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Documents

VAR Models in Macroeconomic Research

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1. Introduction

The study of possible sources of economic fluctuations has been the major preoccupation in macroeconomics in recent years. The question is fundamental if one shall gain insight into the workings of the economy, and aid in the formulation and conduct of economic policy. Earlier empirical studies addressing the sources of aggregate economic variability in the Norwegian economy have typically been conducted using large scale models (or partial econometric analysis). Here I draw on recent developments in modern business cycle research and econometric methodology and discuss how one can analyse business cycles with the aid of complete, yet small and transparent systems.

That cyclical analysis is relevant, is illustrated in figures 1 to 4, which respectively charts and compares real gross domestic product (GDP) (after removing a linear trend) in the United States, the United Kingdom and Germany, the unemployment rate in the same three countries, real GDP (again after removing a linear trend) in Norway and, finally, the unemployment rate in Norway. The figures illustrate some of the stylized facts that the modern business cycle literature seek to explain, in particular, the persistence of economic fluctuations and correlations (or lack thereof?) across economic aggregates.

Figure 1. Cyclical GDP, (pct. change): USA, UK and Germany

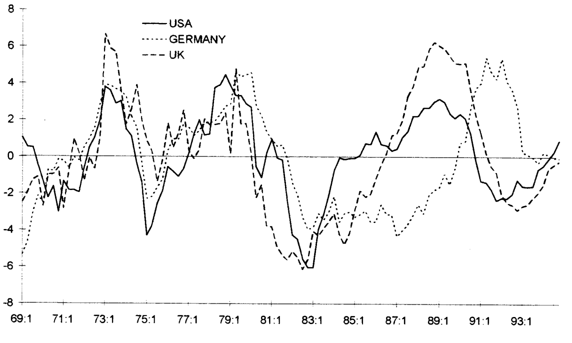


Figure 2. Unemployment rate: USA, UK and Germany

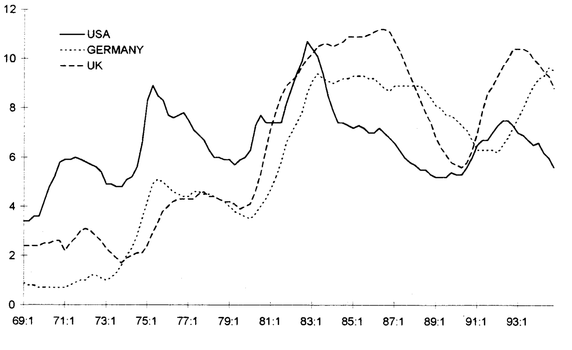


Figure 3. Cyclical GDP, (pct. change)[1]: Norway

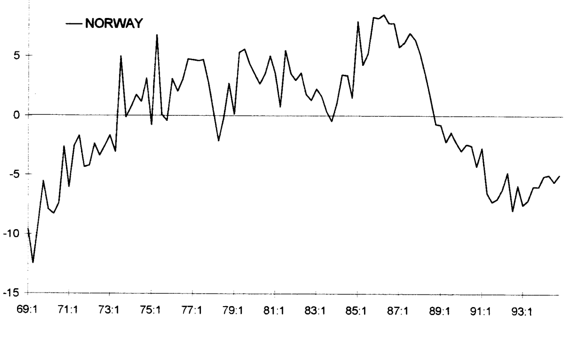
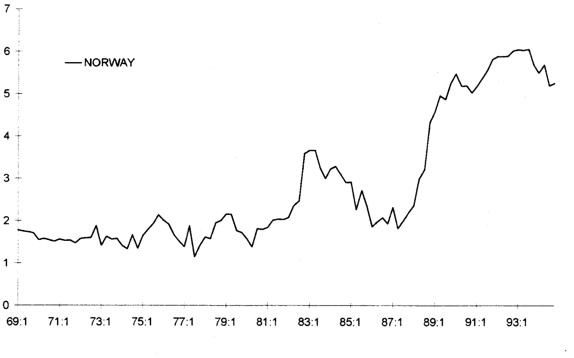


Figure 4. Unemployment rate: Norway



[1] GDP mainland Norway.

However, the term business cycles is a misnomer insofar as no unique periodicities are involved. Unlike its theoretical counterpart - the equilibrium- the business cycle is in its first place an empirical phenomenon, established through historical experiences, (see Zarnowitz 1991). Generally, business cycles are referred to as the regular periods of expansion and contraction in the major economic aggregate variables, lasting on average from 4-6 years, (see Zarnowitz and Moore 1986). They are often international in scope, showing up in a multitude of processes, not just in total output and unemployment.

Most economic variables are also growing as well as fluctuating. An empirical study of the business cycle dynamics will therefore typically be conditioned on the way in which one chooses to separate the stationary component from the non-stationary (growth) component of the observed series. In section 2 below, I start by briefly discussing some of the issues involved in the analysis of economic fluctuations. As the main focus here is to identify sources of business cycles, section 3 discusses in length structural vector autoregressions (VAR) as a device to analyse sources of business cycles. In section 4 I present an example of an empirical VAR model applied to Norway, Germany, the UK and the US.

2. Empirical studies of the business cycle

Post-war analyses of business cycles prior to the early 1980s, usually saw the decomposition of a time series into a trend component and a cyclical component as a straightforward exercise. The prevailing view was that the two components would be driven by different types of shocks. Those that had permanent effects (like productivity shocks) would contribute towards the trend, whereas those with transitory effects (like monetary changes) would contribute towards the cycle. In this framework, the data could be easily detrended using for instance a smooth deterministic trend, prior to the analysis of business cycles. Equation (1) illustrates how a cycle can be specified as an autoregression about a trend:

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

where ε_t is a sequence of white noise disturbances. When $|\alpha| < 1$, the process in (1) is trend stationary, the effect of a shock today dies out over time, and the process reverts back to the deterministic trend. Hence, an innovation in the process will not change one's forecast of the process in the long run.

In figure 1 and 3 above, I eliminated the growth component in GDP by removing a linear deterministic trend as described in equation (1). However, this may not be an appropriate way to deal with the growth component in the data, in particular not if the growth rate is unstable. Recently, Nelson and Plosser (1982) have questioned this traditional view, and argued instead that many macroeconomic variables like gross national product (GNP) could be well approximated by unit root or near unit root behaviour. For instance, assume instead that y_t is non-stationary, and follows a simple random walk:

(2) $$y_t = y_{t-1} + \varepsilon_t$$

again with ε_t given as above. (2) can be solved to yield an infinite moving average representation of y_t:

(3) $$y_t = \varepsilon_t + \varepsilon_{t-1} + \varepsilon_{t-2} + \varepsilon_{t-3} + \ldots$$

with y_0 taken to be zero. From (3) it can be seen that each shock, ε_t, will contribute its full value to y_t. Hence, the shocks will have a permanent effect on the series, so for a pure unit root, all fluctuations will represent permanent changes in the "trend" rather than stationary fluctuations around a deterministic trend. A shock to a random walk will therefore not die out, but will persist forever.

If a non-stationary variable like y_t can be made stationary by differencing as in equation (2), we say that y_t is integrated by first order, I(1), whereas its first difference Δy_t ($= y_t - y_{t-1}$) is integrated of zero order, I(0).

The presence of unit roots implied that the traditional trend and business cycle decomposition would be incorrect. Business cycles and the secular component could no longer be seen as separate and independent components, as the fluctuations in a series with a unit root would themselves represent an accumulation of permanent shocks. Most of the recent empirical work has proceeded under this assumption that variables follow linear stochastic processes with constant coefficients, (see e.g. Beveridge and Nelson 1981).

The findings of Nelson and Plosser had also implications for the understanding of economic fluctuations. In particular, Nelson and Plosser interpreted the unit root behaviour of many variables as evidence that real (supply) shocks were a major source of economic fluctuations, a view emphasised by the Real Business Cycle approach advocated by e.g. Prescott (1986). Subsequently, this view has been challenged by several authors, for example West (1988) and Quah (1992), who do not rule out monetary disturbances as a source of economic fluctuations.

More recently, Perron (1989) and Rappoport and Reichlin (1989) have argued that the persistent effects of the shocks found by Nelson and Plosser may have been severely exaggerated as economists have failed to take into account the fact that there may have been an important structural change in the trend. Hence, instead of arguing that time series are accumulations of a series of permanent stochastic shocks as for a random walk, time series may still display transitory fluctuations around a determinist trend, when one allows for a structural break in the trend. These findings have motivated tests of the unit root hypothesis against the trend-stationary alternative where the deterministic trend is allowed to have a structural break.

Independent of how one interpret the sources of business cycles, a description of the aggregate fluctuations in a set of economic variables in a country is an important exercise in itself, to establish the stylized facts of business cycles in a given country, to compare these cycles to the cyclical pattern in other countries, and to divert attentions to phenomenon that should be explained by economic theory. However, as the cycles will not be invariant to how one describes the trend component in the data, the results should be tested against alternative trend specifications, see Bjørnland (2000a).

Symmetries in economic fluctuations across countries are particularly important when these countries are to coordinate their economic policies. Figure 1 suggests that during the 1970s and early 1980s, USA, UK and Germany are in phase, with cyclical downturns (recessions) in the middle 1970s and early 1980s, corresponding approximately to the first and second oil price shocks. Associated with these cyclical downturns, are upward movements in unemployment rates in all countries (cf. figure 2). From the middle of the 1980s, the countries seem to diverge. The cycles in GDP in UK and USA continue to move closely together and experience a recession in the early 1990s, whereas in Germany, the recession in GDP lasts throughout the 1980s and is replaced by a boom in the early 1990s. Norway, on the other hand, behaves very differently from the three larger economies (c.f. figures 3 and 4). There is no evidence of the cyclical downturns experienced in the other countries in the 1970s. Further, unemployment remains low until the late 1980s, when Norway experiences its worst recession in the post war period.

The fact that the cycles in UK and USA are synchronised, whereas Germany and UK are much less in phase, may have implications for economic policy in the European Union. However, to analyse the prospects of synchronisation, one needs to investigate the nature of the shocks that causes the cycles to relate or diverge. To do so, one needs to work within the framework of a multivariate model and to invoke some theory, either tight or loose. In particular, multivariate models should be specified that consider among other things, long run or possible cointegration restrictions among variables.

