THE DYNAMIC EFFECTS OF AGGREGATE DEMAND AND SUPPLY DISTURBANCES FURTHER EVIDENCE

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Abstract. In a bivariate Vector Autoregressive approach Blanchard and Quah [1989] used the unemployment rate as a stationary indicator to disentangle the effects of permanent and transitory innovations to output. This paper examines the stability of their results with respect to a wider class of time series models and the choice of the stationary variable. We take a Vector Autoregressive Moving Average approach to allow for a more parsimonious representation of the process. Furthermore, capacity utilization and the rate of inflation are used as alternative cyclical indicators. It turns out that the decomposition is fairly stable, with the exception of the model where we used the GNP-deflator as stationary variable. Finally, we discuss the interpretation of permanent and transitory innovations as supply and demand innovations.

Zusammenfassung. In einer bivariaten Vektorautoregression haben Blanchard und Quah [1989] die Arbeitslosenrate als stationäre Variable verwendet, um die Auswirkungen von permanenten und transitorischen Schocks zu trennen. Diese Arbeit untersucht die Stabilität ihrer Ergebnisse im Hinblick auf eine größere Klasse von Zeitreihenmodellen und auf unterschiedliche stationäre Variablen. Um eine sparsame Darstellung des Prozesses zu erreichen, verwenden wir Vektor Autoregressive Moving Average Modelle. Als alternative Variablen wurden die Kapazitätsauslastung und der BIP-Deflator benutzt. Als Ergebnis läßt sich zusammenfassen, daß die Zerlegung stabil ist, solange nicht der BIP-Deflator als stationäre Variable verwendet wird. Abschließend wird die Interpretation der permanenten und transitorischen Schocks als Angebot- und Nachfrageschocks diskutiert.

1 Introduction

In business cycle literature different types of output decompositions into trend and cyclical components are reported. The traditional approach characterizes the economy as growing along a smooth deterministic trend from which it temporarily deviates in a cyclical way. This approach has been criticized over the last couple of years. Building on the work of Nelson and Plosser [1982] it is now a widely held view (see e.g. Campbell and Perron [1991]) that real GNP is better characterized as a stochastic process with a unit root. From this perspective, shocks to aggregate output have permanent effects.

To measure the long run persistence of real GNP and the relative importance of permanent shocks, many authors use univariate Autoregressive Integrated Moving Average (ARIMA) models or unobserved components ARIMA (UC-ARIMA) models (see Stock and Watson [1988]). In this type of models all fluctuations are attributed to a single disturbance that has a permanent effect just by application of the first difference filter on the time series. Real world phenomena and economic theory, however, force one to reinterpret the sources of output fluctuations in the light of more than one type of disturbance affecting output. One possible way is to add transitory innovations influencing short run movements in output. A first attempt to disentangle permanent and transitory components was suggested by Beveridge and Nelson [1981]. Assuming perfectly correlated permanent and transitory disturbances, they decomposed output into a nonstationary random walk and stationary fluctuations. Since that assumption contradicts the more common notion of low or zero correlation between innovations in trend and cycle components, alternative types of decompositions were suggested by several authors.

One approach is to work with an unobserved components model and to assume a zero correlation between disturbances. For this purpose one has to assume two distinct data generating processes for the trend and cycle components of the time series. Clark [1987] for instance used a local approximation to a linear trend to model the nonstationary part of output and a pure autoregressive process to catch stationary fluctuations. The shortcoming of these models are restrictions on the data generating processes needed for identification, which confine the movement of both components.

Another more promising effort to identify disturbances is the use of additional information contained in a cyclical indicator. Blanchard and Quah [1989] (BQ henceforth), Campbell and Mankiw [1987b] and Evans [1989] developed bivariate models to decompose output. Evans [1989] estimated a recursive vector autoregressive system including output and the unemployment rate and used the Cholesky decomposition for identification. Campbell and Mankiw [1987b] assumed the cyclical component to be that part of output contemporaneously correlated with the unemployment rate, while the trend component being the uncorrelated part of GNP.

In contrast BQ assumed in a bivariate Vector Autoregressive system (VAR) two uncorrelated disturbances influencing the system in distinct ways. One of the disturbances results in transitory output movements, whereas the other generates a permanent effect on output. The choice of the second variable in the VAR depends on three characteristics. First, it must be a stationary variable. Second, as Quah [1992] proofs, growth rates in output must not be Granger causally prior to the second variable. This is a necessary condition to achieve a unique decomposition of output. Third, and most important it should be a fairly good cyclical indicator implying that more or less regular deviations of actual output from potential output are reflected in the second variable.

Given the problems associated with univariate methods of detrending and the measurement of persistence in output we find the approach of BQ very appealing. This paper addresses the question, whether this kind of decomposition is robust against alternative ways to approximate the data generating process and whether other cyclical indicators cause substantial changes of their results. Another interesting aspect refers to the interpretation of BQ that transitory and permanent innovations correspond to demand and supply shocks. In particular the paper deals with the following issues: First, do the results depend on the limitation of using only VAR processes? Second, how important is the choice of the unemployment rate as cyclical indicator? Third, we discuss critically the interpretation of both innovations.

The remainder of the paper is organized as follows. Section 2 presents a short model to motivate the rate of capacity utilization and the rate of inflation as further candidates for cyclical indicators. In section 3 we try to assess the sensitivity of the BQ-decomposition by using various VARMA-models and alternative cyclical indicators. Section 4 discusses the assumption of zero correlation between supply and demand shocks. The last section gives a summary of our results and some conclusions.

2 A Model for Alternative Cyclical Indicators

An appropriate cyclical indicator is very important for the outcome of the BQ-decomposition. Thus different results may be achieved by replacing the second stationary variable in the bivariate system with an alternative one. According to the business cycle literature starting with Burns and Mitchell [1946] a vast amount of variables can serve as an indicator for the business cycle. However, to avoid a relapse into the 'Kepler stage' of measurement without theory (see Koopmans [1947], p. 186 ff.), we stick to the small scale model presented in BQ.

The model generates short term fluctuations in output by means of Fischer-type wage contracts in the labour market, i.e. nominal rigidities. A combination of productivity disturbances, unexpected movements in the money stock and wage rigidity creates fluctuations in output:

$$
\begin{aligned}
y_t &= m_t - p_t + a \cdot \theta_t && (1)\\
y_t &= n_t + \theta_t && (2)\\
p_t &= w_t - \theta_t && (3)\\
w_t &= w| \{E_{t-1} n_t = \bar{n}\} \;, && (4)
\end{aligned}
$$

where y_t, m_t, p_t and θ_t represent the logs of output, money supply, the price level and the level of productivity at time t, respectively. The log-level of full employment is characterized by $\bar{n}$ and the log of wages in period t by w_t.

The model includes a function for aggregate demand, which depends on real balances and one more variable reflecting a direct impact of productivity disturbances on aggregate demand. Equation (2) is a constant returns to scale production function and shows that aggregate supply depends in the short run on labour input and productivity disturbances. Long run considerations would include the capital stock as a further explanatory variable for the determination of aggregate supply. In this sense the model lacks a detailed explanation of the nonstationary component of output fluctuations. However, the purpose of the model is to derive a short term relation between innovations and endogenous variables and therefore this weakness seems negligible. Price setting behavior is given in equation

(3). Firms follow a mark up rule. Equation (4) specifies the wage setting rule. Nominal wages are set one period in advance such that expected employment is equal to full employment. Since nominal wages are fixed one period ahead, unexpected disturbances eventually give rise to deviations of output from its potential level. The evolution of the money stock and the level of productivity introduces dynamics and closes the model. It is assumed that both variables follow a random walk.

$$m_t = m_{t-1} + e_t^d \tag{5}$$

$$\theta_t = \theta_{t-1} + e_t^s , \tag{6}$$

where e_t^d and e_t^s are serially uncorrelated orthogonal demand and supply disturbances. This small model offers three cyclical indicators that might be used to decompose output into a transitory and permanent component. First of all, the rate of unemployment already used by BQ. But there are two more variables, namely the rate of capacity utilization and the rate of inflation.

