DRIVING FORCES AND EMPLOYMENT
FLUCTUATIONS

Steven J. Davis
John Haltiwanger

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ABSTRACT

We rely on a decomposition of employment changes into job creation and job destruction components - and a novel set of identifying restrictions that this decomposition permits - to develop new evidence about the driving forces behind aggregate fluctuations and the channels through which they operate. We implement our approach to identification using quarterly postwar U.S. data on oil shocks, monetary shocks, and manufacturing rates of job creation and destruction. Our analysis delivers several inferences:

1. The data favor a many-shock characterization of fluctuations in employment and job reallocation.

2. Theories of employment fluctuations that attribute a predominant role to aggregate shocks must, in order to fit the data, involve contemporaneous effects of such shocks on job destruction that are at least as large as the effects on job creation.

3. Theories in which aggregate shocks primarily affect the first moment of the cross-sectional density of employment growth imply that allocative shocks have bigger contemporaneous effects on destruction than on creation and, hence, that allocative shocks reduce aggregate employment.

4. Allocative shocks drive most fluctuations in the intensity of job reallocation.

5. Oil shocks drive employment fluctuations through a mixture of allocative and aggregate channels.

6. Monetary shocks trigger job creation and destruction dynamics that fit the profile of an aggregate shock.

Steven J. Davis
Graduate School of Business
University of Chicago
Chicago, IL 60637
and NBER
sjd@gsbsjd.uchicago.edu

John Haltiwanger
Department of Economics
University of Maryland
College Park, MD 20742
and NBER
halt@glue.umd.edu

I. Introduction

What types of disturbances drive cyclical fluctuations in aggregate employment? Through what channels do particular observable disturbances like oil price shocks and monetary policy innovations affect employment? These are fundamental questions in macroeconomics. We rely on a decomposition of net employment changes into job creation and job destruction components – and a novel set of identifying restrictions that this decomposition permits – to develop new evidence that bears on the answers. Our empirical analysis focuses on the U.S. manufacturing sector from the late 1940s through the late 1980s.

We are especially interested in isolating the role that allocative disturbances played in aggregate fluctuations during our sample period. By "allocative disturbances" we mean events that alter the closeness of the match between the desired and the actual distributions of labor and capital inputs. Transforming the locational and skill characteristics of the workforce – similarly, transforming the productive characteristics of the capital stock – is likely to entail significant costs for the parties involved.[1] At the aggregate level, these costs imply that variations in the intensity of shifts in the distribution of employment opportunities across physical locations, or across points in a multi-dimensional space of skill requirements, carry potentially important consequences for aggregate employment.

Our earlier work (Davis and Haltiwanger, 1990) develops a simple dynamic equilibrium model that highlights the aggregate consequences of allocative disturbances that impinge on the locational distribution of job opportunities. Aside from showing how allocative disturbances can drive

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[1]Hamermesh (1989), Topel (1990) and Jacobson et al (1993) discuss costs that fall on workers. Davis, Haltiwanger and Schuh (1996, chapter 5) discuss reallocation costs more broadly.

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aggregate fluctuations, our analysis stresses how aggregate disturbances interact with a continual stream of allocative disturbances to further drive employment fluctuations.[2]

The cornerstone of our empirical strategy for isolating the aggregate consequences of allocative disturbances is the distinction between net and gross changes in employment. In particular, we decompose net quarterly employment changes into the component accounted for by employment increases at new and growing establishments and the component accounted for by employment decreases at dying and shrinking establishments. We refer to these components as job creation and job destruction, respectively.

One virtue of the decomposition is that allocative and aggregate disturbances induce qualitatively different job creation and destruction dynamics. In particular, unfavorable aggregate disturbances simultaneously reduce job creation and increase job destruction, whereas allocative disturbances increase both creation and destruction. This qualitative difference serves as a source of identifying information in our structural vector autoregressions (VARs). Recent theories of job creation and destruction dynamics imply tighter qualitative restrictions on the gross job flow responses to aggregate and allocative disturbances. We use these tighter qualitative restrictions to narrow the admissible range of structural VAR parameters, which leads to more precise inferences about the relative importance of aggregate and allocative disturbances as driving forces.