The analysis can be carried out using structural vector autoregressions. This methodology has recently gained widespread use in empirical business cycles analysis, as it has proved to be a flexible and tractable way to analyse economic time series. In particular, vector autoregression (VAR) models have been capable of describing the rich dynamic structure of the relationships between economic variables.

The VAR models are usually presented through impulse responses (that measure the effects of the different shocks on the variables of study), and variance decomposition (which measures the relative importance of the different shocks to the variation in the different variables).The unrestricted VAR is on reduced form, and the innovations generated by the model are therefore uninterpretable. To go from the reduced form to the structural model, a set of identifying restrictions must be imposed on the variables in the model. In this thesis, the different structural disturbances will be identified through plausible short-run and long-run restrictions, that are based on economic theory.

The use of long run restrictions to identify different shocks in a VAR model, also provides for a method for how to decompose a nonstationary variable like output into a trend and a cyclical component. For instance, the component of output that is due to the shocks that can have a permanent effect on output will be nonstationary, contributing towards the long run movements (the trend) in the output series. The component that is due to the shocks with only short term effects on output will be stationary, making up the short run movements (the business cycles) in output. However, as the permanent shock can also affect output in the short term, it may as well contribute towards the business cycles. This allows for a more flexible interpretation of the cyclical component, that is consistent with most models of macroeconomic fluctuations. The next section clarifies some of the concepts of the methodology. Some of the gains and limitations of using the VAR methodology to study economic time series are also discussed.

3. Vector autoregression (VAR) models as a device to study sources of business cycles

The instability of the world economy in the aftermath of the oil price shocks in the 1970's brought a renewed interest in the study of business cycles. By then, the use of large scale macroeconometric models for policy analysis, (that had dominated macroeconomic research in the post war period) had been highly criticised by Lucas, as their assumptions of invariant behavioural equations were shown to be inconsistent with dynamic maximising behaviour (see Lucas 1976).[1]

A group of economists referred to as the New Classical economists, set out to replace the Keynesians macroeconometric models, and argued instead for the use of classical market clearing models of economic fluctuations. One of the goals of the New Classical Economics, was to reconcile business cycles with the postulates of dynamic competitive general equilibrium theory. More recently, a new branch of the classical models referred to as the Real Business Cycle (RBC) models have been developed, that emphasise real productivity shocks, as opposed to aggregated demand shocks, as a source of economic fluctuations (e.g. Kydland and Prescott 1982).

While the new classical research agenda was developed in the 1970's, Keynes macroeconomics was in a state of confusion. Keynes had emphasised how shifts in aggregate demand could cause economic fluctuations. However, during the 1970s, aggregate supply seemed to dominate. When the large scale macroeconometric models failed to predict the 1970s turmoil, many of the models were abandoned, and internationally business cycles studies were put on the agenda. The response of a significant part of the economic profession has been to turn to the use of structural vector autoregression (VAR) models to analyse business cycles. At a first stage, all variables are modelled together as endogenous. The VAR models may not satisfy Lucas's criteria for policy intervention, but are still useful to indicate the impact of policy actions that fall within the realm of historical experience. In particular, shifts in policy rules can be somewhat subsumed under stable policy rules.

Sims (1980) first introduced VAR models as an alternative to the large scale macroeconometric models. Since then the methodology has gained widespread use in applied macroeconomic research.[2] The methodology grew out of a dissatisfaction of the economic profession with the traditional large scale

[1] Similar arguments had already been put forward by Haavelmo (1944).
[2] See Canova (1995a,b) for an excellent discussion on the VAR approach.

macroeconometric models working in the tradition of the Cowles commission, in which identification was achieved by excluding variables - most often lagged endogenous variables - without any theoretical or statistical justifications. The idea behind the traditional macroeconometric procedure was that variables could be classified as either endogenous or exogenous. The exogenous variables were determined outside the system and could therefore be treated independently of the other variables. Imposing exclusion restrictions on the lags of some variables, was the practical way to deal with the problem. Sims (1980) questioned the idea of developing sophisticated econometric models identified via what he called incredible (non-justified) exclusion restrictions, that were neither innocuous nor essential for the constructing of a model that could be used for policy analysis and forecasting.

According to Sims, all variables appearing in the structural models could be argued to be endogenous. Economic theory place only weak restrictions on the reduced form coefficients and on which variables that should enter a reduced form model. Similar ideas had already been put forward by Liu (1960), but the proposed solution by Sims was new. Sims suggested that empirical research should use small-scale models identified via a small number of constraints.

At the first stage, the analyst's a priori knowledge should only be used to decide what variables should enter the reduced form. Thereafter, lag length of the autoregression, choice of deterministic components and appropriate treatment of the nonstationary components should be decided on. Once the model is dynamically well specified, the in-sample effects of a shock on the rest of the system can be assessed through the computation of impulse responses and variance decompositions. Economic hypothesis can be formulated and tested, and the historical dynamics of the data can be examined.

The VAR models have the advantage over traditional large-scale macroeconometric models in that the results are not hidden by a large and complicated structure (the "black box"), but are easily interpreted and available. Sims argued that VARs provide a more systematic approach to imposing restrictions and could lead one to capture empirical regularities which remain hidden to standard procedures. In contrast, the results from policy exercises on large scale macreconometric models are hard to compare and recreate, and can easily be amended by their users with judgmental ex-post decisions. Finally, the lack of consensus about the appropriate structural model to use has led many economists instead to favour the use of a VAR model to examine the effects of different policies.

However, VAR models have also been much criticised, although the criticism usually refers to particular applications and interpretations of empirical results, rather than the methodology itself. Before I discuss this further, I will explain in somewhat more detail how estimation and identification of VARs are performed.

3.1. Estimation and identification

When specifying a VAR, one first has to decide which variables to include into the model. Since one can not include all variables of potential interest, one has to refer to economic theory or any a priori ideas when choosing variables. This involves some process of marginalization, in that the joint probability density of the VAR model must be interpreted as having been marginalized with respect to some variables that are potentially relevant (see e.g. Clements and Mizon 1991, or the discussion in Canova, 1995a,b).

Having specified the model, the appropriate lag length of the VAR model has to be decided. In deciding the number of lags, it has been common to use a statistical method, like the Akaike information criteria. Alternatively, one can choose a rather large lag length a priori, and thereafter check that the results are independent of this assumption (this is the approach taken in Blanchard and Quah 1989). However, a large lag length relatively to the number of observations, will typically lead to poor and inefficient estimates of the parameters. On the other hand, a too short lag length, will induce spurious significance of the parameters, as unexplained information is left in the disturbance term.

The approach suggested here is to use some of the statistical information criteria to select the smallest possible lag length. Adjustment can thereafter be made to allow for more lags if the residual are non-white. In contrast to what has been practice in many traditional VAR papers like Bernanke (1986) or more recently by Bayoumi and Eichengreen (1992), more emphasis should be put into assuring that the models are dynamically well specified. That is, non-correlation, heteroscedasticity, and normality should be checked, and the order of integration, cointegration and possible regime changes should be dealt with appropriately. In this sense, the approach taken should be more in line with the works of Hendry and Mizon (1990) and Clements and Mizon (1991). They select an unrestricted VAR that is congruent, that is a model that captures the dynamic relationships in the data, is well specified and has constant parameters.

The VAR can be estimated through single equation methods like OLS, which would be consistent, and under the assumption of normality of the errors, efficient (see Canova 1995a,b). In this paper, I have confined attention to linear models. Much recent research in both theoretical and applied time series analysis has focused attention on nonlinear models. Although there is some evidence of nonlinearity in disaggregated production series, there is relatively little evidence of nonlinearities in aggregate time series like real GDP and its components (see e.g. Brock and Seyers 1988). Also, as most macroeconomic variables are sampled quarterly and therefore of moderate length, any possible nonlinear behaviour may be reflected only in a small number of observations. Removal of these few "data points" through an outlier procedure or the introduction of deterministic dummies, can enable linear models to provide good approximations to a possibly nonlinear time series model (see e.g. Balke and Fomby 1994).

The unrestricted VARs are on reduced form, and are therefore uninterpretable without "reference" to theoretical economic structures. Suppose that z_t is a (n x 1) vector of macroeconomic variables whose dynamic behaviour is governed by a finite structural model:

$$(4) \qquad \beta_0 z_t = \gamma + \beta_1 z_{t-1} + \beta_2 z_{t.2} + \ldots + \beta_p z_{t-p} + u_t$$

where γ is a constant, β_i is a (nxn) matrix of coefficients, and u_t is a (n x 1) vector of white noise structural disturbances, with covariance matrix Σ. A reduced form of z_t can be modelled as:

$$(5) \qquad z_t = \delta + \alpha_1 z_{t-1} + \alpha_2 z_{t-2} + \ldots + \alpha_p z_{t-p} + e_t$$

where $\delta = \beta_0^{-1}\gamma$, $\alpha_i = \beta_0^{-1}\beta_i$ and $e_t = \beta_0^{-1}u_t$ is a white noise process, with nonsingular covariance matrix Ω. To go from the reduced form to the structural model, a set of identifying restrictions must be imposed. It is now common to assume that the covariance matrix for u_t (Σ), is diagonal, while β_0 has unity on its main diagonal but elsewhere is yet unrestricted. This implies that each member of z_t is assigned its own structural equation which ensures that the shocks can be given an economic interpretation.

The α_is and Ω can be estimated by applying OLS to the reduced form (5). However, if the β_is are unrestricted, one can not estimate β_0 as the α_is contains pn^2 known elements and there are $(p+1)n^2$ unknown elements in the β_is. Instead one solve for β_0 from:

$$(6) \qquad \Omega = \text{cov}(e_t) = \text{cov}(\beta_0^{-1} u_t) = \beta_0^{-1} \Sigma (\beta_0^{-1})'$$

There are n(n+1)/2 distinct covariances (due to symmetry) in Ω. The assumption that Σ is diagonal and contains n elements, implies that one need n(n-1)/2 further restrictions to identify the system. These restrictions can take several forms.