As regards the second variable, the rate of capacity utilization is an appropriate measure of the overall under- or overutilization of factors of production. It is based on the firm's own conception of the difference between its potential output and the actual realization faced. Assuming a constant stock of capital in the short run, the capacity utilization is defined as $cap_t = y_t - \bar{y}_t$, where $\bar{y}_t$ represents potential output. Using this definition and solving the system for output growth and capacity utilization gives the same reduced form as in BQ:

$$\Delta y_t = e_t^d - e_{t-1}^d + a \cdot (e_t^s - e_{t-1}^s) + e_t^s \tag{7}$$

$$cap_t = e_t^d - a e_t^s . \tag{8}$$

Lagged and current realizations of demand and supply shocks determine output growth, whereas capacity utilization depends only on current innovations. Equations (7) and (8) show a striking feature of the model: Both variables are hit by both shocks within the same period. Thus the standard Cholesky decomposition is no more applicable and one needs to employ the identifying assumption of transitory and permanent effects of disturbances.

The third cyclical variable in the model is the rate of inflation Δp_t. When looking at the mark up equation (3), one can infer that the price level is determined by two nonstationary variables: nominal wages and the level of productivity. Thus the price level itself will only be stationary if there exists a cointegrating vector $(1,-1)$. Otherwise the rate of inflation will be the variable to focus on. The cyclical pattern of the inflation rate can be seen by taking first differences of equation (3)

$$\Delta p_t = \Delta w_t + e_t^s \quad . \tag{9}$$

Given a constant level of full employment $\bar{n}$, unemployment in period t will cause a lower nominal wage in period $t+1$, or correspondingly a negative growth rate of nominal wages. On the other hand, if actual employment is above full employment, wages in the next period have to rise in order to clear the labor market in advance. The cyclical movement of wages is directly embodied in the rate of inflation. The procyclical behavior of prices is also a common feature of models for aggregate supply and demand with nominal rigidities. Dynamic IS-LM models with adaptive expectations as presented in Sargent [1987, p. 117 ff.] are a familiar representative. Since the solution of the model for output growth and the rate of inflation does not allow current demand shocks to have an influence on the rate of inflation a slightly modified version of (3)

$$p_t = w_t - \theta_t + be_t^d \tag{10}$$

has been used to derive the following reduced form:

$$\begin{aligned} \Delta y_t &= (1-b)e_t^d + (1-a)e_t^s - (1-2b)e_{t-1}^d - ae_{t-1}^s & (11) \\ \Delta p_t &= be_t^d - e_t^s + (1-2b)e_{t-1}^d + ae_{t-1}^s \quad , & (12) \end{aligned}$$

where both variables are determined by actual and lagged demand and supply disturbances. Therefore, one must again rely on the identifying assumption of transitory and permanent impacts of the two innovations. The reduced forms (7)-(8) and (11)-(12) form the theoretical ground for the analysis in the next section. Before going into a detailed discussion of the consequences of these modifications we present some characteristics of the data and the impact of several different estimation approaches.

3 Results

For estimation we use quarterly series of the log U.S. real gross national product (1982 = 100), the U.S. capacity utilization for the manufacturing sector, and the log GNP deflator (1972=100) [1]. The pattern of autocorrelations and cross-correlations for all the series is given in tables 1 and 2. The autocorrelations are relatively high for the first few lags but decline thereafter, most rapidly for annualized output growth. Only the rate of capacity utilization and the rate of inflation show significant values even at lag 12.

The contemporaneous relationship between output and the other series appears to be rather weak. Just capacity utilization is significantly correlated with output growth at lag zero. The other variables show the highest correlation with output growth at lags 3 and 5, respectively. This indicates that output growth is a leading indicator for the rates of unemployment and inflation rather than a coincident relation between those series at quarterly frequency. Moreover, while the unemployment rate and capacity utilization show the highest correlation around lag zero, both series are leading the inflation rate.

The results for statistical tests on stationarity are given in the appendix in tables A1 to A4. According to augmented Dickey-Fuller and Phillips-Perron tests output and prices follow nonstationary stochastic processes, whereas the unemployment rate, capacity utilization, and the rate of inflation are stationary. Although part of the statistical results may call into question the stationarity of the unemployment rate, we believe this variable to be stationary for theoretical reasons.[2]

The system comprises annualized quarterly growth rates of output and a stationary variable (s_t). BQ-decomposition works as follows: Starting with the original moving average

[1] Sources are NIPA for real GNP; Bureau of Labor Statistics No. 2096 and 2307; Fed.Res. Bulletin various issues for capacity utilization; Balke and Gordon [1986] for the GNP deflator 1947-83, and IMF Int.Fin.Stat. for 1984-87. The estimation period runs from 1950:2 through 1987:4

[2] In their basic variant BQ accounted for a shift in mean GNP growth in 73:4 and for a time trend in unemployment rate. To facilitate comparability, we mirror their specification.

Table 1: **Autocorrelations of the series**

lag	Δ y	ur	cap	Δ p
1	0.36	0.94	0.91	0.64
2	0.24	0.80	0.75	0.59
3	-0.01	0.63	0.59	0.51
4	-0.11	0.48	0.43	0.40
5	-0.12	0.35	0.33	0.36
6	-0.06	0.26	0.29	0.29
7	-0.02	0.19	0.27	0.29
8	-0.07	0.12	0.27	0.33
9	-0.08	0.08	0.27	0.34
10	0.02	0.04	0.26	0.37
11	-0.02	0.00	0.22	0.27
12	-0.10	-0.03	0.17	0.32

representation of the bivariate process

$$x_t = A(L)u_t, \quad \text{where} \quad x_t = (\Delta y_t, s_t)' \tag{13}$$

estimated residuals u_t are decomposed into innovations $\epsilon_t = A_0^{-1}u_t$ such that Σ_ϵ is the identity matrix and the upper left element of the 2 x 2 - matrix $A(1)^* = A(1)A_0$ is equal to zero. From that we obtain an unique alternative representation $x_t = A(L)A_0\epsilon_t = A^*(L)\epsilon_t$, where x_t is driven by uncorrelated transitory and permanent innovations.

3.1 The Vector Autoregressive Moving Average

BQ estimated a VAR for the vector $(\Delta y_t, ur_t)'$ with lag length 8. They argued that high order VAR allows a well enough approximation for the moving average representation can

Table 2: Cross-correlations between variables

series1	Δ y			ur		cap
series2	ur	cap	Δ p	Δ p	cap	Δ p
lag [a]						
-8	-0.21	0.13	0.00	-0.16	0.07	-0.03
-7	-0.24	0.16	-0.01	-0.15	0.06	-0.05
-6	-0.24	0.19	-0.05	-0.13	0.04	-0.06
-5	-0.26	0.22	-0.12	-0.10	-0.01	-0.09
-4	-0.33	0.30	-0.01	-0.08	-0.09	-0.12
-3	-0.37	0.42	-0.03	-0.09	-0.23	-0.11
-2	-0.33	0.45	0.04	-0.11	-0.40	-0.09
-1	-0.20	0.41	0.05	-0.13	-0.57	-0.05
0	0.01	0.24	0.06	-0.15	-0.70	-0.01
1	0.26	-0.08	-0.03	-0.14	-0.72	-0.05
2	0.40	-0.25	-0.11	-0.11	-0.65	-0.13
3	0.42	-0.31	-0.20	-0.03	-0.53	-0.22
4	0.38	-0.30	-0.20	0.07	-0.41	-0.32
5	0.30	-0.25	-0.30	0.18	-0.31	-0.43
6	0.24	-0.17	-0.20	0.26	-0.25	-0.48
7	0.20	-0.11	-0.10	0.29	-0.22	-0.47
8	0.16	-0.12	-0.03	0.32	-0.18	-0.45

a) Cross-correlation between series1(t) and series2(t-lag) be obtained. It may be argued, however, that this approach completely neglects estimation problems due to over-parameterization (see e.g. Judge et al. [1988] p. 776). The number of available observations may be inadequate for obtaining precise estimates of the large number of coefficients in the VAR. In fact only two significant parameter estimates appear from lags 4 to 8. The computation of impulse response functions in BQ is mainly based on insignificant estimates. The process also could be characterized as an VAR(3) without much loss of information. In order to find a more parsimonious representation, we extend the VAR class by fitting Vector Autoregressive Moving Average (VARMA) processes.

