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THE DYNAMIC EFFECTS OF AGGREGATE DEMAND AND SUPPLY DISTURBANCE

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No. 497 May 1988

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by

Olivier Jean Blanchard and Danny Quah *
February 1988.

* Both authors are with the Economics Department, MIT, and the NBER. We thank Stanley Fischer, Julio Rotemberg, and Mark Watson for helpful discussions, and the NSF for financial assistance. We are also grateful for the comments of participants at an NBER Economic Fluctuations meeting, and for the hospitality of the MIT Statistics Center.

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Abstract

We decompose the behavior of GNP and unemployment into the dynamic effects of two types of shocks: shocks that have a permanent effect on output and shocks that do not. We interpret the first as supply shocks, the second as demand shocks.

We find that demand disturbances have a hump shaped effect on both output and unemployment; the effect peaks after a year and vanishes after two to three years. Up to a scale factor, the dynamic effect on unemployment of demand disturbances is a mirror image of that on output. The effect of supply disturbances on output increases steadily over time, to reach a peak after two years and a plateau after five years. "Favorable" supply disturbances may initially increase unemployment. This is followed by a decline in unemployment, with a slow return over time to its original value.

While this dynamic characterization is fairly sharp, the data are not as specific as to the relative contributions of demand and supply disturbances to output fluctuations. We find that the time series of demand-determined output fluctuations has peaks and troughs which coincide with most of the NBER troughs and peaks. But variance decompositions of output at various horizons giving the respective contributions of supply and demand disturbances are not precisely estimated. For instance, at a forecast horizon of four quarters, we find that, under alternative assumptions, the contribution of demand disturbances ranges from 30 to 80 per cent.

Introduction.

In response to an innovation in GNP of 1%, one should revise one's forecast by more than 1% over long horizons. This fact is documented by Campbell and Mankiw (1987a), building on earlier work by Nelson and Plosser (1982).

What does this statistical fact mean for macroeconomics? If there were only one main type of disturbance in the economy, its implications would be clear; all we would need to do would be to find what those disturbances are, and why their dynamic effects have the shape characterized by Campbell and Mankiw. But if, as is likely, GNP is affected by more than one main type of disturbance, say by aggregate demand and by aggregate supply disturbances, the interpretation becomes more difficult. In that case, the univariate moving average representation of output is a combination of the dynamic response of output to each of the two disturbances. Clearly, knowing only the aggregate effect does not allow us to recover those two responses. Campbell and Mankiw show that their estimated univariate representation for GNP is equally consistent with, for example, either white noise productivity growth and small, short-lived, effects of demand disturbances on GNP, or instead, with serially correlated productivity growth and larger, serially correlated, effects of demand disturbances.

We are interested in investigating the dynamic effects of disturbances that have only transitory impact on output as well as of disturbances that have permanent impact. Studies that impose strict random walk behavior in the permanent component are necessarily incapable of addressing this issue (and we feel strongly that this *is* the interesting characterization to obtain). Allowing the permanent component to have rich serial correlation however destroys identification to a profound extent: Quah (1988) shows how any general difference stationary process can always be decomposed into permanent and transitory components where the components are orthogonal at all leads and lags, and such that the variance of the first difference of the permanent component is arbitrarily close to zero.

To proceed, one must either impose additional a priori restrictions on the response of output to each of the disturbances, or use information from time series other than GNP, and estimate a multivariate representation. The first approach has been followed in Clark (1987a), and Watson (1986) among others. This paper adopts the second approach and considers the joint behavior of GNP and unemployment. This approach has

also been taken in Clark (1987b), Campbell and Mankiw (1987b), and Evans (1986); our approach differs mainly in its choice of identifying restrictions. Not surprisingly, we find our restrictions more appealing than theirs.

Our approach is conceptually straightforward. We assume that there are two kinds of disturbances. We assume that neither has a long run effect on unemployment. We assume however that the first has a long run effect on output while the second does not. These assumptions are sufficient to just identify the two types of disturbances, their time series and their dynamic effects on output and unemployment.

While the disturbances are *defined* by the identification restrictions, we believe that they can be given a simple economic interpretation. We think of the disturbances that have a long run effect on output as being mostly productivity shocks. We think of the disturbances that have no such long run effect as being mostly non-productivity-induced demand disturbances. We find this interpretation useful and reasonable, as well as supported by the results of the paper. For short, (and we hope, not too misleadingly) we refer to these types of disturbances as aggregate supply and aggregate demand disturbances respectively.

Under these identification restrictions and this economic interpretation, we obtain the following characterization of fluctuations: demand disturbances have a hump shaped effect on both output and unemployment; the effect peaks after a year and vanishes after two to three years. Up to a scale factor, the dynamic effect on unemployment of demand disturbances is a mirror image of that on output. The effect of supply disturbances on output increases steadily over time, to reach a peak after two years and a plateau after five years. "Favorable" supply disturbances may initially increase unemployment. This is followed by a decline in unemployment, with a slow return over time to its original value.

While this dynamic characterization is fairly sharp, the data are not as specific as to the relative contributions of demand and supply disturbances to output fluctuations. On the one hand, we find that the time series of demand-determined output fluctuations, that is the time series of output constructed by putting all supply disturbance realizations equal to zero, has peaks and troughs which coincide with most of the NBER troughs and peaks. But, when we turn to variance decompositions of output at various horizons, we find that the respective contributions of supply and demand disturbances are not precisely estimated. For instance, at a forecast horizon of four quarters, we find that, under alternative assumptions, the contribution

of demand disturbances ranges from 30 to 80%.

The paper has five sections. Section 1 discusses identification. Section 2 discusses our economic interpretation of the disturbances. Section 3 discusses estimation. Section 4 characterizes the dynamic effects of demand and supply disturbances on output and unemployment. Section 5 characterizes the relative contributions of demand and supply disturbances to fluctuations in output and unemployment.

1. Identification.

We assume that there are two types of disturbances affecting unemployment and output. The first has no long run effect on either unemployment or output. The second has no long run effect on unemployment, but may have a long run effect on output. We assume further that these disturbances are uncorrelated at all leads and lags. These restrictions in effect define the two disturbances. As indicated in the introduction, and discussed at length in the next section, we refer to the first as demand disturbances and to the second as supply disturbances.

We now discuss how these restrictions identify the two disturbances and their dynamic effects. Let Y and U denote the logarithm of GNP and the level of unemployment, respectively. As will be clear below, our assumptions imply that the first difference of Y, ΔY, and the level of unemployment, U, have a jointly stationary bivariate autoregressive representation:

$$D(L)X_t = v_t, \qquad \text{where } D(0) = I \text{ and } E(v_t v_t') = \Omega \tag{1}$$

where X denotes the 2×1 vector $[\Delta Y \quad U]'$. The matrix polynomial in lag operators $D(L)$ is of order n, with all determinantal roots outside the unit circle. The white noise bivariate vector sequence v is serially uncorrelated, with $v = [v_Y \quad v_U]'$.

Under our assumption that there are two types of disturbances in the economy, demand and supply, equation (1) is the reduced form of a model which describes the dynamic effects of those disturbances on output and unemployment. The vector v comprises reduced form disturbances, which are linear combinations of these demand and supply disturbances.

By specifying the reduced form as above, we have already imposed a number of restrictions on the model. We have required that neither of the two reduced form disturbances has a long run effect on

unemployment; this implies in turn that neither of the two types of underlying disturbances has a long run effect on unemployment. By contrast, since it is the first difference and not the level of output which appears in equation (1), we have allowed both reduced form disturbances, and thus both demand and supply, to have a long run effect on the level of output. The only restriction that we have not yet imposed is that demand disturbances have no long run effect on output. This is the key assumption that will allow us to identify the demand and supply disturbances, and to recover interpretable dynamics from the reduced form. We now show how it is used.

The first step is to obtain the moving average representation of the reduced form. Multiplying both sides of equation (1) by $D(L)^{-1}$ gives:

$$X_t = C(L)v_t, \quad \text{where } C(L) \equiv D(L)^{-1}, \text{ so that } C(0) = I. \tag{2}$$

On the other hand, the moving average representation corresponding to our demand and supply disturbance model is:

$$X_t = A(L)e_t \tag{3}$$

where e_t is the vector of demand and supply disturbances, $e_t = [e_{dt} \quad e_{st}]'$, with e_{dt} being the demand disturbance and e_{st} the supply disturbance. Given the assumption that demand and supply disturbances are uncorrelated, we can without loss of generality take the covariance matrix of e to be the identity matrix. The condition that demand disturbances have no long run effect on output implies that $a_{11}(1) = 0$ in equation (3). In words, the coefficients on current and lagged demand disturbances in the output growth equation must sum to zero.

We now show that our model is just identified from the estimated reduced form. Combining equations (2) and (3) gives:

$$X_t = A(L)e_t = C(L)v_t, \quad \text{where } C(0) = I, \text{ and } E(v_t v_t') = \Omega.$$

Thus, our model is just identified if and only if there exists a unique matrix S such that $Se_t = v_t$ and

$$SS' = \Omega, \text{ and } A(L) = C(L)S \text{ and } a_{11}(1) = 0.$$

The first condition states that S is a square root of the covariance matrix of the reduced form disturbances: this imposes three restrictions on the four elements of S. The second imposes a linear restriction on the first

column of S. This is the fourth restriction needed for identification. That restriction is given explicitly by:

$$c_{11}(1)s_{11} + c_{12}(1)s_{21} = 0.$$

There always exists a unique matrix S that satisfies these restrictions.[1]

Identification is thus achieved by using a long run restriction. This raises a knotty technical issue. It is well-known that, in the absence of precise prior knowledge of lag lengths, inference and restrictions on asymptotic behavior of the kind we are interested in here is delicate.[2] More precisely, viewed in terms of Fourier transforms, the restriction immediately above operates on a zero measure interval of the range of frequencies, and so is especially suspect. It is easy however to generalize this restriction to one that applies to some δ-neighborhood of frequency zero, and then to perform estimation in the frequency domain. By imposing that the restriction holds over a frequency band, we would be using an overidentifying rather than just identifying restriction. Under appropriate regularity conditions, we can show that our results are the limit of the results from frequency domain estimation, as δ tends to zero.

In summary, our procedure is as follows. We first estimate the reduced form, equation (1), and derive its moving average representation, equation (2). We then construct the matrix S, and use it to recover the moving average representation of the demand and supply disturbance model, equation (3).