To discuss identification in VAR models, it is useful to cast the model in a moving average format. Rewriting first (5) as:

$$\alpha(L)z_t = \delta + e_t \tag{7}$$

where $\alpha(L)=I - \alpha_1 L - \alpha_2 L^2 - ... - \alpha_p L^p$. Assuming z_t is a covariance stationary vector, the Wold moving average theorem implies that (7) can be written in the following way (ignoring the constant from now):

$$z_t = \sum_{i=0}^{\infty} \phi_i e_{t-i} = \phi(L)e_t \tag{8}$$

where $\phi(L)=\alpha(L)^{-1}$ and $\phi_0 = I$. (8) is not identified, so there are many equivalent representations for the model. To identify the system, one need to *orthogonalise* the different shocks (innovations) by making the disturbances uncorrelated across time and across equations. A simple way to deal with the problem of identification is to choose any nonsingular matrix P, such that the positive definite symmetric matrix Ω can be written as the product $\Omega=PP'$ (see Lütkepohl 1993, pp. 40-41). Rewriting (8) gives:

$$\begin{aligned} z_t &= \sum_{i=0}^{\infty} \phi_i P P^{-1} e_{t-i} \\ &= \sum_{i=0}^{\infty} \theta_i \varepsilon_{t-i} \end{aligned} \tag{9}$$

where $\theta_i=\phi_i P$ and $\varepsilon_t = P^{-1}e_t$. The errors ε_t are white noise errors with covariance matrix $cov(\varepsilon_t) = P^{-1}\,\Omega(P^{-1})' = I$. As they have uncorrelated components, they are orthogonal. There are many possible factorisations of a positive definite Ω. If P is chosen to be a lower triangular matrix with positive diagonal elements, it gives a unique factorisation into PP′, called the *Choleski* factorisation. If P^{-1} is exactly equal to β_0, then the orthogonalised innovations would coincide with the true structural disturbances: $u_t = \beta_0 e_t = P^{-1}e_t = \varepsilon_t$. However, if P^{-1} differs from the true structural β_0, then I have not managed to uncover any structural relationship.

Sims (1980) made the assumption that β_0 was lower triangular so orthogonalization of the reduced form innovations was done through a Choleski decomposition. The system can then be identified recursively. However, this implies a causal ordering on how the system works, and it is hard to justify the contemporaneously recursive structural models, (see e.g. Cooley and Leroy 1985). Since economic theory rarely provides such an ordering, the Choleski decomposition is often dismissed as a tool of limited value for providing structural information to a VAR. However, recently, Keating (1996) has shown that the Choleski decomposition of the covariance matrix of the VAR models can be a useful indication tool for the set of partially recursive structural models. In particular, it can be useful for evaluating macroeconomic models.

Subsequently, Sims (1986), Bernanke (1986), Blanchard and Watson (1986) and Blanchard (1989) have suggested that one might choose a more 'structural' system of the VAR, by choosing restrictions on β_0 which are based on economic or statistical reasoning. As long as the number of unknowns in β_0 remains the same, any such alternative pattern will be observable equivalent as they give rise to the same VAR (in terms of α (or ϕ) and Ω). This method has the advantage over the Choleski decomposition if the theory provides a valid description of economic behaviour and enough identifying restrictions.

As an example, consider the following structural specification that gives the contemporaneous interactions among the innovations as:

$$y = b_1 r + u^D \qquad (10) \quad \text{(IS equation)}$$

$$r = b_2 y + b_3 m + u^R \qquad (11) \quad \text{(LM equation)}$$

$$m = u^M \qquad (12) \quad \text{(Money supply equation)}$$

where y denotes the log of real output, m is the log of the money supply and r is the nominal interest. u^D, u^R and u^M are stochastic processes, describing shocks to the spending (IS) equation, money demand (LM) equation and the money supply equation respectively. The b_i's are coefficients. The specification here is a standard textbook IS-LM model, used by among others Gali (1992) and James (1993) to identify some of the structural shocks in their VAR models. With three zero off-diagonal restrictions, the model above is just identified.

Ordering the variables such that $z_t = (y_t, i_t, m_t)'$, then the different structural shocks in (10) - (12) can be identified by imposing the following restrictions on β_0:

$$\beta_0 = \begin{bmatrix} 1 & -b_1 & 0 \\ -b_2 & 1 & -b_3 \\ 0 & 0 & 1 \end{bmatrix} \qquad (13)$$

Other researchers have exploited other types of restrictions. Blanchard and Quah (1989) and Shapiro and Watson (1988) have used long run restrictions on the dynamic effects of the innovations in the z_t variables, by appealing to a class of models that imposes generic restrictions on the model, such as long run neutrality or superneutrality. The use of long run restrictions has proved to be very appealing, as the restrictions used are widely accepted and the results obtained have been plausible and consistent with economic models. As mentioned above, the method also provides for a better way to interpret permanent and transitory components in nonstationary data, than the univariate Beveridge and Nelson (1981) approach. The idea can be illustrated simply below.

Assume the economy is hit by two types of shocks, an aggregate demand and an aggregate supply shock. The shocks can be distinguished from each other by assuming that only aggregate supply shocks can have a permanent effect on the level of output (cf. Blanchard and Quah 1989, or Bayoumi and Eichengreen 1992). This is consistent with the interpretation of an upward sloping short run supply schedule, but a vertical long run supply schedule in the price-output space. A positive demand shock (e.g. a monetary expansion) will shift up the (downward sloping) aggregate demand curve, increasing both output and price. In the long run, the aggregate supply curve is vertical in correspondence to the full employment level of output, hence the economy moves back to its initial level of output, where prices have increased to a permanent higher level. On the other hand, a positive supply shock (e.g. a technological improvement) that shifts both the short run and long run aggregate supply schedule to the right, will increase output and reduce prices permanently.

In the above framework, the component that is due to the demand (temporary) shocks will be stationary, making up the short run fluctuations in output. The component that is due to the permanent (supply) shocks will be non-stationary, making up the long run movements in output. However, as the permanent shocks can also affect output in the short term, they may also contribute towards the business cycles.

More formal theoretical models have also been presented, that for instance implies long run neutrality for certain variables. A combination of short run and long run restrictions is used in Gali (1992). However, although the methodology has appealing features, it has also been criticised as having a limited behavioural interpretation. This will be discussed further below.

Finally, if the variables are cointegrated, the number of identifying restrictions required will be smaller. In particular, if the VAR is of dimension *n* and has *r* cointegrating vectors, the variables are said to be driven by *n-r* common stochastic trends (see Stock and Watson 1988). Hence, instead of requiring n^2 restrictions to identify the system, the (*n-r* common trends) VAR model is identified using *n(n-r)* restrictions only. However, although the number of restrictions needed to identify the structural shocks in the VAR model will be smaller, one has to introduce additional a priori identifying restrictions so that the cointegrated model can be uniquely determined (see Wickens 1996).

3.2. Impulse responses and forecast error variance decomposition

Having estimated and identified the model, the next step in applied VAR modelling is to establish the impulse responses and the variance decomposition. An impulse response gives the response of one variable, to an impulse in another variable in a system that may involve a number of other variables as well. In terms of the notation above, the matrix θ_s in equation (9) contains the effect of a unit increase in each of the variable's innovations at time *t* on all the variables in z at time *t+s*:

(14) $$\theta_s = \frac{\partial z_{t+s}}{\partial \varepsilon_t'}$$

The row *i*, column *j* element of the matrix θ_s , ($\theta_{ij,s}$), is then the specific impulse response of a unit increases in the *j'th* variable's innovation at date *t* ($\varepsilon_{j,t}$), for the *i'th* variable at time *t+s* ($z_{i,\, t+s}$), holding all other innovations constant:

(15) $$\theta_{ij,s} = \frac{\partial z_{i,t+s}}{\partial \varepsilon_{j,t}'}$$

A plot of the row *i*, column *j* element of θ_s as a function of *s* is called the impulse response function, and gives the cumulative effect on variable *i* of an innovation in *j*. However as discussed above, only when the different shocks are uncorrelated, are the impulse responses valid. If the shocks should be correlated, then any experiment changing $\varepsilon_{j,t}$ but keeping the other shocks constant, would violate past relations that existed between these shocks. This has been a weakness of traditional regression methods. In particular, experiments have been conducted in which a regressor is varied and its impacts assessed without paying attention to the fact that the other regressors cannot be held constant.

Another important use of the VARs has been to describe the proportion of the forecast error variance of the endogenous variables that is due to each of the shocks. Equation (16) describes the mean square error (MSE) matrix of the s-period ahead forecast as (see Lütkepohl 1993, p. 56-58):

(16) $$MSE(\hat{z}_{t+s|t}) = E[(z_{t+s} - \hat{z}_{t+s|t})(z_{t+s} - \hat{z}_{t+s|t})'] = \sum_{i=0}^{s-1} \theta_i \theta_i' = \sum_{i=0}^{s-1} \phi_i \Omega \phi_i'$$

where the conditional variance of the level of z_{t+s}, at various horizons s, is split into the variance from the different unforecastable structural shocks, ε_{t+s}.

3.3. The limitations of the VAR approach

A major limitation of the VAR approach is that it has to be estimated to low order systems. All effects of omitted variables will be in the residuals. This may lead to major distortions in the impulse responses, making them of little use for structural interpretations (see e.g. Hendry 1995), although the system may still be useful for predictions (see e.g. Hendry and Doornik 1997, and the references stated there). Further, all measurement errors or misspecifications of the model will also induce unexplained information left in the disturbance terms, making interpretations of the impulse responses even more difficult. However, this does not imply that that impulse responses are useless, but emphasises instead that a careful empirical analysis should be applied when specifying the VAR. Ericsson et al. (1997) put it more strongly and argue that if inferences are to be made about the characteristics of the underlying data generating process on the basis of impulse response analysis of an estimated VAR, it is imperative that the model be congruent, encompass rival models, and be invariant to extension of the information used. However, the sensibility of the impulse responses to omitted variables and all types of misspecifiations, should caution the reader against overinterpreting the evidence from VAR models.

Using VAR models, special concern should therefore be given to check against dynamic misspecifications. All models should also be identified using an economic theory, either tight or loose. Checks can be made as to whether the impulse responses remain invariant to variations in the model specifications, by introducing other relevant variables. Overidentifying restrictions are also often used to test for credibility of the identifying restrictions used.

