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Do Bivariate SVAR Models with Long-Run Identifying Restrictions Yield Reliable Results? The Case of Germany

by

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Do Bivariate SVAR Models with Long-Run Identifying Restrictions Yield Reliable Results? An Investigation into the Case of Germany

Abstract:

Bivariate SVAR models employing long-run identifying restrictions are often used to investigate the source of business cycle fluctuations. Their advantage is the simplicity in use and interpretation. However, their low dimension may also lead to a failure of the identification procedure, with the result that the identified shocks are a mixture of the 'true' shocks. To investigate this issue, we evaluate for German data the consistency of results from different bivariate SVAR models employing the same long-run identifying restrictions. We find that these models do not offer reliable evidence on the sources of output fluctuations.

Keywords: Business Cycle Fluctuations, Structural Vector Autoregression Models, Long-run Restrictions
JEL classification: E32, C32

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Contents

I. Introduction

In 1989, Blanchard and Quah introduced in their seminal article "The Dynamic Effects of Aggregate Demand and Supply Disturbances" an econometric procedure based on the Structural Vector Autoregression (SVAR) methodology to identify aggregate demand and supply disturbances in a bivariate framework. A key contribution of this article was the introduction of an identification strategy which employed long-run identifying restrictions. Variations of the bivariate Blanchard/Quah procedure proved popular in the literature thereafter. Applications include Bayoumi and Eichengreen (1993) and Whitt (1995), who use this methodology to identify aggregate demand and supply shocks for a sample of countries belonging to the European Union. They proceed to investigate whether there are substantial positive correlations of demand and supply shocks, since such findings would suggest that these countries are good candidates for monetary union. Another application is found in the work by Sterne and Bayoumi (1995) and Bergman (1996). These authors focus on the dynamic responses of the economy to aggregate demand and supply disturbances in order to measure the relative importance of these two types of disturbances for output fluctuations. This line of research is related to earlier work by authors like Nelson and Plosser (1982) and Campbell and Mankiw (1987), who attempt to determine in an univariate framework whether output fluctuations are dominated by permanent innovations or by temporary deviations from a deterministic time trend, which proxies a fairly constant underlying growth rate of output. The latter hypothesis corresponds to the "Keynesian synthesis" view of output fluctuations being the result of the interaction of transitory shocks with a sticky aggregate price level, while the former hypothesis reflects the view of Real Business Cycle

(RBC) models[1], which emphasise the role of supply shocks for output fluctuations at business cycle horizons. Since Quah (1992) has shown that this issue cannot be settled within a univariate framework, it was a logical next step to turn to bivariate models. This line of inquiry was also part of the motivation of the Blanchard and Quah (1989) paper.[2]

In recent years the use of long-run identifying restrictions has also become popular in larger models. A non-exhaustive list of examples include Gali (1992), Clarida and Gali (1994), Fackler and MacMillin (1998) and Astley and Yates (1999). Still, the availability of more elaborate models is no reason to abandon the bivariate framework. After all, the low dimension of bivariate models is sufficient for many purposes and has some advantages of its own, since bivariate models do not require much data input, are simple to implement and produce intuitive results in the sense that these models impose the structure of simple textbook models on the data. However, if the low dimension is liable to lead to misleading inferences, this would be a strong argument to turn to larger models instead. The problem with the low dimension of bivariate models is that even if the assumption is maintained that all shocks buffeting the economy can be classified as belonging either to the class of supply shocks or to demand shocks, which is central to the Blanchard/Quah methodology, there are still many different types of those shocks. For example, the class of supply shocks is likely to comprise productivity and labor supply shocks, while the class of demand shocks comprises foreign and domestic demand shocks. This implies that the identified shocks derived from a bivariate SVAR model have to be viewed as aggregates of a larger number of underlying shocks. This raises the possibility that the iden-

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1 See for instance Long and Plosser (1983).

2 Another application of the Blanchard/Quah methodology is given by Funke (1997), who employs it to estimate supply potential and output gaps in West German manufacturing.

tification scheme may fail to preserve the shock categories, so that the identified shocks commingle the underlying demand and supply disturbances, thereby invalidating their economic interpretation. It is the objective of this paper to investigate the reliability of results from bivariate SVAR models employing long-run identifying restrictions by checking the consistency of results across different models. To this end, different types of bivariate Blanchard/Quah models, which have been employed in the literature, are re-estimated for German data and their consistency is evaluated using the test procedure proposed for this purpose by Faust and Leeper (1997). Moreover, the robustness of the results is investigated with respect to the estimated impulse response functions, variance decompositions and historical decompositions.

The paper is organized as follows. In section 2 the theoretical and empirical foundations of the Blanchard/Quah methodology is discussed. In section 3 the empirical results for a number of bivariate models are presented and their consistency is evaluated. Section 4 contains the conclusion.

II. Identification of Aggregate Demand and Supply Shocks

This section introduces the two standard macroeconomic models often employed to motivate the long-run identifying restriction used in the empirical application of the Blanchard/Quah methodology. In addition to the theoretical foundations of the identifying restrictions, this section also introduces the Blanchard/Quah methodology itself. Furthermore, it discusses potential shortcomings of this approach, and proposes a strategy to test for the robustness of the results. This strategy is implemented in the remainder of this paper. With respect to the theoretical foundations of Blanchard/Quah models, it will become apparent that the two standard macroeconomic models used in this regard share a number of features: in particular, they take both a Keynesian perspective of business cycle fluctuations, since nominal rigidities play a key role in the transmission of the effects of demand shocks. Even though it is rarely emphasized in the literature, the fact that the identifying restrictions are derived from this particular theoretical framework somewhat limits their usefulness for the discussion of the relevant theory explaining the sources of business cycle fluctuations. In this respect, the Keynesian view, which emphasizes the role of aggregate demand shocks for business cycle fluctuations, is often contrasted with the Real Business Cycle (RBC) perspective, which explains output fluctuations as a function of supply disturbances. Since Blanchard/Quah models provide an empirical model of output as a function of both type of shocks, these models are often employed to shed some light on their relative importance for output fluctuations. However, while the identifying restrictions central to the Blanchard/Quah methodology can be derived from Keynesian models, it is not clear whether RBC models can be expressed in the bivariate model form discussed below. In particular, typical RBC types of models do not allow for demand shocks to have short-run real effects on output; instead, demand shocks induce an equiproportional change of the corresponding nominal variables. Since a bivariate model containing output and the unemployment rate, for instance, does not contain nominal variables, it is not clear from the RBC perspective how one can identify a demand shock in this set-up. This suggests that Blanchard/Quah models are less well suited to discriminate between the two competing theories than is often assumed, at least implicitly, in the literature, since they are compatible with only one of the two theories. As Cochrane puts it, "shock accounting does not really say that much about the plausibility of broad classes of economic models. They say even less about modeling *methodologies*, which is really at stake. I don't think Prescott would feel vindicated if the profession converged on the view that technology shocks account for 80% (or all) of output fluctuations, yet do so through fluctuations in the aggregate supply curve of an IS-LM model."[3] Accordingly, some care is needed when interpreting the results.

2.1. Identification of Supply and Demand Shocks in an Output and Unemployment Model

To provide for the theoretical underpinnings of the first set of bivariate models, comprised of the growth rate of output as the first variable and the unemployment or capacity utilization rate as the second variable, an open economy model with nominal rigidities in wage and price formation is presented here. This model has been proposed by Hansen (1995) and is an open economy variant of the theoretical model employed by Blanchard and Quah to motivate their empirical set-up. Since the open economy aspect is of some relevance for a small open economy like that of Germany, this section shows how domestic and foreign domestic shocks are accounted for in the empirical framework below. In addition to these demand disturbances a supply shock is introduced, which is related to technological innovations driving productivity growth.

As has become common in most modern macroeconomic models, the goods market of the model considered here is characterized by monopolistic competition. There are two goods in the economy, one foreign and one domestically produced, which are assumed to be perfect substitutes. The demand for domestic goods is given by

$$(1) \qquad Y_t^d = \left(\frac{P_t^*}{P_t} \right)^{\alpha} D_t \ , \alpha \geq 1,$$

where P and P^* are the prices of domestic and foreign goods, D represents additional, exogenous, real demand factors, and α is the price elasticity. Subscript t stands for the time period.

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[3] Cochrane (1994), p. 5.

The supply side of the economy is characterized by a production technology exhibiting decreasing returns to labor, L, which is the only factor.[4] When a measure of productivity, A, is allowed for, the supply of domestic goods becomes

(2) $$Y_t^s = \frac{A_t}{g}(L_t)^g \quad , g < 1 \ .$$

It can be shown that these two equations lead to the following profit maximization problem,

$$\max_P P_t\left(\frac{P_t^*}{P_t}\right)^a D_t - W_t\left[\frac{g}{A_t}\left(\frac{P_t^*}{P_t}\right)^a D_t\right]^{\frac{1}{g}},$$

where the square brackets contain the equilibrium quantity of labor. Solving the monopolist's maximization problem for a given the wage rate W yields the price setting rule given by

$$P_t = \left[\frac{a}{a-1} g^{\frac{1}{g}-1} W_t P_t^{*(\frac{a}{g}-a)} D_t^{\frac{1}{g}-1} A_t^{\frac{-1}{g}}\right]^{-\frac{a}{g}-1+a} \ .$$

In a logarithmic form this expression becomes,

(3) $$p_t = b_0 + b_1 w_t + b_2 p_t^* + b_3 d_t + b_4 a_t$$

where lower case letters denote logarithms. Taking logarithms of the optimal labor quantity and replacing p_t by the right hand side of equation (3) yields in a next step the labor demand equation

(4) $$l_t = d_0 + d_1(w_t - p_t^*) + d_2 d_t + d_3 a_t ,$$

---

[4] This model abstracts from imported goods like raw materials serving as production factors. Hence the terms of trade represent a pure demand factor.

where

$$b_1 = \left(\frac{a}{g} + 1 - a\right)^{-1},\ b_0 = \ln\left(\frac{a}{a-1} g^{\frac{1}{g}-1}\right) b_1,\ b_2 = a\left(\frac{1}{g} - 1\right) b_1,\ b_3 = \left(\frac{1}{g} - 1\right) b_1,\ b_4 = \frac{-1}{g} b_1$$

and

$$d_0 = \frac{1}{g}\ln g - \frac{a}{g} b_0,\quad d_1 = \frac{-a}{g} b_1,\quad d_2 = \frac{1}{g}(1 - a b_3),\quad d_3 = \frac{-1}{g}(1 + a b_4)\,.$$

Up to now, the wage level W has been treated as given in the profit maximization problem. Regarding the determination of wages, it is assumed that, as in Fischer (1977), the wage setters will set wages before the period begins, aiming at a given employment level, l^*. The assumption of predetermined wages introduces some nominal rigidity into the model, which ensures that demand disturbances can have real effects in the short-run. More specifically, the fact that wages are predetermined prevents the agents in the model from offsetting the effects of a demand disturbance through an immediate adjustment of wages and prices that would restore initial demand conditions. At the same time, the assumption that wage setters pursue the exogenous employment goal l^* ensures that neutrality holds in the long-run, since employment returns to the employment level l^* as soon as the wage setters have the opportunity to respond to the shock. Since it is assumed that the exogenous variables in the model follow stochastic processes, wage setters have to form expectations about these variables when determining w. Accounting for this specification of the wage setting process, the labor demand equation (4) becomes:

(5) $$l_t^* = d_0 + d_1(w_t - E_{t-1}p_t^*) + d_2 E_{t-1} d_t + d_3 E_{t-1}\, a_t\,.$$

The stochastic process of the exogenous variables has still to be specified; in this context productivity, foreign prices and the real demand factors are all assumed to follow a random walk process:

(6) $$a_t = a_{t-1} + e_{a,,t}\,,$$

$$(7) \qquad p_t^* = p_{t-1}^* + e_{p^*,t}\, a_t ,$$

$$(8) \qquad d_t = d_{t-1} + e_{d,t} ,$$

so that $E_{t-1}\, a_t = a_{t-1}$, $E_{t-1}p_t^* = p_{t-1}^*$ and $E_{t-1}d_t = d_{t-1}$ hold. The terms $e_{a,t}$, $e_{p^*,t}$ and $e_{d,t}$ are interpreted as supply shocks, foreign demand shocks and domestic demand shocks respectively, and are supposed to be uncorrelated with each other, to be stationary and have each a mean of zero. These shocks are central to the SVAR approach proposed by Blanchard and Quah, who identify them in their empirical model via theoretically motivated predictions about their long-run effects on output and unemployment.