---

[1] The proof is as follows. First obtain the Choleski factorization of Ω. Then any matrix S is an orthonormal transformation of the Choleski matrix. The restriction on the first column imposed by $a_{11}(1) = 0$ determines the orthonormal transformation uniquely, up to column sign changes. This is the method we actually use to construct S.

[2] See for instance Sims (1972). We are extrapolating here from Sims's results which assume strictly exogenous regressors. We conjecture that similar problems arise in the VAR case. If anything, one would expect the difficulties to be compounded. Cochrane (1988) has also recognized this.

2. Interpretation.

Interpreting residuals in small dimensional systems as "structural" disturbances is always perilous, and our interpretation of disturbances as supply and demand disturbances is no exception. We discuss various issues in turn.

Granting our assumption that the economy is affected by two main types of disturbances, productivity and non-productivity-induced demand shocks, one may reasonably argue that even demand disturbances have long run effects on output: changes in the subjective discount rate, or changes in fiscal policy may well affect the saving rate and the long run capital stock and output. The presence of increasing returns, and of learning by doing, also raises the possibility that all demand shocks may have some long run effects. Even if they do not, their effects through capital accumulation may be sufficiently long lasting to be indistinguishable from truly permanent effects in the sample. We believe that demand shocks may well have such long run effects on output. To the extent however that the long run effects of demand shocks are small compared to that of supply shocks, a proposition we consider reasonable, our decomposition is "nearly correct" in the following sense: in a sequence of economies where the size of the long run effect of demand shocks becomes arbitrarily small relative to that of supply, the correct identifying scheme approaches that which we actually use. This is shown in the technical appendix. This proposition is the analogue in our context to the "near identification" proposition in traditional approaches to identification.

Granting our assumption that the economy is affected by two main types of disturbances, one with permanent effects on output, the other only with transitory effects, alternative interpretations are possible: following Prescott (1987), one might instead view the economy as being affected by two types of supply disturbances, some with permanent and some with transitory effects on output. Our identifying assumptions will then identify those two disturbances. While this is not our prefered interpretation, we shall briefly discuss our results under that alternative interpretation below.

This raises a final set of issues constituting problems inherent in estimation and interpretation of any low dimensional dynamic system. Suppose that, there are in fact many sources of shocks, each of them having different dynamic effects on output and unemployment. Clearly, if there are many supply shocks, some with permanent and some with transitory effects on output, as well as many demand shocks, some

with permanent and some with transitory effects on output, and if they all play an equally important role in aggregate fluctuations, our decomposition is likely to be meaningless. A more interesting case is that in which all or most supply shocks have permanent effects on output, and all or most demand shocks have only a transitory effect on output. One might hope that, in this case, our procedure is able to distinguish correctly the dynamic effects of demand disturbances from those of supply disturbances. This is unfortunately not true in general. We show this explicitly in the technical appendix, where we establish necessary and sufficient conditions for this separation to occur. From the reasoning in the technical appendix, we also see that there are important sets of circumstances under which our procedure does correctly identify the different effects of demand and supply. Roughly speaking, the different components in output and unemployment must bear a stable dynamic relation to each other, across the individual demand disturbances and across the individual supply disturbances. Thus if there is only one supply disturbance, and there is a stable production function confronting the different demand disturbances, our procedure correctly isolates the dynamic effects of demand and supply disturbances. This particular set of conditions we find to be not at all unreasonable.

To summarize, our interpretation of shocks is subject to various caveats. We believe it nevertheless to be reasonable, and to be supported by the results presented below.

We now briefly discuss the relation of our paper to others on the same topic. We first examine how our approach relates to the business-cycle-versus-trend distinction :

Following estimation, we can construct two output series, a series reflecting only the effects of supply disturbances, obtained by setting all realizations of the demand disturbances to zero, and a series reflecting only the effects of demand disturbances, obtained by setting supply realizations to zero. By construction, the first series, the supply component of output, will be non-stationary while the second, the demand component, is stationary. By construction also, the two series are uncorrelated.

A standard distinction in describing output movements is the "business cycle versus trend" distinction. While there is no standard definition of these components, the trend is usually taken to be that part of output that would realize, were all prices perfectly flexible; business cycles are then taken to be the dynamics of actual output around its trend.[3]

[3] A precise definition would obviously be tricky but is not needed for our argument. In models with

It is tempting to associate the first series we construct with the "trend" component of output and the second series with the "business cycle" component. In our view, that association is unwarranted. If prices are in fact imperfectly flexible, deviations from trend will arise not only from demand disturbances, but also from supply disturbances: business cycles will occur due to both supply and demand disturbances. Put another way, supply disturbances will affect both the business cycle and the trend component. Identifying separately business cycles and trend is likely to be difficult, as the two will be correlated through their joint dependence on current and past supply disturbances.

With this discussion in mind, we now review the approaches to identification used by others.

Campbell and Mankiw (1987b) assume the existence of two types of disturbances, "trend" and "cycle" disturbances, which are assumed to be uncorrelated. Their identifying restriction is then that trend disturbances do not affect unemployment. The discussion above suggests that this assumption of zero correlation between cycle and trend components is unattractive; if their two disturbances are instead reinterpreted as supply and demand disturbances respectively, the identifying restriction that supply disturbances do not affect unemployment is equally unattractive.

Clark (1987b) also assumes the existence of "trend" and "cycle" disturbances, and also assumes that "trend" disturbances do not affect unemployment but allows for contemporaneous correlation between trend and cycle disturbances. While this is an improvement over Campbell and Mankiw, it still severely constrains the dynamic effects of disturbances on output and unemployment in ways that are difficult to interpret.

The paper closest to ours is that of Evans (1986). Evans assumes two disturbances, "unemployment" and "output" disturbances, which can be reinterpreted as supply and demand disturbances respectively. By assuming the existence of a reduced form identical to equation (1) above, he also assumes that neither supply nor demand disturbances have a long run effect on unemployment, but that both may have a long run effect on the level of output. However, instead of using the long run restriction that we use here, he assumes that supply disturbances have no contemporaneous effect on output. We find this restriction less appealing as a way of achieving identification; it should be clear however that our paper builds on Evans' work.

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imperfect information, this would be the path of output, absent imperfect information. In models with nominal rigidities, this would be the path of output, absent nominal rigidities. In models that assume market clearing and perfect information, such as Prescott (1987), the distinction between business cycles and trend is not a useful one.

3. Estimation.

One final problem needs to be confronted before estimation. The representation we use in equation (1) assumes that both the level of unemployment and the first difference of the logarithm of GNP are stationary around given levels. The unemployment data suggest however a small secular increase in unemployment over the post war period in the US. This raises a number of issues.

One possibility is that, in fact, unemployment is permanently affected by either supply or demand disturbances, or by both. This might occur if for example the economy were characterized by the type of hysteresis studied by Summers and coauthor (1986).[4] This would require an altogether different modeling approach. We do not consider it further here.

A second possibility is that there are, in addition to demand disturbances, two types of supply disturbances. The first, which might include changes in productivity, has long run effects on output but not on unemployment. The second, which might include changes in the composition of the labor force, changes in search technology and so on, does have long run effects on unemployment. If this is the case, one strategy would be to postulate the existence of those three disturbances, one from demand and two from supply, and characterize their dynamic effects. This is substantially more difficult than what we want to do. A short cut, acceptable if equilibrium unemployment drifts slowly through time, is to allow for a deterministic time trend in unemployment. This is what we do below, by first regressing unemployment on a linear time trend and using the residuals to estimate equation (1). The estimated time trend implies an increase in equilibrium unemployment of 3.6% over the post war period. As we find this estimate to be high, we report three sets of results, those obtained removing this estimated trend from unemployment (which we shall call the "trend removed" case below), those obtained removing a trend with slope equal to half of the estimated value ("half trend removed"), and those obtained not removing any trend ("no trend removed").

We estimate equation (1) using quarterly data for real GNP and the aggregate unemployment rate from 1950-2 to 1987-2. We present the results of estimation allowing for eight lags. (We performed estimation with twelve lags with little difference in the results. We also experimented with estimating the system omitting the first five years, as the Korean War era seems anomalous. Again, the empirical results remain practically

[4] We understand their argument as applying more to Europe than to the post war US.

unchanged.) The system is the same as that estimated by Evans, with a longer sample; we refer the reader to Evans for a description of the characteristics of the estimated autoregressive system. We directly turn to interpreting the dynamic effects of supply and demand disturbances.

4. Dynamic effects of demand and supply disturbances.

The dynamic effects of demand and supply disturbances are reported in Figures 1 and 2. These figures correspond to the case where half of the estimated unemployment trend is removed from unemployment before estimation of the joint process.[5] The corresponding figures for the other two cases are for the most part similar, and are given in the Appendix. Differences between the three sets of results will be pointed out in the text.

The upper part of Figure 1 gives point estimates of the dynamic effects of a demand disturbance on output and unemployment. The scale for the logarithm of output is given on the left, the scale for unemployment on the right. Similarly, the lower part of Figure 1 gives point estimates of the dynamic effects of a supply disturbance on Y and U. Figure 2 again provides point estimates of the dynamic responses, but now with one standard deviation bands around those estimates.[6]

Demand disturbances have a hump shaped effect on output and unemployment. Their effects peak after 2 to 4 quarters, depending on the treatment of the unemployment trend. The effects of demand then decline to vanish after 8 to 14 quarters. The size of the effect on output is largest in the case when the trend in unemployment is fully removed. The responses in output and unemployment are mirror images of each other; we return to this aspect of the results below after discussing the effects of supply disturbances.

These dynamic effects are consistent with a traditional view of the dynamic effects of aggregate demand on output and unemployment, in which movements in aggregate demand build up until the adjustment of prices and wages leads the economy back to equilibrium.

