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An Application of Estimating Structural Vector Autoregression Models with Long-Run Restrictions*

This paper estimates the contribution of aggregate demand and supply shocks to economic fluctuations. Following Blanchard and Quah we estimate a vector autoregression with long-run restrictions to identify structural demand and supply shocks. We investigate the effects of temporal aggregation on the contribution of these shocks to business cycle fluctuations. Using the industrial production index which is a more cyclically volatile measure of output than GNP, we find results qualitatively similar to theirs. Quantitatively, however, our results differ in that we find a larger fraction of output variation is explained by supply shocks and a larger fraction of unemployment variation is explained by demand shocks.

1. Introduction

Large structural macroeconometric models lost much of their appeal in the early 1970s for two reasons. First, their forecasting performance deteriorated particularly compared to simple time series models. Second, the emergence of the rational expectations hypothesis during the 1970s cast doubt on the validity of many of the exclusion restrictions used to identify large scale structural macroeconometric models. One response to these criticisms regarding forecasting performance and ad hoc restrictions was proposed by Christopher Sims (1980, 1982). He developed an "atheoretical" approach to model building called vector autoregressions (VARs).

Although these models have proved useful for forecasting, Cooley and LeRoy (1985) showed that it is not proper to interpret innovations to a VAR as structural policy shocks without imposing a set of identifying restrictions on the system.

In response to the criticism levied by Cooley and LeRoy, sev-

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eral researchers have developed techniques to impose identifying restrictions on VARs. This paper illustrates the methodology of using long-run restrictions between variables to identify structural relationships within a VAR model.

The attractiveness of these long-run restrictions is that they are often common among theories which yield vastly different implications for the short-run behavior of variables. For example, both New Keynesian and New Classical theories of the business cycle may maintain long-run natural rate properties, but differ in their predictions about the short-run influence of aggregate demand.

We follow the Blanchard and Quah (1989) approach by imposing the long-run restrictions implied by the natural rate hypothesis, but allow the data to provide evidence on short-run dynamics. In their paper they use a long-run restriction to identify transitory and permanent shocks in a bivariate VAR consisting of the differenced log of real output and the prime age male unemployment rate. These two shocks are referred to as aggregate demand and aggregate supply shocks respectively.[1]

Our aim in this paper is to employ the Blanchard and Quah technique to investigate the contribution of aggregate supply and demand disturbances to business cycle fluctuations using industrial production rather than GNP as our measure of aggregate economic activity. By replacing GNP with industrial production we are able to extend the Blanchard and Quah analysis to address several additional questions. First, since industrial production is observed monthly rather than quarterly we are able to investigate the effect of temporal aggregation on the measurement of supply and demand shocks. Second, since industrial production is a more cyclically volatile measure of aggregate economic activity than GNP we are able to investigate whether the difference in their cyclical behavior is due to transitory demand or permanent supply shocks. Finally, because industrial production is observed monthly rather than quarterly, it provides important information to forecasters and policymakers about the short-term performance of the economy. It is therefore useful to determine whether movements in industrial production are driven by transitory demand or permanent supply disturbances.

Our empirical results suggest that permanent supply shocks account for more of the variation in both monthly and quarterly

[1]We attach the labels supply shocks to permanent innovations and demand shocks to temporary innovations. This is done for expository convenience.

industrial production than in quarterly GNP. In addition, we find that almost all of the variation in unemployment is explained by transitory demand shocks. Temporal aggregation appears to have little effect on our results.

This paper is organized as follows. Section 2 outlines the theoretical and empirical developments which led to the questions raised by Blanchard and Quah, hereafter BQ. Section 3 describes the data and specification tests. Section 4 presents the results of our estimation. Section 5 concludes.

2. Theoretical and Empirical Background

For most of the post World War II period, the study of macroeconomics was neatly divided into two separate non-overlapping subfields: the study of growth and the study of business cycle fluctuations. Growth theorists abstracted from fluctuations and business cycle theorists abstracted from growth. Most intermediate text books in macroeconomics still maintain this separation.

The empirical foundation for this division of labor in macroeconomics was that real output was believed to fluctuate randomly around a fixed trend path. The model presented by Robert Solow (1956) has been widely accepted as the explanation for secular movements in trend growth. In empirical work the factors that determine the trend path (human and physical capital, productivity, and resource endowment) are often treated independently from the factors that determine the fluctuations (aggregate demand, monetary and fiscal policy).

Empirical evidence presented by Nelson and Plosser (1982) raised serious questions about this arbitrary distinction between cycle and trend. Using statistical techniques developed by Dickey and Fuller (1979), Nelson and Plosser presented evidence suggesting many aggregate economic series, including the log of real gross national product, contain a unit root. The implication of this finding is that business cycle movements in real GNP are due in part to permanent shocks. To carry the analysis one step further, by interpreting permanent shocks as aggregate supply shocks, this empirical result implies that movements in aggregate supply may account for some of the movements in real GNP which have previously been interpreted as aggregate demand fluctuations.

Several researchers have employed univariate methods to identify permanent and temporary movements in aggregate real output. Univariate identification of permanent and temporary shocks involves estimating an ARIMA model for the log of real GNP and then imposing a restriction on the contemporaneous correlation between the permanent and temporary components. For example, Beveridge and Nelson (1981) assume that the permanent and temporary components are perfectly correlated. Other researchers, such as Campbell and Mankiw (1987a and 1987b) and Cochrane (1988) assume that the permanent and temporary components of real GNP are orthogonal.