The unemployment rate is defined as $u_t = n_t - l_t$, where n_t is the logarithm of the labor force.[5] The variable for the employment goal l_t^* should coincide with the labor force variable n_t in a full employment environment, but it is hard to see that wage setters in Germany have actually have aimed at full employment in this sense during the past two decades. Rather, there appears to be an underlying trend in the unemployment rate targeted by employers and unions in the wage bargaining process, which is denoted in the following by u_t^*. Accordingly the relevant employment goal for Germany is probably more accurately described as $l_t^* = n_t - u_t^*$. Using this definition of the employment target together with the equations (4) to (8), it is possible to express the unemployment rate as a function of the stochastic shocks hitting the system:

$$
\begin{aligned}
& u_t = n_t - l_t = u_t^* + (l_t^* - l_t) \\
(9) \qquad & \quad = u_t^* + d_1(p_t^* - E_{t-1}p_t^*) - d_2(d_t - E_{t-1}d_t) - d_3(a_t - E_{t-1}a_t) \\
& \quad = u_t^* + d_1 e_{p^*,t} - d_2 e_{d,t} - d_3 e_{a\ \cdot,t}
\end{aligned}
$$

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[5] Since n_t and l_t are in logarithms, the relationship determining unemployment is an approximation.

Analogously, expressing real output as given by (2) in logarithms, one obtains

$$
\begin{aligned}
& y_t = -\ln g + a_t + g l_t \\
(10) \qquad & \quad = -\ln g + a_t + g[-d_1(p_t^* - E_{t-1}p_t^*) + d_2(d_t - E_{t-1}d_t) + d_3(a_t - E_{t-1}a_t) + l_t^*],
\end{aligned}
$$

implying

$$(11) \qquad \Delta y_t = e_{a,t} + g(-d_1\Delta e_{p*,t} + d_2\Delta e_{d,t}) + g d_3 \Delta e_{a,t} - g\Delta u_t^* \,.$$

The empirical model corresponding to this theoretical framework presented below is based on the equations (9) and (11). Two features of these equations will be central for the specification of the empirical model. First, according to (9) the unemployment rate u is a stationary variable, once one controls for the underlying trend given by u^*. In other words, none of the three shocks considered here has a lasting effect on the unemployment rate. The stationarity property of the transformed unemployment rate $u - u^*$ will turn out to be an important criterion for the modeling of the underlying trend given by u^*. Second, with respect to the output equation, it is apparent that the productivity shock $e_{a,t}$ has a permanent effect on the level of output, but the two demand shocks $e_{p*,t}$ and $e_{d,t}$ have only a transitory effect on this variable.[6] This latter observation will provide an important identifying restriction, since it implies that one can restrict the long-run effect of the demand shock on the level of output to zero. It also shows that the domestic and the foreign demand shock are identical in this respect; thus, one can define an aggregate demand shock encompassing these two shocks

[6] This is apparent once one notices that a productivity shock leads to a one period change in the growth rate of output, which changes the level of output permanently; in contrast, for instance a positive shock to domestic demand conditions given by $e_{d,t}$ induces initially a one period acceleration of output growth, but in the next period, when the shock has passed, output growth decelerates by the same amount, so that there is no long-run effect on the level of output.

which also shares this property. Hence, the empirical model will aim to identify an aggregate supply and an aggregate demand shock, which are distinguished by their differing long-run implications for the output series.

This model can easily be reformulated in terms of real output growth and the capacity utilization rate.[7] All that is required is to modify equation (9) by using Okun's law, the empirical relation which states that a reduction in the unemployment rate of 1 percentage point is associated with an output increase usually in the range of $2^1/_2 - 3$ per cent. According to this relationship a deviation of unemployment from its underlying trend implies that actual output also deviates from potential output:

$$u_t - u_t^* = h(y^p - y_t),$$

where $y^p - y_t$ denotes the output gap and η is the Okun's law coefficient. Since the output gap and the capacity utilization rate c_t are closely linked via the production technology, one can rewrite this relationship:

$$u_t - u_t^* = hc_t \,.$$

Substituting this result in (9), and dropping the last term in (11), one obtains

(12) $c_t = u_1 e_{p*,t} - u_2 e_{d,t} - u_3 e_{a,t}$

(13) $Dy_t = e_{a,t} + g(-d_1 De_{p*,t} + d_2 De_{d,t}) + gd_3 De_{a,t}$

where $u_i = d_i/\eta$. Hence the results from the discussion of the model with the unemployment rate are also applicable to a model with the capacity utilization rate as the second variable.

2.2. Identification of Supply and Demand Shocks in a Model with Output and Prices

A second class of models within the Blanchard/Quah framework uses prices instead of unemployment or the capacity utilization rate as the second variable. This approach has been pioneered by Bayoumi and Eichengreen (1993) and has become fairly popular, presumably because the intuition behind this approach can be illustrated with the familiar aggregate demand and aggregate supply (AD-AS) diagram. Even though the AD-AS analysis only provides insights into the comparative static properties of the model and treats the dynamic adjustment process in a rather rudimentary fashion, it still yields precise long-run predictions of the effects of aggregate demand and supply shocks on output and prices. Hence this approach can provide long-run identifying restrictions suitable for the Blanchard/Quah methodology. The AD-AS diagram contains an aggregate demand curve (AD), a long-run aggregate supply curve (LRAS) and a short-run aggregate supply curve (SRAS). The aggregate demand curve is downward sloping in the price output plane, since lower prices induce a rise in real money balances, which boosts demand. The short-run aggregate supply curve is upward sloping, reflecting the assumption that wages are sticky; consequently, higher prices imply lower real wages, which increases labor demand.[8] The long-run supply curve is assumed to be vertical, since nominal wages adjust to changes in prices in the long run, so real wages return to their equilibrium value.[9]

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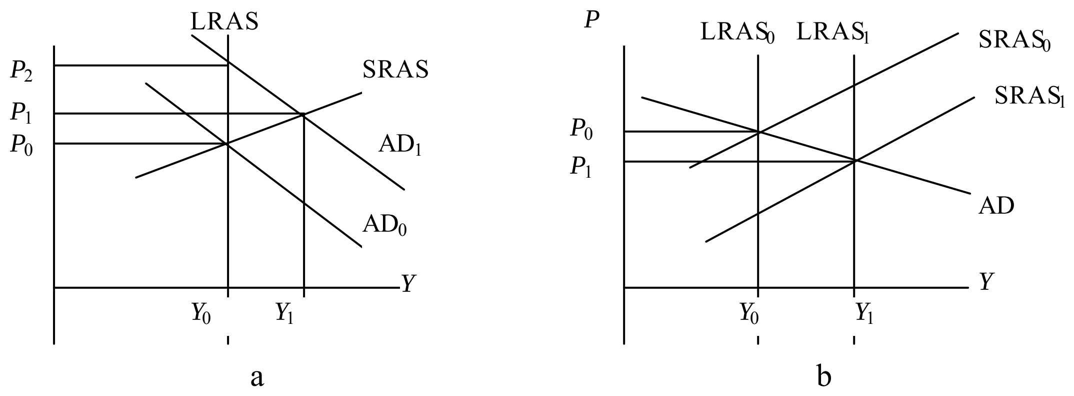
[7] Quah (1995, p.248) emphasizes: "Next, BQ assumed unemployment U to be stationary. But their focus was *not* on unemployment itself. As emphasized in Quah (1992), any other series would do provided it is stationary and has dynamic interactions with Y."

[8] As in the model discussed in the preceding section, the assumption of temporarily sticky nominal wages is again crucial to introduce short-run real effects of demand shocks.

[9] In contrast to the model presented in the preceding section, the model discussed here is a closed economy model. However, this model can be extended in a straightforward way to include the exchange rate and trade. This is not pursued here, since the results relevant for the empirical analysis extend to the open-economy version, just as was the case in the preceding section.

Figure 1: The AD-AS model. (a) Demand disturbance. (b) Supply disturbance.



The effects of an aggregate demand and a supply shock are depicted in Figure 1. The left hand panel shows that the initial effect of a positive shock to aggregate demand is to raise both output and prices (from Y_0 to Y_1 and P_0 to P_1). As the aggregate supply curve becomes more vertical over time, the economy gradually returns to the initial level of output while the price level continues to rise to a permanently higher level (from Y_1 back to Y_0 and from P_1 to P_2). So in the long-run a demand shock has no long-run effect on output, but changes the price level permanently.

The effects of a supply shock are shown in the right-hand panel of Figure 1. A positive supply shock, such as a reduction in the price of raw materials or a technological innovation, shifts both the short-run supply curve (SRAS) and the long-run supply curve (LRAS) outward. As is apparent from panel (b), the initial effect of this shock is to raise output and reduce prices. As the supply curve becomes increasingly vertical over time, the increase in output and the reduction in prices remain. Hence, unlike demand shocks, supply shocks result in permanent changes in output.

This model yields the same identifying restriction as the model considered in the preceding section. In particular, in both models the different long-run implications of demand and supply shocks on output allow it to discriminate between these two shocks. Since the models share the same underlying structure in form of a vertical long-run supply curve and nominal rigidity leading to short-run real effects of demand shocks, this is to be expected. Another important result of the model considered here is that demand and supply shocks have different effects on prices; positive demand shocks raise prices while positive supply shocks reduce them. This yields an overidentifying restriction, which will turn out useful in the empirical section to verify whether the supply and demand shocks have been correctly identified.