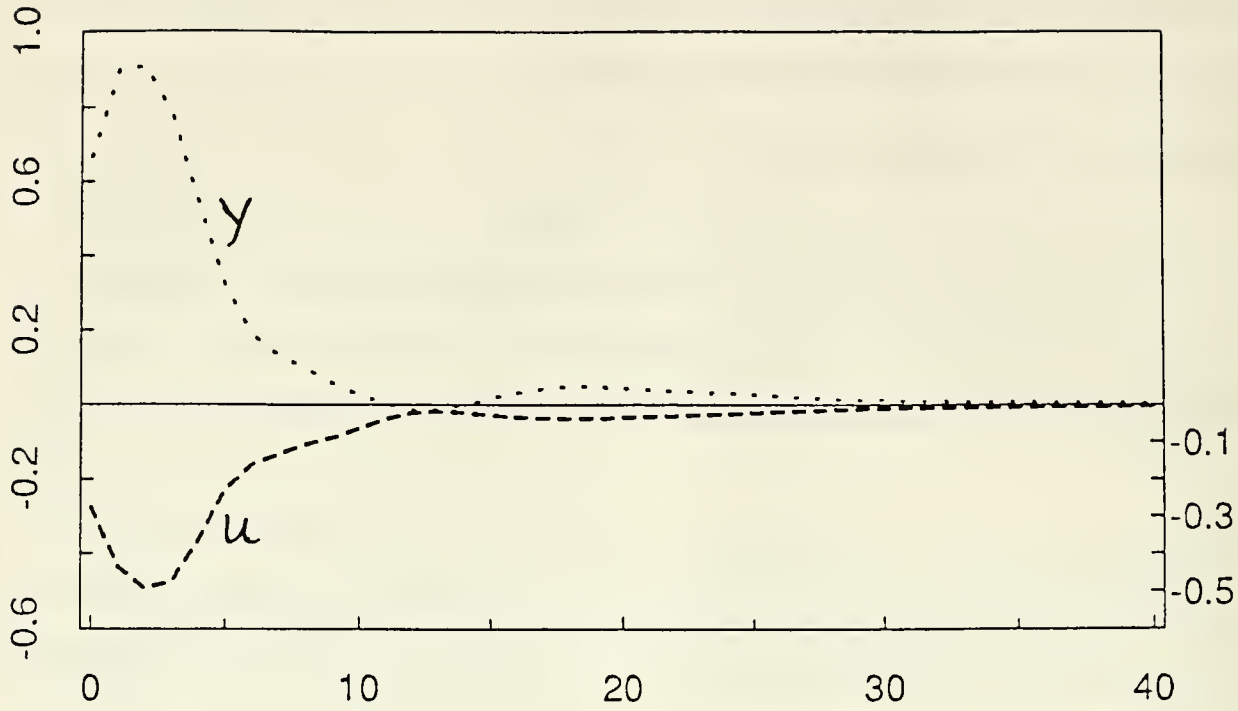
Supply disturbances have an effect on the level of output which cumulates steadily over time. The

[5] We have chosen to present the figures for this case in the text not because we like it best but simply because the results are -not surprisingly- in between those of the two other cases.

[6] More precisely, these figures give the square root of mean squared deviations from the point estimate in 1000 bootstrap replications. Thus, the bands need not be and indeed are not symmetric. In every case, entire pseudo-histories are created by drawing with replacement from the empirical distribution of the VAR innovations. These calculations were performed using a combination of RATS and S on a Sun workstation running UNIX BSD 4.2.

Figure 1

responses to demand



responses to supply

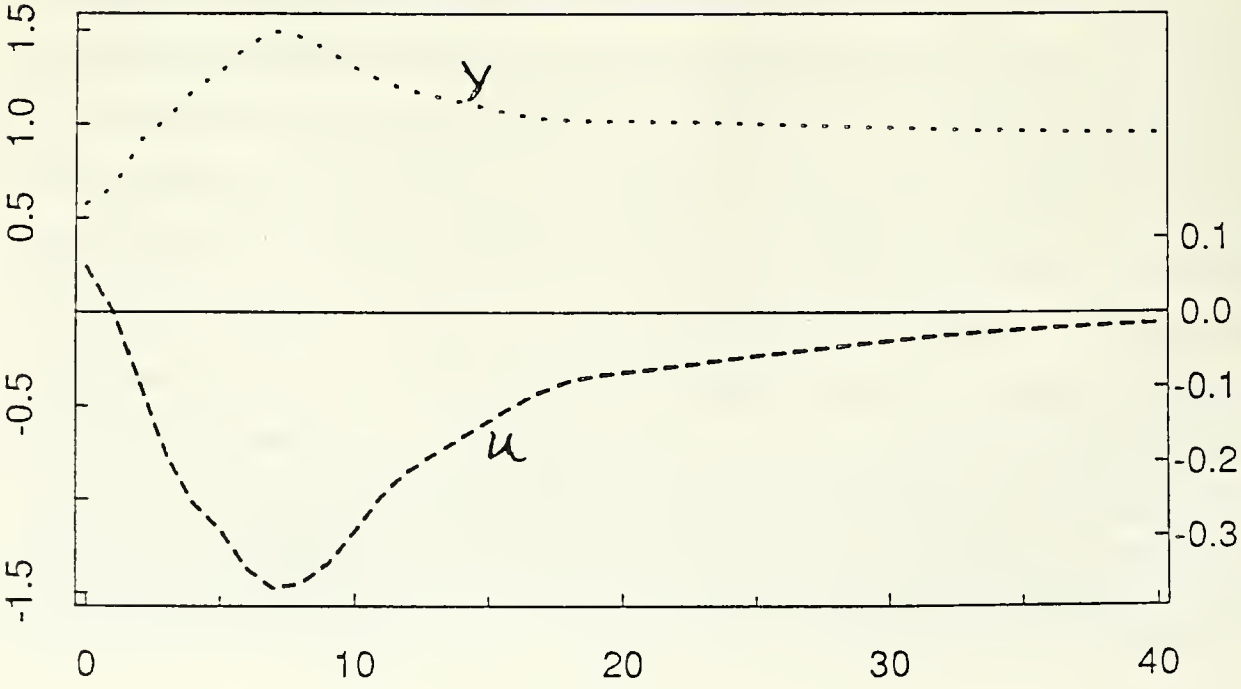
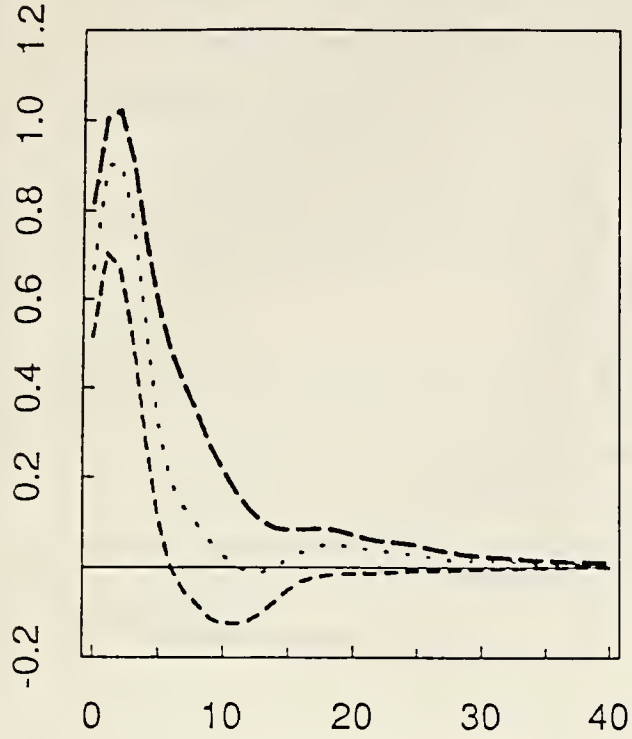
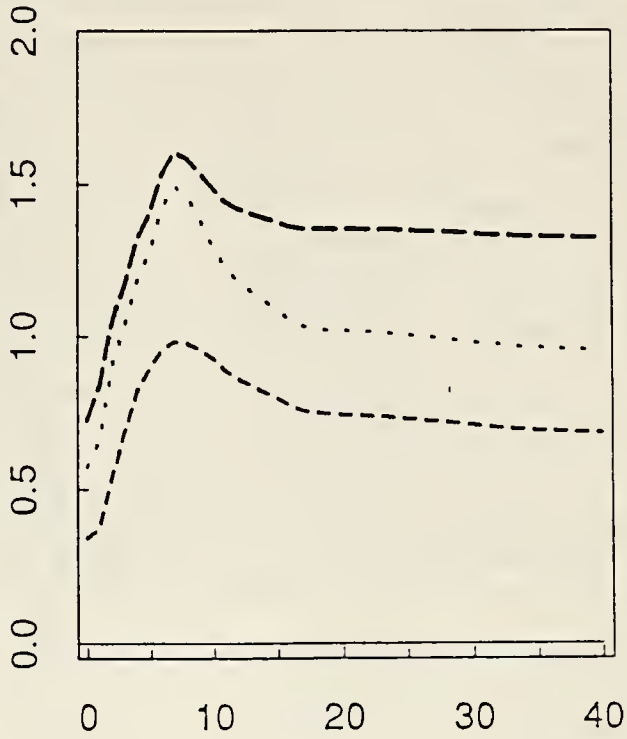


Figure 2.

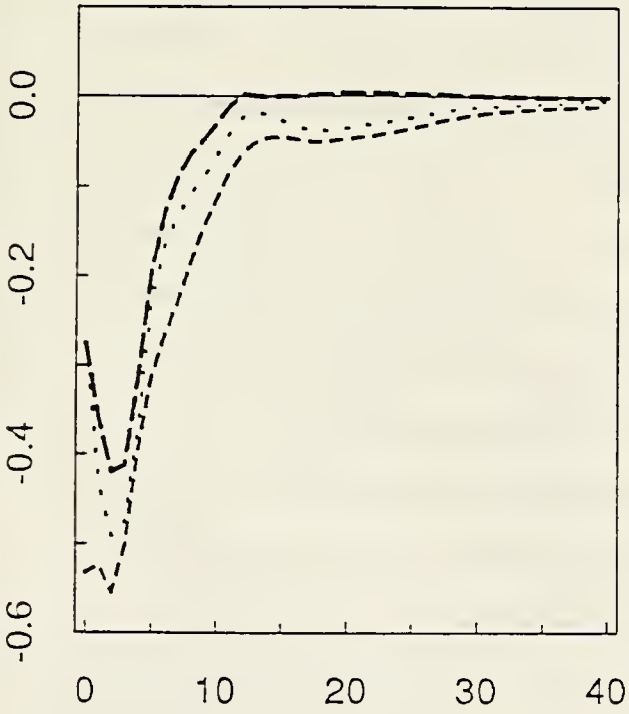
output response to demand



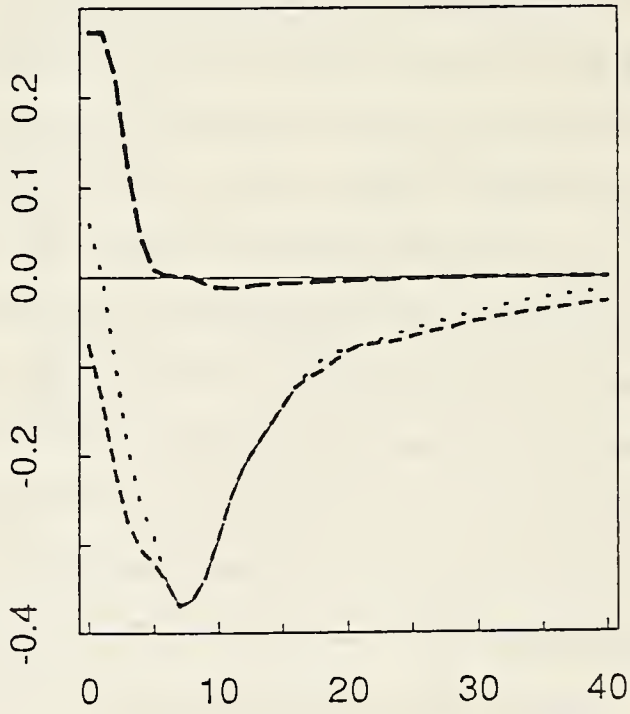
output response to supply



unempl response to demand



unempl response to supply



peak response is about two to three times the initial effect and takes place after eight quarters. The effect decreases to stabilize eventually at two thirds of its peak value. The dynamic response in unemployment is quite different: a positive supply disturbance (that is, a supply disturbance that has a positive long run effect on output) may initially increase unemployment slightly. If this increase occurs, the effect is reversed after a few quarters, and unemployment slowly returns to its original steady state value. The dynamic effects of a supply disturbance on unemployment are largely over by about five years.

