L)$ is the p^{th} order lag polynomial and ε_t are the structural disturbances, with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon$, which is a diagonal matrix, i.e. the structural innovations originate from uncorrelated and independent sources. In the SVAR framework the B_0 matrix plays a key role, as it connects the structural and reduced form representations. A normalisation assumption is made so that its main diagonal elements are equal to one. With the normalisation restriction, B_0 has $(n^2 - n)$ distinct unknown elements. However, the structural model given cannot be directly estimated with contemporaneous regressors, as this would lead to correlation existing between the structural error terms and the regressors in each equation. Hence, the estimation method is to estimate the reduced form model, since regressors and the reduced form residuals in each equation are uncorrelated and unbiased parameter estimates can be found. It is possible to move from the structural model to the reduced form by premultiplying by B_0^{-1} to give $Y_t = a + D(L)Y_{t-1} + u_t$, where $D(L) = B_0^{-1}B(L)$ and $u_t = B_0^{-1}\varepsilon_t$ is a $n \times 1$ vector of reduced form residuals. In this case $E(u_t u_t') = \Sigma_u = B_0^{-1}\Sigma_\varepsilon(B_0^{-1})'$. Since Σ_u is symmetric it has $(n^2 + n)/2$ distinct elements. The reduced form estimation produces coefficient matrices $D_1, ..., D_p$. These can be used to identify the structural coefficients $B_1, ..., B_p$, as they have the same number of separate elements, n^2. These estimates can be used to identify B_0 and Σ_ε. The problem now is to take the observed values of u_t and to restrict the system so as to recover the structural disturbances, $\varepsilon_t = B_0 u_t$. In order to identify the n^2 unknowns[22] from the $(n^2+n)/2$ independent elements of Σ_ε, it is necessary to impose an additional $n^2 - [(n^2+n)/2] = n^2 - n$ further restrictions to exactly identify the structural model. These restrictions are based on the model from Sims and Zha (1998). The structural disturbances, ε_t, which are of central interest so that the final column of Table 4.7 can be calculated, can then be uncovered from the SVAR model by implementing the following sets of restrictions on $B_0 u_t = \varepsilon_t$.

these models were principally designed with the US economy in mind. As such, they are difficult to modify so that they take capture the monetary transmission mechanism of the Euro area. The models estimated here, however, have the advantage of being general enough to capture a wide variety of monetary transmission channels.

[22] $n^2 - n$ values for B_0 and plus n values for $Var(\varepsilon_t)$, which gives a total of n^2 unknown coefficients.

Sims and Zha's (1998) set of restriction is

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ b_{21} & 1 & 0 & 0 & 0 \\ b_{31} & b_{32} & 1 & b_{34} & 0 \\ 0 & 0 & b_{43} & 1 & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 \end{bmatrix} \begin{bmatrix} u_t^y \\ u_t^p \\ u_t^m \\ u_t^i \\ u_i^e \end{bmatrix} = \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^p \\ \varepsilon_t^m \\ \varepsilon_t^i \\ \varepsilon_i^e \end{bmatrix} \tag{4.3}$$

The Sims and Zha (1998) model is made up of five equations and five variables; real output, inflation, money stock, nominal interest rate and the REER. The first two equations represent the sluggish action of the real sector (output and prices) to shocks in the monetary sector (money, interest rate and exchange rate). It is assumed that there is no contemporaneous impact of monetary policy, money demand and exchange rate shocks on output and prices. The third equation can be interpreted as a short-run money demand function. Money demand is allowed to respond immediately to innovations in output, prices and interest rates. The monetary policy reaction function is defined so that the monetary authorities set interest rates after observing the current money stock and the exchange rate, but do not respond contemporaneously to disturbances in output and the price level. The argument for the latter assumption is that information about output and prices is only available with a lag. Finally, the exchange rate, being an asset price, reacts immediately to all other shocks. This model is estimated with a lag length of two, based upon standard lag length selection tests. The model is estimated in levels form. The ordering of the VAR follows Sims and Zha (1998).

The standard deviation of the monetary structural shocks from the sign restriction VAR and the two SVAR models in the 1993 - 2005 sample period, relative to the standard deviation in the earlier period, are reported in Table 4.7. The results from both models suggest monetary shocks were more volatile in the first period relative to the second. However, the results suggest that monetary policy shocks have not played a stabilising role in moderating output fluctuations. Both models support one another, in that all indicate monetary policy shocks to had been a negative influence on output fluctuations in the Euro area economy.

Fiscal Policy Shocks

The first row in the fiscal policy shocks panel of Table 4.7 is calculated using the VAR sign restriction approach of Uhlig (2005), with the restrictions in accord with Mountford and Uhlig (2005). The VAR is made up of real output, GDP deflator, money M1, real interest rate, government expenditure and government revenue. This corresponds to a positive sign restriction on government spending, prices and real GDP. As before, the VAR is estimated with a lag length of two. The VAR is insensitive to ordering. All variables are estimated in levels form.

The second model is a baseline model used in Blanchard and Perroti (2002), to which they compared their derived model framework. This model is based upon the same SVAR framework described earlier. In this case, however, a recursive approach is used, which restricts B to be a $k-$dimensional identity matrix and B_0 to be a lower triangular matrix with unit diagonal, which implies the decomposition of the variance-covariance matrix $\Sigma_u = B_0^{-1}\Sigma_\varepsilon(B_0^{-1})'$. This decomposition is obtained from the Cholesky decomposition $u_t = AA'$ by defining a diagonal matrix D which has the same main diagonal as A and by specifying $B_0^{-1} = AD^{-1}$ and $\Sigma_\varepsilon = DD'$, i.e., the elements on the main diagonal of D and A are equal to the standard deviation of the respective structural shock. The recursive approach implies a causal ordering of the model variables. Note that there are $k!$ possible orderings in total. This chapter orders the variables as follows; government spending is ordered first, output is ordered second, inflation is ordered third, government revenue is ordered fourth and the interest rate is ordered last. This implies that the relationship between the reduced-form disturbances, u_t, and the structural disturbances, ε_t, takes the following form,

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix} \begin{bmatrix} u_t^g \\ u_t^y \\ u_t^\pi \\ u_t^\tau \\ u_t^i \end{bmatrix} = \begin{bmatrix} \varepsilon_t^g \\ \varepsilon_t^y \\ \varepsilon_t^\pi \\ \varepsilon_t^\tau \\ \varepsilon_t^i \end{bmatrix} \tag{4.4}$$

This particular ordering of the variables has the following economic implications; (i) Government spending does not react contemporaneously to shocks to other variables in the VAR; (ii) output does not react contemporaneously to government revenue, inflation and interest rate shocks, but is affected contemporaneously by government spending shocks; (iii) inflation does not react contemporaneously to government revenue and interest rate shocks, but is affected contemporaneously by government spending and output shocks; (*iv*) government revenue does not react contemporaneously to interest rate shocks, but is affected contemporaneously by government spending, output and inflation shocks; (*v*) the interest rate is affected contemporaneously by all shocks in the system. Note that after the initial period the variables in the system are allowed to interact freely, for example, government revenue shocks can affect output in all periods after the one in which the shock occurred.

The assumptions on the contemporaneous relations between the variables were motivated by the following arguments. Movements in government spending, unlike movements in government revenue, are largely unrelated to the business cycle. Therefore, it seems plausible to assume that government spending is not affected contemporaneously by shocks originating in the private sector. Ordering output and inflation before government revenue can be justified on the grounds that shocks to these two variables have an immediate impact on the tax base and, thus, a contemporaneous effect on government revenue. This particular ordering of variables thus captures the effects of automatic stabilisers on government revenue, while it rules out (potentially important) contemporaneous effects of discretionary tax changes on output and inflation. Ordering the interest rate last can be justified on the grounds of a central bank reaction function where the interest rate is set as a function of the output gap and inflation and, second, given that government spending and revenue as defined here (net of interest payments) are not sensitive to interest rate changes.

The results for this model suggest a zero to five percent reduction in fiscal policy shocks volatility. However, the results from both models only predict a very small contribution from fiscal policy shocks to GDP variance reduction. This result is similar to that found by Stock and Watson (2003a) for the US economy.

Productivity Shocks

Ever since Kydland and Prescott's (1982) seminal article, traditional RBC theory has claimed a central role for exogenous variations in technology as a source of economic fluctuations in industrialised economies. As discussed in Chapter 2, standard measures of productivity shocks, such as the Solow residual, suffer from measurement problems, which include variations in capacity utilisation, imperfect competition and other sources. Hence, Table 4.7 relies on three different models to capture productivity shocks. All models are generally regarded in the literature as seminal.

The first was suggested by King *et al.* (1991), and explores balanced-growth innovations using a common trends model, in which the assumptions are taken from a wide class of RBC models. The shocks are taken from Chapter 3.

The second model is that of Galí (1999, 2004), which modelled productivity shocks in a VAR framework, using both short and long-run coefficient restrictions, which supported his theoretically derived two-sector RBC model. This amounted to using a long-run restriction on labour hours worked, whilst allowing real output to be determined by the dynamics in the data. Because the innovations in labour hours worked and real output are uncorrelated, estimates of the model can be obtained using simple instrumental variable estimation. This is calculated as in Chapter 3.

The third model is that of Blanchard and Quah (1989), implemented using a long-run restriction in which demand shocks, estimated as innovations in real output, are neutral with respect to output. The model is bivariate; containing real output and unemployment. Only labour supply shocks, measured as innovations to unemployment, have a positive influence on output. In the Blanchard and Quah (1989) framework, output is integrated, but unemployment is stationary, and supply shocks are responsible for the stochastic growth component of output. The model is set out in the form $X_t = A(L)X_{t-1} + \varepsilon_t$ or $[I - A(L)L]X_t = \varepsilon_t$, where $A(L)$ is a 2×2 matrix. Given that the matrix X_t is ensured to be stationary - transforming $I(1)$ variables into $I(0)$ variables if necessary - there exists a moving-average form, $X_t = C(L)B_0u_t$, where $C(L) = [I - A(L)L]^{-1}$ and B_0 is a 2×2 matrix relating the structural disturbances and the regression residuals and is normalised. The residual covariance matrix is $E(u_tu_t') = \Sigma_u$. In this model restrictions are placed on the matrix of long-run multipliers $\Sigma_{i=1}^{p} C_i = C(1)$. Since the coefficient sums are obtained from $C(1)B_0$, these restrictions translate into the assumption that each element above the principle diagonal in $C(1)B_0$ be zero. The key point to note is that we can impose these restrictions on $C(1)B_0$ from a Choleski decomposition of $C(1)B_0B_0'(C(1))'$. The identification problem arises in that there are four unknown parameters - b_{02}, b_{03}, ε_{11} and ε_{22}, where the ε_{ij} are the structural disturbances to be identified - whereas estimation yields only three independent pieces of information from the reduced form residuals - $\sigma_u^{11}, \sigma_u^{12}, \sigma_u^{22}$ - as due to the symmetry of the covariance matrix, $\sigma_u^{12} = \sigma_u^{21}$. Therefore, one additional restriction is needed for identification. The restrictions placed on the matrix of long-run multipliers, $A(1) = C(1)B_0$, $\varepsilon_t = A(1)u_t$, are those imposed by Blanchard and Quah (1989),

$$\begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{ut} \end{bmatrix} = \begin{bmatrix} 0 & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} u_{yt} \\ u_{ut} \end{bmatrix} \tag{4.5}$$

In this case, the restrictions state that demand shocks have no long-run impact on output, so that the coefficients in $a_{11}(L)$ is zero. However, productivity shocks, i.e., shocks in unemployment, do have a long-run impact on real output and employment. The model is estimated with a lag of two, which was selected according to standard AIC and BIC lag length selection tests.

Galí's (1999, 2004) productivity shock, which investigates the relationship between output and labour productivity per hour in a SVAR framework, shows a 30 percent reduction in volatility. In contrast to Galí's (1999) shock, the balanced-growth innovations from King *et al.* (1991) illustrate that productivity shocks, although positive, have played a much reduced role in moderating the cycle. The results from the Galí (1999, 2004) and King *et al.* (1991) models show that productivity shocks, have in general, been a positive force in the reduction of real output volatility. The same analysis and interpretation can also be applied to shocks from the Blanchard and Quah (1989) model. The results suggest that productivity shocks, perhaps due to their less frequent nature, have played a positive role with regards to their effect in moderating real output fluctuations. This result would support the impressions gained from Figures 4.1 part C and D, which illustrate most of the decline in real output volatility to be as a result of a decline in the permanent component.

Table 4.7: Changes in the Standard Deviation of Various Shocks

Shocks	Period 1	Period 2	$\frac{S_{period2}}{S_{period1}}$	Rel. Contribution to GDP Var. Reduction
Monetary Policy				
Uhlig (2005)$^+$	1981- 1992	1993 - 2003	0.68	-0.03
Sims & Zha (1998)	1981 - 1992	1993 - 2003	0.61	-0.10
Productivity Shocks				
King et al. (1991)*	1981 - 1992	1993 - 2003	0.92	0.10
Gali (1999, 2004)	1982 - 1992	1993 - 2003	0.71	0.54
Blanchard & Quah (1989)	1981 - 1992	1993 - 2003	0.75	0.48
Oil Prices				
Nominal Price	1980 - 1992	1993 - 2005	0.83	0.04
Real Price	1980 - 1992	1993 - 2005	0.84	0.05
Hamilton (1996)	1980 - 1992	1993 - 2005	0.87	0.25
Commodity Prices				
All	1980 - 1992	1993 - 2003	0.97	0.38
Non-Fuel Primary Commodities	1980 - 1992	1993 - 2005	1.06	0.35
Metals	1980 - 1992	1993 - 2005	0.80	0.49

Notes: + The monetary shocks are derived using a sign restriction VAR model based on Mountford (2005). The restrictions are modelled on accepted priori beliefs of the effects of monetary shocks on the wider economy. The length of the shock is set equal to two quaters, as in Uhlig (2005). This assumption is consistent with Christiano et al. (1999) who argues that monetary policy shocks do not usually last past one to two quarters. * is a balanced growth shock, as in King et al. (1991), using a VECM model with long-run restrictions on output, consumption and investment.

Oil Price Shocks

The recent high oil prices that have affected the world economy appear not to have had the same disastrous outcome on real output across the industrialised world as was the case for the 1973 and 1979 oil price shocks. One possibility is that individuals and firms have learnt to adapt to oil price fluctuations. In contrast, Hamilton (2003, 2005a) provides a more nuanced interpretation, in which the oil price fluctuations that matter for macroeconomic stability are those that are associated with political upheaval and major supply disruptions, which in turn increase uncertainty in the minds of consumers and investors and, in some cases, induce rationing of petroleum products. Because all but one of the disruptions Hamilton (2003) identifies as important and exogenous occurred before 1984, this interpretation may explain the recently small measured effect of oil prices on the economy. Both these views - oil price effects having simply disappeared, and oil price effects being only associated with supply disruptions - may explain the historical data, but they have different implications in the sense that one of them leaves the door open for oil shocks, in the form of oil supply disruptions and turmoil in the Middle East, being potentially important in the future.

The oil price shock panel of Table 4.7 illustrates the impact of oil shocks calculated in real and nominal terms in quarterly growth rates. A third measure, due to Hamilton (1996), is also included. Hamilton (1996) investigated the affects of asymmetric oil price shocks by measuring oil price innovations as the percentage difference between the current price and the maximum price during the previous year.[23]

The nominal, real and Hamilton (1996) oil price shocks all show close to a 15 percent reduction in the variability of oil shocks from the first period relative to the second. All oil price estimates suggest a positive relative contribution of oil price shocks to the reduction in the variance of real output. This is perhaps surprising, since the second sample period includes the oil price hikes from the two Gulf war's and the very recent rises in crude oil prices due to rising demand from quickly growing developing economies like China and India. The first sample period was characterised by relatively stable oil prices compared to the 1970s.

Other commodity price shocks

The final panel in Table 4.7 shows results for a wide variety of commodity prices, which include a non-fuel commodity price index which captures food price changes, a metals and a wider industrial

[23]The construction here ranges from 1980:1 - 2004:4 using the formula as in Hamilton (1996): $\max(0, 100^* \{\ln(o_t) - \ln[\max(o_{t-1}, o_{t-2}, o_{t-3}, o_{t-4})]\})$ where o_t is the oil price variable.

materials index, labelled 'All'. The estimates are calculated in the same fashion as the oil price shocks. The results suggest that the volatility in all three indices has fallen. All indices seem to have been a positive factor in the stabilisation of the Euro area cycle.

As mentioned by Stock and Watson (2002a), it is tempting to add up the entries in the final column to produce a composite number, but this would be misleading. It is often assumed that the innovations derived in Table 4.7 are mutually uncorrelated. Yet, as pointed out by Rudebusch (1998) and Stock and Watson (2002a), this is not always the case. There remains little consensus on whether these series are plausible proxies for the structural shocks they purport to estimate.

The results suggest that the shocks in Table 4.7 provide a reasonable analysis of the role economic shocks have played in the moderation of the business cycle. The variety of shocks estimated would certainly seem to support the earlier finding of a smaller variance/covariance matrix, Σ, of unforecastable errors in the second period relative to the first in Table 4.5, i.e., smaller reduced form errors. The results support Galí and Gambetti's (2007) form of good luck, in which they describe a proportional decline in the variance of *most* shocks as 'strong good luck'.[24]

4.5.3 Institutional Change

Empirical studies, mainly on the US economy, have suggested that changes in monetary policy have played a significant role in reducing the fluctuations in output variability. There have been a number of studies investigating the extent to which a change in monetary policy has led to a reduction in the variance of output growth. Seminal work includes Clarida *et al.* (2000), Galí *et al.* (2002), Boivin and Giannoni (2002), Stock and Watson (2002a, 2003a), Giannone *et al.* (2002, 2004), Ahmed *et al.* (2004), Basistha and Startz (2004), Cogley and Sargent (2001, 2005) and Sims and Zha (2006). Indeed, Samuelson (1998) inferred that improvements in countercyclical monetary policy help explain the moderated business cycle. An illustration is the case of the US economy, where Clarida *et al.* (2000) estimate a large increase in the response to inflation from a Taylor-type monetary policy rule. This, it has been argued, has had the effect of stabilising agents expectations of inflation, which has had a consequential effect on stabilising output.

Developments in the financial markets over the last 20 years is consistent with a shift in monetary policy. Measuring the largest (median unbiased) AR root for quarterly observations of the short and long-term interest rates finds increased persistence from $\gamma_1 = 0.835$ in the first sample period

[24] They also allude to the possibility of a 'weak form' of good luck, which attributes the decline in aggregate volatility to a reduction in the variance of a small subset of the relevant shocks.

to $\gamma_1 = 0.942$ in the second sample period. Both results are consistent with the near unity root found in the general literature for short-term interest rates.

Median Unbiased Estimates of Short-term Interest Rates

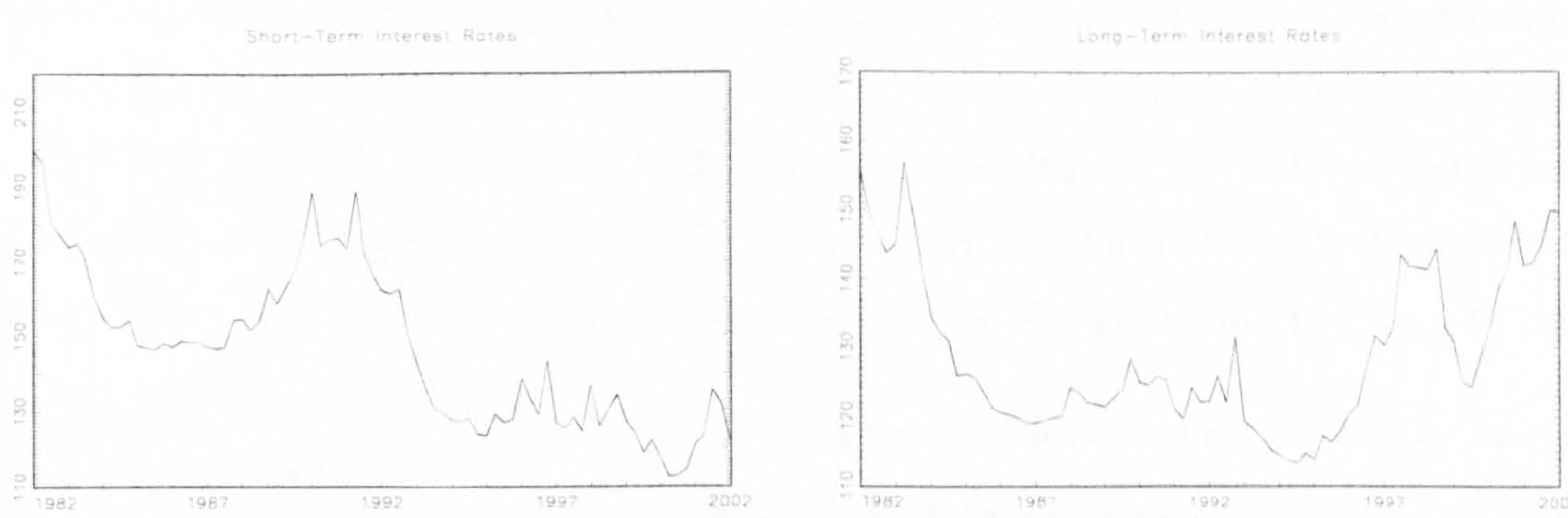
Series	Sample Period	Larg. AR Root	$\widehat{\tau}_{\mu}$	90% Conf. Interval
Short-term	1980 - 1992	0.835	-3.555	(0.727 1.024)
	1993 - 2002	0.942	-4.275	(0.824 1.035)

Note: These results are based on a univariate regression including a constant term. $\widehat{\tau}_{\mu}$ denotes the t-statistic that the sum of AR coefficients is equal to 1. The 90% confidence intervals are constructed from $\widehat{\tau}_{\mu}$, using the procedure developed in Stock (1991).

This increase in persistence has had a large effect on the variance of expected future values of the short-term rate and, hence, on the expectations component of long-term rates. Indeed, while the variance of the short rates have fallen since the break date, 1992, the variance of the long rate, relative to short rates, has increased. Taken together, it appears there has been a shift in monetary policy priorities pre and post-1992, which has led to an increase in the variability of long-term interest rates.

Figure 4.4 highlights the fall in volatility of short-term interest rates to be very close to the break date of 1992. Similarly, this break date is near the point at which the volatility in long-term rates start rising. The rise in long-term rates, post-1992, suggest agents anticipate less accommodating monetary policy; a view supported by the coefficient estimates in Table 4.8.

Figure 4.4. Standard Deviation of Short and Long-term Interest Rates



In deciphering the effects of monetary policy on output, the general strategy in the literature has been to combine some structural intuition with VARs that fit the dynamics of the data, but within this general framework the details of the approach differ widely (Stock and Watson, 2002a).

A counterfactual policy evaluation is performed using real GDP (y_t), GDP deflator inflation (π_t), a short-term interest rate (r_t), and a crude oil price commodity index (z_t). The identification is based on a model with an IS equation, a forward-looking New Keynesian Phillips Curve (NKPC), a forward looking Taylor-type monetary policy rule and a crude oil price index, which acts as an exogenous variable. The virtue of this weakly restricted estimated specification remains that it is plausible in the context of a wide variety of macroeconomic frameworks.

$$y_t = \theta r_t + \sum_{j=1}^{p} \varphi_j y_{t-j} + \varepsilon_{y,t} \tag{4.6}$$

$$\pi_t = \gamma Y(\delta)_t + \sum_{j=1}^{p} \varphi_j \pi_{t-j} + \varepsilon_{\pi,t} \tag{4.7}$$

$$r_t = \beta_\pi \overline{\pi}_{t+h/t} + \beta_y \overline{y}^{gap}_{t+h/t} + \varepsilon_{r,t} \tag{4.8}$$

$$z_t = \sum_{j=1}^{p} \varphi_j z_{t-j} + \alpha_y \varepsilon_{y,t} + \alpha_\pi \varepsilon_{\pi,t} + \alpha_r \varepsilon_{r,t} + \varepsilon_{z,t} \tag{4.9}$$

where r_t represents the real rate of interest, which is defined as $r_t = i_t - \overline{\pi}_{t+k/t}$[25] in which $\overline{\pi}_{t+k/t}$ is the expected average inflation rate over the next k periods, where k is the term of the interest rate i_t and $Y(\delta)_t = \sum_{i=0}^{\infty} \delta^i y^{gap}_{t+1/t}$ is the discounted expected future output gap, where $\overline{y}^{gap}_{t+h/t}$ is defined as the expected future average output gap over the next h periods.[26] Consistent with the general literature, the estimation of the New Keynesian model is usually carried out by treating inflation and its driving variable(s) as the realisation of stationary processes. The model is estimated using $y_t = \ln(Y_t/Y_{t-1})$, where Y_t is the real value of GDP; $\pi_t = 4 \times (\pi_t/\pi_{t-1})$, where π_t is constructed from GDP deflator (this is consistent with the results in Chapter 3 which showed inflation to contain a unit root); i_t is the short-term interest rate and $z_t = \ln(oil_t/oil_{t-1})$, the world oil price inflation. The model is estimated with a lag length of two.[27] Equation (4.6) is an IS equation,

[25] The real rate is actually calculated using $r_t = i_t - \Delta p$, where i_t is the nominal interest rate and Δp is inflation calculated from GDP deflator.

[26] Gali *et al.* (2001) find evidence in support of forward looking behaviour, and conclude that the NKPC fits Euro area data very well, possibly better than the US. This implies that the NKPC should be able to track actual inflation over periods with both high and disinflation for the Euro area.

[27] One way to model the inflation series in order to generate agents' next period expectations of inflation is to use first differenced inflation data. However, first differencing has some drawbacks. First differencing results in the loss of long run information in the data. Moreover, many authors - Cochrane (1991) and Stock (1991) - argue that the question of whether a series has a unit root or not is inherently unanswerable when dealing with a finite sample. From this point forward inflation will continue to be defined as used in the estimation of the New Keynesian model.

with the following equation (4.7) a hybrid NKPC with a discount factor δ.[28] The NKPC allows for forward looking behaviour with δ interpreted as the weight on forward inflation. A very similar approach was used by Galí *et al.* (2001). Equation (4.8) is a forward-looking real interest rate rule, a Taylor rule, where parameter h represents the horizon period, which is set at $h = 2$, meaning that monetary policy is set with a view to the state of output and inflation, $\overline{\pi}_{t+h/t}$ and $\overline{y}^{gap}_{t+h/t}$, two quarters ahead. Hence, equation (4.8) models the traditional trade-off between inflation and output stabilisation faced by central banks. The same short-term interest rate is used in both (4.6) and (4.8).[29] The structural innovations, ε_t, are assumed orthogonal.[30]

Before proceeding, it is important to note, that during most of the sample period in question, there was no central monetary authority in the Euro area. Consequently, estimates from the use of a monetary policy rule, in which the central bank is faced with a trade-off between output stabilisation and inflation, may appear misleading since, during the sample period, many of the central banks in the Euro area were charged with maintaining their currencies within a fixed range *vis-à-vis* the German deutschemark. However, Gerlach and Schnabel (2000) have shown that, since the early 1990s, average interest rates in the Euro area are characterised reasonably successfully by a Taylor rule. This result was given further credence by an earlier finding from Clarida *et al.* (1998), who found that a Taylor-type monetary policy reaction function is able to describe the behaviour of both the Bundesbank, which acted as the *de facto* anchor of the ERM, and the French and Italian central banks since the early 1980s. In support, more recent work by Eleftheriou *et al.* (2006) uncovered a monetary policy rule where a one-percentage point rise in the German interest rate implies almost a one-for-one rise in the French rate pre-Euro. They also found that the inclusion of the German interest rate in the policy rule for France results in a dramatic fall in the interest rate smoothing parameter for France. Since central banks in all three countries are located in economies that constitute over 70 percent of Euro area output, it is fairly reasonable to assume that any shifts that have occurred in the relationship between monetary policy and output and inflation will be captured by equation (4.8).[31]

[28] A New Keynesian Phillips curve could be represented by setting $\delta = 0$.

[29] Although in principle it would be more plausible to use a long-term rate in equation (4.6) and a short-term rate in (4.8). Both long and short-term rates could be included by adding a term structure equation, as in Bernanke *et al.* (1997).

[30] It is important to note that the model represents the 'new consensus' view on how monetary policy is conducted, which presupposes no role for money in the transmission mechanism of monetary policy. A view popularised with the rise of inflation targeting central banks.

[31] As Eichengreen and Wyplosz (1993) mention, both France and Italy imposed strict capital controls in the 1980s that made feasible their ERM participation. The controls provided each central bank with some leeway to pursue

Estimation of the model relies on *a priori* knowledge of the three key parameters θ (the slope of the IS curve), γ (slope of the Phillips relation) and δ (parameter governing the forward-looking properties of the Phillips curve relationship). However, there remains little agreement over the correct parameter values for θ, γ and δ.[32] For the Euro area, Galí *et al.* (2001) find δ to be 0.088 using a Calvo (1983) specification. Their study further finds that backward price setting has been a relatively unimportant factor behind the dynamics of Euro area inflation, which allowed Galí *et al.* (2001) to construe that backward looking behaviour is unimportant for the Euro area. This low discount rate stands in contrast to the high value set by Tillmann (2005), who simulated a variety of models with δ set between 0.91 and 0.98, finding that the fit improves with lower values of δ.

For the Phillips curve relationship, O'Reilly and Whelan (2005) estimate $\gamma = 0.596 - 0.675$, which stands in contrast to the small coefficient values found by Galí *et al.* (2001) for the Euro area. A simple snapshot of the results for the Euro area reveals very little agreement over the correct calibration parameters. Hence, the benchmark model is calibrated with the loadings $\theta = -0.20$, $\gamma = 0.25$ and $\delta = 0.50$, which are assumed to remain constant over the sample period.[33] The Phillips curve value, γ, was estimated by Clarida *et al.* (1998) in their simulations of the effects of changes in monetary policy on output and inflation variability for the EU 3.

domestic policy objectives but maintain their commitments to intervene in support of their respective currencies. Furthermore, Peersman and Smets (1999) find a standard Taylor rule, estimated from 1975:1 - 1997:4, to perform quite well for the EU(5) - Germany, France, Austria, Belgium and the Netherlands - with similar results between the countries. All five countries represent close to two-thirds and Euro area output. Thus, Smets and Wouters (2003) and Peersman and Straub (2004) estimate a Taylor rule, as in equation (4.8), to model the Euro area economy using a dynamic stochastic general equilibrium (DSGE) framework.

[32] See Gali *et al.* (2002), Rudebusch (2002), Clarida *et al.* (2000) and Rudebusch and Svensson (1999).

[33] These loading were also used by Stock and Watson (2002a). The forward looking parameter on the NKPC is very close to the estimate found by Lindé (2001).

Table 4.8: Implied Standard Deviation from Sample-Specific Structural VAR

A: Estimated Taylor Rule Coefficients, Benchmark Specification
θ=-0.20, δ=0.50, γ=0.25

	β_π	β_y
Sample Period 1	-0.951 (0.097)	0.150 (0.106)
Sample Period 2	0.501 (0.237)	0.286 (0.159)

B: Implied Standard Deviations of Four-Quarter GDP Growth, Benchmark Specification

Variable	Sample Standard Deviation		Standard deviations implied by VAR							
			VAR with $\Phi=\Phi_1$				*VAR with $\Phi=\Phi_2$*			
	1980-1992	1993-2002	Ω_1, A_1	Ω_1, A_2	Ω_2, A_1	Ω_2, A_2	Ω_1, A_1	Ω_1, A_2	Ω_2, A_1	Ω_2, A_2
GDP	1.31	1.09	1.32	1.28	0.93	0.60	1.99	1.76	1.24	0.88
Inflation	1.15	0.56	1.67	1.12	2.33	1.55	0.84	0.66	1.06	0.78
Monetary Policy Rate	1.55	1.40	1.59	1.09	1.89	0.95	2.02	1.93	1.66	1.00

C: Sensitivity Analysis: Alternative Parameter Values

IS and Phillips curve Parameters			*Estimated Taylor Rule Coefficients*				*Standard deviations implied by VAR*								
			Period 1		Period 2		*VAR with $\Phi=\Phi_1$*				*VAR with $\Phi=\Phi_2$*				
θ	γ	δ	β_π	β_y	β_π	β_y	Ω_1, A_1	Ω_1, A_2	Ω_2, A_1	Ω_2, A_2	Ω_1, A_1	Ω_1, A_2	Ω_2, A_1	Ω_2, A_2	Imp.
-0.20	0.30	0.50	-0.91	0.16	0.56	0.28	1.32	1.28	0.95	0.60	1.98	1.76	1.23	0.88	.10
-0.10	0.30	0.50	-1.02	0.06	0.46	0.19	1.32	1.30	0.71	0.60	1.98	1.80	1.05	0.88	.05
-0.00	0.30	0.50	-1.09	0.00	0.37	0.09	1.32	1.35	0.59	0.60	1.98	1.88	0.94	0.88	-.08
-0.20	0.30	0.10	-1.02	0.13	0.32	0.29	1.32	1.27	0.89	0.60	1.98	1.75	1.23	0.88	.13
-0.20	0.10	0.50	-1.05	0.12	0.33	0.29	1.32	1.27	0.86	0.60	1.98	1.75	1.22	0.88	.13
-0.20	0.50	0.50	-0.54	0.28	0.80	0.28	1.32	1.30	0.82	0.60	1.98	1.78	1.40	0.88	.05
-0.50	0.10	0.50	-0.98	0.41	0.40	0.60	1.32	1.26	1.38	0.60	1.98	1.65	1.70	0.88	.16
-0.20	0.30	0.90	-1.50	0.02	2.81	0.23	1.32	1.25	1.04	0.60	1.98	1.48	1.80	0.88	.18
-0.20	0.30	0.70	-0.12	0.41	1.00	0.27	1.32	1.32	0.64	0.60	1.98	1.80	1.93	0.88	.00
-0.20	0.10	0.70	-1.00	0.14	0.47	0.29	1.32	1.28	0.90	0.60	1.98	1.75	1.24	0.88	.10
-0.50	0.10	0.70	-0.70	0.67	0.65	0.59	1.32	1.32	1.09	0.60	1.98	1.79	1.36	0.88	.00

Notes: *Data series runs from 1980:1 till 2002:4. The two sample periods are 1980:1-1992:4 and 1993:3-2002:4. Imp. denotes the fraction of the moderation which is attributable to a change in monetary policy over the two periods.*

The counterfactual estimation is undertaken by first running a reduced form VAR of the all the variables in the four equation system and replacing the variables by the reduced form VAR residuals. The forecasts of the output gap and inflation are computed from the VAR, so that innovations in these variables are also functions of the reduced form VAR innovations. Next, innovations in the expected future gap are replaced with innovations in expected future output, which is plausible if one assumes that the forecast errors of trend output are negligible. Then, with θ, γ and δ given, the errors, ε_y and ε_π, follow from equations (4.6) and (4.7). Since the error terms are uncorrelated, these errors are in turn used as instruments to estimate the parameters in the Taylor rule, yielding ε_r. The unknown coefficients in (4.9) can then be estimated by OLS. The parameter estimates for the Taylor rule are obtained under the stated assumption that ε_r is uncorrelated with ε_y and ε_π. Hence, the errors are in turn used as instruments to estimate the parameters in the Taylor rule, yielding ε_r. Once the structural disturbances are saved, the standard errors of forecasts are computed for real output, inflation and real interest rates. Once, the structural disturbances have been calculated for all equations in the two sample periods, it remains a simple case of calculating the standard deviation.

Table 4.8 is characterised by three sets of parameters; the VAR distributed lag coefficients Φ, the covariance matrix of innovations, $\Omega = (\varepsilon_y, \varepsilon_\pi, \varepsilon_r, \varepsilon_z)$, and A which represents the structural coefficients $(\theta, \gamma, \delta, \beta_\pi, \beta_y, \alpha_y, \alpha_\pi, \alpha_r)$ that link the structural innovations and reduced form residuals. The Ω parameter - the covariance matrix - represents the change in the variability of the variables which can be attributable to shocks, with A corresponding to changes in the variability of output attributable to policy. The results are presented for the two sample periods 1980 - 1992 and 1993 - 2002; $\sigma(\Phi_i, \Omega_j, A_k)$ where i, j and k represent the two sample periods.

The estimated Taylor rule coefficients in Table 4.8 part A imply that monetary policy is less accommodating of inflation in the second period than was the case in the first period. The key result is the estimate of the coefficient on the inflation gap, $\beta_\pi = 0.50$, with a standard error of 0.24. A rise in expected annual inflation of one percent induces the ECB to raise nominal rates by 1.50, which is identical to the theorised coefficient value for expected inflation in the Taylor rule. This coefficient value is significant at the five percent level. In contrast, in the first period, if the same scenario is predicted, real interest rates fall. The results suggest the monetary authorities have taken a tougher stance against inflation in the second period relative to the first. Similarly, the second period is also characterised by a larger output gap coefficient, β_y, suggesting that output above trend is more likely to lead to a rise in interest rates.[34] Thus, holding constant expected inflation, a one percent rise in the output gap induces the ECB to increase real rates by 0.29, compared with 0.15 in period one. The implication, of course, is that the central bank responds to the real economy independently of its concern about inflation. [35]

These results are consistent with those found for the US economy by Clarida *et al.* (1998, 2000), Stock and Watson (2002a) and Ahmed *et al.* (2004), in that monetary policy in the 1980s was a lot more accommodative and expansionary than was the case in the 1990s and post-2000. The finding of less accommodating monetary policy in the second subperiod has important implications for the dampening of output fluctuations. As Taylor (1998) emphasised, if the Taylor rule coefficient on inflation is less than one then the economy can become unstable, in the sense that a surprise increase in the rate of inflation results in insufficient tightening. In many economic models, especially those with a limited role for rational expectations, insufficiently aggressive monetary policy can result in an explosive root in the difference equation describing the model's dynamics. This explosive root results in time paths for output and inflation that are unstable, so that inflation can, and eventually will, depart arbitrarily far from its target value, and output can deviate arbitrarily far from potential. A more arcane implication of the insufficiently aggressive monetary policy implied in the first subperiod by the coefficient estimates in Table 4.8 involves the idea that rational expectations play a key role. In rational expectation models, multiple equilibria arise because of self-fulfilling expectations. Expecting an inflationary boom makes it happen, because individuals in the economy correctly understand that the monetary authorities will respond too passively to an inflationary shock. Prices can jump for reasons unrelated to economic fundamentals and, once they do, the increase gets built into expectations and, hence, into future inflation.[36] These are known as 'sunspot' equilibria, as in Clarida *et al.* (2000). As a result, much work has been expended examining the role of a central bank in building up its anti-inflation credentials, which were central concerns for both the ECB, as well as the Bank of England, soon after they were given operational independence. Unlike the problem of explosive roots, in these models the sunspot equilibria are stable. The problem, from the point of economic performance, is that some of the equilibria have

[34] The fact that the monetary authorities respond more aggressively to coefficient estimates for β_y could be due to the informational content contained in the output gap about future inflationary pressures.

[35] The results are also similar to Gerlach and Schnabel (2000), who find average short-term interest rates in the Euro area can be described as following the Taylor principle.

[36] As mentioned by Ahmed *et al.* (2004), if improved monetary policy during the second period has worked predominately through ensuring a unique expectations equilibrium, innovation variances could be reduced, as shifts in expectations, unrelated to macroeconomic fundamentals, would be prevented from influencing the economy.

large 'sunspot' changes in expectations that lead to high variances of inflation and output gaps. If, however, the inflation and output gap policy responses are known to be sufficiently aggressive, then individuals recognise that the central bank will not accommodate an inflation shock, thereby eliminating these high volatility sunspot equilibria. In both scenarios, explosive roots and 'sunspot' equilibrias, the coefficient estimates for the first subperiod are more likely to result in volatile output than is the case for the coefficient estimates of the second subperiod, which are less accommodating of inflation.

Starting with $(\widehat{\Phi}_1, \widehat{\Omega}_1, \widehat{A}_1)$, the standard deviation of output growth is 1.32 in comparison to $(\widehat{\Phi}_2, \widehat{\Omega}_2, \widehat{A}_2)$, which has a standard deviation of 0.88,[37] inferring that volatility has fallen given the monetary policy regime, the structure of the economy and the shocks that have hit the economy in the second period. However, the results suggest that had the same first period shocks hit the economy, but the monetary policy regime was that of the second period with the economic structure of the first period $(\widehat{\Phi}_1, \widehat{\Omega}_1, \widehat{A}_2)$, output volatility would have been lower than was the case for the first period: 1.32 against 1.28. The results suggest that 10 percent of the decrease in the variance of output growth is due to changes in the monetary policy coefficients.[38] Put differently, most of the reduction in the variability of output stems from smaller shocks. In contrast, changes in the monetary policy coefficients are responsible for close to 70 percent of the reduction in the volatility of inflation. This indicates that the policy differences between the two time periods are quite substantial. If the monetary policy of the second period had been enacted in the first period, with the lag structure and economic shocks of the first period, $(\widehat{\Phi}_1, \widehat{\Omega}_1, \widehat{A}_2)$, inflation volatility would have been lower than it otherwise was, 1.12 instead of 1.67. If the first period policy had been imposed upon the second period, $(\widehat{\Phi}_2, \widehat{\Omega}_2, \widehat{A}_1)$, inflation volatility would have been higher than it would have otherwise, 1.06 against 0.78.

Looking at the other calibrated models in Table 4.8 part C, there remains uncertainty about whether the widely perceived shift in monetary policy in the early 1990s produced the moderation in output volatility. Looking across these results, the estimated effect of the change in monetary policy is larger when the output gap receives more weight in the Phillips curve - γ is larger - and when the NKPC curve is more forward looking - δ is more forward looking. One notable special case is when $\theta = 0$, so that monetary policy has no effect on output growth within the period. This

[37] These estimates are calculated from the sample moments of GDP.

[38] The total decrease in the variability of output suggested by the VAR is $1.32^2 - 0.88^2$. The decrease associated with the changes in A is $1.32^2 - 1.28^2$. The ratio is 0.10.

assumption corresponds to a common VAR identifying restriction as in Christiano *et al.* (1999), implying that the change in monetary policy had little to do with the decline in output growth volatility. The results show that for $\theta = 0.00$, $\gamma = 0.30$ and $\delta = 0.50$ the change in monetary policy priorities has actually led to an eight percent *increase* in output volatility. On the whole, however, the results suggest that changes in monetary policy over the two periods have played, if any, a very modest role in moderating output fluctuations.

Assertions that improved monetary policy is the cause of business cycle moderation concentrate around a few key hypotheses, the first being unstable equilibria. Monetary policy in the 1980s is characterised by 'stop-go' policies, in which the brakes on an over-heating economy were applied too hard and too late. As a result of this, along with the fact that the econometric models tested have only linear properties, the results above may not address the stop-go hypothesis. The second is the anchored inflation expectations hypothesis. The models tested above imply a fully credible central bank with the central bank's long-term inflation target known by all. However, whether inflation expectations are anchored, as is assumed by the models, is difficult to assess directly. What little evidence exists suggests that if inflation expectations are anchored, then this is a quite recent phenomenon. It is, for example, difficult to argue that inflation expectations were anchored in the mid-1980s, despite attempts to anchor inflation expectations through the fixing of exchange rates. Indeed, the literature regarding the importance of inflationary expectations only really took off in the mid-1980s. Most of the evidence revolves around the idea of a short-run trade-off between inflation and output or, expressed in terms of the unemployment rate, the slope of the short-run Phillips curve. The premise is that anchored inflationary expectations mean that the central bank can affect output growth without affecting inflation, implying that the short-run Phillips curve has become flatter or, alternatively, the sacrifice ratio (the reduction in output required for a given reduction in inflation) has increased. There has been an ongoing debate about whether the short-run Phillips curve has become flatter or, alternatively, whether the NAIRU has simply shifted. This first hypothesis is not addressed by the two models either. Tests are conducted to investigate any signs of non-linear behaviour in the Taylor rule. The estimated results are shown in Appendix C. The linear Taylor rule is extended to contain nonlinear terms, such as a threshold once inflation reaches a certain level. Despite the limitations of the model just outlined, Appendix C finds little evidence of nonlinearities, such as threshold effects, that match descriptions of stop-go policies. Even if nonlinear behaviour were present, as a statistical matter, the nonlinear policy rule would appear to be well approximated by the linear Taylor-type rule summarised in Table 4.8. In addition, the results concerning the behavioural change of the monetary authorities to changes in economic activity do raise specific issues. The idea that policy is limited to systematic reactions by the monetary authorities that change interest rates in response to changes in inflation and output is a limited definition of policy. In essence, models which place the role of expectations at their centre conclude that one explanation for the high volatility of the early subperiod may be that the economy was buffeted by volatile expectations, an equilibrium outcome that only occurred because of the nature of monetary policy in place. Such definitions do not encompass the possibility that central banks in the Euro area may have reacted in one way when they were worried about price stability, and reacted in a different way when faced with a similar economic situation when worried about maximising purchasing power. In addition, it must be noted that the model estimated assumed a closed economy. Very recent literature, has began to ask questions over how the main conclusions would change in an open economy setting with several large players.

Quantitative Evidence from Two Macro Models

The finding of changing monetary policy coefficients suggest that structural shifts in monetary policy have occurred. Consequently, this section continues to investigate whether the long-term decline in volatility may be partly attributable to the gradual development of macroeconomic policy and to the policy makers' long and variable learning curve.[39] Here the effect of improved monetary policy on output volatility through counterfactual simulations of a changing monetary policy rule is estimated. This is achieved by estimating what the standard deviation of output growth would have been under a counterfactual environment in which monetary and structural factors are post-1993, but subjected to pre-1992 shocks.

In addition to the Stock and Watson (2002a) model from the previous section, the Rudebusch and Svensson (1999) model is also estimated counterfactually. A very similar exercise was undertaken by Judd and Rudebusch (1998). The Rudebusch and Svensson (1999) model consists of three equations,

[39]The learning legacy is made up of lender of last resort facilities, deposit insurance, financial safety nets and automatic fiscal stabilisers.

$$\Delta\pi_{t+1} = \alpha_0 + \alpha_{\pi 1}\Delta\pi_t + \alpha_{\pi 2}\Delta\pi_{t-1} + \alpha_{\pi 3}\Delta\pi_{t-2} + \alpha_y y_t^{gap} + \epsilon_{t+1} \tag{4.10}$$

$$y_t^{gap} = \beta_0 + \beta_{y1} y_t^{gap} + \beta_{y2} y_{t-1}^{gap} + \beta_r(\overline{R}_t - \overline{\pi}_t) + \eta_{t+1} \tag{4.11}$$

$$R_{t+1} = \phi_0 + \phi_{R1} R_t + \phi_{R2} R_{t-1} + \phi_\pi \overline{\pi}_{t+1} + \phi_{y1} y_{t+1}^{gap} + \phi_{y2} y_t^{gap} + \psi_{t+1} \tag{4.12}$$

Equation (4.10) represents a Phillips curve where π_t and y_t^{gap} represent inflation and the output gap. Equation (4.11) represents the IS curve, where $\overline{R}_t$ and $\overline{\pi}_t$ are the four quarter averages of the short-term interest rate and inflation. The model is closed with equation (4.12), which is a Taylor rule equation from Judd and Rudebusch (1998). $\pi_t = 100 \times \ln(p_t/p_{t-1})$, where p_t is the quarterly value of the GDP deflator; $y_t^{gap} = 100 \times (y_t - y_t^{trend})$ where y_t is the quarterly value of real GDP and y_t^{trend} is the fitted value from a regression of y_t onto $(1, t, t^2)$. The model, as before, is estimated for the two sample periods: full OLS coefficient results and heteroskedastic robust standard errors for the Rudebusch and Svensson (1999) model are shown in the following table.

In general terms, as with the model estimated in Table 4.8, the Taylor rule coefficients post-1993 are not as accommodative compared with the first subsample; in other words monetary policy did not react as strongly to movements in inflation and real output in the first period as was the case in the second period. The estimations also imply an increase in interest-rate smoothing over the two periods.

The counterfactual exercise is estimated by undertaking a simple computational exercise. Equations (4.10) - (4.11) are calculated using simple OLS for the whole sample period, which is equivalent to estimating a reduced form VAR, and saving the residuals. Equation (4.12), the Taylor rule, is estimated only for the second sample period, saving the coefficient estimates and the residuals. The forecasts of the output gap and inflation are computed, so that innovations in these variables are functions of the reduced form VAR innovations. Real output and inflation are then simulated for the second period using the second period shocks and the second period Taylor rule; this represents the 'base model'. Similarly, the same regressions are run again, but this time the Taylor rule is estimated in period one only, which is the sample period characterised by less accommodative policy according to the parameter estimates of the model. Once more, the standard deviations of output and inflation are estimated by forecasting using the second period shocks, estimated previously, and policy shocks retrieved from estimating the Taylor rule in the *first* period only; this represents the 'base+pre-1992 monetary policy' column of Table 4.9. The standard deviation of the forecasted output is then computed for both periods. Similarly with the lower panel of Table 4.9, in which case the monetary policy rule is estimated for the whole sample period, but residual estimates from the two sample periods of equations (4.10) and (4.11) are alternated instead. Finally, the standard deviations of the 1980 - 1992 period are calculated in the same way, forecasting real output and inflation using the Taylor rule and the shocks from the first period only. Table 4.9 presents the results for real output only. The inflation results are contained in Appendix D.

Parameter Estimates for the Rudebusch-Svensson Model

Parameter	*1980:1 - 2002:4*	*1980:1 - 1992:4*	*1993:1 - 2002:4*
α_0	-0.165 (0.136)		
$\alpha_{\pi 1}$	-0.543 (0.116)		
$\alpha_{\pi 2}$	-0.527 (0.073)		
$\alpha_{\pi 3}$	-0.168 (0.110)		
α_y	-0.012 (0.027)		
β_0	0.029 (0.109)		
β_{y1}	1.200 (0.136)		
β_{y2}	-0.256 (0.118)		
β_r	-0.127 (0.027)		
ϕ_0		3.254 (0.659)	0.009 (0.177)
ϕ_{R1}		0.914 (0.098)	1.291 (0.130)
ϕ_{R2}		-0.387 (0.092)	-0.462 (0.123)
ϕ_π		0.341 (0.093)	0.376 (0.128)
ϕ_{y1}		0.011 (0.096)	0.512 (0.148)
ϕ_{y2}		0.154 (0.109)	-0.555 (0.150)
σ_ε	0.617		
σ_η	1.515		
σ_ξ		0.557	0.444

Note: Heteroskedastic robust standard errors are given in parenthesis.

The results from the model in Table 4.9 part A portray a very similar conclusion to the monetary models estimated in Table 4.8. As estimated in Table 4.8, monetary policy was more accommodative in the first period than was the case in the second sub period. The Rudebusch and Svensson (1999) model reveals that the less accommodative monetary policy of the first period has had a negative impact in its relative contribution to output stabilisation, i.e., monetary policy has actually *increased* the volatility of output. However, the result is very close to zero, suggesting that monetary policy has no role in the moderation of output fluctuations. As noted in Stock and Watson (2003a), however, the two models tested here focus on the use of the short-term interest rate as a tool for achieving inflation and/or output stabilisation goals over the short to medium term. Central banks, however, have a much wider remit than that considered here. Such responsibilities include short-term crisis management, such as providing liquidity and preventing financial crises. Hence, it is possible that the reduced volatility of output is in part a result of better management by the monetary authorities, a channel not addressed by conventional models of monetary policy transmission. The Rudebusch and Svensson (1999) model also suggests that over 50 percent of the variance reduction in inflation is down to improved monetary policy (Appendix D). This result is supported by the Stock and Watson (2002a) model (Appendix D). Such a result is consistent with the idea that central banks face a trade-off between inflation and output stabilisation.

Table 4.9 part B analyses output volatility under a shock based counterfactual scenario. The results in Table 4.7 and 4.8 imply that shocks, beyond monetary ones, are important in explaining the reduction in output volatility. As mentioned, Table 4.8 suggests that perhaps 10 percent of the reduction in output volatility is due to changes in the monetary policy coefficients, implying that most of the reduction is caused by other factors. This is calculated by estimating what the standard deviation of output would have been under a counterfactual scenario in which monetary policy and the economic structures are reflected in the post 1993 environment, with the economy subjected to shocks as large as those pre-1992. This estimation is undertaken with both the Rudebusch and Svensson (1999)and Stock and Watson (2003a) models. The calculations suggest that, in both the Rudebusch and Svensson (1999) and the Stock and Watson (2003a) models, four quarter growth volatility would have been larger than its actual post-1993 value. The Stock and Watson (2003a) model indicates that the decreased shock volatility explains over 50 percent of the variance reduction in output volatility. The Rudebusch and Svensson (1999) model suggests that smaller shocks can account for close to 80 percent of the variance reduction seen in the second period relative to the first. Both models imply that the output volatility increase arising from using pre-1992 shocks is much larger than the increase from using pre-1992 monetary policy, suggesting that shocks more disperse than monetary shocks are important in explaining the variance reduction in real output, supporting the assertions made in previous sections of this chapter and the literature in general.[40] This pattern is coherent with what one would expect if little changed on the real side of the economy, except that the standard deviations of all economic shocks fell. The results are also consistent with the sectoral evidence in Table 4.2, which showed widespread volatility reduction across sectors but no change in correlation with y_t. The results provide support to those found in Tables 4.5 and 4.7 in that smaller shocks hitting the economy in the second period, relative to the first, has been a significant contributor to the moderation seen in the Euro area business cycle.