2.3 The Blanchard/Quah Methodology

The previous two sections have introduced two theoretical models, which both imply that aggregate demand shocks, in contrast to aggregate supply shocks, have no long-run effect on the level of output. Blanchard and Quah have shown how such a long-run restriction can be imposed on a bivariate model consisting of output growth and a second variable, which represents in this paper either the unemployment rate controlled for the underlying trend, the capacity utilization rate or a differenced price series. An important requirement for the second variable is that it be stationary. In the following, output growth is denoted as Δy_t, while the second variable is denoted as w_t. For a more compact notation the vector X_t is introduced, which is defined here as

$$X_t = \begin{pmatrix} \Delta y_t \\ w_t \end{pmatrix}.$$

The vector

$$\boldsymbol{e}_t = \begin{pmatrix} \boldsymbol{e}_{s,t} \\ \boldsymbol{e}_{d,t} \end{pmatrix}$$

contains the two structural shocks, where $\boldsymbol{e}_{s,t}$ and $\boldsymbol{e}_{d,t}$ denote the aggregate supply and aggregate demand shock respectively. A convenient starting point to illustrate the Blanchard/Quah methodology is the vector moving average representation of the theoretical model. Using the lag operator L, this model can be written as

(14) $$\begin{bmatrix} \Delta y_t \\ w_t \end{bmatrix} = \sum_{i=0}^{\infty} L^i \begin{bmatrix} \theta_{11,i} & \theta_{12,i} \\ \theta_{21,i} & \theta_{22,i} \end{bmatrix} \begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{d,t} \end{bmatrix},$$

or in a more compact form

(15) $$X_t = \theta_0 \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \theta_3 \varepsilon_{t-3} \ldots = \sum_{i=0}^{\infty} L^i \theta_i \varepsilon_t ,$$

where θ contains the four elements of the second matrix in (14) and $\theta(L) = \theta_0 + \theta_1 L + \theta_2 L^2 + \ldots$ denotes a matrix polynomial in the lag operator. The matrices θ_i represent the impulse response functions of the shocks to the elements of X_t. Since output enters this model in differenced form, the identifying restriction that the demand shock has no long-run effect on the level of output is equivalent to the restriction that the cumulative effect of this disturbance on the change of output (Δy_t) is zero. Formally this restriction can be imposed on the model by requiring that

(16) $$\sum_{i=0}^{\infty} \theta_{12,i} = 0 .$$

To estimate the structural model defined by equation (15) together with the restriction given by (16), as a first step a reduced form vector autoregression (VAR) system is estimated, where each element of X_t is regressed on n lagged values of the elements of X. Using A to denote the estimated coefficients, this yields:

(17) $$X_t = A_1 X_{t-1} + A_2 X_{t-2} + \ldots + A_n X_{t-n} + e_t ,$$

or

(18) $$X_t = A(L) X_{t-1} + e_t ,$$

where *e* represents the residuals from the reduced form equations estimated here. In order to make equation (17) comparable with (15), it is transformed in the following step into its moving average form:

$$
\begin{aligned}
& X_t = (I - A(L))^{-1} e_t \\
(19) \qquad & = \left(I + A(L) + A(L)^2 + \ldots\right) e_t \\
& = e_t + \Phi_1 e_{t-1} + \Phi_2 e_{t-2} + \Phi_3 e_{t-3} + \ldots \ .
\end{aligned}
$$

Comparison of equation (19) with (15) shows that the reduced form disturbances and the structural shocks are related by

$$
(20) \qquad q_0 \mathbf{e}_t = e_t \ ,
$$

consequently $q_i = \Phi_i q_0$ holds for all i = 1,2… . This implies that once one has determined with the help of identifying restrictions the matrix q_0, it is possible to recover the structural shocks ε_t from the estimated reduced form disturbances e_t and in addition the structural impulse responses q_i from the estimated reduced form VMA coefficients Φ_i. Since the matrix q_0 has four elements, four identifying restrictions are needed to construct an empirical estimate of this matrix. Two of those are simple normalizations, which define the variance of the structural shocks $\mathbf{e}_{s,t}$ and $\mathbf{e}_{d,t}$. A third restriction comes from the assumption that the aggregate demand and supply shocks are orthogonal. The significance of this assumption will be discussed further below. The fourth identifying restriction is the long-run restriction given by (16), which implies for the empirical model:

$$
(21) \qquad \sum_{i=0}^{\infty} L^i \begin{bmatrix} \Phi_{11,i} & \Phi_{12,i} \\ \Phi_{21,i} & \Phi_{22,i} \end{bmatrix} \begin{bmatrix} q_{0,11} & q_{0,12} \\ q_{0,21} & q_{0,22} \end{bmatrix} = \begin{bmatrix} \cdot & 0 \\ \cdot & \cdot \end{bmatrix} .
$$

In summary, the Blanchard/Quah procedure works as follows. In the first step a VAR system is estimated for *X*, which is then inverted to obtain the moving average representation. In a next step the matrix q_0 is constructed using the identifying restrictions outlined here. This matrix is subsequently used to compute the impulse response functions given by $q_i = \Phi_i q_0$ for i = 1,2... . At this stage it is also possible to retrieve the aggregate demand and supply shocks from the estimated reduced form residuals, since $e_t = q_0^{-1} e_t$ holds. Finally, having obtained estimates of the structural parameters q_i and e_t, using (14) one can express output as a function of aggregate demand and supply shocks, which will prove useful for the analysis of the relative importance of these shocks in accounting for output fluctuations.

In general, the Blanchard/Quah methodology offers three tools to shed light on the sources of business cycle fluctuation. First, with the help of the impulse response functions it is possible to investigate the dynamic response of output to aggregate demand and supply disturbances. Moreover, as has been pointed out above, the price response to the structural shocks provides an overidentifying restriction, since the theoretical model predicts that prices move in the same direction as output in response to a demand shock and in the opposite direction in response to a supply shock. A second tool is the forecast error variance decomposition (FEVD), which shows for different forecast horizons the contribution of the two structural shocks to the forecast error variance of output. More specifically, the k quarter-ahead forecast error is defined as the difference between the actual value of output and its forecast based on the model given by (14) as of k quarters earlier. As is apparent from (14), this forecast error is due to aggregate demand and supply shocks hitting the economy in the last k quarters. The forecast error variance decomposition gives the percentage of variance of the k-quarter ahead forecast error accounted for by each of the two shocks. In other words, the variance decompositions shows the relative contribution of these two shocks to output fluctuations. The third tool is a historical decomposition of the output series. As has become clear in the preceding discussion, the Blanchard/Quah methodology allows it to decompose the output series into a supply and a demand component. The demand component represents the time path of output that would have obtained in the absence of supply disturbances. Similarly, by setting the aggregate demand shock to zero for the entire sample period one obtains a time series of the supply component. The historical decomposition of the output series in its supply and demand component can be used as an informal tool to investigate the role of these two components in accounting for important episodes in the business cycle chronology, such as their contributions to recessions, for instance.[10]

2.4 Why Bivariate Systems are Potentially Unreliable

It is a major advantage of the models discussed here that they impose the structure of simple textbook models on the data and thereby provide for an intuitive interpretation of the results. Also, by focusing on the class of aggregate supply and demand shocks they capture the two fundamental shocks underlying most of the applied business cycle research work. However, even though the Blanchard/Quah type of models are attractive on these counts, they also have been sharply criticized in the literature. Since a comprehensive review of all the issues raised is beyond the scope of this paper, this section will focus on a point that is particularly relevant for the analysis of the sources of business cycle fluctuations.[11] Here it is shown that the focus on only two structural shocks also entails a major

[10] This measure can also be modified so that it corresponds more closely to the concept of the variance decomposition, providing a plot of the forecast error attributable to each disturbance for different forecast horizons. Assuming, for instance, a forecast horizon of two years, the historical forecast error decomposition shows for a given point in time the cumulative effect of supply (demand) shocks occurring in the past two years on output. This modification of the historical decomposition is helpful to focus the analysis on a time horizon relevant for applied business cycle analysis. However, to preserve space these results are not presented here. But they are available from the authors upon request.

[11] For a fundamental critic of the VAR approach in general, see for example Rudebusch (1998). For a critical discussion of the Blanchard and Quah (1989) approach see for instance Lippi and Reichlin (1993) and Faust and Leeper (1997).

disadvantage, because this may lead to unreliable inferences about the sources of business cycle fluctuations.

The problem with the low-dimensional system proposed by Blanchard and Quah is that even though it is in accordance with simple textbook version of the macroeconomy, the system's low dimension proves to be highly restrictive when seen in the context of the more elaborate theoretical models where there are more than two shocks. Blanchard and Quah recognized this potential weakness and derived the conditions under which this approach may still lead to meaningful results. The starting point of their analysis is the assumption that the economy is driven by m shocks, but each shock is either a supply or a demand shock. This is still quite restrictive, because it implies that all shocks can be classified as belonging either to the one group or to the other. It also implies that all supply disturbances have permanent output effects, while all demand disturbances have only a transitory effect on output. The two authors demonstrate in their next step that this additional assumption is not sufficient to prevent the commingling of shocks, i.e. the identified shocks are likely to be a mixture of both underlying shocks. In their final step, they proceed to prove that the commingling of shocks is avoided when the dynamic relationship between output and unemployment remains the same across different supply disturbances, with the same result holding for all demand disturbances. The authors note that this is highly plausible for demand disturbances, but not for supply disturbances. To illustrate this point for supply shocks, a productivity and a labor supply shock are considered. Beginning with the former, a rise in productivity is likely to be associated with a permanent increase of output and a temporary fall of unemployment. In contrast, an exogenous increase in labor supply increases output and employment too, but unemployment will not fall but rise temporarily if employment rises initially by less than the labor force. This example shows that these two shocks have different effects on the relation between output and unemployment, since both variables move in either the same or opposite directions, depending on the specific supply shock hitting the economy. It follows that the presence of several large productivity and labor supply shocks is likely to lead to a commingling of shocks in the empirical model discussed here. Blanchard and Quah conclude that their bivariate model is likely to work well only under the additional assumption that the economy is subject to only one source of supply disturbances. Nevertheless, many demand shocks may be present. In this case, the effect of the 'demand shock' identified by the empirical model represents the average of the dynamic effects of the different 'true' demand shocks.

This analysis has recently been extended by Faust and Leeper (1997). In addition to the issue of the commingling of shocks, Faust and Leeper ask under what conditions the timing of shocks will not be distorted. They point out, for instance, that even when the identified aggregate demand shock involves only the 'true' demand shocks, the SVAR identification procedure may still fail to preserve the timing of the shocks in the sense that the dynamic response of the economy to any particular demand shock will differ from the estimated impulse response to the identified aggregate demand shock. To put it differently, since the average response of output to demand disturbances is not particular informative for a number of purposes, it is well worth asking under what conditions the estimated output response corresponds exactly to the effects of the 'true' demand shocks.[12] Faust and Leeper (1997, p. 349) show that preserving both the categories of the shocks and the timing of the responses requires "that each underlying shock of a given type affects the economy in the same way up to a scale factor." The intuition behind this result is simple: Since the empirical analysis

[12] For instance, the estimated output response to an aggregate demand response is of little help when the effects of a foreign demand shock are of interest. The problem is that under the conditions outlined by Blanchard and Quah to avoid the commingling of shocks, the estimated aggregated demand response represents an average of the output response to diverse demand shocks and there is no way of disentangling the response of output to the foreign demand shock, which is of interest here.

yields only one output impulse response function to a demand disturbance, this one demand response can have preserved the timing of the different ‘true’ demand disturbances only if those shocks all affect output in essentially the same way.[13] The two authors point out that this is implausible in most cases. However, in the simple model presented in section 2.2 this condition actually holds for the foreign and domestic demand shock considered there. As is apparent from the equations (9) and (11), the effect of a foreign demand shock on output is $-gd_1$ and on unemployment it is d_1, while the respective effects of a domestic demand shock are gd_2 and $-d_2$. Consequently, their effect on the economy differs only by a scale factor $-\frac{d_1}{d_2}$. Still, for models which specify the dynamics in a more elaborate way this restriction is likely to be violated.

The problem with the low dimension of the bivariate models becomes even more serious when one does not believe that there are only two groups of fundamental shocks. A shock to the nominal exchange rate for example has effects both on the supply and demand side of the economy, therefore this shock is not easily classified as belonging only to one or to the other group, but should be modeled as a distinct shock. Seen from this standpoint of view, the orthogonality restriction, which is based on the notion that there are only two fundamental sources of shocks, becomes rather difficult to justify.[14] Given that it is impossible to identify three structural shocks using a bivariate model, this would suggest to turn to larger systems.