The response of unemployment and output are suggestive of the presence of rigidities, both nominal and real. Nominal rigidities can explain why in response to a positive supply shock, say an increase in productivity, aggregate demand does not initially increase enough to match the increase in output needed to maintain constant employment; real wage rigidities can explain why increases in productivity can lead to a decrease in unemployment after a few quarters, which persists until real wages have caught up with the new higher level of productivity.

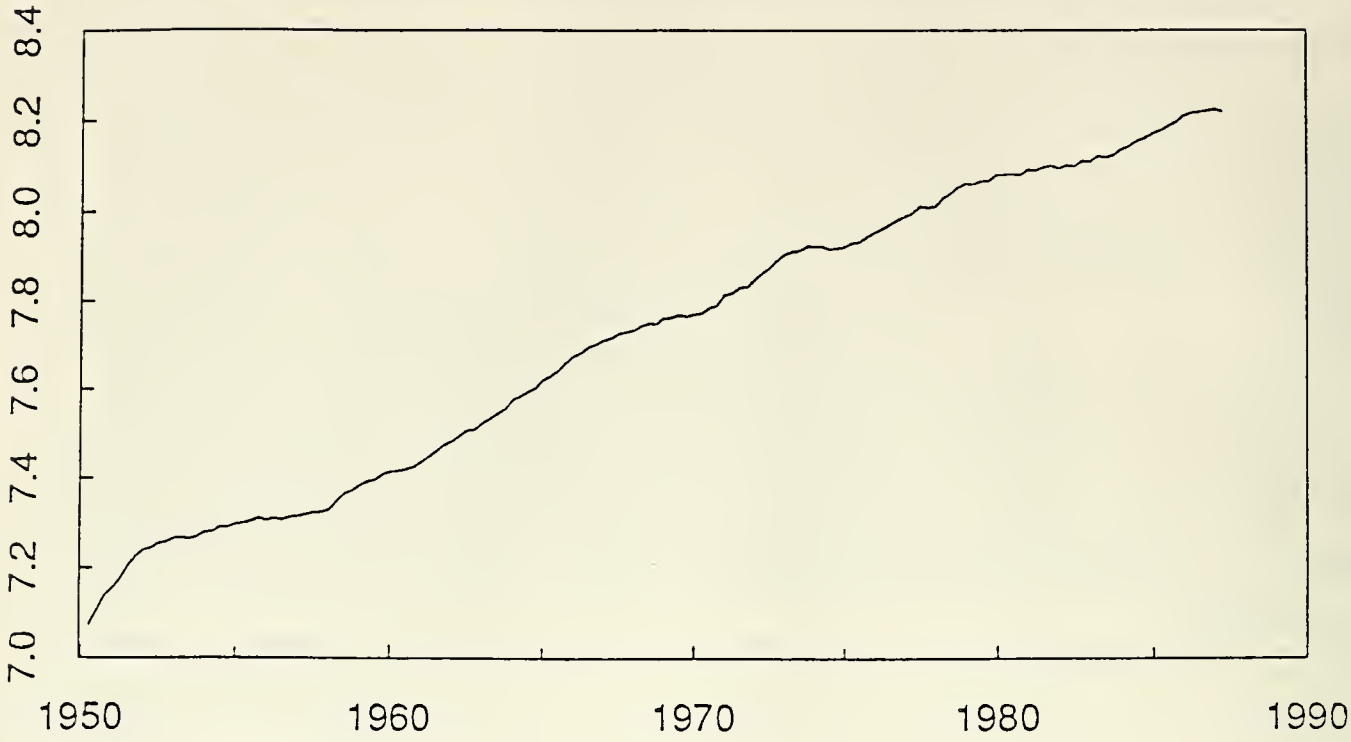
Figure 1 also sheds interesting light on the relation between changes in unemployment and output known as *Okun's Law*. In our sample, a regression of annual percentage changes in output on annual changes in unemployment yields a coefficient of -2.4, the absolute value of which is known as Okun's coefficient. Under our interpretation, this coefficient is a mongrel coefficient, as the joint behavior of output and unemployment depends on the type of disturbance affecting the economy. In the case of demand disturbances, Figure 1 suggests that there is indeed a tight relation between output and unemployment. The absolute value of the implied coefficient is roughly equal to 2, lower than Okun's coefficient. In the case of supply disturbances, there is no such close relation between output and unemployment. In the short run, output increases, unemployment may rise or fall; in the long run, output remains higher whereas by assumption unemployment returns to its initial value. In the intervening period, unemployment and output deviations are of opposite sign, and the absolute value of the implied coefficient is close to 4, higher in absolute value than Okun's coefficient. That the absolute value of the coefficient is higher for supply disturbances than for demand disturbances is exactly what we expect. Supply disturbances are likely to affect the relation between output and employment, and to increase output with little or no change in employment.

Finally, we return to the issue of alternative interpretations of the data. Suppose for example that the

two disturbances we have isolated were in fact both supply disturbances, the first having only temporary effects, the second having permanent effects, and that all markets cleared under perfect information. What interpretation could be given to the dynamic responses given in Figure 1? Temporary productivity disturbances should lead to strong intertemporal substitution effects on labor supply, and this clearly could explain the behavior of output and unemployment in the upper part of Figure 1. As permanent disturbances to productivity cumulate over time, this could explain the dynamic effects of the disturbances on output in the lower part of Figure 1. The anticipation of higher productivity later would induce workers, in reaction to a positive innovation in productivity, to intertemporally substitute away from current work toward work in the future; this would explain the initial increase and the subsequent decline in unemployment. Thus, in the absence of more information, the dynamic effects presented in Figure 1 are clearly susceptible to alternative interpretations.

Figure 3

Output fluctuations absent Demand.



Output fluctuations due to Demand.