Table 4.9

A: The Effect of Improved Monetary Policy on Output Volatilty

Model	Base Model	Base+pre-1992 Monetary Policy	Percent of Variance Reduction Explained
Rudebusch-Svensson	0.57*	0.56*	-1%
Historical Values			
Period	1993 - 2002	1980 - 1992	
Standard Deviation	1.09	1.27	

B: The Effect of Smaller Shocks on Output Volatility

	Base Model	Base+pre-1992 Shocks	Percent of Variance Reduction Explained
Rudebusch-Svensson	0.57	0.82	79%
Stock & Watson	0.57	0.75	58%
Historical Values			
Period	1993 - 2002	1980 - 1992	
Standard Deviation	1.09	1.27	

Notes: * Based on simulation using estimated shocks from 1993 - 2002. The base model specification reflects the actual shocks and monetary policy in the Euro area post-1993 and the resulting solved model standard deviations of output growth are reported in the first column. The second column reports the solved model standard deviations with the pre-1992 monetary policy, computed by replacing the post-1993 monetary policy rule coefficients with pre-1993 coefficients. The final row reports the actual sample standard deviations over the post-1993 and pre-1992 samples. The final column reports an estimate of the fraction of the actual reduction in the variance of output explained by the model, for example, the first entry in the final column is $(0.56 - 0.57^2) / (1.27 - 0.57^2) \approx 0.01$

[40] This result was also found by Blanchard and Simon (2001), Stock and Watson (2002a), Ahmed *et al.* (2004) and Sensier and van Dijk (2004) for the US economy.

In summary, this diverse collection of results from Tables 4.7 - 4.9 suggests that improved monetary policy has brought inflation under control (Table 4.8 suggests 70 percent of the reduction is down to changes in the monetary policy coefficients, a result also supported in Appendix D), but would seem not to totally account for the reduction in output volatility (around zero to 10 percent). A range of shocks more diverse than monetary disturbances would appear more important, supporting the conclusions drawn by Blanchard and Simon (2001), Stock and Watson (2002a, 2003b, 2005a), Sensier and van Dijk (2004), Ahmed *et al.* (2004) and Galí and Gambetti (2007), who all found similar results for the US economy.

4.5.4 Common Factor Analysis

As discussed by Lucas (1977), the business cycle commonly refers to comovements in different forms of economic activity. Influential studies from Burns and Mitchell (1946) and Mitchell (1951) provided evidence that economic activity in various sectors of the economy move together. As the foregoing discussion of the moderation of the business cycle makes clear, instability in measures of comovement could arise even if the true underlying structural relations governing macroeconomic dynamics are constant, as long as there are external changes such as changes in policy or in the types of shocks impinging on the economy. The advantage of investigating how changes in shocks, or the propagation mechanism, have changed over time by using a factor structural VAR (FSVAR) over the standard VAR or SVAR equivalents are two-fold. Firstly, the structural shocks in FSVARs can be directly mapped to structural innovations in business cycle models. Second, the volatility of structural shocks can be easily disentangled from the volatility of the VAR residuals.

As a result, this section adopts a principal first laid out in Sargent and Sims (1977). This principal argues that fluctuations in economic activity are due to a few unobserved components. Sargent and Sims (1977) found that two unobserved components explained more than 80 percent of the variance of major economic variables for the US economy, including unemployment, industrial production growth and wholesale price inflation; one of these dynamic factors is primarily associated with real variables, while the other is primarily associated with prices. The analysis here explores whether the moderation in the volatility of these common components between macroeconomic variables may have played a role in dampening Euro area output fluctuations. There are many frameworks available for developing an econometric model that permits the answering of how much, as a fraction of a variables cyclical variance, is due to common factor shocks or idiosyncratic shocks and how these shocks have evolved over time. The advantage of using factor models over VAR analysis is due to the limitations of standard VAR frameworks. As in section 4, these commonly used models require that the structural disturbances be obtained from the VAR innovations. However, for these results to be accurate, this requires the assumption that there is no omitted variable bias. Economic agents, and central banks in particular, track hundreds of variables at any one time, making omitted variable bias likely in standard VAR analysis. As such, shock identification procedures are sensitive to the fact that economic agents and policy makers base their forecasts on more variables than are usually included in any reduced form VAR. Factor models partially address this problem by increasing the amount of information in the VAR so that the innovations span a wider structural space of disturbances than conventional VAR frameworks; the three most prominent examples of the use of factor models to increase the span of information space in structural modelling is Stock and Watson (2002b, 2002c, 2005b) and Bernanke *et al.* (2005). In factor analysis, these shocks are only revealed when exploring a wide array of macroeconomic variables and distilling the small number of common sources of comovements. Long and Plosser (1987), Norrbin and Schlagenhauf (1988, 1990, 1996) and Pesaran *et al.* (1993) found that disaggregated shocks, like those tested in earlier sections, are important but aggregate shocks still remain the most important source of business cycles. Similar findings were obtained by Altonji and Ham (1990), who investigated the effects of internal and external factors of employment growth in Canada. All studies support the notion, first set out by Sargent and Sims (1977), that an economy can be modelled by a few underlying common factors.

The estimates presented below are extracted from a VAR framework, which allows for lagged effects, with the identification of common shocks as those that affect all macroeconomic time series within the same period. The model in principal is identical to a standard VAR apart from restrictions imposed on the error terms. The choice of variables is based on those that are of primary concern to macroeconomists and macroeconomic forecasters. Hence, the variables included in the data vector Y_t are real GDP, industrial production, GDP deflator, consumption, stock price index, money stock, employment, the REER and a trade balance measure. Variables which are $I(1)$ are converted into $I(0)$.[41] The variables are chosen to reflect all sectors of the economy; real, nominal, financial, international and any possible labour market changes. All variables are often used in the building of reference coincident and leading indicator series of the business cycle, as in Stock and

[41] This was examined using the standard ADF unit root test, as well as the KPSS statistic. The GDP deflator, consumption, stock price index, money stock, employment and the REER were all found to contain a unit root root. First differencing for all variables was enough to ensure stationarity.

Watson's (1991, 1992, 1993a) and Filardo (2003) coincident leading index or experimental recession index. It is often the case with factor models that the choice of variables is often at the discretion of the practitioner, with no 'right or wrong' way to proceed.

A similar econometric specification to equation (4.13) below has been exploited by Altonji and Ham (1990), Norrbin and Schlagenhauf (1996), Clark (1998), Clark and Shin (2000) and Stock and Watson (2005a). The advantage of the model is that the factor structure allows a decomposition of the $h-$step ahead forecast error for GDP growth into three sources; unforeseen common shocks, unforeseen domestic shocks and spillover effects arising from unforeseen domestic shocks to other variables in the model. The advantage of a factor model is that, since it exploits comovements between many macroeconomic time series, the dynamics of each variable can be represented as the sum of a low-dimensional component which is common to all variables in the economy and an orthogonal idiosyncratic component.

$$Y_t = A(L)Y_{t-1} + \varepsilon_t \tag{4.13}$$

$$\varepsilon_t = \Gamma f_t + \omega_t, \text{ where } E(f_t f_t') = \Sigma_{ff} = diag(\sigma_{f1}, ..., \sigma_{fk}) \; \forall \; t \text{ and } E(\omega_t \omega_t') = diag(\sigma_{\omega 1}, ..., \sigma_{\omega k}) \tag{4.14}$$

Equation (4.13) represents the reduced form model, where $A(L)$, the matrix of lag polynomials, has p_1 diagonal elements, and p_2 off-diagonal elements. The vector Y_t contains nine variables. The model is invariant to the ordering of the VAR and ε_t is $i.i.d.$ The error term ε_t is assumed to be uncorrelated with its own lags, i.e., it is serially uncorrelated. Hence, the model is estimated as a VAR$(2, 1)$.[42]

The restrictions embedded in the residuals of equation (4.13), represented by (4.14), means the FSVAR is sometimes described as an 'error model', with the following factor assumptions built into the errors terms. In equation (4.14) f_t is a $k \times 1$ vector that denotes the common international factors. Second, Γ is the $9 \times k$ matrix of factor loadings and ω_t are the variable-specific idiosyncractic shocks, with the standard normalisation assumptions applied $E(\omega_t) = 0$ and $E(\omega_t \omega_s') = 0 \; \forall \; s \neq t$ and $Cov(f_t, \omega_t) = E(f_t, \omega_t') = 0$. In essence, the matrix Γ summarises the

[42]The lag lengths are chosen based on the AIC and BIC lag length criteria tests, which are estimated using seemingly unrelated regression (SUR). It must be noted that the VAR$(2, 1)$ specification is the preferred specification, so as to reduce any sampling uncertainty associated with a small dataset in a VAR framework. This is especially so when the sample is split into the two subperiods.

contemporaneous relationships amongst the different variables in Y_t. Γ_{ij} represents the factor loading of the i^{th} variable on the j^{th} factor. Hence, each element in the factor loading matrix gives information about the effect of a unit change in the common factor on the observed vector Y_t. This matrix is of central importance in the VAR framework, as incorrect identification of Γ invalidates all subsequent economic analyses, including structural impulse response functions. It must also be noted that there remains little agreement on the shocks ω_t, since ω_t is, in fact, a white noise residual. In other words, they form part of the reduced-form VAR residuals ε_t, which is not explained by the structural, economically meaningful and interpretable shocks f_t. As a result, the idiosyncratic disturbances ω_t are sometimes used as a proxy for measurement or approximation error. This noise parameter is often referred to as a measure of 'ignorance' and, consequently, the question of what the idiosyncratic shock represents has been open to criticism and inquiry.

The dynamics are hence captured by autoregressive processes, in contrast to the approach taken by Norrbin and Schlagenhauf (1996), which modelled the dynamics as weighted averages of lagged dependent variables. Supplementary to the common factor shock, all shocks which are variable-specific, ω_t, and whose effects spillover over to other sector of the economy, will be picked up by the VAR lag dynamics p_2. This is an interesting facet of the model, since it injects a more accurate description of how modern economies operate. Assuming a shock in the REER, there is usually a lag before the effects, if any, are felt on real output. The model presented allows for this, classing such effects from a REER shock on output in the spillovers category. Equation (4.14) generalises the reduced form VAR by allowing unrestricted response coefficients on the common and variable-specific shocks.

Here there are $n > k$ common factors, where k is the number of common factors and n the number of variables. The scale of the factors is identified by the restriction that each column of Γ has unit length, that is $\Gamma_i\Gamma_i' = 1$ for $i = 1, 2$. Equation (4.14) identifies international shocks as those shocks that affect output in multiple economies contemporaneously. The coefficients in Γ determine the responsiveness of each variable to the common shocks. In principle the model laid out is similar to Watson and Engle's (1983) dynamic multiple indicator-multiple cause (DYMIMIC) model. The advantage of the use of the FSVAR over traditional reduced and structural VAR models is that the number of shocks can exceed the number of variables. In this case there are at least $9 + k$ shocks, where k is the number of common factor shocks. This model is different from recently popularised unobserved component models (known as Factor Augmented VAR - FAVAR), in which the factors are modelled explicitly using principal components. In this case equation

(4.13) would become $Y_t = A(L)Y_{t-1} + \Phi(L)F_{t-1} + \varepsilon_t$, where F is a vector of dynamic factors.[43] The framework estimated here, however, like the unobserved component framework, allows the factors to be dynamic in nature as well as associated with observed variables. In the FSVAR model, the reduced-form innovations ε_t are a linear combination of the common factor shocks, f_t, and of series-specific idiosyncratic noise ω_t. Hence, the model in explicit form is,

$$y_{it} = \sum_{s=1}^{p} a_{is} y_{i,t-s} + \sum_{s=1}^{p} a_{js} y_{jt-s} + \Gamma_{ij} f_t + \omega_{it}$$

where i represents each of the nine variables, s is the lag length and $j = 1, ..., 8$ representing the eight other variables included in the equation with lag s.

From equations (4.13) and (4.14) it is possible to estimate the variance decompositions, which are the central interest here, between the common factor and idiosyncratic shocks. The procedure follows that presented by Altonji and Ham (1990), Norrbin and Schlagenhauf (1996), Clark and Shin (2000) and Stock and Watson (2005a). Substituting the factor structural disturbances from (4.13) yields the FSVAR, $Y_t = A(L)Y_{t-1} + \varepsilon_t = A(L)Y_{t-1} + \Gamma f_t + \omega_t$. Under the normalisation and orthogonality assumptions - common factor and idiosyncratic shocks are mutually independent - it is possible to disentangle the innovation variance of Y_t into common factor and idiosyncratic components as $V(Y_t) = \Gamma f_t f_t' \Gamma' + \omega_t \omega_t' = \Gamma \Sigma_{ff} \Gamma' + \Sigma_{\omega_t}$. Restrictions are placed upon both variance - covariance matrices. To find the innovation variance that takes into account the proportion accounted for by the specific variable of total economic activity, w_t, as shown in Alontji and Ham (1990), Elliot and Fatás (1996) and Clark and Shin (2000), the decomposition would become $w'\Gamma\Sigma_{ff}\Gamma' w + w'\Sigma_{\omega_t} w$. This weighting issue is discussed in the subsequent chapter. The variance for a variable depends not only on the variances for the common factors, f_t, but also on the covariances across the variables. Thus, the variance/covariance matrix has two components; common and idiosyncratic. Inverting the reduced form into a moving-average representation, the decomposition of the common component yields $\Lambda^{com} = \Lambda_i^{com} + \Psi_{i1}\Lambda_i^{com}\Psi_{i1}' + \Psi_{i2}\Lambda_i^{com}\Psi_{i2}' + ... + \Psi_{ip}\Lambda_i^{com}\Psi_{ip}'$, where $\Lambda^{com} = \Gamma\Sigma_{ff}\Gamma'$, $\Psi_{ip} = [I - A(L)L]^{-1}$, p denotes lag length and $i = 1, ..., 9$ represents each of the nine variables. The decomposition of the domestic (idiosyncratic) component of the variance is $\Lambda^{ido} = \Lambda_i^{ido} + \Psi_{i1}\Lambda_i^{ido}\Psi_{i1}' + \Psi_{i2}\Lambda_i^{ido}\Psi_{i2}' + ... + \Psi_{ip}\Lambda_i^{ido}\Psi_{ip}'$, where $\Lambda_i^{ido} = E(\omega_t, \omega_t') = \Sigma_\omega$. The variance decompositions sum up to $\Lambda = \Lambda^{com} + \Lambda^{ido}$. Decompositions are reported for the one, two, four and eight-step ahead forecast error variances, and as in Clark and Shin (2000), calculated

[43] A very similar framework was used by Bernanke *et al.* (2005) and Stock and Watson (2005b, 2002c)

using growth rates of the vector Y_t. It is important to note that, although not estimated, the impulse response functions can also be calculated from this moving-average representation of the FSVAR model.

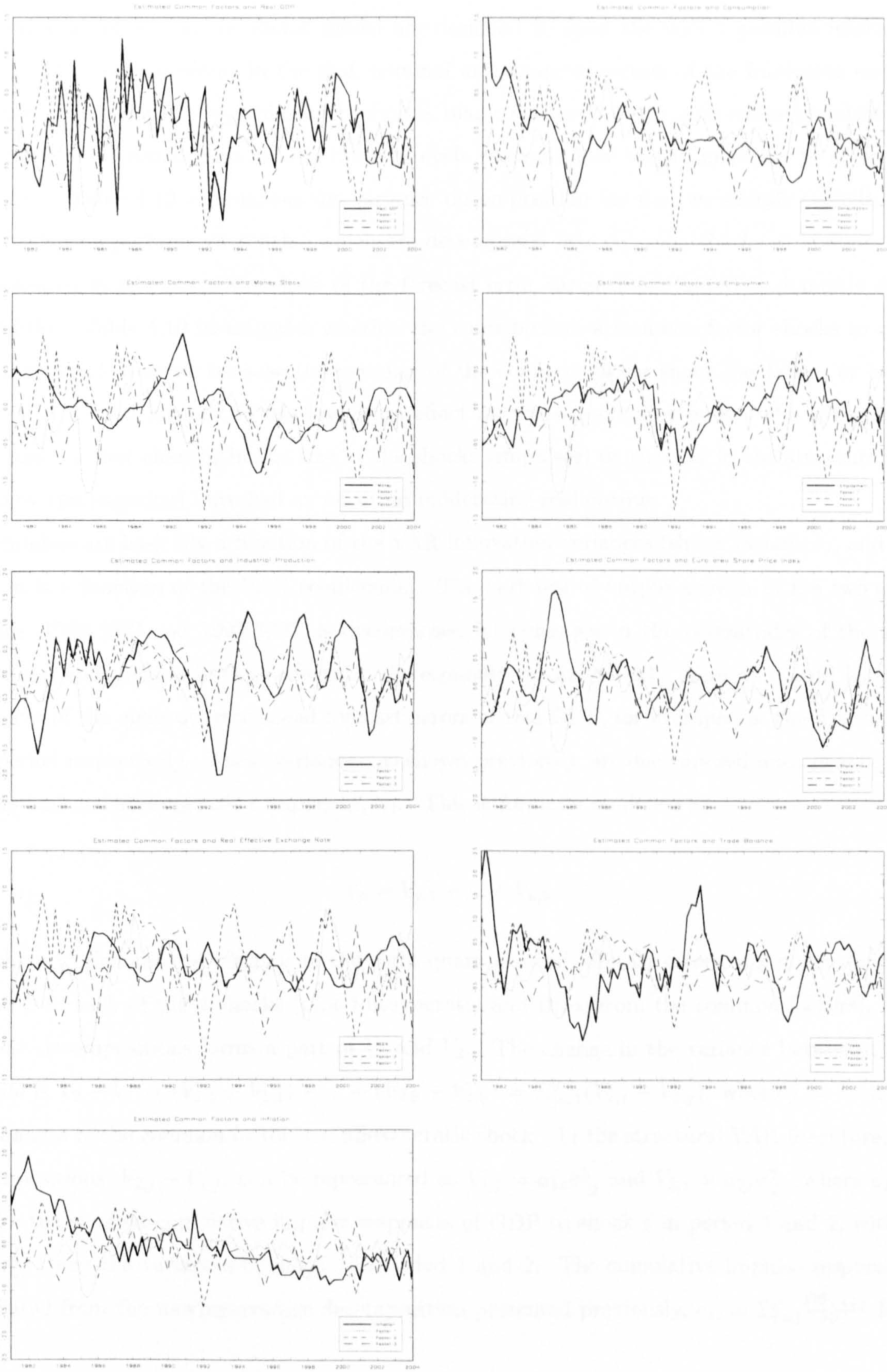
Tests of k-factor FSVAR vs. Unrestricted VAR

		1980 - 2005		*1980 - 1992*		*1993 - 2005*	
No. of k	d.f.	L.R. Statistic	p-value	L.R. Statistic	p-value	L.R. Statistic	p-value
1	2	48.1	0.01	51.3	0.00	47.7	0.01
2	1	20.9	0.34	25.2	0.15	29.9	0.05
3	1	11.2	0.51	13.9	0.31	17.5	0.13

Notes: The results are based on detrended growth rates. The cell entries are estimated from the likelihood ratio test statistic testing the null hypothesis that a VAR(2,1) error covariance matrix has a k-factor structure, against the alternative of full rank.

Likelihood ratio tests - also known as reduced rank identification - are undertaken to determine the number of factor loadings. This can only be achieved by obtaining the variance/covariance matrix, which is done by constructing GLS estimates of the regression coefficients. In both sample periods and the pooled sample, the hypothesis of $k = 1$ is rejected against the alternative of the covariance matrix, Σ_ε, having full rank at the one percent significance level; the covariance matrix is made up of linearly independent columns. In contrast, the null $k = 2$ cannot be rejected at the five percent significance level for the full and first subsample period although, for the second subsample, the p-value represents a borderline result, and can be rejected at the 10 percent level. The results suggest that $k = 2$ may be appropriate. The result for $k = 2$ would imply that the nine variables in Y_t were characterised by more coherence than was the case in the second period. The results for the second period suggest a possible divergence in the comovements of the variables. Over the full sample period, the first period coherence would appear to outweigh the second period divergence, given the result that for the full sample period $k = 2$ cannot be rejected. Tests with three common factors are undertaken, with inferences for all subperiods suggesting that it is not possible to reject the null of $k = 3$ at either the 10 or five percent significant level. An adopted specification of three common factors is accepted. This is partly as a result of the likelihood ratio tests and partly due to the arguments set out in Forni *et al.* (2001), Stock and Watson (2002b, 2002c, 2005b) and Eickmeier and Breitung (2006), in which factors are more likely to be estimated consistently if the number of common factors is overestimated, but not if the number of factors are underestimated. The factor structure imposes 27 (9×3) restrictions when $k = 3$.

Figure 4.5. Estimated Factor 1, Factor 2 and Factor 3 from FSVAR



4.5.5 Results

The variables chosen in the factor model are designed to span the widest possible information space, capturing movements in the real, nominal and financial sectors of the Euro area economy. The use of a factor model which incorporates many macroeconomic time series variables helps overcome a long standing concern in business cycle research; how best to measure the state of the economy. Table 4.10 summarises the variance decomposition for the two sample periods. The comparative importance of shocks, which are decomposed into common shocks or spillovers, can be measured as one minus the share of the forecast error variance attributed to domestic shocks. In addition, Table 4.10 investigates whether the contribution of common factor shocks to output volatility could decrease because the variance of the common factor shock has fallen, or because a shock of a fixed magnitude has less of an effect on the economy, or both. Put differently, it considers whether changes in the size of the shocks (impulses) or changes in the structure of the economy (propagation) have had an effect on moderating real output.

Impulses are basically a function of the VAR innovation variances (shock variances), and propagation is a function of the VAR coefficients. The variance of output growth in the two sample periods, 1980-1992 and 1993-2002, is decomposed into changes in the magnitudes of the shocks (impulses) and changes in their effects on the economy (propagation). Assume V_1 and V_2 are the variances of the eight quarter ahead forecast errors of real GDP, for example, in the first and second period respectively. These variances, as shown previously, are decomposed into three common factors and one idiosyncratic component, ω_t. This is formally modelled as

$$V_p = V_{p,1} + ... + V_{p,9} \tag{4.15}$$

where V_p denotes the variance of the eight-quarter-ahead forecast errors in a given variable in period p to each of the 4 shocks (nine idiosyncratic and three from the common factors). Each of these decompositions forms a part of V_1 and V_2. The change in the variance between the two periods is $V_2 - V_1 = (V_{2,1} - V_{1,1}) + ... + (V_{2,9} - V_{1,9}) = \Sigma_{j=1}^{9}(V_{2,j} - V_{1,j})$, where $j = 1, ..., 9$, are the changes in the common factor and idiosyncratic shock. In the structural VAR literature, these decompositions, $V_{2,j} - V_{1,j}$, can be represented as $V_{1,j} = a_{1j}\sigma_{1j}^2$ and $V_{2,j} = a_{2j}\sigma_{2j}^2$, where a_{1j} and a_{2j} are the squared cumulative impulse responses of GDP to shock j in period 1 and 2, with σ_{1j}^2 and σ_{2j}^2 being the variances of shock j in period 1 and 2. The cumulative impulse responses are calculated from the moving-average decomposition presented previously, $a_{ij} = \Sigma_{t=1}^{p}\frac{\partial\Psi_{i,t+s}}{\partial\Psi_{i,t}}$ for the

i^{th} variable. The variances of the shocks are determined by $\Gamma_i \Gamma_i'$ and σ_ω^2. In this case σ_{ij} denotes the variance of the i^{th} variable of Y_t. Then σ_{ij} can be written as $\sigma_{ij} = \gamma_{il}^2 + ... + \gamma_{ik}^2 + \omega_i$, where γ_i is the i^{th} row of the factor loading matrix Γ, ω_{ij} is the i^{th} element of the diagonal matrix Σ_ω, and j is the subperiod. This analysis comes from the SVAR literature, in which the variance component is the product of the cumulative impulse response of real GDP and the variance of the shock. Due to the decomposition of variance being additive, i.e., contributions can be aggregated together from those arising from common shocks, spillovers and idiosyncratic shocks, Martin and Rowthorn (2005), Stock and Watson (2005a) and Tekatli (2006) use the following formula to show that the change in the contribution of the j^{th} shock can be decomposed exactly as

$$V_{2,j} - V_{1,j} = \left(\frac{a_{1j} + a_{2j}}{2}\right)(\sigma_{2j}^2 - \sigma_{1j}^2) + \left(\frac{\sigma_{1j}^2 + \sigma_{2j}^2}{2}\right)(a_{2j} - a_{1j}) \tag{4.16}$$

In equation (4.16) the first part on the right-hand side shows the contribution from the change in the shock variance, with the second part calculating the contribution from the change in the impulse response. The changes impulses are represented by σ_{ij}^2 and changes in the propagation mechanism by a_{ij}, where $i = 1, 2$ denotes the sample period. These decompositions are additive, allowing them to be aggregated into variance changes arising from the common factor shocks, spillovers and idiosyncratic shocks. Each type of shock in turn is decomposed into changes in shock and impulse response variances. This is undertaken for each of the eight other variables.

Table 4.10 presents the decomposition of the change in variance of the four quarter-ahead forecast errors in the main macroeconomic time series. In principle, the contribution of common factor shocks to output volatility could decrease because the variance of the common factor has decreased, because a shock of a fixed magnitude has less of an effect on the economy, or both. In other words, the variance of real output, or any other macroeconomic variable, can change because the magnitude of the shocks impinging on the Euro area economy have changed or because the effects of those shocks have changed.

Table 4.10: Decomposition of Changes in the Variance of four-quarter-ahead FSVAR Forecast Errors into Changing Impulses and Changing Propagation

	Variances			*Contribution of change in Shock Variance*				*Contribution of change in Impulse function*			
	1980-1992	1993-2005	change	Factor Shocks	Spill over	own	total	Factor Shocks	Spill over	own	total
GDP	1.29 (0.33)	0.78 (0.21)	-0.52 (0.40)	-0.36 (0.32)	-0.02 (0.03)	-0.27 (0.16)	-0.65 (0.38)	-0.19 (0.44)	0.00 (0.07)	0.32 (0.14)	0.13 (0.49)
Share Price	4.74 (1.32)	2.23 (0.60)	-2.51 (1.25)	-0.33 (0.64)	-0.17 (0.13)	-0.66 (0.82)	-1.16 (0.94)	0.48 (1.06)	0.01 (0.24)	-1.84 (0.69)	-1.36 (1.40)
Cons.	3.28 (0.93)	0.59 (0.13)	-2.68 (0.94)	0.27 (0.47)	-0.10 (0.08)	0.46 (0.41)	0.63 (0.60)	-3.17 (0.92)	0.01 (0.18)	-0.15 (0.19)	-3.31 (0.96)
Employment	0.60 (0.15)	0.16 (0.04)	-0.44 (0.15)	-0.10 (0.10)	0.00 (0.01)	-0.16 (0.06)	-0.27 (0.12)	-0.16 (0.17)	0.01 (0.03)	-0.02 (0.03)	-0.17 (0.18)
Deflator	0.93 (0.22)	0.55 (0.13)	-0.38 (0.26)	-0.03 (0.17)	-0.01 (0.03)	-0.28 (0.18)	-0.32 (0.28)	-0.05 (0.31)	0.03 (0.06)	-0.04 (0.10)	-0.06 (0.34)
Money	1.51 (0.40)	1.86 (0.53)	0.34 (0.68)	-0.21 (0.36)	-0.08 (0.07)	-0.81 (0.42)	-1.10 (0.59)	0.64 (0.71)	-0.09 (0.13)	0.89 (0.40)	1.44 (0.88)
REER	0.61 (0.18)	0.39 (0.11)	-0.22 (0.21)	-0.13 (0.15)	-0.03 (0.03)	0.30 (0.13)	0.13 (0.21)	-0.41 (0.25)	0.04 (0.05)	0.02 (0.06)	-0.35 (0.28)
Ind. Prod.	5.63 (1.51)	5.52 (1.50)	-0.11 (2.15)	-2.46 (1.71)	0.04 (0.31)	-1.20 (0.63)	-3.62 (1.74)	2.76 (2.07)	0.57 (0.61)	0.17 (0.33)	3.50 (2.36)
Trade	7.06 (1.83)	3.60 (0.95)	-3.47 (2.05)	0.32 (0.95)	-0.06 (0.36)	-2.77 (0.82)	-2.51 (1.12)	-0.45 (1.48)	-0.17 (0.62)	-0.34 (0.41)	-0.96 (1.82)

Notes: *The columns under the 'Variances' subheading give the variance of the bandpass-filtered GDP in percentage terms, using the estimated FSVAR model. Finally, the sum of the 'international', 'spillover' and 'own' columns equate to the 'total' column, with the sum of the two 'total' columns equalling the 'change' column. Estimated standard errors are shown in the parentheses.*

The first fact to notice is that there has been a variance decline across all the key variables of the macroeconomy, supporting the assertion first made in Table 4.2. Indeed, with regards to real output, the first and second subperiods are differentiated by a 40 percent reduction in output volatility according to the estimated model. Second, supporting the shock based results of Table 4.5, the results in Table 4.10 support the view that changes in the variance of shocks have played a significant role in the decline of volatility in real output; smaller shocks hitting real GDP. Indeed, the decline in shock variance, 0.65, more than accounts for the drop in the variance of the real output forecast errors, 0.52. Most of the fall in the shock variance has come from the common factor rather than the idiosyncratic component, suggesting that the decline in shock variance is broad based across the whole economy, an assertion supported in Table 4.10.

This result is supported by industrial production, which has experienced a large fall in the shock variance. Like real output, the results in Table 4.10 show that the decline in the variance of industrial production is not attributed to changes in the propagation mechanism. The opposite would appear true for consumption however, with changes in the propagation mechanism playing a central role in the decline in volatility of consumption. Further, supporting the results in Table 4.2, money has been more volatile in the second period than the first.

In summation, the results suggest that shock reduction has played an important role in stabilising economic fluctuations in the Euro area. The results in Table 4.10 agree with those in Tables 4.5, 4.7 and 4.9. This does, however, leave an unsettling conclusion, that the moderation will continue only as long as the shocks impacting on the economy remain of a similar magnitude to those in the second subperiod.

4.6 Conclusion

The evidence of a decline in the volatility of economic activity, as measured by both broad aggregates and by a wide variety of other series that track specific facets of economic activity, is strong. For real output growth, the decline cannot be characterised as a break model, or as part of a continuing long-term decline in output volatility. This result suggests that the decline in output volatility for the Euro area is complex, and cannot simply be characterised as a break or trend decline. This decline in real output growth volatility coincides with similar declines witnessed in consumption and investment. The short and long-term interest rates have shown a slight rise in volatility.

The results here concur with the conclusions drawn by other authors, including Blanchard and

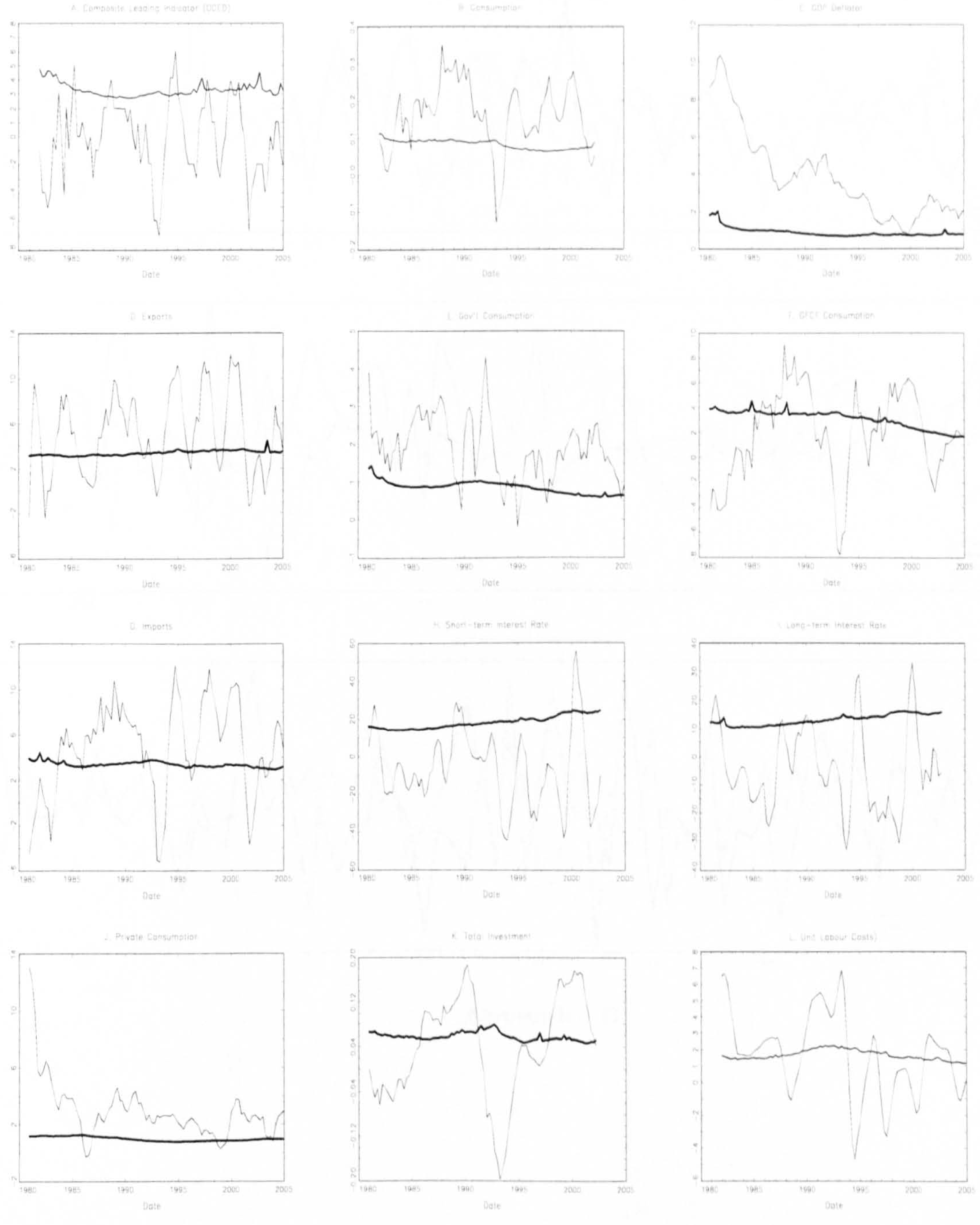
Simon (2001), Stock and Watson (2002a, 2003a) and Giannone *et al.* (2002), that the shocks hitting the Euro area have been smaller in number and size in the past 15 years, and that this must account for some of the decline in volatility. Identifiable shocks, such as productivity and oil price shocks, have played a significant role in the stabilisation of real output. Consequently, the evidence from the reduced-form model in section 4 asserts that the stabilisation in output is associated with an increase in the precision of forecasts of output growth.

With business cycle moderation due to improved monetary policy attaining little support from the results presented, zero to 20 percent, it would seem that the moderation in real output may continue even with a change in the policy regime. As seen in Tables 4.5, 4.9 and 4.11, a significant proportion of the reduction seems to be due to good luck in the form of smaller economic disturbances, which also leaves the Euro area with the same unsettling conclusion as that found for the US economy by Stock and Watson (2002a), in which the quiescence of the past two decades could well be a hiatus before a return to more turbulent economic times. In other words, the reduction in the output business cycle is more down to good luck than skill; primarily to fewer shocks hitting the Euro area economy and, secondly, to better monetary policy. If it merely is the case that the moderation reflects a decade of good luck, that is smaller macroeconomic shocks, then economists at institutions such as central banks and other monetary authorities should be prepared for a return to more turbulent business cycles of the past as soon as this period of good luck ends. Moreover, the break tests show a break in the conditional mean for Euro area real output, suggesting that the moderation in output fluctuations may not only be a case of good luck, but also due to lower economic growth.

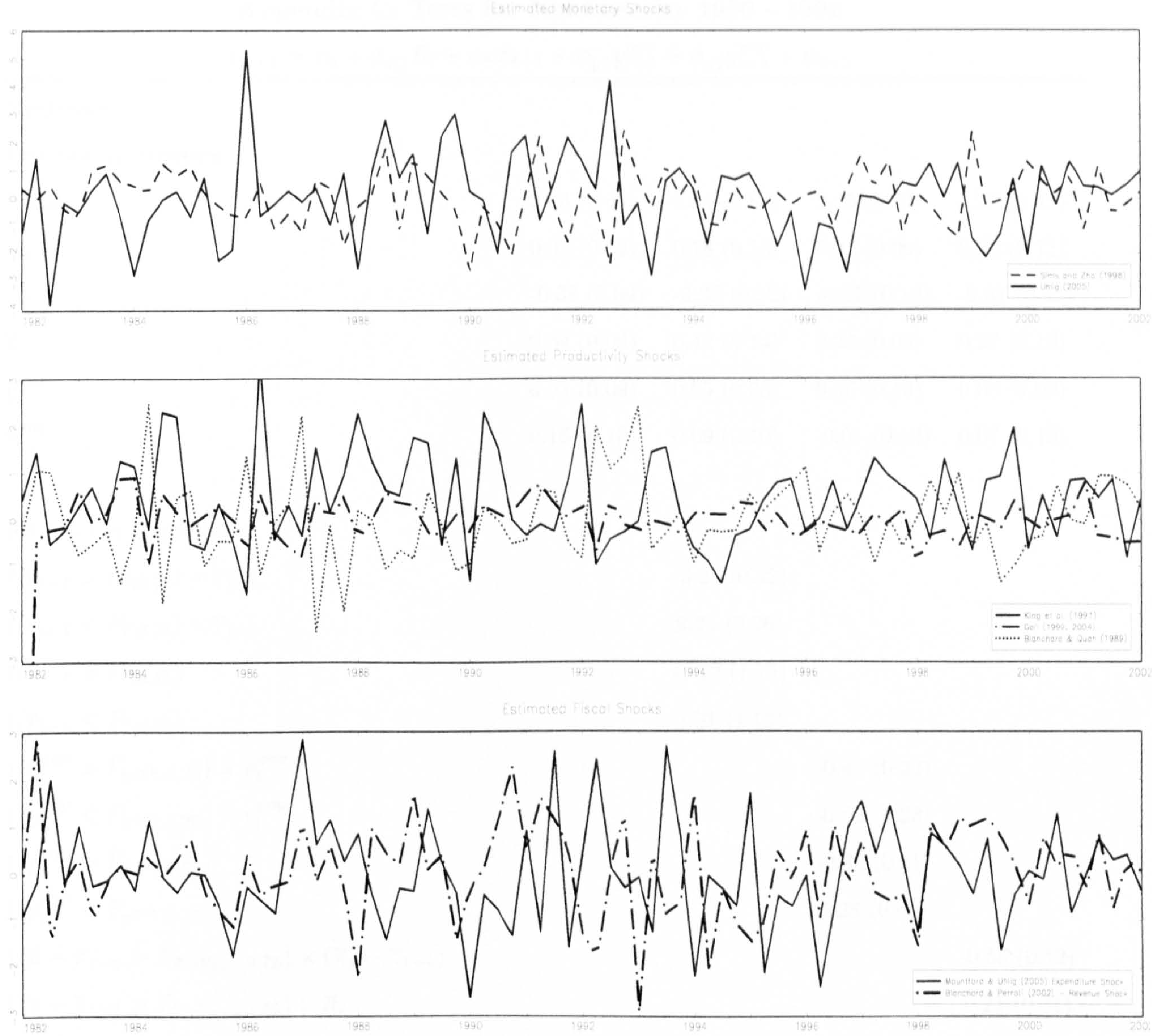
It must also be noted that other secular changes have occurred within the Euro area, including the increased participation of women in the paid workforce, and major technological innovations, including computers, information technology and transportation improvements. Improvements in technology are factors that would be felt over a passage of time. The gradual decline in real output volatility would certainly fit this explanation. Indeed, in recent years the Euro area economy has achieved progress in international competitiveness, as evidenced by rising exports of the most sophisticated types of goods and services. It is, however, very difficult to evaluate the new trends of rationalisation and globalisation, perhaps particularly with respect to their implications for domestic versus international growth fluctuations, which is investigated in the following chapter. One reason is that these perspectives are still new so that historical perspectives and lessons are lacking. Another reason is the basic difficulty of measuring such important variables as the productivity gains from computerisation and services. Also hard to assess is the mutuality of advantage from increased trade among economies with major differences in political and social systems, cultures and stages of development.

Appendix for Chapter 4

Appendix A: Volatility results for the principal series



Note: In contrast to Figure 4.4, interest rates are measured in first differences.


Estimated Monetary Shocks
Sims and Zha (1998)
Uhlig (2005)
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
Estimated Productivity Shocks
King et al. (1991)
Gali (1999, 2004)
Blanchard & Quah (1989)
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
Estimated Fiscal Shocks
Mountford & Uhlig (2005) Expenditure Shock
Blanchard & Perotti (2002) - Revenue Shock
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002

Appendix B

Appendix C: Tests for Nonlinearity 1980 - 1992

$$R_{t+1} = \phi_0 + \phi_{R1} R_t + \phi_{\overline{\pi}} \overline{\pi}_{t+1} + \phi_{y1} y^{gap}_{t+1} + \phi_{y2} y^{gap}_{t+1} + \psi_{t+1}$$

Regressor				
Baseline Regressors				
constant	3.25 (0.65)	3.84 (0.80)	2.15 (0.73)	2.93 (0.61)
R_{t-1}	0.91 (0.09)	0.78 (0.13)	0.91 (0.09)	0.90 (0.11)
R_{t-2}	-0.38 (0.09)	-0.35 (0.12)	-0.27 (0.12)	-0.31 (0.12)
$\overline{\pi}$	0.34 (0.09)	0.42 (0.14)	0.26 (0.09)	0.27 (0.10)
y^{gap}_t	0.01 (0.09)	0.05 (0.08)	0.36 (0.16)	0.08 (0.09)
y^{gap}_{t-1}	0.15 (0.10)	0.09 (0.10)	-0.01 (0.12)	0.07 (0.10)
Additional Regressors				
$1(\overline{r}_{t-1} > F_{\overline{r},0.75}) \times \overline{r}_{t-1}$		-0.21 (0.22)		
$1(\overline{r}_{t-1} < F_{\overline{r},0.25}) \times \overline{r}_{t-1}$		0.21 (0.26)		
$1(\overline{r}_{t-1} > F_{\overline{r},0.75})$		-1.12 (1.75)		
$1(\overline{r}_{t-1} < F_{\overline{r},0.25})$		1.01 (1.13)		
$1(y^{gap}_t > F_{y^{gap},0.75}) \times y^{gap}_t$			-0.43 (0.32)	
$1(y^{gap}_t < F_{y^{gap},0.25}) \times y^{gap}_t$			-0.62 (0.23)	
$1(y^{gap}_t > F_{y^{gap},0.75})$			-0.32 (0.61)	
$1(y^{gap}_t < F_{y^{gap},0.25})$			1.23 (0.62)	
$1(\overline{\pi} - \overline{\pi}_{t-4} > F_{\overline{\pi}-\overline{\pi}_{t-4},0.75}) \times (\overline{\pi}_t - \overline{\pi}_{t-4})$				-0.55 (0.12)
$1(\overline{\pi} - \overline{\pi}_{t-4} > F_{\overline{\pi}-\overline{\pi}_{t-4},0.75}) \times \overline{\pi}_t$				0.21 (0.31)
$1(\overline{\pi} - \overline{\pi}_{t-4} > F_{\overline{\pi}-\overline{\pi}_{t-4},0.75})$				-0.33 (0.03)
F-statistic (p-value) for exclusion of additional regressors		1.04 (0.38)	1.67 (0.11)	1.88 (0.59)

Notes: Tests for nonlinearities were carried out using the above equation 1980:1 - 1992:4. The tests were conducted by adding several 'threshold' variables to the base specification. To define these threshold variables let $F_x 0.75$ denote the $75th$ percentile of the empirical distribution of x over the 1980 - 1992 sample period, and let $F_x, 0.25$ be similarly defined. Let $r_t = \overline{R}_t - \overline{\pi}_t$.The table shows results with additional variables, the estimated coefficients, standard errors and F-stastistics for joint significance.

Appendix D: Additional Results for the Rudebusch-Svensson and Structural VAR Models

	Rudebusch-Svensson			Stock and Watson		
	Base Model	Base+pre-1990 Monetary Policy	Base+pre-1992 Shocks	Base Model	Base+pre-1992 Monetary Policy	Base+pre-1992 Shocks
$\sigma(\pi_t - \pi_{t-4})$	0.97	1.48	1.51	0.52	1.98	0.41
$\sigma(\overline{\pi})$	1.75	1.75	1.82	1.75	2.45	1.59

Note: $\sigma(\pi_t - \pi_{t-4})$ denotes the standard deviation of $\pi_t - \pi_{t-4}$, similarly for $\sigma(\overline{\pi})$.

Appendix E: Time-Series Descriptions

Series	Sampling Frequency	Description	Code
		Asset Prices	
ITN	Q	Real Interest Rate: Policy Rate	STRQ(ECB)
LTN	Q	Real Interest Rate: 1 year bill	LTN (ECB)
EXR	Q	Real Effective Exchange Rate	EAROCC011(D)
		Activity	
YER	Q	Real GDP	EAOEXP03D~E (D)
CONS	Q	Total Consumption	PCR (ECB)
GCONS	Q	Gov't Consumption	EAOEXP02D~E (D)
GINV	Q	GFCG Investment	EAOEXP04D~E (D)
RINV	Q	Residential Investment	EAOCFIHSD~E (D)
NINV	Q	Non-Residential Investment	EAOCFIBSD~E (D)
IPG	Q	Ind. Prod. Goods	EAOPRI35H (D)
IPN	Q	Ind. Prod. Non Durable Goods	EAOPRI51G (D)
IPC	Q	Ind. Prod. Capital Goods	EMESPIESG (D)
IPCO	Q	Ind. Prod. Construction	EAOPRI30G (D)
EMP	Q	Employment	EMEMPTOTO (D)
COM	Q	Composition Leading Ind.	OECD
IMP	Q	Imports	EAOCM006G (D)
EXP	Q	Exports	EAOCM005G (D)
HOU	Q	Average Hours Worked	IFS
		Wages, Goods and Commodity Prices	
PPI	Q	Producer Price Index	EAESPPIIF (D)
INFL	Q	Consumer Price Index	EAOCP009F~E (D)
GDPD	Q	GDP Deflator	EAOEXP13D~E (D)
UL	Q	Unit Labour Costs	EAOCFULME (D)
		Monetary Aggregates	
M1	Q	Money M1	EAOMA033G~E (D)
M3	Q	Money M3	EAOMA001G~E (D)
MON	Q	Money Stock	EAOMA033G~E (D)

Note: D= Datastream, ECB = European Central Bank, IFS = International Financial Statistics.

Break Results for Univariate Autoregressions for Selected Macroeconomic Time Series

Series	Variance			Conditional Mean			Conditional Variance: break only			Conditional Variance Trend and break		
	p - value	Break date	67% confidence level	*p* - value	Break date	67% confidence level	*p* - value	Break date	67% confidence level	*p* - value	Break date	67% confidence level
YER	0.00	1993:2	1992:4-1995:2	0.00	1992:2	1991:4-1992:4	0.00	1989:1	1988:3-1990:4	0.98	0.59	.
CONS	0.00	1993:1	1992:4-1996:2	0.00	1987:2	1986:2-1987:4	0.00	1993:3	1992:4-1995:1	0.97	0.23	.
GCONS	1.00	.	.-.	0.00	1984:4	1984:2-1985:2	0.23	.	.-.	0.02	0.00	1988:4
ITR	0.94	.	.-.	0.00	1985:1	1984:3-1985:3	0.43	.	.-.	0.03	0.00	1993:1
GINV	0.04	1996:2	1994:4-1999:3	0.01	1987:3	1987:1-1988:1	0.00	1998:3	1998:1-2000:2	0.00	0.08	.
RINV	0.98	.	.-.	0.00	1999:1	1998:3-1999:3	0.00	1996:2	1995:4-1997:2	0.79	0.01	1996:2
NINV	0.04	1996:2	1994:4-1994:4	0.00	1995:1	1994:3-1995:3	0.15	.	.-.	0.20	0.74	.
EXP	0.74	.	.-.	0.00	2000:4	2000:2-2001:2	0.44	.	.-.	0.36	0.94	.
IMP	0.03	2001:4	2001:2-2005:3	0.00	1999:2	1991:4-1992:4	0.17	.	.-.	0.58	0.22	.
IPG	0.00	1994:4	1993:4-1995:3	0.00	1993:2	1992:4-1993:4	0.22	.	.-.	0.00	0.01	1992:2
IPN	1.00	.	.-.	0.00	1999:4	1999:2-2000:2	0.31	.	.-.	0.12	0.42	.
IPC	0.30	.	.-.	0.00	2001:1	2000:3-2001:3	0.70	.	.-.	0.37	0.38	.
IPCO	0.02	1997:2	1997:1-2001:1	0.00	2000:1	1999:3-2000:3	0.01	1997:1	19964-1999:2	0.62	0.04	1997:1
PPI	0.01	1986:4	1986:1-1988:3	0.00	1985:3	1985:1-1986:1	0.25	.	.-.	0.20	0.62	.
INFL	1.00	.	.-.	0.00	1999:1	1998:3-1999:3	0.73	.	.-.	0.39	0.75	.
GDPD	0.00	1983:4	1982:4-1984:2	0.00	1999:4	1999:2-2000:2	0.00	1991:3	1991:1-1993:2	0.94	0.22	.
EMP	0.04	2000:4	2000:3-2003:3	0.00	2000:4	2000:2-2001:2	0.14	.	.-.	0.01	0.05	1988:4
UL	0.25	.	.-.	0.00	1993:2	1992:4-1993:4	0.07	.	.-.	0.00	0.10	
HOU	1.00	.	.-.	0.01	1991:1	1990:3-1991:3	0.21	.	.-.	0.02	0.03	1994:2
COM	0.66	.	.-.	0.01	1992:1	1991:3-1992:3	0.19	.	.-.	0.86	0.31	.
M1	0.00	1990:1	1986:3-1990:2	0.05	1996:3	1996:1-1997:1	0.07	.	.-.	0.05	0.85	.
M3	0.81	.	.-.	0.00	2000:4	2000:2-2001:2	0.14	.	.-.	0.67	0.25	.
ITN	0.35	.	.-.	0.07	-	.-.	0.04	1993:2	1992:4-1996:1	0.02	0.21	.
LTN	0.14	.	.-.	0.50	.	.-.	0.88	.	.-.	0.67	0.98	.

Notes: *The first column reports tests of the hypothesis that the variance of the series is constant. against the alternative of a single break. The remaining columns are similar to those presented in Table 3. The transformation of the data also follows from Table 3.*

Appendix F

Chapter 5

Understanding the Interaction between International and Euro area Business Cycle Dynamics

5.1 Introduction

Ever since the worldwide growth slowdown in the major industrialised economies of the world during 2000-2001, attention has refocused on international business cycle linkages. This is mainly because the unexpected breadth of this slowdown was initially expected to remain largely confined to the US. These expectations reflected the sanguine belief in benign business cycle linkages. In spite of all that's been written, the almost simultaneous downturn in the major world economies is widely considered to have been unusual. As discussed previously, much effort has been expended on investigating the causes of the moderation in the business cycle across the industrialised world. The literature so far has tended to focus on three main factors as to why output fluctuations may have moderated. These are shifts in the structure of the economy - moving from an industrial to a services based economy - improved policies - such as inflation targeting and the widespread delegation of monetary policy to an independent monetary authority - and, finally, a 'good luck' factor due to a placid external environment. Naturally, linking these issues together leads to one pointed question. Has the recent unexpectedly strong degree of synchronisation amongst the developed economies contributed to the moderation witnessed in the Euro area business cycle, as explored by Doyle and Faust (2005)? Is the moderation due to fewer global shocks and spillovers? This chapter contributes by exploring an important historical transformation that may have occurred in the global business cycle, as highlighted by Bergman *et al.* (1998). This hypothesis opens the door to the possibility that the stabilisation in real output for the Euro area is down to the Euro area being synchronised with a greater number of economies, such that developments in one core country no longer influence all other countries. Levy (1982), for example, notes that when the UK dominated the world economy prior to World War I, mistakes emanating from the Bank of England could initiate a severe recession not only in the domestic economy but also in its trading partners. However, the increased integration of the world economy may limit the negative influences emanating from dominating economies, thus having a stabilising effect on the business cycle.