Faust and Leeper (1997) have criticised the use of long run restrictions to identify the structural shocks. They show that unless the economy satisfies some types of strong restrictions, the long run restrictions will be unreliable. The arguments are essentially the same as above, where the problem stems from the fact that the underlying model has more sources of shocks (with sufficiently different dynamic effects on the variables considered) than the estimated model. For the long run restrictions to give reliable results, the aggregation of shocks in small models should be checked for consistency using alternative models.

The critique of Faust and Leeper (1997) refers specifically to the bivariate model using only *one* long run restriction like that of Blanchard and Quah (1989). By allowing for more variables and using several (short run and) long run restrictions together, may make this criticism less relevant.

To sum up, the reader should bear in mind that due to its limited number of variables and the aggregate nature of the shocks, a VAR model should be viewed as an approximation to a larger structural system.

4 The Dynamic Effects of Aggregate Demand, Supply and Oil Price Shocks[3]

Below I will illustrate how one can use a structural VAR model to identify sources of business cycles. The VAR model will be identified by a mixture of short and long run restrictions that are motivated by economic theory.

4.1. Introduction

The debate as to whether the two successive adverse oil price shocks in 1973/1974 and 1979/1980, could be blamed for the severe periods of recessions facing the world economy in the middle 1970s and early 1980s has been controversial. Early studies like Hamilton (1983), Burbidge and Harrison (1984) and Gisser and Goodwin (1986) have typically argued that the two oil price shocks lowered world output, through a reduction in the supply of a major input of production. On the other hand, Rasche and Tatom

[3] This section is based on a short version of Bjørnland (2000b).

(1981), Darby (1982) and Ahmed et al. (1988) have blamed the poor economic performance in the 1970s and 1980s on other factors. Especially, the tight macroeconomic policies implemented in many industrial countries in the aftermath of the oil price shocks, to combat the high inflation rates experienced, may have worsened the recession that was already associated with the energy price increases.

This paper uses a structural vector autoregression (VAR) model to analyse the dynamic effects of a real oil price shock on real GDP and unemployment in Germany, Norway, United Kingdom and United States. Of these countries, Norway and UK have been self sufficient with oil resources during most of the period examined, whereas the remaining two countries are net oil importers. The complexity of ways that energy shocks can influence the economy, typically motivates the use of a VAR model instead of a fully specified large scale model (that is specified through a whole set of relations restrictions). In addition to oil price shocks, I assume that there may be demand and supply shocks that also hit the economy.

Many of the previous studies analysing the effects of oil price shocks on the macroeconomic performance have used VAR models identified through exclusion restrictions that follow a recursive structure, as in Sims (1980) original work. However, this type of identification structure implies a causal ordering on how the system works in the short run and the results will be very sensitive to how identification was achieved (see e.g. Cooley and LeRoy 1985). New orderings will typically imply differing degrees of importance for each shock. This was demonstrated by among others Ahmed et al. (1988), who showed how the contribution of money and energy prices in the variance decomposition of industrial production in OECD changed substantially as a result of variation in the ordering of these variables.

In this paper, the different disturbances will be identified through a combination of short run and long run restrictions that are implied by an economic model. The real oil price shocks will be identified by imposing plausible contemporaneous restrictions on the equation for oil prices. No restrictions are imposed on the effect of oil price shocks on real output and unemployment. In particular, I do not want to exclude any short run effects from the oil price shocks on the real economy, as this may be when producers adjust their capital stocks to a new configuration of relative prices. Demand and supply disturbances are defined and distinguished from each other by assuming that only aggregate supply shocks can have long run effects on output. This is consistent with the interpretation of an upward sloping short run supply schedule, but a vertical long run supply schedule. The long run restriction is similar to that employed by Blanchard and Quah (1989), although here I will in addition allow real oil price shocks to affect output in the long run.

This paper is organised as follows. In section 4.2 below, I describe a model of economic fluctuations, where energy price shocks are among the disturbances hitting the economy. Section 4.3 discusses how one can identify a structural VAR model that is consistent with the economic model put forward in section 4.2. In section 4.4 I review the effects of the different shocks on average for output and unemployment, and the relative importance of the different shocks in accounting for the forecast errors in the variables is assessed. In section 4.5 the impacts of the different shocks on output are analysed in different historical periods. Section 4.6 concludes.

4.2. Oil price shocks and economic fluctuations

Analysis of the linkages between energy and the aggregate economy is complicated. An oil price shock may typically have a real effect, as a higher energy price may affect output via the aggregate production function by reducing the net amount of energy used in the production. The argument that energy shocks can have a negative effect on the economy is however not new, and has been demonstrated by for instance the significance Jevons (1865) paid to the supply of coal in Britain. The effects on the other resources used in the production will depend on whether one substitute more or less of the other resources. The employed resources may further be indirectly affected, if wage rigidities prevent markets from clearing.

In addition, aggregate demand may also change in response to energy price changes. An oil price increase will typically lead to a transfer of income from the oil importing countries to the oil exporting countries. This reduction in income will induce the rational consumers in oil importing countries to hold back on their consumption spending, which will reduce aggregate demand and output. However, to the extent that the increase in income in the oil exporting countries will increase demand from the oil importing countries, this effect will be minimised.[4] Finally, the level of demand may also change due to actions taken by the government in response to changes in oil prices. For instance, several countries pursued tight monetary policy following the second oil price shock to offset the increase in the general price level, which may have lowered real activity.

Below I propose a simple economic model where energy price shocks may affect the economy through several channels. In addition to energy price shocks, I assume that there are other demand and supply shocks that also hit the economy. The model is a variant of a simple (Keynesian) model of output fluctuations presented in Blanchard and Quah (1989) that builds on Fischer (1977). The model consists of an aggregate demand function, a production function, a price setting behaviour and a wage setting behaviour.

$$(17) \quad y_t = m_t - p_t + a\theta_t + bo_t$$

$$(18) \quad y_t = n_t + \theta_t + co_t$$

$$(19) \quad p_t = w_t - \theta_t + do_t$$

$$(20) \quad w_t = w\left[E_{t-1}n_t = \bar{n}\right]$$

where y is the log of real output, o is the log of real oil prices, n is the log of employment, θ is the log of productivity, p is the log of the nominal price level, w is the log of the nominal wage, and m is the log of nominal money supply. $\bar{n}$ implies the log of full employment. The unemployment rate is defined as u = $\bar{n} - n$.

Equation (17) states that aggregate demand is a function of real balances, productivity and real oil prices. Real oil prices are introduced into the aggregate demand function as the level of aggregate demand may change with higher oil prices. Both productivity and real oil prices are allowed to affect aggregate demand directly. If a>0, a higher level of productivity may imply higher investment demand (cf. Blanchard and Quah 1989, p. 333), whereas if b<0, higher real oil prices may imply a lower level of demand by e.g. the rational consumers.[5]

The production function (18) relates output to employment, technology and real energy prices, through an increasing return Cobb-Douglas production function. Real oil prices are explicitly included as a third factor of production. As will be seen below, it is through this mechanism that oil prices will affect output in the long run. The real price of oil is used in the production function instead of an energy quantity, as competitive producers treat the real price of oil as parametric. Hence, c reflects the inverse of the energy elasticity and one would expect (c≤0), see e.g. Rasche and Tatom (1981, pp. 22-24) and Darby (1982, p. 739).[6]

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[4] See e.g. Bohi (1989) and Mork (1994) for a further discussion.

[5] b>0 is plausible for Norway, where the oil producing sector is large compared to the rest of the economy. Higher oil prices will typically increase the level of demand from energy producers (like the government).

[6] Rasche and Tatom (1981) specify a production function that relates output to labour input, capital input, the real price of oil and a time trend through a constant return to scale technology.

The price setting behaviour (19) gives nominal prices as a mark up on real oil prices and wages adjusted for productivity. Oil prices are introduced into the price setting equation, so that oil prices can also affect the level of aggregate demand through the price effect in (19). Wages are chosen one period in advance to achieve full employment (20). The model is closed by assuming m, θ and o evolve according to:

$$(21)\quad m_t = m_{t-1} + \varepsilon_t^{AD}$$

$$(22)\quad \theta_t = \theta_{t-1} + \varepsilon_t^{AS}$$

$$(23)\quad o_t = o_{t-1} + \varepsilon_t^{OP}$$

where, ε^{AD} , ε^{AS} and ε^{OP} are serially uncorrelated, orthogonal demand, supply and real oil price shocks. Solving for Δy and u yield:

$$(24)\quad \Delta y_t = \Delta\varepsilon_t^{AD} + a\Delta\varepsilon_t^{AS} + (b-d)\Delta\varepsilon_t^{OP} + \varepsilon_t^{AS} + c\varepsilon_{t-1}^{OP}$$

$$(25)\quad u_t = -\varepsilon_t^{AD} - a\varepsilon_t^{AS} + (c+d-b)\varepsilon_t^{OP}$$

From (24) one can see that only supply and oil price shocks will affect the level of output (y_t) in the long run (through the production function), as y_t will be given as accumulations of these two shocks. However, in the short run, due to nominal and real rigidities, all three disturbances can influence output. From (25) one can see that neither of the shocks will have long run effects on unemployment. This is consistent with a view that there is a 'natural' level of unemployment, determined by social institutions like e.g. union bargain power. Supply and demand shocks have only temporary effects on unemployment, and in the long run, wages and prices will adjust so unemployment returns to its natural level, see e.g. Layard et al. (1991).

The finding that aggregate demand shocks have only short term effect on output, is also consistent with the interpretation of an upward sloping short run supply schedule, but a vertical long run supply schedule. A positive demand shock (e.g. a monetary expansion) will typically increase output (and prices) along the short run supply schedule, inducing a temporary fall in unemployment. In the long run, the economy adjusts to higher prices, and the short run supply schedule shifts backwards to its long run equilibrium output level, consistent with a natural rate of unemployment. However, the speed of adjustment to a demand shock is unrestricted and may be instantaneous (as in the New Classical School) or slow (as in the Keynesian models with a relatively flat short run supply schedule).[7]

4.2. The econometric methodology

The VAR model specified here, focuses on three variables; Real GDP, real oil prices and unemployment. As suggested by equations (23)-(25), these variables are a minimum of variables that are necessary to identify three structural disturbances; aggregate demand, supply and oil price shocks.