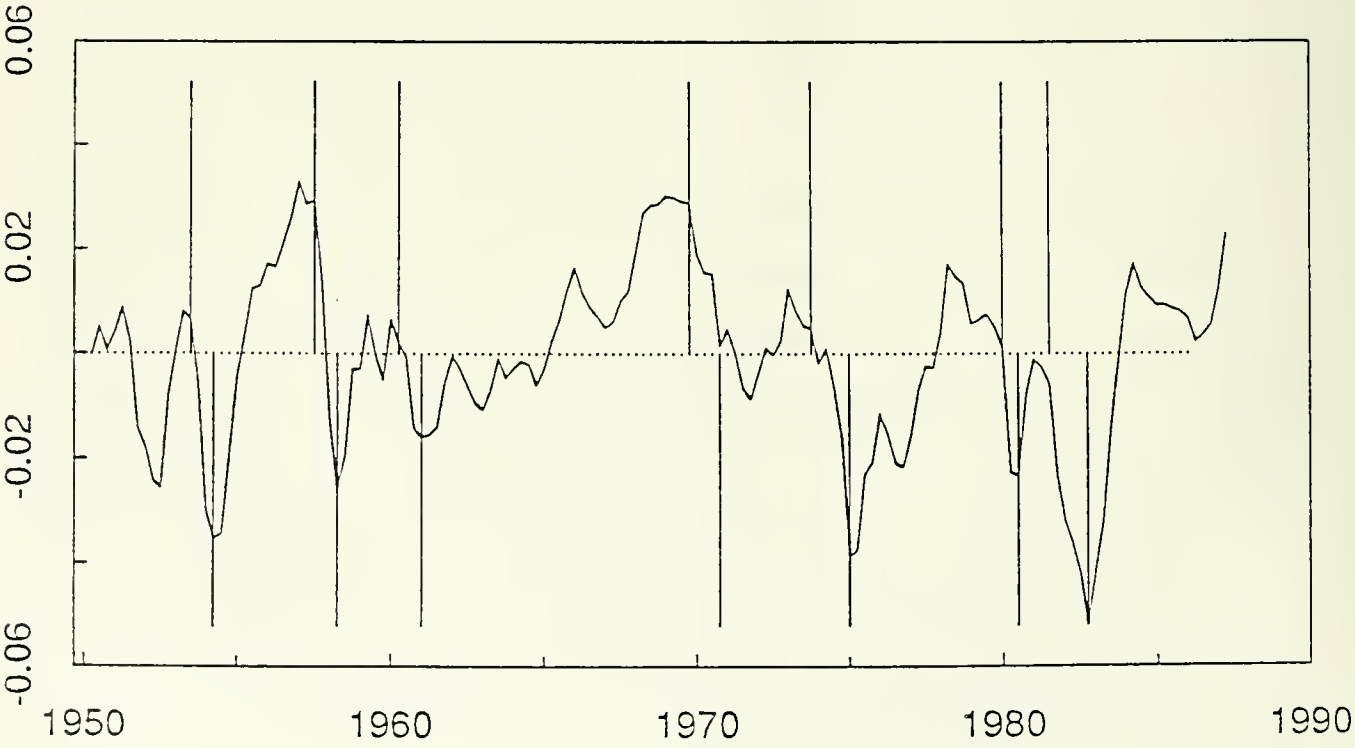
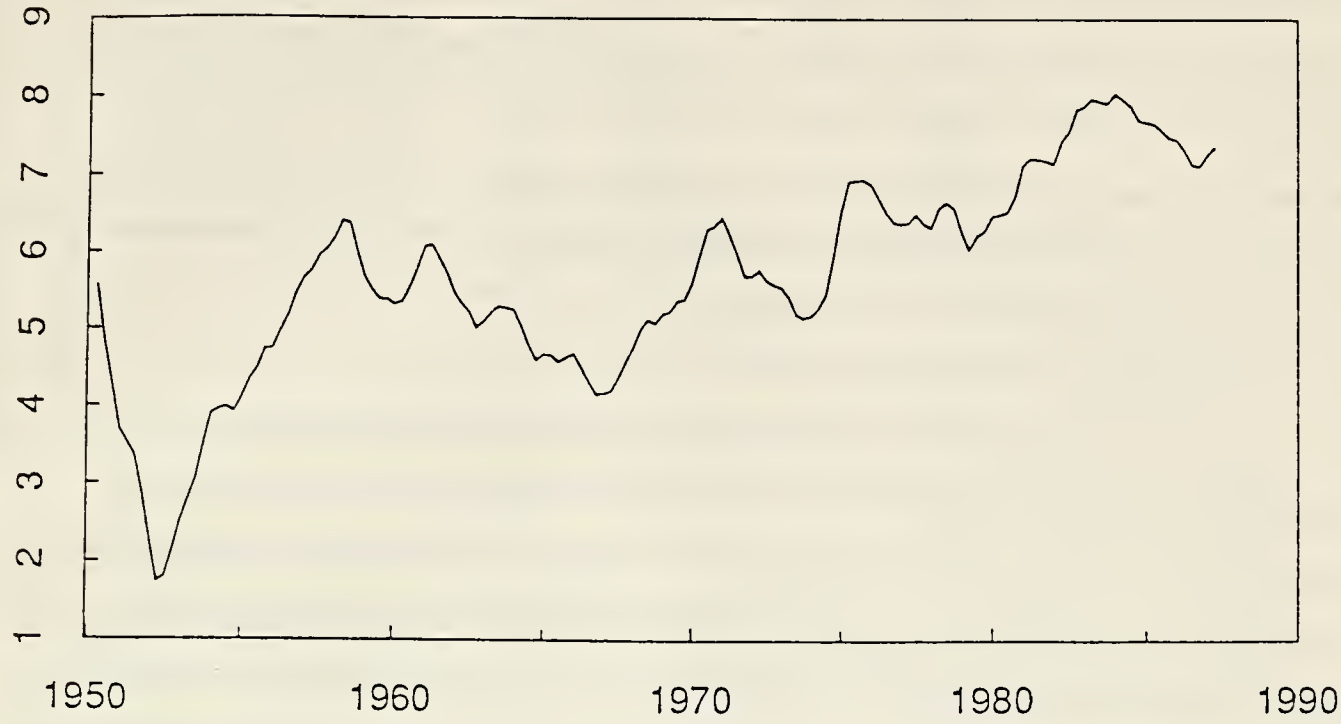
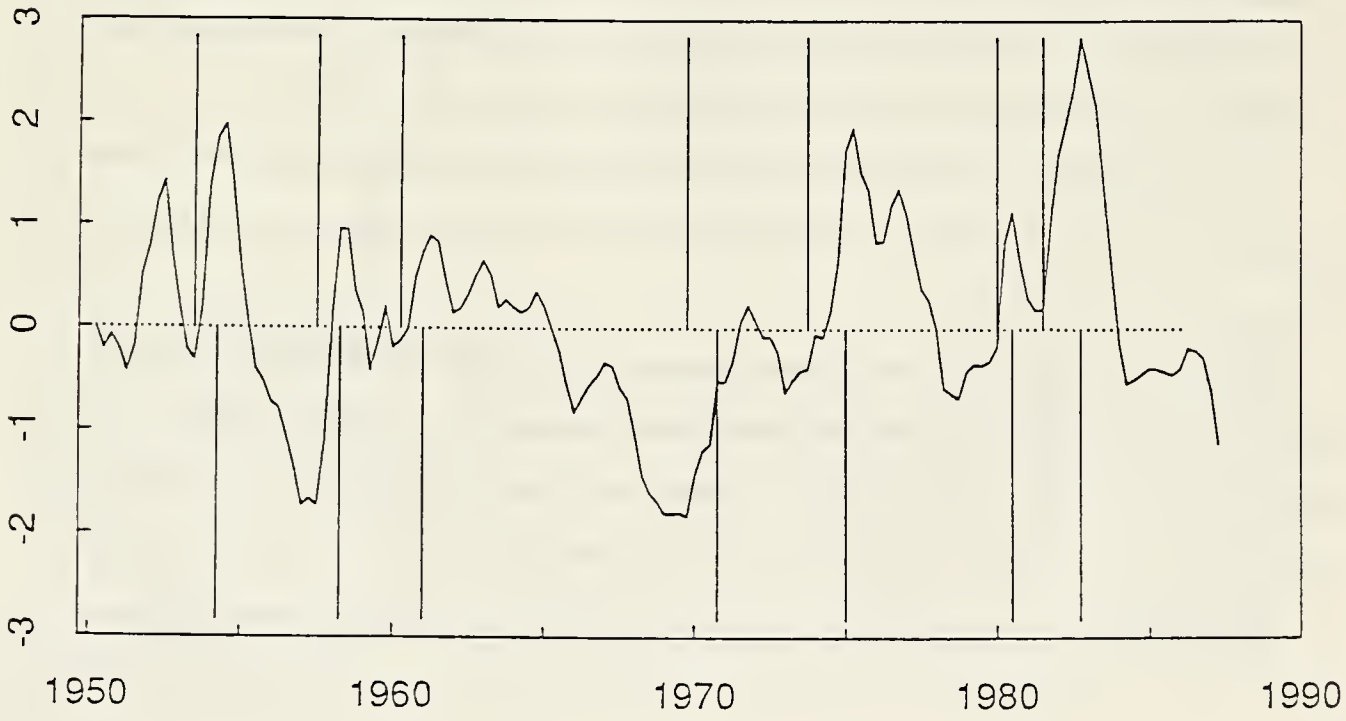


Figure 4

Unemployment fluctuations absent Demand.



Unemployment fluctuations due to Demand.



5. Relative contributions of demand and supply disturbances.

Having shown the dynamic effects of each type of disturbance, the next step is to assess their relative contribution to fluctuations in output and unemployment. We do this in two ways. The first is informal, and entails a comparison of the historical time series of the demand component of output to the NBER chronology of business cycles. The second examines variance decompositions of output and unemployment in demand and supply disturbances at various horizons.

a. *Demand disturbances and NBER business cycles.*

From estimation of the joint process for output and unemployment, and our identifying restrictions, we can compute the demand components of output and unemployment. These are the time paths of output and unemployment that would have obtained in the absence of supply disturbances. Similarly, by setting demand innovations to zero, we can generate the time series of supply components in output and unemployment. From the identifying restriction that demand disturbances have no long run effect on output, the resulting series of the demand component in the level of output is stationary. By the same token, both the demand and supply components of unemployment are stationary.

The time series corresponding to the "half-trend removed" case is presented in Figures 3 (output) and 4 (unemployment). The upper panel presents the historical supply component, the lower panel presents the historical demand component. Superimposed on these time series are the NBER peaks and troughs. Peaks are drawn as vertical lines above the horizontal axis, troughs as vertical lines below the axis.

All three assumptions about the trend in unemployment yield qualitatively similar results. The demand component is quite large, approaching 5% on each side of the origin. (The demand component is larger on average in the "trend removed" case.)

The peaks and troughs of the demand component in output match closely the NBER peaks and troughs. The two recessions of 1974-1975 and 1979-1980 deserve special mention. Our decomposition attributes them in about equal proportions to adverse supply and demand disturbances. This is best shown by giving the estimated values of the supply and demand innovations over these periods:

	73-3	73-4	74-1	74-2	74-3	74-4	75-1
e_d	-0.1	0.2	-0.8	0.9	-1.4	-1.2	-3.0
e_s	-1.6	-0.1	-1.0	-1.1	-1.4	0.4	1.2

	79-1	79-2	79-3	79-4	80-1	80-2
e_d	-0.7	1.1	0.3	-0.4	-0.4	-3.1
e_s	-0.6	-2.0	0.5	-0.9	0.9	-0.9

The recession of 1974-75 is therefore explained by an initial string of negative supply disturbances, and then of negative demand disturbances. Similarly, the 1979-80 recession is first dominated by a large negative supply disturbance, and then a large negative demand disturbance. Without appearing to interpret every single residual, we find these estimated sequences of demand and supply disturbances quite plausible.

It may also simply be that the supply disturbances of these two periods were different from typical supply disturbances, such as changes in productivity, which dominate the sample. They had a stronger short-run contractionary effect, with both declines in output and increases in unemployment. As a result, they may look more like demand disturbances under our identification restrictions, and are therefore classified as demand disturbances.[7]

Notice that the supply component in output, presented in the upper panel in Figure 3, is clearly not a deterministic trend. It exhibits slower growth in the late 1950's, as well as in the 1970's.

Figure 4 gives the supply and demand components in *unemployment* (the time trend is added back to the supply component). Unemployment fluctuations due to demand correspond closely to those in the demand component of GNP. This is consistent with our earlier finding on the mirror image moving average responses of unemployment and output growth to demand disturbances. The model attributes substantial fluctuation in unemployment to supply disturbances, again with increases in the late 1950's and around the time of the oil disturbances of the 1970's.[8]

[7] This suggests extending the analysis to incorporate information from another variable. That variable would be chosen so that it itself is likely to react differently to supply and demand disturbances. Obvious candidates would be the price level or the relative price of raw materials. In Blanchard and Watson (1986), evidence from four time series is used to decompose fluctuations into supply and demand disturbances. There the recession of 1975 is attributed in roughly equal proportions to adverse demand and supply disturbances, that of 1980 mostly to demand disturbances. In view of those results, we reestimated the model, leaving out 1973-1 to 1976-4. The estimated dynamic effects of both demand and supply disturbances were nearly identical to those described above.

[8] By construction, the supply component of unemployment is close to actual unemployment for the first few observations in the sample. Thus, the large decrease from 1950 to 1952 in the supply component simply reflects the actual movement in unemployment in this period. In light of this, we re-estimated the model from 1955-2 through the end of our sample. We found little change in the empirical results.

b. Variance decompositions.

While the above empirical evidence is suggestive, a more formal statistical assessment can be given by computing variance decompositions for output and unemployment at various horizons.