The issue of global business cycle inferences remains an important topic of discussion. A well-documented empirical regularity for the industrialised economies is the comovement that exists between a wide variety of economic variables, as explored by Dellas (1986), Backus and Kehoe (1992) and Canova and Dellas (1993). This stylised fact remains a central focus for why economists believe in the existence of business cycles and has led to many explanations for these comovements within a country and across countries. A common explanation for the comovements within a specific country is aggregate policy sources such as monetary or fiscal policy. These types of impulses could also explain international comovements if the country-specific effect is transmitted rapidly to other countries through trade and financial interdependence. In earlier work, McKinnon (1982) argued that monetary policies across countries are coordinated, leading to common global impulses. Long and Plosser (1983) presented a disaggregated explanation for the business cycle phenomenon within a country that could be expanded to a multi-country setting. In their model, individual sectors of the economy are confronted with taste and productivity shocks, which are propagated through input-output relationships and smoothed across time by forward looking consumption behaviour to result in persistent comovements across sectors and time. If these shocks are correlated between countries within an industry, then business cycles would co-move across countries. The comovement in output between economies could also be explained by common shocks, such as oil price shocks. Kose *et al.* (2003a, b), Imbs (2004) and Baxter and Kouparitsas (2005) have shown that increasing trade can lead to business cycle synchronisation and, as such, lead to similar impulses across economies in response to an oil price shock.

From a historical perspective, in general, increasing globalisation will lead to more open and intensive foreign trade, with investment raising growth in all participating economies and, as precedent teaches us, economies that grow strongly suffer fewer business cycles. However, trade between two countries can, theoretically, result in both greater and weaker effect on Euro area output cycles. If two economies engage in Heckscher-Ohlin or Ricardian type trade, they become more specialised in certain economic sectors or industries. Thus their business cycles tend to be more idiosyncratic, and perhaps are less likely to influence one another. As trade in dissimilar products between two countries increases, with one country specialising in the production of, say, cars and the other specialising in the production of palm oil, both economies will react differently to exogenous shocks. Hence, business cycles will differ and any moderation in economic cycles is unlikely to spillover abroad. Consequently, the work presented in this chapter is related to a different line of inquiry from that which is usually pursued. On the one hand, it follows papers such as Gert and Peersman (2005) and Uhlig (2005), which assess the importance of different shocks in propagating economic fluctuations in a closed economy. The model presented examines economic shocks by introducing shocks from international business cycle linkages, as well as maintaining a role for domestic innovations.

This chapter has two specific objectives. The first is to provide a concise summary of the empirical facts about the moderation in output volatility for the Euro area and changes in the cyclical patterns for the Euro area's main trading partners relative to the Euro area.[1] The investigation will seek to explore the hypothesis that business cycles in the Euro area have moderated partly in response to increasing business cycle stability seen in the main trading partners of the Euro area. The second objective is to provide quantitative estimates of the sources of these changes. Do these results reflect the magnitudes of structural shocks or, rather, changes in the response of the Euro area to these shocks? Thus, the main goal is to put recent events into an international perspective by documenting some quantitative aspects of international business cycle linkages amongst the main trading partners of the Euro area since 1980. Little analysis has been undertaken on the role of the Euro area in propagating international business cycles. Therefore, the objectives provide a first study of the role the Euro area plays in international business cycles.

Despite the increasing volume of research examining international business cycle linkages, the comovement between economic cycles for the Euro area and its international counterparts has yet to be ascertained, which is perhaps surprising given that the Euro area, as well as being the largest currency union, is the largest trading block in the world. The methods employed in sections 5.4, 5.5 and 5.6 have the added advantage of measuring the interaction between Euro area and UK business

[1] The approach here attempts to use a relatively small scale model based on Altonji and Ham (1990), Norrbin and Schlagenhauf (1996), Clark (1998), Clark and Shin (2000), Stock and Watson (2005a) and Tekatli (2006), contrasting with much of the literature which has tended to concentrate on large-scale structural dynamic factor models, such as Helg *et al.* (1995), Forni *et al.* (2001, 2000), Stock and Watson (2002b, c), Helbling and Bayoumi (2003), Banerjee *et al.* (2005) and Eickmeier and Breitung (2006).

cycles, which have potentially important implications in any future policy debate on whether the UK should adopt the Euro currency. A discussion which at present time appears to have fallen out of public discourse.

The analysis undertaken in this chapter uses the models presented in Chapter 4. The data and modelling methodology used to remove the trends and isolate the business cycle is described in section 2. Section 3 shows the stylised facts about changes in volatility and persistence for the individual economies, whilst section 4 summarises the changes in international correlations. The main modelling strategy utilised, a Factor Structural Vector Autoregression (FSVAR), is explained in section 5. Section 6 explores the counterfactual simulations using calculations based on the FSVAR model, with section 7 concluding.

5.2 Data

The data gathered is quarterly and spans 1980:1 till 2005:2. The economies represented are the largest trading partners of the Euro area, which are Denmark, the 10 accession countries, Japan, Sweden, UK and the US. It must be noted that China and Russia are also amongst the largest trading partners of the Euro area. However, because of the lack of a real output dataset spanning 1980 till 2005, these economies were omitted. A sufficiently long dataset is a necessary prerequisite when utilising vector-autoregression (VAR) technology.

Trade Weight of the Euro area's main Trading Partners

Rank	*Economy*	*Weight*
1	United Kingdom	17.05
2	United States	14.20
3	E. Europe	9.23
4	Japan	4.53
5	Sweden	3.83
6	Denmark	2.41

Notes: ECB calculations based on Eurostat trade data: 1) Trade Weights are the sum of exports and imports expressed as total of Euro area exports and imports and are average figures for 1996-2005. 2) E. Europe: Czech Rep. Cyprus, Estonia, Latvia, Lithuania, Hungary, Malta, Poland, Slovenia and Slovakia

The focus here is on economic fluctuations over horizons relevant for short and medium term macroeconomic policy over business cycles. Due to a lack of GDP data for the 10 accession countries, a proxy is constructed that will help capture movements in the business cycle and the state of the economy of these countries. Hungary and Poland are chosen partly because they have annual datasets that span 1980 till 2005, which can be interpolated into a quarterly frequency, but also because the two countries together represent just over two-thirds of the economic output of the 10 accession countries. As a result, any shocks emanating from the accession countries to the Euro area are, statistically at least, more than likely to be picked up by the shocks to Hungary and Poland. Finally, the common business cycle between Poland and Hungary is calculated using principal component analysis of their real GDP data.[2] This common cycle is used as a proxy for the ten accession countries, and is denoted as 'Eastern Europe'. Principal components have long been utilised to extract a common cycle between countries. The most prominent recent examples include Forni *et al.* (2000, 2001), Helbling and Bayoumi (2003) and Eickmeier and Breitung (2006); the first and last of these studies used such an analysis to identify a common business cycle amongst the EU member economies. Principal component analysis is often used for dimensionality reduction in a data set, retaining those characteristics that contribute most to its variance by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the 'most important' aspects of the business cycle, while the converse is true for higher-order components.

5.2.1 Plots of Real Output

Figure 5.1 plots first differenced real GDP for each constituent economy over the sample period 1980 - 2005. Evidently, many of the constituent economies have episodes of considerable comovement, or synchronisation, with aggregate fluctuations. Figure 5.1 illustrates the four quarter growth rate of real output for each economy, along with the unweighted complete sample average of the real output growth rate. The figure shows Euro area real output growth, since the early 1990s, to have moved more closely with the average growth rates of the Euro area's main trading partners. The late 1980s early/1990s are characterised by differing real output growth rates for the Euro area relative to its main trading partners. Finally, up and down swings in the Euro area and the UK mirror each other quite closely.

[2] The procedure is laid out in Appendix C.

Figure 5.1. Detrended real GDP Growth Rate individual economies (solid line) and economies sample average (dashed line)

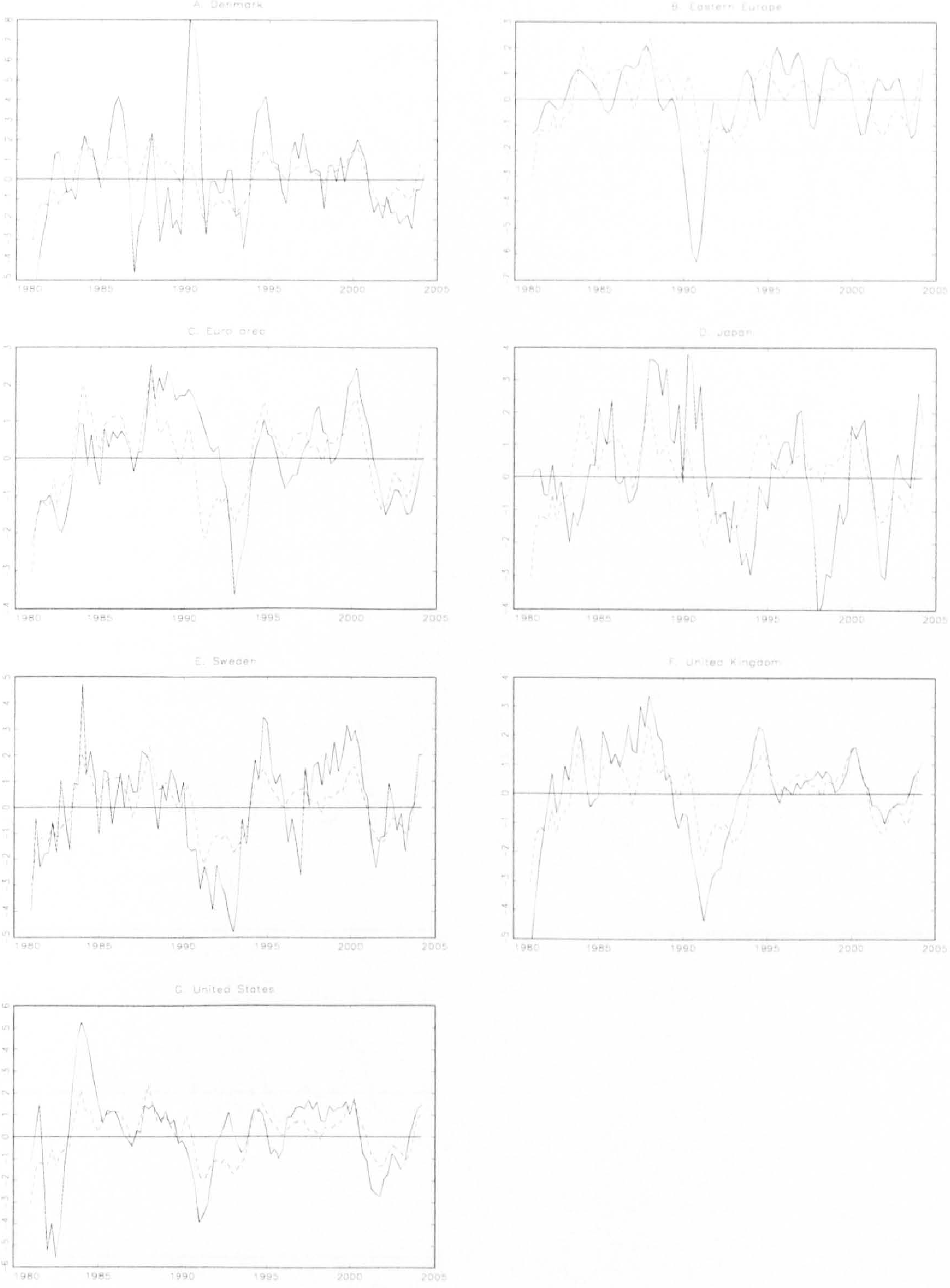


Figure 5.2. Band-Pass Filtered real GDP growth individual economies (solid line) and economies sample average (dashed line)

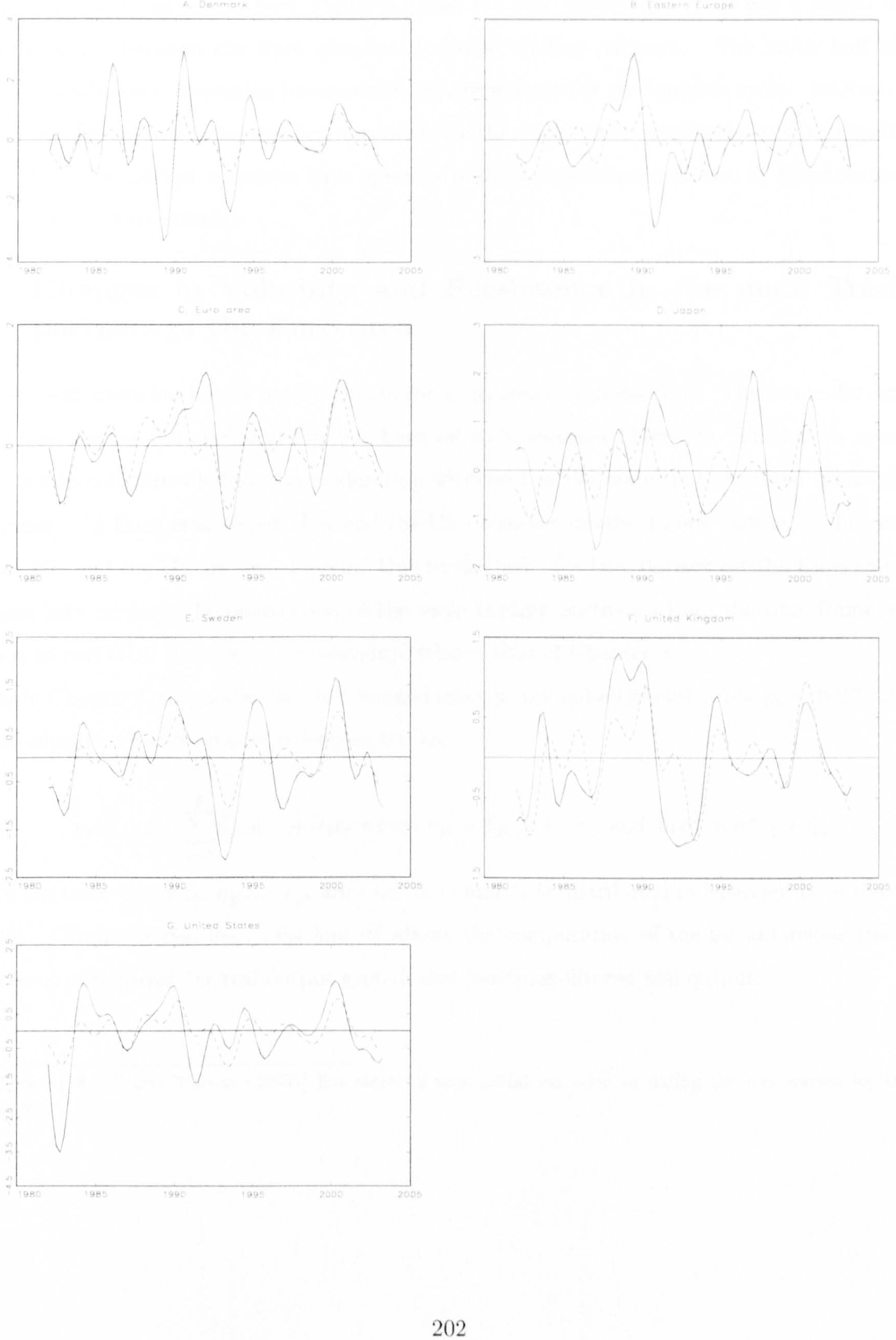


Figure 5.2 shows the bandpass filtered logarithms of real GDP. The bandpass-filtered real output is calculated by focusing on business cycle frequencies between six to 32 quarters. The estimates confirm the results from Figure 5.1 that the late 1980s/early 1990s was a period of de-synchronisation between the Euro area and its main trading partners. The latter half of the decade has witnessed increasing international synchronisation of the business cycle. Interestingly, the period of greatest synchronisation appears to be the early 1980s. Evidently, as with Figure 5.1, many of the constituent countries have episodes of considerable comovement, or synchronisation, with aggregate fluctuations.

5.3 Changes in Volatility and Persistence in the main Trading partners of the Euro area

As discussed, there has been a moderation in the Euro area's business cycle. The results for smaller economies, such as Denmark and Sweden, have yet to be examined however. The results here also allow one to compare whether the moderation witnessed in the major industrialised economies of the world - the Euro area, Japan, UK and the US - coincide relative to one another.[3] The results for the UK and the US are tested again. Due to the lack of a long dataset for the Euro area, the analysis here explores the moderation of the main trading partners within the time frame of the Euro area real GDP dataset. The procedure follows that of Chapter 4.

As in Chapter 4, the moderation is examined using y_t annualised growth rates; $y_t = 400\Delta \ln(GDP_t)$. The stochastic volatility model is represented as,

$$y_t = \alpha_{0t} + \sum_{j=1}^{p} \theta_{jt} y_{t-j} + \sigma_t \varepsilon_t \text{ where } \theta_{jt} = \theta_{jt-1} + c\eta_{jt} \text{ and } \ln \sigma_t^2 = \sigma_{t-1}^2 + \zeta_t \tag{5.1}$$

where the error terms $\varepsilon_t, \eta_{1t}, ..., \eta_{pt}$ are $i.i.d.(0,1)$ and ζ_t is distributed independently of the other shocks. Obtaining α_{0t}, $\theta_{1t}, ..., \theta_{pt}$ and σ_t^2 allows the computation of the instantaneous standard deviations of four-quarter real output growth and bandpass-filtered real output.

[3] Work by Stock and Watson (2005a) has shown a substantial variation in dating the moderation for the G7 economies.

Table 5.1:

A. Estimates and Tests for Changes in the Autoregressive Parameters

$y_t = \alpha + \theta_t(L)y_{t-1} + \varepsilon_t$

		Conditional Mean			Condiational Variance: Break only			Conditional Variance: Trend and break		
Economic area	Sample period	P-value	Break date	67% confidence interval	P-value	Break date	67% confidence interval	P-value trend	P-value break	Break date
Denmark	1980:1 – 2005:2	0.02	1990:3	1990:1 - 1991:1	0.13	.	. - .	0.00	0.00	1986:3
Eastern Europe	1980:1 – 2005:2	0.00	1990:3	1990:1 - 1991:1	0.18	.	. - .	0.09	0.53	.
Euro area	1980:1 – 2005:2	0.00	1992:2	1991:4 - 1992:4	0.00	1989:1	1988:3 - 1990:4	0.98	0.62	.
Japan	1980:1 – 2005:2	0.00	1996:4	1996:2 - 1997:2	0.47	.	. - .	0.25	0.10	.
Sweden	1980:1 – 2005:2	0.15	.	. - .	0.12	.	. - .	0.04	0.15	.
United Kingdom	1980:1 – 2005:2	0.04	1988:4	1988:2 - 1989:2	0.00	1990:3	1990:1 - 1992:2	0.97	0.66	.
United States	1980:1 – 2005:2	0.98	.	. - .	0.00	1984:4	1984:3 - 1986:2	0.99	0.15	.

B. Changes in Volatility of Four-Quarter Growth of Real GDP 1980 – 1992 and 1993 – 2005

	Standard Deviation, 1980:1– 1992: 4	Standard Deviation, 1993:1– 2005: 2	$\frac{\text{std. dev. 93-05}}{\text{std. dev. 80-92}}$	$\frac{\text{variance 93-05}}{\text{variance 80-92}}$
Denmark	6.30	3.33	0.51	0.26
Eastern Europe	2.21	1.57	0.71	0.50
Euro area	2.31	1.45	0.62	0.38
Japan	3.36	3.09	0.91	0.83
Sweden	4.76	3.71	0.78	0.61
United Kingdom	3.25	1.14	0.35	0.12
United States	3.65	1.96	0.54	0.29

Notes: *The p-test results are based on the QLR test for changes in the coefficients of an AR(4). The second column is the OLS estimate of the break date. The final column shows the 67% confidence interval for the break date. The 'Conditional Mean Coefficients' are represented by the parameters α and θ. The 'Conditional Variance' corresponds to ε_t, either with or without a time trend in the QLR regression. In panel B, entries in the first two columns are the standard deviations of the four-quarter growth in GDP over the indicated time periods. The third column contains the ratio of standard deviation in the second column to that in the first; the final column presents the square of this ratio, which is the ratio of the variances of four-quarter GDP growth in the two periods.*

Table 5.1 tests for breaks in the autoregressive lag coefficients - the conditional mean - and the autoregressive innovation variance - the conditional variance, with the same procedure as in Chapter 4. The test of a constant conditional variance allows for the possibility of a break in the conditional mean at an unknown date that differs from the break date for the conditional variance. The break date and the 67 percent confidence interval is reported if the heteroskedasticity-robust Quandt likelihood ratio (QLR) statistic, evaluated over the central 70 percent of the sample,[4] finds the possibility of a break in the conditional mean at an unknown date which differs from the break date for the conditional variance. The model also tests a nested specification, in which the innovation variance is modelled as a linear function of time with a discrete jump at an unknown break date, thereby nesting the single break and the linear time trend specifications.

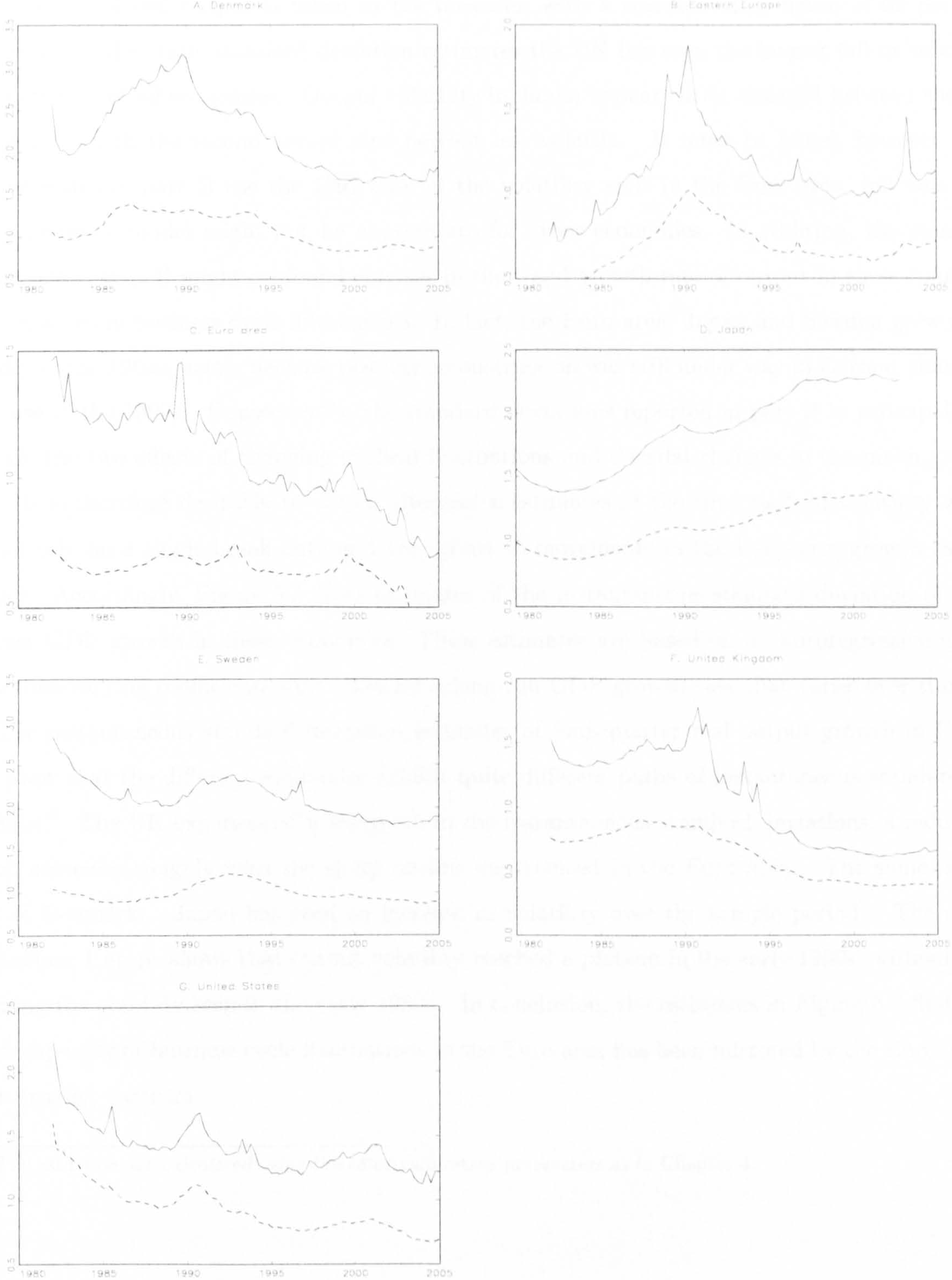
The results in Table 5.1 show that the Euro area and the UK to be quite similar, with a break in the conditional mean and variance at relatively similar dates. The results for both the Euro area and the UK suggest that neither the trend term nor the break term are individually significant in the nested specification. However, this result does not imply that the variance for the Euro area and the UK are constant, as the contrary is shown in Figure 5.3. Although not reported in Table 5.1, testing for a break in the unconditional variance again reveals very similar break dates for the Euro area and the UK; 1993 and 1992. Since the UK remains the largest trading partner of the Euro area, the results would seem to give rise to the tentative hypothesis that moderation in the UK cycle helped contribute to the stability witnessed in the Euro area cycle since the early 1990s. This will be explored in further detail in subsequent sections. The result for the US partially confirm that of Kim and Nelson (1999) and Stock and Watson (2002a, 2005a), with a break in the conditional variance in 1984. However, this variance reduction cannot be described as a discrete reduction in the variance, as found by Stock and Watson (2002a). Only Denmark, Sweden and Eastern Europe have a significant trend term in the final three columns of Table 5.1 part A, providing support for the view that the decline in output volatility is part of a continuing long-term trend decline. Indeed, for Denmark the results in Table 1 suggest a break model is appropriate for modelling output volatility reduction.

Moving on to examine breaks in the conditional mean, in five of the seven countries the hypothesis of a constant conditional mean is rejected at the five percent level. Taken together, Table 5.1 interprets the patterns of changes in GDP volatility for the Euro area's main trading partners, within the sample period, to be complex. As such it is difficult to make any generalisations.

[4] A 15 percent trimming, $\delta_0 = 1 - \delta_1 = 0.15$.

Figure 5.3. Instantaneous standard deviation of four-quarter real GDP growth

Detrended output (solid line), Bandpass-filtered output (dashed line)



The standard deviation estimates in Table 5.1 part B show that output volatility has fallen by just under 40 percent for the Euro area. This fall in real output volatility is even greater if the variance of real output is taken as the measure, with a corresponding figure of 62 percent. According to the static standard deviation estimates the UK has seen the largest fall in volatility - 65 percent - of all economies. Output volatility in Japan appears little changed between the two subperiods, with the second period nine percent less volatile. It must be noted, however, that the estimates in part B use the 1992 date of the volatility shift in the Euro area, but this date or single-break model might not be appropriate for other economies. In addition, the standard deviations in part B might confound changes in the trend growth rate of output in these countries with changes in business cycle fluctuations. In fact, the Euro area, Japan and Sweden grew more rapidly in the 1980s, partly because postwar reconstruction was still under way in Europe, than was the case in the 1990s. Consequently, the standard deviations reported in part B in principal may contain the two effects of changing cyclical fluctuations and decadal changes in the mean growth rate. It is therefore desirable to obtain alternative estimates of the time path of volatility which do not rely on a single break date and are robust to movements in the long-term growth rate of output. Accordingly, Figure 5.3 plots estimates of the instantaneous standard deviation of four-quarter GDP growth in these economies. These estimates are based on an autoregressive model with time-varying coefficients that allow for a long-run GDP growth rate that varies over time.

The instantaneous standard deviation estimates of four-quarter real output growth in Figure 5.3, show that the different economies exhibit quite different paths of instantaneous standard deviations.[5] The UK experienced a sharp fall in the instantaneous standard deviations, a reduction which coincides roughly with the sharp decline experienced in the Euro area. The same is also true of Denmark. Japan has seen an increase in volatility over the sample period. The result for Eastern Europe shows that output volatility reached a plateau in the early 1990s, without ever reaching the stability seen in the early 1980s. In conclusion, the estimates in Figure 5.3 find that the dampening of business cycle fluctuations in the Euro area has been mirrored by the Euro area's main trading partners.

[5] The estimates are calculated using the same calibration parameters as in Chapter 4.

5.4 International Business Cycles: Stylised Facts from the Seven Economies

This section aims to arrive at a set of stylised facts for all seven economies concerning (*i*) the presence of structural change in each constituent economy, (*ii*) any shifts in the structural relationship between the Euro area and its main trading partners using break tests and, (*iii*) whether there has been changes in international business cycle synchronisation over the last 25 years. These stylised facts will help shed light on any possible dynamic shifts that may have taken place between the business cycles of the economies in the sample.

5.4.1 Persistence and Size of Univariate Shocks

This subsection investigates the changing autocovariances of real output growth by examining changes in the variance of the AR innovations and the sum of the AR coefficients using rolling AR regressions. As stated by Cogley (1990) and Stock and Watson (2003a, 2005a), an increase in the sum of the AR coefficients, $\widehat{a}(1)$, implies an increase in the frequency mass, and a change in the innovation variance, $\widehat{\sigma}_{\varepsilon}$, implies a shift in the level of the spectrum. The time variation in the AR coefficients is captured in two ways. Firstly, a discrete break is allowed for in 1992. This break date is chosen since it remains the break date estimated for the Euro area, and also coincides with the fall in the instantaneous standard deviations seen in Figure 5.3 for the Euro area. The second modelling strategy uses an AR model estimated over rolling samples. Both models are estimated as an $AR(4)$ to ensure eradication of any serial correlation.

Table 5.2 presents the estimates from the two models by showing the sum of the AR coefficients and the one-step ahead forecast standard error for the split-sample AR models. The sum of the AR coefficients provides an indication of the persistence of an innovation in real output. The results show that innovations to real output have become more persistent in the Euro area and the UK, with the opposite being the case for Eastern Europe and Japan. Eastern Europe had the largest AR coefficient sum during the first period, a time when central planning was still the norm. The large rise in the persistence of Euro area real output might be explained by the often cited criticism of the Euro area economy, inflexibility. The ability of an economy to respond to a shock is, to a large part, dependent upon how labour markets respond with the subsequent adjustment in real wages and prices.[6] However, because persistence has increased, this could also suggest that

[6] As noted by De Grauwe and Storti (2005), labour market inflexibility remains a large problem in the Euro area.

more of the volatility in real output is being explained by the lower frequency components of real GDP. There has also been a rise in persistence for UK and US real output.

Table 5.2: Autoregressive Parameters for GDP Growth Rates: Sums of AR Coefficients and Standard Error of the Regression

$$\Delta y_t = a(L) \, \Delta \, y_{t-1} + \varepsilon_t$$

	Sum of AR Coefficients ($\widehat{a}(1)$)		Standard Error of Regression (σ_ε)	
	1980 - 1992	*1993 - 2005*	*1980 - 1992*	*1993 - 2005*
Denmark	-0.12	0.03	5.54	3.46
E. Europe	0.75	0.41	0.94	0.89
Euro area	0.23	0.60	2.20	1.28
Japan	-0.05	0.14	3.32	3.31
Sweden	-0.17	-0.16	4.47	3.79
UK	0.39	0.45	2.61	1.17
US	0.52	0.53	2.89	1.87

Note: Results are based on AR(4) models, estimated using annualised GDP growth rates. The inverse of one minus the sum of the AR coefficients is the long-run effect of a shock on real output.

For all economies the magnitude of real output innovations, as measured by the standard error of the regression, has fallen. In other words, one-quarter ahead forecasts based on univariate autoregressions have become more accurate. The largest fall occurred in the UK, with the second and third largest declines seen in the US the Euro area. The fact that Eastern Europe saw a large fall in persistence, but a relatively small fall in the standard error, suggests that the economies of Eastern Europe are still undergoing structural economic shifts, which as a result makes them difficult to forecast accurately. The results are presented in graphic form in Figures 5.4 and 5.5.

Figure 5.4 illustrates the results for the rolling *AR* models, estimated at date t using weighted least squares, with a discounted weighting, as in Pesaran and Timmerman (2005) and Stock and Watson (2005a). Unlike in standard weighted least squares, instead of weighting the observation in inverse proportionally to their variance, this procedure uses weights, $\delta^{|t-s|}$, such that the observation at date s receives a fixed weight of $\delta = 0.97$, instead of a variable weighting. That is, the estimate plotted at date s is based on a weighted least squares estimation of the *AR* using all observations up to s, with the observation at date s receiving a weight $0.97^{|t-s|}$.[7] More formally, setting out the

[7]Discounted weighted rolling regressions are based on an assumption that the importance of old observations

estimator as in Pesaran and Timmerman (2005), let $X_{s,i}$ be the s^{th} observation where X-variables are lagged values of real output. Further, let $\omega_{s,t} \in [0;1]$ be the weight on observation s at time t. Then, the rolling estimator is

$$\widehat{\beta}_{t,i} = \left(\sum_{s=0}^{t-1} \omega_{st} X_{s,i} X'_{s,i}\right)^{-1} \sum_{s=0}^{t-1} \omega_{s,t} X'_{s,i} y_{t+1} \quad \text{where } \omega_{s,t} = \frac{(1-\delta)\,\delta^{t-1-s}}{(1-\delta^{t})}$$

One advantage of using the discounted weighted least squares procedure is to model the influence of government policies, which can cause volatility in real output. Government policies across the economies in the sample differ widely and, consequently, have contributed, albeit to varying degrees, to real output volatility. Since standard weighted least squares uses weights which change inversely to the level of volatility, the weighting may sometimes be partly determined by changes in government policy, as well as structural economic changes. Therefore, by providing a constant weighting this issue can be negated, since the weight is constant across economies ensuring Marcet and Ravn's (2001) rule, that parameters should be constant across economies to ensure comparability.

The rolling AR estimates in Figure 5.4 have stayed relatively constant, supporting the assertions made in Table 5.4, which found no evidence of a break in the lag coefficients of y_t for each economy. Interestingly, the Euro area, and to a lesser extent Japan, are the only two economies to have experienced a slight rise in persistence. In conjunction with the estimates in Table 5.2, the results for the Euro area are supportive of the view that there has been a change in the frequency mass over the last 20 years. The results for the Eastern Europe show persistence to have stayed relatively flat, falling from around 1991 onwards.

The results in Figure 5.5, however, are more conclusive. In general, the time path of the estimates in Figure 5.5 are similar to those in Figure 5.3. The innovation variance fell in the Euro area, with an estimated time path very similar to that estimated by Stock and Watson (2005a) for Germany. The start of the progressive fall in the innovation variance for the Euro area is close to the estimated conditional variance break date in Table 5.1. The time path of $\widehat{\sigma}_{\varepsilon}$ for the UK is very similar to that of the Euro area. The US has experienced an increase in the standard error of innovations, with Japan's decline reaching a plateau following the 1992 break. Finally, the time paths of Denmark and Eastern Europe are very similar to one another, where in both cases the standard error was rising pre-1991, subsequently falling post-1992.

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declines at a constant rate over time.

Figure 5.4. Rolling autoregressions: sum of AR coefficients ($\widehat{\alpha}(1)$)

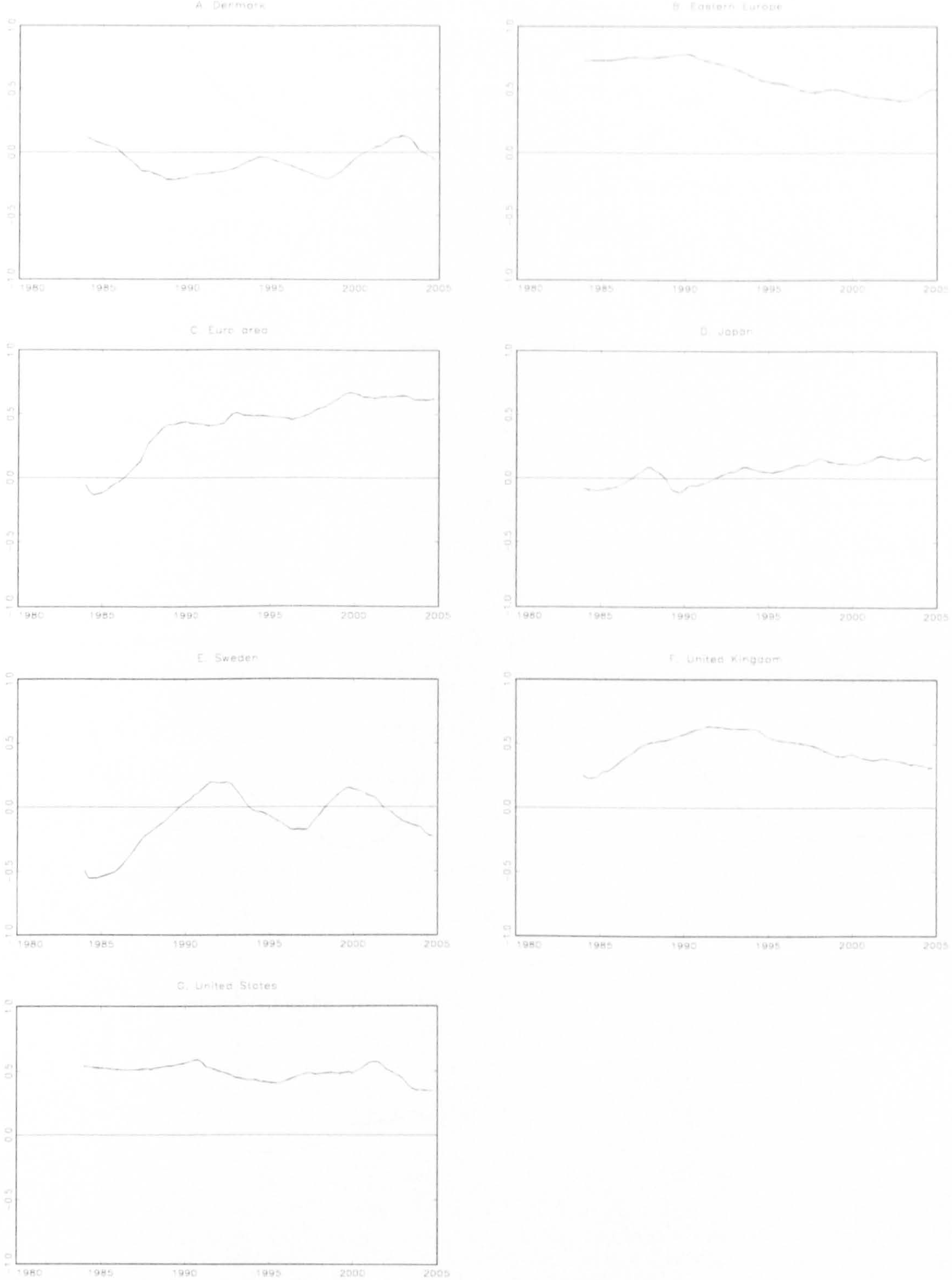
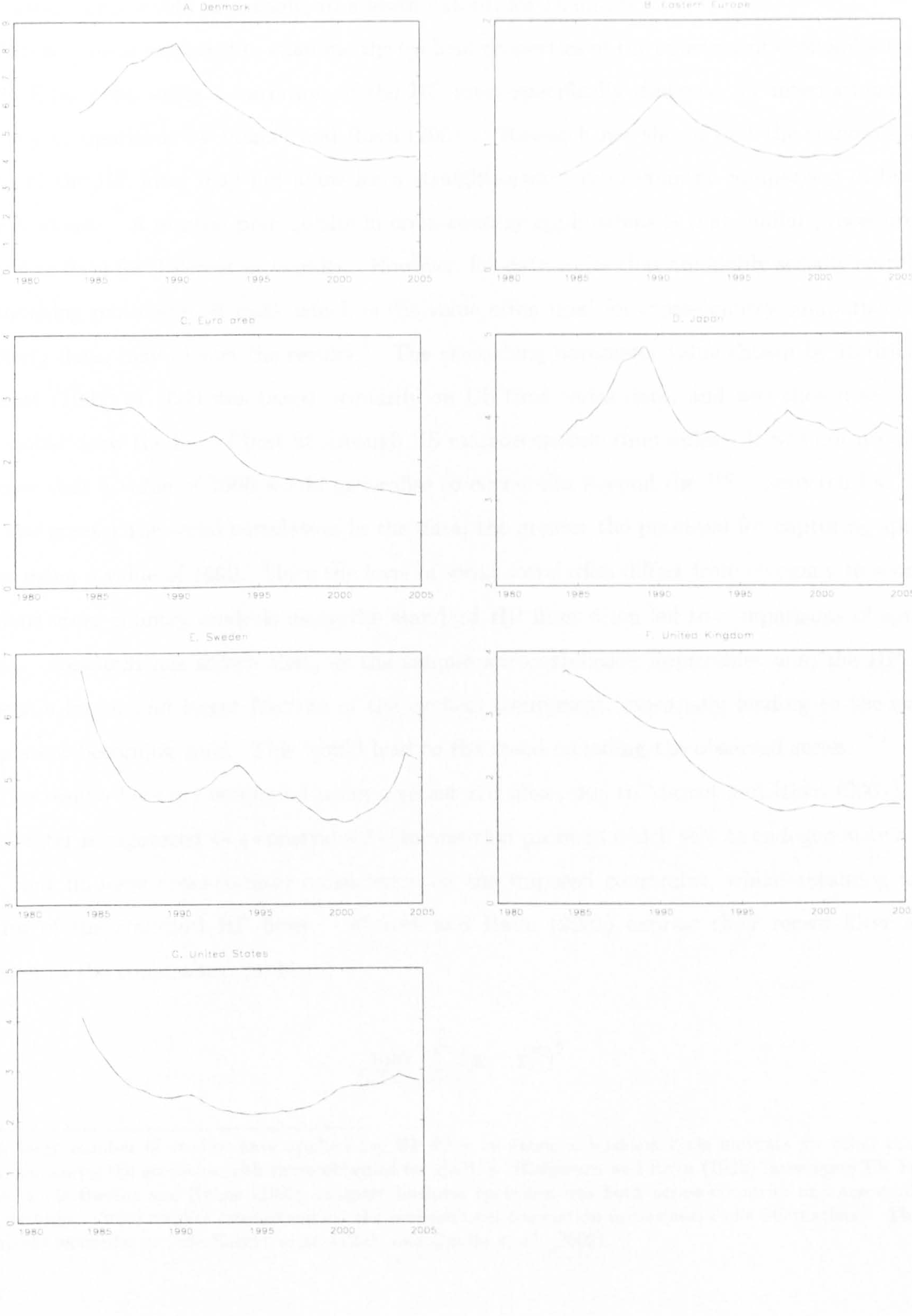


Figure 5.5. Rolling autoregressions: innovation standard error ($\widehat{\sigma}_{\varepsilon}$)



Once more it must be noted that the time paths for the UK are very similar to those of the Euro area. This would also apply, to a lesser extent, for Denmark.

This section is extended to examine the cyclical properties of the constituent economies relative to the Euro area, using a variation of the HP filter specifically designed for international cross economy comparisons by Marcet and Ravn (2001). Research has shown that the standard application of the HP filter may not allow for a straightforward cross-country comparison of business cycle moments. A natural prerequisite in cross-country applications is that similar procedures are applied to data for different economies. However, for data series that are highly serially correlated, a smoothing parameter of 1600, which is the value often used for cross-country comparison using quarterly data, may distort the results.[8] The smoothing parameter value chosen by Hodrick and Prescott (1997) of 1600 was based primarily on US time series data, and was chosen as a value that would draw the line of best fit through US macroeconomic time series. It was not necessarily the case that a value of 1600 would generalise to economies beyond the US. Research has shown that the greater the serial correlation in the data, the greater the potential for capturing spurious cycles using a value of 1600. Since the level of serial correlation differs from economy to economy, previous cross country analysis using the standard HP filter often led to comparisons of spurious cycles. Research has shown that, as the sample autocorrelation approaches one, the HP trend absorbs a larger and larger fraction of the cyclical component, eventually leading to the cyclical component becoming zero. This would lead to the trend equalling the observed series.

The results here are estimated using a recast HP filter, due to Marcet and Ravn (2001). The recast filter is expressed as a constrained minimisation problem which selects endogenously a value of λ that imposes cross-country consistency on the imposed constraint, whilst retaining all the virtues of the standard HP filter. Marcet and Ravn (2001) express their recast filter as the solution to the constrained problem,

$$\min_{\{y_t^{tr}\}_{t=1}^{T}} \sum_{t=2}^{T} (y_t - y_t^{tr})^2 \tag{5.2}$$

[8]A large number of studies have applied the HP filter to examine business cycle movents for other countries, often comparing the statistics with those obtained for the US. Blackburn and Ravn (1992) investigate UK business cycles, while Backus and Kehoe (1992) compare business cycle features both across countries and across different time periods. Other studies have examined the international correlation in business cycle fluctuations. The most prominent examples include Backus *et al.* (1992) and Cardia *et al.* (2002).

$$s.t. \ : \ \frac{\sum_{t=2}^{T-1}((y_{t+1}^{tr} - y_t^{tr}) - (y_t^{tr} - y_{t-1}^{tr}))^2}{\sum_{t=1}^{T}(y_t - y_t^{tr})^2} \leq V \tag{5.3}$$

where y^{tr} is the trend and V can be though of as a value that controls for the variability in the trend relative to the cyclical component. Marcet and Ravn (2001) show that setting V constant across economies ensures comparability, in the sense that the variability of the acceleration of the trend relative to the variability of the cyclical component is common. For appropriate choices of λ and V the standard HP filter and this recast version are the same. For example, if $V = 0$, the above problem results in a linear trend component, while letting V rise to infinity implies that the trend becomes equal to the series y_t. Hence, changing V allows for the same level of flexibility as changing λ in the standard HP filter. Marcet and Ravn (2001) show that on multiplying both sides of the recast filter (5.3) by $\Sigma_{t=1}^{T}(y_t - y_t^{tr})^2$, the Lagrangian minimisation problem solves,

$$\min_{\{y_t^{tr}\}_{t=1}^{T}} (1 - \overline{\lambda}V)\sum_{t=1}^{T}(y_t - y_t^{tr})^2 + \overline{\lambda}\sum_{t=2}^{T-1}((y_{t+1}^{tr} - y_t^{tr}) - (y_t^{tr} - y_{t-1}^{tr}))^2 \tag{5.4}$$

where $\overline{\lambda}$ is the Lagrange multiplier of the transformed constraint (5.3). The approach here is to impose a comparable level of variability of the acceleration of the trend and cyclical component across economies. The solution to the Lagrangian and the HP filter are equivalent if and only if

$$\lambda = \frac{\overline{\lambda}}{1 - \overline{\lambda}V} \text{ where } V \leq 0 \tag{5.5}$$

The constrained minimisation problem will reproduce the results of the HP filter with a given value of λ if V is chosen to equal the ratio on the left hand side of the recast HP filter (5.3) implied by the HP filter's trend component. The usual value of $\lambda = 1600$ can then be interpreted as the value of λ that satisfies (5.4), when $\overline{\lambda}$ is the Lagrange multiplier of the rewritten constraint (5.3) for each value of V (Marcet and Ravn, 2001).

In Marcet and Ravn (2001), the aim is to impose a comparable level of variability of the acceleration of the trend and cyclical components across economies. In this filter V, rather than λ, is kept constant across economies. For appropriate choices of λ and V, the Lagrangian and the HP filter are equivalent. Hence, by implication, changing V allows the same sort of flexibility that can be achieved by changing λ in the standard HP-filter formulation.

The λ that will be applied for each economy will be endogenously determined by solving for the

Lagrange multiplier constraint for each economy using the recast filter equation (5.2). Computation is undertaken by mapping between $\lambda \in [0, \infty)$ and $\overline{\lambda} \in [0, V^{-1})$, which is one-to-one. Hence, solving for λ is equivalent to solving for $\overline{\lambda}$. For a given value of λ, the trend on the basis of the HP filter for each possible value of λ is defined as

$$F(\lambda) = \frac{\sum_{t=2}^{T-1}[(y_{t+1}^{tr}(\lambda) - y_t^{tr}(\lambda)) - (y_t^{tr}(\lambda) - y_{t-1}^{tr}(\lambda))]^2}{\sum_{t=1}^{T}[y_t - y_t^{tr}(\lambda)]^2} \tag{5.6}$$

where $y^{tr}(\lambda)$ is the trend component that relates to λ. The problem is to find a value λ that solves the equation $F(\lambda) = V$.

Hence (5.4) keeps V constant across economies, allowing λ to change in order to give a better representation of the properties of real output for each constituent economy. Put differently, the usual practice of keeping λ constant when using the HP filter amounts to changing the constraint across countries arbitrarily. By setting V instead, it is possible to overcome this problem: this is referred to as 'model 1'.

As in Marcet and Ravn (2001), to examine the robustness of the results to the precise form of the constraint in (5.3), a second method replaces (5.3) by the following constraint,

$$\frac{1}{T-2}\sum_{t=2}^{T-1}((y_{t+1}^{tr} - y_t^{tr}) - (y_t^{tr} - y_{t-1}^{tr}))^2 \leq W \tag{5.7}$$

In (5.7), denoted 'model 2', the constraint restricts the variability of the acceleration in the trend component directly, with λ now taking on the interpretation of the Lagrange multiplier. This problem is solved by choosing W on the basis of the value implied by applying the standard HP-filter to each constituent economy. The main difference between the two models is that model 2 imposes the same variability of the growth of the trend across countries, whilst model 1 allows for a larger variability of the growth rate in countries with a more volatile cyclical component. The results here are especially important for Eastern Europe, since it is well known that interpolated series are likely to be highly serially correlated.

Table 5.3: Cyclical Properties of Hodrick-Prescott Filtered y_t over the period 1980 - 2005

	1980 - 1992							*1992 - 2005*						
				Autorcorrelation of order							Autorcorrelation of order			
	λ	$\sigma(y^c)$ (%)	$\sigma(y^c_i)$ / $\sigma(y^c_{Euro})$	$\hat{\rho}_1$	$\hat{\rho}_2$	$\hat{\rho}_2$	$\hat{\rho}_4$	λ	$\sigma(y^c)$ (%)	$\sigma(y^c_i)$ / $\sigma(y^c_{Euro})$	$\hat{\rho}_1$	$\hat{\rho}_2$	$\hat{\rho}_2$	$\hat{\rho}_4$
Denmark	1600	1.89	2.52	0.64	0.18	-0.04	0.00	1600	0.88	1.39	0.58	0.42	0.17	0.00
Model 1	441.1	1.69	2.26	0.58	0.05	-0.17	-0.09	723.3	0.82	1.30	0.56	0.38	0.11	-0.05
Model 2	1369	1.87	2.50	0.64	0.16	-0.05	-0.01	1323	0.87	1.37	0.59	0.41	0.16	-0.02
E. Europe	1600	1.19	1.59	0.93	0.74	0.51	0.28	1600	0.58	0.92	0.77	0.25	-0.25	-0.48
Model 1	1507	1.18	1.57	0.93	0.74	0.50	0.27	347.6	0.59	0.85	0.75	0.18	-0.34	-0.55
Model 2	3721	1.43	1.92	0.95	0.81	0.62	0.43	263.1	0.53	0.83	0.74	0.17	-0.35	-0.55
Japan	1600	1.14	1.52	0.74	0.58	0.43	0.14	1600	1.13	1.80	0.76	0.54	0.33	0.07
Model 1	1309	1.10	1.46	0.73	0.56	0.40	0.10	671	1.05	1.67	0.77	0.48	0.26	0.00
Model 2	2723	1.26	1.68	0.78	0.64	0.49	0.22	1804	1.15	1.82	0.80	0.55	0.34	0.09
Sweden	1600	1.28	1.68	0.55	0.46	0.34	0.34	1600	1.07	1.69	0.68	0.53	0.36	0.14
Model 1	1628	1.26	1.69	0.55	0.50	0.35	0.34	632.5	0.99	1.54	0.63	0.47	0.30	0.08
Model 2	4091	1.59	2.12	0.71	0.62	0.51	0.46	1179	1.04	1.64	0.70	0.52	0.35	0.12
UK	1600	1.41	1.89	0.89	0.77	0.64	0.49	1600	0.43	0.68	0.79	0.46	0.15	-0.10
Model 1	1959	1.52	2.02	0.91	0.80	0.67	0.50	506.1	0.39	0.62	0.76	0.40	0.08	-0.16
Model 2	6002	2.06	2.76	0.96	0.87	0.76	0.61	252.7	0.36	0.57	0.72	0.34	0.00	-0.22
US	1600	1.58	2.11	0.88	0.68	0.40	0.10	1600	0.89	1.41	0.88	0.75	0.54	0.35
Model 1	1120	1.49	1.99	0.87	0.66	0.36	0.03	1245	0.85	1.35	0.87	0.73	0.52	0.33
Model 2	3849	1.82	2.43	0.90	0.74	0.50	0.23	2110	0.93	1.47	0.88	0.76	0.56	0.38

Notes: *The table examines the cyclical properties of real GDP for each constituent economy relative to the Euro area. The results are estimated from a recast Hodrick-Prescott filter. The $\sigma(y^c_i)$ / $\sigma(y^c_{Euro})$ presents estimates of the cyclical volatility in economy i relative to the Euro area in the two subsample, 1980 – 1992 and 1993 – 2005.*

Both models are estimated since they differ in being able to capture particular facets of business cycle fluctuations. For example, model 1 might be more applicable if the deviation of actual observations from a linear trend is similar across economies. This may happen if economies share common industrial structures and are subject to similar economic conditions, such as the UK and the US. Model 2, on the other hand, is more applicable if some of the economies considered had very different levels of initial wealth at the beginning and at the end of the sample period. This could be due to transitional growth, as in a standard growth model, implying that the constituent economy grew faster in the first part of the sample as it was converging to a higher steady state income level. Consequently, one would expect large deviations from linear trends in those economies. This may be particularly relevant for those series representing Eastern Europe and, to a lesser extent, Sweden.