However, before abandoning the bivariate systems, one should establish whether these conceptual problems are actually empirically relevant. For this purpose, Faust and Leeper have suggested a strategy for dealing with this prob-

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[13] The scaling does not affect the shape of the impulse response function.

[14] If there are indeed three types of fundamental shocks, the two structural shocks identified in the bivariate framework are likely to represent linear combinations of these three shocks and there is no reason to expect them to be orthogonal.

lem. In particular they suggest checking for consistency of results across various small models. The remainder of this paper will follow this route and investigate the robustness of results over the different Blanchard/Quah type of models that have been applied to German data in the literature. Consistency will be evaluated over several dimensions. On the one hand the results for the output impulse response functions will be compared. On the other hand a specific procedure proposed by Faust and Leeper will be followed, who check whether the identified supply shocks of one model are uncorrelated with the demand shocks of another model. If the orthogonality assumption holds and commingling of shocks is empirically not an issue, then one can expect the estimated supply shocks to be uncorrelated asymptotically with the estimated demand shocks. However, if the supply shock from one model is correlated with the demand shock from another model, then this provides clear evidence that one or both of the models have commingled the 'true' supply and demand shocks. This becomes clear once one recalls that the Blanchard/Quah methodology presupposes that all shocks buffeting the economy can be classified as belonging either to the class of aggregate supply shocks or to aggregate demand shocks. In addition, these groups of underlying shocks are assumed to be orthogonal to each other. Accordingly, if the estimated supply shock of one model correlates with the demand shock of another model, this implies that either one or both of these two assumptions does not hold at least for one of the models, thereby invalidating the identification procedure. Moreover, consistency is also checked for the forecast error variance decomposition and the historical decomposition of the output series since these two measures are of particular interest for the question of the sources of business cycle fluctuations.

III. Empirical Results

This section revisits a number of the Blanchard/Quah types of models proposed in the literature and attempts to evaluate their robustness for German data. The first candidate is the original Blanchard and Quah (1989) model with output growth and unemployment. A related model is the one with output growth and capacity utilization, which has been analyzed by Lütkepohl and Breitung (1996). In both models the gross domestic product (GDP) is used as a proxy for the output variable. A second class of models consists of output growth and a differenced price series. The seminal paper by Bayoumi and Eichengreen (1993) uses real GDP for output and the GDP deflator as the price series. Bayoumi (1992) and Sterne and Bayoumi (1995) employ a similar set-up. Bergman (1996) uses the consumer price index (CPI) instead of the GDP deflator. Whitt (1995) and Funke (1997) choose industrial production and producer prices to measure output and prices. Taken together, this provides for a broad range of models, which all employ the Blanchard/Quah methodology but differ on the choice of variables.

Before proceeding with the SVAR analysis, a closer look at stationarity properties of the proposed time series is warranted. To conform with the theoretical model presented in section 2 the output variable has to be nonstationary, as supply shocks have permanent effects on the level of real activity, while the second variable in the system is supposed to be stationary.[15] In a pre-testing exercise, univariate unit root tests are employed to check whether these properties hold for the time series considered here. In addition, possible co-integration between output and the price level is tested. Since both variables enter the bivariate systems in differenced form, this implicitly implies that no co-integra-

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[15] In this context Quah (1995, p. 249) points out: "If *Y* were not difference stationary, the entire exercise has no meaning (why try to find a *permanent* component in something that is already stationary?). (3) If *U* were not stationary, the researcher should turn to some other variable that is."

tion relationship is supposed to be present. Moreover, the absence of a co-integration relationship between the level variables can also be motivated from a theoretical standpoint, since the neutrality proposition underlying the theoretical model implies that the output level is determined independent from the price level in the long-run.[16] Finally, the stability of the reduced form VAR equations has to be confirmed and the residuals must conform to the white noise property.

3.1 Data and Data Properties

To avoid complications arising from the German unification, quarterly data for West Germany are used. The sample period begins in 1962:1 and ends in 1998:4, when a number of statistics ceased to be available. Details are given in Table 1. A plot of the time series in levels and in differences is given in Figure 1A in the appendix.

Table 1: The data

Series	Description	Source	Datastream Code
Y	Real GDP West Germany; SA (WG)	Deutsche Bundesbank	WGGDP...D
-	Nominal GDP, SA (WG)	Deutsche Bundesbank	WGGDP...B
P	Implicit GDP deflator: ratio of nominal and real GDP		
IP	Industrial Production, Volume Index, SA (WG)	Deutsche Bundesbank	WGINPRODG
PPI	Producer Price Index - Industrial Products (WG)[a]	Statistisches Bundesamt	WGPRODPRF
CPI	Consumer Price Index, SA (WG)	Deutsche Bundesbank	WGCP....E
CAP	Capacity Utilization, Manufacturing, SA (WG)	Ifo Institute	BDIFOCAPE
u	Unemployment Rate, SA (WG)	Deutsche Bundesbank	WGTOTUN%E

[a]This series has been seasonally adjusted with the help of Census X11(m). Time series denoted with SA have been seasonally adjusted by the Bundesbank.

[16] See also Fisher and Seater (1993) for a detailed discussion of this point.

In the following, all level variables are in logarithms, with the exception of the unemployment rate.[17] Regarding the differenced series, the growth rates of the variables real GDP (*dy*) and industrial production (*dip*) have been calculated as the first difference of the logarithm of the respective level series. The same transformation is applied to the price level series to obtain the inflation rates based on the GDP deflator (*dp*), the producer price index (*dppi*) and the consumer price index (*dcpi*). The letter *d* denotes differencing.

In table 2, the results of the unit root test are reported. Three type of tests have been computed. The tests proposed by Perron (1997) and Elliott et al. (1996) are variants of the familiar augmented Dickey Fuller (ADF) tests with the null hypothesis of non-stationarity. The Perron (1997) test considers as alternative

Table 2: Unit root tests

Variable	Levels			First differences			Order of Integration
	Perron (1997)	DFGLS	KPSS	Perron (1997)	DFGLS	KPSS	
y	−5.28 (c,t)	−1.16 (c,t)	0.28 (τ)**	−5.27 (c,t)*	−3.31 (c)**	0.34 (μ)	I(1)
p	−3.77 (c,t)	−1.08 (c,t)	0.39 (τ)**	−5.21 (c,t)*	−1.61 (c)	0.64 (μ)*	I(1)/Break
ip	−4.37 (c,t)	−1.22 (c,t)	0.26 (τ)**	−5.50 (c,t)*	−4.01 (c)**	0.26 (μ)	I(1)
ppi	−3.95 (c,t)	−1.17 (c,t)	0.32 (τ)**	−4.23 (c,t)	−3.32 (c)**	0.33 (μ)	I(1)
cpi	−4.92 (c,t)	−1.81 (c,t)	0.33 (τ)**	−4.09 (c,t)	−1.89 (c)	0.36 (μ)	I(2)
cap	−6.10 (c,t)*	−2.57 (c)*	0.20 (μ)				I(0)
u	−4.40 (c,t)	−2.73 (c,t)	0.12 (τ)				I(1)

Asteriks denote: * = significant at 5% level; ** = significant at 1% level. Perron (1997) denotes the unit root test statistic proposed by Perron (1997) allowing for a shift in the slope of the time trend and a shift of the intercept at an unknown date (in case of the differenced series only the latter is allowed for). The null hypothesis is a non-stationary behavior of the time series. The timing of the break is determined by selecting the date which minimizes the t-value of the lagged endogenous variable in the regression. DFGLS denotes a modified Dickey-Fuller *t* test statistic proposed by Elliot et al. (1996). The terms in the bracket indicate the inclusion of a constant and a trend respectively. This statistic also tests the null of non-stationary behavior. The lag length is chosen on the basis of the Pantula formula (AIC+2). KPSS denotes the test statistic proposed by Kwiatkowski et al. (1992), which tests the null of stationarity around a level (*m*) or trend-stationarity (*t*). A lag truncation parameter of 8 is used.

[17] Logarithms are denoted in the following by small letters.

hypothesis stationary fluctuations around a deterministic trend function and makes allowances for possible changes in its intercept or its slope. The modification of the Dickey-Fuller test (DFGLS) statistic suggested by Elliott et al. is intended to improve the power of the conventional ADF test. The third test is a unit root test with the null of stationarity, which has been proposed by Kwiatkowski et al. (1992).

For the output variables *y* and *ip,* all tests agree that these are best construed as I(1) variables. Regarding the differenced deflator series, the Perron tests provides evidence that there has been a break in the time series, suggesting that the intercept shifted upwards in the late sixties. It also points towards a slight downwards trend in the series. The break is probably responsible for the rejection of stationarity indicated by the two other tests. To obtain a stationary inflation series on the basis of the GDP deflator, the series *dp* is adjusted for the break and the time trend. The adjusted time series is plotted together with the differenced deflator series in Figure 1A. Regarding the inflation series on the basis of the producer price index, the Perron test fails to reject the null of nonstationarity, but the DFGLS test statistic clearly rejects this hypothesis and the KPSS test cannot reject the null of stationarity at conventional significance levels. Hence the stationarity assumption is maintained for this series in the remainder of this paper. For the differenced *cpi* series the Perron and the DFGLS test point to a degree of integration of order two of the consumer price index, while the KPSS test rejects the null of stationarity at the ten percent significance level, but not at the five percent level. On balance the consumer price level appears to be I(2), not I(1). For this reason the model proposed by Bergman consisting of output growth and *cpi* inflation is not further considered in the remainder of this paper, as this inflation variable is unlikely to be stationary as required by the Blanchard/Quah methodology.[18] The capacity utilization rate, which is based on survey data, is clearly stationary. For the unemployment rate, however, this is not the case, even if one allows for a deterministic trend. To obtain a stationary measure of cyclical unemployment to be used in the empirical analysis below, a band-pass filter is used to detrend the unemployment series.[19] As Baxter and King (1995) show, this procedure ensures the stationarity property of the trend deviation. The cyclical unemployment rate is denoted *u_cyc*.

Next, the co-integration rank of the systems specified in levels is investigated using the maximum likelihood procedure suggested by Johansen (1988, 1991).[20] Table 3 reports the values of the l-trace statistic testing the null hypothe-

Table 3: Co-integration statistics

Bivariate models	H_0: *rank* r *equals*	
	0	*1*
y, u_cyc	35.05**	8.29
y, p	29.45*	9.61
ip, cap	61.95**	8.85
ip, ppi	19.86	6.10
Critical values 5% (1%)	25.87 (31.15)	12.52 (16.56)

Asteriks denote: * = significant at 5% level; ** = significant at 1% level. A trend is allowed for in the co-integration relationship. Critical values for the trace statistic are taken from McKinnon (1999).

18 Differencing the *cpi* series twice to obtain a stationary series is not an option here, as estimating a Blanchard/Quah type of model with output growth and the rate of change of inflation requires superneutrality to hold. The other models considered here only assume neutrality. Bullard and Keating (1995) shed for Germany some doubt on the notion that superneutrality is an exact description of the German postwar experience. See also Fisher and Seater (1993) for a general discussion of the order of integration and the relevant neutrality concept involved.