Tables 1 through 3 give those variance decompositions, under the three alternative assumptions about the unemployment trend. These tables have the following interpretation. Define the k quarter-ahead forecast error in output as the difference between the actual value of output and its forecast from equation (1) as of k quarters earlier. This forecast error is due to both unanticipated demand and supply disturbances in the last k quarters. The number for output at horizon $k, k = 1, \ldots, 40$ gives the percentage of variance of the k-quarter ahead forecast error due to demand. The contribution of supply, not reported, is given by one hundred minus that number. A similar interpretation holds for the numbers for unemployment. The numbers in parentheses are standard deviations.[9] The results are given for all three assumptions about the unemployment trend, as there are important differences across these alternative hypotheses.

Our identifying restrictions impose only one restriction on the variance decompositions, namely that the contribution of supply disturbances to the variance of output tends to unity as the horizon increases. All other aspects are unconstrained.

Two main conclusions emerge from these tables.

First, the data do not give a precise answer as to the relative contribution of demand and supply disturbances to movements in *output* at short and medium term horizons. The results vary with the treatment of the unemployment trend: the relative contribution of demand disturbances, four quarters ahead, ranges from 30% (no trend removed) to 82% (trend removed); eight quarters ahead, it still ranges from 13% to 50%. The reason for this may be seen by comparing Figure 1 with the corresponding Figures in the Appendix, derived under alternative assumptions about the unemployment trend. While they are qualitatively similar, the effects of demand disturbances are smaller, and the effects of supply disturbances are stronger and quicker, in the "no trend removed" case.

Even for a given assumption about trend, the standard deviation bands are large. For example, in the "half trend removed" case, the one standard deviation band on the relative contribution of demand

[9] Again, these standard errors are asymmetric, and obtained as described above.

Table 1. Variance decomposition of output and unemployment
(no unemployment trend removed)
Percentage of variance due to demand:

Horizon (Quarters)	Output	Unemployment
1	35.8	100.0
	(22.3, 37.6)	(22.3, 0.0)
2	40.5	96.0
	(24.8, 35.3)	(25.4, 2.8)
3	35.5	89.0
	(22.1, 37.3)	(24.8, 7.8)
4	30.1	80.5
	(19.0, 38.4)	(22.4, 13.8)
8	13.0	50.1
	(6.9, 36.7)	(12.8, 36.7)
12	8.4	37.5
	(4.0, 31.7)	(6.6, 47.3)
40	2.9	29.5
	(1.5, 14.6)	(3.7, 54.1)

Table 2. Variance decomposition of output and unemployment
(Half trend removed)
Proportion of variance due to demand:

Horizon (Quarters)	Output	Unemployment
1	57.6	95.5
	(21.4, 24.1)	(24.8, 3.2)
2	62.1	98.7
	(22.3, 21.6)	(27.2, 0.9)
3	56.7	97.6
	(21.2, 23.4)	(26.0, 1.4)
4	50.3	93.8
	(20.0, 24.4)	(23.4, 3.7)
8	23.9	68.1
	(10.4, 25.3)	(13.5, 20.8)
12	15.4	54.0
	(6.3, 20.2)	(9.3, 31.9)
40	6.4	48.6
	(3.1, 6.8)	(7.8, 36.3)

Table 3. Variance decomposition of output and unemployment
(trend removed)
Proportion of variance due to demand:

Horizon (Quarters)	Output	Unemployment
1	86.4	73.2
	(22.8, 8.3)	(20.0, 15.2)
2	89.8	83.7
	(23.5, 6.3)	(27.2, 8.7)
3	86.5	89.9
	(24.2, 7.9)	(30.3, 5.5)
4	81.8	93.2
	(25.7, 9.2)	(30.7, 3.4)
8	49.5	86.6
	(19.6, 14.6)	(23.8, 6.6)
12	34.0	77.2
	(14.7, 12.2)	(19.1, 11.4)
40	15.9	73.5
	(9.7, 4.8)	(17.6, 13.2)

disturbances four quarters ahead ranges from 30% to 75%. Eight quarters ahead, it still ranges from 14% to 49%. At longer horizons, the contribution of demand disturbances goes to zero by construction; it is typically small after four years.

The second main conclusion is that the contribution of demand disturbances to *unemployment* is more substantial and more precisely estimated, at short and medium term horizons. In all three cases, demand disturbances contribute between 80% and 90% of the variance of unemployment four quarters ahead; their contribution, eight quarters ahead, varies between 50% to 87%. The one standard deviation band in the "half trend removed" case ranges from 60% to 98% four quarters ahead, and from 55% to 89% eight quarters ahead. There is considerable uncertainty as to the relative contribution of demand and supply disturbances at long horizons.

6. Conclusion.

We have assumed the existence of two types of disturbances generating unemployment and output dynamics, the first type having permanent effects on output, the second having only transitory effects. We have argued that these two types of disturbances could usefully be interpreted as productivity and non-productivity induced demand shocks respectively, or, for short, as supply and demand shocks. Under that interpretation, we have concluded that demand disturbances have a hump shaped effect on output and unemployment which disappears after approximately two to three years, and that supply disturbances have an effect on output which cumulates over time to reach a plateau after five years. We have also concluded that demand disturbances make a substantial contribution to output fluctuations at short and medium term horizons; however, the data do not allow us to quantify this contribution with great precision.

Our identifying restrictions allow us to ask interesting questions of the dynamic effects of disturbances that have permanent effects. These questions cannot be addressed by studies that restrict the permanent component to be a pure random walk.

While we find this simple exercise to have been worthwhile, we also believe that further work is needed, especially to validate and refine our identification of shocks as supply and demand shocks. We have in mind two specific extensions. The first is to examine the co-movements of what we have labeled the demand and

supply components of GNP with a larger set of macroeconomic variables. Preliminary results appear to confirm our interpretation of shocks. We find in particular the supply component of GNP to be strongly positively correlated with real wages at high to medium frequencies, while no such correlation emerges for the demand component.[10] The second extension is to enlarge the system to one in four variables, unemployment, output, prices and wages. This would re-examine the empirical questions in Blanchard (1986), by using the long run identification restriction developed in this paper. This extension appears important; one would expect that wage and price data will help identify more explicitly supply and demand disturbances.

[10] The methodology and results will be described in a future paper. The statement in the text refers to the sum of correlations from lags -5 to +5 between the supply innovation derived in this paper and the innovations in real wages obtained from univariate ARIMA estimation.

Technical Appendix

This technical appendix discusses further and establishes the claims made in the section on interpretation.

First, we asserted in the text that our identification scheme is approximately correct even when both disturbances have permanent effects on the level of output, provided that the long-run effect of demand on output is small. We now prove this.

The first element of the model, output growth, has the moving average representation in demand and supply disturbances:

$$\Delta Y_t = a_{11}(L)e_{dt} + a_{12}(L)e_{st}$$

where $a_{11}(1)$ is the cumulative effect on the level of output Y of the disturbance e_d. The moving average representation $C(L)$, together with the innovation covariance matrix Ω, is related to our desired interpretable representation through some identifying matrix S, such that:

$$SS' = \Omega, \quad \text{and } A(L) = C(L)S.$$

The model is identified by choosing a unique identifying matrix S. In the paper, we selected the unique matrix S such that $a_{11}(1) = 0$.

Let the long-run effect of the demand disturbance be δ instead, where $\delta > 0$ without loss of generality. For each δ, this implies a different identifying matrix $S(\delta)$. Let $|S(\delta) - S(0)| = \max_{j,k} (S_{jk}(\delta) - S_{jk}(0))^2$; this measures the deviation in the implied identifying matrix from that which we use. Since the approximation is thus seen to be a finite-dimensional problem, any matrix norm will induce the same topology, which is all that is needed to study the continuity properties of our identification scheme. All of the empirical results vary continuously in S relative to this topology. Thus, it is sufficient to show that

$$|S(\delta) - S(0)| \to 0 \quad \text{as } \delta \to 0.$$

In words, if an economy has long-run effects in demand that are small but different from zero, our identifying scheme which incorrectly assumes the long-run effects to be zero nevertheless recovers approximately the correct point estimates.

We prove this as follows. Since both $S(0)$ and $S(\delta)$ are matrix square roots of Ω, there exists an orthogonal matrix $V(\delta)$ such that:

$$S(\delta) = S(0)V(\delta), \quad \text{where } V(\delta)V(\delta)' = I.$$

Then the long-run effect of demand is the $(1,1)$ element in the matrix:

$$A(1;\delta) = C(1)S(\delta) = C(1)S(0)V(\delta).$$

But recall that the elements of the first row of $C(1)S(0)$ are respectively, the long-run effects of demand and of supply on the level of output, when the long-run effect of demand is restricted to be zero. Thus for any $V(\delta)$, the new implied long-run effect of demand is simply the long-run effect of supply (under our identifying assumption that the long-run effect of demand is zero) multiplied by the $(2,2)$ element of the orthogonal matrix $V(\delta)$. As δ tends to zero, the $(2,2)$ element of $V(\delta)$ tends continuously to zero as well. But, up to a column sign change, the unique $V(\delta)$ with $(2,2)$ element equal to zero is the identity matrix. This establishes that $S(\delta) \to S(0)$, element by element. Hence, we have shown that $|S(\delta) - S(0)| \to 0$ as $\delta \to 0$. *Q.E.D.*

Next, we turn to the effects of multiple demand and supply disturbances: Suppose that there is a $p_d \times 1$ vector of demand disturbances f_{dt}, and a $p_s \times 1$ vector of supply disturbances f_{st}, so that:

$$\begin{pmatrix} \Delta Y_t \\ U_t \end{pmatrix} = \begin{pmatrix} B_{11}(L)' & B_{12}(L)' \\ B_{21}(L)' & B_{22}(L)' \end{pmatrix} \begin{pmatrix} f_{dt} \\ f_{st} \end{pmatrix}$$

where B_{jk} are column vectors of analytic functions; B_{j1} has the same dimension as f_d, B_{j2} has the same dimension as f_s, and $B_{11}(z) = (1-z)\beta_{11}(z)$, for some vector of analytic functions β_{11}. Each disturbance has a different distributed lag effect on output and unemployment.

Since our VAR method allows identification of only as many disturbances as observed variables, it is immediate that we will not be able to recover the individual components of $f = (f_d' \; f_s')'$.