Blanchard and Quah (1989) take a multivariate approach using information from two macroeconomic time series to distinguish between two sources of output fluctuations. First, they observe that the log of GNP contains a unit root while the unemployment rate (for prime age males) is stationary about a linear trend. Combining this time series information with the natural rate hypothesis they identify aggregate demand and aggregate supply shocks within the context of a bivariate VAR consisting of the differenced log of real output and the prime age male unemployment rate. They assume the two kinds of shocks are uncorrelated.[2]

3. The Data and Specification Tests

The data used in the tests that follow are the seasonally adjusted quarterly U.S. total industrial production index (1987 = 100) and unemployment rate for males 20 years old and over. Figure 1 shows the industrial production index from 1948 through 1990. The average annual growth rate has been about 3.4%. The economic downturns in 1954, 1958, the early 1960s, 1970–71, 1974, and 1981–82 are clearly seen. However, there appears to be a downward level shift in 1974. Prior to 1974 the quarterly growth rate averaged 1.08%; thereafter it was about 0.5%. There is greater "cyclical" variation in the growth of industrial production compared to real GNP. The ratio of standard error to mean growth rate is 1.18 for real GNP and 2.07 for industrial production prior to 1974 and 1.71 for real GNP and 3.12 for industrial production afterwards. The monthly growth rate of the industrial production series is even more volatile; the pre 1974 ratio is 3.39 and the post 1974 ratio is 4.92.

Figure 2 shows the unemployment rate for the same sample. The unemployment measure using males age 20 and over was cho-

[2]The BQ identification method imposes the restriction that demand shocks have no permanent effect on real output. To the extent that the economy experiences hysteresis, the impact of demand shocks will be underestimated.

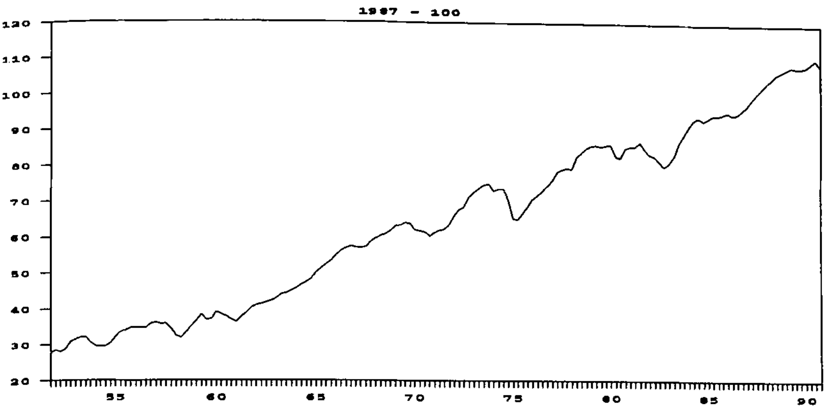

Figure 1.
Log of Industrial Production 1987–100

sen because we are trying to identify productivity type supply shocks not demographic or labor force participation type supply shocks. Prior to 1974 the unemployment rate averaged about 3.7%. From 1974 through 1990 the average rose about 2.0 percentage points. There appears to be a slight upward trend over the entire sample.

The graphical evidence presented above suggests that the industrial production index and possibly the unemployment rate are

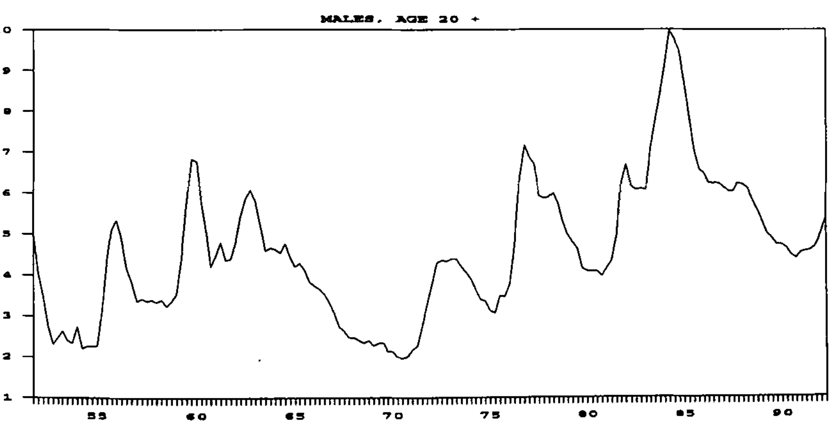

Figure 2.
Unemployment Rate
Males Age 20+

TABLE 1. *Unit Root Tests for Stationarity, Sample Period 1951:04–1990:12 with Trend Removed for UE and Means Removed pre and post 1973:12 for IP*

Equation	Null Hypothesis	Test Statistic	Description	UE	IP	Critical Value 10%
1	$\alpha_1 = 0$	t-ratio	*Valid when series mean is 0*	−0.6372	3.5924	−1.62
2	$\alpha_1 = 0$	t-ratio		−2.813	−1.3282	−2.57
2	$\alpha_0 = \alpha_1 = 0$	F-test Φ_1	*Unit root test (zero drift)*	4.0131	8.0534	3.78
3	$\alpha_1 = 0$	t-ratio		−3.295	−1.8539	−3.13
3	$\alpha_0 = \alpha_1 = \alpha_2 = 0$	F-test Φ_2	*Unit root test (zero drift)*	3.6585	6.3094	4.03
3	$\alpha_1 = \alpha_2 = 0$	F-test Φ_3	*Unit root test (non-zero drift)*	5.43	2.2645	5.34

NOTE: The unit root tests were performed using the COINT procedure in SHAZAM (1991).