First, I define z_t as a vector of stationary macroeconomic variables $z_t = (\Delta y_t, \Delta o_t, u_t)'$, where Δy_t is the first differences of the log of real GDP, Δo_t is the first difference of the log of real oil prices and u_t is the unemployment rate.[8] A reduced form of z_t can be modelled as:

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[7] In a related model, Bjørnland (1998) tests this overidentifying assumption by solving the model for prices rather than for the unemployment rate.

[8] The assumptions of stationarity are discussed and verified empirically below in section 4.3.

$$z_t = \alpha + A_1 z_{t-1} + \ldots + A_p z_{t-p} + e_t$$
(26)
$$A(L) z_t = \alpha + e_t$$

where A(L) is the matrix lag operator, $A_0 = I$ and e_t is a vector of reduced form residuals with covariance matrix Ω. To go from the reduced form to the structural model, a set of identifying restrictions must be imposed. As all the variables defined in z_t are stationary, z_t is a covariance stationary vector process. The Wold Representation Theorem implies that under weak regularity conditions, a stationary process can be represented as an invertible distributed lag of serially uncorrelated disturbances. The implied moving average representation from (26) can be found and written as (ignoring the constant term for now):

$$z_t = C_0 e_t + C_1 e_{t-1} + C_2 e_{t-2} + \ldots$$
(27)
$$z_t = C(L) e_t$$

where $C(L)=A(L)^{-1}$ and C_0 is the identity matrix. The C_j matrix refers to the moving average coefficient at lag j. As the elements in e_t are contemporaneously correlated, they can not be interpreted as structural shocks. The elements in e_t are orthogonalized by imposing restrictions. I first denote the orthogonal structural disturbances, ε_t, and assume that they can be written as linear combinations of the Wold innovations, $e_t = D_0 \varepsilon_t$. This assumption is essential, as without it the economic interpretations of certain VAR models may change, see e.g. Lippo and Reichlin (1993) and Blanchard and Quah (1993) for a discussion of the problem of nonfundamentalness. With C_0 as the identity matrix, a (restricted) form of the moving average containing the vector of original disturbances can be found as:

$$z_t = D_0 \varepsilon_t + D_1 \varepsilon_{t-1} + D_2 \varepsilon_{t-2} + \ldots$$
(28)
$$z_t = D(L) \varepsilon_t$$

where $C_j D_0 = D_j$, or:

(29) $$C(L) D_0 = D(L)$$

The structural disturbances will be normalised for convenience, so they all have unit variance, e.g. $\text{cov}(\varepsilon_t)=I$. If D_0 is identified, I can derive the MA representation in (28) since C(L) is identifiable through inversions of a finite order A(L) polynomial. Consistent estimates of A(L) can be found by applying OLS to (26). However, the D_0 matrix contains nine elements, and to orthogonalise the different innovations we need nine restrictions. First, from the normalisation of $\text{var}(\varepsilon_t)$ it follows that:

(30) $$\Omega = D_0 D_0'$$

There are n(n+1)/2 distinct covariances (due to symmetry) in Ω. With a three variable system, this imposes six restrictions on the elements in D_0. Three more restrictions are then needed to identify D_0. One will come from a restriction on the long run multipliers of the D(L) matrix, whereas the other two will come from restrictions on the contemporaneous matrix D_0 directly.

I first order the three serially uncorrelated orthogonal structural shocks as: $\varepsilon_t = (\varepsilon_t^{AD}, \varepsilon_t^{OP}, \varepsilon_t^{AS})'$, where ε_t^{AD} is an aggregate demand shock, ε_t^{OP} is a real oil price shock and ε_t^{AS} is an aggregate supply (or productivity) shock. The long run restriction applied here is motivated by the findings in (24), namely that aggregate demand shocks have no long run effects on output. From (28) the effect of a demand shock on the rate of change in output, Δy_t, after j periods is given as $D_{11,j}$, whereas the effect of a demand shock on the level of output, y_t, after k periods is $\sum_j^k D_{11,j}$. The restriction that aggregate demand shocks have no long run effects upon the level of y_t, is then simply found by setting the infinite number of lag coefficients, $\sum_j^\infty D_{11,j}$, equal to zero. From (29), the long run expression, $\sum_{j=0}^\infty C_j D_0 = \sum_{j=0}^\infty D_j$, can be written out in its full matrix format as:

$$(31) \quad \begin{bmatrix} C_{11}(1) C_{12}(1) C_{13}(1) \\ C_{21}(1) C_{22}(1) C_{23}(1) \\ C_{31}(1) C_{32}(1) C_{33}(1) \end{bmatrix} \begin{bmatrix} D_{11,0} D_{12,0} D_{13,0} \\ D_{21,0} D_{22,0} D_{23,0} \\ D_{31,0} D_{32,0} D_{33,0} \end{bmatrix} = \begin{bmatrix} D_{11}(1) D_{12}(1) D_{13}(1) \\ D_{21}(1) D_{22}(1) D_{23}(1) \\ D_{31}(1) D_{32}(1) D_{33}(1) \end{bmatrix}$$

where $C(1) = \sum_{j=0}^\infty C_j$ and $D(1) = \sum_{j=0}^\infty D_j$ indicate the long run matrixes of C(L) and D(L) respectively. C(1) is observable, found by inversion of A(1). The long run identification then implies that $D_{11}(1) = 0$. Hence:

$$(32) \quad C_{11}(1) D_{11,0} + C_{12}(1) D_{21,0} + C_{13}(1) D_{31,0} = 0$$

In our trivariate system, two further restrictions are required to identify the system. These are found by assuming two short-run restrictions on oil prices. In (7), oil prices were assumed to be exogenous, with changes in oil prices driven by exogenous oil price shocks. In a more complex model, demand and supply shocks may also affect oil prices, at least from large economies as the US. However, oil prices have been dominated by a few large exogenous developments, (e.g. the OPEC embargo in 1973, the Iranian revolution in 1978/1979, the Iran-Iraq War in 1980/1981, the change in OPEC behaviour in 1986, and most recently the Persian Gulf War in 1990/1991). The oil price is a financial spot price that reacts quickly to news. I therefore assume that if demand and supply shocks influence oil prices they do so with a lag. Hence the contemporaneous effects of demand and supply shocks in each country on real oil prices are zero, and only exogenous oil price shocks will contemporaneously affect oil prices. However, after a period (one quarter), both demand and supply shocks are free to influence oil prices. The two short term restrictions on real oil prices then imply that:

$$(33) \quad D_{21,0} = D_{23,0} = 0$$

The system is now just identifiable. By using a minimum of restrictions I have been able to disentangle movements in three endogenous variables (real output, real oil prices and unemployment) into parts that are due to three structural shocks (aggregate demand, supply and oil price shocks). It turns out that the system is linear in its equations, and can be solved numerically. The joint use of short run and long run constraints used in the VAR model, should also be sufficient to side-step some of the criticism of Faust and Leeper (1997), who argue that for a long-run identifying restriction to be robust, it has to be tied to a restriction on finite horizon dynamics.

Despite the many advantages of using a simple structural VARs, it is also subject to some limitations. Especially, a small VAR should be viewed as an approximation to a larger structural system, since the limited number of variables and the aggregate nature of the shocks, implies that one will for instance not be able to distinguish between different aggregate demand shocks (like e.g. increases in money supply or fiscal policy). One way to assess whether the identification structure applied here is meaningful, is to empirically examine whether the different shocks have had the effects as expected on average and in the different historical periods. This will be discussed in the sections that follows.

4.3. Empirical results

In the VAR model specified above, the variables were assumed to be stationary and the level of the variables were not cointegrating. Below I perform some preliminary data analyses, to verify whether I have specified the variables according to their time series properties.[9] The dynamic effects of the different shocks on the variables are thereafter estimated.

The data used for each country are the log of real GDP (non-oil GDP for Norway), the log of real oil prices converted to each country's national currency and the total unemployment rate (see appendix A for data descriptions and sources). The data are quarterly, and the sample varies somewhat between the different countries, reflecting data availability (USA; 1960-1994, Germany; 1969-1994, UK; 1966-1994, and Norway; 1967-1994).

The lag order of the VAR-models are determined using the Schwarz and Hannan-Quinn information criteria and F-forms of likelihood ratio tests for model reductions. Based on the 5 pct. critical level, I decided to use three lags for the US, five lags for Germany, and six lags for Norway and the UK. None of the models showed any evidence of serial correlation in the residuals.[10]

Above it was assumed that GDP and real oil prices were nonstationary integrated, I(1), variables, whereas unemployment was assumed to be stationary, I(0). To test whether the underlying processes contain a unit root, I use the augmented Dickey Fuller (ADF) test of unit root against a (trend) stationary alternative. However, a standard ADF test may fail to reject the unit root hypothesis if the true data generating process is a stationary process around a trend with one structural break. Misspecifying a 'breaking trend' model as an integrated process, would mean that one would attribute to much persistence to the innovations in the economic variables. To allow for the posibility of a structural break in the trend, I therefore also conduct the Zivot and Andrews' (1992) test of a unit root against the alternative hypothesis of stationarity around a deterministic time trend with a one time break that is unknown prior to testing.

In none of the countries can I reject the hypothesis that GDP and oil prices are I(1) in favour of the (trend) stationary alternative or the trend stationary with break alternative.[11] However, I can reject the hypothesis that oil prices and GDP are integrated of second order I(2).

Based on the ADF tests, in none of the countries can I reject the hypothesis that the unemployment rate is I(1). However, using the test suggested by Zivot and Andrews (1992), I can reject the hypothesis that unemployment is I(1) in favour of the trend-break alternative at the 5 pct. level in Norway, at the 10 pct. level in the UK and Germany, but only at the 20 pct. level in the US. The break points occurred in 1974Q3 in the US, in 1980Q2 in the UK, in 1985Q3 in Germany and in 1988Q2 in Norway. Although a deterministic trend is included in the estimation procedure, for Norway, UK and US, the trend in the unemployment rate is virtually flat before and after the break, (and barely significant judged by a standard t-test). In the remaining analysis I therefore de-trend the unemployment rate using the break dates indicated above. For the US where the results for unemployment were more ambiguous, I also perform the analysis using a deterministic trend with no break.

The use of trend with a one time break in the unemployment rate, has some substantial economic implications. Although theoretically, the unemployment rate may be a bounded variable that will return to its natural level in the long run, many countries have the last 10-15 years experienced a prolonged

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[9] See Bjørnland (2000b) for all the test results.