To clarify the issues involved, we provide an explicit example where our procedure produces misleading results. Suppose that there is only one supply disturbance and two demand disturbances: $f_{dt} = (f_{d1,t}, \; f_{d2,t})'$. Suppose further that the first demand disturbance affects only output, while the second demand disturbance

affects only unemployment. The supply disturbance affects both output and unemployment. Formally, assume that the true model is:

$$X_t = \begin{pmatrix} \Delta Y_t \\ U_t \end{pmatrix} = \begin{pmatrix} 1-L & 0 & 1 \\ 0 & -1 & 1 \end{pmatrix} \begin{pmatrix} f_{d1,t} \\ f_{d2,t} \\ f_{st} \end{pmatrix}.$$

An unrestricted VAR representation corresponding to this data generating process is found by applying the calculations in Rozanov (1965) Theorem 10.1 (pp. 44-48). (A slightly more readable discussion of those calculations may be found in Essay IV in Quah (1986).) The implied moving average representation is:

$$X_t = \begin{pmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}}(2-L) \\ \sqrt{2} & 0 \end{pmatrix} \eta_t, \qquad E\eta_t\eta_t' = I.$$

It is straightforward to verify that the matrix covariogram implied by this moving average matches that of the true underlying model. Further, the unique zero of the determinant is 2, and consequently lies outside the unit circle. Therefore this moving average representation is, as asserted, obtained from the vector autoregressive representation of the true model.

However, this moving average does not satisfy our identifying assumption that the "demand" disturbance has only transitory effects on the level of output. We therefore apply our identifying transformation to obtain:

$$X_t = \begin{pmatrix} \frac{1}{2}(1-L) & \frac{1}{2}(3-L) \\ -1 & 1 \end{pmatrix} \begin{pmatrix} e_{dt} \\ e_{st} \end{pmatrix}.$$

This moving average representation is what we would recover if in fact the data is generated by the three disturbances (f_{d1}, f_{d2}, f_s). Notice that while the supply disturbance f_s affects both output growth and unemployment equally and only contemporaneously, we would identify e_s to have a larger effect on output than on unemployment, together with a distributed lag effect on output. Further a positive demand disturbance, restricted to have only a transitory effect on output, is seen to have a contemporaneous negative impact on unemployment. In the true model however, no demand disturbances affect output and unemployment together, either contemporaneously or at any lag. In conclusion, a researcher following our bivariate procedure is likely to be seriously misled when in fact the true underlying model is driven by more than two disturbances. Having seen this, we ask under what circumstances will this mismatch in the number of actual and explicitly modeled disturbances be benign?

We state the necessary and sufficient conditions for this as a Theorem which is proved below.

Theorem: *Let X be a bivariate stochastic sequence generated by*

(i.) $X_t = B(L) f_t$;

(ii.) $f_t = (f'_{dt} \quad f'_{st})'$, with f_d $p_d \times 1$, f_s $p_s \times 1$;

(iii.) $E f_t f_{t-k} = I$ if $k = 0$, and 0 otherwise ;

(iv.) $B(z) = \begin{pmatrix} B_{11}(z)' & B_{12}(z)' \\ B_{21}(z)' & B_{22}(z)' \end{pmatrix}$;

(v.) $B_{11}(z) = (1 - z)\beta_{11}(z)$;

(vi.) β_{11}, B_{21}, B_{12}, B_{22} *are column vectors of analytic functions;* β_{11} *and* B_{21} $p_d \times 1$, B_{12} *and* B_{22} $p_s \times 1$;

(vii.) BB^* *is full rank on* $|z| = 1$, *where* * *denotes complex conjugation followed by transposition.*

Then there exists a bivariate moving average representation for X, $X_t = A(L)e_t$, *such that:*

(viii.) $A(z) = \begin{pmatrix} a_{11}(z) & a_{12}(z) \\ a_{21}(z) & a_{22}(z) \end{pmatrix}$, *with* a_{11}, a_{12}, a_{21}, a_{22} *scalar functions,* $\det A \neq 0$ *for all* $|z| \leq 1$;

(ix.) $a_{11}(z) = (1 - z)\alpha_{11}(z)$, *with* α_{11} *analytic on* $|z| \leq 1$; *and*

(x.) $e_t = \begin{pmatrix} e_{dt} \\ e_{st} \end{pmatrix}$, $E e_t e_{t-k} = I$ *if* $k = 0$, *and is 0 otherwise.*

In the bivariate representation, e_d *is orthogonal to* f_s, *and* e_s *is orthogonal to* f_d, *at all leads and lags if and only if there exists a pair of scalar functions* γ_1, γ_2 *such that:*

$$B_{21} = \gamma_1 \cdot \beta_{11},$$

$$B_{22} = \gamma_2 \cdot B_{12}.$$

Conditions (i.) - (vii.) describe the true data generating process for the observed data in output growth and unemployment. There are p_d demand and p_s supply disturbances; (v.) expresses the requirement that demand disturbances have only transitory effects on the *level* of output. Condition (vii.) is a regularity condition that allows the existence of a VAR mean square approximation. The moving average recovered by our VAR procedure is described by (viii.) - (x.): the Theorem guarantees that there always exists such a representation.

The second part of the Theorem establishes necessary and sufficient conditions on the underlying model such that the bivariate identification procedure does not inappropriately confuse demand and supply disturbances. In words, correct identification is possible if and only if the individual distributed lag responses

in output growth and unemployment are sufficiently similar across the different demand disturbances, and across the different supply disturbances. This does *not* mean that the dynamic responses in output growth and unemployment across demand disturbances must be identical or proportional, simply that they differ up to a scalar lag distribution.

Thus even though in general a bivariate procedure is misleading, there are important and reasonable sets of circumstances under which our technique provides the "correct" answers. For instance, suppose that there is only one supply disturbance but multiple demand disturbances. Suppose further that each of the demand components in the level of output has the same distributed lag relation with the corresponding demand component in unemployment. This assumption is consistent with our "production function"-based interpretations below. Then our procedure correctly distinguishes the dynamic effects of demand and supply components in output and unemployment.

Proof of Theorem: *By (i.) - (vi.), the matrix spectral density of X is given by $S_X(\omega) = B(z)B(z)^*|_{|z|=1}$. By reasoning analogous to that in pp.44-48 in Rozanov (1965), there exists a 2×2 matrix function C, each of whose elements are analytic, with $\det C \neq 0$ for $|z| \leq 1$, and $S_X = CC^*$ on $|z| = 1$. This represents X as a moving average in unit variance orthogonal white noise, obtainable from its VAR mean square approximation. However such a moving average C need not satisfy the condition that the first (demand) disturbance have only transitory impact on the level of output (condition (ix.)). Form the 2×2 orthogonal matrix M whose second column is the transpose of the first row of C evaluated at $z = 1$, normalized to have length 1, as a vector. Then $A \equiv CM$ provides the moving average representation satisfying (viii.) - (x.). For the second part of the Theorem, notice that A has been constructed so that on $|z| = 1$:*

$$|1-z|^2|\alpha_{11}|^2 + |a_{12}|^2 = |1-z|^2\beta'_{11}(\beta'_{11})^* + B'_{12}(B'_{12})^*;$$

$$(1-z)\alpha_{11}a^*_{21} + a_{12}a^*_{22} = (1-z)\beta'_{11}(B'_{21})^* + B'_{12}(B'_{22})^*;$$

$$|a_{21}|^2 + |a_{22}|^2 = B'_{21}(B_{21})^* + B'_{22}(B_{22})^*.$$

For e_d to be orthogonal to f_s, and e_s to be orthogonal to f_d at all leads and lags, it is necessary and sufficient that on $|z| = 1$:

(a.) $|\alpha_{11}|^2 = \beta'_{11}(\beta'_{11})^*$;

(b.) $|a_{12}|^2 = B'_{12}(B'_{12})^*$;

(c.) $\alpha_{11} a_{21}^* = \beta'_{11} (B'_{21})^*$;

(d.) $a_{12} a_{22}^* = B'_{12} (B'_{22})^*$;

(e.) $|a_{21}|^2 = B'_{21} (B'_{21})^*$;

(f.) $|a_{22}|^2 = B'_{22} (B'_{22})^*$.

Consider relations (a.), (c.), and (e.). Denoting complex conjugation of B by $\bar{B}$, the triangle inequality implies that:

$$|\beta_{11} \cdot B_{21}| = |\sum_{j=1}^{p_d} \beta_{11j} B_{21j}^*| \leq \sum_{j=1}^{p_d} |\beta_{11j} B_{21j}^*|,$$

where the inequality is strict unless B_{21} is a complex scalar multiple of β_{11} for each z on $|z| = 1$. Next, by the Cauchy-Schwarz inequality,

$$\sum_j |\beta_{11j} B_{21j}^*| \leq \left(\sum_j |\beta_{11j}|^2 \right)^{1/2} \cdot \left(\sum_j |B_{21j}|^2 \right)^{1/2}$$

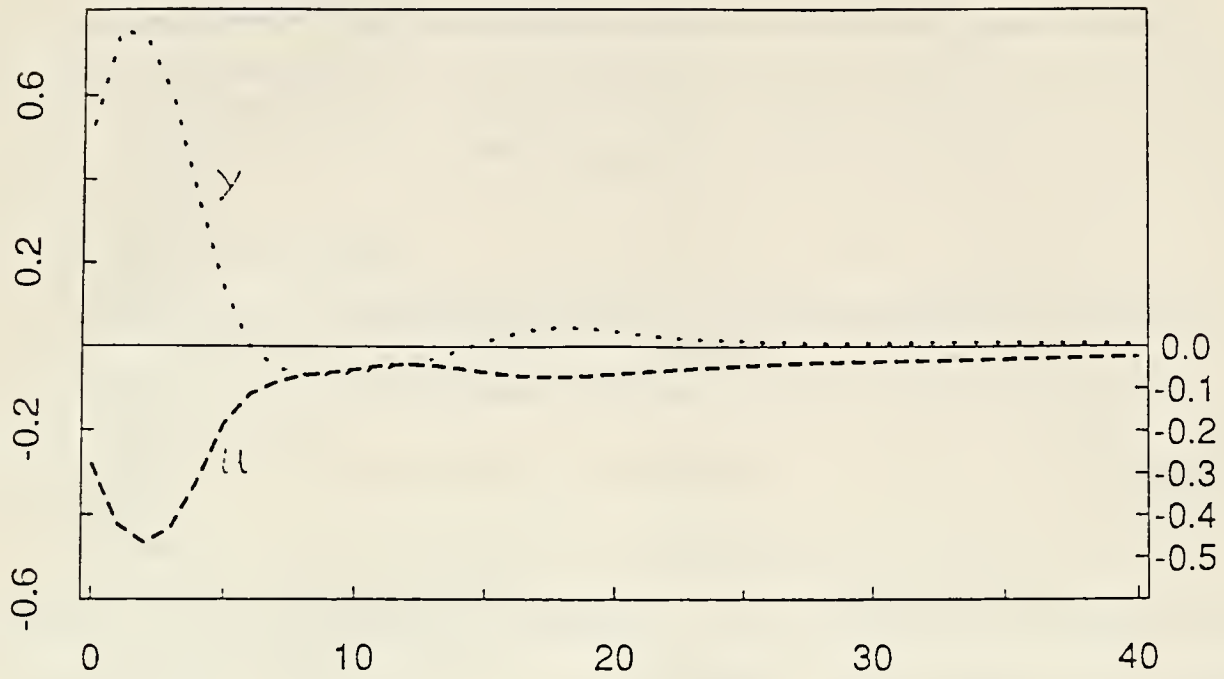
again with strict inequality except when B_{21} is a complex scalar multiple of β_{11}, for each z on $|z| = 1$. Therefore:

$$|\alpha_{11} a_{21}^*|^2 \leq |\alpha_{11}|^2 \cdot |a_{22}|^2, \qquad \text{on } |z| = 1,$$