nonstationary.[3] We therefore employ a series of augmented Dickey-Fuller tests (see, for example, Dickey and Fuller 1979) to investigate whether unit roots are the source of nonstationarity. We follow Campbell and Perron's (1991) rules (of thumb) for investigating whether a series contains a unit root. In particular, we begin by estimating the following three forms of the augmented Dickey-Fuller test where each form differs in the assumed deterministic component(s) in the time series.

$$\Delta Y_t = \alpha_1 Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \epsilon_t\,; \tag{1.1}$$

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \epsilon_t\,; \tag{1.2}$$

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 t + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \epsilon_t\,. \tag{1.3}$$

The ϵ_t is assumed to be a white noise disturbance. In the first equation there is no constant or trend. The second contains a constant, but no trend. Both a constant and trend are included in the third equation. The number of lagged differences, p, is chosen to ensure that the estimated errors are not serially correlated. The order is chosen at the highest significant lag order from the autocorrelation function or the partial autocorrelation function of the first differenced series.

The standard (augmented) Dickey-Fuller test has been subject to criticism recently by Perron (1990) and Balke and Fomby (1991). They argue that when the true generating process involves stationary fluctuations around a shifting trend it cannot be distinguished from a difference stationary process. Perron found a one-time break in U.S. output growth following the oil price shock in 1973. Since this could potentially affect our results we estimate models with the means removed for the two subperiods as a specification check. This approach implicitly assumes a deterministic shift in trend in 1974. Balke and Fomby present the alternative view that trend shocks are stochastic.

Table 1 presents the unit root test results following Equations

[3]Hereafter we refer to industrial production and output interchangeably.

(1.1), (1.2), and (1.3) using the monthly industrial production and unemployment data.[4] The unemployment series, UE, is found to reject the null hypothesis of a unit root when a constant term is included, as in Equation (1.2). This suggests that the unemployment rate is a stationary process when a trend term is included. The growth rate in output is stationary but with a mean shift in 1974:01. These results are identical to BQ. When a constant and or trend term is included in the augmented Dickey-Fuller test, Equations (1.2) and (1.3), no additional explanatory power is added.

Table 2 presents the unit root test results following Equations (1.1), (1.2), and (1.3) using the quarterly average of industrial production and unemployment. The unemployment series, UE, is found to reject the null hypothesis of a unit root when a constant term is included, as in Equation (1.2). This suggests that the unemployment rate is a stationary process when a trend term is included.[5] The growth rate in output is stationary but with a mean shift in 1974:Q1. Again, these results are identical to BQ. When a constant and or trend term is included in the augmented Dickey-Fuller test, Equations (1.2) and (1.3), no additional explanatory power is added.

4. Methodology and Results

We begin by estimating a VAR consisting of the differenced log of industrial production (Δy) and the unemployment rate (u). Our sample is from 1951:2 through 1990:4.[6] Following BQ as indicated by the unit root results from Section 3 we remove a linear time trend from the unemployment rate and two different means from the growth rate of industrial production. The estimated trend in quarterly unemployment is 0.0155, the mean pre 1974 was 3.68, and post 1973 it was 5.8%. The mean quarterly growth of industrial production was 1.08 from 1951:2 through 1973:4 and 0.55 from 1974:1 through 1990:4.

[4]Recent literature has stressed the lower power of the unit root tests against alternatives like segmented trends or infrequent permanent shocks. In addition, the power of the test against a null hypothesis of $\alpha_1 = 0.95$ is low. For example, see DeJong and Whiteman (1991). Thus we report the results with a critical value of 10%.

[5]Clearly, the unemployment rate cannot have a deterministic trend asymptotically, since it is bounded by 0% and 100%. In small samples however, this may be a sensible way to model the series.

[6]BQ's sample ended in 1987:*iv*. Our slightly longer sample period does not account for the differences in our results. We obtained results similar to those reported in the text when we ended the sample in 1987:*iv*.

TABLE 2. *Unit Root Tests for Stationarity, Sample Period 1951Q2–1990Q4 with Trend Removed for UE and Means Removed pre and post 1973Q4 for IP*

Equation	Null Hypothesis	Test Statistic	Description	UE	IP	Critical Value 10%
1	$\alpha_1 = 0$	$T\hat{\alpha}_1$	*Valid when series mean is 0*	−12.049	−6.5231	−5.60
1	$\alpha_1 = 0$	t-ratio	*Valid when series mean is 0*	−2.8622	−1.8284	−1.61
2	$\alpha_1 = 0$	$T\hat{\alpha}_1$		−12.171	−6.6633	−11.00
2	$\alpha_1 = 0$	t-ratio		−2.8742	−1.8636	−2.58
2	$\alpha_0 = \alpha_1 = 0$	F-test Φ_1	*Unit root test (zero drift)*	4.1442	2.0161	−3.86
3	$\alpha_1 = 0$	$T\hat{\alpha}_1$		−12.339	−7.6031	−17.50
3	$\alpha_1 = 0$	t-ratio		−2.9063	−1.8905	−3.15
3	$\alpha_0 = \alpha_1 = \alpha_2 = 0$	F-test Φ_2	*Unit root test (zero drift)*	2.9668	1.4256	4.16
3	$\alpha_1 = \alpha_2 = 0$	F-test Φ_3	*Unit root test (non-zero drift)*	4.4366	1.8603	5.47

NOTE: The unit root tests were performed using the COINT procedure in SHAZAM (1991).