[10] To investigate whether the results are sensitive to the truncation of lags, I also estimated VAR models using eight lags for all countries. The results using eight lags did not differ much from the results presented below and can be obtained from the author on request.

[11] Using a very similar test procedure as Zivot and Andrews (1992), Banerjee et al. (1992) do neither find any evidence against the unit-root null hypothesis for real GDP in the relevant countries analysed here.

upward drift in the unemployment rates. This upward drift may suggest that the natural rate itself at some point has increased, due to, for instance growing union power, or the introduction of policies that have obstructed the free workings of the labour market.

To be able to capture this potential structural shift in the natural rate, the use of a deterministic trend with an endogenous break date may then be a plausible, although crude, approximation to the observed upwards drift in the unemployment rate. In fact, by using a deterministic trend that is allowed to shift up (or down) once, I introduce some flexibility between the two contrasting economic views that, on the one hand, the unemployment rate is stationary, deviating only temporarily from its natural level, and, on the other hand, the notion that the unemployment rate is non-stationary, with no tendency to return to its natural rate. Proponents of the last view, typically argue that there is hysteresis in the unemployment rate, so that all shocks can have a permanent effect on the unemployment rate.

All the break dates suggested above coincide with periods of important structural changes in the given countries. For instance, the break suggested in 1974 in the US, may reflect the sharp decline in labour productivity growth at that time (see e.g. Sachs 1982), although the fist oil price shock may also be an important contributor. In UK, the break in 1980 coincides with the change in policies after the Thatcher government took over the year before, which implied severe negative permanent effects on the labour market. The break in unemployment in Norway in 1988, most likely reflects the severe recession in the late 1980s, which was preceded by a financial deregulation. The break in Germany is somewhat different, as it is the slope of the trend in the unemployment rate that is changing. In fact, the trend has a positive drift until the middle 1980s, reflecting the fact that the natural rate is increasing steadily during this period. After 1985, the slope of the trend in unemployment is virtually flat. The plausibility of the estimated break dates will be discussed further in section 4.5, when I focus on specific historical periods using the VAR model.

Finally, using the maximum likelihood estimation procedure advocated by Johansen (1988, 1991), I can confirm that none of the variables in the VAR models are cointegrated. Hence, the variables are appropriately modelled as described by the VAR model above.

4.4. Dynamic responses to aggregate demand, aggregate supply and oil price shocks

The cumulative dynamic effects (calculated from equation 28) of demand, supply and oil price shocks on GDP are reported in figures 5A-H, whereas the dynamic effects of the same three disturbances on unemployment are seen in figures 6A-H. In each figure, the dynamic effect of the oil price shock is reported with a standard deviation band around the point estimate.[12]

In Germany, United Kingdom and United States, an adverse oil price shock (increase in the real price of oil) lowers GDP the first two to three years. The effect is largest after six quarters, where the (one standard error) oil price shock reduces GDP by 0.3-0.5 pct. The effect thereafter essentially dies out in Germany and UK, whereas for US, real GDP is permanently reduced with 0.4 pct. In Norway, the adverse oil price shock has an initial (negligible) negative effect on GDP, but the effect thereafter becomes positive, and GDP has increased by about 0.4 pct. after two years. However, as the one standard error band includes zero and becomes wider as the horizon increases, the effect may not be significant in the long run.

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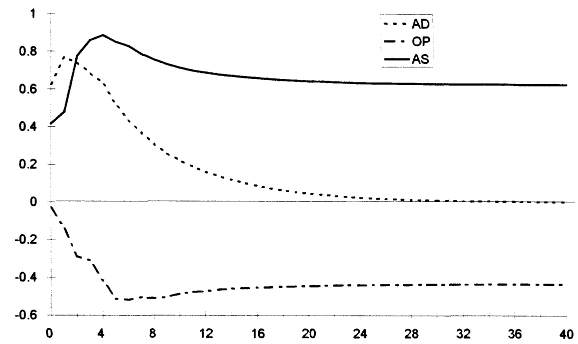
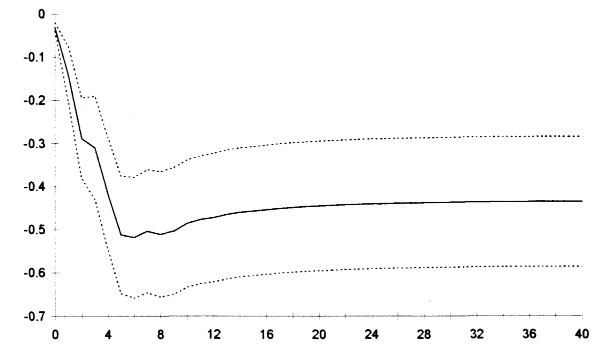
[12] The standard errors are calculated using Monte Carlo simulation based on normal random drawings from the distribution of the reduced form VAR. The draws are made directly from the posterior distribution of the VAR coefficients, as suggested in Doan (1992). The standard errors that correspond to the distributions in the D(L) matrix are then calculated using the estimate of D_0. Impulse responses for all shocks with a standard deviation band, can be obtained from the author on request.

Figure 5. GDP impulse responses to an oil price (OP) shock, an aggregate demand (AD) shock and an aggregate supply (AS) shock, (pct. change)

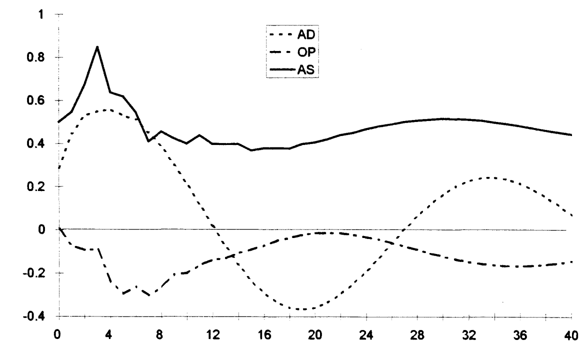
A) US; OP, AD and AS shocks



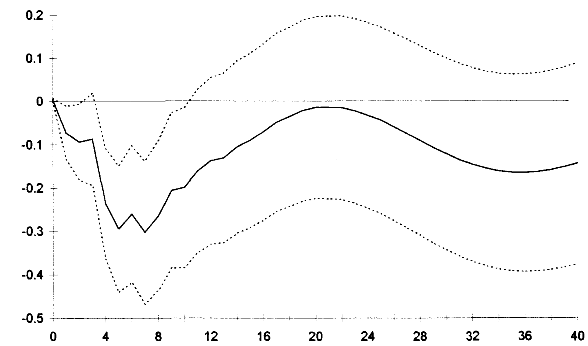
B) US; OP shock, one standard error band



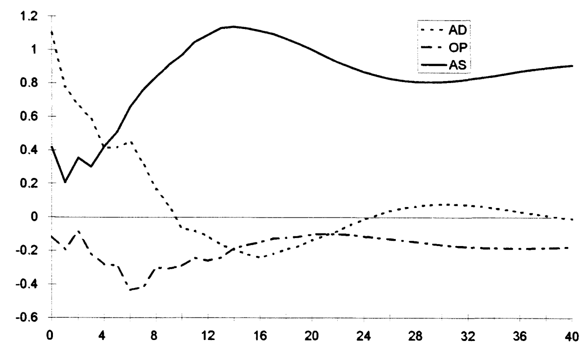
C) Germany; OP, AD and AS shocks



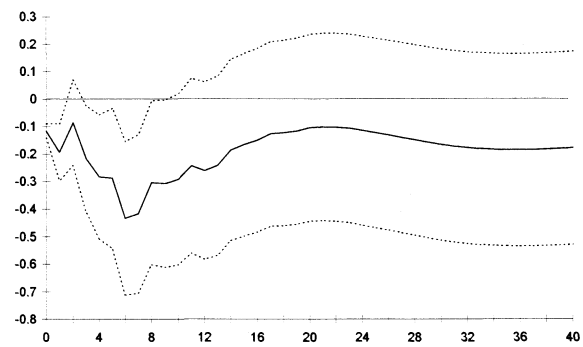
D) Germany; OP shock, one standard error band



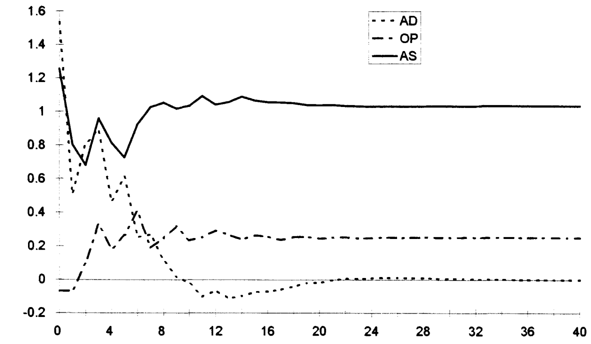
E) UK; OP, AD and AS shocks



F) UK; OP shock, one standard error band



G) Norway; OP, AD and AS shocks



H) Norway; OP shock, one standard error band

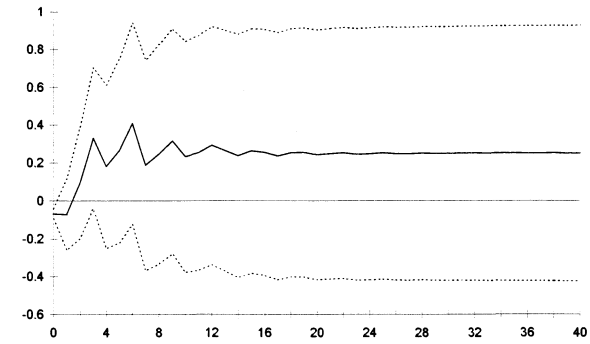
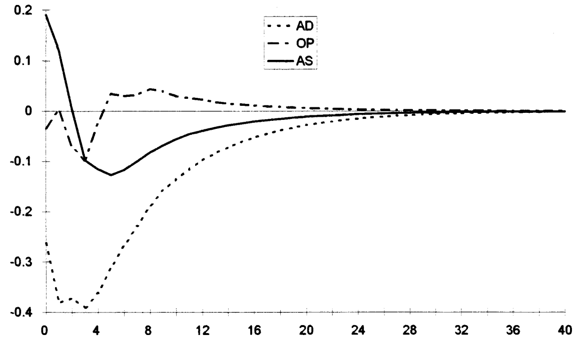
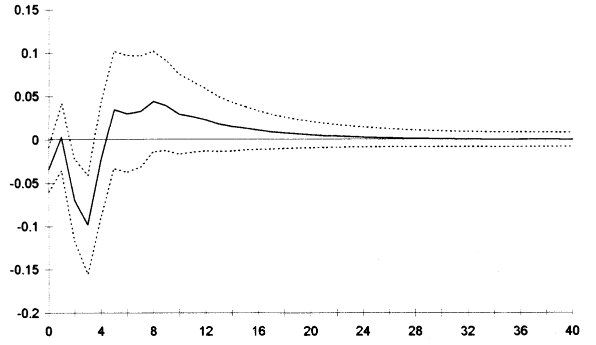