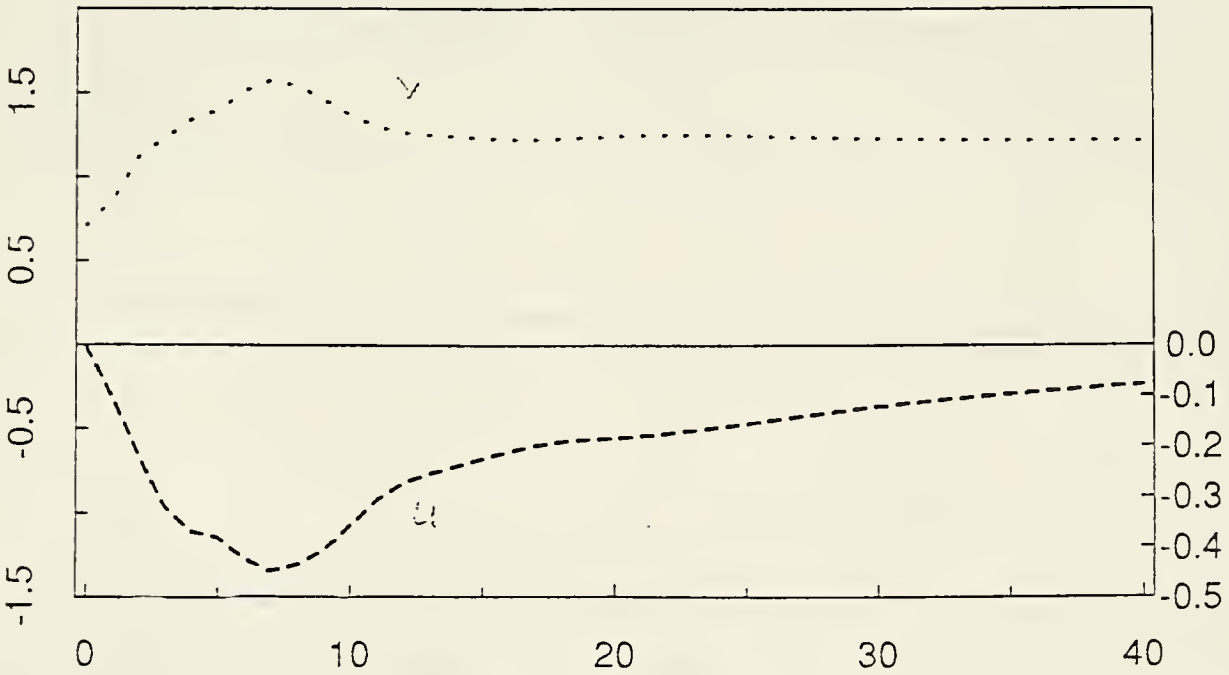
where the inequality is strict except when B_{21} is a complex scalar multiple of β_{11} on $|z| = 1$. But the strict inequality is a contradiction as α_{11} and a_{22} are just scalar functions. Thus (a.), (c.), and (e.) can be simultaneously satisfied if and only if there exists some complex scalar function $\gamma_1(z)$ such that $B_{21} = \gamma_1 \cdot \beta_{11}$. A similar argument applied to (b.), (d.), and (f.) shows that they can hold simultaneously if and only if there exists some complex scalar function $\gamma_2(z)$ such that $B_{22} = \gamma_2 \cdot B_{12}$. This establishes the Theorem. Q.E.D.

Figure 1'

responses to demand



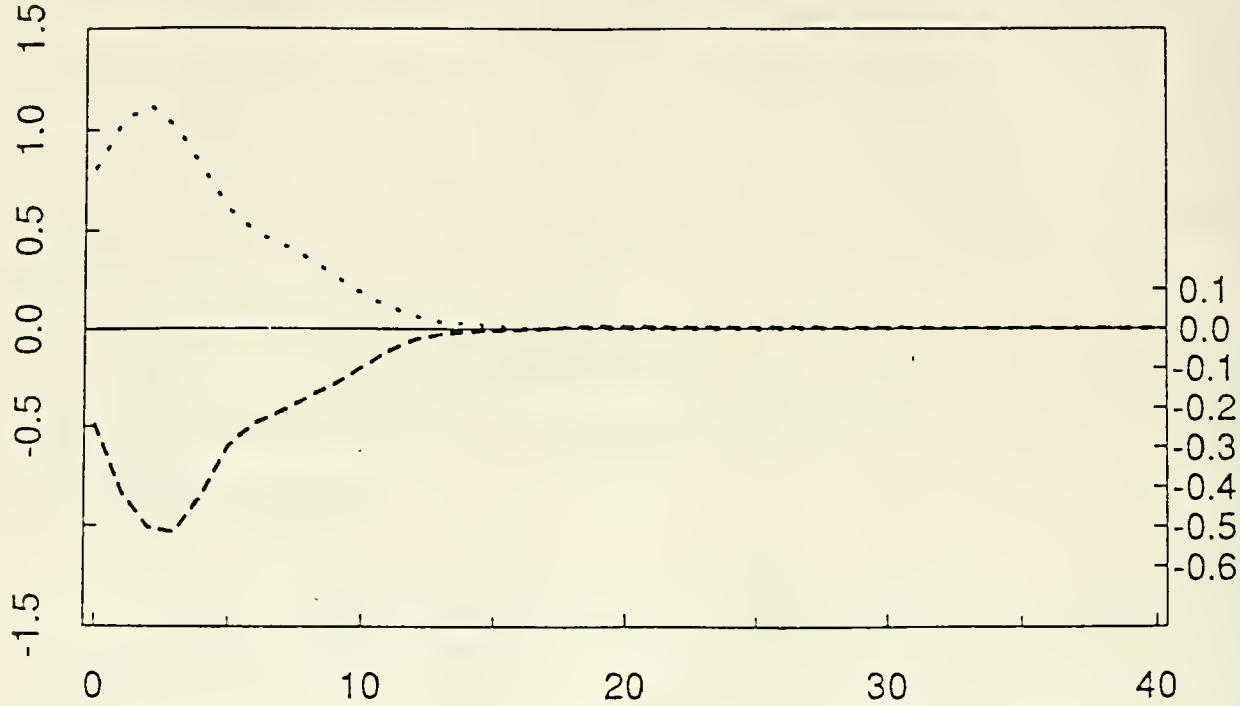
responses to supply



No unemployment Trend Removed.

Figure 1"

responses to demand



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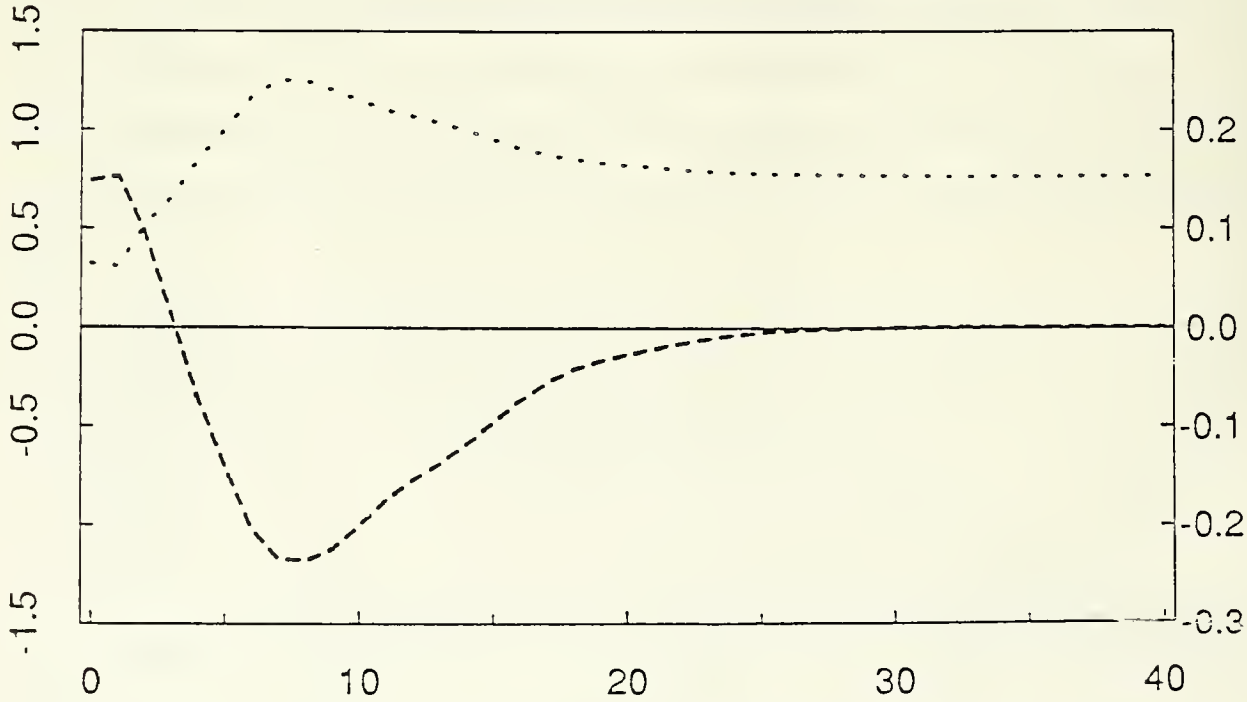

Unemployment Trend Removed.

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