Following BQ we include two years of lags in the estimated VAR, that is, eight lags for the quarterly system and twenty four lags for the monthly system. We first estimate the two-variable VAR system using ordinary least squares:

$$B(L)Z_t = \mu_t$$

where

$$Z_t = \begin{bmatrix} \Delta y \\ u \end{bmatrix}$$

and

$$\mu_t = \begin{bmatrix} \mu^{\Delta y} \\ \mu^{u} \end{bmatrix}, \tag{2}$$

where $B(L)$ is a polynomial in the lag operator. Output growth is represented by Δy and unemployment by u. The innovations to this system ($\mu^{\Delta y}$, μ^{u}) have covariance matrix Ω. This (stationary) autoregressive model can be represented in terms of an infinite order moving average model of the form:

$$Z_t = C(L)\,\mu_t\,;$$

where

$$C(L) = B(L)^{-1}\,,$$

$$\begin{bmatrix} \Delta y \\ u \end{bmatrix} = \begin{bmatrix} C_{11}(L) & C_{12}(L) \\ C_{21}(L) & C_{22}(L) \end{bmatrix} \begin{bmatrix} \mu^{\Delta y} \\ \mu^{u} \end{bmatrix}. \tag{3}$$

The C_{ij}'s are constructed by simulating the response of equation (i) to a one unit innovation in equation (j). For example, to construct $C_{11}(L)$ and $C_{21}(L)$, a unit innovation to the Δy equation at time period 1 is fed into Equation (2). The sequence of numbers generated from the Δy equation is $C_{11}(L)$ and the sequence of numbers generated from the u equation is $C_{21}(L)$. This process is repeated with an innovation to the u equation to construct $C_{12}(L)$ and $C_{22}(L)$. By construction, the first element in the matrix of impulse responses, which we denote by $C(0)$, is the identity matrix.

TABLE 3. *Estimated Parameters of the A(0) Matrix*

Parameter	Monthly Data	Quarterly Data
var ($\mu^{\Delta y}$)	0.7679	2.733
cov ($\mu^{\Delta y}$, μ^{u})	−0.059	−0.3376
var (μ^{u})	0.0315	0.0799
ΣC_{11} (L)	0.5	0.5941
ΣC_{12} (L)	1.346	2.25
Solution to the system A (0)	0.4704, 0.7393 −0.1747, 0.3115	1.066, 1.263 −0.281, −0.029

The C_{ij}'s are the impulse response functions of this bivariate system. The problem with trying to interpret these impulse response functions, however, is that they represent the response of equation (i) to a one-unit *orthogonal* innovation to equation (j). In general, the innovations in a VAR will not be orthogonal. This raises

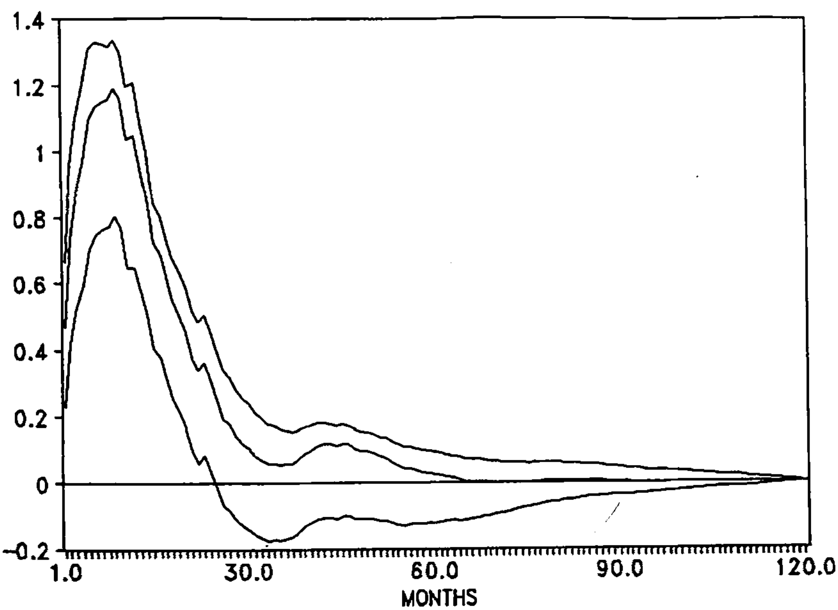

Figure 3a.
IP Response to Demand
Monthly Data

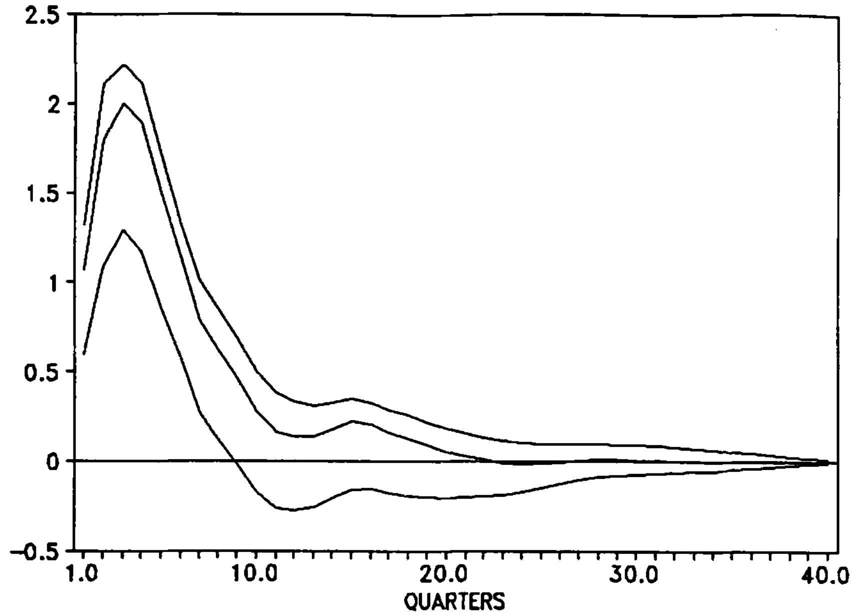

Figure 3b.
IP Response to Demand
Quarterly Data

the issue of how to assign the covariation between the innovations to a particular innovation. The early literature on VARs simply assigned all of the covariation to one of the equations and then tested to see if the results were robust to changes in the ordering of the system. As pointed out by Keating (1990) this ad hoc assignment of covariance is equally as arbitrary as the exclusion restrictions imposed on large scale macroeconometric models.