The results for the UK seem to indicate that the choice of the model has a strong impact on λ. An interesting result is that, for the UK's second subsample, both models lead to a fall in the smoothing parameter ($\lambda \leq 1600$). One possible explanation for this is that the variabilities of both the trend and cyclical component are, in reality, smaller than otherwise thought. For the second Swedish subsample, model 1 estimates a larger smoothing parameter than model 2. This may be due to the fact that although, as with the UK, the variabilities of both the trend and cyclical component are quite small for Sweden, this is more pronounced for the trend component. The most important conclusion that can be taken from the modified HP filter is that all of the main trading partners of the Euro area suffered higher levels of volatility in real output compared to the Euro area. This stylised fact for the first subperiod, however, has been reversed for all economies, with the two largest falls witnessed in Eastern Europe and the UK. All economies now experience real output volatility lower than that of the Euro area. Suffice to say, both economies, Eastern Europe and the UK, are two of the most prominent trading partners of the Euro area. The results provide further support for the view that the moderation experienced in the Euro area cycle has coincided with the increasing stability seen in the Euro area's main trading partners.

5.4.2 Stability of International Business Cycles

This section reports various measures of time-varying international comovements of real output, by beginning with estimating a reduced form VAR. Bergman *et al.* (1998), argued that cyclical relationships in the industrialised economies are stable across time, regime and countries, leading to common impulses across economies and, hence, more synchronised business cycles internationally.

The model presented in this subsection is specified in a manner such that restrictions are imposed on certain countries at any one time. In this case, the restriction is that the lagged foreign economy enters with a different number of lags than domestic real GDP growth. A similar approach was undertaken by Altonji and Ham (1990), Helg *et al.* (1995), Norrbin and Schlagenhauf (1996), Stock and Waston (2005a), Tekatli (2006). The model can be expressed as a traditional reduced form VAR,

$$Y_t = A(L)Y_{t-1} + \varepsilon_t, \quad \text{where } E(\varepsilon_t \varepsilon_t') = \Sigma \tag{5.8}$$

where Y_t is a vector of quarterly real output growth rates. The matrix lag polynomial, $A(L)$, is constructed so that the diagonal elements of the matrix lag polynomial have degrees p_1 and the off-diagonal elements have degree p_2. This means that the lag structure of the independent variables are different. Consequently, as $p_1 \neq p_2$ the near-VAR is computed using seemingly unrelated regression (SUR). SUR is an extension of the linear regression model which permits an analysis of a system of multiple economies with cross-equation parameter restrictions and correlated error terms. Since the equations have different right-hand-side variables, the efficiency of the estimates can be improved using SUR. Once SUR model estimates are obtained, inferences are mainly about testing the validity of cross-equation parameter restrictions. The lag length specification results point towards a VAR$(2,1)$ specification (Appendix B). It is also important to note that this lag length combination would have been favoured even if the lag length tests suggested otherwise, so as to limit any possible sampling uncertainty associated with estimating reduced form equations with a relatively short sample.

Table 5.4 tests for instability in the estimated VAR$(2,1)$ using the split-sample Chow test and the *sup*-Wald test from Andrews (1993). The entries in parentheses are estimates of the *sup*-Wald p-values. The *sup*-Wald test, unlike the Chow test, does not assume knowledge of the date at which the break in the parameters occurs. Under the null hypothesis of both tests, the coefficients are time-invariant. The p-values in the parentheses in Table 5.4 probably understate the evidence of parameter instability, since there is no single break date preselected. The corollary being that values not in the parentheses may overstate the statistical evidence of parameter instability, since the break date, 1992, was selected on the basis of the break date estimate in Table 5.1 for the Euro area. Such attempts aim to maximise the individual cell entries. In any event, the results are qualitatively similar with regards to the Euro area.

Table 5.4: Tests for Instability of Reduced Form VAR Parameters

	All Coefficients	*Own Lags*	*Other Lags*	*Variance*
Denmark	0.16 (0.78)	0.02 (0.21)	0.50 (1.00)	0.02 (0.19)
E. Europe	0.11 (0.68)	0.03 (0.30)	0.44 (0.99)	0.71 (1.00)
Euro area	0.48 (0.99)	0.22 (0.89)	0.99 (1.00)	0.00 (0.01)
Japan	0.55 (1.00)	0.09 (0.59)	0.77 (1.00)	0.78 (1.00)
Sweden	0.03 (0.32)	0.39 (0.99)	0.01 (0.19)	0.09 (0.57)
UK	0.04 (0.40)	0.58 (1.00)	0.02 (0.21)	0.00 (0.00)
US	0.77 (1.00)	0.35 (0.98)	0.81 (1.00)	0.01 (0.17)

The cells that are under the heading 'own lags' test the hypothesis that the two coefficients on the lags of the constituent economy growth equation are the same in the two periods. This cannot be rejected for any economy using the *sup*-Wald test. However, the Chow test shows that for the Denmark and Eastern Europe there have been changes in the coefficients at the five percent significance level. The result for Eastern Europe is perhaps not surprising given that the early 1990s marked the start of the collapse of the command economy period. Further, supporting the conclusions made in previous sections, the Chow and *sup*-Wald p-values for the Euro area reject the null hypothesis of constant variance at the one percent significance level, implying that real output variance differs across both subsamples. This result provides credence for splitting the sample at 1992. The fact that there appears a break in the variance for the Euro area, but not an apparent break under the other headings, implies that the moderation in the variance for the Euro area is not linked to any structural shift in the Euro area's relationship with its main trading partners, casting doubt on the hypothesis that structural shifts taking place between the Euro area and its main trading partners have played a contributing factor in the dampening of Euro area output fluctuations. Finally, according to the *sup*-Wald test statistic, all economies reject evidence of coefficient instability under the heading 'other lags', suggesting relative stability between the interaction of economies. However, the Chow tests indicate this not to be the case for Sweden and the UK. Hence, the results only partially support the assertions in Bergman *et al.* (1998), that cyclical patterns across the industrialised economies are stable across time, regime and countries.

5.4.3 International Synchronisation

This line of inquiry investigates the correlation of business cycles across economies, which has a long history in international business cycle linkages. Mitchell (1927), for instance, found a positive correlation of business cycles across countries, and concluded that this correlation was growing over time. This was attributed to the growth in international financial linkages. Understanding changes in the synchronisation between the Euro area and international business cycles will help deepen the understanding of where possible international disturbances that inflict the Euro area economy are most likely to come from and, second, whether the integration amongst economies has become diversified or more concentrated, i.e., economies integrating to an extent where there is now an 'English-speaking' or 'Euro only' cluster.

International synchronisation is explored in this subsection by analysing various correlation coefficient estimates, using raw, detrended and bandpass filtered real output. Panel A and B in Table 5.5 show the correlation of four-quarter real output growth rates using the raw data, with panel B illustrating estimates based on the VAR$(2,1)$ model.

The moments from the VAR$(2,1)$ can all be computed directly from estimates of the VAR parameters as in Altonji and Ham (1990), Elliot and Fatás (1996), Norrbin and Schlagenhauf (1996) and Stock and Watson (2005a). The notation follows Stock and Watson (2005a), with the spectral density matrix of quarterly real output growth given as $S_{YY}(\omega) = C(e^{i\omega})\Sigma C(e^{-i\omega})'/2\pi$, where $C(L)^{-1} = [I - A(L)]$ is the moving average of the reduced form model. The implied spectral density matrix is $|1 + e^{i\omega} + e^{2i\omega} + e^{3i\omega}|^2 S_{YY}(\omega) = [s_{ij}(\omega)]$, so that $s_{ij}(\omega)$ is the cross country spectrum between economy i and economy j at frequency ω. Using bandpass-filtered real output changes the spectral density matrix. In this case the spectral matrix of real output is $|b(e^{i\omega})/(1 - e^{i\omega})|^2 S_{YY}(\omega) = [s_{ij}(\omega)]$, where b is the bandpass filter, so that $|b(e^{i\omega})|^2 = 1$ for $\omega_0 \leq \omega \leq \omega_1$, where the frequencies ω_0 and ω_1 correspond to periodicities of between six and 32 quarters, with $|b(e^{i\omega})|^2 = 0$ otherwise. The contemporaneous correlation, denoted ρ_{ij}, between economies i and j can be estimated by

$$\rho_{ij} = \frac{\int_{-\pi}^{\pi} s_{ij}(\omega)d\omega}{\left(\int_{-\pi}^{\pi} s_{ii}(\omega)d\omega\right)^{1/2}\left(\int_{-\pi}^{\pi} s_{jj}(\omega)d\omega\right)^{1/2}} \tag{5.9}$$

where ρ_{ij} represents the correlation of the four-quarter real output growth rate. This statistic is used to estimate cross correlations from the model and are presented in Table 5.5 part B.

The average absolute difference between the correlations in panel A and their counterparts in panel B is -0.05, indicating that the reduced form VAR$(2,1)$ captures most of the business cycle comovements. However, there is one exception to this generalisation. The correlation between the Euro area and the US from the estimated VAR$(2,1)$ veers from being close to zero to being strongly positive, whereas in panel A the correlation coefficient between the Euro area and the US is always positive. Finally, panel C of Table 5.5 shows estimation of the correlation coefficients using bandpass-filtered real output using the correlation statistic of (5.9).

The estimates from the standard correlation coefficients in Panel A imply that, out of the three major economies in the sample, Japan, the UK and the US, the latter two have become more closely correlated with the Euro area. This applies, albeit to a lesser extent, for Eastern Europe. The results for Sweden and Denmark are similar to those for the UK and the US. The conclusions drawn from the standard correlation coefficients in panel A are consistent with the correlation coefficients presented in panel B. The final section of panel A shows the changes in the raw correlations over the two subsamples. The average change across subsamples is 0.04.

There appears to have been an increase in the 'clustering effect' of the correlation amongst the major industrial economies, except Japan. The average change in the correlation between Japan and the other economies over the two sample periods is -0.12. However, grouping together economies classed as 'Anglophone'[9] - Denmark, Sweden, UK and US - the correlation change amongst the group is 0.27 on average from the first period relative to the second; removing Denmark and Sweden the average correlation change is 0.21. Taking economies that are only located in continental Europe - Denmark, Euro area and Sweden - the average change in correlation between the economies from period one to period two is 0.36, strongly suggesting the formation of closer ties between economies located in continental Europe; a 'European cluster'. Finally, taking the Euro area and the English speaking economies, UK and US, the average change in the cross-group correlation is 0.23 from the first subperiod to the second. The average change in the cross-group correlation between the 'English' and 'European' cluster increases it slightly to 0.24. This result suggests that there has been a move towards closer integration between the Euro area and other European economies with the UK and US economies over time. The increasing correlation between the Euro area and the UK eases one possible economic argument against the UK adopting the Euro currency.

[9]These economies tend to be classified as 'Anglophone' due to their more flexible labour markets.

Table 5.5

A. Four-quarter growth rates, simple correlation coefficients

	Sample Period: 1980 - 1992						
	Denmark	E. Europe	Euro Area	Japan	Sweden	UK	US
Denmark	1.00						
E. Europe	-0.36	1.00					
Euro area	0.34	-0.14	1.00				
Japan	0.24	-0.31	0.67	1.00			
Sweden	0.11	0.51	0.39	0.14	1.00		
UK	0.16	0.64	0.34	0.16	0.74	1.00	
US	0.05	0.44	0.30	0.01	0.53	0.44	1.00
	Sample Period: 1993 - 2005						
	Denmark	E. Europe	Euro Area	Japan	Sweden	UK	US
Denmark	1.00						
E. Europe	-0.03	1.00					
Euro area	0.63	-0.12	1.00				
Japan	0.19	-0.08	0.17	1.00			
Sweden	0.51	0.00	0.76	0.04	1.00		
UK	0.75	-0.24	0.64	0.10	0.66	1.00	
US	0.61	-0.07	0.45	0.13	0.46	0.65	1.00
	Difference: 1980 - 1992 v. 1992 - 2005						
	Denmark	E. Europe	Euro Area	Japan	Sweden	UK	US
Denmark	1.00						
E. Europe	0.33	1.00					
Euro area	0.30	0.02	1.00				
Japan	-0.05	0.23	-0.50	1.00			
Sweden	0.40	-0.51	0.37	-0.10	1.00		
UK	0.59	-0.88	0.30	-0.05	-0.08	1.00	
US	0.56	-0.51	0.16	0.12	-0.07	0.21	1.00

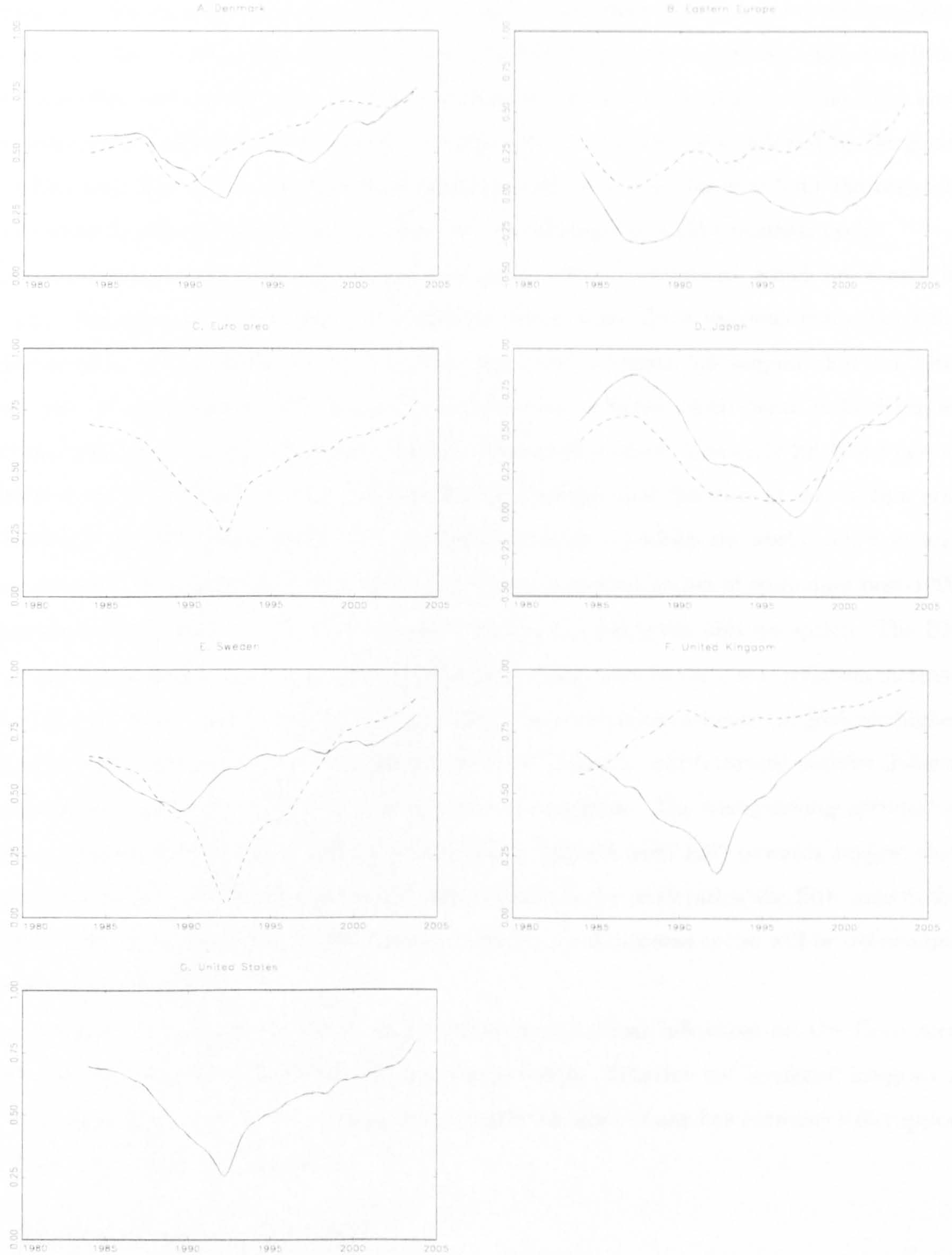
B. Four-quarter growth rates, implied by reduced form VAR(2,1)

	Denmark	E. Europe	Euro area	Japan	Sweden	UK	US
			Sample Period: 1980 - 1992				
Denmark	1.00						
E. Europe	-0.36	1.00					
Euro area	0.31	-0.10	1.00				
Japan	0.32	-0.37	0.62	1.00			
Sweden	0.03	0.54	0.43	0.05	1.00		
UK	0.08	0.68	0.26	0.01	0.69	1.00	
US	-0.06	0.47	0.22	-0.02	0.41	0.41	1.00
			Sample Period: 1993 - 2005				
Denmark	1.00						
E. Europe	0.11	1.00					
Euro area	0.58	-0.15	1.00				
Japan	0.12	-0.17	0.18	1.00			
Sweden	0.50	0.13	0.56	0.04	1.00		
UK	0.63	0.08	0.54	0.10	0.64	1.00	
US	0.64	0.12	0.55	0.18	0.46	0.66	1.00

C. Bandpass-Filtered, implied by reduced form VAR(2,1)

			Sample Period: 1980 - 1992				
Denmark	1.00						
E. Europe	-0.43	1.00					
Euro area	0.32	-0.12	1.00				
Japan	0.39	-0.43	0.67	1.00			
Sweden	-0.02	0.61	0.44	0.05	1.00		
UK	-0.02	0.71	0.25	-0.03	0.75	1.00	
US	-0.10	0.51	0.22	-0.05	0.48	0.45	1.00
			Sample Period: 1993 - 2005				
Denmark	1.00						
E. Europe	0.11	1.00					
Euro area	0.59	-0.17	1.00				
Japan	0.16	-0.18	0.21	1.00			
Sweden	0.63	0.16	0.60	-0.03	1.00		
UK	0.68	0.08	0.54	0.11	0.73	1.00	
US	0.66	0.15	0.56	0.22	0.55	0.70	1.00

Figure 5.6. Rolling Correlation Band-pass Filtered real GDP Growth



Note: Solid lines indicate rolling correlation with the Euro area. The corresponding dashed line represents the rolling correlation with the US.

The results on the whole suggest stronger and more diverse economic integration amongst the economies, with the exception of Japan. This may lead to two effects that counteract one another. Firstly, the fact that economies are more closely synchronised suggests that shocks emanating from foreign economies are possibly more likely to influence the domestic economy, i.e., the Euro area is more susceptible to foreign developments. On the other hand, and as mentioned by Bergman *et al.* (1998) and Levy (1982), the increased integration of the economies may limit the negative influences from dominating economies, thus having a stabilising role on the business cycle.

These conclusions are further explored by examining rolling correlations, which are shown in Figure 5.6. The graphical illustration shows how the conclusions of the previous two paragraphs have developed over the passage of time. The estimates in Figure 5.6 suggest that pre-1990 business cycles were diverging with regards to the Euro area, a trend which began to be reversed from around 1992 onwards; the estimated break date for the Euro area. The early 1990s is a period characterised by the collapse of communism in Eastern Europe, and the start of the dotcom era, which led to great strides being made in information technology, especially the world wide web, and financial markets. The de-synchronisation and subsequent synchronisation of economies post-1990 also appears to be the case for the US economy, with the UK being the only exception. The UK economy has, apart from a small fluctuation in the early 1990s, seen its output correlation increase with the US every year. In all cases, apart from Japan, the correlation estimates in 2005 are higher than those in 1992. This reaffirms the results in panel B of Table 5.5, which showed positive changes in the correlation coefficients, except for Japan, which was negative. The strengthening correlation coefficients between the Euro area and its main trading partners from 1992 onwards suggest that international business cycle linkages may have played a role in the moderating the Euro area cycle. How much of the Euro area cycle is determined by international business cycles will be determined in subsequent sections.

In conclusion, the results presented suggest that international influences on the Euro area business cycle are more diversified than was the case pre-1992. Whether the increased integration of the world economy has served to mitigate the negative influence of any one economy's disruption on the Euro area will be examined next.

5.5 Factor-Structural VAR

There are many frameworks available for developing an econometric model, which permits the answering of how much (as a fraction) of a country's cyclical variance is due to international shocks and how these shocks have evolved over time. An issue with all such studies, however, is how to bespoke the econometric model so as to resolve the issue of how best to identify an international shock. The literature has, in general, identified four alternative econometric models, highlighted by Stock and Watson (2005a), which could be utilised to capture international shocks. Firstly, a world shock could be estimated as an innovation in a univariate time series model of world GDP growth. There are, however, limitations to this framework. Since US output receives a large weight amongst the economies being considered here due to its size, it may confound world shocks with US shocks and idiosyncratic shocks to other large economies. Assuming no common world shock or the presence of international trade, this identification scheme would nonetheless attribute a large fraction of US output fluctuations to a common shock as an arithmetic implication of its construction. The second modelling framework, which overcomes some of the flaws of a univariate model, utilises a parametric dynamic factor model, as in Watson (1994) and Kose *et al.* (2001a, b), where the number of shocks is greater than the number of series and the comovements across series at all leads and lags are attributed to the common shock. This results in an unobserved components model that can be estimated using the Kalman filter. Employing such a framework has one hypothetical advantage. In the case of no economic spillovers and no common shock, the framework would indicate no comovements, with the common shocks being correctly identified as having zero variance. Yet due to the cross-dynamics being associated with the world shock, this approach is perhaps not best suited to identifying the separate effects of a common world shock and any spillovers arising through trade. The third approach focuses upon the use of non-parametric methods to estimate a dynamic factor model. As in Stock and Watson (2002b), Helbling and Bayoumi (2003) and Eickmeier and Breitung (2006), if a large number of series have a dynamic factor structure, then the common component, or the common dynamic factor, can be estimated using principal components, as in Forni *et al.* (2000, 2001). This procedure has been used by Helbling and Bayoumi (2003) to estimate the importance of common factors in G7 fluctuations and also by Helg *et al.* (1995) to extract European industry and country specific shocks. The notion that the principle components/nonparametric approach has the advantages of the second approach without the disadvantage of assuming that all comovements stem from the common disturbance rather than through trade spillovers, is tainted by the fact that individual countries are sometimes necessarily heavily weighted, like the US, leading to the same disadvantage as the first approach. The fourth approach, employed here, adopts a VAR framework as in Altonji and Ham (1990), Norrbin and Schlagenhauf (1990, 1996), Clark (1988), Clark and Shin (2000), Stock and Watson

(2005a) and Tekatli (2006), who extended the VAR to include Bayesian uncertainty. However, unlike Altonji and Ham (1990), Norrbin and Schlagenhauf (1996), Clark (1998) and Clark and Shin (2000), the model presented here is developed at an aggregate output level, rather than at an industry or region-specific level. In this case output fluctuations may arise from either nation specific factors - an idiosyncratic factor, a common factor - an international shock, or spillovers from the idiosyncratic shock.

The procedure follows Chapter 4. The VAR framework allows for lagged effects and the identification of world shocks as those that affect all economies within the same period. Hence, each equation for each country includes its own lags as well as lags of the other countries - a model based on the VAR structure of equation (5.8). A similar econometric model was also exploited by and Altonji and Ham (1990), Norrbin and Schlagenhauf (1996), Clark (1998), Clark and Shin (2000), Stock and Watson (2005a) and Tekatli (2006). The factor structure allows a decomposition of the h-step ahead forecast error for GDP growth into three sources; unforeseen common shocks, unforeseen domestic shocks and spillover effects arising from unforeseen domestic shocks to other countries in the model. The model used for each economy is nested in equation (5.10), and is similar in structure to equation (5.8),

$$Y_t = A(L)Y_{t-1} + \varepsilon_t \tag{5.10}$$

$$\varepsilon_t = \Gamma f_t + \omega_t, \text{ where } E(f_t f_t') = \Sigma_{ff} = diag(\sigma_{f1}, ..., \sigma_{fk}) \; \forall \; t \text{ and } E(\omega_t \omega_t') = diag(\sigma_{\omega 1}, ..., \sigma_{\omega 7}) \tag{5.11}$$

where $A(L)$ represents the matrix of lag polynomials. Equation (5.10) has the advantage of being agnostic about the structure of the economy, with no restrictions imposed on the matrix of contemporaneous coefficients, as in SVAR models with the structure of Sims (1980, 1986). This is advantageous since some of the economies have differing structures. Consequently, there are no overly tight restrictions which are sometimes imposed on structural models, especially when estimated with limited data series. When compared with SVARs, FSVARs allow for the inclusion of additional variables in a VAR which do not imply the existence of additional structural shocks and, hence, identifying restrictions for key structural shocks are not modified to distinguish the key structural shocks from other shocks. In other words, unlike in traditional SVAR models, where the inclusion of more variables implies more restrictions are needed, this is not the case for factor models, whilst the estimated structural shocks can be directly mapped to structural innovations in business cycle models allowing the volatility of structural shocks to be disentangled from the volatility of VAR residuals, as is customary in SVAR models.

The so-called 'error model' considered in Equation (5.11) builds in the following factor structure into the error terms of the reduced form equation (5.10). The structural error term, ε_t, is serially uncorrelated, f_t is a vector containing the common international factors, and Γ is a $7 \times k$ matrix of factor loadings (where k denotes the number of estimated common factors), where Γ_{ij} denotes the common factor restriction on the i^{th} factor on the j^{th} variable. In essence, the matrix Γ summarises the contemporaneous relationships amongst the different variables in Y_t. Finally, ω_t contains the country-specific idiosyncractic country shocks, with the normalisation assumptions $E(\omega_t) = 0$ and $E(f_t, \omega_t') = 0 \; \forall \; t$. The covariance restrictions imply that a disturbance to an economy is uncorrelated with other country-specific or the common factor disturbances. In other words, the ω_t shock is idiosyncratic. It's importance stems from the fact, that when these covariance restrictions are coupled with the assumption that there are k common factors, as determined by the likelihood ratio test, the result is an identified factor system.

In factor modelling, identifying restrictions are necessary to estimate any factor. The approach taken here can be interpreted as taking a model with real output shocks for the constituent economy, and then asking whether orthogonal international shocks affect the variance in real output in the constituent economy in an economically meaningful way. In turn, the covariance matrix of the common factors is uncorrelated with the idiosyncratic disturbances in each factor equation. This permits a decomposition of the variances of the h-step ahead forecast error using the formulae in Chapter 4. Equation (5.11) identifies international shocks as those shocks that affect output in multiple economies contemporaneously, therefore, attributing international shocks to the common components stored in Γ_{ij} of the innovation in the seven variable VAR. This approach has one very desirable property. This would be true even if lagged trade effects produced dynamic international comovements. Any lagged spillover effects of an economy would be captured by the VAR lag dynamics. In addition, supplementary to the international shock, all shocks which are country-specific, ω_t, have an international transmission requiring around one quarter, i.e., 'spillovers'. The identification of the common factors differs from traditional dynamic factor models as in Forni *et al.* (2000, 2001), Stock and Watson (2002b, 2003a), Helbling and Bayoumi (2003) and Eickmeier and Breitung (2006) in that the model presented does not depend on the specification of the unobserved factors (often estimated through principal components analysis) as first developed by

Sims and Sargent (1977), but rather depends upon the covariance restrictions embedded in equation (5.11).

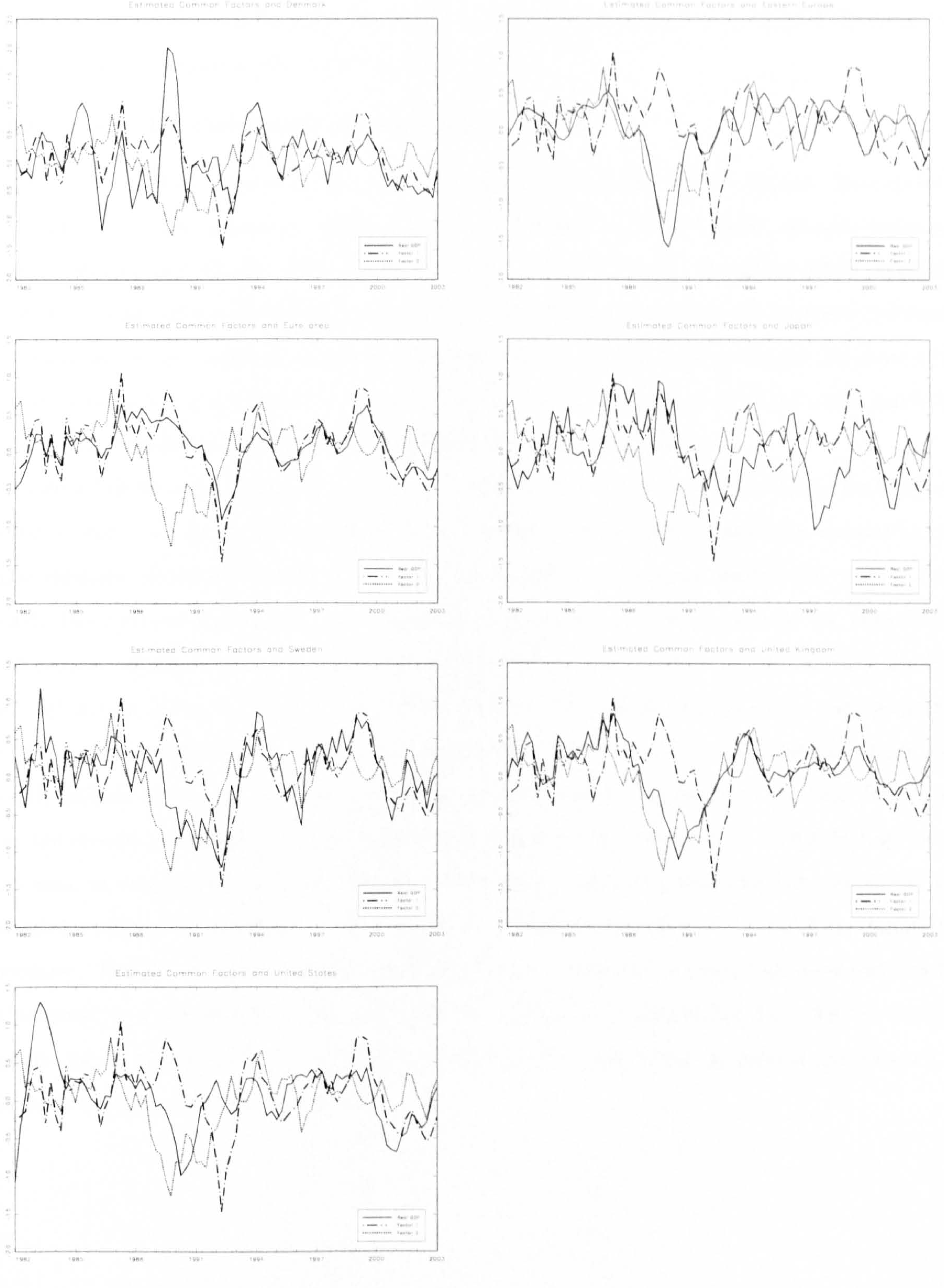
Table 5.6: Tests of k-factor FSVAR vs. Unrestricted VAR

		1980 - 2005		*1980 - 1992*		*1993 - 2005*	
No. of k	d.f.	L.R. Statistic	p-value	L.R. Statistic	p-value	L.R. Statistic	p-value
1	14	32.7	0.00	21.4	0.09	13.7	0.47
2	8	7.63	0.47	8.02	0.43	2.76	0.94
3	3	2.07	0.56	1.05	0.79	0.56	0.91

Notes: The results are based on detrended growth rates. The cell entries are estimated from the likelihood ratio test statistic testing the null hypothesis that a VAR(2.1) error covariance matrix has a k-factor structure, against the alternative of full rank.

As mentioned previously, the advantage of this model is that there are $n > k$ common factors, where k is the number of common factors and n is the number of variables, meaning there are $n+k$ number of shocks. The scale of the factors is identified by the restriction that each column of Γ has unit length, that is $\Gamma_i\Gamma_i' = 1$ for $i = 1, 2, ..., k$. Empirical evidence is needed to determine the number of factors k, i.e., the number of overidentifying restrictions. Likelihood ratio tests, sometimes referred to as reduced rank identification tests, are summarised in Table 5.6. In the pooled full sample and the first subsample the hypothesis that $k = 1$ against Σ_ε having full rank is rejected at the one and 10 percent significance levels, which stands in contrast to the second subsample. This result would seem to imply that the constituent economies have become more closely synchronised over the sample period, which is consistent with the correlation analysis presented previously. The null hypothesis that $k = 2$ cannot be rejected for the pooled sample or the two subsamples at any conventional significance levels, so an adopted specification with two international shocks, i.e., two common factors, is estimated. This suggest that the interlinkage between constituent economies can be explained by two common components that drive international cycles. The factor structure imposes 14 (7×2) restrictions when $k = 2$. The two common factor estimates are illustrated in Figure 5.7.

Figure 5.7. Common Factor Estimates and Detrended real GDP



Notes: Real GDP is calculated at quarterly growth rates. To reduce excess noise, the factors and real GDP for each economy are plotted as four quarter moving averages.

5.5.1 Results

This section reports results based on the two-factor FSVAR, including an analysis of the sensitivity of the results to changes in the modelling strategy.

Importance of International and Idiosyncratic Shocks

As highlighted in the formulas in Chapter 4, the factor structure allows the variance decomposition to be split into three separate categories: first, unforeseen common shocks, second, unforeseen domestic shocks and, finally, spillover effects of unforeseen domestic shocks to other economies. Calculating these follows directly from Chapter 4. The relative importance of international sources of fluctuations, either common shocks or spillovers, can be measured as one minus the share of the forecast error variance attributed to domestic shocks, i.e., a small domestic share corresponds to a relatively larger role for international rather than domestic disturbances.

Table 5.7 shows estimates of the variance decompositions of real output growth and for bandpass-filtered output. At the one quarter horizon the spillover variance decompositions account for zero of the variance of real output for all economies. This is an important assumption since it helps identify the international shock. At longer horizons spillovers tend to account for between five to 10 percent of the variance in real output for the Euro area. Most of the variance for Euro area real output in both subperiods is attributable to the common factor shock and, second, to the idiosyncratic disturbance. In the first subsample, the Euro area appears to have been more strongly influenced by common shocks, f_t, than was the case for the other economies. This is less so in the second subsample, with idiosyncratic shocks playing a larger role. This finding for the Euro area, in conjunction with the stronger correlation coefficients, supports the hypothesis that increasing economic integration has had the effect of limiting international shocks from dominating economies. Finally, it is interesting to note that for the smaller economies, Denmark and Sweden, the proportion of output fluctuations that can be attributed to international shocks has doubled; a result that is probably due to increased globalisation in trade, which in general has affected the smaller economies more than larger ones.

Table 5.7:
Two Factor FSVAR: Common Shocks, Spillovers and Own Country Shock Variance Decomposition

		1980-1992				1993-2005			
		Forecast error standard deviation	*Fraction of Forecast error variance due to* Int'l Shocks	Spillovers	Own Shock	Forecast error standard deviation	*Fraction of Forecast error variance due to* Int'l Shocks	Spillovers	Own Shock
Economy									
				A: De-trended real GDP					
Denmark	1	5.33	0.16	0.00	0.84	3.09	0.55	0.00	0.45
	2	4.42	0.18	0.02	0.80	2.12	0.55	0.04	0.41
	4	2.92	0.21	0.05	0.74	1.59	0.55	0.08	0.36
	8	2.02	0.21	0.07	0.72	1.19	0.55	0.12	0.33
E. Europe	1	0.89	0.28	0.00	0.72	0.83	0.07	0.00	0.93
	2	1.17	0.30	0.01	0.69	0.99	0.06	0.02	0.92
	4	1.49	0.29	0.06	0.65	0.96	0.04	0.07	0.89
	8	1.38	0.28	0.09	0.63	0.59	0.03	0.12	0.85
Euro area	1	2.13	0.98	0.00	0.02	1.35	0.67	0.00	0.33
	2	1.62	0.95	0.03	0.02	1.21	0.67	0.02	0.31
	4	1.21	0.93	0.05	0.02	1.09	0.68	0.05	0.27
	8	0.88	0.92	0.06	0.02	0.91	0.68	0.08	0.23
Japan	1	3.08	0.20	0.00	0.80	2.91	0.05	0.00	0.95
	2	2.12	0.32	0.02	0.66	2.28	0.03	0.02	0.95
	4	1.51	0.38	0.04	0.58	1.66	0.03	0.04	0.94
	8	1.09	0.41	0.06	0.53	1.20	0.02	0.05	0.92
Sweden	1	4.00	0.36	0.00	0.64	3.53	0.61	0.00	0.39
	2	2.58	0.45	0.04	0.50	2.47	0.66	0.05	0.29
	4	1.89	0.48	0.12	0.41	1.75	0.67	0.08	0.25
	8	1.46	0.47	0.21	0.32	1.28	0.67	0.11	0.22
UK	1	2.38	0.45	0.00	0.55	1.06	0.24	0.00	0.76
	2	1.92	0.52	0.03	0.45	0.92	0.27	0.03	0.69
	4	1.65	0.54	0.14	0.32	0.79	0.27	0.06	0.67
	8	1.41	0.51	0.27	0.22	0.62	0.25	0.09	0.66
US	1	2.86	0.00	0.00	1.00	1.75	0.29	0.00	0.71
	2	2.38	0.01	0.01	0.98	1.30	0.29	0.02	0.69
	4	1.94	0.04	0.05	0.91	1.08	0.30	0.05	0.64
	8	1.61	0.07	0.14	0.79	0.85	0.31	0.08	0.62
				B: Band-Pass Filtered GDP					
Denmark		1.68	0.21	0.08	0.70	0.93	0.53	0.14	0.33
E. Europe		1.26	0.28	0.11	0.61	0.65	0.05	0.11	0.84
Euro area		0.71	0.91	0.07	0.02	0.71	0.66	0.10	0.24
Japan		0.88	0.42	0.08	0.50	0.97	0.04	0.06	0.91
Sweden		1.19	0.44	0.28	0.28	1.01	0.67	0.13	0.20
UK		1.23	0.45	0.36	0.19	0.50	0.27	0.10	0.63
US		1.33	0.10	0.21	0.70	0.66	0.30	0.10	0.60

Notes: *The estimates are the standard deviations and the three-way decomposition of variance of bandpass-filtered real GDP. Panel A shows results for the FSVAR model, presented in equation (5), forecast errors at the one, two, four and eight quarter horizon. The standard deviation in panel A. are in percentage points at an annual rate – 400/h times the forecast error, where h is the forecast horizon. Panel B. shows results for the ideal six- 32 quarters bandpass-filtered values of real GDP. The standard deviations are in percentage points.*

The variance decompositions for bandpass-filtered real output in panel B yield similar conclusions to the results presented in panel A. Finally, in both panels A and B, the forecast error standard deviation has fallen for the Euro area, suggesting improved forecasting properties in the second period relative to the first subsample.[10]

Further sensitivity analysis can be undertaken by using some of the conclusions gained from the correlation results presented in Table 5.5 and the likelihood ratio tests of Table 5.6. The correlation results raise the question of whether only one of the factors in the estimated model might be interpreted as an 'English only' factor, which in this case only applies to the UK and the US. The hypothesis that one of the common factors loads only the UK and the US provides two testable restrictions on the FSVAR, which can be tested using the likelihood ratio test as in Table 5.6. However, this restriction is rejected at the one percent significance level ($p = 0.00$) over the full sample and in the first subsample period, 1980-1992, at the five percent significance level ($p = 0.05$). However, in the second subsample period, 1993-2005, the null cannot be rejected ($p = 0.34$), which suggests the possible emergence of an 'English speaking' cluster. Undertaking a similar analysis for the three industrialised continental European economies, Denmark, the Euro area and Sweden, suggests the emergence of a 'European' cluster, with the first subsample not rejecting the null hypothesis ($p = 0.13$) and with the corresponding hypothesis for the second subsample also not being rejected ($p = 0.37$). This result stands in contrast to Canova *et al.* (2006), in which they identify a world cycle but show that, apart from an increase in synchronicity in the late 1990s, there is weak evidence in support of a distinct European business cycle, or of its emergence. Finally, imposing a restriction in which the second factor is limited to the Eastern European cycle and the Euro area cycle suggests that the accession countries may be becoming more synchronised with the Euro area. The overall sample rejects the restriction imposed at the one percent level ($p = 0.00$), and in the first subsample the restriction is rejected at the five percent level ($p = 0.04$). However, in the final subperiod the restriction cannot be rejected ($p = 0.32$). The testable restriction results confirm the impressions gleaned from the correlation coefficients in Table 5.5, in which, because of deeper integration, there is an emergence of a 'European' and 'English' speaking group which have developed stronger ties over the past few decades. As noted in Table 5.5 the correlation between

[10]These results appear robust to different lag length permutations in the VAR(p_1, p_2) model. Changing the model to a VAR(4, 1) has little effect on the Euro area. The main difference is that in the first subsample international shocks account for about five to 10 percent less of overall output fluctuations for the Euro area than the results presented in Table 5.7. The only economy which appears relatively sensitive to changes in the lag length is the UK.

these two clusters has also significantly increased over time.

Changes in Volatility: Impulse or Propagation

The work of Frisch (1933) and Slutsky (1937) suggested that movements in output arise from the interaction of an internal propagation mechanism and impulses. This would result in impulses or shocks affecting output through a propagation mechanism, producing serially correlated fluctuations in output. Using this principle, this section investigates whether the contribution of international shocks to output volatility in the Euro area has decreased because the variance of international shocks has decreased, or because shocks of a fixed magnitude has less of an effect on the economy, or both. In other words, this section tests the hypothesis that the variance of real output growth in a given economy can change because the magnitude of the shocks impacting upon the Euro area have changed, or because the effects of those shocks have changed. This section decomposes the change in the variance from the first subsample to the second into changes in the magnitude of the shocks - impulses - and changes on their effect on the economy - propagation.

This is modelled as in Chapter 4, with the variance of four-quarter ahead forecast errors of the Euro area denoted as V_p, where p corresponds to the subsample $p = 1, 2$. The variance decomposition attributes a portion of V_p to each of the nine shocks in the model (seven domestic shocks and the two common factor shocks). This can be expressed as $V_p = V_{p,1} + ... + V_{p,9}$, where $V_{p,j}$ is the variance in period p attributed to the j^{th} shock. The change in the variance between two periods can easily be calculated as $V_2 - V_1 = (V_{2,1} - V_{1,1}) + ... + (V_{2,9} - V_{1,9})$. In the standard SVAR literature the variance component $V_{p,j}$ is expressed as $a_{pj}\sigma^2_{pj}$, where a_{pj} represents the cumulative squared impulse response function of an economy to a shock in economy j in period p and σ^2_{pj} is the variance of shock j in period p. Thus, using the following formula (as in Tekatli (2006), Stock and Watson (2005a)), the change in the contribution of the j^{th} shock can be decomposed using the following formula,

$$V_{2,j} - V_{1,j} = \left(\frac{a_{1j} + a_{2j}}{2}\right)(\sigma^2_{2j} - \sigma^2_{1j}) + \left(\frac{\sigma^2_{ij} + \sigma^2_{2j}}{2}\right)(a_{2j} - a_{1j}) \tag{5.12}$$

The first part of the right hand side of equation (5.12) represents the change in the variance of shock j from the first subsample, 1980 - 1992, to the second subsample, 1993 - 2005, whilst the final terms show the change in the contribution from the impulse response. As mentioned by Stock and Watson (2005a), the decomposition is additive, which implies that these contributions can be aggregated into a variance arising from the common shocks, spillovers, and own shocks, with each type of shock in turn decomposed into changes in variances arising from changing shock variances and from changing impulse responses.

The results are presented in Table 5.8, which show a six-way decomposition of the change in the variance of real output. The first result to notice is that three of the largest trading partners of the Euro area - Eastern Europe, UK and the US - have all seen large falls in output variance. Second, confirming the stochastic volatility model results earlier, Japan is the only economy to have seen an increase in volatility. The results for the Euro area suggest that the decline of the variance in real output in the second subperiod, relative to the first subsample, is primarily attributable to changes in the impulse response function, i.e., the international shocks impinging on the Euro area economy are having a smaller effect due to changes in the propagation mechanism. A small proportion, -0.17 (-0.01 overall), of the decline in the variance of Euro area output is attributed to a decline in the magnitude of international shocks. A small share when compared with the two smallest economies in the sample; Denmark and Sweden. For Denmark, Sweden and the US, a decline in total shock variance (both international and domestic) has been the largest contributor to dampening output fluctuations. In the case of Denmark and Sweden, however, the magnitude of shock reduction over the two periods is mainly down to country-specific rather than international innovations, suggesting that possibly innate changes in monetary or productivity factors have played an important role in the two economies. As with the Euro area, the results for the UK suggest a larger role for changes in the propagation mechanism of shocks than changes in the size of shocks hitting the economy.

The results for the Euro area present something of a paradox. Table 5.2 implied that propagation changes over the last 15 years mean that shocks hitting the economy no longer disperse as quickly. Table 5.8 shows that the contribution of the domestic impulse function to have actually led to an *increased* contribution to output volatility, with the international analogous showing the opposite. There has been little work undertaken on why international shocks may propagate for a shorter period than domestic ones. One possible reason may be that domestic rather than international disturbances get built into expectations more easily. In addition, developments in financial markets, such as futures markets, has meant households and firms find it easier to mitigate against negative international developments.

Table 5.8: Decomposition of Changes in the Variance of four-quarter-ahead FSVAR Forecast Errors into Changing Impulses and Changing Propagation

	Variances			*Contribution of change in Shock Variance*				*Contribution of change in Inpulse function*			
	1980-1992	1993-2005	change	Int'l	Spill over	own	total	Int'l	Spill over	own	total
Denmark	8.51 (2.56)	2.74 (0.80)	-5.77 (2.68)	-0.33 (1.10)	-0.32 (0.38)	-4.68 (1.57)	-5.34 (1.71)	0.05 (1.47)	0.12 (0.65)	-0.61 (1.04)	-0.44 (2.14)
E. Europe	2.21 (0.56)	0.96 (0.25)	-1.25 (0.60)	-0.06 (0.55)	-0.11 (0.11)	0.17 (0.48)	0.00 (0.87)	-0.53 (0.89)	0.06 (0.16)	-0.77 (0.30)	-1.25 (0.96)
Euro area	1.46 (0.43)	0.86 (0.24)	-0.60 (0.49)	-0.17 (0.42)	-0.05 (0.07)	0.21 (0.37)	-0.01 (0.59)	-0.70 (0.63)	0.02 (0.11)	0.09 (0.17)	-0.59 (0.72)
Japan	2.27 (0.65)	2.68 (0.81)	0.41 (1.04)	-0.09 (0.41)	-0.15 (0.25)	0.12 (0.63)	-0.12 (0.81)	-0.73 (0.76)	0.15 (0.38)	1.10 (0.58)	0.52 (1.14)
Sweden	3.57 (0.92)	2.28 (0.63)	-1.29 (1.12)	-0.23 (0.76)	-0.45 (0.36)	-1.42 (0.64)	-2.10 (0.86)	0.52 (0.96)	0.27 (0.52)	0.02 (0.25)	0.81 (1.23)
UK	2.72 (0.70)	0.55 (0.17)	-2.16 (0.73)	-0.09 (0.41)	-0.02 (0.11)	-0.78 (0.50)	-0.89 (0.64)	-1.20 (0.73)	-0.32 (0.21)	0.25 (0.26)	-1.27 (0.87)
US	3.76 (1.07)	1.22 (0.36)	-2.54 (1.13)	-0.06 (0.40)	-0.14 (0.17)	-2.28 (0.77)	-2.47 (0.91)	0.38 (0.74)	0.04 (0.26)	-0.49 (0.58)	-0.06 (1.04)

Notes: *The columns under the 'Variances' subheading give the variance of the bandpass-filtered GDP in percentage terms, using the estimated FSVAR model. Finally, the sum of the 'international', 'spillover' and 'own' columns equate to the 'total' column, with the sum of the two 'total' columns equalling the 'change' column. Estimated standard errors are shown in the parentheses.*

Figure 5.8 tracks the time-varying estimates of the variance decomposition results of the bandpass-filtered real output in Table 5.7, based on rolling estimates of the two-factor FSVAR. This is undertaken since it permits an analysis of how the conclusions of Table 5.7 have developed over the passage of time. Figure 5.8 illustrates the total variance - top line - the international shocks plus spillovers - middle line - and international shocks - lower line - so the gap between the top and middle lines is the contribution to the variance of domestic shocks. The estimates for the Euro area show that the decline in the overall volatility in the 1990s tracks a decline in the variance arising from international shocks. The results would seem to imply that international shocks are playing a smaller role in driving output fluctuations in the Euro area. This applies even more so to Sweden and the UK. Finally, the results also support the view that international shocks have played a very minor role in driving real output fluctuations in Japan, which is consistent with the general consensus in the literature regarding the limited international forces at work on the Japanese economy.

Figures 5.9A and 5.9B illustrate the impulse response functions for real output growth in the two subsamples, with respect to the first and second common factors. The illustrations suggest that important changes in the effect of an international shock, of a fixed magnitude, have taken place over the sample period. For the first common factor there has been a fall in the magnitude of the shock on the Euro area economy, although the propagation has remained the same. The estimates suggest that the first factor has become less important one year following the subsequent shock. In contrast, the response to the second factor suggests that it's effects on real output have fallen, which is consistent with estimates in Table 5.8, which showed international shocks of a fixed magnitude and changes in the propagation mechanism to have played some role in the moderation. Similar conclusions can also be drawn for Denmark. The estimates for the UK and US imply that factor 1 has become more dominant.