A look at the auto- and cross-correlation functions in tables 1 and 2 indicates that the bivariate process could be adequately characterized as low order VARMA (p,q)-process (henceforth referred to as V(p,q)). Output growth Δy seems to follow a low order MA-process, unemployment rate a low order AR–process. Cross-correlations also may be captured sufficiently by a low order autoregressive specification.

For model selection we rely on information criteria and the ECCM-table (Tiao and Tsay [1983]) [3]. This approach is based on the significance values of partial autocorrelation matrices estimated by iterated OLS. Under the assumption of a V(p,q)-process the procedure provides consistent estimates for the autoregressive parameters. The autoregressive part is estimated for all pairs (p,q) and subsequently the residual correlation matrices are tested against zero. The idea is to find the process with lowest order that has clean residuals.

This procedure suggests a V(1,2) or a V(2,1)-model. Starting from a V(1,1)-model we estimate various extended models and compare them by likelihood ratio tests and information criteria, respectively. Results are shown in table 3. First of all, a V(1,1) is clearly rejected by both V(1,2) and V(2,1). V(2,2) rejects both V(1,2) and V(2,1) and thus seems to be the appropriate specification. Table 1 also contains the likelihood of several purely autoregressive specifications. Note that also a V(3,0)-process may be a sufficient specification. At least it has clearly better information criteria values than higher order VAR specifications. However, since omission of significant lags leads to biased estimates, the aim of the selection procedure is not necessarily to specify a process of lowest possible order.

[3] For estimation of VARMA models and computation of ECCM tables we use SCA. All other computations were done in RATS

Table 3: Model Selection Criteria

	- 2 * ln L	AIC	SIC	Q(20)	df
V(1,1)	-2527.7	−18.586	−18.366	73.28	72
V(1,2)	-2540.1	−18.618	−18.319	60.30	68
V(1,3)	-2548.5	−18.630	−18.250	65.93	64
V(2,1)	-2545.3	−18.655	−18.355	71.09	68
V(2,2)	-2557.5	−18.692	−18.313	57.23	64
V(3,0)	-2542.3	−18.624	−18.325	61.93	68
V(5,0)	-2548.0	−18.569	−18.109	54.23	60
V(8,0)	-2562.9	−18.496	-17.797	46.15	48

Results of BQ-decompositions are presented for V(8,0), V(2,2), V(3,0), V(1,2) and V(2,1) specifications. We find the residuals from different models - and accordingly the residual Covariance matrices - to be highly correlated. This fact also holds for transformed shocks, where correlations are given in tables 4a and 4b. Apparently various models generate almost identical innovations.

To keep the exposition concise we concentrate in the following on the reaction of output to demand and supply disturbances. Figures 1 and 2 show the dynamic effects of demand and supply disturbances on output for different specifications (exact values for impulse responses can be gathered from tables 5a and 5b). The vertical axis denotes the percentage deviation of output after a one percent demand or supply shock hit the system. The horizontal axis denotes time in quarters.

Similarity of results across different specifications also holds for impulse response curves. *Demand disturbances* have a hump-shaped effect on output across all specifications peaking after three quarters. The response of output vanishes after five years. Impulse response curves differ among models only slightly in the magnitude of the peaks and in the speed of decline.

Table 4: Correlation of shocks from VARMA(p,q) models

4a: Demand Shocks

	V(8,0)	V(3,0)	V(2,1)	V(1,2)	V(2,2)
V(8,0)	1.00	.94	.94	.95	.93
V(3,0)		1.00	.97	.99	.85
V(2,1)			1.00	.97	.87
V(1,2)				1.00	.87

4b: Supply Shocks

	V(8,0)	V(3,0)	V(2,1)	V(1,2)	V(2,2)
V(8,0)	1.00	.93	.90	.94	.89
V(3,0)		1.00	.96	.99	.85
V(2,1)			1.00	.97	.85
V(1,2)				1.00	.87

Table 5: Impulse responses for VARMA(p,q) models

5a: Demand Shocks

Quarter	V(8,0)	V(3,0)	V(1,2)	V(2,1)	V(2,2)
1	0.779	0.757	0.776	0.758	0.772
2	1.000	1.024	1.031	0.990	0.903
3	1.115	1.143	1.168	.1.081	0.928
4	1.060	1.072	1.111	1.003	0.909
8	0.655	0.419	0.454	0.391	0.601
12	0.262	0.119	0.099	0.044	0.243
40	-0.001	0.000	0.000	0.000	0.002

5b: Supply Shocks

Quarter	V(8,0)	V(3,0)	V(1,2)	V(2,1)	V(2,2)
1	0.072	0.261	0.213	0.226	-0.116
2	-0.069	0.182	0.121	0.106	-0.321
3	0.077	0.348	0.293	.0.180	-0.183
4	0.166	0.450	0.403	0.197	-0.019
8	0.693	0.549	0.533	0.361	0.408
12	0.615	0.517	0.522	0.433	0.524
40	0.438	0.505	0.505	0.446	0.446

Table 6: Impulse Responses for Stationary Variables [a)]

Quarters	Demand Shocks ur	cap	Δp	Supply Shocks ur	cap	Δp
1	.996 (.06)	.743 (.06)	.494 (.03)	.947 (.01)	.670 (.03)	.870 (.05)
2	1.284 (.07)	1.109 (.07)	.667 (.05)	-.821 (.02)	.768 (.04)	1.127 (.06)
3	1.431 (.08)	1.203 (.08)	.814 (.06)	.109 (.02)	1.051 (.05)	1.346 (.07)
4	1.357 (.08)	1.167 (.08)	.802 (.06)	.224 (.03)	1.088 (.05)	1.386 (.07)
8	.830 (.09)	.635 (.09)	.280 (.08)	.900 (.06)	1.301 (.03)	1.503 (.06)
12	.328 (.06)	.443 (.07)	.159 (.08)	.803 (.05)	.935 (.03)	1.355 (.05)
20	-.166 (.05)	.565 (.06)	.097 (.09)	.627 (.04)	.734 (.02)	1.352 (.05)
40	-.134 (.04)	- .462 (.05)	.206 (.10)	.573 (.04)	.635 (.01)	1.380 (.05)
∞	.000 (.04)	.000 (.05)	.000 (.10)	.576 (.04)	.634 (.01)	1.386 (.05)

a) Values in parentheses indicate asymptotic standard deviations according to Lütkepohl [1990].

Some differences arise for output response to *supply disturbances.* In the base case the effect on output peaks after eight quarters, then it decreases steadily and eventually stabilizes after five years. However, for all other specifications impulse response curves exhibit no peak. The long run effect is slightly stronger for the V(3,0) and V(1,2) specification. Surprisingly the V(2,2) model generates a negative response of output to a positive supply shock in the first three quarters. There is no clear cut economic interpretation of this behavior.

3.2 Alternative cyclical indicators

We now turn to the use of alternative cyclical indicators and present the results for VAR(8) specifications to facilitate the comparison with BQ. table 6 and figures 3 and 4 give the response of output for models including the unemployment rate, the capacity utilization, and the rate of inflation.

Demand disturbances give rise to a hump-shaped reaction of output. When peaking after two quarters a more or less regularly decline takes place in the long run. The output

Table 7: Corr. Among Shocks for Different Variables

	Demand Shocks				Supply Shocks		
	ur	cap	Δp		ur	cap	Δp
ur	1.00			ur	1.00		
cap	0.67	1.00		cap	0.44	1.00	
Δp	0.48	0.47	1.00	Δp	0.14	0.70	1.00

response to a demand shock tapers off for all systems after four to five years, showing convincingly the non-persistence of this shock. Interestingly, capacity utilization as well as the rate of inflation cause a smaller output reaction during the first two years.