19 The 'high pass' filter specification suggested by Baxter and King (1995), p. 22, is used.

20 The lag length of every system is determined on the basis of the Hannan-Quinn (HQ) information criterion; according to a Godfrey Portmanteau test testing for freedom of autocorrelation up to fifth order none of the systems displays signs of autocorrelation.

sis of no co-integration relationship (second column) and the null that the rank of the system is at most one (third column).[21]

For the models involving unemployment and capacity utilization, the test for the co-integration rank serves as a multivariate unit root test, as these variables are supposed to be stationary and therefore cannot co-integrate with the non-stationary output variable.[22] If a stationary variable is present in the bivariate system, this yields a co-integration vector of the form [0,1]. Table 3 shows for both models that the null hypothesis of no co-integration relationship is rejected at the 1 percent significance level, which is encouraging as it confirms the results from the univariate unit root tests. In addition, the restriction [0,1] has been tested and was not rejected at conventional significance levels. However, for the capacity utilization rate this restriction only holds if a deterministic time trend is included in the co-integration space; thus, the co-integration analysis suggests that this variable is stationary around an upward sloping trend.[23] Hence, in the following empirical analysis a trend is allowed for in the system containing this variable. Regarding the system with real GDP and the GDP deflator, the null of no co-integration relationship cannot be rejected at the 1% significance level, but at the 5% level there is evidence for a long-run relationship between these two variables, thereby contradicting the notion of long-run neutrality underlying the theoretical model. Since this model has been widely used in the literature, it is given the benefit of doubt by assuming that no long-run relationship between output and prices is present. As expected, the model involving in-

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[21] The l-trace statistic, as opposed to the l-max statistic, has the advantage of being robust to non-normality in the residuals (see Cheung and Lai (1993)).

[22] Since the capacity utilization measure employed here is based on survey data for the manufacturing sector, using industrial production instead of real GDP as the corresponding output variable appears to be more appropriate.

[23] The detailed results are available from the authors upon request.

dustrial production and producer prices shows no signs of a co-integration relationship.

3.2 Specification of the VAR Models

The lag length of the reduced form models is specified on the basis of the HQ information criterion. If necessary, the lag length has been increased to ensure that the white noise property of the residuals holds. Table 4 displays the results for the lag order together with some diagnostic results. The systems have been subjected to the joint stability test proposed by Hansen (1992). This test is approximately the Lagrange multiplier test of the null of constant parameters against the alternative that the parameters follow a martingale. This alternative incorporates simple structural breaks of unknown timing as well as random walk parameters. In addition the residuals have been tested for normality and autocorrelation up to fifth order. All systems are estimated with a constant; the system with the capacity utilization rate also includes a time trend.

Table 4: VAR specification statistics

System	Lag order	Stability test	AR 1–5	Vector AR 1-5	Normality	Vector Normality
dy	4	2.19	1.57	2.03	2.22	8.66
u_cyc		1.90	0.85		6.46*	
dy	6	2.79	1.29	1.34	3.99	4.74
dp		3.55*	2.03		0.16	
dip	2	0.93	0.94	1.11	0.88	9.85*
lcap		1.20	0.97		7.47*	
dip	2	1.17	1.80	1.08	0.25	3.35
dppi		0.59	1.80		3.16	

Asteriks denote: * = significant at 5% level; ** = significant at 1% level. The Stability test gives the joint stability test statistic based on Hansen (1992). The AR 1–5 statistic gives the result of a LM test for autocorrelated residuals up to fifth order. The test for normality is the test proposed by Doornik and Hansen (1994). The autocorrelation and the normality test statistics are computed for each single equation and for the system (vector).

The results presented in table 4 suggest that all systems are fairly well specified. The system with industrial production and producer prices displayed a large outlier in the first quarter of 1974, which led to problems with the normality assumption. For this reason an impulse dummy which is one in 1974:1 and zero otherwise has been added to the specification. The system comprised of capacity utilization faced similar problems due to the metal worker strike in 1984. To control for this episode, an impulse dummy for the second quarter of 1984 has been included together with an additional dummy for the following quarter, which accounts for the rebound in production after the strike ended.

3.3 Dynamic Responses to Supply and Demand Disturbances

Having specified the empirical models, this section turns to the dynamic responses of the variables to supply and demand disturbances. The corresponding impulse response function serve as a diagnostic tool to check whether the Blanchard/Quah identifying restrictions yield plausible results. In particular, they provide a first indication of consistency. In section 2 it has been shown that prices and output are expected to move in opposite directions in response to a supply shock. Since this restriction has not been formally imposed on the models comprised of output growth and inflation, it serves as an overidentifying restriction. If the respective impulse response functions fail to satisfy this overidentifying restriction, this provides strong evidence against the identification procedure employed here, since in this case the interpretation of disturbances with permanent and transitory effects on output as supply and demand disturbances respectively cannot be sustained.[24]

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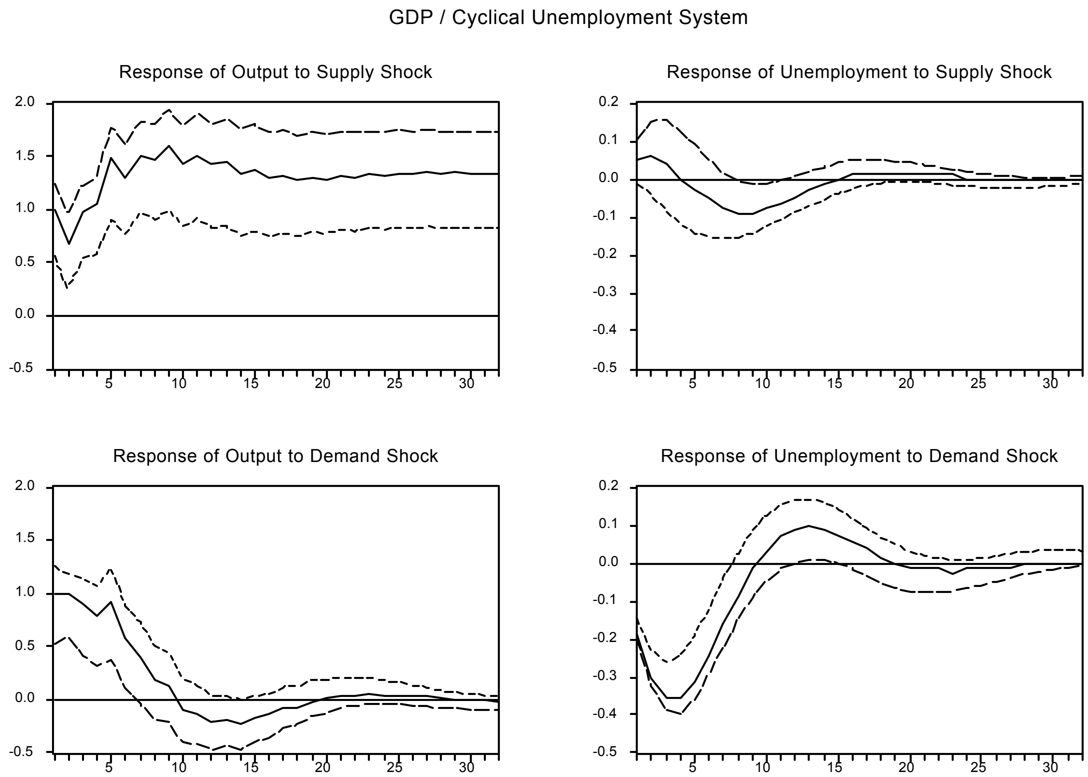
[24] See also Bayoumi and Eichengreen (1993), p. 202, on this point.

Figures 2 to 5 show for all four models considered here the impulse response functions of the level of each variable to supply and demand disturbances.[25] The structural disturbances have been scaled so that they raise the respective output variable on impact by one percent.[26] The solid line in each figure represents the point estimate, while the dotted lines give the 5 percentile and the 95 percentile respectively. The horizontal axis is the time axis, measured in quarters. The units of the vertical axis are percent, with the exception of the unemployment response, which is given in percentage points.

Figure 2: Impulse Response Functions for the GDP/Unemployment System (in percent/percentage points)



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[25] For the variables that enter the models in differences, the cumulated impulse response functions are given.

[26] This scaling of shocks has been chosen to facilitate the comparison over different models.

The impulse response functions for the model with real GDP growth and the cyclical unemployment rate is displayed in figure 2. Beginning with the supply shock, an initial one percent increase in output is followed by a further gradual increase of output, which reaches its maximum effect after about 8 quarters when output is about 1.5 percent above its baseline level. In the long run output increases by about 1.35 percent. The effects of the supply shock on the variation of the cyclical unemployment are generally small and hardly significant. According to the point estimates unemployment initially rises and then declines temporarily; after eight quarters unemployment is by about 0.1 percentage points below the baseline. After four years the effect of the supply shock dies out.

While the output response to a supply shock is in line with the predictions from the theoretical model outlined in section 2, on first glance this does not appear to be the case for unemployment, since the theoretical model predicts that unemployment declines initially in response to a productivity shock.[27] However, the unemployment response reported in figure 2 is compatible with the interpretation of the aggregate supply shock as a labor supply shock. An exogenous increase in German labor supply as when, for example, the East German labor force was added to the German economy following unification is likely to lead first to higher unemployment, with unemployment subsequently declining as factor prices adjust and the additional labor supply is integrated into the economy.[28] Since the theoretical model could be reformulated to account for a labor supply shock instead of a productivity shock, the results depicted in figure 2 do not contradict the theoretical framework employed here. An alternative view

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[27] See equation (9).

[28] Since the empirical model includes only the cyclical and not the total unemployment rate, it is possible that a labor supply shock has long-run effects on total unemployment. The specification of the model only ensures that the cyclical component of unemployment eventually returns to its baseline.

more in line with the theoretical model presented in section 2 is offered by Blanchard and Quah (1989), who report in their seminal paper a similar impulse response function for the USA. They interpret the supply shock as a productivity shock and argue that in the presence of nominal rigidities aggregate demand does not initially increase enough to match the increase in output needed to maintain constant unemployment. Furthermore, once aggregate demand has caught up, real wage rigidities prevent an immediate adjustment of real wages to increased productivity, which accounts for the temporary decline of unemployment. This discussion suggests that the impulse response functions to supply disturbances displayed in figure 2 are not implausible regarding the sign, size and persistence of the effects.[29]

Regarding the effects of a demand shock, the third panel in figure 2 shows that this shock lifts output above its baseline level for about 10 quarters, then output undershoots slightly and eventually the effect of the demand shock vanishes, in accordance with the long-run neutrality restriction imposed on the model. The effect of the demand shock on the cyclical unemployment rate is considerably stronger than the corresponding effect of the supply shock. The unemployment rate declines in response to the demand shock, reaching its minimum after four quarters when it is by about 0.4 percentage points below the baseline. After ten quarters the unemployment rate begins to overshoot its initial

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[29] The discussion suggests also that the identified supply shock could be interpreted as either a labor supply shock or a productivity shock. But this does not imply that the identified supply shock is taken to represent both type of shocks. As has been stressed Blanchard and Quah (1989) and Faust and Leeper (1997), if both productivity shocks and labor supply shocks matter for the German economy, the identification strategy pursued here is likely to fail. The reason for this is that it would be quite a coincidence if labor supply and productivity shocks have similar effects on the German economy in the sense that they leave the dynamic relationship between output and unemployment unaffected. As has been discussed in 2.4, this condition has to hold to avoid commingling of shocks. The discussion in this section shows that this in principle possible, but it is nevertheless unlikely.

level for some time and then returns to the baseline. It is apparent from the lower panel of figure 2 that the output and unemployment responses to the demand shock are the mirror image of each other. This was to be expected if Okun's law holds. The impulse response functions suggest that output has to rise by 2.5 percent to reduce unemployment by one percentage point, which corresponds to typical estimates of the Okun's law coefficient. In general, these dynamic effects are broadly consistent with the conventional view of the effects of aggregate demand shocks on the economy.