Figure 6. Unemployment responses to an oil price (OP) shock, an aggregate demand (AD) shock and an aggregate supply (AS) shock, (pct. point change)

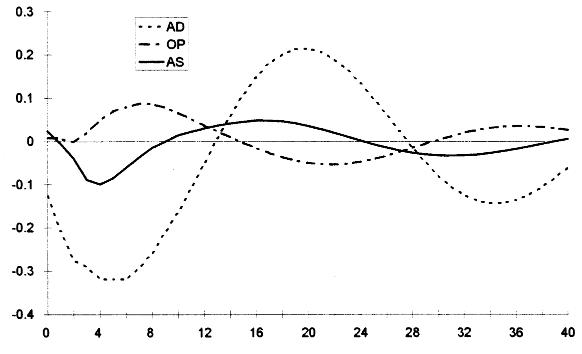
A) US; OP, AD and AS shocks



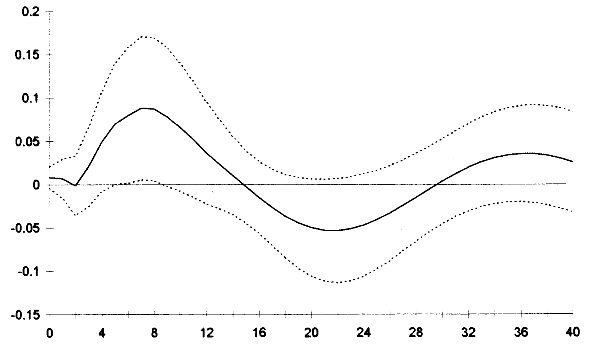
B) US; OP shock, one standard error band



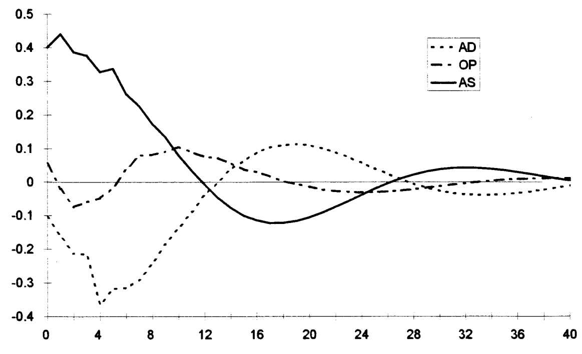
C) Germany; OP, AD and AS shocks



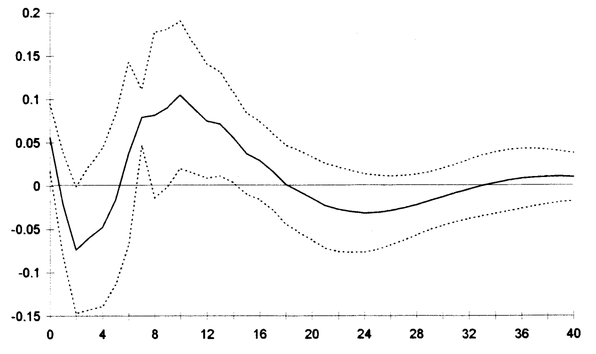
D) Germany; OP shock, one standard error band



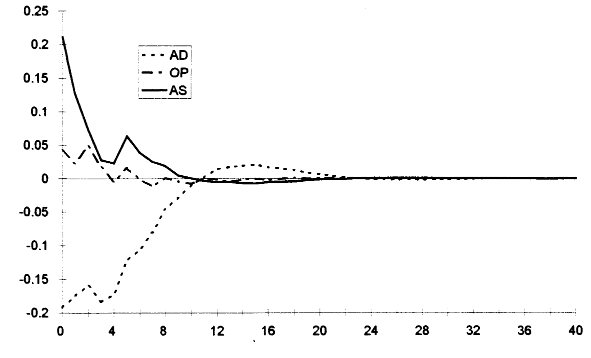
E) UK; OP, AD and AS shocks



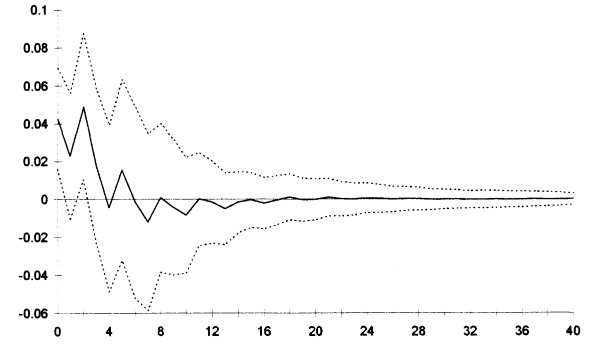
F) UK; OP shock, one standard error band



G) Norway; OP, AD and AS shocks



H) Norway; OP shock, one standard error band



A demand shock has a positive impact on the level of GDP in all countries and the response is highest in the smallest country; Norway. The response of GDP in all countries thereafter declines gradually as the long run restriction bites. A supply disturbance has a permanent positive effect on the level of GDP in all countries, increasing GDP by 0.5-1 pct. after ten years. However, the immediate impact effect of a one unit supply shock varies between the different countries, with again the highest response in the smallest country; Norway.

It is interesting to compare the results for the US, with the findings in Blanchard and Quah (1989). Whereas Blanchard and Quah found the initial output response in the US after a supply shocks to be small and approaching zero the first two quarters, I find the output response in the US to be much higher initially. On the other hand, I find real oil price shocks to have negative effects on output at all horizons. Hence, the initial negative response in output to supply shocks reported in Blanchard and Quah (1989), may therefore be due to the fact that they have not separated the effects of oil price shocks from the other supply (productivity) shocks.

A real oil price shock has small effects on the unemployment rate all the countries, which increase by less than 0.1 pct. points after two years. The wide standard deviation bands also indicate that the effect of the oil price shocks on unemployment, is only really significant for a few quarters.

The response of the unemployment rate to an aggregate demand shock mirrors the response of output to the same disturbance. Following a positive demand shock the unemployment rate falls immediately in all countries, but the effect is no longer significant different from zero after four years. A positive supply disturbance on the other hand, works to increase the unemployment rate in all countries initially, (although the effect is negligible in Germany), but after two-three years, the effect has died out.

Tables 1-4 present the forecast-error variance decompositions (the relative contribution of the different shocks) for GDP and unemployment in US, Germany, UK and Norway respectively. A real oil price shock has only a small effect on output initially. However, after two years, oil price shocks explain 15 pct. of the output fluctuations in the US (increasing to 20 pct. after three years), 10 pct. of the output fluctuations in the UK, 7-8 pct. of the output movements in Germany and less than 5 pct. of output movements in Norway. The oil price shocks have little importance in explaining unemployment fluctuations in any of the countries.

In the short term, aggregate demand disturbances are the most important source of output fluctuations in the US, UK and Norway, with 50-80 pct. of the variance in GDP explained by aggregate demand shocks the first year. The relative contribution of aggregate demand disturbances thereafter declines towards zero, as supply disturbances become more important. Aggregate demand shocks explain 70-90 pct. of the variation in unemployment in Norway, US and Germany the first two years, whereas in the UK, less than 40 pct. of the variation in unemployment is explained by demand shocks.

Note that although an oil price shock has a larger effect on output in the US than in Germany and the UK, the effect on unemployment from an oil price shock in the US is small. However, recall that for US I have allowed for an increase in the unemployment rate by shifting the trend upwards in 1974 (cf. section 4.1), which coincides with the time of the first severe oil price shock. The effect on unemployment from an oil price shock may as a consequence have been underestimated. As I have only weak evidence that the unemployment rate experienced a structural break in 1974, I also tried to re-estimate the model using a linear trend with no break in the unemployment rate in US, but allowing instead for 8 lags in the VAR model. The results are virtually unchanged, except that the negative effect of an oil price shock on output is somewhat smaller in the long run, explaining 13 pct. of the output variation after three years. The effect on the unemployment rate from an oil price shock is unchanged the first year, but after two years, more than 10 pct. of the variation in unemployment is explained by oil price shocks.