Later developments in the literature on VARs introduced innovative ways to divide up the covariance between the innovations (see Keating 1990 for a review of the various techniques). The method proposed by BQ makes use of the long-run implications of the natural rate hypothesis. According to the natural rate hypothesis, aggregate demand shocks have no long-run impact on the log level of real output.

Since the system represented by (3) suffers from the problem discussed above, our goal is to construct an alternative representation of $(\Delta y, u)'$ in which the innovations have a structural interpretation. In particular, we wish to construct the following representation:

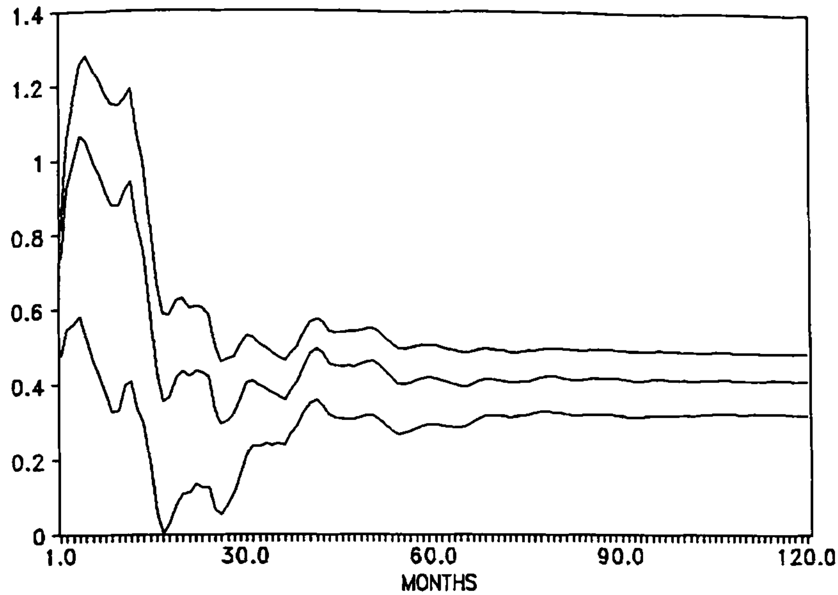

Figure 4a.
IP Response to Supply
Monthly Data

$$\begin{bmatrix} \Delta y_t \\ u_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} \epsilon_t^D \\ \epsilon_t^s \end{bmatrix}, \tag{4}$$

where ϵ^D and ϵ^S are orthogonal demand and supply shocks. Recalling that $C(0)$ is the identity matrix, it follows that moving average coefficients in the alternative representation (4) obey the identity: $A(j) = C(j)\,A(0)$, for $j = 0, 1, 2, 3, \ldots$. The innovations to the alternative representation obey the identity:

$$\begin{bmatrix} \epsilon^D \\ \epsilon^S \end{bmatrix} = A(0)^{-1} \begin{bmatrix} \mu^{\Delta y} \\ \mu^u \end{bmatrix}. \tag{5}$$

From these identities it is clear that the alternative representation (4) can be derived by identifying the 4 elements of the $A(0)$ matrix. Two sets of restrictions are used to identify these four elements. The first set of restrictions normalizes the variance of the structural shocks to be one: $A(0)A(0)' = \Omega$. Since there are only 3 unique elements of Ω, this condition identifies three of the ele-

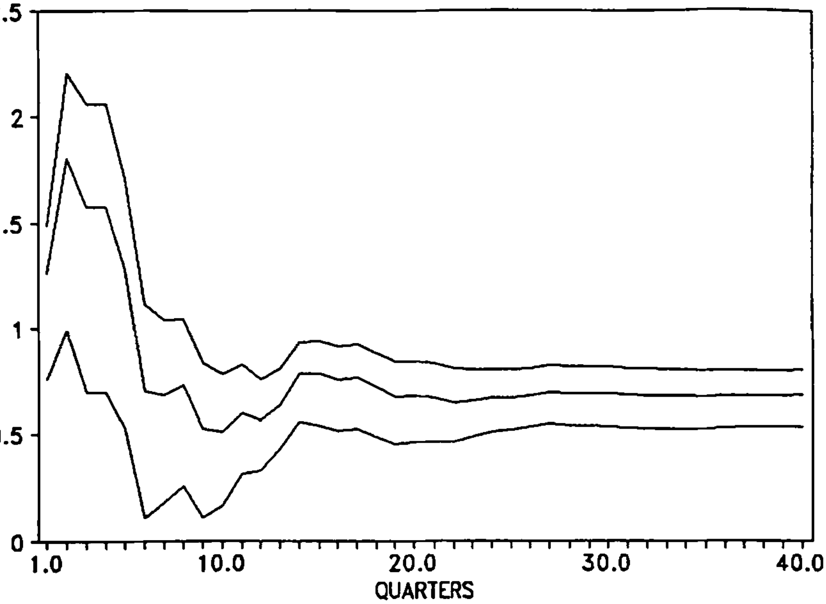

Figure 4b.
IP Response to Supply
Quarterly Data

ments of $A(0)$. The remaining element is identified by imposing the restriction that the demand shock, ϵ^D, has no long-run impact on the log level of real output. This restriction requires that the (1, 1) element of $[\Sigma_{i=0}^{\infty} C(L)]*A(0) = 0$. Together, the variance normalization restriction and the long-run natural rate restriction just identify the elements of the $A(0)$ matrix.