Figure 3 reports the results for the system comprising the real GDP growth rate and the inflation rate calculated on the basis of the GDP deflator. It is apparent that the output response to the supply shock is remarkably similar to the corresponding response displayed in figure 2. As for the price response, the GDP

Figure 3: Impulse Response Functions for the GDP/Deflator System (in percent)

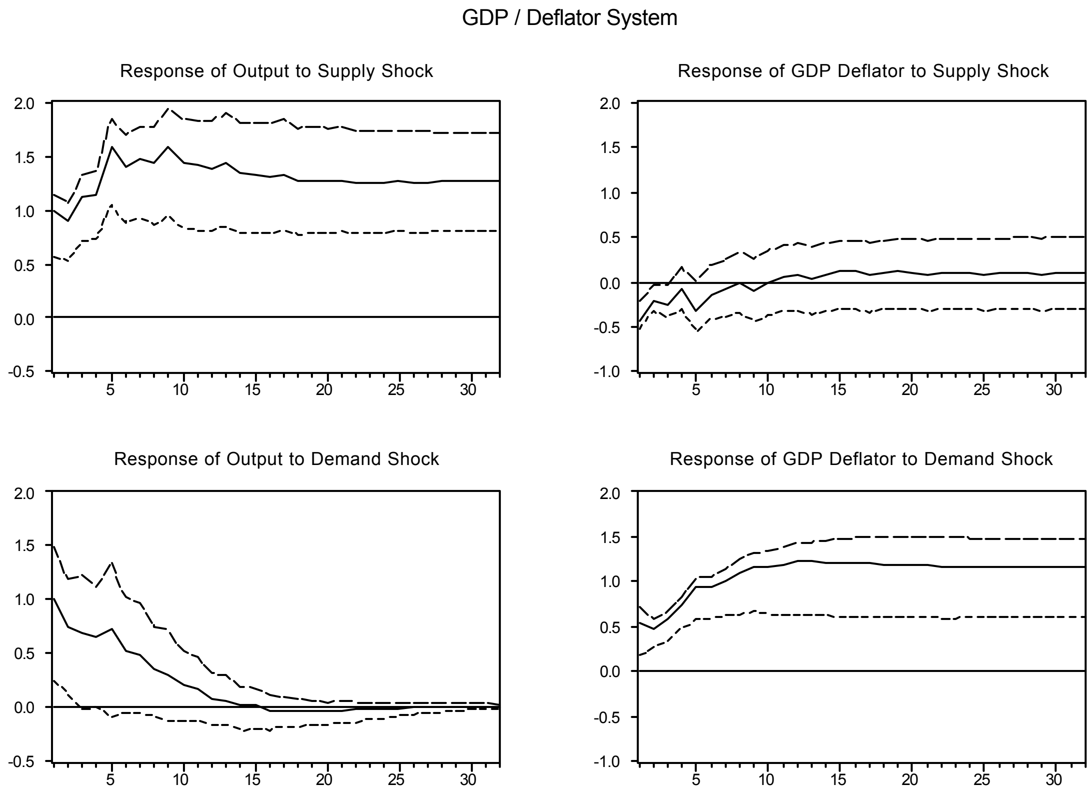
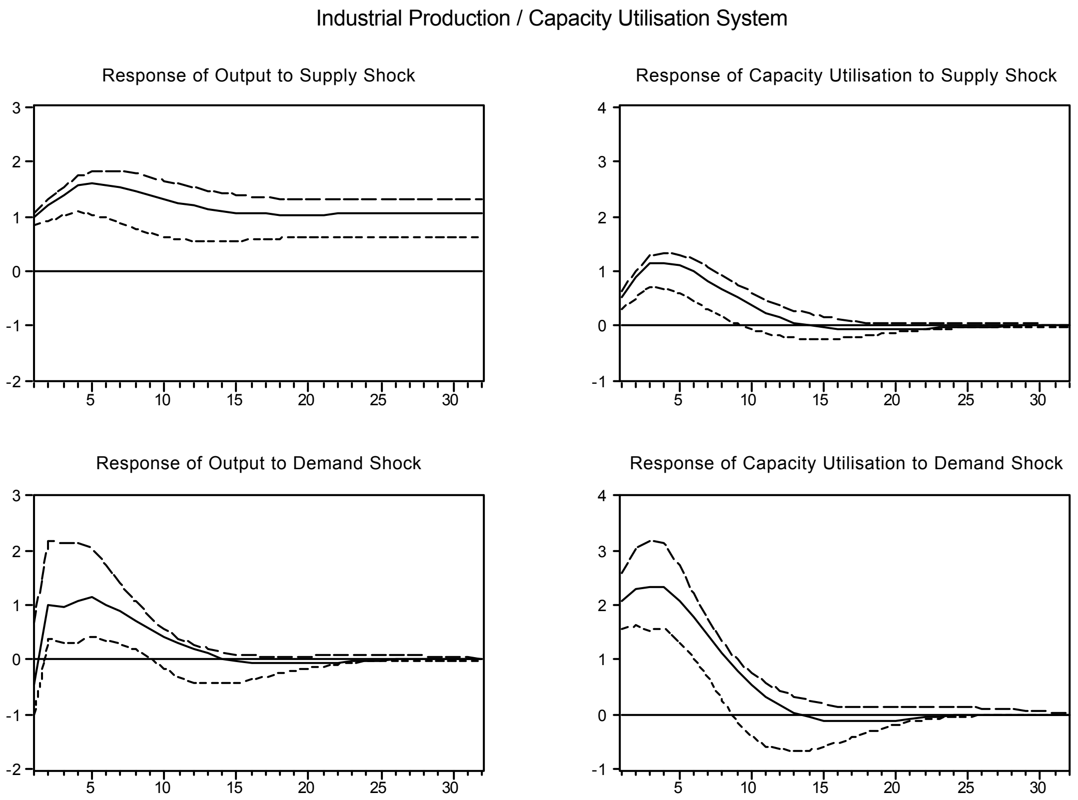


Figure 4: Impulse Response Functions for the Industrial Production/Capacity Utilization System (in percent)



deflator declines initially in response to the supply shock, hence this model fulfils the overidentifying restriction discussed above. The output response to a demand shock is broadly similar to the one shown in figure 2, but output declines more monotonically and does not undershoot. The price response has the expected sign and accumulates steadily over the first three years, afterwards the price level stabilizes. Considering the output and price response together, it is apparent that the real effect of the demand shock vanishes as the adjustment of prices leads the economy back to equilibrium. This is in line with widely held views about the role of nominal rigidities for the real effects of demand disturbances.

Figure 4 shows the impulse response functions for the system with industrial production as the proxy for the output variable and capacity utilization in the manufacturing sector as the second variable.[30] Qualitatively the output response to a supply shock is similar to those reported for the systems with real GDP as output variable. In the long-run the output response is somewhat smaller in the industrial production system, but one should not interpret too much in such differences, since the dynamic behavior of the industrial sector is only broadly comparable with that of the rest of the economy. Capacity utilization rises in response to a supply shock and then returns to its baseline within three years. Since the capital stock is likely to adjust only slowly to increased production, this is a plausible response. Regarding the output response to a demand shock, the impact effect is negative according to the point estimate. This is clearly implausible and not in line with the results from the other three models. However, this initial effect is insignificant; hence, this model should not be rejected out of hand. Accordingly, the demand shock has been scaled so that it raises output by one percent in the first period after the shock. In contrast to the output response in the preceding two models, output does not begin to decline immediately, but does so after four quarters. After four years the effect of the demand shock dies out. The response of capacity utilization to the demand shock is considerably stronger than the corresponding response to the supply shock. This is to be expected, since the supply shock adds capacity to the economy; hence, capacity utilization rises by less to accommodate a similar increase in output. In general the capacity utilization response to a demand shock tracks the response of output closely. With the exception of the initial output response to a demand shock, this model displays reasonable responses to supply and demand disturbances.

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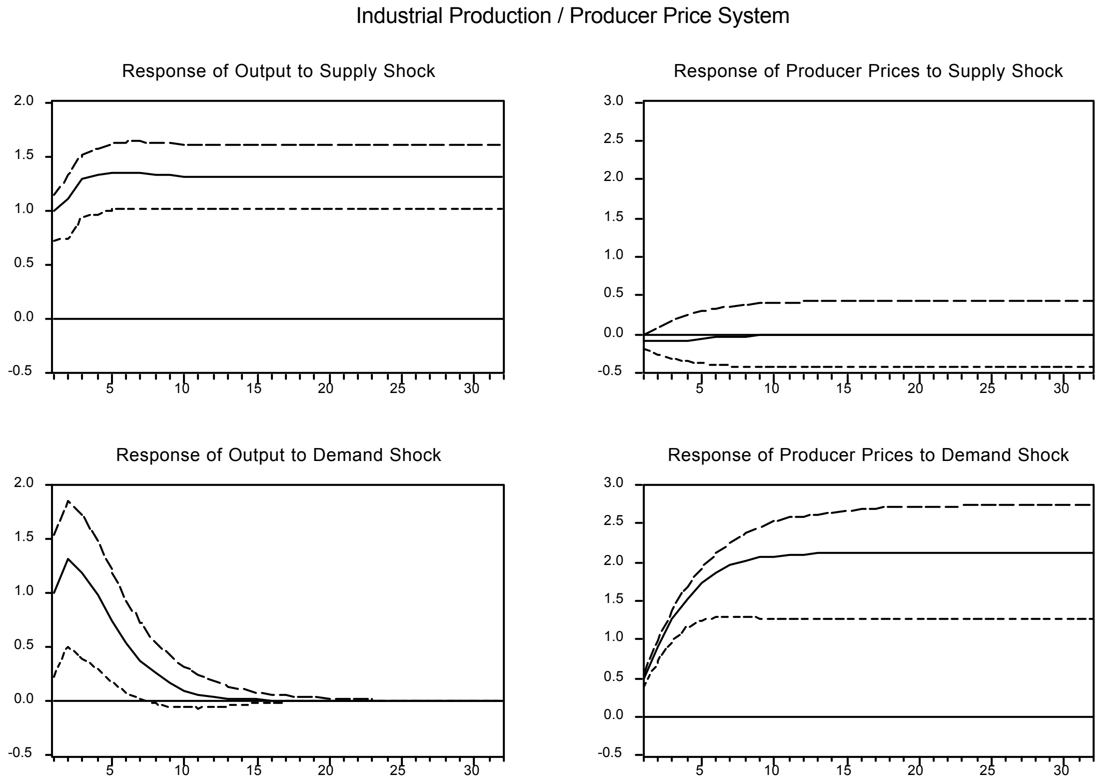
[30] The impulse response functions in figure 4 and 5 are considerably smoother than those presented in figure 2 and 3. This is a simply a reflection of the fact that the systems in figure 2 and 3 have been estimated with a higher lag order, which generally leads to more detailed dynamics of the impulse response functions. Since these are generally not significant, interest focuses here on the basic shape of the impulse response functions.

Figure 5: Impulse Response Functions for the Industrial Production/Producer Price System (in percent)



The fourth model is comprised of the growth rate of industrial production and producer price inflation. The impulse response functions displayed in figure 5 are broadly comparable to those in figure 2. The maximum effect of the supply shock on the level of output is reached somewhat earlier, but the long-run response is similar. Prices move initially again into the opposite direction as output, which is in accordance with the predictions from the AS/AD model. The maximum output effect of a demand shock is reached only one quarter after the shock has occurred, but otherwise the output response to a demand shock is similar to that in the corresponding panel in figure 2. The same holds for the price response, even though producer prices increase in the long-run by considerably more than the GDP deflator.