Supply disturbances have a permanent effect on output by definition. Although, the degree of persistence depends crucially on the cyclical indicator chosen. The contemporaneous reaction of output to a supply shock is a big deal greater for the alternative variables and the short run hump is more pronounced. The negative reaction of output to a positive supply shock in the first quarter disappears completely when using alternative measures. In the long run the persistence of a supply shock in output is essentially the same for capacity utilization and the rate of unemployment. However, the rate of inflation generates a completely different picture. Starting with the highest contemporaneous reaction, the response peaks after seven quarters and levels off at a permanent increase of 1.4 %. Even a two standard error confidence interval does not include the border line case of a random walk for output, thus indicating a substantial and permanent overshooting response to a supply shock.

In contrast to our results for various VARMA models, the innovations from VAR's including different stationary variables show just moderate correlations. Demand innovations from models including the unemployment rate (henceforth UR-model) and the capacity utilization (CAP-model) exhibit a higher correlation of 0.7 as compared to the model including the inflation rate (ΔP-model). On the other hand for supply innovations correlation is highest between the CAP-model and ΔP-model, whereas between the UR-model and the ΔP-model it is not significantly different from zero.

Apart from the high persistence measure of the ΔP-model one more aspect strikes us with doubt about its appropriateness. As Quah [1992] shows, a necessary condition for application of the BQ-decomposition is that the stationary variable Granger-causes output growth. This may not hold for the inflation rate in the ΔP-model. Tests for Granger causality in VAR(8) models give the p-values of 0.001, 0.03, and 0.26 for the UR-model, CAP-model, and the ΔP-model, respectively.

4 Interpretation of Structural Shocks

The economic interpretation of orthogonal disturbances directly hinges on theoretical assumptions made before the decomposition of the Covariance matrix. In a recent paper, Lippi and Reichlin [1993] showed that economic theory does not in general provide sufficient structure to solve the problem of nonfundamental representations. This is a crucial point because for nonfundamental representations the identification of orthogonal disturbances is no more unique. However, the reduced form derived by BQ does not suffer from this problem. The same holds for our model including the capacity utilization. On the other hand, there might be some troubles as regards the reduced form (11)-(12) comprising the rate of inflation. For this system the range of admissible parameter values for a and b, the coefficients for the productivity shock in the demand equation and the monetary shock in the price equation respectively, is restricted. A graphical illustration of the constraints is given in figure 5. A value of a close to but smaller than one requires also a value for b close to one. Lower values for a are compatible with a broad range of b-values. A fundamental representation can therefore be achieved for a couple of reasonable parameter values.

Apart from the representation problem, the interpretation of permanent and transitory innovations as demand and supply shocks is questionable. First, permanent income hypothesis implies that intertemporal utility maximizing consumers will respond immediately to a permanent change in income by changing actual consumption expenditures. This will give rise to a permanent shift of the demand curve. The comovement of aggregate demand and productivity is contained in the BQ-model itself. Equation (1) shows the direct influence of productivity on aggregate demand. Depending on the magnitude of the parameter a the demand curve shifts more or less outside in response to a positive productivity shock. This suggests a further transformation of the innovations, such that demand shocks are a weighted sum of (standardized) transitory and permanent innovations, whereas supply shocks are attributed solely to permanent innovations.

Second, a response of monetary authorities to supply shocks also implies a correlation between supply and demand. For example, replacing the money equation (5) by $m_t = m_{t-1} + e_t^d + \lambda e_t^s$ introduces this kind of feedback into the model of BQ. From a time series perspective an immediate monetary response shows up as correlation between demand and supply shocks.

Both examples indicate that a permanent shock affects supply as well as demand curves. Thus we cannot regard supply and demand shocks as being uncorrelated. How does this affect the results and interpretation of the BQ-decomposition? We can show, that alternative linear transformations of transitory and permanent innovations into supply and demand shocks leave the total persistence measure of output unchanged. This can be formally proven by using the multivariate framework developed in Lee et. al. [1992]. Consider just the first equation of the VAR describing $\Delta y_t = a(L)\epsilon_t$, where ϵ_t is a 2 x 1 vector of shocks and $a(L) = (a_1(L), a_2(L))$ is a 1 x 2 matrix polynomial, accordingly. Lee. et. al [1992] present a persistence measure $P_{\Delta y}$ for Δy_t is given by

$$P_{\Delta y}^2 = \frac{a(1)\Sigma_\epsilon a(1)'}{a(0)\Sigma_\epsilon a(0)'}. \tag{14}$$

Any transformation of the orthogonal residuals $\nu_t = B^{-1}\epsilon_t$ leads to $\Delta y_t = a(L)B\nu_t$ and Covariance matrix $\Sigma_\nu = B^{-1}\Sigma_\epsilon B^{-1'}$. Plugging $a(L)B$ and Σ_ν into (14) leaves $P_{\Delta y}^2$ unchanged. The above approach may be regarded as direct extension of the Campbell and Mankiw [1987a] measure. For orthonormal shocks ϵ_t one arrives quickly at

$$P_{\Delta y}^{2} = (a_1(1)/a_1(0))^2 + (a_2(1)/a_2(0))^2 , \tag{15}$$

where the two components on the right hand side correspond to the squared persistence measure of Campbell and Mankiw. Note that the BQ decomposition sets $a_1(1)$ equal to zero.

For correlated shocks the above persistence decomposition will involve a cross term. If we leave supply shocks unchanged and construct demand shocks as a weighted sum of permanent and transitory innovations, the cross term will offset any persistence of demand shocks.

It may be of some interest to have a look at the relations between original residuals from the VAR and orthogonal innovations. They are visualized in figure 6 for the unemployment rate and capacity utilization. In the two-dimensional space spanned by the transformation matrix A_0 the angles between the particular innovations and residuals are given by the arccosines of their contemporaneous correlations. Since unemployment is a negative cyclical indicator, we use the negative of unemployment residuals in figure 6. For the UR-model transitory innovations correspond closely to original residuals from the Δy_t equation of the VAR system. This can be seen by the small angle between the vector representing transitory innovations and the vector for Δy_t. However, in the CAP-model transitory innovations almost coincide with residuals from the cap_t equation. This difference may be due to lagged response of unemployment to the business cycle. Consequently transitory innovations first will show up in the output equation of the UR-model. Then, as figure 6 shows, the unemployment rate reacts to transitory innovations mainly through lagged output changes. On the other hand capacity utilization seems to be a roughly coincident cyclical indicator. Thus transitory shocks are associated with residuals of the capacity equation in the CAP-model. We conclude that with respect to interpretation of transformation matrices the CAP-model seems to be the more satisfactory approach.

Let us now return to the discussion of correlated demand and supply shocks. If we simply regard demand shocks as the sum of transitory and permanent innovations, i.e. $a = 1$

in equation (1), then this shows up in figure 6 as the 45 degree line corresponding to the vector labeled 'demand'. According to our hypothetical experiment residuals from the unemployment equation are only weakly contemporaneously correlated with demand. This view is in sharp contrast to an approach of Campbell and Mankiw [1987b]. The authors regressed output growth on its own leads and lags and on the contemporaneous unemployment rate. In their interpretation residuals of this equation reflect the change in the (stochastic) trend component, while fitted values refer to the change in business cycle. In fact, contemporaneous correlation between GNP growth and unemployment is close to zero (see table 2). Thus neglecting lagged unemployment response to cyclical shocks leads to an inappropriate model.

5 Conclusion

Summing up, the above results suggest a fairly high degree of robustness of the BQ-decomposition with respect to the model specification. There is a simple statistical explanation for the stability of the transformation. The cyclical indicators follow autoregressive processes with a fairly high degree of inertia, whereas autocorrelation in GNP growth dies out after two lags. The corresponding properties of the moving average polynomial seem to be rather insensitive to the details of specification. Thus we conclude that the decomposition will work fairly well, as long as a good cyclical indicator is chosen, which then naturally exhibits high first order autocorrelation. Both the unemployment rate and capacity utilization provide fairly good cyclical indicators. But aggregate price changes, as used by Bayoumi and Eichengreen [1992], are not really suitable for the purpose of extracting the business cycle component. That is not only reasonable in the light of an instable output-inflation-trade off as stressed in Phillips-curve discussion. One glimpse at figure 7 reveals that the inflation rate gives a meager image of the NBER dated peaks and troughs. Moreover, the inflation rate does not Granger-cause output growth and therefore does not fulfill theoretical preconditions for the BQ-decomposition.