Figure 5.8. Time-varying Variance of Bandpass-Filtered real GDP

International Shocks (lower); international shocks+spillovers (middle)

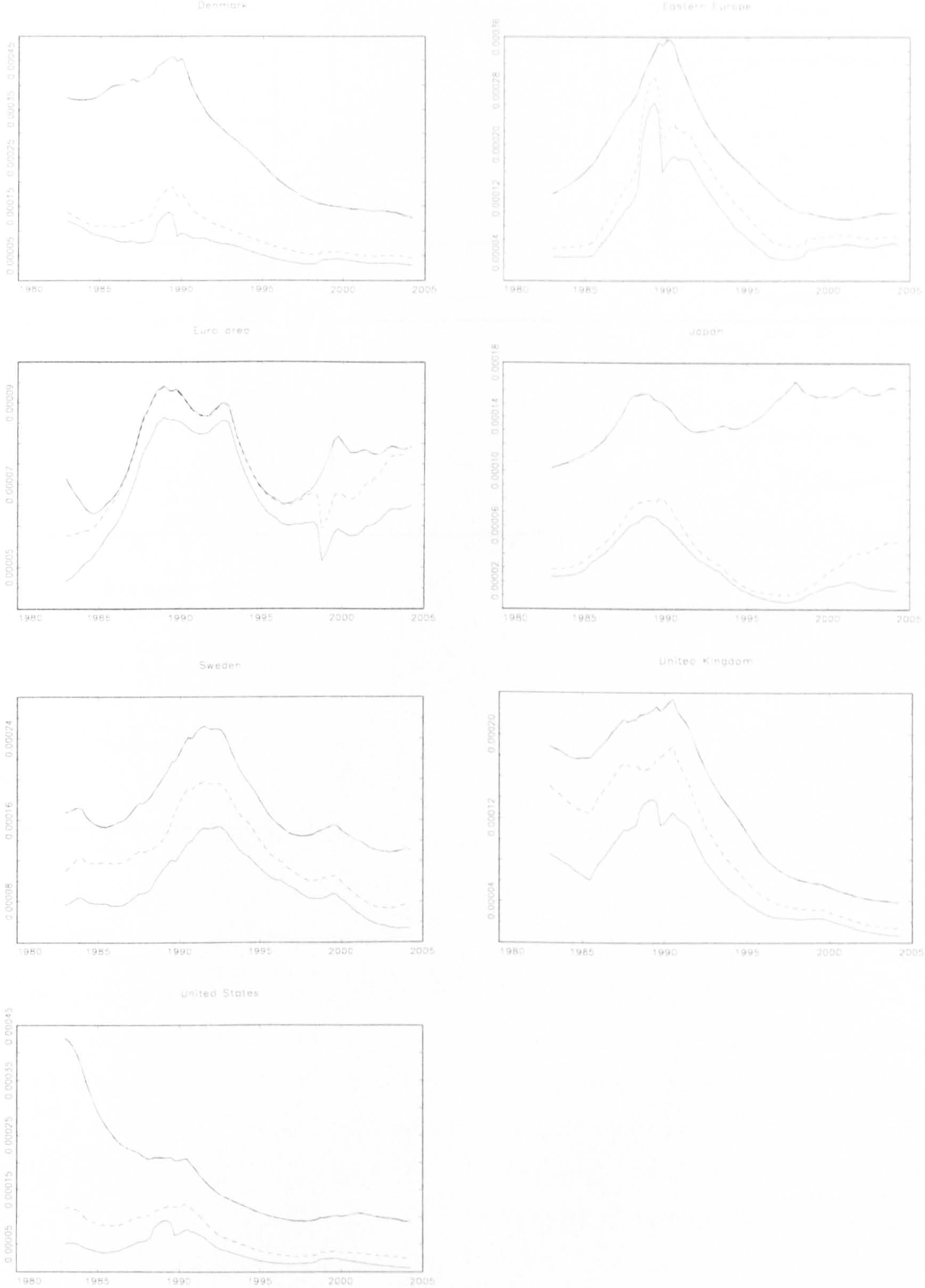


Figure 5.9A. Cumulative IRF of Economy GDP growth rate w.r.t. the First Common Factor 1980 - 1992 (solid) and 1993 - 2005 (dashed line)

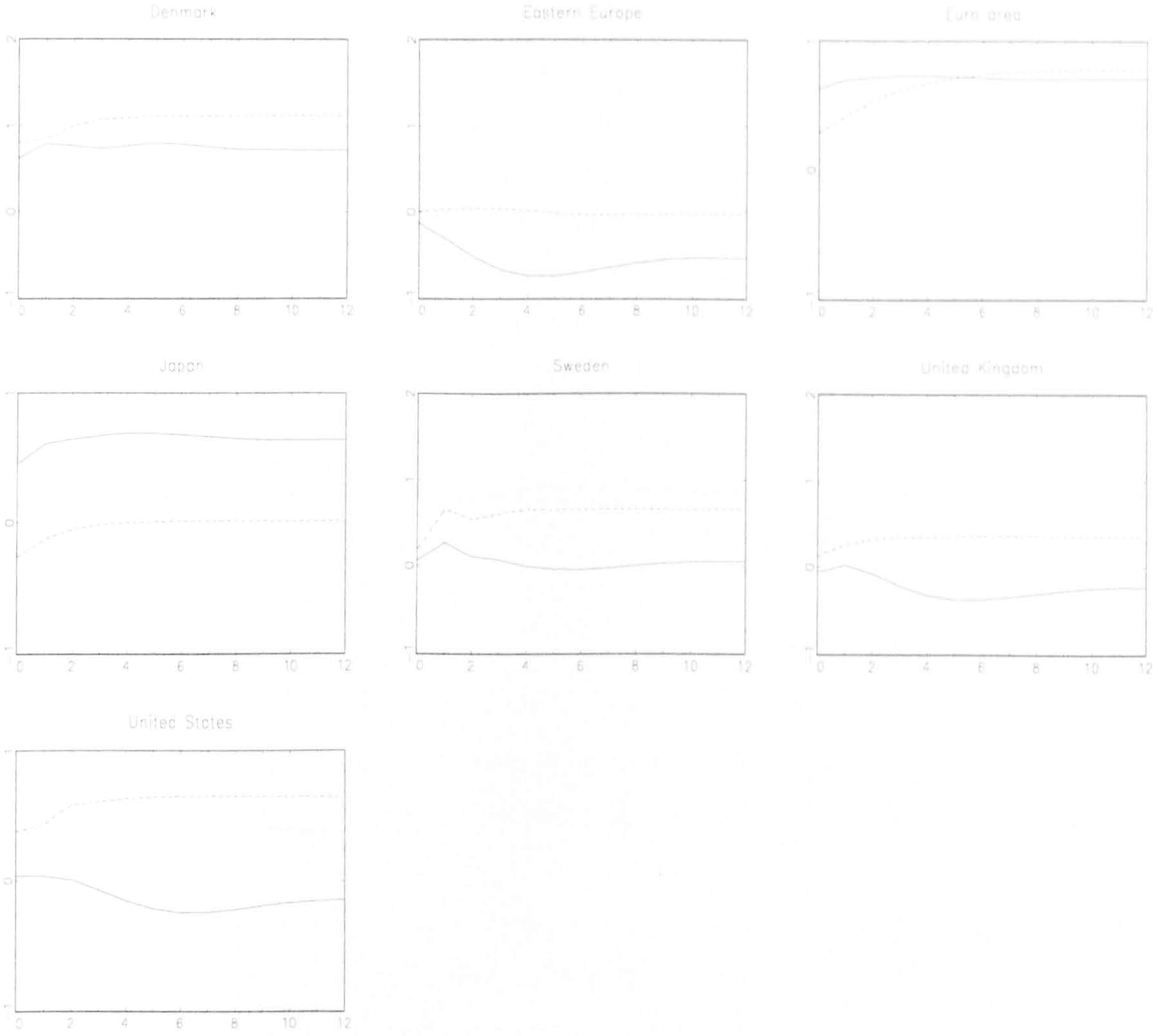
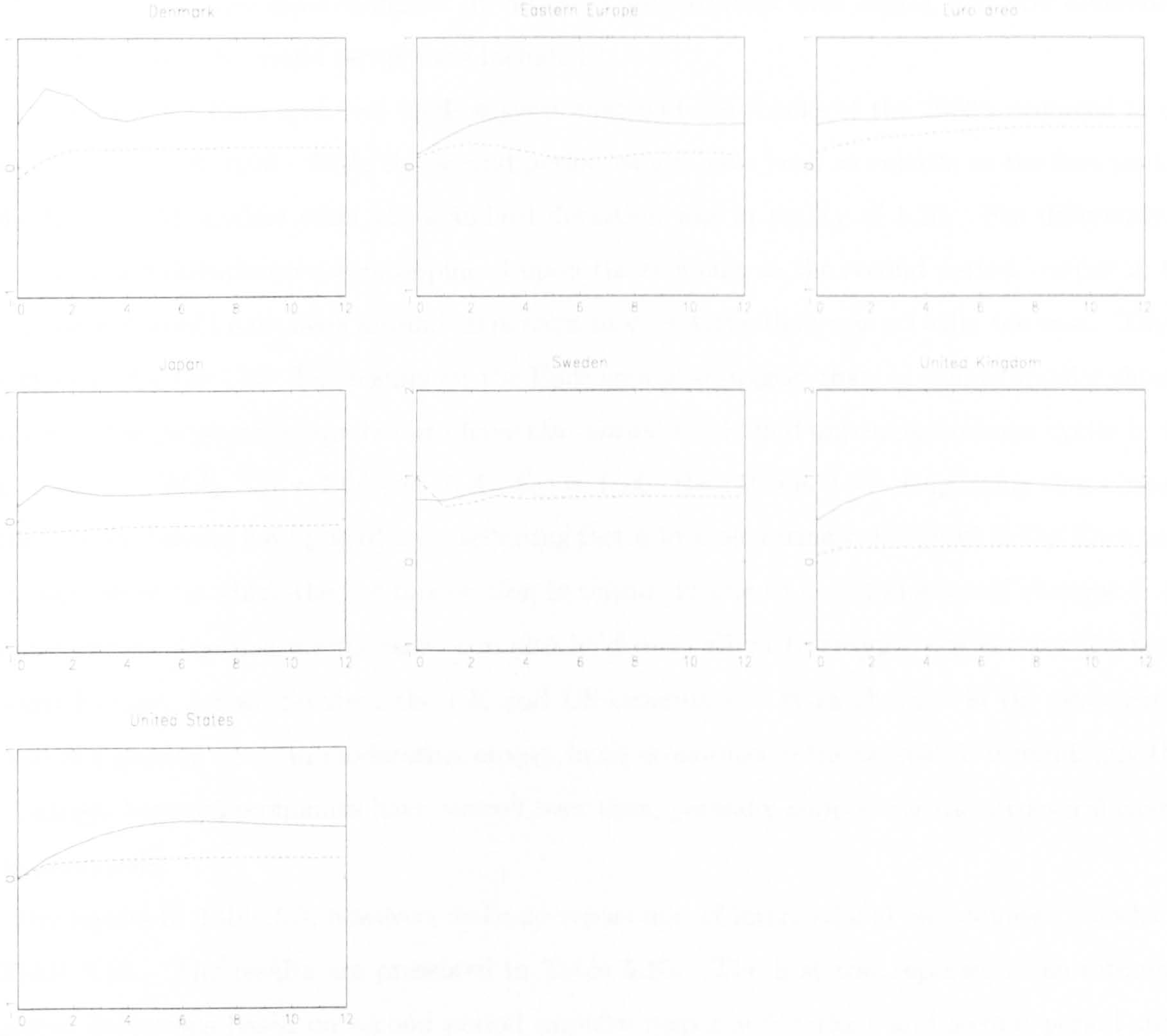


Figure 5.9B. Cumulative IRF of Economy GDP growth rate w.r.t. the Second Common Factor 1980 - 1992 (solid) and 1993 - 2005 (dashed line)



5.5.2 Counterfactual Simulations

The results presented in this subsection explore the hypothesis, drawn from conclusions in Table 5.8, that volatility in the second subsample, 1993 - 2005, would have been higher if the second subsample has been subjected to the international shocks of the first subsample, 1980 - 1992. This is examined by counterfactual simulation, using the principles in Chapter 4. Hence, like the reduced form VAR of equations (4.4) and (4.5), which are estimated in two separate time periods, 1980 - 1992 and 1993 - 2002, the near VAR(2, 1) of equation (5.10) is estimated counterfactually. This allows a calculation of how much of the reduction in mean output growth is due to changes in the VAR coefficients (propagation mechanism) and due to changes in the covariance matrix (impulse), i.e., how much of the moderation in the Euro area business cycle may be due to changes in shocks emanating from other economies, or whether changes in the propagation of international shocks in the Euro area economy have changed. In addition, all variables were *logged*, and first differenced before estimation. No trend terms were included.

The results for Euro area real GDP suggest that had the shocks of the 1980's occurred in the second time period, 1993 - 2002, the second period would have been as volatile as the first period, $\sigma(\widehat{A}_2, \widehat{\Sigma}_1) = 1.32$, against what the standard deviation was in reality of 1.30. Put differently, if the first period disturbances were impinged upon the economy in the second period, output in the second period would have been around 20 percent more volatile than was actually the case. This is also the case for the UK. The results for the Euro area also suggest that, as well as smaller shocks, changes in the propagation mechanism have also played a role in dampening business cycles in the Euro area, i.e., $\widehat{\sigma}(\widehat{A}_2, \widehat{\Sigma}_2) = 1.04$ and $\widehat{\sigma}(\widehat{A}_1, \widehat{\Sigma}_2) = 1.64$ - the ratio is 0.63 - suggesting that changes in the *AR* coefficients have played a contributing factor in moderating real output in the Euro area. This conclusion, in which the the moderation in output in due to a combination of changes in the impulse and propagation mechanisms, can also be drawn, albeit to varying degrees, for Denmark, Eastern Europe, Japan, Sweden, the UK and US economies. With changes in the propagation mechanism playing a role in moderating output in all economies in the sample, it would imply that the linkages between economies have altered over time, partially supporting the structural change tests previously.

The results in Table 5.9, however, make no separation of international and domestic shocks, as in Table 5.10. The results are presented in Table 5.10. The first row represents the estimated standard deviations based on second period impulse response functions and second period shock variances, with the second row showing the first period variance of the common shocks which is used to counterfactually estimate the variance of the second subsample, $\Lambda_2 = \Lambda_1^{int} + \Lambda_2^{dom}$. The last row is represented by $\Lambda_2 = \Lambda_1^{int} + \Lambda_1^{dom}$.

Table 5.9: Implied Standard Deviations of Four-Quarter GDP Growth from Subsample VARs

$X_t = A(L)\,X_{t-1} + \varepsilon_t, \qquad \mathrm{Var}(\varepsilon_t) = \Sigma$

First Sample Period: 1980 – 1992 (Estimated Parameters $\hat{A}_1(L)$ and $\hat{\Sigma}_1(L)$)

Second Sample Period: 1993 – 2005 (Estimated Parameters $\hat{A}_2(L)$ and $\hat{\Sigma}_2(L)$)

Economy	*Sample standard deviation*		*Standard deviation of four-quarter GDP growth in VAR model*			
	1980-1992	**1993-2005**	**$\sigma(A_1, \Sigma_1)$**	**$\sigma(A_2, \Sigma_2)$**	**$\sigma(A_1, \Sigma_2)$**	**$\sigma(A_2, \Sigma_1)$**
Denmark	2.87	1.69	5.66	1.51	3.40	2.98
E. Europe	1.96	1.03	2.99	1.51	1.49	2.98
Euro area	1.30	1.20	1.98	1.04	1.64	1.32
Japan	1.77	1.67	1.27	1.06	0.68	2.02
Sweden	1.94	1.79	1.63	1.65	1.33	1.96
United Kingdom	2.23	0.74	2.84	2.29	2.20	2.07
United States	2.39	1.23	1.26	0.43	0.58	1.07

Notes: *The entries represent the square root of the variance of the four-quarter growth in GDP for all economies in the sample.*

Table 5.10: FSVAR Counterfactual Volatility Measures during 1993 – 2005 using Common and Country Shocks Variance from 1980 – 1992

Period for shocks variance		*A. Standard deviation of four-quarter real GDP growth*						
Common Shocks	Country Shocks	Denmark	Eastern Europe	Euro area	Japan	Sweden	UK	US
1993 - 2005	1993 - 2005	1.71	1.19	1.06	1.65	1.58	0.77	1.16
1980 - 1992	1993 - 2005	1.82	1.19	1.12	1.66	1.68	0.80	1.21
1980 - 1992	1980 - 1992	2.89	1.25	1.17	1.74	2.33	1.31	1.97
		B. Standard deviation of bandpass-filtered real GDP growth						
Common Shocks	Country Shocks	Denmark	Eastern Europe	Euro area	Japan	Sweden	UK	US
1993 - 2005	1993 - 2005	0.98	0.67	0.62	0.95	0.85	0.46	0.68
1980 - 1992	1993 - 2005	1.05	0.67	0.66	0.95	0.91	0.48	0.71
1980 - 1992	1980 - 1992	1.65	0.71	0.73	1.00	1.24	0.77	1.16

Notes: *Panel A represents the standard deviations of four-quarter GDP growth in percentage points at an annual rate based on the estimated FSVAR impulse response function estimated using data from 1993- 2005, using the shock variances estimated over the sample indicated in the first two columns. The first row is the model based estimate of the actual standard deviation during 1993 – 2005, the remaining rows are counterfactuals. The entries in panel B. are analogous to those in panel A. but are based on bandpass-filtered real GDP, with the bandpass set to capture cycles between 6 and 32 quarters.*

Comparing the first row of each panel (the estimated standard deviations based on second-period international and common shocks) with the second row (in which the first-period common shock variance is used) shows that, had the international shocks of the first period impacted on the Euro area economy in the second period, the Euro area economy would have been slightly more volatile. These results also hold for estimates based on bandpass filtered real output. These conclusions, albeit to varying degrees, hold for the other economies, bar Japan, which would see little, if any, difference counterfactually. Indeed, counterfactual estimates of international shocks suggest the largest change in output volatility would be witnessed in Sweden. The results for Denmark, UK and the US imply that, although shocks have played a substantial role in reducing output volatility, a significant proportion of the decline due to shocks is down to fewer domestic rather than international shocks.

The broad range of results from Tables 5.6 to 5.9 suggest that, although international innovations play a large role in driving output fluctuations, impulses from international business cycles have played, at best, a small role in the dampening of Euro area business cycles. Changes in the propagation of international shocks have played a slightly larger role. In comparison to the other constituent economies, international impulses have played more of a role in dampening output volatility in Sweden. The results on the whole imply that the moderation seen across all sample economies is more down to internal than external forces.

5.5.3 An examination of international shocks

The results suggest that the moderation in the Euro area cycle can be only very partially be attributable to the moderation witnessed in the Euro area's main trading partners, i.e., less international shocks. It is of interest to see if these international shocks can be linked to observable and interpretable time series.

Although all the shocks presented are domestic in origin, if they were to affect other countries within the quarter that they occur, then they would be classified as common international shocks in the FSVAR identification scheme. The first shock candidate is Euro area monetary policy, modelled by the framework of Uhlig (2005). The next two candidates are measures of productivity shocks, based on King *et al.* (1991) and Galí (1999, 2004). The use of two different measures of productivity shocks is based upon the belief that standard measures of productivity shocks, such as the Solow residual, suffer from measurement problems, which include variations in capacity utilisation, imperfect competition and other sources. The third set of shocks are innovations to commodity prices, measured as a metals price index, an agricultural price index and two measures of oil prices. The first measure is the standard nominal crude oil price, with the second based on Hamilton's (1996) non-linear crude oil price measure.

Table 5.11 reports the largest canonical correlations between the factors and the leads and lags of the candidate observable shock series. The largest canonical correlation is the correlation between a linear combination of the factors and a linear combination of the leads and lags of the observable shock series, where the linear combinations are chosen to maximise the squared correlation. This procedure has the advantage of not requiring additional normalisations for identifying the two factors separately.

Table 5.11: Canonical Correlations between International Factors and Various Observable Shocks

	1980 - 2005	*1980 - 1992*	*1993 - 2005*
Monetary Shock (Uhlig, 2005)	0.041	0.027	0.042
Productivity Shock (Gali, 1999, 2004)	0.303	0.379	0.038
Productivity Shock (King et al. 1991)	0.006	-0.056	0.058
Oil Price Nominal	-0.014	0.009	0.032
Oil Price (Hamilton, 1996)	0.002	0.030	-0.069
Metals Price Index	0.002	0.078	-0.036
Agricultural Price Index	0.002	0.078	-0.040

Notes: Entries represent the largest canonical correlation (adjusted for degree of freedom) between the two factors from the estimated FSVAR model and two leads and lags of the series listed in the first column.

The results in Table 5.11 would seem to suggest that international shocks are hardly correlated with Euro area monetary policy shocks. The results are more conclusive for two out of the three productivity shocks. The estimates suggest that international shocks are positively correlated with Euro area productivity shocks. This is perhaps not surprising, since the Euro area is a large open economy. Otherwise, the canonical correlations are nearly zero or negative, indicating that the common international shocks in the FSVAR are, in this case, unrelated to the candidate observable shocks. Stock and Watson (2005a) found similar results using observable US shocks and common factors estimated from the G7 economies. It must be noted, however, that Table 5.11 represents a rather coarse attempt to identify the source of international factors as several of the candidate shocks are Euro are centric.

5.5.4 Sensitivity Results and Possible Extensions to the Model

This section provides a brief discussion of the robustness of the estimates presented in sections 4, 5 and 6 to possible changes in the model specification and assumptions.

Trade-Weighted VAR lag restrictions

Elliot and Fatás (1996) argued for the need for restrictions on the VAR in which the coefficients on real output are proportional to trade shares. Norrbin and Schlagenhauf (1996) used a similar approach. Incorporating the use of trade shares in the VAR model can be nested within the framework presented in equation (5.3),

$$Y_t = A(L)Y_{t-1} + D(L)WY_{t-1} + v_t \text{ where } E_t(v_t v_t') = \Sigma_v$$

where $A(L)$ and $D(L)$ represent diagonal lag polynomial matrices, with W containing the fixed weights of the trade shares between the Euro area and the constituent economies. The diagonal elements of W are zero and the (i, j) element is the share of gross trade (imports plus exports) of trading partner j in all of economy's i trade with all the other economies in the sample. Attributing a weight would turn the variance decomposition into $E(v_t v_t') = W'\Gamma\Sigma_{ff}\Gamma'W' + W'\Sigma_{\omega_t}W$, where the first term on the right-hand side is the decomposition of the common factor, and the final term the idiosyncratic disturbance.

Unfortunately, due to a lack of trade shares data for Denmark, Eastern Europe, Euro area and Sweden spanning the necessary time span, 1980 - 2005, the nested model above cannot be estimated without creating large sampling uncertainty due to a very small sample size. It must also be noted that since the economies were chosen based on their relative trading weight with the Euro area, the FSVAR model estimated takes into account the concerns raised by Elliot and Fatás (1996).

Average Coherence

The analysis of international synchronisation so far has relied on the contemporaneous cross correlation of four-quarter real output growth and that of the bandpass-filtered real output as the measures of comovements. However, this approach can be criticised on the grounds that it can mask lagged associations. Hence, the sensitivity of the results presented are checked against an alternative measure of comovement which is invariant to these lagged effects. This section measures the average coherence at business cycle frequencies. This is done using the coherence test statistic of Stock and Watson (2005a),

$$R_{ij}^2(\omega_0, \omega_1) = \frac{\int_{\omega_0}^{\omega_1} ||s_{ij}(\omega)||^2 d\omega}{\left(\int_{\omega_0}^{\omega_1} ||s_{ii}(\omega)|| d\omega\right)^{1/2} \left(\int_{\omega_0}^{\omega_1} ||s_{jj}(\omega)|| d\omega\right)^{1/2}} \tag{5.13}$$

In equation (5.13), ω_0 and ω_1 represent the lower and upper frequencies of the bandpass filter that defines the business cycle portion of the spectrum, with $s_{ij}(\omega)$ acting as the cross spectrum between the four quarter growth rates in economies i and j. The statistic in equation (5.13) reduces to the usual definition of coherence when evaluated at a single frequency rather than over ω_0 and ω_1.

Table 5.12: FSVAR based Counterfactual Correlations of Four-quarter real GDP growth rates

	A. FSVAR estimates of 1980 - 1992 correlations						
	Denmark	E. Europe	Euro Area	Japan	Sweden	UK	US
Denmark	1.00						
E. Europe	0.44	1.00					
Euro area	0.31	0.20	1.00				
Japan	0.48	0.48	0.65	1.00			
Sweden	0.21	0.60	0.45	0.16	1.00		
UK	0.23	0.75	0.26	0.19	0.75	1.00	
US	0.26	0.55	0.26	0.15	0.46	0.46	1.00
	B. FSVAR estimates of 1993 - 2005 correlations						
	Denmark	E. Europe	Euro Area	Japan	Sweden	UK	US
Denmark	1.00						
E. Europe	0.12	1.00					
Euro area	0.65	0.15	1.00				
Japan	0.23	0.08	0.19	1.00			
Sweden	0.66	0.17	0.66	0.09	1.00		
UK	0.70	0.09	0.58	0.11	0.74	1.00	
US	0.70	0.13	0.60	0.24	0.59	0.73	1.00

Note: The results are the square root of the average coherence at business cycle frequencies.

The results in Table 5.11 summarise the square root of the average coherence, $R_{ij}(\omega_0, \omega_1)$. As the coherence has the interpretation of an R^2, using the square root of the average coherence makes this measure more directly comparable to the correlation results in Table 5.11. The qualitative conclusions from the counterfactual estimates in Table 5.11 are similar to those in Table 5.5, apart from Eastern Europe. The evidence in Table 5.12 suggests that the cross country lead-lag relations are modest, leading to similar results in Table 5.12 and Table 5.5.

5.6 Conclusion

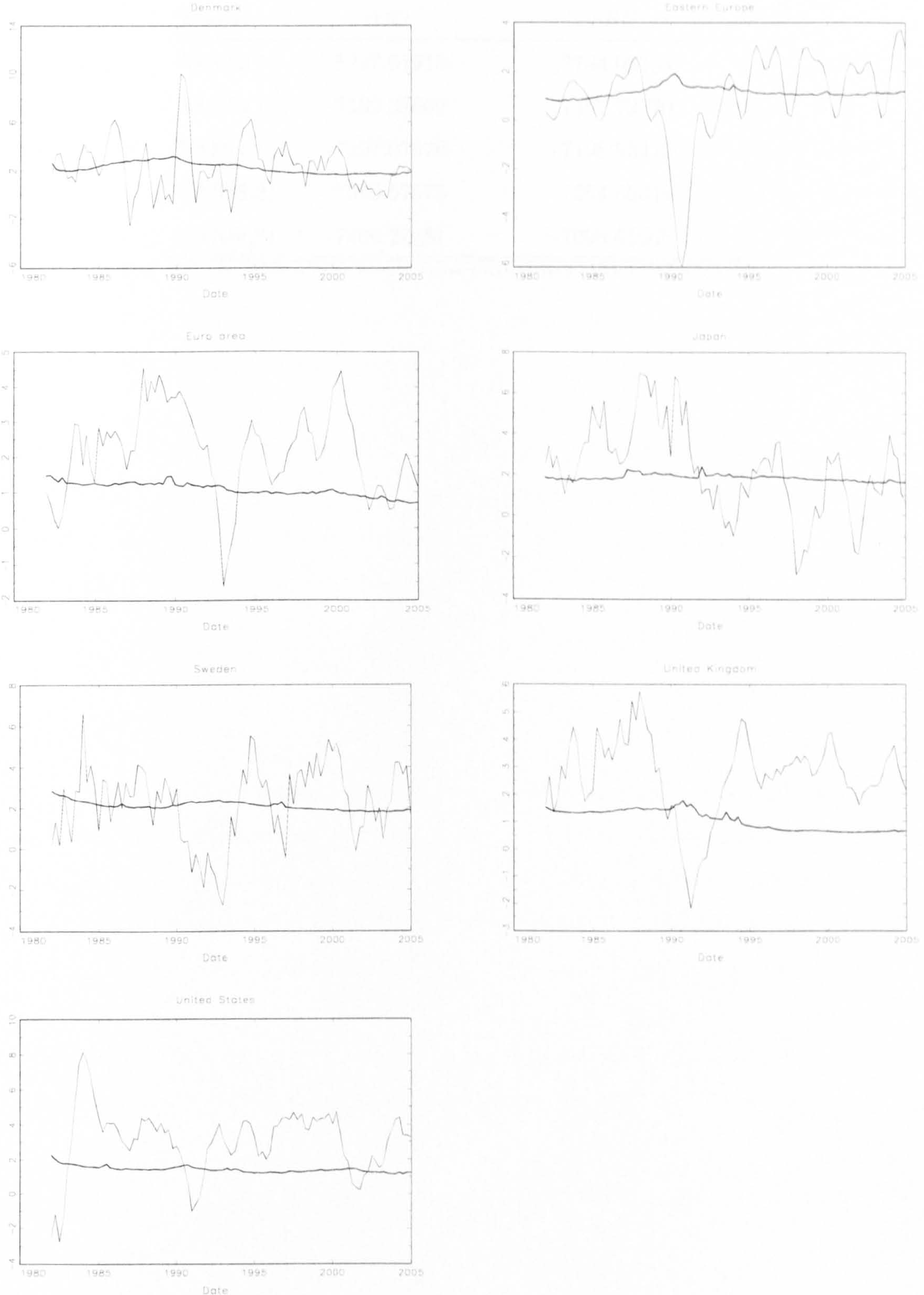
The results presented find an increasing degree of business cycle synchronisation between the Euro area and its main trading partners, apart from Japan. This is represented both by the correlation coefficient estimates and by the strengthening evidence of one common factor being able to explain the comovements between the Euro area and its trading partners in the second subperiod. However, with regards to the new accession countries, although synchronisation has increased, it would appear that there remains significant differences in the synchronisation of cycles between the Euro area and the accession economies, with a relatively small correlation of about 0.25. Finally, the results find that international shocks do play a large role in driving output fluctuations in the Euro area. However, any attempts to link the moderation in the Euro area business cycle with a fall in the shock variance of international disturbances would be misplaced. Such shocks have played, at most, a marginal factor in dampening the Euro area cycle.

The evidence suggests that a more pertinent route in exploring the factors behind the increasing stability witnessed in the Euro area business cycle would be to follow the investigative line of Chapter 4, in which the various idiosyncratic components of the Euro area were investigated.

Appendix for Chapter 5

A: Four-quarter real GDP

growth rates and instantaneous standard deviation



Appendix B: VAR(p_1, p_2) Lag Length Selection

Model	*AIC*	*SBC*
VAR(2,1)	-8012.67913	-7784.08103
VAR(3,1)	-7539.38609	-7357.72770
VAR(4,1)	-7397.97670	-7198.93420
VAR(3,2)	-7563.67575	-7254.85649
VAR(4,2)	-7406.27081	-7098.65968

Note: Both information criterion were calculated using seemingly-unrelated regression (SUR).

Appendix C

Principal component analysis is a statistical method used to simplify a dataset. It is a linear transformation that selects the maximum amount of variance in components. Each of these components is ranked in order so that the first principal component accounts for the greatest variance. The second component accounts for the maximum variance that is not accounted by the first component. Therefore, the n^{th} component accounts for the maximum variance that is not accounted in all the previous components. These ranked weights are found by looking at the eigenvalues, which represents the variation in each component. Principal component analysis has the property of all components being uncorrelated with each other, allowing the avoidance of the multicollinearity problem that frequently arises in modelling a country's economy, or in this case a set of different economies.

Assume $X_1, ..., X_p$ represent a set of random variables, with a mean vector μ and covariance matrix Σ, with the assumption that the elements of each are finite. The rank of Σ is $r \leq p$, with p representing the largest characteristic roots of Σ, which are all distinct, $\lambda_1, ..., \lambda_p$. From n independent observation vectors, it can be written in matrix form,

$$\mathbf{X} = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix}$$

With the ordered ranks of Σ and $\mathbf{X}$, the first component, which represents the largest variance, is a linear combination $Y_1 = a_{11}X_1 + ... + a_{p1}X_p = a_1'x$, whose coefficients a_{i1} are the elements of the characteristic vector with the greatest characteristic roots ι_1 of the covariance matrix from the sample. If it is the case that $a_1 a_1' = 1$, the characteristic root is interpreted as the variance of the same Y_1 . Similarly, the second principal component is the linear combination $Y_1 = a_{12}X_1 + ... + a_{p2}X_p = a_2'x$, where $a_1'a_2 = 0$, which embodies an orthogonality property. This orthogonality property also allows the variances of successive components to sum the total variance. Finally, the j^{th} principal component of the sample of p-variate observation is $Y_j = a_{1j}X_1 + ... + a_{pj}X_p = a_j'x$.

Part III

Forecasting Properties of Euro area Macroeconomic Time Series

Chapter 6

Has the Moderation in the Euro Area Cycle Revived the Role of Money in Forecasting Output?

6.1 Introduction

The presupposition that asset prices are forward looking, and as a result contain useful information about the level of future economic activity, embodies key foundational concepts in macroeconomics. Indeed, as far back as Cassel (1918) and Hawtrey (1919), the importance of money as a determinant of future economic activity was being examined. One of the earliest, and most exhaustive, pieces of research on business cycle fluctuations, by Burns and Mitchell (1938), included the Dow Jones composite index of stock prices as a leading indicator of expansions and contractions of US output fluctuations. Financial variables tend to capture the principal of reflecting market participants' expectations of discounted future earnings, known as the Fisher hypothesis. The inherent unknowability of the future and the inherent subjectivity of expectations about the future enables the forces of 'time and ignorance' to affect the performance of real-world market economies. The use of such indices as information variables allows a reconciliation with Keynes (1936), who argued that economies are driven by a mass psychology which he termed 'animal spirits'.

The main novelty of this chapter is to re-examine the time-series evidence for the Euro area, emphasising the distinction between movements in expected (*ex ante*) asset prices and movements in expected output and inflation. This very classification, by definition, explores an insight suggested by Fama (1982), that the incremental predictive content of financial variables for future real variables arises solely because economic agents have some information about future real activity, beyond that contained in current and lagged real variables, which shows up first in the prices of financial assets, particularly nominal interest rates. The knowledge of which asset prices are useful for forecasting constitutes a set of stylised facts for understanding the workings of modern economies.

The last two decades have seen an increased literature investigating the informational content of real and nominal variables for future output. This literature has identified a number of key asset prices as having significant information content on future economic activity. These include interest rates, term spreads, stock returns and exchange rates. Identifying variables with strong predictive power for future output is important for a variety of reasons. Firstly, those whose task it is to produce forecasts, such as central bank institutions, need to know which, if any, asset prices provide useful forecasts of future output growth. Knowing such information became especially important from the early 1990s onwards, as the popularity of constructing coincident and leading indicator indices, like the NBER coincident index, increased. Such indices are used to date business cycle turning points or forecast future levels of economic activity. The accuracy of the constructed indices rest entirely upon the informational content of the individual series in the index, since such indicators synthesise information contained in a range of economic variables. Secondly, recent work by Kim and Nelson (1999), Blanchard and Simon (2001) and Stock and Watson (2002a, 2003a) have explored the moderation seen in the business cycle over the last three decades.[1] This moderation has been widespread across sectors in the economies of the G7. Such an investigation is important since it could lead to changes or refinements in macroeconomic models that contain 'ambiguous' variables due to a highly unstable relationship with future levels of output. It must be noted that the moderation witnessed in the Euro area cycle might have made it easier to forecast real economic activity. Real output, like many other time series of economic activity, has become less volatile, so the root mean square error (RMSE) of relatively poor forecasts should have declined since the mid-1980s. In this sense real output should be easier to forecast. The imprecision of real output forecasts, as measured by the mean square forecast errors (MSFE), has fallen; the results in Chapters 4 and 5 show that the forecast error standard deviation has fallen in the second subsample, 1992 - 2005, relative to the first subsample, 1980 - 1992.

Using results gathered from Chapters 4 and 5 the sample is split into two, a high volatility period, 1980:1 - 1992:4, and a low volatility period 1993:1 - 2005:4, to examine whether the stability witnessed in the Euro area cycle over the last two decades has brought about more stable forecasts

[1] Also see Martin and Rowthorn (2005), Sensier and van Dijk (2004), Mills and Wang (2003), Boivin and Giannoni (2002), Ahmed, Levin and Wilson (2001) and McConnell and Perez-Quiros (2000).

of future levels of economic activity. Most forecasting analysis has tended to forecast over the entire sample period, without taking into account any structural breaks that may have occurred. Although Stock and Watson (2003b) have examined the potential role of asset price forecasting for the G7 economies, the complex interplay between variables that affect economic activity has still to be worked out for the Euro area. Using the properties of Euro area time series data, the analysis presented provides an insight into the variables that would best be suited to building coincident and leading indicator series for the Euro area, as well as providing further information on the time-varying processes that are present in the Euro area macroeconomic data. The introduction of a common currency has increased the interest and need for business cycle analysis at the level of the Euro zone as a single economic entity.

The results are laid out as follows. Section 6.2 presents a brief literature review on the seminal work undertaken on the main leading indicators used in forecasting economic activity. Section 6.3 explains the pseudo out-of-sample forecasting model utilised, along with the in-sample stability tests used. The subsequent section explains the time series data used, along with the properties of the data. Section 6.5 investigates the bivariate estimates from the pseudo out-of-sample forecasting model. Section 6.6 focuses on the stability of the forecasting relationships unearthed in section 6.5 using Granger-causality and a QLR test statistic. Finally, section 6.7 shows the results for the constituent forecasts using in-sample procedures, as well as tests for forecasting stability. The penultimate section looks at various multivariate forecasting models, with the final section concluding.

6.2 The Rise and Fall of Future Output Indicators

This survey looks at the use of asset prices as predictors of output. The survey tries to capture significant historical milestones within the research area.

6.2.1 Failure of money

The issue of whether money accurately predicts future economic activity is an old one. Following the oil shocks of the 1970s and the work of Lucas (1976a), a reconsideration of the relative importance of monetary and of real factors in the generation of business cycles intensified. Sims (1972, 1980), empirical consideration of whether money (or any other monetary factor) can usefully play a role in the monetary policy process focused on not just whether fluctuations in money help predict future fluctuations of output or prices, but on whether they help predict future fluctuations of output that are not already predictable on the basis of fluctuations of income itself, or other readily observed variables. In theory, money can play an important role in the determination of the price level due to various nominal frictions in the economy, which can result in movements in real quantities. However, monetarist frameworks received a set back with Friedman and Kuttner (1992). Their empirical finding showed that evidence based on the US and UK experience did not indicate a close or reliable relationship between money and economic activity, once one controls for other aggregate variables, in particular interest rates. They found the relationship that had existed between money and income or prices broke down in the 1980's. This conclusion had a precedent in Sims (1980). Using the VAR framework, Sims (1980) found that the predictive content of money fell with the inclusion of a nominal interest rate. Most results since Sims' original work have arrived at similar conclusions. For example, Sims (1986, 1996), Bernanke and Blinder (1992), Eichenbaum (1992) and Christiano *et al.* (1996) all found, to varying degrees, that money was a poor predictor of future levels of economic activity. This has led to the theoretical argument that the stock of money is redundant. However, work by Nelson (2003) and Leeper and Roush (2003) have attempted to reverse this trend by building Taylor type rules which incorporate monetary aggregates in an attempt to highlight the importance of money as a future predictor.

Despite this, from an information variable perspective, there is no reason for the monetary authorities to react to fluctuations in money if those fluctuations bear no subsequent implication for real output or prices in the future. This has had strong implications for many central banks with policy frameworks that centred their design and implementation of policy on money. It has recently become increasingly common for central banks to implement inflation targets. This has led to agents expectations being centered around various interest rate measures rather than any specific monetary aggregate.

The perceived failure of money as an indicator of future economic activity has led to an investigation of whether there are more suitable indicators of future economic activity. This is highlighted by the visible shift from money to interest rates, nominal and real, that has taken place in the analytical framework of monetary policy. Clarida *et al.* (1999) presented, in canonical form, what has become the standard model in macroeconomics. This is a two-equation model consisting of an aggregate demand (or IS) curve, relating today's output level to expected future output and the expected real interest rate, and an aggregate supply (or short-run Phillips) curve relating today's inflation rate to both today's level of output, relative to some capacity benchmark, and to expected inflation. Frameworks such as that just described have been used as justification for the use of a wide variety of variables, like capacity utilisation, labour hours worked and unit labour costs, in trying to improve the performance of standard macroeconomic models in forecasting economic activity. Indeed, it is more common for empirical work on monetary policy and economic activity to include commodity prices than money.

6.2.2 Interest Rates

With the declining importance of monetarist ideas over the last two decades, the elevated position once held by money as a predictor of future levels of economic activity has been lost to other asset prices, which have demonstrated considerably more predictive content. This is especially true over the last decade, where the term spread, long minus short-term interest rates, has gained importance. Examples include Plosser and Rouwenhorst (1994), Estrella and Mishkin (1997), Bernard and Gerlach (1998) and Berk and Bergeijk (2000) on the European economies, or Stock and Watson (1989, 2003b, c) and Estrella and Hardouvelis (1991, 2003) on the US economy. It has become increasingly the norm to include the term spread in the construction of leading indicator series. Studies have shown an inverted yield curve (short rate exceeding long rates) to contain significant information content, being especially useful in predicting the onset of a future recession or a decline in economic activity. Studies of the US economy have found that, from the mid-1960s onwards, every recession to have been predicted by an inverted yield curve, there being only one 'false positive'. In addition, Davis and Fagan (1997) found that the interest rate spread led to an improvement in the forecasting performance of output for around half of the European countries examined, while Galbraith and Tkacz (2000) find this to be the case for all G7 countries apart from Japan.

Recent theoretical studies, however, have questioned the stability of the term spread as a predictor. A particular facet of this argument revolves around the idea that the predictive power of the term spread may depend on factors such as the monetary policy reaction function or the relative importance of real and nominal shocks, which may change over time. To refute possible instability, Estrella *et al.* (2003) show that, in the case of Germany and the US, the term spread is a more stable predictor of real output than inflation. Furthermore, recession prediction was stable over the whole sample period for Germany and the US.

Nominal interest rates are also perceived to be a good leading indicator, due to nominal rates being the instrument of choice for central banks across the industrialised world. Nominal interest rates are contemporaneously procyclical. Hence, part of the strength of the view that monetary changes have been an important generator of business cycle fluctuations stems from certain statistical timings and patterns in the data. Looking at the time series data for real GDP and nominal interest rates across the G7 economies, those periods of rising interest rates are always associated with periods of falling growth. Further, central banks, especially inflation targeting banks, regularly take notice of forward looking indicators such as capacity utilisation, building permits, employment and bond yields, to gain a valuable insight into the potential state of the economy a few quarters ahead, with a view to changing the nominal interest rate within the month. As a result, it has been noted that the nominal interest rate is a significant predictor of future levels of economic activity. Stock and Watson (1998) find strong evidence in support of nominal interest rates, but less so for real rates.

6.2.3 Financial Variables

The use of variables other than interest rates has also increased over the last 15 years. Exchange rates have long been championed, due to the effects of exchange rate volatility on the volume of trade, as found by Kenan and Rodrik (1986), De Grauwe (1988), Franke (1991) and Viaene and de Vries (1992). However, whether the change is positive or negative is less clear. In addition, the exchange rate may also have an effect on future levels of economic activity through the role it plays in the monetary transmission mechanism, as in the Mundell-Fleming-Dornbusch framework.

Stock prices are also viewed by economists as a gauge of agents expectations on the level of future economic activity. Burns and Mitchell (1938) included the Dow Jones composite index of stock prices in their leading indicators of expansions and contractions of US output fluctuations. Stock price indices capture the principal that stock markets reflect market participants' expectations of discounted future earnings. Stock and Watson (1998) have shown stock prices to be a reliable leading indicator of future economic activity.

Various housing measures are also gaining importance and popularity. Housing constitutes a large component of aggregate wealth and is sometimes included in the CPI basket.

6.2.4 Forecasts using Nonfinancial Variables

Over the years, economic forecasters have found many series which are precursors of the aggregate cycle. Building permits, which are a measure of future housing expenditures, and new orders, which are a measure of future expenditure on durable goods, are both procyclical and have considerable predictive content for output. Expectations of future economic variables play an important role in modern macroeconomic theories. Consumer expectations are procyclical, i.e., they lead the aggregate cycle, and have some predictive content for output.

In addition, Blanchard (1993) and Cochrane (1994) both used consumption as a successful predictor of future output. This is not surprising, since consumption shocks, or 'foresight', are simply the reflection and anticipations by consumers of other shocks and their effect on future income. Such exogenous shifts in consumption have been cited as causes of certain cyclical episodes in the US. Gordon (1980) cities the 1955 auto boom as an example of an essentially unexplainable consumption shock which spurred an investment boom, leading to higher output. The corollary, but just as important, is that consumption changes reflect, in part, movements in consumption not due to changes in expectations of future income. This may be due to changes in intertemporal preferences, sudden realisations of past borrowing, panic and so on. These so-called 'animal spirits' may lead to shifts in consumption through a combination of dynamic multiplier and accelerator effects. Both scenarios allow consumption to be a potentially useful variable in forecasting future output. This is especially true in the industrialised economies, where consumption activity accounts for a significant proportion of economic activity.

6.3 Forecasting Model

The question of determining which variables are useful in detecting future movements in real output is essentially an empirical one. The results surveyed in the literature review mainly rely on in-sample forecasting. The results presented here use both out-of-sample and in-sample forecasting to investigate the stability properties of the variables. Forecasting based on current, leading, and lagging indicators has a long history (Clements and Hendry, 1997). However, since the aim is to closely simulate real time forecasting, the major work is undertaken using a pseudo-out-of-sample forecasting methodology, which relies on iterated forecasts. Work by Marcellino *et al.* (2006) has shown that the relative performance of iterated forecasts outperform direct forecasts, which entails regressing a multiperiod-ahead value of the dependent variable on current and past values of the variable.[2]

The following variables are defined; $Y_t = \Delta \ln Z_t$, where Z_t is the level of output (either the level of real GDP or the an index of total industrial production, excluding construction), and X_t is a candidate predictor. Let $Y_{t+n}^h = (400/h)\ln(Z_{t+n}/Z_t)$ denote output growth over the next n

[2]It must be noted, though, that Chevillon and Hendry (2005) have shown that in some cases a direct multi-step estimation may be asymptotically preferable, although this requires a very well-specified model.

quarters, expressed at an annual rate. The strategy employed here is to transform all series of interest to approximate stationarity by first or second differencing, and then to compute the $h-$step forecast of the original series produced by that model.[3]

This simple modelling framework includes past values of Y_t since, as is typically the case for most time series, own past values are themselves useful predictors. This is especially true with real output, which contains a highly persistent component. Moreover, additional lagged values of X_t might also be useful predictors. The regression model is an autoregressive distributed lag (ADL) model,

$$Y_{t+n}^{h} = \alpha + \sum_{i=0}^{p} \beta_i X_{t-i} + \sum_{i=0}^{q} \gamma_i Y_{t-i} + \varepsilon_{t+n}^{h} \tag{6.1}$$

where ε_{t+n}^{h} represents the error term and $\alpha, \beta_0 ..., \beta_{p-1}, \gamma_0, ..., \gamma_{q-1}$ are unknown regression coefficients. Forecasts are calculated for 2, 4 and 8 quarter horizons (h = 2, 4, 8). If $\beta_i \neq 0$, then the value in period t of X_{t-i} contains useful information regarding the state of Y in the following period. In the context of the ADL model in (6.1), the hypothesis that X has no predictive content for Y_{t+1}, above and beyond that provided by the lags of Y, can be tested by using a (heteroskedasticity robust) F-statistic. The predictive power of X can also be assessed using the standard error of the regression; the estimate of the standard deviation of ε_{t+1}. Nonetheless, due to the possibility of a heteroskedastic error term, i.e. the variance of ε_{t+1} may depend on X and/or be autocorrelated with its previous values, the t-statistics are computed using heteroskedasticity and autocorrelation consistent (HAC) standard errors.

To simulate real-time forecasting, the coefficients in (6.1) were estimated using only data prior to the forecast date, i.e., for a forecast made at the first quarter of 2001, equation (6.1) is estimated using only data available through the first quarter of 2001. To ensure a parsimonious model, the lag lengths p and q for X and Y are selected using the BIC, with $1 \leq p \leq 4$ and $1 \leq q \leq 4$. Again, this was calculated using data available only through the date of the forecast. The lag length is thus data dependent so that the model can adapt to potentially different dynamics over time; this may be especially important if real output growth has moderated over time. The advantage of restricting estimation to data available through the forecast date prevents the forecasts from being misleadingly accurate by using future data, whilst also helping to identify shifts in the forecasted relationship between X and Y during the period that matters for forecasting - the end of the

[3]The stationary property implies that history is relevant for forecasting.

sample. Such an approach, in which all estimation and model selection is done using only data prior to the forecast date, is commonly referred to as pseudo out-of-sample forecasting.

As is traditional in such a forecasting framework, the results are compared to a benchmark model. The benchmark is a multistep autoregressive (AR) forecast, in which (6.1) is estimated with no X predictor, and with the lag length chosen using the BIC ($1 \leq q \leq 4$). As an additional benchmark, a recursive random walk forecast is estimated in which $\widehat{Y}^h_{t+n|t} = h\widehat{\mu}_t$, where $\widehat{\mu}_t$ is the sample average of Y_s, $s = 1, ..., t$. Like the leading indicator forecasts, these benchmark forecasts were computed following the pseudo out-of-sample methodology.

An in-sample analysis examines how useful X would be for predicting Y if the coefficient estimates from the full-sample regression were used. However, if the coefficients suffer from structural shifts over time, such a full-sample analysis could be misleading for out-of-sample forecasting. Consequently, evaluations of the predictive content should also rely on statistics that are designed to closely simulate actual real-time forecasting, which is sometimes referred to as 'pseudo out-of-sample forecasting evaluation'.

6.3.1 Pseudo Out-of-Sample Measures of Predictive Content

Assume a researcher has quarterly data. To make a pseudo-forecast for 2001:4 they estimate the model using data available through 2001:3, then uses the estimated model to predict 2001:4, just as they would were it truly 2001:3. This recursive procedure is repeated throughout the sample, moving ahead one quarter at a time, thereby producing a sequence of pseudo out-of-sample forecasts. Pseudo out-of-sample forecasts have the desirable property that they are able to detect changes in the parameters towards the end of the sample.

The most commonly used method of computing pseudo out-of-sample forecast performance is to compute the MSFE of the candidate forecast (forecast i), relative to a benchmark forecast (forecast j). Assume the candidate forecast based on a leading indicator i is denoted $\widehat{Y}^h_{i,t+h|t}$, and is estimated by pseudo out-of-sample forecasts of Y^h_{t+h} made using data through time t, and with the benchmark estimated from a univariate autoregression, denoted as $\widehat{Y}^h_{j,t+h|t}$. The $h-$step ahead MSFE of forecast i relative to the benchmark forecast j can be defined as;

$$Relative\ MSFE = \frac{\frac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2-h} (Y^h_{t+h} - \widehat{Y}^h_{i,t+h|t})^2}{\frac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2-h} (Y^h_{t+h} - \widehat{Y}^h_{j,t+h|t})^2} \tag{6.2}$$

where T_1 and $T_2 - h$ are the first and last dates over which the pseudo out-of-sample forecast is computed. Following Stock and Watson (2003b), the sample is split into two: a high and low volatility period, which will provide an indication into how the forecasting properties may have changed during the 'great moderation' in business cycle fluctuations. Thus, where possible, the MSFE is set so that T_1 starts at 1980:1 and T_2 is set to 1992:4 when estimating the first period. Analogously, T_1=1993:1 and T_2=2005:1 when forecasting for the second period. These periods are roughly of equal length.

In this equation, if the estimated MSFE is less than one, the candidate forecast is said to have performed better than the benchmark. Since both models are nested, to provide a robustness check of this result, the hypothesis that the population relative $MSFE = 1$, is tested against the alternative that $MSFE < 1$ using the Clark and McCracken (2001) test. On a note of caution, the data used may not be perfectly applicable for simulating real-time forecasting. Such concern is founded on the fact that the most recently available data is utilised to undertake the forecast estimation, rather than the data that was actually available in real time. This may not pose a serious problem in terms of leading indicators such as interest rates and consumer expectations, in which the data are not revised. However, in the case of real output (GDP) and industrial production (IP), the data may have been subject to fairly substantial revision, and since the simulated real-time forecast uses both GDP and IP growth as a predictor in (6.1), their performance may appear better compared to what it might have been in real time, when preliminary values of GDP and IP would have been used.

6.3.2 In-sample statistics

Two in-sample tests statistics are utilised. First, the heteroskedasticity-robust Granger-causality test statistic, estimated in a one-step ahead regression; second, the Quandt (1960) likelihood ratio (QLR) test for coefficient stability is computed over all possible break dates in the central 70 percent of the sample.[4] Consider the case of an ADL(1, 1)

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \delta_1 X_{t-1} + \gamma_0 D_t(\tau) + \gamma_1[D_t(\tau) \times Y_{t-1}] + \gamma_2[D_t(\tau) \times X_{t-1}] + u_t \qquad (6.3)$$

where $D_t(\tau) = 1$ if $t \geq \tau$, and $= 0$ otherwise. If $\gamma_0 = \gamma_1 = \gamma_2 = 0$, then the coefficients are constant over the full sample. If at least one of γ_0, γ_1 or γ_2 are nonzero, then the regression

[4]The QLR test used here is the modified version due to Stock and Watson (1998).

function changes at date τ. The QLR statistic is equal to the maximal of the Chow statistic. Assume that $F(\tau)$ is the Chow statistic testing the hypothesis of no break at date τ. The QLR test statistic is the maximum of the Chow F-statistics over a range of τ, $\tau_0 \leq \tau \leq \tau_1$, i.e., $QLR = \max[F(\tau_0), F(\tau_0 + 1), ..., F(\tau_1 - 1), F(\tau_1)]$. τ_0 and τ_1 are chosen to give the inner 70 percent of the sample; a 15 percent trimming. The modified QLR test continues to test the null hypothesis of constant regression coefficients against the alternative that the regression coefficients change over time.[5] This statistic is often referred to as the *sup*-Wald statistic, since part of the estimating procedure involves calculating the heteroskedasticity-robust Wald statistic. The *sup*-Wald statistic tests for both changes in the constant term and the coefficients on X_t and its lags.[6]

6.4 Data

The data is sourced from a variety of organisations, principally Eurostat, the European Central Bank and the International Monetary Fund International Financial Statistics database. The data collected spans from 1980 to 2005 where possible. Additional series, including spreads, real asset prices and *ex-ante* real interest rates, were constructed from 39 series, producing a total of 79 series. The objective in constructing the data set was to obtain a sample of economic time series for the Euro area which is representative of the relations of primary concern to macroeconomists and macroeconomic forecasters. The sample series were obtained by applying subjective judgement, using four criteria as a guideline;

1. The sample should include the main quarterly economic aggregates and coincident indicators. This resulted in the inclusion of series such as industrial production (IP), capacity utilisation and unit labour costs.

2. The sample should include important leading economic indicators, such as monetary aggregates, interest rates, interest rate spreads and stock prices.

3. The series should represent broad classes of variables which can be expected to have quite different time series properties. With this in mind, and with economic activity of the Euro area being concentrated in three countries, Germany, France and Italy, all with differing

[5] As shown by Stock and Watson (1998, 2002a, 2003b, c), this test has good power for testing wider forms of parameter instability, such as slowly drifting parameters.

[6] The intercept term under the hypothesis that the remaining coefficients are constant.

degrees of business cycle coherence, asset prices from all three countries were included to capture any heterogeneity that there may be across the Euro area.

4. The time-series should have consistent historical definitions.

The time-series were subjected to two types of possible transformations. First, some of the series exhibited spikes in the data as a result of large outliers. Those outliers were replaced with interpolated values constructed as the median of the values three periods on either side of the outlier. Second, highly persistent or trending variables were differenced, second differenced, or as estimated as a 'gap', that is a deviation from a stochastic trend. As mentioned in Stock and Watson (2003b, c), variables that are in 'gap' form, when used for forecasting, need to be computed in a way that preserves their temporal ordering. Hence, the gaps are estimated using a one-sided version of the Hodrick Prescott filter, which is constructed as the Kalman filter estimate of ϵ_t from the model $y_t = \tau_t + \epsilon_t$ and $\tau_t^2 = \eta_t$, where y_t is the observed series, τ_t is its unobserved trend component. The error terms, ϵ_t and η_t, are mutually uncorrelated white noise sequences. Finally, for consistency and wherever possible, the stationarity transformation was in general applied to entire classes of series rather than on an adhoc basis.