The four elements of the $A(0)$ matrix are obtained by solving the following four nonlinear equations:

$$a_{11}^2(0) + a_{12}^2(0) = \text{var}\,(\mu^{\Delta y})\,, \tag{i}$$

$$a_{11}(0)a_{21}(0) + a_{12}(0)a_{22}(0) = \text{cov}\,(\mu^{\Delta y}, \mu^{u})\,, \tag{ii}$$

$$a_{21}^2(0) + a_{22}^2(0) = \text{var}\,(\mu^{u})\,, \tag{iii}$$

$$[\Sigma c_{11}(L)]a_{11}(0) + [\Sigma c_{12}(L)]a_{21}(0) = 0\,. \tag{iv}$$

Table 3 presents the estimated parameters for both the monthly and quarterly VARs.

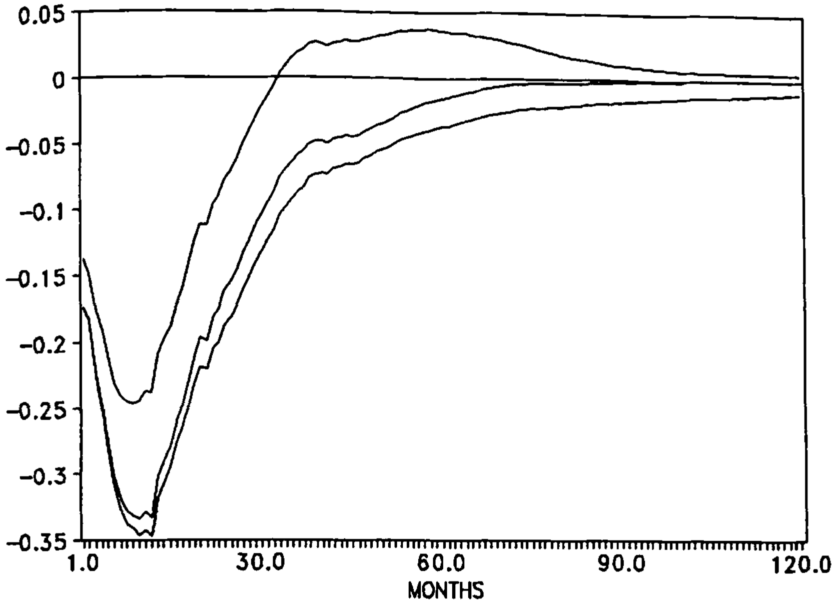

Figure 5a.
U Response to Demand
Monthly Data

Once the $A(0)$ matrix is constructed the identity $A(j) = C(j)A(0)$ can be used to construct the remaining elements of the impulse response functions. These results are reported in Figures 3 through 6. The figures using the monthly model are presented in the second column and those using the quarterly data are presented in the third column.

Below we compare our results with BQ. Recall that they used real GNP growth for their measure of output.

To gain insight into the significance of the point estimates we present the point estimates of the impulse response function along with one-standard error bands. The standard error bands are constructed using the bootstrapping method suggested by Runkle (1987). This method involves randomly sampling the estimated residuals from Equation (2). Using these sampled residuals and the estimated coefficients new series of Δy and u are constructed. These newly constructed series are then run through the same process as described above to construct a new $A(0)$ matrix. This entire procedure is repeated 1000 times to produce a mean $A(0)$ and standard deviation about the mean. Since the standard error bands are about the mean

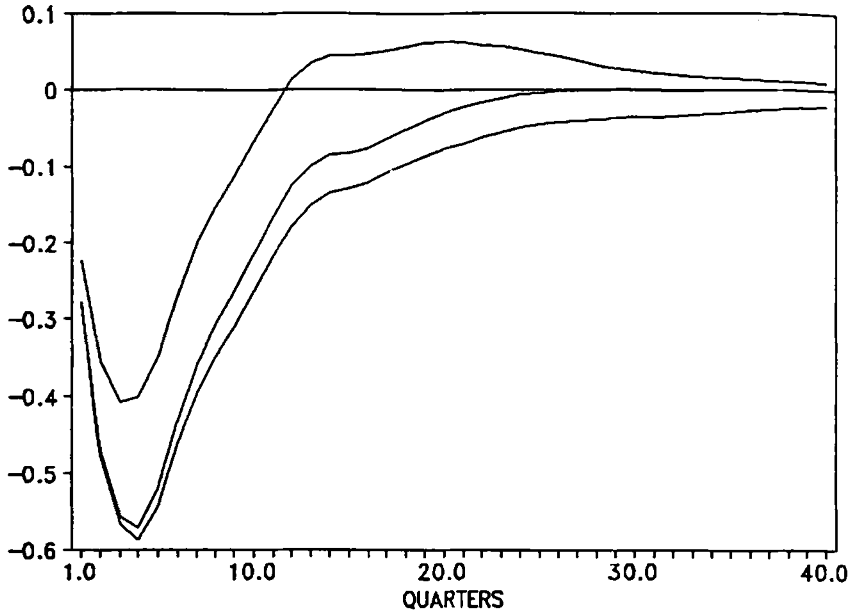

Figure 5b.
U Response to Demand
Quarterly Data

and not the point estimate the bands are not symmetric. The area encompassed by the bands represents a 68% confidence interval about the mean.