While the BQ-decomposition may be useful for the extraction of the cyclical component, interpretation of permanent and transitory innovations as supply and demand shocks is subject to some criticism. Several theoretical models give rise to a correlation between unexpected changes in permanent income and a corresponding reaction of aggregate demand. We suggest that supply shocks can be associated with permanent shocks but demand shocks must be viewed as a weighted combination of transitory and permanent innovations. This does neither affect the persistence measure nor the value of the BQ-decomposition as a robust method to filter out the business cycle from an output series.

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Fig. 1: Output Response to a Demand Shock

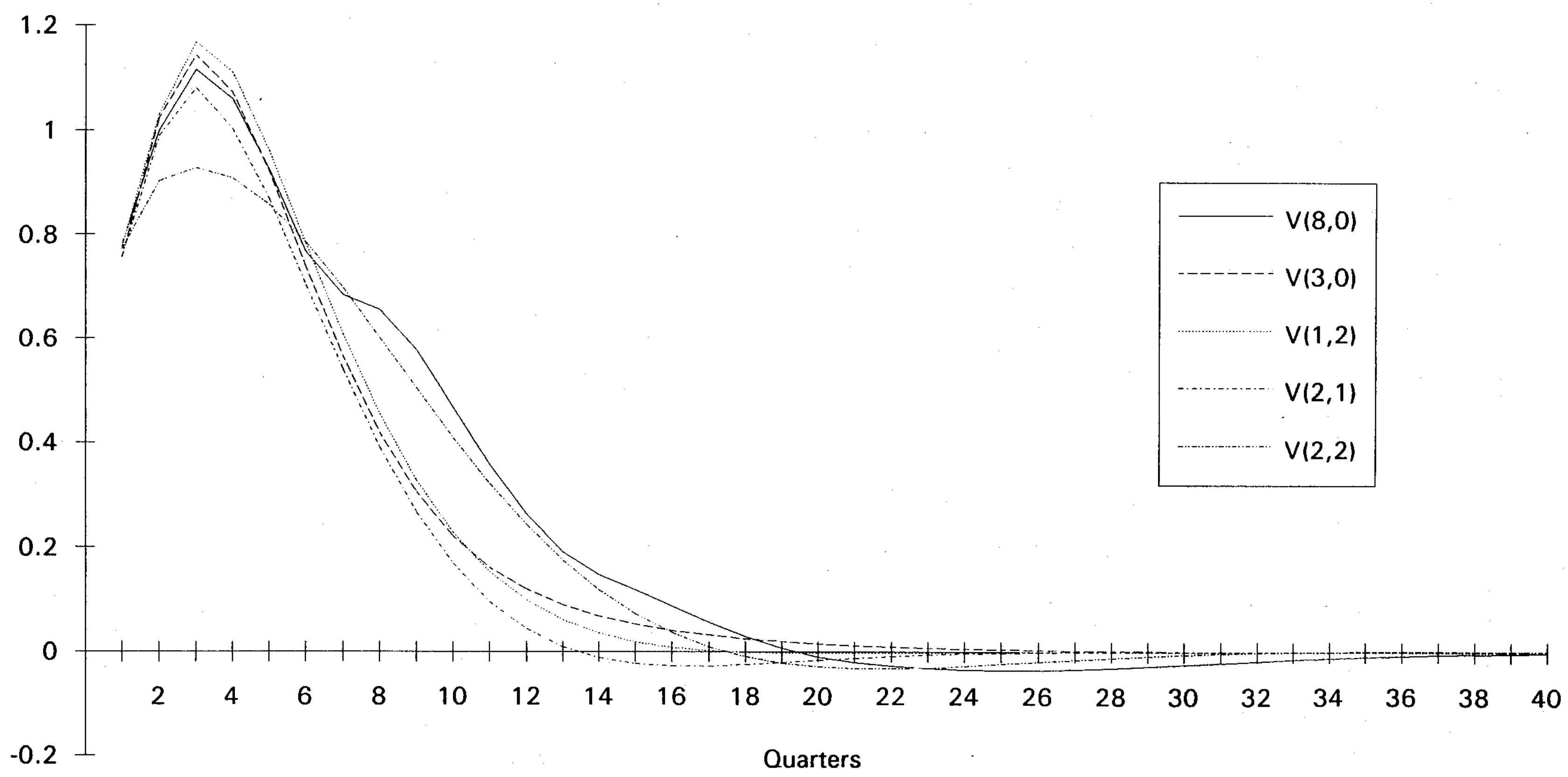


Fig. 2: Output Respone to a Supply Shock

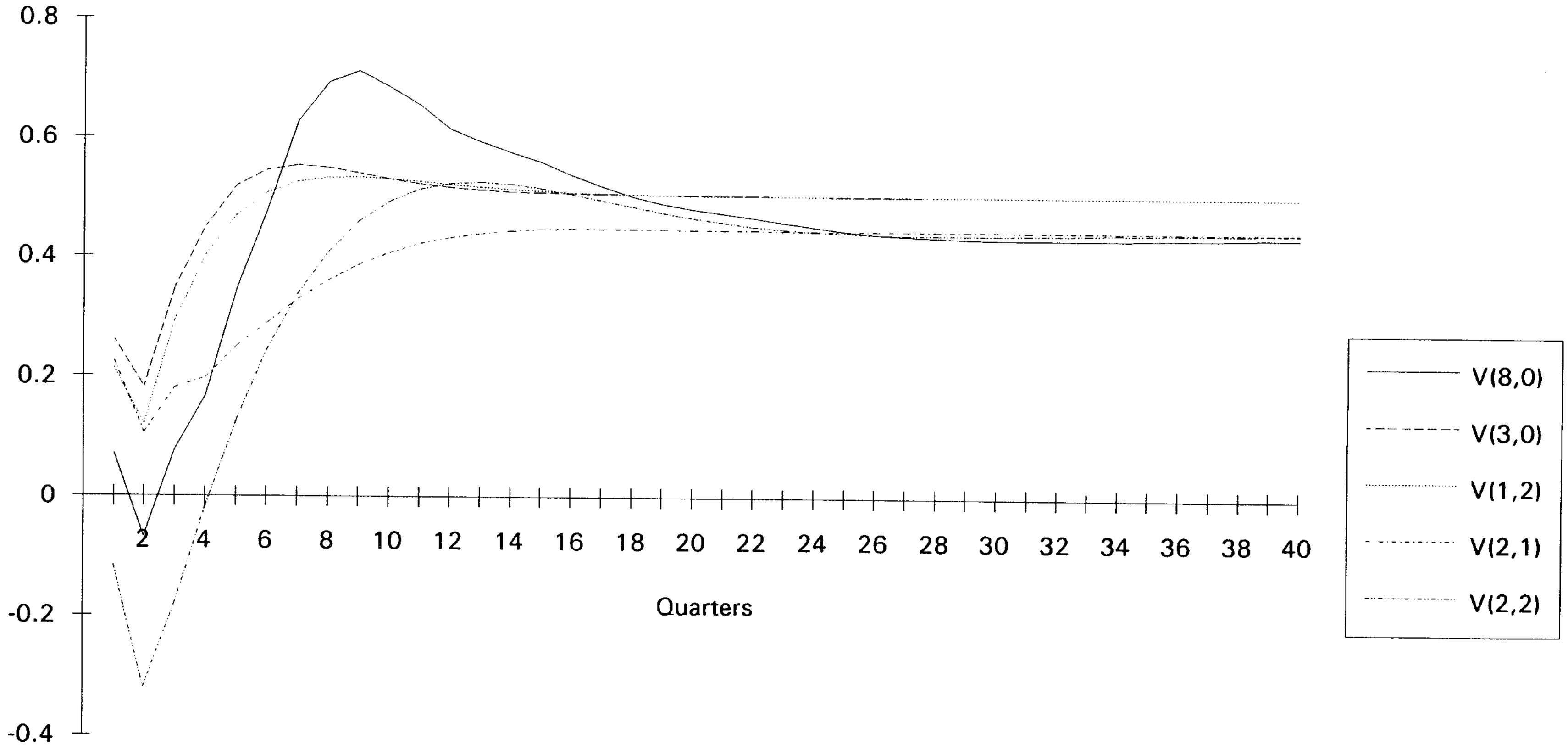


Fig. 3: Output Response to a Demand Shock

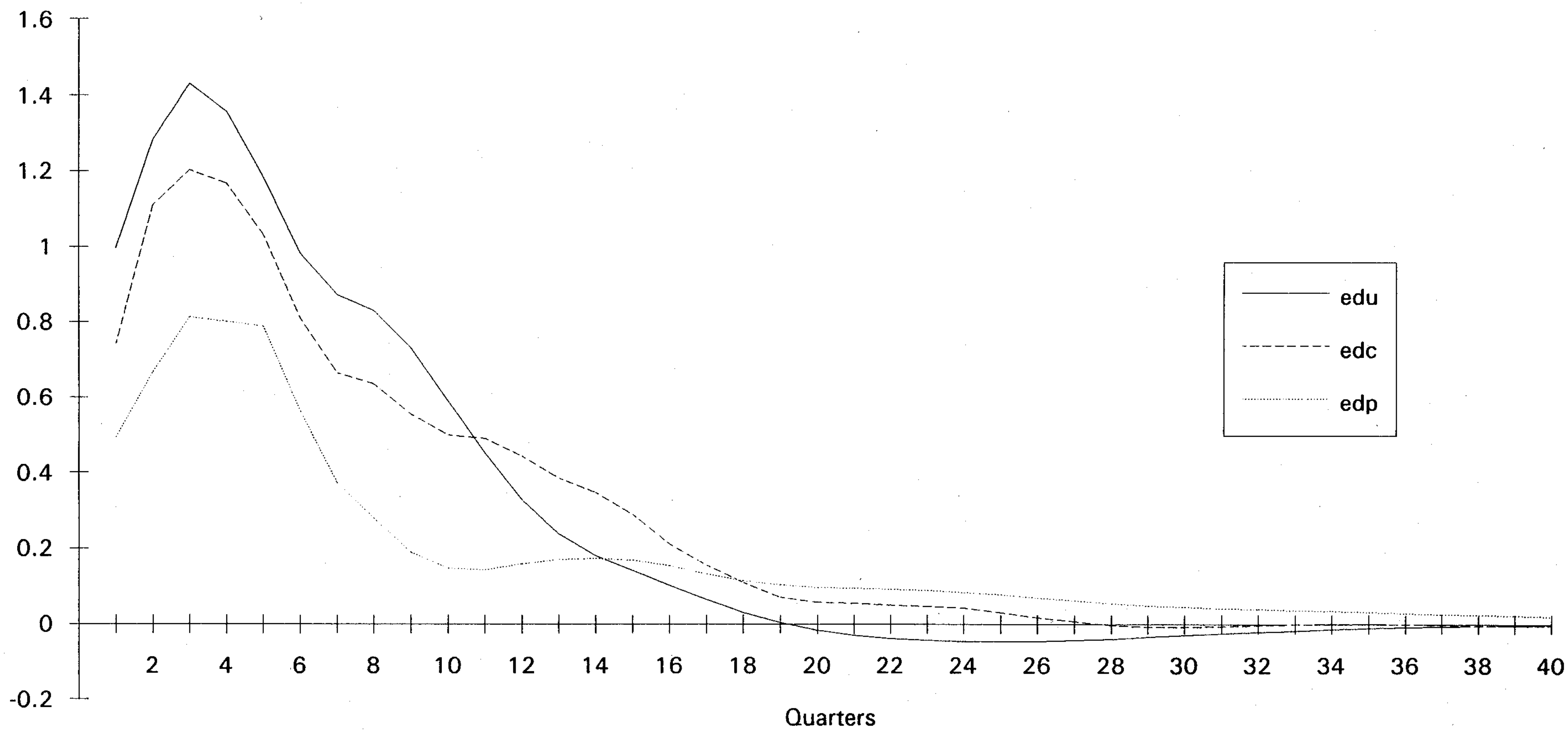


Fig. 4: Output Response to a Supply Shock

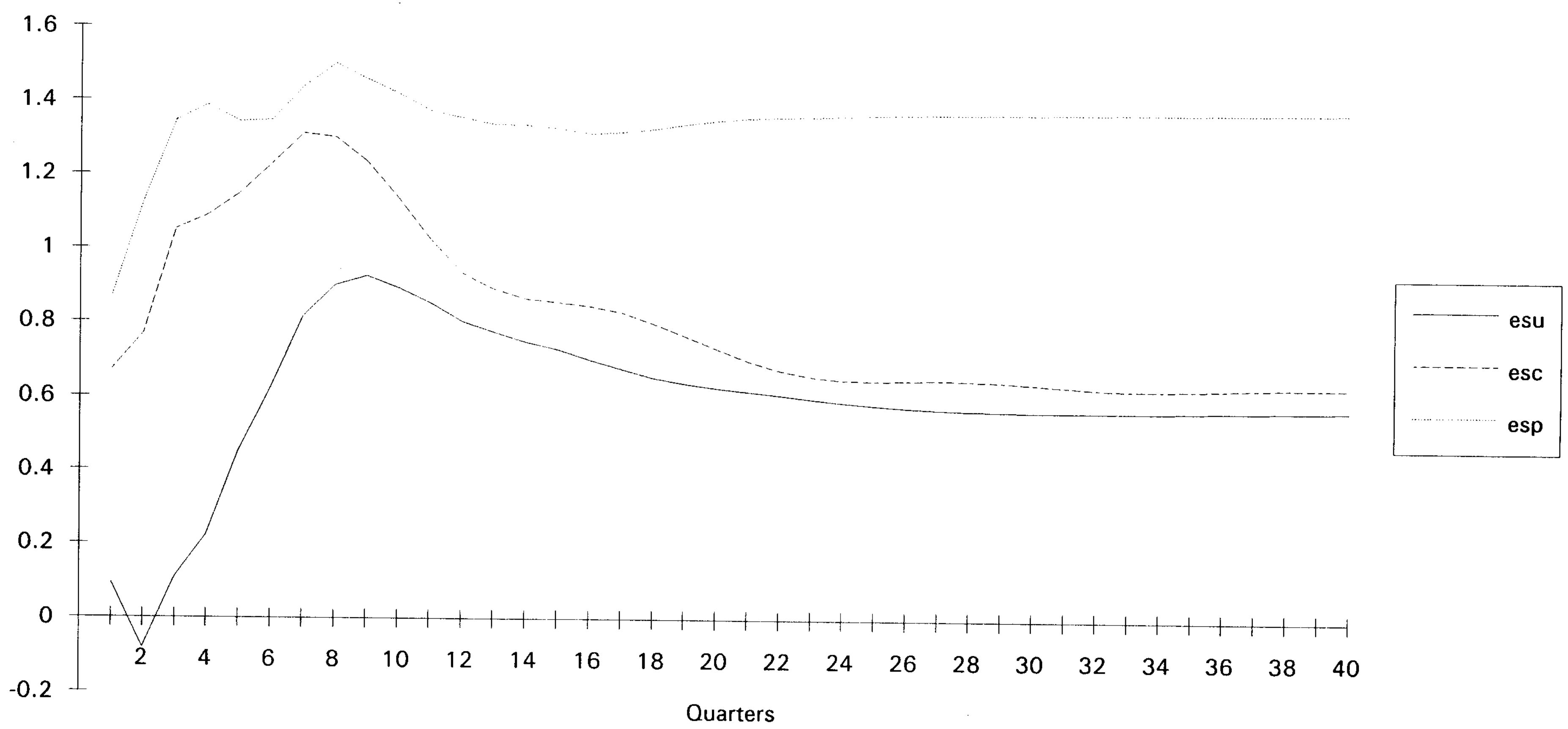


Fig. 5: Admissible Parameter Space for model (dy, dp)