Series Descriptions

	Time	Frequency	Description
			Asset Prices
exrate	1980 - 2005	Q	Nominal Effective Exchange Rate
rexrate	1980 - 2005	Q	Real Effective Exchange Rate
stockp	1980 - 2005	Q	Euro-wide Share Price Index
sharei	1980 - 2005	Q	Italian Share Price MIB Index
shareg	1980 - 2005	Q	German Share Price DAX Index
sharef	1980 - 2005	Q	French Share Price CAC 250 Index
gold	1980 - 2005	Q	Gold Price Index
rgold	1980 - 2005	Q	Real Gold Price
silver	1980 - 2005	Q	Silver Price Index
rsilver	1980 - 2005	Q	Real Silver Price
fbill3	1980 – 2005	Q	French 3-month T-bill
ibill3	1980 – 2005	Q	Italian 3-month T-bill
gbill3	1980 - 2005	Q	German 3-month T-bill
ltn	1980 – 2002	Q	Long-term Euro-wide interest rates
strq	1980 – 2002	Q	Real Short-term Euro-wide interest rates
stn	1980 – 2005	Q	Nominal Short-term Euro-wide interest rates
rspreadg	1980 – 2005	Q	rbndm – gbill
rspreadf	1980 – 2005	Q	ira10 – fbill
rspreadi	1980 – 2005	Q	ita10 – ibill
fra10	1980 – 2005	Q	10Yr Term French Bond Yields
ita10	1980 – 2005	Q	10Yr Term Italian Bond Yields
ita5	1980 – 2005	Q	5 Yr Italian Bond Yields
rfra10	1980 – 2005	Q	Real 10Yr Term French Bond Yields
rita5	1980 – 2005	Q	5 Yr Italian Bond Yields
rita10	1980 – 2005	Q	Real 10Yr Term Italian Bond Yields
rgerp	1980 - 2005	Q	Real German Monetary Policy Rates
rfrap	1980 - 2005	Q	Real French Monetary Policy Rates
ritap	1980 - 2005	Q	Real Italian Monetary Policy Rates
rtbill	1980 - 2005	Q	Nominal 1 Yr German Bond Yield
rbnds	1980 - 2005	Q	Nominal 5 Yr German Bond Yield
rbndm	1980 - 2005	Q	Nominal 10 Yr German Bond Yield
rrtbill	1980 - 2005	Q	Real 1 Yr German Bond Yield
rrbnds	1980 - 2005	Q	Real 5 Yr German Bond Yield
rrbndm	1980 - 2005	Q	Real 10 Yr German Bond Yield
			Real Activity
emp	1980 - 2005	Q	Employment
capu	1980 - 2005	Q	Capacity Utilisation
ip	1980 - 2005	Q	Industrial Production
rgdp	1980 - 2005	Q	Real GDP
			Wages, Goods and Commodity Prices
ppi	1980 - 2005	Q	Producer Price Index
oil	1980 - 2005	Q	Crude Oil Price
earn	1980 - 2005	Q	Wages (Manufacturing)
comod	1980 - 2005	Q	World Bank Commodity Price Index
agri	1980 - 2005	Q	World Bank Agricultural Commodities Price Index
nfuel	1980 - 2005	Q	World Bank Non-fuel Price Commodity Price Index
unitl	1980 - 2005	Q	Unit Labour Costs (Manufacturing)
cpi	1980 - 2005	Q	Consumer Price Index
roil	1980 – 2005	Q	Real Oil Price
pgdp	1980 - 2005	Q	GDP Deflator
			Monetary Quantities
moneys	1980 – 2005	Q	Money Stock
M1	1980 – 2005	Q	Money M1
M3	1980 – 2005	Q	Money M3
rmoneys	1980 – 2005	Q	Real Money Stock
rM1	1980 – 2005	Q	Real Money M1
rM3	1980 – 2005	Q	Real Money M3
rfram1	1980 – 2005	Q	Real Money M1 – France
rfram2	1980 – 2005	Q	Real Money M2 – France
rfram3	1980 – 2005	Q	Real Money M3 – France
ritam1	1980 – 2005	Q	Real Money M1 – Italy
ritam2	1980 – 2005	Q	Real Money M2 – Italy
ritam3	1980 – 2005	Q	Real Money M3 – Italy
fram1	1980 – 2005	Q	Nominal Money M1 - France
fram2	1980 – 2005	Q	Nominal Money M2 - France
fram3	1980 – 2005	Q	Nominal Money M3 - France
itam1	1980 – 2005	Q	Nominal Money M1 – Italy
itam2	1980 – 2005	Q	Nominal Money M2 – Italy
itam3	1980 – 2005	Q	Nominal Money M3 - Italy
rbndl	1980 – 2005	Q	Nominal Money M1 - Germany
mon2	1980 – 2005	Q	Nominal Money M2 – Germany
mon3	1980 – 2005	Q	Nominal Money M3 - Germany
rrbndl	1980 – 2005	Q	Real Money M1 – Germany
rmon2	1980 – 2005	Q	Real Money M2 – Germany
rmon3	1980 – 2005	Q	Real Money M3 - Germany

Notes: *Variables denoted as France, Germany, and Italy represent variables from the three largest economies in the Euro area. Variables without the demarcation are Euro area wide variables.*

One would expect monetary variables from the three countries to have predictive content for the general future state of the Euro area economy as a whole. Work by Estrella and Mishkin (1997), for example, has found the German yield spread to have significant predictive power for Euro area recessions in particular, whilst also having good forecasting powers overall. Furthermore, given the problems related to data aggregation from a heterogenous set of countries, and given that Germany did not have to make major adjustments to satisfy the Maastricht criteria, it is plausible to expect that, at least for some variables, German data may be preferable to Euro wide data. A good example is Bruggeman *et al.* (2006), who find that monetary variables based on German data are superior to Euro area data. Their results suggest that longer time series constructed from German data may also be useful for analysing Euro area models. A similar idea also applies to data from France and Italy.

6.5 Models with Individual Indicators

This section considers the forecasts of inflation and output growth using pseudo out-of-sample forecasting. The results focus on four-quarter ahead forecasts of GDP and IP growth as well as two measures of inflation, based on the CPI and the GDP deflator. For the interest rate time series it remains unclear whether differencing should be undertaken, so both levels and differences are considered.

6.5.1 Forecasts of Output

It is important to note that there has been a dramatic improvement in the forecasting performance of the standard benchmark AR model in forecasting GDP and IP over the two sample periods, supporting the assertions made previously that the moderation in the Euro area business cycle should lead to improved forecast accuracy. Table 6.1 begins the analysis by investigating the term spreads, due to their perceived importance in the empirical literature. The forecasts based on the term spread are partly consistent with this literature. German and Italian spreads improve upon the AR benchmark in both the first and second period for Euro area GDP growth (a figure less than one signifies an improvement over the AR benchmark). However, there is a deterioration in the forecast performance of German spreads, which is consistent with the literature. Further, French spreads do not seem to provide any considerable improvement over the benchmark. More importantly perhaps, they do not appear worse at forecasting GDP growth and IP than the AR benchmark. First differencing the spreads leads to a deterioration in forecasting performance.

A mixed story persists for other asset prices as well. For German bond yields in levels form, both real and nominal, the forecasting performance for GDP fell in the second period relative to the first, with the opposite true for IP. The best asset price performers are, however, differenced German bond yields (nominal and real) and the real policy interest rates for Germany, France and Italy in levels form for forecasting IP. These sets of variables offer much superior forecasting performance over the benchmark model. In addition, the real policy rates for Germany, France and Italy are better forecasters of IP in the second period than was the case in the first. Similarly, the 3 month t-bills perform well for both GDP and IP in differenced form, and well for IP only in levels form. In levels form the 3-month bills have, however, seen a dramatic decline in the forecasting performance of GDP. Interestingly, Euro area interest rates do not offer any superior forecasting ability over and above the benchmark model and other interest rates. In general, the interest rates in levels form appear to have improved accuracy over the two periods in forecasting IP.

Moving beyond various interest rate measures, both nominal real exchange rates do not appear to improve upon benchmark model for GDP and IP growth. Gold, both real and nominal, appear to be better forecasters than silver for GDP in the second period, but both gold and silver do reasonably well for IP. The share price index for the whole Euro area has superior forecasting properties compared to the benchmark model in the second period relative to the first. All share price indices are more accurate forecasting GDP than IP. With regards to money, both real and nominal aggregates do not offer any significant forecasting advantages over the benchmark model. The performance of various monetary indicators remain the same throughout both periods, suggesting that despite the moderation in output volatility, the information content of money has not improved markedly. The only exception being Euro area M1. In fact, with some money indicators the forecasting performance appears to have fallen in the second period.

Predictors that are not asset prices fare no better or, occasionally, even worse. Unit labour costs contain significant informational content in the first period, in contrast to the second period. In general, prices and wages do not improve upon the benchmark AR model for GDP, but the opposite remains true for IP, where GDP deflator, CPI, PPI and unit labour costs improve upon the benchmark in period two. The real activity section shows capacity utilisation to have far superior informational content over the benchmark model for forecasting GDP. Finally, forecasts based on the GDP output gap perform better than the AR forecasts for IP.

Table 6.1: Relative MSFE's of Individual Indicator Forecasts of Euro area Output Growth, 1980:1 – 2005:4

Predictor	Transformation	*GDP* 1980-1992	*GDP* 1993-2005	*IP* 1980-1992	*IP* 1993-2005
		Root Mean Square Forecast Error			
Univariate Autoregression Predictor		1.75	0.95	1.81	0.83
		MSFE Relative to Univariate AR Model			
$(1-L)^2y_t = \varepsilon_t$	level	0.97	1.05	0.97	1.15
Asset Prices					
Real Policy Rate (Germany)	level	0.52	2.07	1.49	0.85
Real Policy Rate (France)	level	0.87	1.68	1.09	0.77
Real Policy Rate (Italy)	level	0.93	1.70	1.29	0.61
Long-term bond (France)	level	1.19	1.24	1.21	0.65
Medium-term bond (Italy)	level	0.85	1.80	1.20	0.73
Long-term bond (Italy)	level	0.91	1.60	1.08	0.69
1-year bond (Germany)	level	1.01	1.15	1.26	0.60
5-year bond (Germany)	level	0.81	1.20	1.15	0.69
10-year bond (Germany)	level	0.84	1.07	1.07	0.70
Real Long-term bond (France)	level	1.18	1.25	1.18	0.67
Real Medium-term bond (Italy)	level	0.82	1.91	1.17	0.74
Real Long-term bond (Italy)	level	0.89	1.67	1.08	0.72
Real 1-year bond (Germany)	level	1.18	1.14	1.28	0.61
Real 5-year bond (Germany)	level	0.84	1.37	1.31	0.61
Real 10-year bond (Germany)	level	1.17	1.10	1.14	0.69
Germany 3 month bill	level	0.52	2.01	1.44	0.84
France 3 month bill	level	0.81	1.81	1.15	0.74
Italy 3 month bill	level	0.80	1.81	1.14	0.63
Real Policy Rate (Germany)	Δ	1.38	1.03	1.00	0.93
Real Policy Rate (France)	Δ	1.02	1.00	1.14	1.00
Real Policy Rate (Italy)	Δ	1.09	0.87	1.16	1.04
Long-term bond (France)	Δ	1.03	1.01	0.92	1.35
Medium-term bond (Italy)	Δ	0.94	0.90	1.15	1.07
Long-term bond (Italy)	Δ	0.98	0.98	0.94	1.19
1-year bond (Germany)	Δ	0.99	0.70	1.03	1.04
5-year bond (Germany)	Δ	0.72	0.78	1.03	1.04
10-year bond (Germany)	Δ	0.77	0.77	0.96	1.04
Real Long-term bond (France)	Δ	1.03	1.09	0.91	1.65
Real Medium-term bond (Italy)	Δ	0.93	1.09	1.10	1.17
Real Long-term bond (Italy)	Δ	0.98	1.09	0.85	1.44
Real 1-year bond (Germany)	Δ	0.99	0.70	1.14	1.01
Real 5-year bond (Germany)	Δ	1.03	0.85	1.15	0.99
Real 10-year bond (Germany)	Δ	1.11	0.82	1.02	1.03
Germany 3 month bill	Δ	1.02	0.98	1.05	0.92
France 3 month bill	Δ	1.01	0.97	1.22	0.99
Italy 3 month bill	Δ	1.00	0.78	0.97	1.03
Nominal Exchange Rate	Δ ln	0.98	1.01	1.17	1.07
Real Exchange Rate	Δ ln	1.01	0.99	1.17	1.08
Share Price Index	Δ ln	1.64	0.95	1.00	1.01
Germany Share Price Index	Δ ln	1.26	0.91	0.99	0.99
French share Price Index	Δ ln	1.04	0.99	1.03	0.98
Italy Share Price Index	Δ ln	1.04	0.99	1.03	0.98
Gold	Δ ln	1.01	0.98	1.01	0.95
Real Gold	Δ ln	1.01	0.98	1.02	0.94
Silver	Δ ln	1.08	1.04	1.02	0.98
Real Silver	Δ ln	2.08	1.09	1.52	0.80
Long rate (Euro area)*	level	0.97	1.48	1.04	1.42
Short rate (Euro area)*	level	0.70	2.22	1.21	0.90
Real short rate (Euro area)*	level	1.07	1.26	1.32	0.78

Relative MSFE's of Individual Indicator Forecasts of Euro area Output Growth, 1980:1 – 2005:4

		GDP		IP	
		1980 - 1992	1993 - 2005	1980 - 1992	1993 - 2005
Long rate (Euro area)*	Δ	1.03	1.02	0.82	1.69
Short rate (Euro area)*	Δ	1.09	0.94	1.06	0.98
Real short rate (Euro area)*	Δ	1.04	1.01	1.12	0.98
Spreads					
Term spread (Germany)	level	0.66	0.88	1.24	1.04
Term spread (France)	level	1.12	1.03	1.01	0.99
Term spread (Italy)	level	0.93	0.82	1.04	1.24
Term spread (Germany)	Δ	0.97	0.90	1.05	0.96
Term spread (France)	Δ	1.03	1.00	1.04	1.00
Term spread (Italy)	Δ	1.20	1.06	0.98	1.09
Activity					
Real GDP	Δ ln	-	-	1.07	0.97
IP – Total Industry	Δ ln	1.26	1.02	-	-
employment	Δ ln	0.74	1.22	1.14	1.31
Capacity utilisation	level	0.67	0.91	1.87	1.02
Real GDP+	gap	-	-	1.19	0.73
IP – Total Industry+	gap	1.78	1.13	-	-
Prices and Wages					
GDP Deflator	Δ ln	1.10	1.28	1.17	0.80
CPI	Δ ln	0.97	1.25	1.19	0.73
PPI	Δ ln	1.60	1.08	1.11	0.94
Unit Labour Costs	Δ ln	0.74	1.68	1.35	0.97
Crude Oil	Δ ln	0.98	1.02	0.92	1.57
Real Crude oil price	Δ ln	1.26	1.00	1.00	0.99
Non Fuel Primary Commodities	Δ ln	1.21	1.17	1.19	0.95
Agriculture Raw Materials	Δ ln	1.21	1.10	1.16	1.00
Metals Price Index	Δ ln	1.20	1.09	1.16	1.00
Wages	Δ ln	1.20	1.11	1.29	1.04
Money					
M1 (France)	Δ ln	1.12	1.00	1.00	1.05
M2 (France)	Δ ln	1.05	0.98	0.98	1.03
M3 (France)	Δ ln	1.04	0.97	0.98	1.00
M1 (Germany)	Δ ln	1.06	1.08	1.02	1.16
M2 (Germany)	Δ ln	1.25	1.04	1.08	1.00
M3 (Germany)	Δ ln	1.22	1.08	0.99	2.40
M1 (Italy)	Δ ln	1.05	1.01	0.99	1.00
M2 (Italy)	Δ ln	1.06	1.00	0.99	1.00
M3 (Italy)	Δ ln	1.06	0.99	0.99	1.00
Real M1 (France)	Δ ln	1.23	1.02	1.02	1.00
Real M2 (France)	Δ ln	1.21	1.06	1.02	1.00
Real M3 (France)	Δ ln	1.20	1.06	1.02	1.00
Real M1 (Germany)	Δ ln	1.16	1.41	1.01	1.04
Real M2 (Germany)	Δ ln	1.04	1.16	1.04	1.02
Real M3 (Germany)	Δ ln	1.10	1.22	1.10	1.04
Real M1 (Italy)	Δ ln	1.21	1.01	1.07	0.98
Real M2 (Italy)	Δ ln	1.21	1.01	1.07	0.98
Real M3 (Italy)	Δ ln	1.21	1.01	1.07	0.98
Euro area Money Stock	Δ ln	1.38	1.06	0.91	2.23
Euro area M1	Δ ln	1.00	0.87	1.11	1.49
Euro area M3	Δ ln	1.22	1.08	0.99	2.40
Real Euro area Money Stock	Δ ln	1.17	1.07	1.06	1.23
Real Euro area M1	Δ ln	0.62	1.47	1.23	1.18
Real Euro area M3	Δ ln	1.11	1.18	1.10	1.36

Notes: * *time-series spans 1980 – 2002. Data taken from Fagan et al. (2001).*
+ Gap calculated using one-side Hodrick Prescott Filter.

6.5.2 Inflation forecasts

The first row of Table 6.2 shows the MSFE of the pseudo out-of-sample benchmark univariate autoregressive forecasts in the two sample periods. The second and third rows report the relative MSFEs of the no-change (random walk) forecast and of the seasonal no-change forecast, which is the Atkeson and Ohanian (2001) forecast at quarterly sampling frequency. Since the Atkeson and Ohanian (2001) forecast is essentially a random walk forecast, a random walk forecast is the same at all horizons.[7] The seasonal no-change forecast is a more accurate forecaster than the random-walk no change forecast.

The results show that the real policy interest rates for France and Germany have significant levels of forecasting information for CPI inflation. The same is also true of the three-month bill for Germany, France and Italy, in both levels and differenced form. The long and nominal short-term Euro area interest rates have strongly improved in forecasting accuracy relative to the first period. The spreads in levels form has improved forecasting performance for CPI in the second period. However, these forecasting successes for interest rates appear sporadic. The forecasting performance of the two exchange rate variables appear ambiguous. Beyond asset prices, unit labour costs, crude oil and real crude oil prices all improve upon the benchmark AR model when forecasting GDP deflator inflation. Unit labour costs and real crude oil prices also appear to be good forecasters of CPI inflation. However, in general different price measures, such as commodity price inflation and wage inflation, do not improve upon the benchmark. Real activity measures such as capacity utilisation, real GDP and employment have significantly improved forecasting performance in the second period for both measures of inflation. The employment result is supportive of the use of the Phillips curve in forecasting inflation, as highlighted by Atkeson and Ohanian (2001) and Stock and Watson (2007). Finally, apart from real German M2 and M3 Euro area M1, monetary aggregates rarely improve upon the benchmark. The results support Bruggeman *et al.* (2006) who argue German monetary aggregates are good predicators of Euro area inflation.

The results, however, appear to exhibit more instability when compared to Table 6.1. Most of the variables mentioned improve upon the benchmark AR model in the second sample period. In the vast majority of cases the forecasting performance of these variables in the first period were inferior to the benchmark. This instability is also present in the univariate forecasts. However, it must be noted that the seasonal no-change forecast works well in both periods.

[7] Atkeson and Ohanian (2001) forecasted the average four-quarter rate of inflation as the average rate of inflation over the previous four quarters.

Table 6.2: Relative MSFE's of Individual Indicator Forecasts of Euro area Inflation, 1980:1 – 2005:4

		Deflator		*CPI*	
Predictor	Transfor-mation	**1980-1992**	**1993-2005**	**1980-1992**	**1993-2005**
		Root Mean Square Forecast Error			
Univariate Autoregression		1.02	0.69	1.11	0.69
Predictor					
		MSFE Relative to Univariate AR Model			
$(1-L)^2 p_t = \varepsilon_t$	level	0.97	1.17	1.21	2.24
$(1-L)^4 p_t = \varepsilon_t$	level	0.76	0.79	0.64	0.64
Asset Prices					
Real Policy Rate (Germany)	level	1.14	0.83	1.27	0.87
Real Policy Rate (France)	level	1.95	1.00	1.04	0.98
Real Policy Rate (Italy)	level	2.13	1.02	1.37	1.17
Long-term bond (France)	level	2.26	0.85	1.18	0.80
Medium-term bond (Italy)	level	1.60	0.97	1.17	0.93
Long-term bond (Italy)	level	1.61	0.95	1.17	0.89
1-year bond (Germany)	level	1.58	1.24	1.12	1.35
5-year bond (Germany)	level	2.11	1.25	1.23	1.22
10-year bond (Germany)	level	2.11	1.23	1.28	1.21
Real Long-term bond (France)	level	2.23	0.95	1.32	1.26
Real Medium-term bond (Italy)	level	1.58	1.70	1.28	1.28
Real Long-term bond (Italy)	level	1.64	1.74	1.30	1.30
Real 1-year bond (Germany)	level	1.52	1.27	1.02	1.45
Real 5-year bond (Germany)	level	1.68	1.21	1.36	1.42
Real 10-year bond (Germany)	level	1.89	1.33	1.16	1.31
Germany 3 month bill	level	2.66	0.89	1.04	0.79
France 3 month bill	level	1.82	0.96	0.98	1.00
Italy 3 month bill	level	2.04	0.84	1.27	0.88
Real Policy Rate (Germany)	Δ	0.97	0.87	0.92	1.07
Real Policy Rate (France)	Δ	1.07	0.96	1.03	0.96
Real Policy Rate (Italy)	Δ	1.05	1.01	1.25	1.03
Long-term bond (France)	Δ	1.18	0.77	1.04	1.25
Medium-term bond (Italy)	Δ	1.02	0.88	1.06	1.11
Long-term bond (Italy)	Δ	1.03	0.87	1.04	1.19
1-year bond (Germany)	Δ	1.17	0.85	1.27	1.01
5-year bond (Germany)	Δ	1.02	1.05	1.34	1.17
10-year bond (Germany)	Δ	1.13	0.89	1.26	1.08
Real Long-term bond (France)	Δ	1.13	1.13	0.98	0.88
Real Medium-term bond (Italy)	Δ	1.10	1.45	1.07	0.92
Real Long-term bond (Italy)	Δ	1.16	1.45	1.03	0.91
Real 1-year bond (Germany)	Δ	1.12	0.87	1.29	1.01
Real 5-year bond (Germany)	Δ	1.09	1.02	1.13	1.13
Real 10-year bond (Germany)	Δ	1.10	0.98	1.28	1.04
Germany 3 month bill	Δ	1.04	0.91	0.91	0.97
France 3 month bill	Δ	0.98	0.93	1.00	0.95
Italy 3 month bill	Δ	1.20	0.90	1.10	0.94
Nominal Exchange Rate	Δ ln	1.37	1.05	1.23	0.95
Real Exchange Rate	Δ ln	1.39	1.04	1.10	0.93
Share Price Index	Δ ln	1.12	1.07	0.99	1.05
German Share Price Index	Δ ln	0.97	1.01	1.03	1.16
French Share Price Index	Δ ln	1.53	1.01	1.20	1.05
Italian Share Price Index	Δ ln	1.53	1.01	1.20	1.05
Gold	Δ ln	1.03	1.14	1.11	1.07
Real Gold	Δ ln	1.06	1.13	1.16	1.07
Silver	Δ ln	0.92	1.10	1.04	1.02
Real Silver	Δ ln	2.02	0.96	1.20	0.84
Long rate (Euro area)*	level	2.01	0.84	0.94	0.88
Short rate (Euro area)*	level	1.74	0.85	0.94	0.74

Relative MSFE's of Individual Indicator Forecasts of Euro area Output Growth, 1980:1 – 2005:4

Predictor	Transfor-mation	Deflator		CPI	
		1980 - 1992	1993 - 2005	1980 - 1992	1993 - 2005
Real short rate (Euro area)*	level	1.23	1.16	1.07	1.55
Long rate (Euro area)*	Δ	1.50	0.93	0.96	0.90
Short rate (Euro area)*	Δ	1.06	0.91	0.93	0.89
Real short rate (Euro area)*	Δ	1.02	1.01	1.08	1.00
Spreads					
Term spread (Germany)	level	2.14	1.02	1.26	0.94
Term spread (France)	level	0.98	1.02	1.13	0.83
Term spread (Italy)	level	1.90	0.93	1.30	0.85
Term spread (Germany)	Δ	0.97	0.98	1.04	1.03
Term spread (France)	Δ	1.02	1.01	1.06	1.07
Term spread (Italy)	Δ	1.58	1.01	1.17	1.02
Activity					
Real GDP	Δ ln	1.21	0.93	1.10	0.99
IP – Total Industry	Δ ln	1.17	1.02	1.26	1.01
employment	Δ ln	1.57	0.92	1.23	0.83
Capacity utilisation	level	1.57	0.57	1.29	0.57
Real GDP+	gap	3.71	1.01	1.88	1.02
IP – Total Industry +	gap	1.85	0.94	2.13	1.02
Prices and Wages					
GDP Deflator	Δ ln	-	-	1.18	0.84
CPI	Δ ln	1.36	0.96	-	-
PPI	Δ ln	1.75	1.11	1.20	0.85
Unit Labour Costs	Δ ln	1.18	0.88	1.18	0.88
Crude Oil	Δ ln	1.04	0.92	0.99	1.05
Real Crude oil price	Δ ln	1.14	0.99	0.99	0.90
Non Fuel Primary Commodities	Δ ln	1.96	1.06	1.25	0.89
Agriculture Raw Materials	Δ ln	1.58	1.13	1.40	1.01
Metals Price Index	Δ ln	1.57	1.13	1.40	1.01
Wages	Δ ln	1.03	1.13	1.05	1.09
Money					
M1 (France)	Δ ln	1.04	1.00	0.99	1.01
M2 (France)	Δ ln	1.02	1.00	1.06	1.00
M3 (France)	Δ ln	0.99	1.00	1.11	1.03
M1 (Germany)	Δ ln	1.60	1.05	1.13	1.09
M2 (Germany)	Δ ln	0.99	1.01	1.06	1.00
M3 (Germany)	Δ ln	0.93	1.21	1.54	1.03
M1 (Italy)	Δ ln	1.01	1.00	1.13	1.03
M2 (Italy)	Δ ln	1.00	0.99	1.13	1.03
M3 (Italy)	Δ ln	0.99	0.99	1.13	1.02
Real M1 (France)	Δ ln	1.01	1.05	1.00	0.94
Real M2 (France)	Δ ln	1.01	1.06	1.00	0.94
Real M3 (France)	Δ ln	1.01	1.06	1.01	0.95
Real M1 (Germany)	Δ ln	1.60	1.00	1.23	0.97
Real M2 (Germany)	Δ ln	1.49	0.93	1.25	0.83
Real M3 (Germany)	Δ ln	2.06	0.83	1.25	0.76
Real M1 (Italy)	Δ ln	0.98	1.01	1.04	1.00
Real M2 (Italy)	Δ ln	0.95	1.01	1.04	1.00
Real M3 (Italy)	Δ ln	0.95	1.01	1.04	1.00
Euro area Money Stock	Δ ln	1..10	1.25	1.08	1.02
Euro area M1	Δ ln	1.56	1.00	1.13	1.04
Euro area M3	Δ ln	0.93	1.21	1.54	1.03
Real Euro area Money Stock	Δ ln	1.11	1.06	0.92	1.19
Real Euro area M1	Δ ln	1.95	0.99	1.23	0.81
Real Euro area M3	Δ ln	0.79	1.47	1.07	1.27

6.6 Forecast Stability

The fact that some forecasts did well in one particular period and not in the other raises questions about the stability of these forecasts. Questions of forecast instability, especially for the various term spread measures, have been well documented, both theoretically and empirically. For example, Duarte *et al.* (2005) have shown that the term spread-output growth relationship may not be stable over time and may be subject to nonlinearities. It is possible that such complications exist for other predictor variables. Findings of forecast instability for the results in Table 6.1 and 6.2 are also present in forecasts with fixed lag lengths, as illustrated with the scatter plots in the Appendix for output and inflation. This suggests that the instability is not due to the recursive BIC lag selection.

This section therefore looks more systematically at the stability of forecasts made using a given predictor and dependent variable combination, as measured by the relative $MSFE$ in the two periods. One possible explanation for the apparent instability is that all these relative $MSFE$s have a sampling distribution, which creates sampling uncertainty, measured as estimation error. It is possible to examine the sampling uncertainty using the Clark and McCracken (2001) method. A nested specification of two competing models of the one-step ahead forecast errors can be written as

$$\widehat{u}_{1,t+1} = y_{t+1} - x'_{1t+1}\widehat{\beta}_{1,t} \tag{6.4}$$

$$\widehat{u}_{2,t+1} = y_{t+1} - x'_{2t+1}\widehat{\beta}_{2,t} \tag{6.5}$$

where $x_{1,t}$ is the set of regressors in the restricted model (univariate AR benchmark model) and $x_{2,t} = (x'_{1,t}, x'_{22,t})'$ represents the set of regressors in the unrestricted model (bivariate model), y_t is the scalar random variable to be predicted, P are the number of forecasts. To calculate the test statistic for each MSE, the Clark and McCracken (2001) test is

$$MSE\text{-}t = P^{1/2}\frac{\overline{d}}{\sqrt{P^{-1}\sum_t(d_{t+1}-\overline{d})^2}} = P^{1/2}\frac{P^{-1}\sum_t(\widehat{u}^2_{1,t+1}-\widehat{u}^2_{2,t+1})}{\sqrt{P^{-1}\sum_t(\widehat{u}^2_{1,t+1}-\widehat{u}^2_{2,t+1})^2-\overline{d}^2}} \tag{6.6}$$

where $d_{t+1} = \widehat{u}_{1,t+1} - \widehat{u}_{2,t+1}$, hence $\overline{d} = P^{-1}\Sigma_t d_t = MSE_1 - MSE_2$.

The Clark and McCracken (2001) tests the null distribution of the relative $MSFE = 1$, against the alternative that $MSFE < 1$. Hence, the Clark and McCracken statistic tests the MSFE of the bivariate models relative to the univariate AR model, with the p-value indicating whether to reject the null, or not, for equal forecast accuracy.[8] The results (see Appendix) suggest that most of the improvements in the second sample period over the benchmark AR model are statistically significant, the only exceptions being gold and nominal and real exchange rates for GDP, and a few of the commodity price indices for IP mainly metals, agriculture, non fuel commodities and Euro area M1. This result does not confirm the findings of Bruggeman *et al.* (2006), who found German monetary aggregates to be, in some cases, superior forecasters of future real Euro area output than Euro wide monetary aggregates themselves. Although, this remains the case for forecasting Euro area inflation. However, in general the results imply that the observed temporal instability of the $MSFE$s is not a consequence of sampling variability alone, especially for series that in population have no predictive content.

Table 6.3 presents, for both output and inflation, the stability of forecasts using a given predictor and horizon combination, as measured by the relative $MSFE$ in the two periods. Table 6.3 part B presents a cross tabulation of four-quarter ahead forecasts for all possible predictor variables for both GDP deflator and CPI. Of the 116 asset price dependent variable combinations, nine percent outperform the benchmark AR model in both periods for output and inflation forecasts, i.e., nine percent of relative $MSFE$s are less than one in both the first and second period. The binary variables cross-tabulated in Table 6.3 appear to be approximately independently distributed. The joint probabilities are very nearly the product of the marginal probabilities. For output, if the row and column variables were independent then the probability of an indicator/dependent variable combination outperforming the benchmark would be $0.32 \times 0.53 = 0.17$, which is slightly higher than the empirically observed probability of 0.09. In panel A the analogous probability of outperforming the benchmark in both periods, computed under independence, is $0.14 \times 0.45 = 0.06$, which is slightly lower than the empirically observed probability of 0.09. These results suggest that whether a predictor asset price dependent variable combination outperforms the benchmark in one period is relatively independent of whether it does so in the other period.[9]

[8]However, the null distribution of the $MSFE$s for Table's 6.1 and 6.2 cannot be calculated due to the number of lags in the models changing over time. As a result, the Clark and McCracken (2001) test is calculated using pseudo out-of-sample forecasting with fixed lag lengths.

[9]It must be noted, because the draws are not independent, a conventional test for independence of the row and column variables is inappropriate.

Table 6.3: **Summary of Pseudo Out-of-Sample Forecast Accuracy for Two Periods: Asset Price Predictions**

A. Output ($N = 116$)

		1980 - 1992 Out-of-Sample Period		
		Relative MSFE < 1	Relative MSFE > 1	Total
1992 - 2005 Out-of-Sample Period	Relative MSFE < 1	0.09	0.43	0.53
	Relative MSFE > 1	0.22	0.25	0.47
	Total	0.32	0.68	1.00

B. Inflation ($N = 116$)

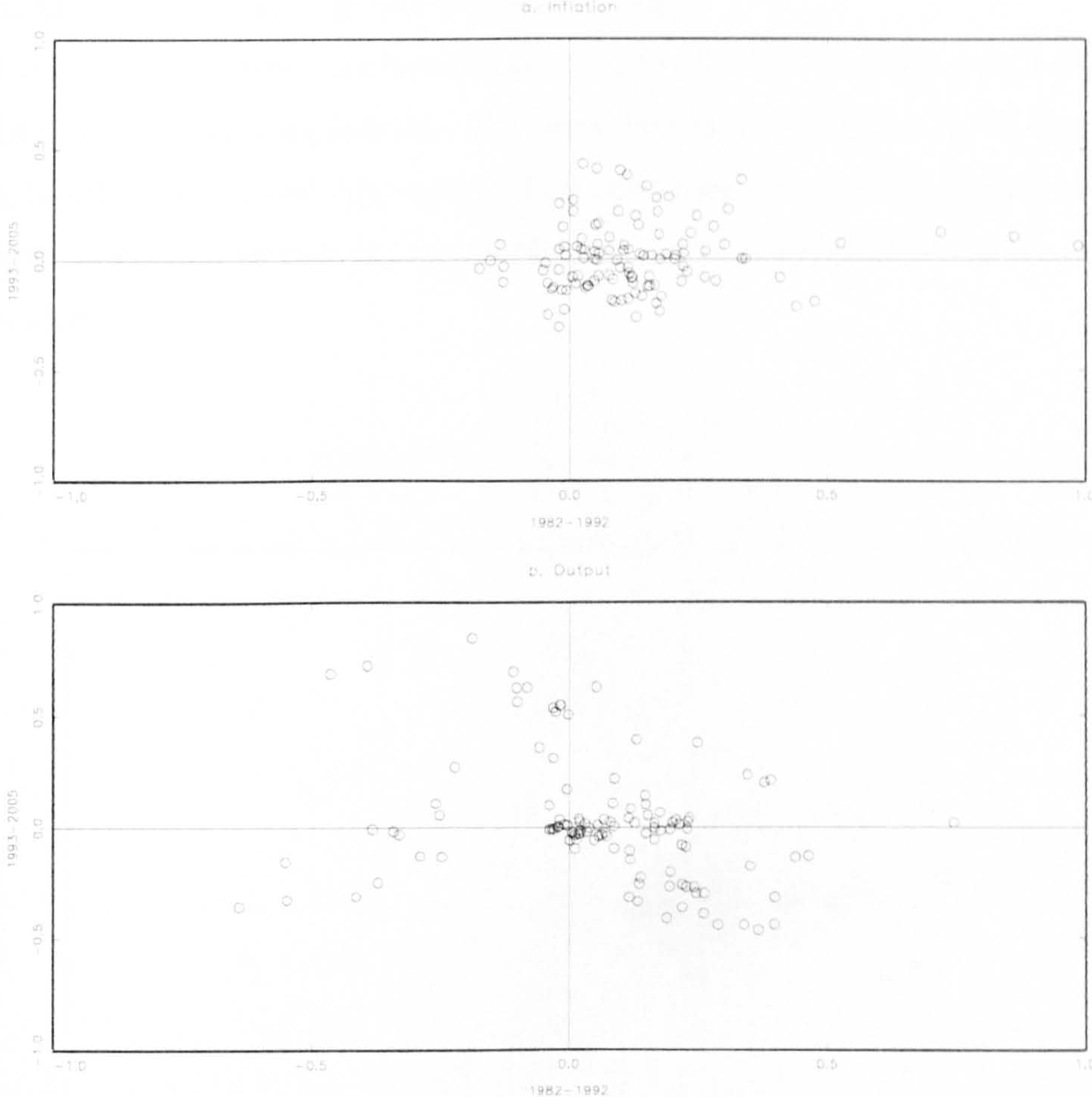
		1980 - 1992 Out-of-Sample Period		
		Relative MSFE < 1	Relative MSFE > 1	Total
1992 - 2005 Out-of-Sample Period	Relative MSFE < 1	0.09	0.36	0.45
	Relative MSFE > 1	0.05	0.50	0.55
	Total	0.14	0.86	1.00

Note: The estimates are relative to the univariate autoregressive benchmark.

Finally, it must be noted that for output forecasting, the percentage of asset price dependent variable combinations with a $MSFE$ below one is larger in the second sample period than in the first, 53 percent against 32 percent, suggesting that, in general, output forecasts using various asset prices have become more accurate.

The weak relationship between the forecasting performance in the two subsamples is illustrated in Figure 6.1a for inflation and Figure 6.1b for output for $h = 4$. The scatterplots represent the logarithm of the relative $MSFE$ in the first relative to the second sample period for the 116 asset price-based forecasts analysed in Table 6.3.

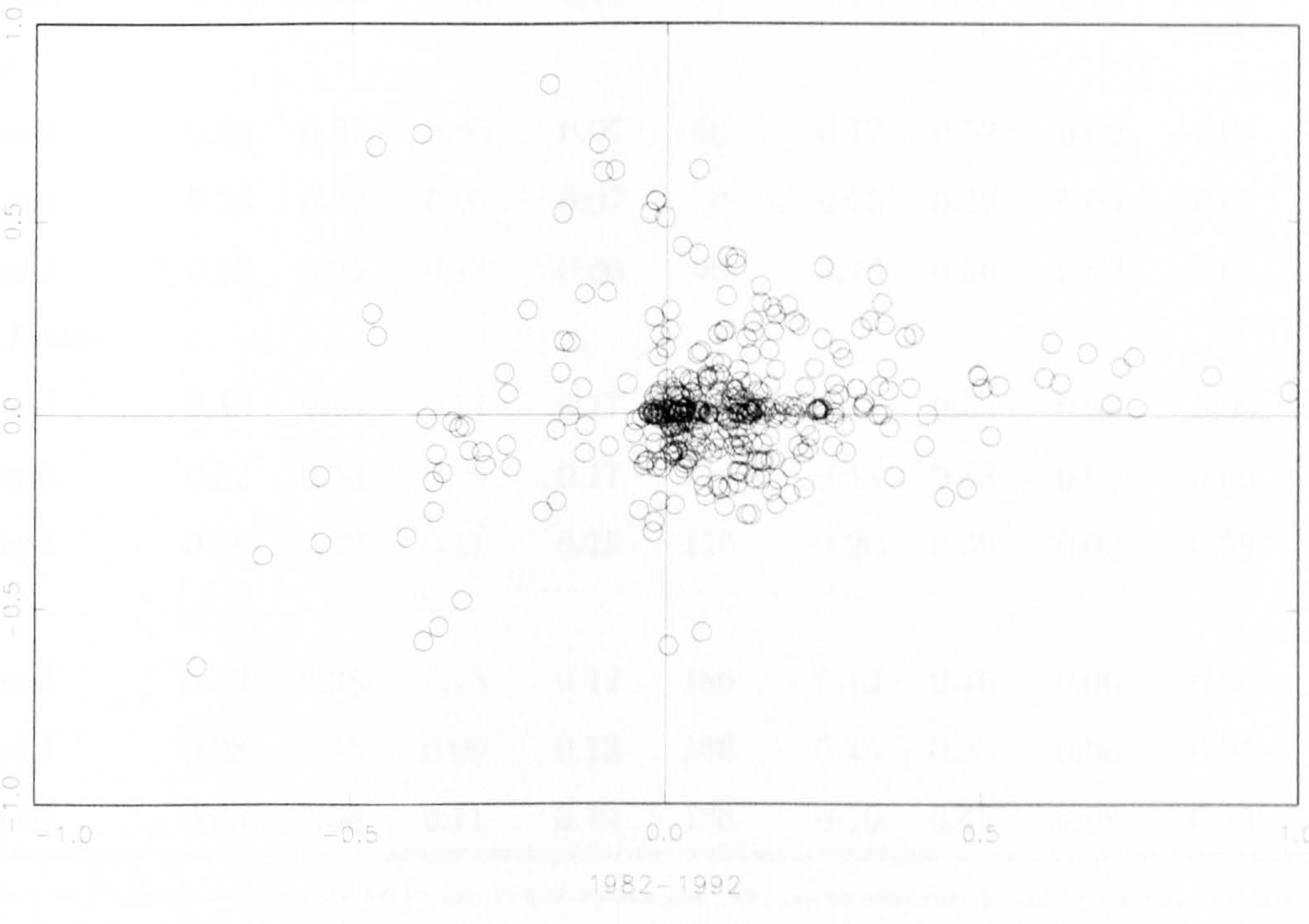
Figure 6.1
Pseudo Out-of-Sample Log Relative MSFE
Asset Prices, 4-Quarter Ahead Forecasts



Points in Figure 6.1 part A and B are heavily clustered near the origin. This being symptomatic of the view that there exists potential predictors, some of which are fairly reliable (i.e. German bond yields), with many others (i.e. metals price index, agriculture price index) limited in value and, consequently, with regression coefficients near zero. An asset price that outperforms the benchmark in both periods is located in the southwest region of the scatterplots. What one observes, however, (far more so for inflation than output) is that there are very few predictors near the forty-five degree gradient in the south west quadrant, with many points far from the origin in the northwest and southeast quadrants. The scattering of the results in Figure 6.1 may allow one to succinctly conclude that the performance of the two periods is nearly unrelated. Asset prices that do not perform well in the first period tend to perform better in the second period for both inflation and output. However, the correlation is small (0.17 and 0.14 respectively). Changing the horizon period to $h = 2$ has little bearing on the overall results, with correlation coefficients for inflation and output being 0.09 and 0.05 respectively.

The robustness of these conclusions can be examined by investigating the findings of forecast instability based on fixed lag lengths. The instability does not appear to be the result of recursive BIC lag length selection (see Appendix). Forecasting models that outperform the AR benchmark in the first period may or may not outperform the AR in the second, but whether they do appears to be random.

Figure 6.2
Pseudo Out-of-Sample Log Relative MSFE
All Predictors, 4-Quarter Ahead Forecasts



In support, Figure 6.2 scatterplots the first relative to the second period log relative MSFE for all available combination of predictors and dependent variables at the four quarter horizon. The scatterplot exhibits a weak correlation of 0.14.

Table 6.4: Summary of Pseudo Out-of-Sample Accuracy - All Predicators

	Forecasting Accuracy for both Periods									
	Output					*Inflation*				
	GC	*QLR*	*G&Q*	$G \times Q$	*N*	*GC*	*QLR*	*G&Q*	$G \times Q$	*N*
Activity										
2Q ahead	0.08	0.42	0.08	0.03	12	0.06	0.50	0.06	0.03	16
4Q ahead	0.25	0.42	0.17	0.10	12	0.00	0.69	0.00	0.00	16
8Q ahead	0.17	0.33	0.08	0.06	12	0.06	0.81	0.06	0.05	16
G&C Prices										
2Q ahead	0.22	0.28	0.11	0.06	18	0.19	0.44	0.06	0.09	16
4Q ahead	0.22	0.39	0.00	0.09	18	0.06	0.44	0.00	0.03	16
8Q ahead	0.44	0.22	0.06	0.10	18	0.13	0.69	0.06	0.09	16
Money										
2Q ahead	0.25	0.27	0.06	0.07	40	0.17	0.52	0.00	0.04	40
4Q ahead	0.23	0.29	0.08	0.07	40	0.25	0.38	0.04	0.09	40
8Q ahead	0.25	0.25	0.13	0.06	40	0.10	0.50	0.06	0.05	40
Asset Prices										
2Q ahead	0.40	0.43	0.17	0.17	116	0.11	0.53	0.08	0.06	116
4Q ahead	0.32	0.53	0.09	0.17	116	0.14	0.45	0.09	0.06	116
8Q ahead	0.36	0.42	0.11	0.15	116	0.20	0.39	0.09	0.08	116
Total										
2Q ahead	0.32	0.38	0.13	0.12	186	0.13	0.45	0.06	0.06	188
4Q ahead	0.28	0.45	0.09	0.13	186	0.15	0.45	0.06	0.07	188
8Q ahead	0.33	0.36	0.11	0.12	186	0.16	0.47	0.08	0.08	188

Note: olumn '1&2' represents beating the AR forecast in both subsamples. The output results are pooled for industrial production and real GDP. Similarly, inflation results are pooled for CPI and GDP deflator inflation.

Table 6.4 shows the marginal probabilities of beating the AR in the first period. The product of the marginal probabilities very nearly equals the joint probability of beating the AR in both periods for either output or inflation, for $h = 2, 4$ and 8, for all variables. This is also true in the case of output forecasting. In other words, any predictor that worked well in the first period is no more likely to beat the AR in the second period than a predictor drawn at random from the pool of predictors.

6.7 In-sample tests for predictive content and instability

Time series econometrics typically involves drawing inferences about the present or future using historical data. Inferences based on forecasts require that the model at hand be stable (that the future is like the past) for such inferences to be valid (Stock and Watson, 2003b). The importance of stability therefore leads to the question of how generic is instability in multivariate time series relations for the Euro area. As mentioned in the previous section, the marginal distributions provide one window on the extent of instability. However, it is possible that some of the instability is of little interest from a forecasting perspective if the constituent variables have low overall predictive content. Exploring this possibility requires examining the joint distribution of instability, along with Granger causality test statistics. This section uses a full-sample Granger causality test for predictive content. The QLR test, set out earlier, is also utilised to test for instability in the predictive relationships.

Table 6.5 shows estimates of the Granger causality test along with the QLR test statistic for all categories of variables. For output the Granger causality test rejects the null hypothesis of no predictive content for close to 30 percent of all asset price variables. The corresponding statistic for inflation is closer to 40 percent.

Table 6.5: Summary of Granger Causality and QLR

Summary by Predictor Category										
	Output					*Inflation*				
	GC	*QLR*	*G&Q*	$G \times Q$	*N*	*GC*	*QLR*	*G&Q*	$G \times Q$	*N*
Activity	0.25	0.50	0.17	0.13	12	0.06	0.50	0.06	0.03	16
G &C Prices	0.22	0.56	0.17	0.12	18	0.25	0.38	0.06	0.09	16
Money	0.13	0.71	0.06	0.09	40	0.25	0.50	0.13	0.13	40
Asset Prices	0.27	0.61	0.09	0.16	116	0.39	0.44	0.20	0.17	116
All	0.23	0.62	0.10	0.14	186	0.32	0.45	0.16	0.14	188

Note: The GC and QLR statistics were computed for a one-quarter ahead bivariate in-sample regression. The statistics in all columns represent the fraction of bivariate models with 95 percent significance estimated test statistics. The 'G&Q' column signifies significant GC and QLR test statistics.

Inspection of the results for each individual indicator dependent variable combination reveals individual Granger causality patterns that are partially consistent with the literature. The German term spread is statistically significant at the one percent level, suggesting that the variable contains useful information regarding future output movements, supporting the results of Estrella and

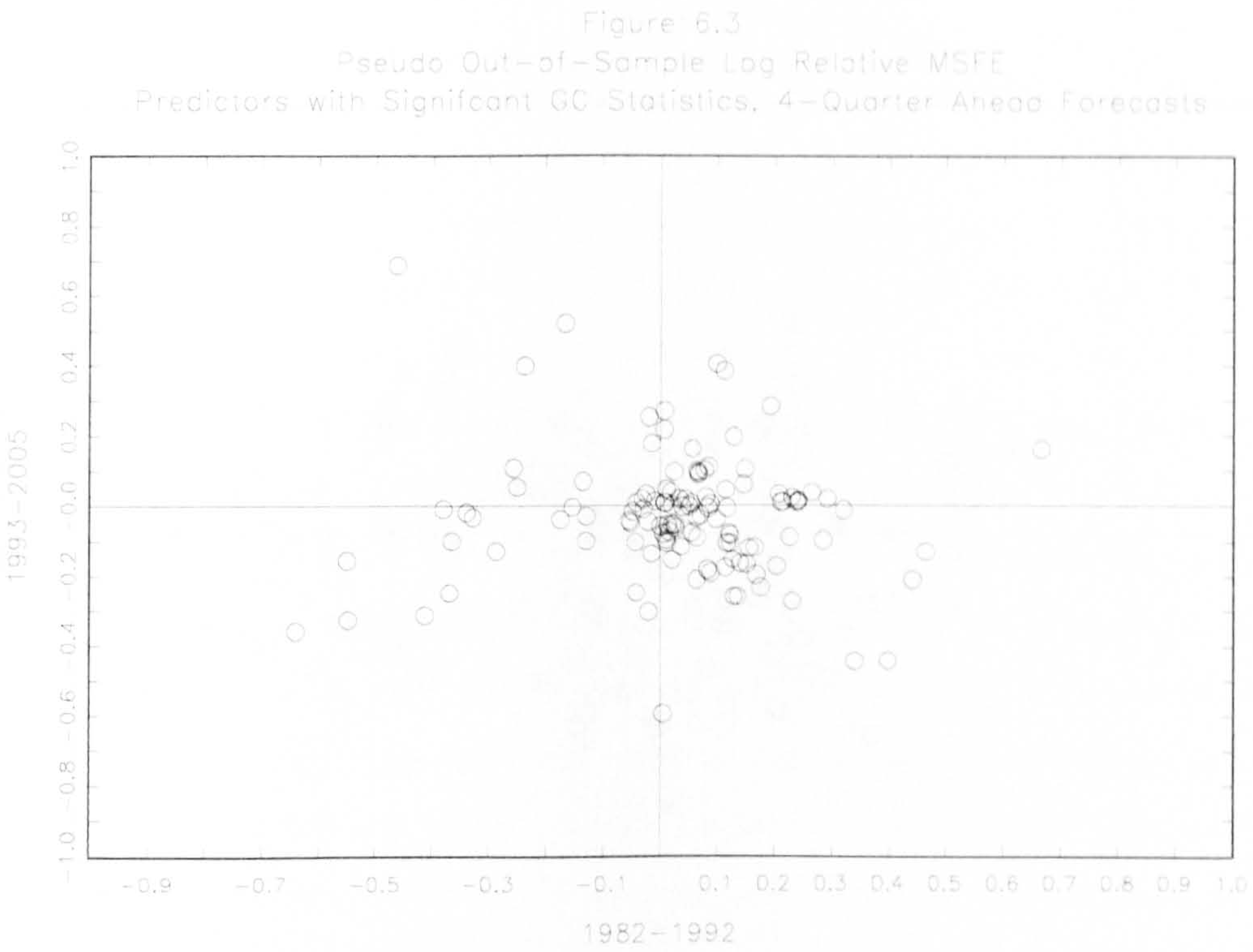
Mishkin (1997). Both the nominal and real exchange rate reject the null of Granger noncausality at the 10 percent level for GDP, which contradicts the findings of Table 6.1, in which nominal and real exchange rates performed no better than the benchmark. However, the policy interest rates from Germany, France and Italy are all insignificant at the one, five and 10 percent levels, contrasting with the results in Table 6.1 which showed policy rates to contain significant information regarding future GDP. Stock prices are insignificant at the 10 percent level, except for the Euro area wide and German share price indices. Further, real and nominal German bond yields, from short to long, contain significant information on Euro area output. Looking at variables beyond asset prices, capacity utilisation and unit labour costs also contain significant information on Euro area output, both reject Granger non-causality at the one and five percent significance levels. The results for IP differ slightly from GDP growth in that CPI and PPI contain significant predictive information. In addition, first differenced French and Italian medium and long-term bond yields contain information for future IP at the five percent level, but not for future GDP. Over all categories, Table 6.5 shows that 23 and 32 percent reject Granger noncausality for output and inflation. This figure is higher for output forecasts when considering asset prices only, which have the highest Granger noncausality rejection rates of all the subcategories at 27 percent, implying they are the most successful predictor category for future output.

With regards to GDP inflation, real German policy rates and nominal and real effective exchange rates all reject Granger noncausality for inflation. German spreads also contain information on future GDP inflation, entering at the one percent significance level. Italian short and long-term bond yields also reject the null of Granger noncausality with p-values of less than 0.01. Finally, Euro area short and long-term rates also contain significant information on future Euro area GDP inflation. Granger noncausality is rejected at the one percent significance level. The results for CPI inflation suggest that asset prices are in general very poor predictors. Looking at the results for various money measures, French and Italian real money measures seem to contain significant predictive content for GDP inflation. German real M3 and nominal M3 Euro area wide aggregates also reject the null. Goods and commodity prices contain no predictive content for GDP inflation. There are exceptions, with the producer price index and oil prices rejecting the null at the one and five percent significance levels for CPI inflation.