Altogether the estimated impulse response functions in all four systems appear to be plausible. The output responses to supply and demand disturbances are also broadly comparable in the sense that the underlying shapes of the impulse response functions are similar, which points to some robustness in the results.

3.4 Does the Bivariate Identification Procedure Correctly Identify Supply and Demand Disturbances?

This section presents the results of the consistency check proposed by Faust and Leeper (1997). As has been discussed in 2.4, Faust and Leeper suggest to assess the consistency of different small models by checking whether they have identified the same structural disturbances. If this is the case, one would expect the estimated supply disturbances of the four models to be highly correlated and the same to hold for the demand disturbances. However, as has been forcefully argued by Sims (1998), it is very well possible that two models have different specifications, which yield different policy shock time series, and yet both models accurately estimate the same response of the economy to a given structural disturbance. In this case the uncorrelatedness of shocks is simply due to the difference in specifications and does not imply that the models disagree on the dynamic effects of the structural disturbances on the economy.[31] For this reason the

[31] Sims (1998), p. 936, illustrates his point using the popular example involving a demand equation for an agricultural good and a supply side shifter like weather, which is often employed in textbooks to illustrate the principle of identification in simultaneous equations models. He writes: "Consider again our simple supply and demand model. Suppose there are two supply shifters, weather and insect density. Suppose one model includes the weather variable, but omits, and thus relegates to the error term, insect density. The other model does the reverse. So long as both supply shifters are legitimate exogenous variables, uncorrelated with the disturbance term in the demand equation, both models can lead to accurate estimates of the demand equation, because each one offers one legitimate instrumental variable for that equation. But of course, since each model includes the other's supply shifter in the 'supply shock', there is no limit to how different their estimated supply shock time series might appear." A similar point is made by Bagliano and Favero (1998).

test proposed by Faust and Leeper is less concerned with the correlation among disturbances belonging either to the class of supply shocks or to demand shocks, but asks whether a supply shock from one model is correlated with a demand shock from another model. If this is the case, this provides strong evidence that the empirical models have commingled the underlying supply and demand disturbances. The results for the contemporaneous correlation among the shocks are displayed in table 5.

There is clear evidence that the four models considered here have aggregated the underlying shocks differently. In particular there is evidence for commingling of shocks among all models considered here: The correlation of the demand shock of the cyclical unemployment model and the supply shocks of the other three models is significant and about as high as the correlation between the supply shocks. The same holds for the demand shock belonging to the system with

Table 5: Contemporaneous Correlation Among the Shocks in the Four Models

	Supply shocks				Demand shocks			
Shocks	dy, u_cyc	dy, dp	dip, lcap	dip, dppi	dy, u_cyc	dy, dp	dip, lcap	dip, dppi
dy, u_cyc – S	1.00	0.58*	0.37*	0.42*	**0.01**	**0.33***	**–0.15**	**0.15**
dy, dp – S		1.00	0.53*	0.42*	**–0.47***	**0.00**	**–0.11**	**0.30***
dip, lcap – S			1.00	0.63*	**–0.50***	**0.42***	**0.04**	**0.41***
dip, dppi – S				1.00	**–0.37***	**0.51***	**–0.13**	**–0.02**
dy, u_cyc – D					1.00	–0.43*	0.04	–0.37*
dy, dp – D						1.00	–0.06	0.18*
dip, lcap – D							1.00	0.04
dip, dppi – D								1.00

Asteriks denote: * = significant at 5% level; two standard error bounds are computed using the formula $\pm 2/\sqrt{T}$.

real GDP growth and the GDP deflator. The demand shock of the model with capacity utilization is uncorrelated with the other three supply shocks, but the supply shock of this model is significantly correlated with all the other demand shocks. Indications for commingling of shocks is also evident for the system involving industrial production and producer prices. As has been discussed in section 2.4, this points to substantial problems with the underlying assumptions of the Blanchard/Quah methodology in at least three of the models considered here.

An interesting hint towards the source of commingling is found in the correlation matrix involving one class of shocks. It is apparent that supply shocks are moderately correlated, suggesting that the different models agree more or less on the supply shocks, but the demand shocks are either uncorrelated or have the opposite sign, pointing to considerable differences regarding these shocks.

3.5 Relative Contributions of Supply and Demand Disturbances

This section turns to the forecast error variance decomposition, introduced in 2.3, to investigate the relative importance of supply and demand disturbances in accounting for output variations. The results for all four models are shown in table 6. The table has the following interpretation. Defining the k quarter-ahead forecast error in output as the difference between the actual value of output and its forecast obtained from (14) as of k quarters earlier, it is apparent from (14) that this forecast error is due to unexpected supply and demand disturbances hitting the economy in the last k quarters. The column denoted ‘Supply’ shows the contribution of the supply shock to the k-step forecast error variance of the output variable, while the column ‘Demand’ shows the corresponding percentage share of the demand disturbance. Both add up to 100, since all unexpected variation in output is attributed to one of the two shocks in the bivariate framework employed here.

Table 6: Variance decomposition of real output (percent)

Forecast Horizon	GDP / Unemployment Model		GDP / Deflator Model		IP / Capacity Utilization Model		IP / Producer Prices Model	
k	Supply	Demand	Supply	Demand	Supply	Demand	Supply	Demand
0	55.13	44.87	71.09	28.91	98.56	1.44	78.39	21.61
1	47.53	52.47	74.15	25.85	96.81	3.19	74.62	25.38
2	51.40	48.60	79.03	20.97	96.82	3.18	77.32	22.68
3	55.84	44.16	81.67	18.33	96.94	3.06	80.14	19.86
4	62.31	37.69	85.21	14.79	96.89	3.11	82.85	17.15
8	78.63	21.37	91.25	8.75	97.49	2.51	89.67	10.33
12	85.11	14.89	93.94	6.06	98.02	1.98	92.72	7.28
16	88.00	12.00	95.25	4.75	98.32	1.68	94.37	5.63
20	89.98	10.02	96.04	3.96	98.53	1.47	95.41	4.59
40	94.66	5.34	97.84	2.16	99.12	0.88	97.61	2.39

In contrast to the results for the impulse-response functions, the results for the variance decomposition differ considerably across the four models considered here. For instance, demand shocks play practically no role in determining output at all horizons in the model involving capacity utilization, but they account for up to 50 percent of output fluctuations at short horizons in the model with cyclical unemployment. The results for the models including inflation cover the middle ground between these two limits. With longer horizons the supply shock begins to dominate in all models, but this simply reflects the corresponding long-run identifying restriction imposed on all models. Apparently the commingling of shocks has left the basic shape of the impulse response functions broadly unaffected, but it has a major effect on the variance decomposition. As a result the bivariate models investigated here do not allow reliable inference on the relative importance of aggregate supply and demand disturbances for business cycle fluctuations.

Large differences in the relative role attributed to supply and demand shocks for business cycle fluctuations are also found in the literature. For example, Bergman (1996) finds for Germany that, at the one year horizon, demand shocks account for only 12.8 percent of the output variation, whereas Whitt (1995) puts this figure at 65.2 percent. This confirms that the results from Blanchard/Quah type of models regarding the source of business cycle fluctuations are not robust over different specifications.

3.6 Historical Decomposition of the Output Series

As a final consistency check for the four models, a historical decomposition of the output series is used to evaluate which type of shocks contributed to major business cycle episodes. For this purpose figure 6 plots for each model the time path of output one would have obtained in the absence of demand shocks, i.e. the output fluctuations due to supply shocks.[32] Similarly, figure 7 plots the demand components in output, which is obtained by setting the supply innovations to zero. To highlight important turning points of the business cycle, periods of recession have been shaded in both figures. These denote the time between subsequent peak and troughs; the dates have been taken from the business cycle chronology proposed by Artis et al. (1997), who use industrial production as the activity variable.[33]

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[32] In the Blanchard/Quah framework output is a function of the stochastic shocks, i.e. the supply and demand shocks, and of the deterministic specification of the models. The latter includes the constant, which is present in all models, and the deterministic time trend and dummy variables, which are used in some but not all models. Even though the deterministic component is quantitatively important in accounting for the path of output, it does not help in accounting for business cycle fluctuations, which are of interest here. For this reason this part has not been plotted here.

[33] Their business cycle dating procedure has been used to extend the series of recession dates to the end of the sample period of this paper. We are grateful to Jörg Döpke for providing us with the updated series.

Figure 6: Output Fluctuations Due to Supply Disturbances (in percent)