Figures (3a) and (3b) show the response of industrial production and Figures (5a) and (5b) show the response of unemployment to a one-unit (and by construction, one-standard deviation) innovation in demand. These figures look very similar in shape to the corresponding figures presented by BQ. The magnitudes of response are much larger, however. The peak response of industrial production is about 1.2 with the monthly model and 2.0 with the quarterly model at 3 quarters compared to BQ's peak response of real GNP of 1.3. The peak response of unemployment is roughly −0.2 with the monthly model, −0.5 with the quarterly model at 4 quarters, the same as BQ's estimate. Our estimates suggest an "Okun coefficient" of about 6 for the monthly model and 5.7 for the quarterly model compared to BQ's estimate of 2.5. These results make sense since the variance of industrial production growth is much larger than the variance of real GNP growth.

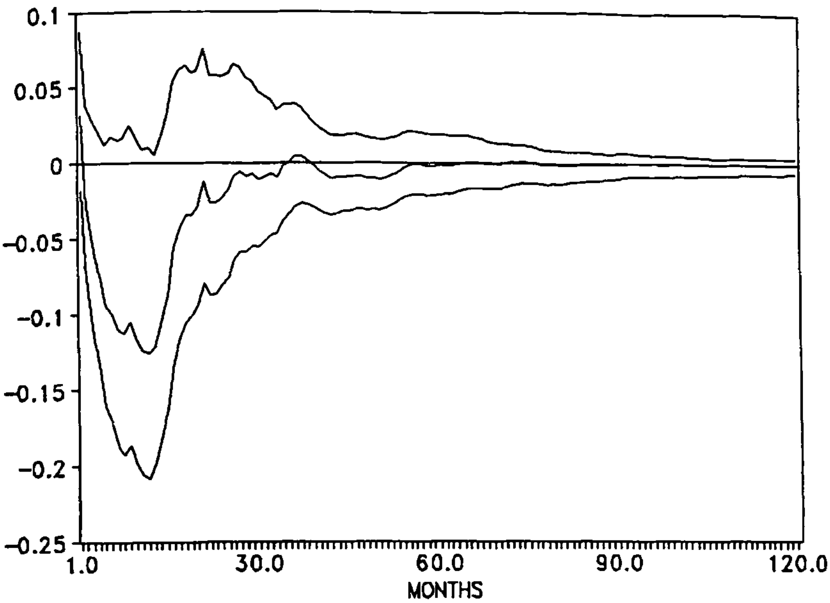

Figure 6a.
U Response to Supply
Monthly Data

The response of industrial production to a one unit innovation in supply is presented in Figures (4a) and (4b). The duration of the impulse response looks significantly different from the ones presented by BQ. The output response to supply peaks at 1.05 and 1.85 with the monthly and quarterly models respectively after only 2 quarters compared to 0.8 at 8 quarters for BQ. After 8 quarters the response of industrial production has fallen by 50% in both models. In the long run it levels out at about 0.5 and 0.65 for the monthly and quarterly models. The permanent effect in the BQ model is about 0.6.

Figures (6a) and (6b) show the response of unemployment to a one-unit innovation in supply. The unemployment response to supply peaks at −0.12 for the monthly model and −0.20 for the quarterly model after 4 quarters. The standard error bounds suggest that these responses are not significantly different from zero. BQ's model actually has a positive effect, unemployment increases, in response to supply shocks. By construction there is no permanent effect from supply shocks to unemployment in both models.

Our final task is to calculate the variance decompositions im-

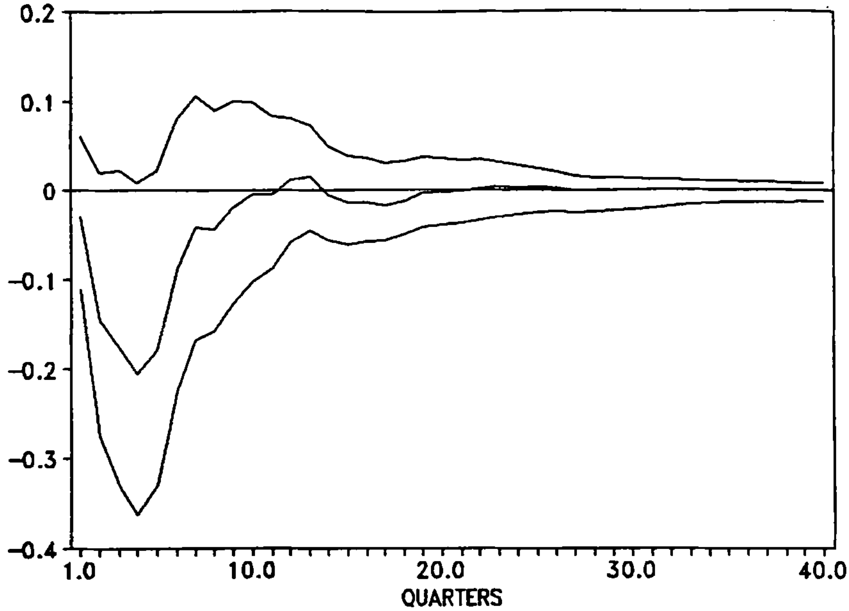

Figure 6b.
U Response to Supply
Quarterly Data

plied by the structural representation (4). To do this, we calculate the variance of the forecast error accounted for by a particular innovation at various horizons. Results for quarters 1 through 4, 8, 12 and 40 are presented in Tables 4 and 5 for the monthly and quarterly series respectively. The numbers below the point estimates represent one-standard error bands. The precision of the distinction between our results and BQ should be tempered by the large standard errors of the estimates.