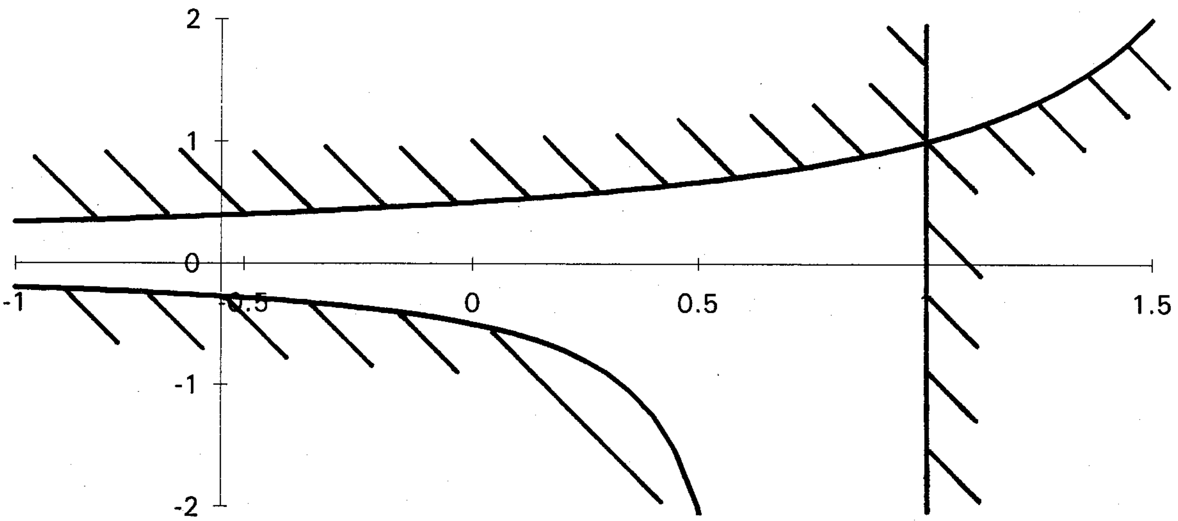
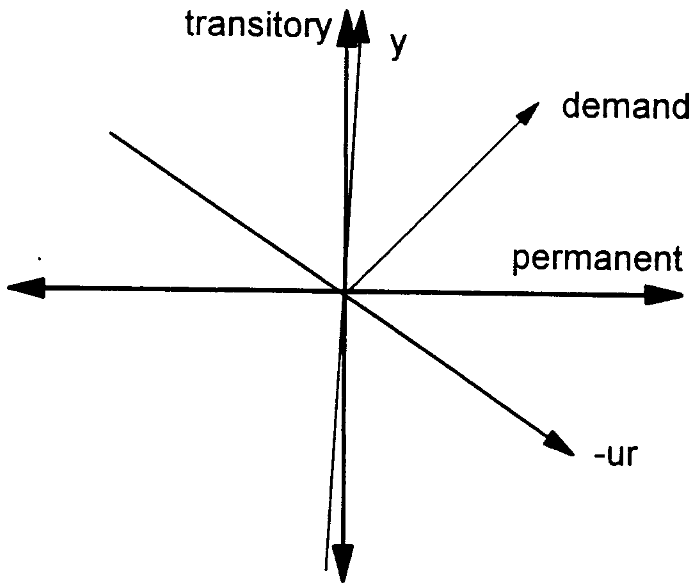


Figure 6:Transformation of shocks

unemployment rate



capacity utilization

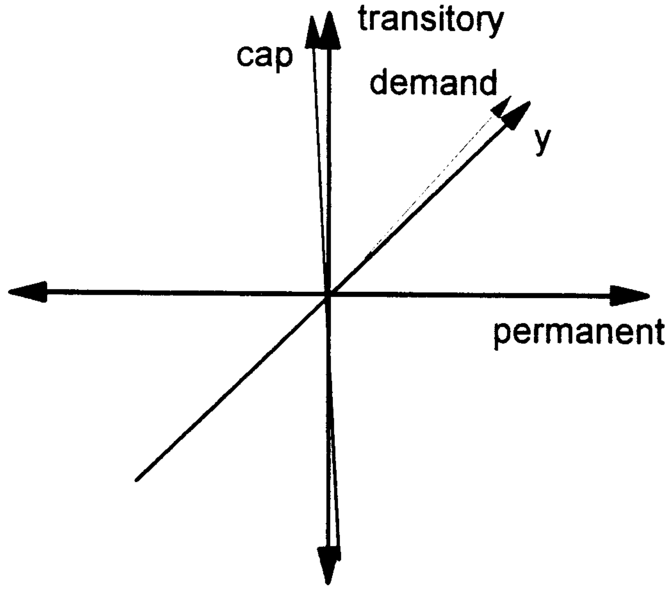


Fig. 7: Stand. Infl. Rate, Cap.Util., and NBER cycles

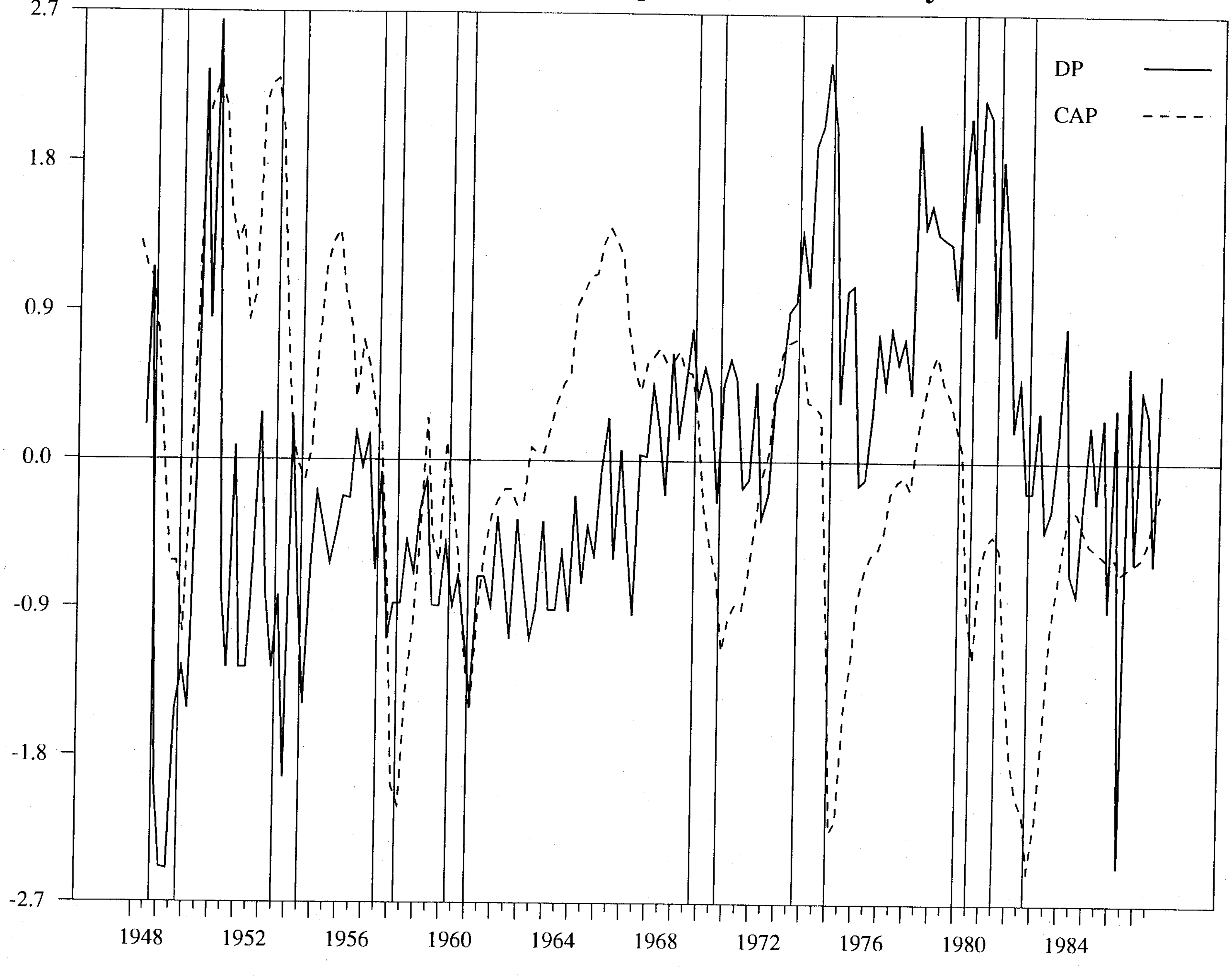


Table A.1: Augmented Dickey-Fuller (Regression includes constant, trend, lagged variables, and k lagged differences)