Table 1. Variance Decomposition of GDP and Unemployment in US

	GDP			Unemployment		
Quarter	AD-shock	OP-shock	AS-shock	AD-shock	OP-shock	AS-shock
1	69.2	0.2	30.6	64.9	1.1	34.0
4	50.7	5.0	44.2	87.0	2.7	10.3
8	32.1	14.6	53.2	86.3	2.1	11.6
12	25.7	18.4	55.9	86.0	2.2	11.8
16	21.5	20.6	57.8	85.9	2.3	11.8
40	11.3	26.3	62.4	85.9	2.3	11.8

Table 2. Variance Decomposition of GDP and Unemployment in Germany

	GDP			Unemployment		
Quarter	AD-shock	OP-shock	AS-shock	AD-shock	OP-shock	AS-shock
1	24.8	0.0	75.2	96.3	0.4	3.3
4	33.1	0.8	66.1	95.5	0.2	4.3
8	36.7	6.9	56.4	91.6	4.0	4.3
12	33.6	7.8	58.6	90.7	5.3	4.0
16	32.2	7.5	60.3	90.2	5.1	4.7
40	25.6	5.9	68.4	90.4	5.4	4.2

Table 3. Variance Decomposition of GDP and Unemployment in UK

	GDP			Unemployment		
Quarters	AD-shock	OP-shock	AS-shock	AD-shock	OP-shock	AS-shock
1	86.6	1.0	12.4	6.2	1.8	92.1
4	82.9	3.3	13.8	16.3	1.6	82.1
8	49.8	10.9	39.2	36.6	1.8	61.6
12	30.2	9.4	60.4	37.6	3.5	58.9
16	21.3	7.1	71.6	37.2	4.0	58.8
40	10.1	4.7	85.1	38.2	4.0	57.8

Table 4. Variance Decomposition of GDP and Unemployment in Norway

	GDP			Unemployment		
Quarters	AD-shock	OP-shock	AS-shock	AD-shock	OP-shock	AS-shock
	59.8	0.1	40.1	44.2	2.2	53.7
	52.0	1.6	46.3	63.6	2.5	33.8
	36.6	3.8	59.7	70.6	2.0	27.4
	27.0	4.5	68.5	70.6	2.0	27.3
	21.3	4.7	74.0	70.7	2.0	27.2
	9.7	5.1	85.2	70.8	2.0	27.2

Hence, of the countries analysed here, the negative effects of an oil price shock on output are clearly largest in the US, with the magnitude of the effects being somewhat dependent on the way the possible structural break in unemployment is taken into account. This large contribution of oil price shocks to the US economy, stands in somewhat contrast to the results reported by Shapiro and Watson (1988), who also estimate the effects of oil price shocks on the US economy through a VAR model. In Shapiro and Watson, oil price shocks play virtually no role in explaining the GDP movements the first year, but from two years and onwards, they explain approximately 8–10 pct. of the GDP variation. However, in contrast to the present analysis, oil price changes are exogenous in Shapiro and Watson (1988). In particular, no shocks other than the oil price shocks can affect the real oil price at any horizon. This identifying restrictions may in fact imply that Shapiro and Watson have underestimated the effects of oil price shocks, and emphasised instead other supply shocks which may have similar effects on the variables in the model (see also the comments made by Quah to their paper in the same journal).

To conclude then, why should output in the US respond more negatively to an oil price shock than output in Germany (and UK), and why do Norway and UK (both being oil exporting countries) respond so differently?

The structure of the economy will probably play an important role for the macroeconomic adjustments to oil price shocks. Countries with low production dependence of oil, low share of oil in the consumption bundle and relatively low labour intensities in production, will suffer less from oil price shocks. Germany has typically had a relatively small value of labour intensity in the traded goods sector and a low share of oil in consumption, and may therefore have been less severely affected by the oil price increases, (see e.g. Lehment 1982, Fieleke 1988 and Nandakumar 1988). Rasche and Tatom (1981) suggest that as Germany has traditionally had higher duty on oil prices than US, it may therefore have replaced oil as an energy source in some of the industry with nuclear power or coal. Especially, between 1973 and 1979, consumption of crude petroleum per capita declined slightly in Germany, whereas in the US it increased. Total import of crude petroleum also declined slightly between 1973 and 1979 in Germany, but increased in the US, (cf. UN Yearbook of World Energy Statistics).

The fact that in the UK output decreased, whereas in Norway, output actually increased in response to an oil price shock, emphasises how two countries that are self sufficient with oil resources can react very differently to oil price shocks. Although the oil sector plays a much larger role in Norway than in the UK, macroeconomic policy has also been conducted very differently in light of the two major oil price shocks in Norway and the UK. In Norway, the oil price increases raised the net national wealth, allowing the government to follow an expansionary fiscal policy during several periods. UK was self sufficient with oil resources when the second oil price shock occurred, but fiscal and monetary policies have remained relative tight during the 1980s, aimed primarily at combating the high inflation rates in that period. With factory closures and rapidly increasing unemployment rates from the late 1970s in the UK, much of the revenues from the increased oil prices instead went into social security in addition to payment of existing external debts.

Finally, the behaviour of output and unemployment in US, UK and Norway, seem consistent with what a Keynesian approach to business cycles would have predicted; Demand disturbances are the most important factor behind output fluctuations in the short run, but eventually prices and wages adjust to restore equilibrium. In Germany, supply disturbances are more important than demand disturbances in explaining output fluctuations in the short term, suggesting that a real business cycle view may be applicable.

4.5. Sources of business cycles

Below I focus on specific historical periods by computing the forecast errors in output. The results are presented in figures 7 for Norway[13]. In panels A-B, I plot the total forecast error in output together with the forecast error that is due to oil price shocks and demand shocks respectively. In panel C, log GDP is graphed together with the forecast error in output that is associated with the supply shock when the drift term in the model is added (I will refer to this as the supply potential). The figure allows me to examine whether the shocks identified can be well interpreted and assessed in terms of actual episodes that occurred in the periods examined.

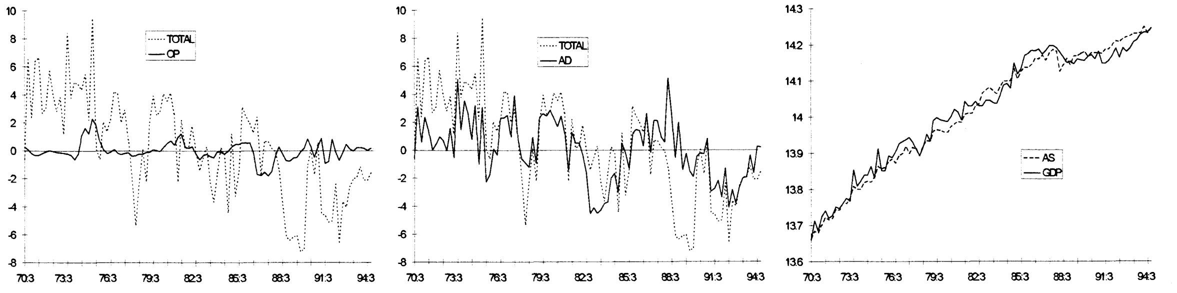
In section 4.4, adverse oil price shocks were found to have positive effects on output in Norway. This is understood more clearly by examining figure 7A. The first oil price shock in 1973/1974 occurred at a

[13] See Bjørnland (2000b) for the results of the other three countries.

time when the Norwegian economy had just discovered huge oil resources in the North Sea. However, the prospect of increased oil revenues brought about by higher oil prices created a potential for profitable output. By the end of the 1970's, Norway was a net exporter of oil, so when the second oil price rise occurred in 1979/1980, overall national wealth and demand increased further. Demand shocks were also important contributors behind the good economic performance in the middle 1970s, as the government followed expansionary fiscal policies from 1974-1977 (see figure 7B).

Figure 7. Forecast Error Decompositions for GDP in Norway

A) Oil price, (pct. change) B) Aggregate demand, (pct. change) C) Aggregate supply, (drift term added)



During the 1980s, Norway experienced two severe recessions. The first, from 1982 to 1985, was primarily demand driven. The economy thereafter experienced a demand driven boom, set off primarily by a financial deregulation. The high growth rates were dampened somewhat by the collapse of oil prices in 1986, which eroded the government of potential future income streams. From 1988, negative supply shocks pushed the economy into another recession, and now both the supply potential and the unemployment rate changed permanently, (c.f. figure 7C and the discussion in section 4.3). The economy recovered somewhat by 1990, but then the international economy was slowing down, and demand shocks contributed negatively to output growth.

4.6. Conclusions

By using a minimum of restrictions on a VAR model, I have been able to interpret economic fluctuations in Germany, Norway, United Kingdom and United States in terms of three different shocks that have hit the economy; Aggregate demand, aggregate supply and oil price shocks. In all countries, the dynamic adjustments of the variables are consistent with the economic model predictions, and the shocks identified fit well with the actual events that have occurred in the different historical periods.

For all countries except Norway, an adverse oil price shock has had a negative effect on output in the short run, and for the US, the effect is negative also in the long run (ten years). In Norway, (whose oil producing sector plays a large role in the economy), the effect of oil price shocks on output is positive at all horizons, although in the long run the effect is not necessarily significant. The different responses in the UK and Norway to an energy price shock, emphasise how two countries that are self sufficient with oil resources can react very differently to oil price shocks, especially if the governments have different priorities when deciding on macroeconomic policies.

Demand disturbances (temporary shocks) are the most important factors driving output in the short run in United States, United Kingdom and Norway, although already after two to three years (at the so called business cycle frequencies), supply shocks (permanent shocks) dominate. In Germany, supply shocks play the most important role for output movements at all horizons.

Appendix A: Data sources

All series are seasonally adjusted quarterly data, unless otherwise stated. The series are seasonally adjusted by their respective sources. The periodicity varies and is given for each country. All variables are measured in natural logarithms except for the unemployment rate that is measured in levels. For each country I use total GDP or GNP, except for Norway, where I use non-oil GDP, which accounts for approximately 80 pct. of total GDP.

All countries:
Nominal Oil price: Saudi Arabian Light-34, USD per barrel, fob- (n.s.a.). Prior to 1980, posted prices, thereafter spot prices. Source: OPEC BULLETIN and Statistics Norway

Real Oil Price: Nominal Oil Price converted to each countries national currency and deflated by each countries implicit GDP deflator, except for Norway which uses the consumer price index (as oil prices may be included in the GDP deflator, with approximately 20 pct. of GDP in Norway generated in the oil sector).

United States: 1960Q1-1994Q4
Gross Domestic Product, constant 1991 prices. Source: OECD
Unemployment, civil labour force. Source: OECD
Implicit GDP deflator. Source: OECD

Germany: 1969Q1-1994Q4
Gross Domestic Product, constant 1991 prices. Source: OECD
Unemployment, (West Germany) . Source: OECD
Implicit GDP deflator. Source: OECD
Exchange rate, mth. average DEM/USD, (n.s.a.). Source OECD.

United Kingdom: 1966Q1-1994Q4
Gross Domestic Product, constant 1991 prices. Source: Datastream
Unemployment rate, total labour force. Source: OECD
Implicit GDP deflator. Source: OECD
Exchange rate, mth. average GBP/USD, (n.s.a.). Source OECD.

Norway: 1967Q1-1994Q4
Gross Domestic Product, *mainland Norway* (GDP less petroleum activities and ocean transport) constant 1991 prices. Source: Statistics Norway
Unemployment rate. Source: Statistics Norway
Consumer Price Index. Source: Statistics Norway
Exchange rate, mth. avg. NOK/USD, (n.s.a.). Source OECD.

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