The QLR statistic detects instability in over a quarter of these relationships. The results in Table 6.5 indicate that, among forecasting equations involving asset prices, the QLR statistic rejects the null hypothesis of stability at the five percent level 61 and 44 percent of the time for output and inflation respectively. As mentioned by Stock and Watson (1996, 2003b, c), this result suggests that the instability revealed by the analysis of the relative $MSFE$s in the two subsamples is not a statistical artifact but rather a consequence of unstable population relations. Indeed, this result is not only confined to asset prices. The QLR statistic rejects the null hypothesis of stability at the five percent level 71 percent of the time between money and output. The corresponding figure for inflation forecasts is 50 percent, which is a very high percentage, supporting the assertion in Bruggeman *et al.* (2003) about the unstable relationship between money, inflation and output for the Euro area.

It must be noted that, by taking the results from the previous section, it can be inferred that a statistically significant Granger causality statistic conveys little information about whether the forecasting relationship is stable. Such counter intuition can be explained if one looks at the findings in Table 6.5 for all indicators. The results in Table 6.3 suggest that only 0.09 percent improve upon the benchmark AR model for both output and inflation in both periods. However, the Granger causality results in Table 6.5 suggest that 27 and 39 percent of variables for output and inflation can reject the null of Granger noncausality at the five percent significance level. Figure 6.3 is a scatterplot of the log relative $MSFE$ restricted to predictors and dependent variables for which the Granger causality test rejects Granger noncausality at the five percent significance level. Relationships that show in-sample predictive stability would lie around the vicinity of the 45 degree line in the southwest quadrant, which for some predictive relationships is the case. However, the vast majority lie in areas beyond the southwest quadrant.

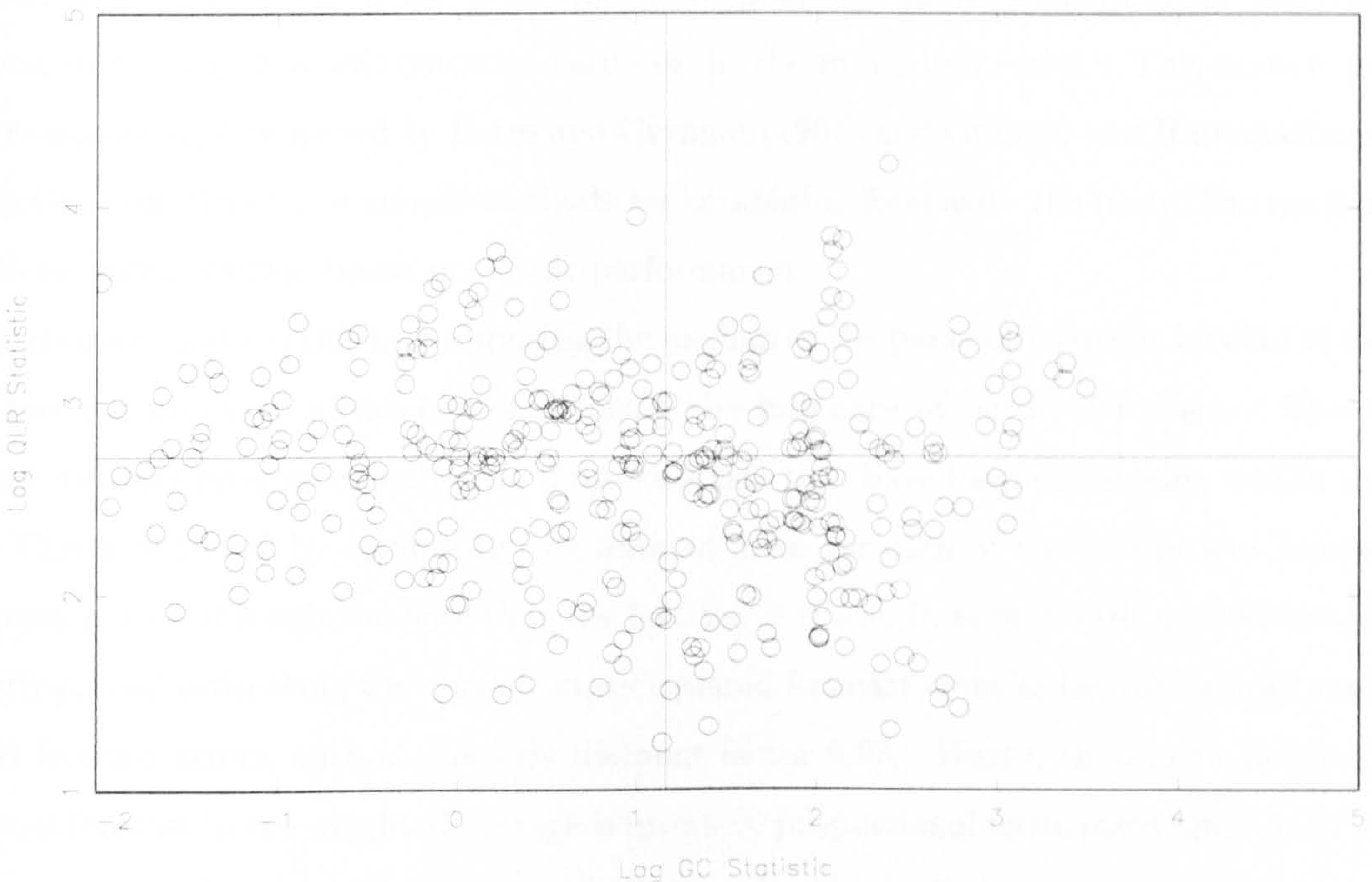
From this, it is possible to conclude that a significant Granger causality statistic makes it no more likely that a predictor outperforms the AR benchmark in both periods. In addition, Table 6.5, which shows the marginal rejection probabilities of the Granger causality and QLR tests and the joint probability of both rejecting, are very similar to one another. This suggests that rejection of Granger noncausality appears to be approximately unrelated to whether or not the QLR statistic rejects.



The QLR statistic implies more instability in output than inflation forecasts. Looking at the predictor categories, real activity appears to be the most unstable predictor of inflation, while output, goods and commodity prices and money appear to be the most unstable forecasters of output growth. Similarly, all 3 month t-bills appear to suffer from structural instability, which is perhaps not surprising given the change in monetary policy priorities pre and post-1992. Euro wide and German share price indices also reject the null hypothesis of constant regression coefficients. Finally, supporting the general consensus in the literature, all variations of the term spreads suffer from instability.

Figure 6.4 illustrates the QLR statistic against the log of the Granger causality F-test statistic. The QLR and Granger causality statistics appear to be approximately independently distributed, as there appears little relation between the two statistics.

Figure 6.4
Granger-Causality and QLR Statistics



6.8 Pooled Forecasts

The forecasts estimated in previous sections relied upon bivariate models. However, central banks across the industrialised world, whose job is to track the swings in the economy and to make forecasts that inform decision-makers in real time, have tended to track hundreds, if not thousands, of variables at any one time. Mitchell and Burns (1938) were strong proponents of looking at many indicators, principally because each constituent indicator provides a different perspective on current and future economic activity.

Using multiple variables can bring much needed accuracy in two ways. First, forecasting with many predictors provides the opportunity to exploit a much richer base of information than is the case with bivariate models. Second, and more importantly with regards to the results presented previously, forecasting with many predictors might provide some robustness against the structural instability that has plagued some of the forecasting exercises. Work by Stock and Watson (2004) has shown that using high-dimensional models can improve forecasts in the sense that the instability of individual forecasting relations might, in some cases, average out. It must be noted that forecasting methods best able to mitigate this instability have been largely unexplored.

6.8.1 Combination Forecasts

An alternative to selecting a few predictors is to pool the information in all of the constituent forecasts, averaging away idiosyncratic variation in the individual series. This section pursues a line of reasoning first proposed by Bates and Granger (1967) and Granger and Ramanatham (1984). This section considers three simple methods for combining forecasts: the mean, the median, and a $MSFE$-weighted average based on recent performance.

The median modifies this by computing the median of the panel of forecasts instead of the mean, which has the potential advantage of reducing the influence of outlier forecasts. The $MSFE$-weighted measure gives more weight to those forecasts that have been performing well in the recent past. This is achieved by computing the forecast error for each of the constituent forecasts over the sample period through the date that the forecast is made, in accord with pseudo out-of-sample forecasting, then estimating the current mean squared forecast error as the discounted sum of past squared forecast errors, with a quarterly discount factor 0.95. Hence, the weight received by any individual forecast in the weighted average is inversely proportional to its discounted $MSFE$. This achieves the aim of giving the greatest weighting to leading indicators that have been performing best most recently. The linear forecast combination using the $MSFE$-weighted average of the pooled forecast can be written as

$$Y^h_{t+h|t} = w_0 + \sum_{i=1}^{n} w_{it} Y^h_{i,t+h|t} \tag{6.7}$$

where w_{it} represents the weight on the i^{th} forecast in period t. Bates and Granger (1967) show that the weights that minimise the mean squared forecast error are those given by the population projection of Y^h_{t+h} onto a constant, w_0, and the constituent forecasts. The constraint of $\Sigma^n_{i=1} w_{it} = 1$ is imposed so that $Y^h_{t+h|t}$ is unbiased when each of the constituent forecasts is unbiased. To compute the discounted weighted average $MSFE$s, where the weights depend inversely on the historical performance of each individual forecast, a weighted average of the individual forecasts is taken, such that

$$w_{it} = m_{it}^{-1} / \sum_{j=1}^{n} m_{jt}^{-1}, \text{ where } m_{it} = \sum_{s=T_0}^{t-h} \rho^{t-h-s} (Y^h_{t+s} - \widehat{Y}^h_{i,s+h|s})^2 \tag{6.8}$$

where ρ represents the discount factor, which is set equal to 0.95.[10] Correspondingly, calculating

[10]The case $\rho = 1$ (no discounting) corresponds to the Bates and Granger (1969) optimal weighting scheme when the individual forecasts are uncorrelated.

the equal-weighted average forecast can be simply derived from equation (6.8) by setting $w_{it} = 1/n$.

Table 6.6: Relative MSFE's of Combination Forecasts

Combination Forecast Method	*GDP*		*IP*	
	1980 -1992	1993 - 2005	1980 -1992	1993 - 2005
Activity				
mean	0.66	0.85	0.82	0.70
median	0.80	0.92	0.73	0.88
Inv. MSFE Wgt.	0.75	0.84	0.83	0.53
G&C Prices				
mean	0.96	1.09	0.97	0.90
median	0.99	1.05	0.89	1.00
Inv. MSFE Wgt.	0.95	1.10	0.82	0.89
Money				
mean	0.97	1.12	1.06	0.97
median	0.98	1.00	1.00	1.00
Inv. MSFE Wgt.	0.94	1.01	1.06	0.97
Asset Prices				
mean	0.91	0.88	0.84	0.76
median	0.84	0.87	0.96	0.79
Inv. MSFE Wgt.	0.74	0.82	0.74	0.73
Total				
mean	0.87	0.91	0.88	0.81
median	0.94	0.96	0.97	0.93
Inv. MSFE Wgt.	0.73	0.86	0.80	0.76

Notes: Entries are the relative MSFE of combination forecasts constructed using the full set of leading indicator forecasts in Table 6.1 Finally, The final result in each subsection represents the estimates from the inverse MSFE weights estimation.

The combination forecasts provide consistent modest improvements over the *AR* benchmark model, apart from money. The forecasting power of asset prices is particularly significant, outperforming all subsets bar activity. There remains one important difference between asset price forecasts and the activity subset. The asset price subset is a better forecaster relative to its performance in the first period for GDP growth, with the opposite appearing true for activity, as well as money, goods and commodity prices and forecasts based on all indicators. The results in general also suggest that the subsets are better at forecasting IP growth than real GDP growth.

6.9 Summary

Despite the moderation in the Euro area business cycle, it has not been sufficient to reduce forecasting instability amongst the main macroeconomic time series of the Euro area, with no re-emergence of money in forecasting future economic activity. The estimates suggest that this instability can be negated by pooling together forecasts. In general, the results from the empirical analysis lead to three main conclusions.

Conclusion 1 *Some asset prices have been useful predictors of output and inflation growth in some time periods for the Euro area.*

Consistent with most of the literature, the German term spread has become a useful predictor of GDP growth. This is less so for IP. In addition, German real bond yields, real German policy rates and three month t-bills have also contained useful information on future levels of output. This is more pronounced for IP than GDP. However, these forecasting relationships with output appear to have broken down. Interestingly, it would appear that first differenced interest rate measures contain more useful information with regards to GDP than their level counterparts. In first differenced form, the various nominal and real interest rate measures for Germany appear to improve upon the benchmark significantly more in the second period than the first. In contrast, however, in levels form the vast majority of interest rate measures for Germany, France and Italy improve upon their benchmark when forecasting IP, and are significantly more accurate forecasting IP than GDP. This is less so for differenced interest rates. Consequently, this result fails to provide an answer to the contention of whether differenced rather than level interest rates should be included in any forecasts of future real output growth for the Euro area. Using Euro area interest rates do not offer any general improvements either. Moving beyond interest rates, share prices have become more useful predictors of GDP growth and GDP deflator, CPI, PPI and unit labour costs have significantly improved performance forecasting IP in the second period than in the first.

Conclusion 2 *There is considerable instability in the bivariate predictive relations involving asset prices and other predictors for the Euro area.*

The pseudo out-of-sample forecasts show that whether a predictor forecasts better than the AR benchmark in the first out-of-sample period is essentially unrelated to whether it will do so in the second period. This finding of instability in the predictive relationships is confirmed by widespread rejections of the null hypothesis of constant coefficients by the (in-sample) QLR statistic, confirming Clements and Hendry (1999) who emphasise the presence of instability in low-dimensional models. As has been mentioned numerous times in the literature, on the one hand this finding of instability is surprising, for the logic behind using asset prices for forecasting includes some cornerstone ideas in economic theory; for example, the Fisher hypothesis, the idea that stock prices reflect expected future earnings, and the notion that temporarily high interest rates lead to an economic slowdown. On the other hand, it makes sense that the predictive power of asset prices could depend on the nature of random events (shocks) hitting the economy. The Euro area economics have witnessed considerable institutional changes in monetary policy and trade integration. The importance of institutional change has been highlighted as one of the main reasons for the moderation witnessed in economic fluctuations in the industrialised economies. This remains an important hypothesis, since a successful shift of monetary policy to an inflation targeting regime, in which future deviations from the target were unexpected, would have the effect of making previously potent predictive relations no longer useful, although such a shift generally would not entirely eliminate the predictability of output fluctuations. In principal, any of these shifts could result in changes to the reduced-form forecasting relations examined in Tables 6.1 and 6.2. This view would support the findings on output growth forecasting in Table 6.3, in which the second subsample forecasts, 1992 - 2005, were sometimes inferior to those in the first subsample, 1980 - 1992, especially when forecasting GDP growth.

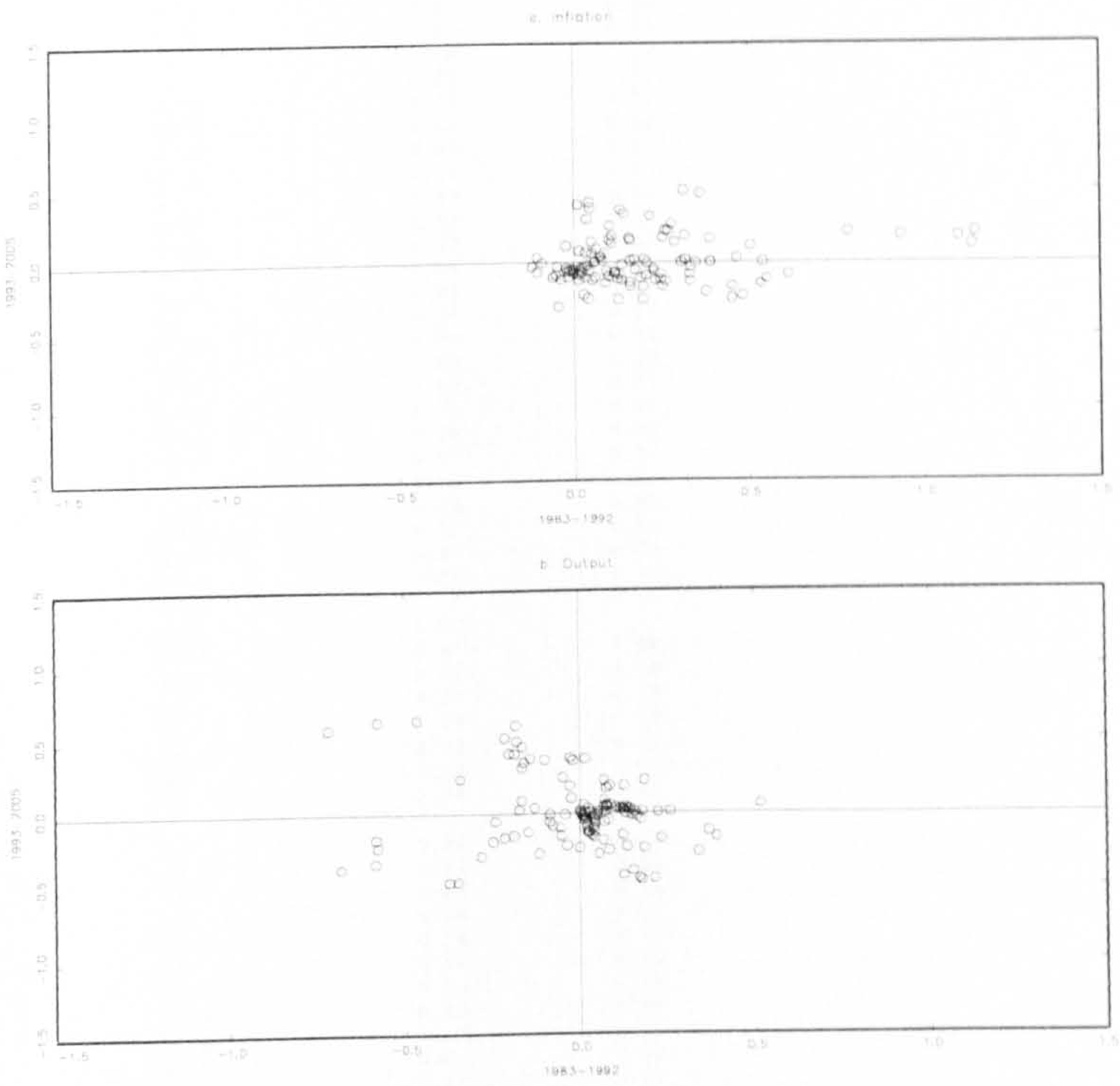
Conclusion 3 *Granger causality tests provide a poor guide to forecast performance for the Euro area.*

As found by Stock and Watson (2003b), the distribution of relative $MSFE$s in the two periods for the subset of predictive relations with a statistically significant Granger causality statistic is similar to the distribution of relative $MSFE$s for all the predictive relations. This implies that rejection of Granger noncausality does not provide useful information about the predictive value of the forecasting relation. In addition, Figure 6.4 illustrated the Granger causality statistic to be essentially uncorrelated with the QLR statistic. This implies that the Granger causality statistic provides no information about whether the predictive relation is stable. Conclusion 3 would seem to support the view that rejection of the null hypothesis of Granger noncausality is uninformative about whether the relationship will be useful for forecasting. The results also suggest that the Granger causality tests provide a poor guide to forecast performance even when moving beyond using one variable, real output, as a measure of the future state of economic activity. However, caution is warranted with regard to the Granger causality tests, as care must be taken when interpreting Granger causality test results. For example, a candidate variable might predict output growth not because it is a fundamental determinant of output growth, but simply because it reflects information on some third variable which is itself a determinant of output growth. Even if Granger causality is interpreted only as a measure of predictive content, it must be remembered that any such predictive content can be altered by the inclusion of additional variables.

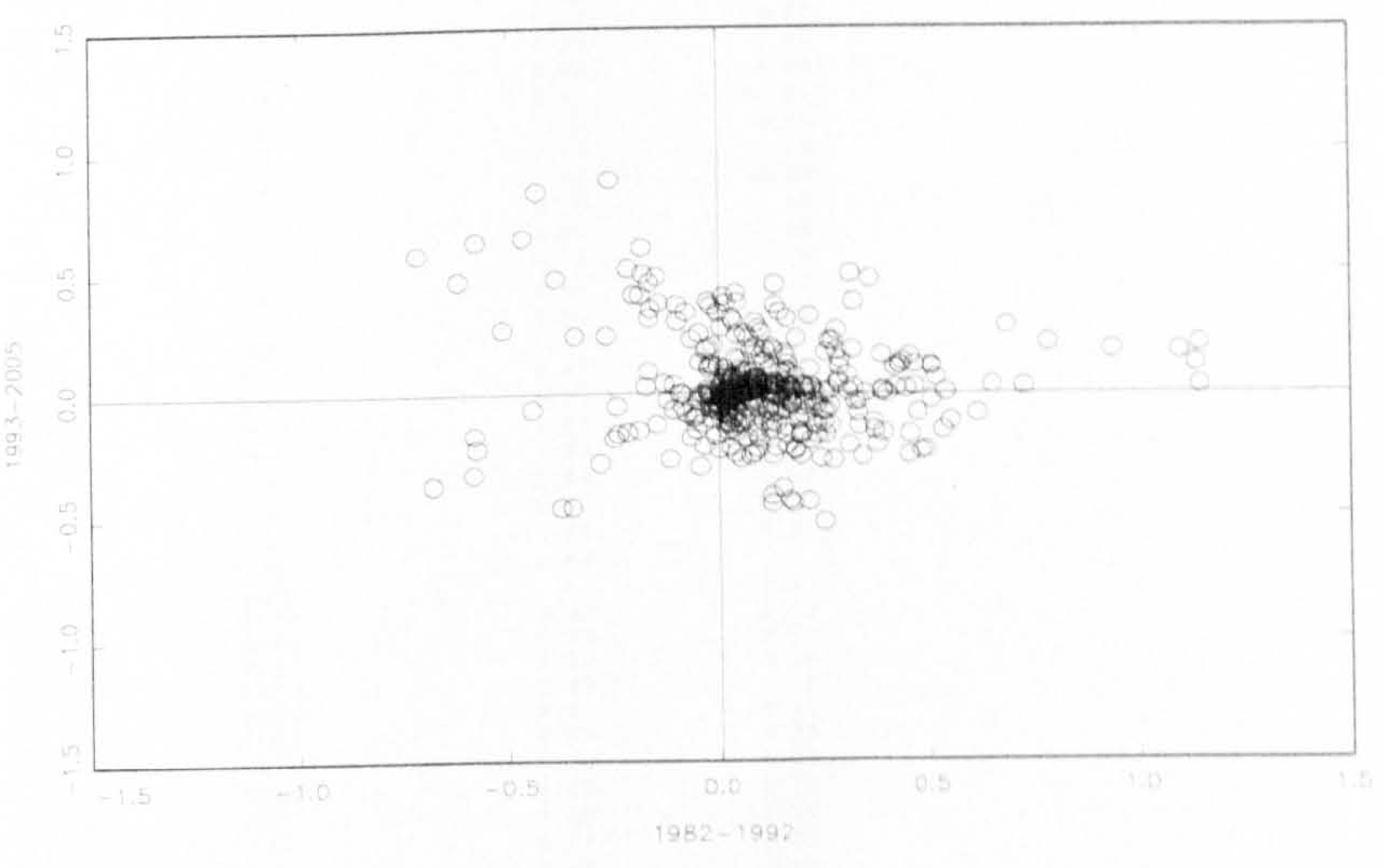
The results suggest that pooling together forecasts considerably improves the forecasting performance of asset prices. The results would seem to support the view that the instability witnessed in the forecasts is sufficiently idiosyncratic across series for the median forecast to average out the instability across the individual forecasting relations. The improvements in forecasts which pool information from a wide variety of sources, gives credence to recent attempts in econometric literature to improve forecasting accuracy through large scale models, which often incorporate unobserved dynamic factors.

Appendix for Chapter 6

Appendix: Pseudo Out-of-Sample Log Relative MSFE, Asset Prices
4-Quarter Ahead Forecasts, Fixed Lag Length



Appendix:
Pseudo Out-of-Sample Log Relative MSFE, All Predictors
4-Quarter Ahead Forecasts, Fixed Lag Length Models



McCraken & Clark (2001) - *P*-value tests of Equal Forecast Accuracy

		Real GDP	*IP*
rtbill	lev	0.05	0.06
rbnds	lev	0.53	0.05
rbndm	lev	0.04	0.04
rtbill	1d	0.00	0.27
rbnds	1d	0.00	0.38
rbndm	1d	0.00	0.30
rrtbill	lev	0.06	0.03
rrbnds	lev	0.86	0.03
rrbndm	lev	0.06	0.04
rrtbill	1d	0.00	0.31
rrbnds	1d	0.00	0.32
rrbndm	1d	0.00	0.33
mon2	ln 1d	0.21	0.26
mon3	ln 1d	0.83	0.99
rmon2	1d	0.98	0.11
rmon3	1d	0.98	0.25
exrate	ln 1d	0.23	0.29
rexrate	ln 1d	0.15	0.26
stockp	ln 1d	0.04	0.29
sharei	ln 1d	0.10	0.17
shareg	ln 1d	0.07	0.04
sharef	ln 1d	0.13	0.19
gold	ln 1d	0.57	0.04
rgold	ln 1d	0.94	0.02
silver	ln 1d	0.94	0.16
rsilver	ln	0.25	0.04
rbndl	ln 1d	0.90	0.98
rrbndl	1d	1.00	0.63
ppi	ln 1d	0.05	0.21
oil	ln 1d	0.80	0.99
earn	ln 1d	0.28	0.41
emp	ln 1d	0.92	0.78
capu	lev	0.00	0.46
comod	ln 1d	0.92	0.28
agri	ln 1d	0.91	0.28
nfuel	ln 1d	0.83	0.14
unitl	ln 1d	1.00	0.17
rgdp	ln 1d		0.12
ip	ln 1d	0.22	
cpi	ln 1d	0.97	0.00
pgdp	ln 1d	0.97	0.00
rgerp	1d	0.24	0.10
rfrap	1d	0.03	0.19
ritap	1d	0.02	0.66
rgerp	lev	1.00	0.07
rfrap	lev	0.98	0.00
ritap	lev	0.96	0.00
rfram 1	1d	0.11	0.22
rfram 2	1d	0.13	0.26
rfram 3	1d	0.16	0.26
ritam 1	1d	0.36	0.17
ritam 2	1d	0.36	0.23
ritam 3	1d	0.34	0.22
fram 1	ln 1d	0.27	0.84
fram 2	ln 1d	0.13	0.69
fram 3	ln 1d	0.05	0.59
itam 1	ln 1d	0.22	0.39
itam 2	ln 1d	0.34	0.24
itam 3	ln 1d	0.25	0.69
rspreadg	1d	0.00	0.08
rspreadf	1d	0.54	0.44
rspreadi	1d	0.90	1.00
rspreadg	lev	0.01	0.23
rspreadf	lev	0.66	0.22
rspreadi	lev	0.01	0.87
fra10	1d	0.31	0.98
ita10	1d	0.00	0.95
ita5	1d	0.00	0.46
rfra10	1d	1.00	0.99
rita5	1d	0.99	0.88
rita10	1d	1.00	0.99
roil	1d	0.17	0.50
ltn	1d	0.01	0.98
strq	1d	0.25	0.10
stn	1d	0.01	0.14
fra10	lev	0.86	0.00
ita10	lev	0.97	0.01
ita5	lev	0.98	0.01
rfra10	lev	0.97	0.10
rita5	lev	1.00	0.01
rita10	lev	1.00	0.04
ltn	lev	0.94	0.82
strq	lev	0.53	0.09
stn	lev	1.00	0.07
ip	gap	0.64	-
rgdp	gap	-	0.03
moneys	ln 1d	0.02	0.94
M1	ln 1d	0.78	0.99
M3	ln 1d	0.67	0.96
rmoneys	ln 1d	0.99	0.20
rM1	ln 1d	0.95	0.82
rM3	ln 1d	0.69	0.75
pcn	ln 1d	0.98	0.01
pcr	ln 1d	0.15	0.27
fbill3	lev	1.00	0.00
fbill3	1d	0.01	0.22
ibill3	lev	0.97	0.00
ibill3	1d	0.00	0.22
gbill3	lev	1.00	0.07
gbill3	1d	0.07	0.11

Real Output Granger Causality and QLR Test P-Values

		Granger Causality		*QLR*	
		GDP	*IP*	*GDP*	*IP*
rtbill	1	0.00	0.14	0.17	0.01
rbnds	1	0.04	0.03	0.05	0.13
rbndm	1	0.00	0.07	0.18	0.13
rtbill	2	0.00	0.64	0.71	0.07
rbnds	2	0.01	0.55	0.64	0.10
rbndm	2	0.00	0.77	0.63	0.08
rrtbill	1	0.00	0.13	0.08	0.01
rrbnds	1	0.10	0.04	0.05	0.11
rrbndm	1	0.00	0.08	0.20	0.05
rrtbill	2	0.00	0.65	0.31	0.05
rrbnds	2	0.07	0.69	0.19	0.07
rrbndm	2	0.00	0.30	0.33	0.06
exrate	2	0.10	0.55	0.02	0.06
rexrate	2	0.04	0.57	0.03	0.04
stockp	2	0.08	0.66	0.01	0.03
sharei	2	0.27	0.39	0.18	0.00
shareg	2	0.02	0.35	0.00	0.02
sharef	2	0.26	0.42	0.17	0.00
gold	2	0.42	0.08	0.26	0.04
rgold	2	0.40	0.23	0.33	0.02
silver	2	0.29	0.13	0.34	0.10
rsilver	2	0.63	0.06	0.00	0.10
rbndl	2	0.86	0.84	0.14	0.08
rrbndl	2	0.56	0.31	0.12	0.20
rmon2	2	0.13	0.86	0.02	0.10
mon2	2	0.58	0.09	0.01	0.07
rmon3	2	0.19	0.91	0.05	0.11
mon3	2	0.75	0.08	0.00	0.00
ppi	2	0.84	0.06	0.04	0.30
oil	2	0.19	0.51	0.14	0.00
earn	2	0.81	0.56	0.09	0.01
emp	2	0.11	0.39	0.42	0.02
capu	1	0.00	0.07	0.00	0.24
comod	2	0.60	0.43	0.14	0.04
agri	2	0.60	0.49	0.13	0.03
nfuel	2	0.03	0.51	0.00	0.09
unitl	2	0.01	0.18	0.00	0.00
rgdp	2	-	0.75	-	0.05
IP	3	0.99	-	0.01	-
cpi	2	0.36	0.00	0.00	0.00
pgdp	2	0.33	0.01	0.00	0.05
rgerp	2	0.73	0.19	0.13	0.22
rfrap	2	0.41	0.99	0.23	0.13
ritap	2	0.23	0.84	0.04	0.11
rgerp	1	0.11	0.44	0.00	0.00
rfrap	1	0.57	0.01	0.01	0.46
ritap	1	0.54	0.02	0.00	0.27
rfram1	2	0.43	0.14	0.11	0.05
rfram2	2	0.41	0.10	0.10	0.06
rfram3	2	0.40	0.08	0.12	0.05
ritam1	2	0.02	0.15	0.11	0.02
ritam2	2	0.02	0.15	0.12	0.03
ritam3	2	0.02	0.14	0.12	0.03
fram1	2	0.88	0.13	0.03	0.01
fram2	2	0.42	0.06	0.00	0.04
fram3	2	0.17	0.02	0.01	0.07
itam1	2	0.86	0.91	0.03	0.01
itam2	2	0.62	0.88	0.06	0.00
itam3	2	0.36	0.82	0.07	0.00
rspreadg	2	0.01	0.27	0.09	0.13
rspreadf	2	0.58	0.99	0.02	0.00
rspreadi	2	0.49	0.75	0.06	0.17
rspreadg	1	0.00	0.60	0.26	0.05
rspreadf	1	0.49	0.93	0.03	0.00
rspreadi	1	0.36	0.61	0.02	0.01
fra10	2	0.60	0.98	0.00	0.09
ita10	2	0.07	0.65	0.09	0.03
ita5	2	0.03	0.56	0.08	0.01
rfra10	2	0.32	0.58	0.00	0.12
rita5	2	0.35	0.58	0.03	0.03
rita10	2	0.62	0.27	0.04	0.06
stn	2	0.20	0.79	0.17	0.21
strq	2	0.82	0.73	0.17	0.16
ltn	2	0.03	0.83	0.24	0.17
fra10	1	0.69	0.00	0.00	0.43
ita10	1	0.65	0.03	0.02	0.26
ita5	1	0.63	0.04	0.01	0.23
rfra10	1	0.29	0.00	0.00	0.42
rita5	1	0.26	0.06	0.00	0.12
rita10	1	0.42	0.02	0.01	0.12
stn	1	0.23	0.03	0.00	0.05
strq	1	0.78	0.47	0.18	0.02
ltn	1	0.14	0.03	0.02	0.36
rgdp	3	-	0.02	-	0.05
IP	2	0.98	-	0.13	-
m1	2	0.02	0.27	0.09	0.03
m3	2	0.79	0.08	0.00	0.00
mtn	2	0.81	0.25	0.00	0.00
rm1	2	0.01	0.89	0.00	0.02
rm3	2	0.33	0.68	0.01	0.02
rmtn	2	0.46	0.11	0.10	0.02
pcr	1	0.90	0.89	0.30	0.13
fbill3	2	0.41	0.01	0.00	0.38
fbill3	1	0.60	0.50	0.15	0.20
ibill3	2	0.59	0.00	0.00	0.06
ibill3	1	0.00	0.88	0.10	0.01
gbill3	2	0.04	0.48	0.01	0.00
gbill3	1	0.46	0.57	0.15	0.45

Note 1 = levels, 2 = first differenced, 3=gap

Part IV

Summary

Chapter 7

Concluding Remarks

This thesis has examined business cycles fluctuations in the Euro area over the last 25 years. This was undertaken by mainly concentrating upon a shock based, or exogenous, view of how economic fluctuations are driven, which in itself may be interpreted as a criticism. However, the research makes a substantial contribution to the subject of business cycle fluctuations with regards to the Euro area as a single economic entity, a need which has increased continuously since the introduction of the Euro currency. Such analysis acts as a reference for economic agents due to its influence on monetary policy decisions. For these reasons, at the present time business cycle analysis of the Euro area has an added significance, given current efforts to understand the workings of the Euro area economy. The subsequent four paragraphs provide a brief summary of the chapters and their conclusions.

Chapter 3 examined balanced growth theory, investigating the stationarity properties of the great ratios using assumptions from a wide class of RBC models. The RBC hypothesis asserts that economic fluctuations are best described by a set of stochastic trends that run through the economy. Consequently, short-term output fluctuations are caused by random disturbances in these trends, which cause output to temporarily move away from equilibrium, with the random movements in the trend treated as being due to productivity/technological disturbances. Despite this hypothesis forming the cornerstone of neoclassical growth theory, as well as a central principal in much of macroeconomics today, it has yet to be examined for any major European economy. The attempt to interlink exogenous productivity innovations and real output fluctuations, using just common trends, has only been detailed for the UK and US economies. Chapter 3 considers the implications of balanced growth theory for business cycle fluctuations in the Euro area, along with its competitor, monetary disturbances. The results, in general, are modestly supportive of standard RBC theory, in which the predominant source of output fluctuations are due to permanent shocks, with a modest role for monetary disturbances. These observed empirical regularities are important for an understanding of how the Euro area economy, as a single economic entity, operates.

Chapter 4 uses the results from Chapter 3, and explores whether, over the last three decades, the business cycle has 'died', if it has permanently dampened, or neither? Using stochastic volatility models, the chapter investigates the structural changes that have taken place in the Euro area over this period. As mentioned in Chapter 1, with post-war reconstruction and democratisation in southern Europe characterising the post-war period, it is imprudent to assume that there have been no changes in the stochastic trend properties of the Euro area economy. Nearly all of the literature, so far, has concentrated upon the US economy. Understanding the causes of instability for the Euro area, and whether they are likely to endure, is important, since increasing instability in output increases the risk associated with the economy. Increases in risk are likely to reduce the level of equilibrium output, possibly leading to both higher saving and a lower capital stock, which may in turn lead to greater capital outflows in an open economy. Hence, policies that reduce anticipated and unanticipated volatility will therefore raise output and welfare in the longer run. The results suggest that there has been a substantial moderation (40 percent) in output fluctuations for the Euro area. In addition, the start of the decline is shown to have accelerated from the early 1990s onwards. The results are also supportive of the exogenous approach taken in the work presented here, in that the analysis suggests a significant proportion of the moderation in output fluctuations for the Euro area is down to fewer shocks impinging upon the economy, implying that exogenous disturbances play quite a large role in driving economic cycles, especially productivity ones. This conclusion has important policy implications, since it implies that, had monetary policy been an important factor in moderating output fluctuations, then it would have been reasonable to assume that, as long as the policy regime was maintained, output would remain moderated. However, since the results imply that changes in monetary policy have played a small role in the moderation of output fluctuations, especially in comparison to shocks wider than monetary ones, then the current benign external environment may be a hiatus before a return to more turbulent economic times.

Chapter 5 follows on from the theme developed in Chapter 4. However, Chapter 5 extends the analysis to include an international dimension. This chapter explores whether there have been changes in either the impulse or propagation of international business cycles on the Euro area cycle. In other words, have output fluctuations in the Euro area's main trading partners moderated and, if so, has this moderation perpetuated the moderation witnessed in Euro area output fluctuations? The results are supportive of the view that economies are increasingly interdependent. The results also show synchronisation between the Euro area and the accession countries to have increased, although from a very low base. The chapter concludes that, although international business cycles play an important role in driving output fluctuations in the Euro area, fewer shocks emanating from abroad have not been an important factor in dampening output fluctuations in the Euro area, suggesting the moderation in output fluctuations in the Euro area is more down to domestic factors. In addition, Eurocentric shocks do not diffuse into the world cycle, despite the Euro area being a large trading area. Taken together, the results highlight support for the idea that the increased integration of the Euro area with a greater number of economies may have limited the negative (or positive) influences from large dominating economies, thus having a stabilising role on the world business cycle.

A consequence of dampening output fluctuations is that, on the one hand, real output, like many other time series of economic activity, has become less volatile, so the root mean square error of relatively poor forecasts should have declined since the mid-1980s. In this sense real output is easier to forecast, as the imprecision of real output forecasts, measured by the mean square forecast error, has fallen. Hence, an obvious question for Chapter 6 to explore is whether the usefulness of various asset price measures in predicting the future level of business cycle activity have improved over the last two decades, especially with regards to various monetary aggregates. The increased use of asset prices, especially over the last decade, for forecasting future levels of economic activity is partly a response to disappointment over the failure of monetary aggregates to provide reliable and stable forecasts during the zenith of monetarist ideas. This chapter explores whether this trend is beginning to be reversed, and whether the moderation in output may lead to a revival in monetary aggregates. In addition, although various forecasting properties have been examined for many industrialised economies, the complex interplay between economic variables that affect economic activity has still to be worked out for the Euro area. Identifying variables with strong predictive power for future output is important for a variety of reasons. Firstly, those whose task it is to produce forecasts, such as the European Central Bank, need to know which, if any, asset prices provide useful forecasts of future output growth. Knowing such information has become especially important since the early 1990s, as the popularity of constructing coincident and leading indicator indices, like the NBER coincident index, increased. Such indices are used to date business cycle turning points or forecast future levels of economic activity. The accuracy of the constructed indices rest entirely upon the informational content of the individual series in the index, since such indicators synthesise information contained in a range of economic variables. Consistent with the literature, the results suggest that German yield spreads provide useful information on the future level of economic activity in the Euro area. This also holds true for various German bond yields. In addition, stock prices from the three largest economies in the Euro area, Germany, France and Italy remain good forecasters of future economic activity. However, monetary aggregates contain little, if any, information over and above the benchmark AR model. Results from the multivariate models suggest that pooling together forecasts from various asset prices leads to a significant improvement over recursive bivariate estimates and the benchmark AR model. In conclusion, the results imply that the use of pooled forecasts provides a richer base of information from which to forecast future levels of economic activity, whilst helping overcome forecast instability.

The results from Chapters 3, 4 and 5 imply that the lower frequency components of real output are playing a greater role in driving output fluctuations. Four examples can be used to highlight this. First, Figure 1.6 in Chapter 1 shows the very high frequency components of real output to have fallen considerably over the last two decades. Second, estimates of the sum of AR coefficients in Chapter 5 show a considerable increase in persistence of output, along with the possible importance of balanced growth innovations in Chapter 3 and, finally, the significant role played by productivity disturbances in dampening output fluctuations in Chapter 4. Taken together, this would imply that output fluctuations are increasingly determined by the low frequency components of the spectrum of output. Moreover, the results generally support the consensus view of the literature that monetary factors play, at most, a modest role in perpetuating output fluctuations. This does not mean, however, that monetary policy has no influence on output fluctuations, as highlighted by the various Taylor rule estimates in Chapter 4.

Nonetheless, these conclusions are far from categorical. Shock based methods, like those presented here, of studying output fluctuations have often faced criticism from models which take an endogenous approach to studying output fluctuations. Indeed, the underlying principle behind any structural analysis of the business cycle remains embedded in classical economic theory, that the economy is inherently stable until impacted by a sudden shock. In contrast, the endogenous approach asserts that cycles are self perpetuating. More recently, however, endogenous models have theorised that cycles are caused by a Schumpeterian view in which fluctuations in economic development are the consequence of the periodic arrival of innovations in education and so forth, i.e., endogenous growth. As mentioned in Chapters 1 and 2, over most of the sample period, the Euro area has probably witnessed more growth cycles than traditional business cycles, where the traditional cycle is hypothesised to last from between six and 32 quarters. However, as an answer to the question first set out in the literature review of Chapter 2, pertaining to whether business cycles should be viewed as endogenous or exogenous, the results of Chapters 3, 4 and 5 suggest that a shock based approach can yield useful explanations of certain business cycle episodes. Shocks in productivity seem to be useful in explaining certain historical macroeconomic episodes in the Euro area (Chapter 3), in addition to commodity price disturbances providing some explanatory power for the dampening of output fluctuations seen over the last three decades (Chapter 4). The results are generally supportive of the continuing use of shock based models to examine output fluctuations in the Euro area, which in turn implies that economic activity is best viewed as a random walk with drift; a stochastic process rather than a deterministic process, as discussed in Chapter 1. In essence, the results support the Frisch (1933) and Slutzky (1937) view that business cycles in the Euro area can be modelled as a result of an interplay between a set of stochastic impulses and certain propagation mechanisms. Also, one can learn from history about the importance of economic shocks and their, often hypothesised, premature demise.

Perhaps one shortcoming of the research presented resides in the 'linear versus non linear' debate in studying output fluctuations. Mitchell (1927), at a very early stage of business cycle research, discussed the topic of the nonlinearity in business cycle dynamics, presenting evidence both in favour and against the asymmetry of business cycles. In general, linear models are not well suited to data exhibiting sudden bursts of very large amplitudes at irregular time periods. Most of the models presented are linear and, hence, do not take into account whether there may be asymmetric effects of certain shocks on real output, i.e., do productivity shocks have a large impact on real output when they are negative rather than positive? This is important, since if technological regress is unlikely, then only positive innovations in output reflect technological progress, therefore affecting the forecast of long-run output differently, and probably to a greater extent, than negative innovations. However, it must be noted that very few theoretical business cycle models include this sort of asymmetry and, hence, any empirical work which examines shock asymmetry, be it demand or supply, is often difficult to compare with any standard macroeconomic model of the business cycle. One notable exception is Friedman's (1992) plucking model, which highlights one of the principal problems with linear time series models of the business cycle, in that they are not ideally suited to data exhibiting time irreversibility. In spite of this, due to the assumption at the outset that business cycles are driven by shocks, the linearity assumption is perfectly justifiable. Therefore, from this extrinsic viewpoint, the main difference between a recession and an expansion is the sign, the size and duration of shocks to the economy. As in the traditional classical view, the underlying structure of the economy does not change from a recession to an expansion.

Is the business cycle dead or was the business cycle ever alive? The answer to these questions for the Euro area is no and yes. After most periods of extended expansion, complacent talk of a 'new era' arrives. History teaches us that it is the arrival of unexpected shocks that usually disturb such periods of credulity. The analysis of the role and effects of exogenous disturbances provides a worthwhile exercise, especially with regard to the Euro area's main macroeconomic time series, in which the stochastic trend properties and impulse and internal propagation mechanisms remain relatively unknown. With the advent of a single currency, the research presented here makes a substantial contribution in our understanding of the Euro area economy, measured as a single economic entity, along with its wider international economic implications.

Bibliography

[1] Adelman, R. and F. Adelman (1959), 'The Dynamic Properties of the Klein-Goldberger Model', *Econometrica*, 4: 596 - 625.

[2] Ahmed, S., B. W. Ickes, P. Wang and B. S. Yoo (1993), 'International Business Cycles', *American Economic Review*, **83**(3): 335 - 359.

[3] Ahmed, S. and J. H. Rogers (2000), 'Inflation and the Great Ratios: Long term evidence from the US', *Journal of Monetary Economics*, **45**: 3 - 35.

[4] Ahmed, S., A. Levin and B. Wilson (2004), 'Recent U.S. Macroeconomic Stability: Good Luck, Good Policies, or Good Practices?', *The Review of Economics and Statistics*, **86**(3): 824 - 832.

[5] Altonji, J. and J. Ham (1990), 'Employment Variation in Canada: The Role of External, Regional and Industrial Factors', *Journal of Labor Economics*, SS198 - 236.

[6] Anderson, H., M. Dungey, D. Osborn and F. Vahid (2006), 'Constructing Historical Euro Area Data', manuscript.

[7] Andrews, D. and W. Ploberger (1992), 'Optimal Changepoint tests for Normal Linear Regression', Cowles Foundation Discussion Paper 1016.

[8] Andrews, D. W. K. (1993), 'Tests of Parameter Instability and Structural Change with Unknown Change Point', *Econometrica*, **61**: 821 - 856.

[9] Andrews, D. W. K. and W. Ploberger (1994), 'Optimal Tests When a Nuisance Parameter is Present Only Under the Alternative', *Econometrica*, **62**: 1383 - 1414.

[10] Artis, M. and W. Zhang (1999), 'Further evidence on the international business cycle and the ERM: Is there a European Business Cycle?', *Oxford Economic Papers*, **51**: 120 - 132.

[11] Artis, M. Krolzig, H. M. and J. Toro (2004), 'The European Business Cycle', *Oxford Economic Papers*, **56**: 1 - 44.

[12] Artis, M. J., M. Marcellino and T. Proietti (2005), 'Business Cycles in the new EU member countries and their conformity with the Euro area', *Journal of Business Cycle Measurement and Analysis*, **2**(1): 7 - 42.

[13] Atkeson, A. and L. E. Ohanian (2001), 'Are Phillips Curves Useful for Forecasting Inflation?', *Federal Reserve Bank of Minneapolis Quarterly Review* **25**(1): 2 - 11.

[14] Attfield, C. (2003), 'Balanced Growth and Output Convergence in Europe', *Discussion Paper No. 03/547*, Department of Economics, University of Bristol.

[15] Attfield, C. and J. Temple (2006), 'Measuring Trend Output: How Useful Are the Great Ratios?'. CEPR Discussion Paper no. 4796. London, Centre for Economic Policy Research. http://www.cepr.org/pubs/dps/DP4796.asp.

[16] Backus, D. K. and P. J. Kehoe (1992), 'International Evidence on the Historical Properties of Business Cycles', *American Economic Review*, **82**: 864 - 888.

[17] Backus, D. K., P. J. Kehoe and F. E. Kydland (1992), 'International Real Business Cycle', *Journal of Political Economy*, **100**(4): 745 - 775.

[18] Bai, J., R. Lumsdaine and J. Stock (1998), 'Testing for and Dating Common Breaks in Multivariate Time Series', *The Review of Economic Studies*, **65**: 395 - 432.

[19] Bai, J. (1997), 'Estimation of a Change Point in Multiple Regression Models', *The Review of Economics and Statistics*, **79**: 551 - 563.

[20] Banerjee, A., M. Marcellino and I. Masten (2005), 'Forecasting Macroeconomic Variables for the New Member States of the European Union', Working Paper 482. ECB.

[21] Banerjee, A., Lumsdaine, R. L and J. H. Stock (1992), 'Recursive and Sequential Tests of the Unit Root and Trend Break Hypothesis: Theory and International Evidence', *Journal of Business and Economic Statistics*, **10**: 271 - 288.

[22] Barro, R. J. (1991), 'Economic Growth in a Cross-Section of Countries', *Quarterly Journal of Economics*, **106**: 407 - 443.

[23] Barsky, R. B and L. Kilian (2002), 'Do we Really Know that Oil Caused the Great Stagflation? A Monetary Alternative?', In Ben. S. Bernanke and Ken Rogoff, eds., *NBER Macroeconomics Annual 2001*, MIT Press: Cambridge, MA, pp. 137 - 183.

[24] Barsky, R. B and L. Kilian (2004), 'Oil and the Macroeconomy since the 1970's', *Journal of Economic Perspectives*, **18**(4): 115 - 134.

[25] Basistha, A. and R. Startz (2004), 'Why were changes in the federal funds rate smaller in the 1990s?', *Journal of Applied Econometrics*, **19**: 339 – 54.

[26] Basu, S. (1996), 'Procyclical Productivity, Increasing Returns or Cyclical Utilisation?', *Quarterly Journal of Economics*, **111**: 719 - 751.

[27] Bates, J. M. and C. W. J. Granger (1969), 'The Combination Forecasts', *Operations Research Quarterly*, **20**: 451 - 468.

[28] Baxter, M. and R. G. King (1999), 'Measuring Business Cycles: Approximate Bandpass-filters for Economic Time Series', *The Review of Economics and Statistics*, **81**(4): 575 – 593.

[29] Baxter, M. and M. A. Kouparitsas (2005), 'Determinants of Business Cycle Comovements: A Robust Analysis', *Journal of Monetary Economics*, **52**(1): 113 - 157.

[30] Beaudry, P. and G. Koop (1993), 'Do Recessions Permanently Change Output', *Journal of Monetary Economics*, **31**: 149 - 163.

[31] Benhabib, J. and Y. Wen (2003), 'Indeterminacy, Aggregate Demand, and the Real Business Cycle', *Journal of Monetary Economics*, **51**: 503 - 530.

[32] Bergman, U. M., M. D. Bordo and L. Jonung (1998), 'Historical Evidence on Business Cycles: The International Experience', Proceedings from the Federal Reserve Bank of Boston Conference Series no. 42.

[33] Bernanke B. S. and A. S. Blinder (1992), 'The Federal Funds Rate and the Channels of Monetary Transmission', *American Economic Review*, **82**(4): 901-927.

[34] Bernanke, B. S., M. Gertler, and M. W. Watson (1997), 'Systematic Monetary Policy and the Effects of Oil Price Shocks', *Brookings Papers on Economic Activity*, **1**: 91 - 142.

[35] Bernanke, B. S. and I. Mihov (1998), 'Measuring Monetary Policy', *Quarterly Journal of Economics,* **113**(3): 869 - 902.

[36] Bernanke, B. S. (2004), 'Remarks by Governor Ben S. Bernanke', At the Meetings of the Eastern Economic Association, Washington, DC, 20 February, Board of Governors of the Federal Reserve System.

[37] Bernanke, B. S. and J. Boivin and P. Eliasz (2005), 'Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach', *Quarterly Journal of Economics*, **120**: 387-422.

[38] Bernard, H. and S. Gerlach (1998), 'Does the term structure predict recessions?', *International Journal of Finance and Economics,* **3**: 195-215.

[39] Beveridge, S and C. R. Nelson (1981), 'A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the Business Cycle', *Journal of Monetary Economics*, **7**: 151-74.

[40] Blackburn, K. and M. O. Ravn (1992), 'Business Cycles in the UK: Facts and Fictions', *Economica*, **59**: 383 - 401.

[41] Blanchard, O. J. (1981), 'What is Left of the Multiplier-Accelerator' *American Economic Review,* May: 150 - 154.

[42] Blanchard, O. J. and M. W. Watson (1984), 'Are Business Cycles All Alike?' NBER Working paper No. 1392.

[43] Blanchard, O. J. and D. Quah (1989), 'The Dynamic Effects of Aggregate Demand and Supply Disturbances', *American Economic Review*, **79**(4): 655 - 673.

[44] Blanchard, O. J. (1993), 'Consumption and the Recession of 1990-1991', *American Economic Review,* **83**(2): 270 - 274.

[45] Blanchard, O. J. and J. Simon (2001), 'The Long and Large Decline in U.S. Output Volatility', *Brookings Papers on Economic Activity,* 135 - 164.

[46] Blanchard, O. J. and R. Perotti (2002), 'An Empirical Characterization of the Dynamic Effect of Changes in Government Spending and Taxes on Output', *Quarterly Journal of Economics,* **117**(4): 1329.

[47] Blundell, R., L. Pistaferri, and I. Preston (2003), 'Consumption Inequality and Partial Insurance', University College London.