Series	T	k	μ	$t(\mu)$a)	ß	t(ß)b)	α	$T(\alpha-1)$c)	$\tau(\alpha)$d)	s(u)
Y	167	1	.3719	2.69	.0004	2.55	.953	-7.98	-2.65	.01
DY	161	2	-.0001	-.02	.0000	.11	.356	-103.63*	-6.50*	.04
UR	163	2	.4153	3.53*	.0014	1.99	.927	-11.83	-3.58*	.32
CAP	160	4	-.0116	-.08	-.0074	-1.90	.870	-20.82*	-3.50*	1.87
P	165	3	.036	2.20	.0000	2.63	.993	-1.17	-2.01	.01
DP	165	2	.000	-0.41	.0000	2.60	.668	-54.79	-4.62	.01

a) the 0.05 one-sided critical value for 100 observations is 3.11 (Dickey/Fuller 1981, table II)
b) the 0.05 one-sided critical value for 100 observations is 2.79 (Dickey/Fuller 1981, table III)
c) the 0.05 one-sided critical value for 100 observations is -20.7 (Fuller 1976, table 8.5.1.)
d) the 0.05 one-sided critical value for 100 observations is -3.45 (Fuller 1976, table 8.5.2.)
*) indicates rejection at the 5% level

Table A2: Augmented Dickey-Fuller Test (regressions include constant, lagged level, and lagged differences)

Series	T	k	μ	$t(\mu)$a)	α	$T(\alpha-1)$b)	$\tau(\alpha)$c)	s(u)
DY	161	2	-.0000	-.01	.3564	-103.62*	-6.52*	.04
UR	163	2	.2696	2.91*	.9533	-7.61	-2.97*	.32
CAP	160	4	-.0125	-.08	.9101	-14.38*	-2.92*	1.88
DP	165	2	0.000	-0.34	.748	-41.64	-3.81	.01

a) the 0.05 one-sided critical value for 100 observations is 2.54 (Dickey/Fuller 1981, table II)
b) the 0.05 one-sided critical value for 100 observations is -13.7 (Fuller 1976, table 8.5.1.)
c) the 0.05 one-sided critical value for 100 observations is -2.89 (Fuller 1976, table 8.5.2.)
*) indicates rejection at the 5% level

Table A3: Phillips-Perron Test (regressions include constant, trend and lagged variable)

Series	l	μ	$Z(t\mu)$ [a]	ß	$Z(tß)$ [b]	a	$Z(a)$ [c]	$Z(ta)$ [d]	$Z(F_2)$ [e]	$Z(F_3)$ [f]	s(u)
Y	2	.2892	2.46	.0003	2.53	.963	-10.68	-2.42	18.16*	2.48	.01
Y	4	.2892	2.99	.0003	3.25*	.963	-16.46	-2.96	13.07*	4.08	.01
Y	8	.2892	3.67*	.0003	4.14*	.963	-25.57*	-3.65*	10.83*	6.46	.01
Y	10	.2892	3.89*	.0003	4.42*	.963	-28.97*	-3.87*	10.61*	7.33*	.01
DY	2	-.0002	-.05	.0000	.18	.362	-104.21*	-8.67*	23.65*	35.70*	.04
DY	4	-.0002	-.05	.0000	.17	.362	-110.93*	-8.83*	24.69*	37.24*	.04
DY	8	-.0002	-.06	.0000	.19	.362	-96.44*	-8.50*	22.47*	33.96*	.04
DY	10	-.0002	-.06	.0000	.22	.362	-78.68*	-8.15*	19.92*	30.21*	.04
UR	2	.2762	3.08	.0005	1.59	.952	-20.59	-3.12	2.91	4.35	.44
UR	4	.2762	4.02*	.0005	2.31	.952	-34.77*	-4.10*	5.40*	8.09*	.44
UR	6	.2762	4.60*	.0005	2.73	.952	-45.32*	-4.70*	7.20*	10.79*	.44
UR	10	.2762	5.19*	.0005	3.16*	.952	-57.60*	-5.31*	9.28*	13.91*	.44
CAP	2	-.0400	-.16	-.0040	-1.64	.897	-33.19*	-4.08*	5.08*	7.62*	2.27
CAP	4	-.0400	-.14	-.0040	-2.11	.897	-49.00*	-4.96*	7.87*	11.80*	2.27
CAP	8	-.0400	-.13	-.0040	-2.33	.897	-57.33*	-5.36*	9.30*	13.95*	2.27
CAP	10	-.0400	-.13	-.0040	-2.28	.897	-55.31*	-5.26*	8.96*	13.43*	2.27
P	2	.027	1.20	.0000	1.65	.996	-1.05	-0.89	45.97*	4.68	.01
P	4	.027	1.27	.0000	1.62	.996	-1.78	-1.05	22.89*	2.66	.01
P	8	.027	1.56	.0000	1.84	.996	-3.66	-1.42	10.42*	1.92	.01
P	10	.027	1.72	.0000	1.99	.996	-4.75	-1.60	8.18*	1.97	.01
DP	2	.000	-.02	.0000	2.31	.558	-60.91*	-6.38*	11.97*	18.12*	.01
DP	4	.000	-.02	.0000	2.42	.558	-70.04*	-6.70*	13.62*	20.56*	.01
DP	8	.000	-.02	.0000	2.78	.558	-101.16*	-7.72*	19.03*	28.63*	.01
DP	10	.000	-.02	.0000	3.01	.558	-122.45*	-8.37*	22.66*	34.06*	.01

a) the 0.05 one-sided critical value for 100 observations is 3.11 (Dickey/Fuller 1981, table II)
b) the 0.05 one-sided critical value for 100 observations is 2.79 (Dickey/Fuller 1981, table III)
c) the 0.05 one-sided critical value for 100 observations is -20.7 (Fuller 1976, table 8.5.1.)
d) the 0.05 one-sided critical value for 100 observations is -3.45 (Fuller 1976, table 8.5.2.)
e) the 0.05 critical F-value for 100 observations is 4.88 (Dickey/Fuller 1981, table V)
f) the 0.05 critical F-value for 100 observations is 6.49 (Dickey/Fuller 1981, table VI)
*) indicates rejection at the 5% level

Table A4: Phillips/Perron Test (regressions include constant and lagged variable)

Series	T	l	μ	$Z(t\mu)$a)	α	$Z(\alpha)$b)	$Z(t\alpha)$c)	s(u)
UR	165	2	.2287	-.27	.9613	-14.51*	-2.76	.44
UR	165	4	.2287	-1.47	.9613	-23.40*	-3.47*	.44
UR	165	6	.2287	-2.12	.9613	-29.95*	-3.92*	.44
UR	165	10	.2287	-2.73*	.9613	-37.42*	-4.37*	.44
CAP	164	2	-.0419	-.17	.9133	-26.80*	-3.76*	2.27
CAP	164	4	-.0419	-.14	.9133	-38.75*	-4.48*	2.27
CAP	164	8	-.0419	-.13	.9133	-44.69*	-4.80*	2.27
CAP	164	10	-.0419	-.13	.9133	-43.11*	-4.72*	2.27
DP	167	2	.000	.01	.614	-50.26*	-5.73*	.01
DP	167	4	.000	.01	.614	-57.19*	-6.00*	.01
DP	167	8	.000	.01	.614	-91.66*	-7.25*	.01
DP	167	10	.000	.01	.614	118.71*	-8.12*	.01

a) the 0.05 one-sided critical value for 100 observations is 2.54 (Dickey/Fuller 1981, table II)
b) the 0.05 one-sided critical value for 100 observations is -13.7 (Fuller 1976, table 8.5.1.)
c) the 0.05 one-sided critical value for 100 observations is -2.89 (Fuller 1976, table 8.5.2.)
*) indicates rejection at the 5% level