These variance decompositions differ from those presented by BQ in the short run, but not in the long run (40 quarters and 120 months). Comparing our results to the results presented in their Table 2 we find that in our model demand shocks at 1 quarter account for a smaller fraction of variation in output 38% and 41% with the monthly and quarterly models respectively against BQ's 99%. In the long run the BQ model suggests 39% of output variation is explained by demand shocks; our monthly and quarterly models suggest the estimate is 36% and 38% respectively. A much larger fraction of the variation in unemployment 95% and 99% is ex-

TABLE 4. *Forecast Error Variance Decomposition for Monthly Data 1951:04–1990:12. Percentage of the Expected Squared Prediction Error Produced by Aggregate Demand and Aggregate Supply Innovations*

Horizon/Quarter	Industrial Production		Unemployment	
	Aggregate Demand	Aggregate Supply	Aggregate Demand	Aggregate Supply
1	38.8 (14.8, 68.7)	61.2 (29.4, 100.0)	95.7 (74.0, 98.5)	4.3 (1.5, 26.0)
2	46.8 (21.3, 74.9)	53.2 (31.3, 85.3)	92.1 (68.0, 99.1)	7.9 (1.0, 32.0)
3	52.5 (26.4, 78.8)	47.5 (25.1, 78.7)	91.0 (65.8, 99.4)	9.0 (0.6, 34.2)
4	54.0 (27.6, 79.8)	46.0 (20.2, 72.4)	90.0 (64.0, 99.2)	10.0 (0.8, 36.0)
8	54.9 (28.8, 79.4)	45.1 (20.6, 71.2)	91.4 (64.9, 98.3)	8.6 (1.7, 35.1)
12	52.5 (27.8, 76.2)	47.5 (23.8, 72.2)	92.0 (65.2, 97.8)	8.0 (2.2, 34.8)
40	36.3 (18.6, 54.5)	63.7 (45.5, 81.4)	92.1 (65.3, 97.7)	7.9 (2.3, 34.8)

NOTE: Numbers in parentheses represent one-standard error bounds estimated from 1000 replications.

TABLE 5. *Forecast Error Variance Decomposition for Quarterly Data 1951Q2–1990Q4. Percentage of the Expected Squared Prediction Error Produced by Aggregate Demand and Aggregate Supply Innovations*

Horizon/ Quarter	Industrial Production		Unemployment	
	Aggregate Demand	Aggregate Supply	Aggregate Demand	Aggregate Supply
1	41.6 (16.4, 70.3)	58.4 (29.7, 83.6)	98.9 (75.7, 100.0)	1.1 (0.0, 24.3)
2	47.4 (21.1, 74.9)	52.6 (25.1, 78.9)	93.1 (68.1, 100.0)	6.9 (0.0, 31.9)
3	53.3 (26.5, 79.0)	46.7 (21.0, 73.5)	91.9 (66.2, 100.0)	8.1 (0.0, 33.8)
4	54.9 (27.9, 80.2)	45.1 (19.9, 72.1)	90.7 (64.4, 99.7)	9.3 (0.3, 35.6)
8	56.0 (29.3, 79.9)	44.0 (20.1, 70.8)	92.0 (65.4, 98.7)	8.0 (1.3, 34.6)
12	54.3 (28.5, 77.4)	45.7 (22.6, 71.5)	92.7 (65.9, 97.8)	7.3 (2.2, 34.1)
40	38.1 (19.2, 56.1)	61.9 (43.9, 80.8)	92.7 (66.0, 97.6)	7.3 (2.4, 34.0)

NOTE: Numbers in parentheses represent one-standard error bounds estimated from 1000 replications.

plained by demand shocks in our two models at one quarter. BQ only find 52% of the variation in unemployment attributed to demand shocks. In the long run, supply shocks explain approximately 63% with the monthly model and 62% with the quarterly model of the output growth forecast error variance and 60% in BQ. The results in both models for the effect of aggregate demand shocks on unemployment converge to about 92% by two years vs. 87% in the BQ model.

5. Conclusion

This paper illustrates the methodology of how long-run restrictions between variables can be used to identify structural relationships within a VAR model. We estimate a bivariate model of output, proxied for by industrial production, and the unemployment rate. Two types of shocks are identified in the model. The first represents a short run shock which could be due to aggregate demand factors. The second can be characterized as having a persistent or long-run effect on the economy.

We compare our results to Blanchard and Quah (1989) who use a different measure of output and slightly shorter sample period. By choosing industrial production, a monthly measure of output which is more cyclically volatile than GNP, we are able to investigate the source of its volatility over the cycle and the effects of temporal aggregation.

The dynamic impacts of permanent and temporary shocks on the two variables are presented. We find dynamic effects similar to BQ in the long run, but not in the short run. The impulse responses in our model suggest that demand shocks have a strong impact on output in the short run. However, examination of the forecast error variances shows that aggregate supply shocks are more important in determining output movements whereas aggregate demand shocks are more important in determining unemployment movements. Our evidence lends support to an eclectic view of the cycle where both transitory demand and permanent supply shocks are important in the determination of business cycle fluctuations.

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