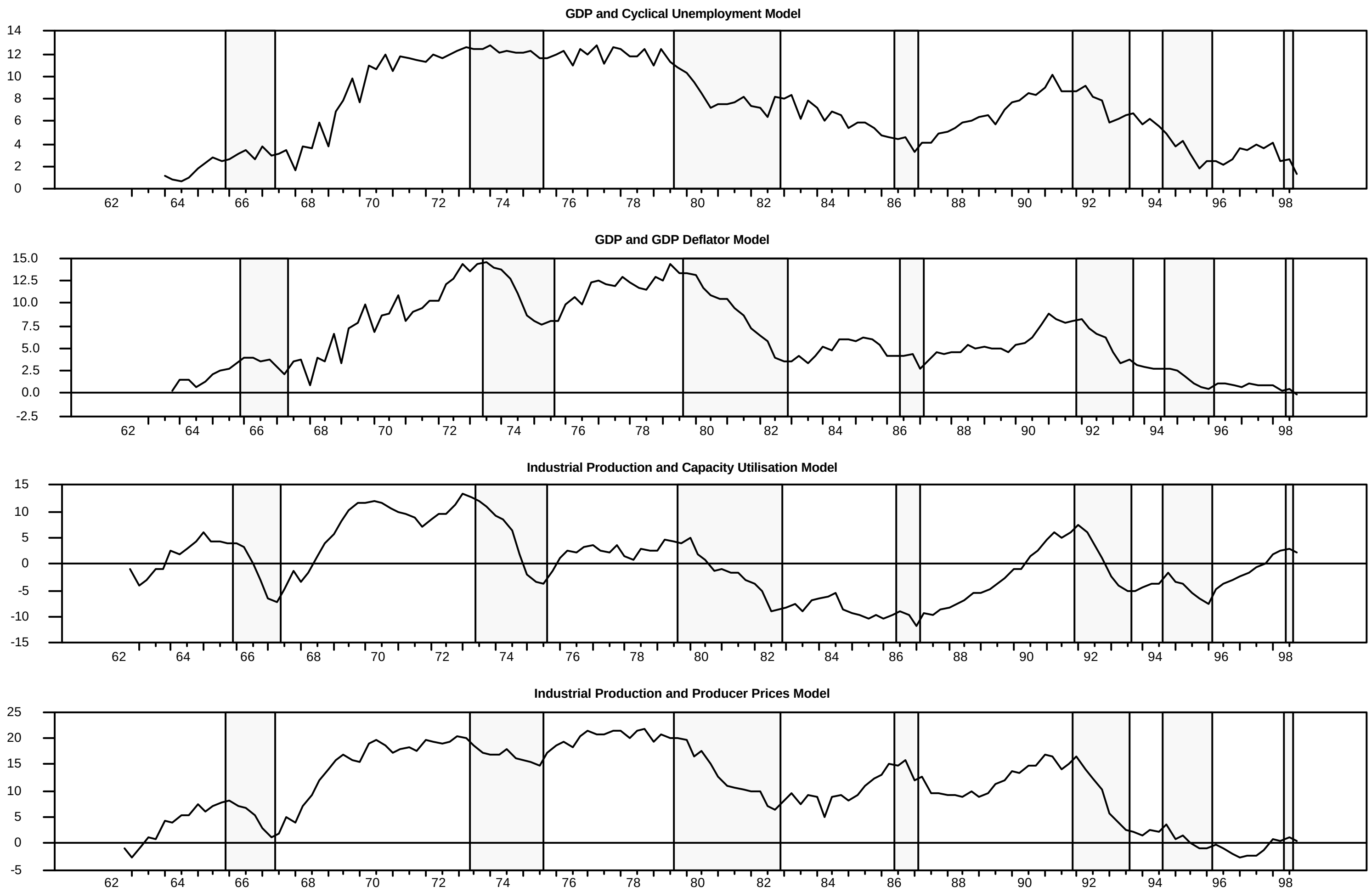
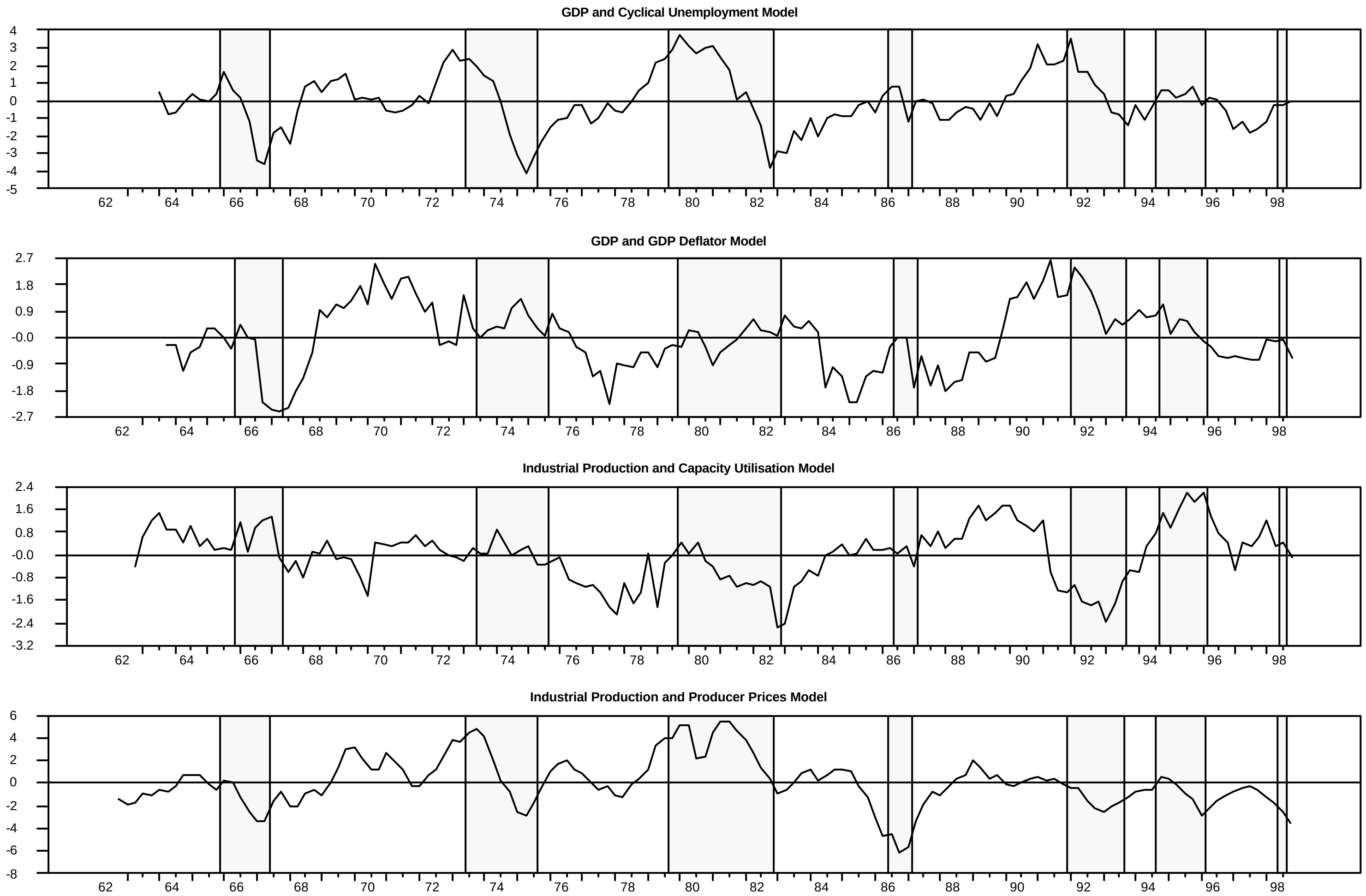


Figure 7: Output Fluctuations Due to Demand Disturbances (in percent)



According to this methodology of dating the business cycle, there are eight recessions in the sample period. The first set in March of 1966 and lasted until May 1967. The two models with real GDP as the output variable attribute this recession to a contraction of demand conditions, while the model with industrial production and capacity utilization identifies a worsening of supply conditions as the dominant factor; the model with industrial production and producer attributes the decline in output both to adverse demand and supply shocks. The next recession lasts from August 1973 until July 1975. This is commonly referred to as the first oil crisis recession. Both models including the GDP deflator and the capacity utilization rate, and to a lesser extent the model with producer prices, explain the recession as a consequence of negative supply shocks. In contrast, the model with cyclical unemployment identifies the recession as being due to negative demand disturbances only, whereas these play a dominant role in the producer price model too. More agreement exists among the models regarding the recession between December 1979 and November 1982, since all of the models point towards a substantial worsening of supply conditions, which is in accordance with the second oil crisis occurring at this time. In addition, all models with the exception of the GDP/GDP Deflator model identify also sizeable negative demand disturbances as an additional factor. The recession from July 1986 until January 1987 does not figure as a particularly noteworthy event in the historical decomposition considered here. The recession between February 1992 and July 1993 is again clearly visible in all four models. There is agreement that negative supply shocks played an important role, while adverse demand shocks were nearly as important in models with real GDP. The recession from December 1994 to January 1996 is again attributed to adverse supply shocks by all four models; the two models including inflation also point to a considerable role of adverse demand shocks. The last recession in the sample period is that lasting from July 1998 to June 1999. Only the models with industrial production indicate a noticeable decline in real activity around this time, attributing it to adverse demand shocks.

In summary, the four models appear to agree to some extent on the overall direction of supply conditions in the sample period. The correlation coefficients for the supply components range between 50 percent and 90 percent, confirming this impression.[34] However, there appears to be considerably more disagreement about the role of demand shocks. Even leaving aside the demand component identified in the model with the capacity utilization rate (which is essentially uncorrelated with that of the other models) the correlation among the demand components does not exceed 50 percent. This confirms the results from the analysis of the structural shocks, which also pointed to substantial differences regarding the identification of demand shocks.

IV. Conclusion

The central question of this paper is whether bivariate models employing the Blanchard/Quah methodology yield reliable results for German data. For this purpose the consistency of results using different specifications is investigated. One result of this analysis is that the models have apparently aggregated the underlying shocks in rather distinct ways. Thus, different models yield dissimilar time series for aggregate demand and supply shocks. This holds in particular for the demand shocks, while there is more agreement regarding the supply shocks. Nevertheless, Sims (1998) shows that this finding in itself does not necessarily imply that these models also disagree on the dynamic responses of the economy to demand and supply disturbances. However, a more worrisome finding in this

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[34] If one leaves out the model with capacity utilization aside, the correlation is at least 85 percent.

respect is that there is considerable evidence for a commingling of shocks, meaning that the supply shock one of model is significantly correlated with the demand shock of another model, and vice versa. Since the Blanchard/Quah methodology assumes that all shocks in the economy can be classified either as a supply or demand shock, both of which are orthogonal to each other, the existence of significant correlation among supply and demand shocks suggests that one or both of these assumptions does not hold in at least three of the four models considered here. While the estimated impulse response functions do not differ fundamentally, the results for the variance decomposition and the historical decomposition show that the contribution of demand and supply disturbances for output fluctuations varies considerably between models. Hence, the commingling of shocks has important implications for the reliability of inference when employing these models. This result suggests that the disadvantages of the low dimension of bivariate models may outweigh their advantages.

It is may be somewhat surprising that all the estimated impulse response functions turn out to be quite plausible, while the models are disagreeing sharply over the role of supply and particularly demand shocks in accounting for output fluctuations. The answer to this puzzle is probably that the bivariate models are too small to account fully for the dynamics inherent in business cycle fluctuations. Each model captures only some aspects of the sources of business cycle fluctuations but does not give the whole picture. This point has been recently discussed in length by Astley and Yates (1999). These authors emphasize that the co-movement between output, unemployment and capacity utilization in response to demand and supply disturbances depends on the sources of rigidities in the economy. In the restrictive case where factor substitution is impossible and there is only one source of nominal rigidity in the economy, there is an exact mapping between movements in output, unemployment and capacity utilization. However, in a more realistic world, for instance, with sticky prices in the goods market and real rigidities in the labor market, and no nominal rigidities in this market, a nominal demand shock will generate output and capacity utilization responses but will have no effect on unemployment. A real demand shock, on the other hand, will trigger an unemployment response too. If the latter type of shocks dominates in the sample period, the impulse response functions in the system comprised of real GDP growth and the unemployment rate would show a significant response of unemployment to a 'typical' demand shock. However, if a nominal demand shock hits the economy, this system would not identify this shock as a demand shock, while the system with output growth and capacity utilization would do so. The impulse response functions to demand shocks would appear to be plausible in both models, and they would look quite similar if the real demand shocks dominate, but these responses actually represent responses to different aggregate demand shocks.[35] Even though in this hypothetical example it is clear that it is the unemployment model that misses part of the picture, no general statement in this effect is possible because the result depends on the specific assumptions regarding the sources of rigidities in the economy.

Although the results in this paper show that the bivariate models considered do not offer particularly reliable conclusions, nevertheless, all four models agree that supply shocks are not negligible for output fluctuations, even at short forecast horizon. This is an interesting result because it stands in marked contrast to the practice of applied business cycle research. Business cycle reports, for instance those published by the joint forecasting group of German economic

[35] More technically, the condition which prevents commingling of shocks is likely to be violated in the case of the model with real GDP growth and the unemployment rate. As discussed in section 2.4, Blanchard and Quah show that commingling of shocks is avoided when the dynamic relationship between output and unemployment remains the same across different demand disturbances. This is not the case here, since the nominal and the real demand shock both have effects on output, but only the latter shock also has an effect on unemployment.

research institutes[36], usually emphasize the role of demand disturbances for business cycle fluctuations, while supply side disturbances receive rather little attention. A typical report includes, for example, a lengthy section on monetary policy, fiscal policy and foreign demand, while there is often not even a single paragraph devoted to factors affecting the supply side of the economy.[37] Since a large part of the theoretical literature in macroeconomics over the past two decades has attempted to incorporate supply side factors into the models, and with substantial empirical evidence pointing to the relevance of these factors for short-run fluctuations, the nearly exclusive focus in many business cycle reports strictly demand conditions is somewhat surprising.[38]

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[36] This institution is better known by its German name 'Gemeinschaftsdiagnose'.

[37] A recent exception is the discussion of the 'New Economy', but apparently it took a rather spectacular growth performance in the United States to draw some attention to such a phenomena.

[38] This paper adds to the evidence regarding the role of supply shocks in a 'Keynesian' framework with nominal rigidities, but it does not offer guidance on the question of the relevant theory, which is often framed as a controversy between RBC and Keynesian type of models, for reasons outlined in the introduction of section II.

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Appendix

Figure 1A: Data Plots