[48] Boivin, J. and M. Giannoni (2002), 'Assessing Changes in the Monetary Transmission Mechanism: A VAR approach', *Federal Reserve Bank of New York Monetary Policy Review*, **1**: 97 - 111.

[49] Brock, W. A. and L. J. Mirman (1972), 'Optimal Economic Growth and Uncertainty: The Discounted Case', *Journal of Economic Theory*, **4**: 479-513.

[50] Bruggeman, A., P. Donati and A. Warne (2003), 'Is the demand for Euro area M3 stable?', Working Paper Series 255, European Central Bank.

[51] Bry, G. and C. Boschan, (1971), 'Cyclical Analysis of Economic Time Series: Selected Procedures and Computer Programs', *NBER* Technical Working Paper No. 20.

[52] Burbridge, J. and A. Harrison (1984), 'Testing for the Effects of Oil-Price Rises Using Vector Autoregressions', *International Economic Review*, **25**: 459 - 484.

[53] Burns, A. F. and W. C. Mitchell (1946), *Measuring Business Cycles.* New York: NBER.

[54] Burnside, C., M. Eichenbaum, M. and S. Rebelo (1993), 'Labor Hoarding and the Business Cycle', *Journal of Political Economy*, **115**: 89 - 117.

[55] Burnside, C., M., Eichenbaum, M. and S. Rebelo (1996), 'Sectoral Solow Residuals', *European Economic Review*, **40**: 861 - 869.

[56] Burns, A. F. and W. C. Mitchell (1938), *Statistical Indicators of Cyclical Revivals*, NBER Bulletin 69, New York, Reprinted as Chapter 6 of G. H. Moore (ed.), *Business Cycle Indicators*, Princeton: Princeton University Press, 1961.

[57] Calvo, G. A. (1983), 'Staggered prices in utility maximising framework', *Journal of Monetary Economics*, **12**: 383 - 398.

[58] Campbell, J. and N. G. Mankiw (1987), 'Are Output Fluctuations Transitory?', *Quarterly Journal of Economics,* **102:** 857 - 880.

[59] Canjels, E. and M. W. Watson (1997), 'Estimating Deterministic Trends in the Presence of Serially Correlated Errors', *Review of Economics and Statistics*, **79**(2): 184 - 200.

[60] Canova, F. and H. Dellas (1993), 'Trade interdependance and the international business cycle', *Journal of International Economics* **34**: 23 - 47.

[61] Canova, F. (1998), 'Detrending and Business Cycle Facts', *Journal of Monetary Economics*, **41**: 475 - 512.

[62] Canova, F. and G. D. Nicoló (2002), 'Do Monetary disturbances matter for business fluctuations in the G-7?', *Journal of Monetary Economics*, **49**(6): 1131 - 1159.

[63] Canova, F., M. Ciccarelli and E. Ortega (2006), 'Similarities and Convergence in the G-7 Cycles' *Journal of Monetary Economics - forthcoming.*

[64] Cardia, E., A. Ambler and C. Zimmermann (2002), 'International Transmission of the Business Cycle in a Multi-Sector Model', *European Economic Review*, **46**: 273 - 300.

[65] Carruth, A. A., M. A. Hooker, and A. J. Oswald (1998), 'Unemployment Equilibria and Input Prices: Theory and Evidence from the United States', *Review of Economics and Statistics*, **80**: 621 - 628.

[66] Cassel, G. (1918), *Theoretische Sozialökonomie.* Leipzig: C. F. Winter. English translation 1923: *The Theory of Social Economy*, London: T. F. Unwin.

[67] Chevillon, G. and D. F. Hendry (2005), 'Non-parametric direct multi-step estimation for forecasting economic processes', *International Journal of Forecasting*, **21**: 201-218.

[68] Christiano, L. J. and M. Eichenbaum (1990), 'Unit roots in GNP: Do we know and do we care', *Carnegie Rochester Conference Series in Public Policy*, **32**: 7 - 62.

[69] Christiano, L. J. and M. Eichenbaum (1992), 'Current Real-Business-Cycle Theories and Aggregate Labor Market Fluctuations', *American Economic Review*, **82**(3): 430-450.

[70] Christiano, L. J., Eichenbaum, M. and C. Evans (1996), 'The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds', *The Review of Economics and Statistics*, **78**(1): 16 - 34.

[71] Christiano, L., M. Eichenbaum and C. Evans (1999), '*Handbook of Macroeconomics'*, Vol. 1.

[72] Christiano, L. J., M. Eichenbaum and R. Vigfusson (2003), 'What Happens After a Technology Shock', NBER International Finance Discussion Papers, No. 768.

[73] Clarida, R., J. Galí and M. Gertler (1998), 'Monetary policy rules in practice: Some international evidence', *European Economic Review*, **42**(6): 1033 - 67.

[74] Clarida, R., J. Galí and M. Gertler (1999), 'The Science of Monetary Policy: A New Keynesian Perspective', *Journal of Economic Literature*, **37**: 1661-1707.

[75] Clarida, R., J. Galí and M. Gertler (2000), 'Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory', *Quarterly Journal of Economics*, **115**(8): 147 - 180.

[76] Clark, P. K. (1987), 'The Cycle Component of the U.S. Economic Activity', *Quarterly Journal of Economics*, **102**: 797 - 814.

[77] Clark, T. E. (1998), 'Employment Fluctuations in U.S. Regions and Industries: The Role of National, Region-Specific, and Industry Specific Shocks', *Journal of Labor Economics*, **16**(1): 202.

[78] Clark, T. E. and K. Shin (2000), 'The Sources of Fluctuations Within and Across Countries', in G. Hess and E. van Wincoop (eds.), *Intranational Macroeconomics*, Cambridge, UK: Cambridge University Press.

[79] Clark, T. E. and M. W. McCracken (2001), 'Tests of Equal Forecast Accuracy and Encompassing for Nested Models', *Journal of Econometrics*, **105**: 85-100.

[80] Clements, M. P. and D. F. Hendry (1998), *Forecasting Economic Time Series*, Cambridge University Press.

[81] Clements, M. P. and D. F. Hendry (1999), *Forecasting Non-stationary Economic Time Series*, Cambridge, MA: MIT Press.

[82] Cochrane, J. (1988), 'How Big Is The Random Walk in GNP?', *Journal of Political Economy*, **96**: 893 - 920.

[83] Cochrane, J. (1991), 'A Critique of the Application of Unit Root Tests', *Journal of Economic Dynamics and Control*, **15**: 243-96.

[84] Cochrane, J. (1994a), 'Shocks', *Carnegie-Rochester Conference Series on Public Policy*, **41**: 295 - 364.

[85] Cochrane, J. (1994b), 'Permanent and Transitory Components of GNP and Stock Prices', *Quarterly Journal of Economics*, **109**: 241 - 265.

[86] Cochrane, J. (1996), 'What do the VARs Mean?: Measuring the Output Effects of Monetary Policy', NBER Working Papers No. 5154.

[87] Cogley, T. (1990), 'International Evidence on the Size of the Random Walk in Output', *Journal of Political Economy*, **98**(3): 501 - 518.

[88] Cogley, T. and J. M. Nason (1995), 'Output Dynamics in Real-Business-Cycle Models', *American Economic Review*, **85**(3): 492 - 511.

[89] Cogley, T. and T. J. Sargent (2001), 'Evolving post-World War II U.S. Inflation Dynamics', *NBER Macroeconomics Annual*, 331 - 372.

[90] Cogley, T. and T. J. Sargent (2005), 'Drift and Volatilities: Monetary Policies and Outcomes in the Post WWII U.S', *Review of Economic Dynamics*, **8**(2): 262-302.

[91] Cooley, T. F., and G. Hansen (1989), 'The Inflation Tax in a Real Business Cycle Model', *American Economic Review*, **79**(4): 733 - 748.

[92] Cooper, R. N. (1988), *The International Monetary System: Essays in World Economics*, MIT Press.

[93] Daniel, B. C. (1997), 'International Interdependence of National Growth Rates: A Structural Trends Analysis', *Journal of Monetary Economics*, **40**: 73 - 96.

[94] Danthine, J-P. and M. Girardin (1989), 'Business Cycles In Switzerland: A Comparative Study', *European Economic Review*, **33**: 31-50.

[95] Darvas, Z. and G. Szapáry (2005), 'Business Cycle Synchornisation in the Enlarged EU', Discussion paper 5179, *CEPR*.

[96] Davis, E. P. and G. Fagan (1997), 'Are financial spreads useful indicators of future inflation and output growth in EU countries', *Journal of Applied Econometrics*, **12**: 701-714.

[97] De Grauwe, P. and C.C. Storti (2005), *Is Monetary Policy in the Eurozone less Effective than in the US?* CESifo Working Paper Series No. 1606, CESifo (Center for Economic Studies and Ifo Institute for Economic Research).

[98] De Grauwe, P. (1988), 'Exchange Rate variability and the Slowdown in Growth of International Trade', *IMF Staff papers*, **35**(1): 63-84.

[99] De Gregorio, J. (1993), 'Inflation, Taxation and Long-run Growth', *Journal of Monetary Economics*, **31**: 271 - 298.

[100] Dellas, H. (1986), 'A real model of the world business cycle', *Journal of International Money and Finance*, **5**: 381 - 394.

[101] DeLong, J. B. (1997), 'America's Peacetime Inflation: The 1970s', in Christina D. Romer and David H. Romer (eds.), *Reducing Inflation: Motivation and Strategy*, Chicago: University of Chicago Press, pp. 147 – 176.

[102] Diebold, F. X. and G. D. Rudebusch (2001), 'Five Questions about Business Cycles', Federal Reserve Bank of San Fransisco, Economic Review.

[103] Diebold, F. X. and A. S. Senhadji (1996), 'The Uncertain Unit Root in Real GNP: A Comment', *American Economic Review*, **86**: 1291 - 1298.

[104] Doan, T. (2004), *Regression and Time-Series Analysis (RATS) Version 6 User Guide*, Estima.

[105] Dooley, M. P., J. A. Frankel and D. J. Mathieson (1987), 'International Capital Mobility: What do Saving-Investment Correlations Tell Us?', *International Monetary Fund Staff Papers*, **34**: 503 - 530.

[106] Doornik, J. A. and H. Hansen (1994). 'A practical test for univariate and multivariate normality', Discussion paper, Nuffield College, Oxford University.

[107] Donaldson, J. B. and J. Mehra (1983), 'Stochastic Growth with correlated shocks', *Journal of Economic Theory*, **29**: 282-313.

[108] Dornbusch, R. (1997), *Business Week*, Issue August, 11, 1997.

[109] Doyle, B. M. and J. Faust (2005), 'Breaks in the Variability and Comovements of G-7 Economic Growth', *The Review of Economics and Statistics*, **87**(4): 721 - 740.

[110] Duarte, A., I. A. Venetis and I. Paya (2005), 'Predicting real growth and the probability of recession in the Euro area using the yield spread', *International Journal of Forecasting*, **21**: 261 - 277.

[111] Eichenbaum, M. (1992), 'Comment on Interpreting The Macroeconomic Time Series Facts: The Effects of Monetary Policy', *European Economic Review*, **36**(5): 1001 - 1011.

[112] Eichengreen, B. and C. Wyplosz (1993), 'The Unstable EMS', *Brookings Papers on Economic Activity*, 1.

[113] Eickmeier, S. and J. Breitung (2006), 'How Synchronised are new EU member states with the Euro area? Evidence from a Structural Factor Model', *Journal of Comparative Economics*, **34**: 538 - 563.

[114] Eleftheriou, M., Gerdesmeier, D. and B. Roffia (2006), 'Monetary Policy Rules in the pre-emu era. Is there a common rule?', European Central Bank Working Paper, No. 659.

[115] Elliott, G. and A. Fatás (1996), 'International Business Cycles and the Dynamics of the Current Account', *European Economic Review*, **40**: 361 - 387.

[116] Engle, R. F. and M. W. Watson (1981), 'A One-Factor Multivariate Time Series Model of Metropolitan Wage Rates, *Journal of the American Statistical Association*, **76**(376): 774 - 781.

[117] Engle, R. F. and C. W. J. Granger (1987), 'Cointegration and error correction: representation, estimation and testing', *Econometrica*, **55**: 512-76.

[118] Estrella, A. and G. A. Hardouvelis (1991), 'The Term Structure as a Predictor of Real Economic Activity', *Journal of Finance*, **46**: 555 - 576.

[119] Estrella, A. and F. Mishkin (1997), 'The predictive power of the term structure of interest rates in Europe and the United States: Implications for the European Central Bank', *European Economic Review*, **41**: 1375 - 1401.

[120] Estrella, A. and Rodrigues, A. P. and S. Schich (2003), 'How Stable is the Predictive Power of the Yield Curve', Evidence from Germany and the United States', *The Review of Economics and Statistics*, **85**(3): 629 - 644.

[121] Fagan, G., J. Henry and R. Mestre (2005), 'An Area Wide Model (AWM) for the Euro Area', *Economic Modelling*, **22**(1), 39 - 59.

[122] Field, A. J. (2003), 'The Most Technologically Progressive Decade of the Century', *American Economic Review*, **94**(4): 1399 - 1413.

[123] Finn, M. (2000), 'Perfect Competition and the Effects of Energy Price Increases on Economic Activity', *Journal of Money, Credit and Banking*, **32**: 400 - 416.

[124] Fisher. I. (1932), *Booms and Depressions: Some First Principles*, New York: Adelphi.

[125] Forni, M., M. Hallin, M. Lippi and L. Reichlin (2000), 'The Generalised Dynamic Factor Model: Identification and Estimation', *The Review of Economic Studies*, **82**(4): 540 - 554.

[126] Forni, M., M. Hallin, M. Lippi and L. Reichlin (2001), 'Coincident and Leading Indicators for the Euro area', *Economic Journal*, **111**: 62 - 85.

[127] Francis, N. and V. A. Ramey (2004), 'The Source of Historical Economic Fluctuations: An Analysis using Long-Run Restrictions', NBER, Working Paper No. 10631.

[128] Francis, N. R., M. T. Owyang and A. T. Thedorou (2003), 'The Use of Long Run Restrictions for the Identification of Technology Shocks', T*he Federal Reserve Bank of St. Louis Review*, November-December: 53 - 66.

[129] Franke, G. (1991), 'Exchange Rate Volatility and International Trading Strategy', *Journal of International Money and Finance*, **10**(2): 292-307.

[130] Friedman, M. and A. J. Schwartz (1963), 'Money and Business Cycles', *The Review of Economics and Statistics*, **45**(1): 32-64.

[131] Friedman, M. and A. Schwartz (1963), 'Money and Business Cycles', *The Review of Economics and Statistics*, **45**(1)2: 32 - 64.

[132] Friedman, M. (1968), 'The Role of Monetary Policy', *American Economic Review*, **68**: 1 - 17.

[133] Friedman, M. (1992), 'The "Plucking Model" of Business Fluctuations Revisited', *Economic Inquiry*, **31**(2): 171 - 177.

[134] Friedman, B. M. and K. N. Kuttner (1992), 'Money, Income, Prices, and Interest Rates', *American Economic Review*, **82**(3): 472 - 492.

[135] Frisch, R. (1933), 'Propagation problems and impulse problems in dynamic economics', in *Economics Essays in Honour of Gustav Cassel*, J. Akerman, (ed.), George Allen, London, pp. 171-205.

[136] Fuhrer, J. C. and S. Schuh (1998), 'Beyond Shocks: What Causes Business Cycles?', Proceedings from the Federal Reserve Bank of Boston Conference Series no. 42.

[137] Galbraith, J. W. and G. Tkacz (2000), 'Testing for asymmetry in the link between the yield spread and output in the G7 countries', *Journal of International Money and Finance*, **19**: 657-672.

[138] Galí, J. (1999), 'Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?', *American Economic Review*, **89**(1): 249-271.

[139] Galí, J., M. Gertler, M. and J. D. Lopez-Salido (2001), 'European Inflation Dynamics', *NBER* Working Paper Series No. 8218.

[140] Galí, J., J. D. Lopez-Salido and J. Valles (2002), 'Technology Shocks and Monetary Policy: Assessing the Fed's Performance', *NBER* Working Paper no. 8768.

[141] Galí, J. and P. Rabanal (2004), 'Technology Shocks and Aggregate Fluctuations: How Well Does the RBC Model Fit Post-War US Data?', CEPR Working Paper DP4522.

[142] Galí, J. (2004), 'On the Role of Technology Shocks as a Source of Business Cycles: Some New Evidence', *Journal of the European Economic Association*, **2** (2-3): 372 - 380.

[143] Galí, J. and L. Gambetti (2007), 'On the Sources of the Great Moderation', mimeo

[144] Garratt, A., D. Robertson and S. Wright (2006), 'Permanent vs Transitory components and economic fundamentals', *Journal of Applied Econometrics*, **21**: 521 - 542.

[145] Gerlach, S. and G. Schnabel (2000), 'The Taylor rule and interest rates in the EMU area', *Economics Letters*, **67**(2): 165 - 171.

[146] Geweke, J. (1977), 'The Dynamic Factor Analysis of Economic Time Series Models', in D. J. Aigner and A. S. Goldberger (eds.), *Latent Variables in Socioeconomic Models*. Amsterdam: North-Holland.

[147] Giannone, D., L. Lucrezia, L. Sala (2004), 'Monetary Policy in real time'. In Gertler, Mark, Rogoff, Kenneth (Eds.), *NBER Macroeconomics Annual*, MIT Press, Cambridge, pp. 161 - 224.

[148] Giannone, D., L. Lucrezia, L. Sala (2002), 'Tracking Greenspan: Systematic and Unsystematic Monetary Policy revisited' *mimeo.*

[149] Gisser, M. and T. H. Goodwin (1986), 'Crude Oil and the Macroeconomy: Tests of Some Popular Notions', *Journal of Money, Credit, and Banking*, **18**: 95 - 103.

[150] Gonzalo, J. and C. Granger (1995), 'Estimation of Common Long-Memory Components in Cointegrated Systems', *Journal of Business and Economic Statistics*, **13**(1): 27 - 35.

[151] Gordon, R. J. (1985), 'Introduction : Continuity and Change in Theory, Behaviour and Methodology', in *The American Business Cycle: Continuity and Change.* Chicago: University of Chicago Press.

[152] Gordon, R. J. (1980), 'Postwar Macroeconomics: The Evolution of Events and Ideas', in M. Feldstein (ed.), *The American Economy in Transition*, University of Chicago Press for the NBER, Chicago.

[153] Gonzalo, J. and C. W. J. Granger (1995), 'Estimation of common long-memory components in cointegrated systems', *Journal of Business and Economic Statistics*, **13**: 27 - 35.

[154] Granger, C. W. J. (1964), *Spectral Analysis of Economic Time Series*, Princeton, NJ, Princeton University Press.

[155] Granger, C. W. J. and R. Ramanathan (1984), 'Improved Methods of Combining Forecasting', *Journal of Forecasting*, **3**: 197-204.

[156] Haberler, G. (1940), *Prosperity and Depression*, 2nd ed. (United Nations, Geneva).

[157] Hall, R. E. (1987), 'Market Structure and Macroeconomic Fluctuations', *Brookings Papers on Economic Activity*, 1: 285 - 322.

[158] Hamilton, J. D. (1983), 'Oil and the Macroeconomy Since World War II', *Journal of Political Economy*, **91:** 228 - 248.

[159] Hamilton, J. D. (1985), 'Historical Causes of Postwar Oil Shocks and Recession', *Energy Journal*, **6**: 97 - 116.

[160] Hamilton, J. D. (1989), 'A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle', *Econometrica*, **57**(2): 357 - 384.

[161] Hamilton, J. D. (1996), 'Monetary Policy Shifts and Long-Term Interest Rates' *Quarterly Journal of Political Economy*, **91**(2): 228 - 48.

[162] Hamilton, J. D. (1996), 'This is What Happened to the Oil Price-Macroeconomy Relationship', *Journal of Monetary Economics*, **38**(2): 215 - 220.

[163] Hamilton, J. D. (2003), 'What is an Oil Shock?', *Journal of Econometrics*, **113**: 363 - 398.

[164] Hamilton, J. D. (2005b), 'Oil and the Macroeconomy', University of California, Prepared for: Palgrave Dictionary of Economics.

[165] Hamilton, J. D. (2005a), 'What's Real About the Business Cycle', *Federal Reserve Bank of St. Louis Review*, **87**(4): 435 - 452.

[166] Hansen, G. D. and E. C. Prescott (1993), 'Did Technology Shocks Cause the 1990 - 1991 Recession', *American Economic Review*, **83**(2): 280 - 286.

[167] Hansen, H. and S. Johansen (1999), 'Some tests for parameter constancy in cointegrated VAR-models', *Econometrics Journal*, **2**: 306 - 333.

[168] Hansen, B. (2001), 'Testing for Structural Change in Conditional Models', *Journal of Econometrics*, **97**: 93 - 115.

[169] Harvey, A. C (1985), 'Trends and Cycles in Macroeconomic Time Series', *Journal of Business and Economic Statistics*, **3**(3): 216 - 227.

[170] Harvey, A. C. and A. Jaeger (1993), 'Detrending, Stylized Facts and the Business-Cycle', *Journal of Applied Econometrics*, **8**: 231 - 47.

[171] Harvey, D. I., Leybourne, S. J. and P. Newbold (2003), 'How Great are the Great Ratios', *Applied Economics*, **35**: 163-177.

[172] Hawtrey, R. (1919), *Currency and Credit*, London: Longham, Green & Co., pp. vii + 393.

[173] Heathcote, J. and F. Perri (2002), 'Financial Globalisation and Real Regionalisation', NBER Working Paper 9292.

[174] Helbling, T. and T. Bayoumi (2003), 'Are they all in the Same Boat? The 2000-2001 Growth Slowdown and the G-7 Business Cycle Linkages' IMF Working Paper WP/03/46.

[175] Helg, R., P. Manasse, T. Monacelli and R. Roveli (1995), 'How much (A)symmetry in Europe? Evidence from Industrial Sectors', *European Economic Review*, **39**: 1017 - 1041.

[176] Hodrick, R. J. and E. C. Prescott, (1997) 'Postwar US Business Cycles: An Empirical Investigation', *Journal of Money Credit and Banking*, **29**(1): 1 - 16.

[177] Horvath, M. T. K. and M. W. Watson (1995), 'Testing for cointegration when some of the cointegrating vectors are prespecified', *Econometric Theory*, **11**: 984 - 1014.

[178] Imbs, J. (2004), 'Trade, Finance, Specialisation and Synchronisation', *The Review of Economic Studies*, **86**(3): 723 - 734.

[179] Jaimovich (2004), 'Firm Dynamics, Markup Variations, and the Business Cycle' mimeo, University of California, San Diego.

[180] Johansen, S. (1988), 'Statistical Analysis of Cointegrating Vectors', *Journal of Economic Dynamics and Control*, **12**: 231-54.

[181] Johansen, S. (1996), Likelihood-based Inference in Cointegrated Vector Autoregressive Models, 2nd edition, Advanced Texts in Econometrics, Oxford: Oxford University Press.

[182] Judd, J. F. and G. D. Rudebusch (1998), 'Taylor's Rule and the Fed: 1970 – 1997', *Federal Reserve Bank of San Francisco Economic Review*, **3**: 3 – 16.

[183] Kaldor, N. (1957), 'A Model of Economic Growth', *Economic Journal*, **67**:591-624.

[184] Kapetanios, G. and M. Marcellino (2006), 'Factor-GMM Estimation with Large Sets of Possibly Weak Instruments', Queen Mary, University of London, Working Paper No. 577.

[185] Kendall, M. G. and A. Stuart (1976), *The Advanced Theory of Statistics*, Vol. 3. Griffin, London.

[186] Kenan, P. B. (1969), 'The optimum currency area: An eclectic view', In: Mundell. R. A., Swoboda, A. K. (eds.), Monetary Problems of the International Economy. University of Chicago Press, pp. 41 - 60.

[187] Kenen, P. and D. Rodrik (1986), 'Measuring and Analyzing the Effects of Short-Term Volatility in Real Exchange Rates', *The Review of Economics and Statistics*, **68**: 311–15.

[188] Levine, R. and D. Renelt (1992), 'A Sensitivity Analysis of Cross-Country Growth Regressions', *American Economic Review*, **82:** 942 - 963.

[189] Keynes, J. M. (1936), *The General Theory of Employment, Interest and Money.* London: Macmillan.

[190] Kim, I-M. and P. Loungani (1992), 'The Role of Energy in Real Business Cycle Models', *Journal of Monetary Economics*, **29**: 173 - 190.

[191] Kim, C. -J. and C. R. Nelson (1999), 'Has the U.S economy become more stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle', *The Review of Economics and Statistics,* **81**: 608 - 616.

[192] Kim, S. (1999), 'Do monetary policy shocks matter in the G-7 countries? Using common identifying assumptions about monetary policy across countries', *Journal of International Economics*, 48: 387 – 412.

[193] Kim, S. and N. Roubini (2000), 'Exchange rate anomalies in the industrial countries: A solution with a structural VAR approach', *Journal of Monetary Economics*, **45**: 561 -586.

[194] Kim, C. -J., C. R. Nelson and J. Piger (2001), 'The Less Volatile U.S. Economy: A Bayesian Investigation of Breadth and Potential Explanations', Board of Governors of the Federal Reserve System, International Finance Discussion Paper no. 707.

[195] King, R. G., Plosser, C. I., J. Stock and M. W. Watson (1991), 'Stochastic Trends and Economic Fluctuations', *American Economic Review,* **81**(4): 819 - 840.

[196] King, R. G. and C. Plosser (1989), 'Real Business Cycles and the Test of the Adelmans', NBER, Working Paper No. 3160.

[197] King, R. G., Plosser, C. I. and S. T. Rebelo (1988a), 'Production Growth and Business Cycles: I. The Basic Neoclassical Model', *Journal of Monetary Economics*, **21**: 195-232.

[198] King, R. G., Plosser, C. I. and S. T. Rebelo (1988b), 'Production Growth and Business Cycles: II. New Directions', *Journal of Monetary Economics*, **21**: 309-42.

[199] King, R. G. and S. Rebelo (1993), 'Low Frequency Filtering and Real Business-Cycles', *Journal of Economic Dynamics and Control,* **17**: 207 - 31.

[200] King, R. G. and M. W. Watson (1994), 'The post-war U.S. Phillips curve: a revisionist econometric history', *Carnegie-Rochester Conference Series on Public Policy*, **41**: 157 - 219.

[201] Klein, L. J. and A. S. Goldberger (1952), *An Econometric Model of the United States 1929-1952*, Amsterdam.

[202] Koopmans, T. C. (1947), 'Measurement without Theory', *Review of Economic Statistics*, **29**: 161 - 172.

[203] Koray, F., Lee T. H. and T. Palivos (1996), 'Stochastic Trends and Fluctuations in National Income, Wages, and Profits', *Southern Economic Journal*, **62** (4): 873-888.

[204] Kose, M. A., Otrok, C. and C. H. Whiteman (2003a), 'International Business Cycle: World, Region and Country-Specific Factors', *American Economic Review*, **93**: 1216 - 1239.

[205] Kose, M. A., C. Otrok, E. Prasad, M. Terrones (2003b), 'How does Globalisation affect the Synchronisation of Business Cycles?', *American Economic Association Papers and Proceedings*, **93**(2): 57 - 62.

[206] Kosobud, R. and L. Klein (1961), 'Some Econometrics of Growth: Great Ratios of Economics', *Quarterly Journal of Economics*, **78**: 173-198.

[207] Kydland, F. and E. Prescott (1990), 'Business Cycles: Real Facts and the Monetary Myth', *Federal Reserve Bank of Minneapolis Quarterly Review*, **14**: 3 - 18.

[208] Kydland, F and E. C. Prescott (1982), 'Time to Build and Aggregate Fluctuations', *Econometrica*, **50**: 1345 - 70.

[209] Kydland, F. and E. Prescott (1980), 'A Competitive Theory of Fluctuations and the Feasibility and Desirability of Stabilisation Policy', in S. Fischer, ed., *Rational Expectations and Economic Policy*, Chicago: University of Chicago Press, 1980.

[210] Leeper, E. M., C. A.Sims and T. Zha (1996), 'What does Monetary Policy Do?' , *Brookings Papers on Economic Activity*, **2**: 1 - 63.

[211] Leeper, E. M. and J. E. Roush (2003), 'Putting "M" Back in Monetary Policy', *The Journal of Money, Credit and Banking*, **35**(6) Part 2: 1217 - 1256.

[212] Lehmann, B. (1982), 'What Happens during Business Cycles?', Unpublised Manuscript. New York: Columbia University, Graduate School of Business.

[213] Levine, R. and D. Renelt (1992), 'A sensitivity Analysis of Cross-Country Regressions', *American Economic Review*, **82**: 942 - 963.

[214] Levy, L. (1982), 'Central Banking and Foreign Trade: The Anglo-American Cycles in the 1930's', In C. P. Kindleberger and J. P. Laffargue, eds., *Financial Crisis: Theory, History and Policy*. New York: Cambridge University Press.

[215] Lindé, J. (2001), 'Estimating New-Keynesian Phillips Curve on Data with Measurement Errors A Full Information Maximum Likelihood Approach', Working Paper Series 129, Sveriges Rikbank.

[216] Long, J. B. and C. I. Plosser (1987), 'Sectoral vs. Aggregate Shocks in the Business Cycle', *American Economic Review*, **70**: 333 - 336.

[217] Lucas, R. E. (1972), 'Expectations and the Neutrality of Money', *Journal of Economic Theory*, 4(2): 103 - 124.

[218] Lucas, R. E. (1973), 'Some International Evidence on Output-Inflation Tradeoffs', *American Economic Review*, **63**: 326 - 334.

[219] Lucas, R.E. (1976a), 'Econometric policy evaluation: a critique' in The Phillips Curve and Labour Markets, *Carnegie-Rochester Conference Series on Public Policy*, 19-46.

[220] Lucas, R. E. (1976b), 'Understanding Business Cycles', in K. Brunner and A. Meltzer (eds.), Stabilisation of the Domestic and International Economy (*Carnegie-Rochester Series on Public Policy*, 5, 7 - 29) Amsterdam: North-Holland.

[221] Lucas, R. E. (1977), 'Understanding Business Cycles', *Carnegie-Rochester Conference on Public Policy*, **5**: 7 - 29.

[222] Lucas, R. E. (1994), 'Review of Milton Friedman and Anna J. Schwartz's A Monetary History of the United States, 1976 - 1960', *Journal of Monetary Economics*, **34**: 5 - 16.

[223] Lundvik, P. (1991), 'Business cycles in a small open economy: Sweden 1871-1987', Unpublised manuscript, Institute for International Economic Studies, Stockholm University, Sweden.

[224] Mankiw, N. G. and M. D. Shapiro (1985), 'Trends Random Walks and Tests of the Permanent Income Hypothesis', *Journal of Monetary Economics*, **16**: 165 - 174.

[225] Mankiw, N. G. (1989), 'Real Business Cycles: A New Keynesian Perspective', *Journal of Economic Perspectives*, **3**(3): 79 - 90.

[226] Marcellino, M., J. Stock and M. Watson (2006), 'A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series', *Journal of Econometrics*, **135**: 499-526.

[227] Marcet, A and M. O. Ravn (2001), 'Adjusting the HP-filter in Cross Country Comparisons', *CEPR* Discussion Paper 4261.

[228] Martin, B. and R. Rowthorn (2005), 'Accounting for Stability', *CESinfo Economic Studies*, **51**(4): 649 - 696.

[229] Maravall, A. (1993), 'Stochastic Linear Trends: Models and Estimators', *Journal of Econometrics*, **55**: 3 - 35.

[230] McAdam, P. and A. Willman (2004), 'Supply, Factor Shares and Inflation Persistence: Re-examining Euro-area New-Keynesian Phillips Curves', *Oxford Bulletin of Economics and Statistics*, **66**: 637 - 670.

[231] McCallum, B.T. (1989), 'Real Business Cycle Models', in R. J. Barro, ed., *Modern Business Cycle Theory (Cambridge: Havard University Press, 1989)*: 16 - 50.

[232] McConnell, M. M and G. Perez-Quiros (2000), 'Output Fluctuations in the United States: What has Changed Since the Early 1980s', *American Economic Review*, **90**(5): 1464 - 1476.

[233] McKinnon, R. (1963), 'Optimum currency areas', *American Economic Review*, **53(4)**: 717 - 225.

[234] Mellander, E., Vredin, A. and A. Warne (1992), 'Stochastic Trends and Economic Fluctuations in a Small Open Economy', *Journal of Applied Econometrics*, **7** (4): 369-394.

[235] Mendoza, E. G. (1996), 'The Terms of Trade, Real Exchange Rate, and Economic Fluctuations', *International Economic Review*, **36**(1): 101 - 137.

[236] Mihov, I. (2001), 'Monetary Policy Implementation and Transmission in the European Monetary Union', *Economic Policy*, **33**: 371-406.

[237] Mills, T. C. (2001), 'Great Ratios and Common Cycles: Do they Exist for the UK?', *Bulletin of Economic Research*, **53**(1): 36 - 51.

[238] Mills, T. C. and P. Wang (2002), 'Plucking Models of Business Cycle Fluctuations: Evidence from the G - 7 countries', *Empirical Economics*, **26**: 255 - 276.

[239] Mills, T. C. and P. Wang (2003), 'Have Output Growth Rates Stabilised? Evidence From the G - 7 Economies', *Scottish Journal of Political Economy*, 50(3): 232 - 246.

[240] Mitchell, W. (1951), *What Happens during Business Cycles: A Progress Report.* New York: NBER.

[241] Mitchell, W. C. and A. F. Burns (1938), *Statistical Indicators of Cyclical Revivals*, NBER Rulletin 69, NY, Reprinted in Business Cycle Indicators. G. H. Moore, ed. 1961. Princeton: Princeton U. Press.

[242] Mitchell, W. C. (1927), 'Business Cycles: The Problem of its Setting', NBER, pp. xxii, 489.

[243] Mitchell, W. C. (1913), *Business Cycles*, University of California Press.

[244] Moffitt, R. A. and P. Gottschalk (2002), 'Trends in the Transitory Variance of Earnings in the United States', *Economic Journal*, **112**: C68 – C73.

[245] Mojon, B. and G. Peersman (2001), 'A VAR description of the effects of monetary policy in the individual countries of the Euro area', ECB Working Paper 92.

[246] Moore, G. H. and V. Zarnowitz (1986), 'The Development and Role of the NBER's Business Cycle Chronologies', in Robert J. Gordon (ed.), *The American Business Cycle: Continuity and Change.* Chicago: University of Chicago Press.

[247] Monfort, A., J. P Renne, R. Ruffer and G. Vitale (2003), 'Is Economic Activity in the G7 Synchronised? Common Shocks vs. Spillover Effects', (November 2003). CEPR Discussion Paper No. 4119.

[248] Morley, J. C., Nelson, C. R. and E. Zivot (2003), 'Why are the Beveridge-Nelson and unobserved-component decomposition of GDP so different?, *The Review of Economics and Statistics*, **82**(2): 235-243.

[249] Morley, J. C. (2007), 'The Two Interpretations of the Beveridge-Nelson Decomposition', University of Washington, mimeo

[250] Mountford, A. (2005), 'Leaning into the wind: A structural VAR investigation of UK monetary policy', *Oxford Bulletin of Economics and Statistics*, **67**(5): 597-621.

[251] Mountford, A. and H. Uhlig (2005), 'What are the Effects of Fiscal Policy Shocks', Deutsche Forschungsgemeinschaft - Economic Risk, SFB 649 Discussion Paper 2005-039.

[252] Mundell, R. A. (1961), 'A theory of optimum currency areas', *American Economic Review*, **51**: 509 - 517.

[253] Musso, A. and T. Westermann (2005), 'Assessing Potential Output Growth in the Euro area: A Growth Accounting Perspective', ECB Working Paper, No. 22.

[254] Neftci, S. N. (1984), 'Trends and Random Walks in Macroeconomic Time Series', *Journal of Political Economy*, **92**(2): 307 - 328.

[255] Nelson, E. (2003), 'The future of monetary aggregates in monetary policy analysis', *Journal of Monetary Economics*, **50**: 1029-1059.

[256] Nelson, C. and C. Murray (2000), 'The Uncertain Trend in U.S. GDP', *Journal of Monetary Economics*, **46**: 79 - 96.

[257] Nelson, C. and C. I. Plosser (1982), 'Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications', *Journal of Monetary Economics*, **10**: 139 - 62.

[258] Nelson, C. and H. Kang (1981), 'Spurious Periodicity in Inappropriately Detrended Time Series', *Econometrica*, XLIX: 741 - 51.

[259] Neusser, K., (1991), 'Testing the long-run implications of the neo-classical growth models', *Journal of Monetary Economics*, **27**: 3-37.

[260] Norrbin, S. C. and D. E. Schlagenhauf (1996), 'The Role of International Factors in the Business Cycle: A Multi-Country Study', *Journal of International Economics*, **40**: 84 - 104.

[261] Norrbin, S. C. and D. E Schlagenhauf (1988), 'An Inquiry into the Sources of Macroeconomic Fluctuations', *Journal of Monetary Economics*, **22**: 44 - 70.

[262] Norrbin, S. C. and D. E Schlagenhauf (1990), 'Sources of Output Fluctuations in te United States during the interwar and postwar years', *Journal of Economic Dynamics and Control*, **14**: 523 - 551.

[263] O' Reilly, G. and K. Whelan (2005), 'Has the Euro-Area Inflation Persistence Changed Over Time?', *The Review of Economics and Statistics*, **87**(4): 709 - 720.

[264] Osterwald-Lenum, M. (1992), 'A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics',*Oxford Bulletin of Economics and Statistics*, **54**: 461-72.

[265] Peersman, G. and F. Smets (1999), 'The Taylor Rule: A Useful Monetary Policy Benchmark for the Euro Area?', *International Finance*, **2**(1): 85 - 116.

[266] Peersman, G. and R. Straub (2004), 'Technology Shocks and Robust Sign Restrictions in an Euro Area SVAR', European Central Bank Working Paper No 373.

[267] Peersman, G. (2005), 'What Caused the Early Millennium Slowdown? Evidence Based on Vector Autoregressions', *Journal of Applied Econometrics*, **20**: 185 - 207.

[268] Pesaran, H. and A. Timmermann (2005), 'Real Time Econometrics', *Econometric Theory*, **21**: 212 - 231.

[269] Pesaran, M. H., R. G. Pierse and K. C. Lee (1993), 'Persistence, Cointegration and Aggregation: A Disaggregated Analysis of Output Fluctuations in the US economy', *Journal of Econometrics*, **56**: 57 - 89.

[270] Phelps, E. (1967), 'Phillps Curves, Expectations of Inflation, and Optimal Inflation Over Time', *Economica*, **34**: 254 - 281.

[271] Perron, P. (1989), 'The great crash, the oil price shock, and the unit root hypothesis', *Econometrica*, **57**: 1361 - 1401.

[272] Pesaran, M. H. and R. P. Smith (1998), 'Structural Analysis of Cointegrating VAR's', *Journal of Economic Surveys*, **12**: 471 - 505.

[273] Ploberger, W., W. Krämer and K. Kontrus (1989), 'A New Test for Structural Stability in the Linear Regression Model', *Journal of Econometrics*, **40**: 307 - 318.

[274] Plosser, C. I. and K. G. Rouwenhorst (1994), 'International Term Structures and Real Economic Growth', *Journal of Monetary Economics,* **33**: 133 - 155.

[275] Prescott, E. (1986), 'Theory Ahead of Business-Cycle Measurement', *Carnegie-Rochester Conference Series on Public Policy,* **25**: 11 - 44.

[276] Proietti, T. (1997), 'Short-run dynamics in cointegrated systems', *Oxford Bulletin of Economics and Statistics,* **59**: 405 - 422.

[277] Quandt, R. E. (1960), 'Tests of the Hypothesis that a Linear Regression System Obeys Two Separate Regimes', *Journal of the American Statistical Association,* **55**: 324 - 353.

[278] Rafiq, M. S. and S. K. Mallick (2008), 'The Effects of Monetary Policy on the EU 3 - A Sign Restriction Approach', forthcoming *Journal of Macroeconomics.*

[279] Rasche, R. H. and J. A. Tatom (1977), 'Energy Resources and Potential GNP', *Federal Reserve Bank of St. Louis Review,* **59**: 10 - 24.

[280] Rasche, R. H. and J. A. Tatom (1981), 'Energy Price Shocks, Aggregate Supply, and Monetary Policy: The Theory and International Evidence', In K. Brunner and A. H. Meltzer, eds., *Supply Shocks, Incentives, and National Wealth, Carnegie-Rochester Conference Series on Public Policy,* vol. 14, Amsterdam: North-Holland.

[281] Raymond, J. E. and R. W. Rich (1997), 'Oil and the Macroeconomy: A Markov State-Switching Approach', *Journal of Money, Credit and Banking,* 29 (May), pp. 193 - 213. Erratum 29 (November, Part 1), p. 555.

[282] Romer, P. M. (1986), 'Increasing returns and long-run growth', *Journal of Political Economy,* 94(5): 1002-37.

[283] Rotemberg, J. and M. Woodford (1996), 'Real-Business-Cycle Models and the Forecastable Movements in Output, Hours and Consumption', *American Economic Review,* **86**: 71-89.

[284] Rotmberg, J. and M. Woodford (1996), 'Imperfect Competition and the Effect of Energy Price Increases on Economic Activity', *Journal of Money, Credit and Banking,* **28**: 549 - 577.

[285] Rotemberg, J. and M. Woodford (1997), 'An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy', *NBER Macroeconomic Annual*, MIT Press, pp. 297 - 346.

[286] Rudebusch, G. (1993), 'The Uncertain Unit Root in Real GNP', *American Economic Review*, **83**: 264 - 272.

[287] Rudebusch, G. (1998), 'Do Measure of Monetary Policy in a VAR make sense?', *International Economic Review*, **39**: 907 - 931.

[288] Rudebusch, G. and L. Svensson (1999), 'Rules for Inflation Targeting', in John B. Taylor (ed.), *Monetary Policy Rules*, University of Chicago Press, Chicago, 1999, 203 - 246.

[289] Rudebusch, G. (2002), 'Assessing Nominal Income Rules for Monetary Policy with Model and Data Uncertainty', *Economic Journal, 112*: 402 - 432.

[290] Samleulson, P (1998), 'Summing up on Business Cycles: Opening Address', Proceedings from the Federal Reserve Bank of Boston Conference Series no. 42.

[291] Santini, D. J. (1985), 'The Energy-Squeeze Model: Energy Price Dynamics in U.S. Business Cycles', *International Journal of Energy Systems*, **5**: 18 - 25.

[292] Santini, C. A. (1992), 'Energy and the Macroeconomy: Capital Spending After an Energy Cost Shock', in J. Moroney, ed., *Advances in the Economics of Energy and Resources*, vol. 7, Greenwich, CN: J.A.I. Press.

[293] Sargent, T. J. and C. A. Sims (1977), 'Business Cycle Modelling without pretending to have too much a-priori information', in C. Sims et al. ads., New Methods in Business Cycle Research (Federal Reserve Bank of Minneapolis, Minneapolis).

[294] Sargent, T. J. (1999), *The Conquest of American Inflation, Princeton*: Princeton University Press, 1999.

[295] Sensier, M., M. Artis, D. R. Osborn and C. Birchenhall (2004), 'Domestic and international influences on business cycle regimes in Europe', *International Journal of Forecasting*, **20**: 343 - 357.

[296] Sensier, M. and D. van Dijk (2004), 'Short-term Volatility versus Long-term Growth: Evidence in US Macroeconomic Time Series', *The Review of Economics and Statistics*, **86**(3): 833 - 839.

[297] Serletis, A. (1994), 'Testing the long-run implications of the neoclassical growth model for Canada', *Journal of Macroeconomics*, **16**: 329-46.

[298] Serletis, A. (1996), 'Government activities and tests of the long-run implications of the neoclassical growth model for Canada', *Canadian Journal of Economics*, **29**(3): 635-642.

[299] Shaprio, M. D. (1987), 'Are Cyclical Fluctuations in Productivity due more to Supply Shocks or Demand Shocks?', NBER Working Paper Series, Working Paper No. 2147.

[300] Shapiro, M.D. and M.W. Watson (1988), 'Sources of Business-Cycle Fluctuations', *NBER Macroeconomics Annual* **3**, 111–148.

[301] Sichel, D. E. (1993), Business Cycle Asymmetry: A Deeper Look', *Economic Inquiry*, April: 224 - 236.

[302] Sichel, D. E. (1994), 'Inventories and the Three Phases of the Business Cycle', *Journal of Business and Economic Statistics*, **12**(3): 269 - 277.

[303] Sims, C. A, (1972) 'Money, Income, and Causality', *American Economic Review*, **62**: 540 - 552.

[304] Sims, C. A. (1980), 'Interwar Macroeconomics From The Perspective of the 1970's Comparison of Interwar and Postwar Business Cycles: Monetarism. Reconsidered', *American Economic Review*, **70**(2): 250 - 257, Papers and Proceedings of the Ninety-Second Annual Meeting of the American Economic Association.

[305] Sims, C. A. (1980), 'Macroeconomics and Reality', *Econometrica*, **48**: 1 – 48.

[306] Sims, C. A. (1992), 'Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy', *European Economic Review*, **36**: 975 - 1011.

[307] Sims, C. A. (1996), 'Comment on "Do Measures of Monetary Policy in a VAR Make Sense?"' by Glenn Rudebusch (1998).

[308] Sims, C. A. and T. Zha (2006), 'Does Monetary Policy Generate Recessions?', *Macroeconomic Dynamics*, **10**(2): 231-272.

[309] Singleton, K. J. (1988), 'Econometric Issues in the Analysis of Equilibrium Business Cycle models', *Journal of Monetary Economics*, 21: 361 - 386.

[310] Slutsky, E. (1937), 'The summation of random causes as the source of cyclic processes', *Econometrica*, **5**: 105-146.

[311] Smets, F. and R. Wouters (2003), 'An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area', *Journal of the European Economic Association*, **1**(5): 1123-1175.

[312] Solow, R. M. (1957), 'Technical Change and the Aggregate Production Function', *The Review of Economics and Statistics*, **39**:312-20.

[313] Solow, R. M. (1970) '*Growth Theory: An Exposition*', Oxford: Clarendon Press.

[314] Stock, J. H. and M. W. Watson (1988b), 'Variable Trends in Economic Time Series', *Journal of Economic Perspectives*, **2**: 147 - 74.

[315] Stock, J. H. and M. W. Watson, (1988a), 'Testing for Common Trends', *Journal of the American Statistical Association*, **83**: 1097-1107.

[316] Stock, J. H. and M. W. Watson (1989), 'New Indexes of Coincident and Leading Economic Indicators', in O. Blanchard and S. Fischer (eds.), *NBER Macroeconomics Annual*, 1989. Cambridge, Mass: MIT Press.

[317] Stock, J. H. (1991), 'Confidence Intervals for the Largest Autoregressive Roots in U.S. Economic Time Series', *Journal of Monetary Economics*, **28**: 435 - 460.

[318] Stock, J. H and M. W. Watson (1991), 'New Indexes of Coincident and Leading Economic Indicators', *NBER Macroeconomic Annual*, 351-393.

[319] Stock, J. H. and M. W. Watson (1992), 'A Probability Model of the Coincident Economic Indicators', in K. Lahiri and G. H. Moore (eds.), *Leading Economic Indicators: New Approaches and Forecasting Records.* Cambridge. Cambridge University Press.

[320] Stock, J.H. and M.W. Watson (1993b) 'A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems', *Econometrica*, **61** (4): 783-820.

[321] Stock, J. H. and M. W. Watson (1993a), 'A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience' in J. H. Stock and M. W. Watson (eds.), Business Cycles, Indicators and Forecasting, 255-284. Chicago: University of Chicago Press for NBER.

[322] Stock, J. H. and M. W. Watson (1998) 'Median Unbiased Estimation of Coefficient Variance in Time-Varying Parameter Model', *Journal of American Statistical Association*, **93**: 349 - 358.

[323] Stock, J. and M. W. Watson (1999), 'Business Cycle Fluctuations in U.S. Macroeconomic Time Series', in J. B. Taylor and M. Woodford eds., *Handbook of Macroeconomics.*

[324] Stock, J. H. and M. W. Watson (2002a), 'Has the Business Cycle Changed and Why?', *NBER Macroeconomics Annual,* 159 - 218.

[325] Stock, J. H. and M. W. Watson (2002b), 'Forecasting Using Principal Components from a Large Number of Predictors', *Journal of the American Statistical Association*, **97**: 1167 - 1179.

[326] Stock, J. H. and M. W. Watson (2002c), 'Macroeconomic Forecasting using diffusion indexes', *Journal of Business and Economic Statistics*, **20**: 147-162.

[327] Stock, J. H. and M. W. Watson (2003a), 'Has the Business Cycle Changed? Evidence and Explanations', FRB Kansas City symposium, Jackson Hole, Wyoming, August 28-30.

[328] Stock, J. H. and M. W. Watson (2003b), 'Forecasting Output and Inflation: The role of asset prices', *Journal of Economic Literature*, **41**(3): 788-829.

[329] Stock, J. H. and M. W. Watson (2003c), 'How Did Leading Indicator Forecasts Perform During the 2001 Recession?' Federal Reserve Bank of Richmond Economic Quarterly, Summer 2003.

[330] Stock, J. H. and M. W. Watson (2005a), 'Understanding Changes In International Business Cycle Dynamics', *Journal of the European Economic Association*, **3**(5): 968-1006.

[331] Stock, J. H. and M. W. Watson (2005b), 'Implications of Dynamic Factor Models for VAR analysis', *mimeo*

[332] Stock, J. H. and M. W. Watson (2007), 'Why Has U.S. Inflation Become Harder to Forecast?', *Journal of Money, Banking and Credit*, **39**: 1.

[333] Taylor, J. B. (1998), 'Monetary Policy and the Long Boom', Federal Reserve Bank of St. Louis Economic Review (November/ December): 3–11.

[334] Taylor, J. B. (1980), 'Aggregate Dynamics and Staggered Contracts', *Journal of Political Economy*, **88**: 1 - 23.

[335] Tekatli, N. (2006), 'Understand Sources of the Changes in International Business Cycles', University of Iowa, mimeo

[336] Temin, P. (1998), 'The Causes of American Business Cycles: An Essay in Economic Historiography', in Jeffrey Fuhrer and Scott Schuh, eds., *Beyond Shocks: What Causes Business Cycles?*, Federal Reserve Bank of Boston.

[337] Tesar, L. J. (1991), 'Savings, Investment, and International Capital Flows', *Journal of Interantional Economics*, **31**: 55 - 78.

[338] Tillman, P. (2005), 'The New Keynesian Phillips Curve in Europe: Does it fit or does it fail?', Discussion Paper, Studies of Economic Research Working Paper, No. 04/2005.

[339] Tinbergen, J. (1937), *An Econometric Approach to Business Cycle Problems*, Actualitės scientifiques et industrielles, Hermann & Cie, Paris.

[340] Uhlig, H. (2005), 'What are the effects of monetary policy on output? Results from an agnostic identification procedure', *Journal of Monetary Economics*, **52**(2): 381 - 419.

[341] Uhlig, H. (1994), 'What Macroeconomists Should Know about Unit Roots: A Bayesian Perspective', *Econometric Theory*, **10**(3/4): 645 - 671.

[342] van Els, P., A. Locarno, B. Mojon and J. Morgan (2003), 'New macroeconomic evidence on monetary policy transmission in the Euro area', *Journal of the European Economic Association*, **1**(2-3): 720-730.

[343] Viaene, J-M. and C. de Vries (1992), 'International Trade and Exchange Rate Volatility', *European Economic Review*, **36**(6): 1311-1321.

[344] Vijselaar, F. and R. Albers (2002), 'New Technologies and Productivity Growth in the Euro area', ECB Working Paper No. 122.

[345] Warne, A. (1993), 'A Common Trends Model: Identification, Estimation and Inference', Seminar Paper No. 555, IIES, Stockholm University

[346] Watson, M. W (1986), 'Univariate Detrending Methods with Stochastic Trends', *Journal of Monetary Economics* **18:** 49 - 75.

[347] Watson, M. W (1994), 'Business-Cycle Durations and Stabilisation', *American Economic Review,* **84**(1): 24 - 46

[348] Watson, M. W (2007), 'How Accurate Are Real-Time Estimates of Output Trends and Gaps?', *Economic Quarterly,* **93**(2): 143 - 161.

[349] Wen, Y. (1998b), 'Capacity Utilisation under Increasing Returns to Scale', *Journal of Economic Theory,* **81**: 7 - 36.

[350] Whelan, K. (2005), 'New Evidence on Balanced Growth, Stochastic Trends, and Economic Fluctuations', Central Bank and Financial Services Authority of Ireland (ESCB) *Working Paper* 7/RT/04.

[351] Zarnowitz, V. (1985), 'Recent work in business cycles in historical perspective: A review of theories and evidence', *Journal of Economic Literature,* **23:** 523 - 580.

[352] Zarnowitz, V. (1992), *Business Cycles: Theory, History, Indicators and Forecasting.* Studies in Business Cycle, vol. 27. Chicago: University of Chicago for the NBER.

[353] Zarnowtiz, V. (1998), 'Has the Business Cycle Been Abolished?', NBER Working Paper No. 6367.