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[2]Other theoretical analyses that consider the aggregate consequences of allocative disturbances include Andolfatto (1996), Black (1982), Blanchard and Diamond (1989,1990), Caballero and Hammour (1994), Hall (1991), Hamilton (1988), Hosios (1991), Mortensen (1994), Mortensen and Pissarides (1994), and Rogerson (1990).

A second virtue of the decomposition for net employment changes is that it allows us to entertain certain long run neutrality restrictions suggested by economic theory as an additional source of identifying information. One identifying assumption we consider maintains that aggregate disturbances have no cumulative effect on the amount of job reallocation. This long run restriction accommodates the view that aggregate disturbances influence the timing of job reallocation, as suggested by some of the theories reviewed in section II, but it maintains that allocative disturbances determine the ultimate extent of job reallocation. This assumption translates into a joint restriction on the dynamic response functions of job creation and destruction to an aggregate innovation. Another identifying assumption we consider maintains that allocative disturbances have no permanent effect on the level of employment. This long run neutrality restriction captures the idea that eventually the economy adjusts fully to an allocative disturbance.[3]

In addition to job creation and destruction rates, our VAR systems consider variables that reflect two sources of observable disturbances: oil price shocks and innovations in monetary policy. The motivation for including the observable disturbances is threefold. First, controlling for observable disturbances in a plausible manner aids in the identification of the

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[3] Campbell and Kuttner (1996) consider long run restrictions similar in spirit to ours, but their analysis focuses primarily on *intersectoral* reallocation. Despite differences in data sources, measures, sample period and identifying restrictions, their results are broadly consistent with ours. Other researchers exploit long run restrictions in structural VARs to disentangle aggregate demand and supply disturbances (e.g., Blanchard and Quah, 1989), identify the role of productivity shocks in business cycles (e.g., King et al, 1991), and identify the effects of monetary policy disturbances (e.g., King and Watson, 1993).

unobservable aggregate and allocative disturbances by accommodating a many-shock interpretation of business cycles. Second, understanding the impact of key observable disturbances on job creation and destruction is intrinsically interesting. Third, we can investigate whether the job creation and destruction responses to observable disturbances more closely fit the pattern predicted for aggregate or allocative disturbances.

With respect to the issue of how oil price shocks drive aggregate employment fluctuations, we build on an idea previously exploited by Davis (1985), Loungani (1986), and Mork (1989). These authors stress the importance of distinguishing between the magnitude and direction of oil price shocks. If oil shocks matter primarily because they alter the closeness of the match between the desired and actual distribution of factor inputs, then employment responds to the magnitude of the price change, irrespective of its direction. Alternatively, if oil shocks matter primarily because they shift aggregate labor supply or labor demand as in Kim and Loungani (1992), Finn (1991) and Rotemberg and Woodford (1996), then employment responds roughly symmetrically to positive and negative oil price shocks.

We exploit the distinction between the magnitude and direction of oil price shocks in two ways. First, our VAR systems incorporate a nonlinear relationship between oil price shocks and employment responses. Since our sample period encompasses two large increases in the relative price of oil and one large decrease (plus several smaller changes), the data offer some power to draw this distinction. Second, as noted above, we inquire whether job creation and destruction responses to oil shocks more closely resemble the response pattern associated with allocative shocks or with aggregate shocks. In other words, we exploit the decomposition of employment changes into gross job flow components to inquire whether oil price shocks affect employment through allocative or aggregate channels. We carry out a similar exercise for monetary shocks.

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II. Fluctuations in Gross Job Flows: Basic Facts and Emerging Theories

A. Measurement and Basic Facts

Our long quarterly time series (1947:1-1988:4) on job creation and destruction measures derive from two sources that we splice together. One source is the quarterly job creation and destruction data constructed from the LRD for the 1972-1988 period by Davis, Haltiwanger and Schuh (1996). The second source is monthly BLS data on accessions, layoffs and quits from 1947 to 1981.

As Blanchard and Diamond (1990) point out, given the BLS turnover data and external information on the fraction of worker quits replaced by employers, simple identities yield job creation and destruction rates. We refine the Blanchard-Diamond method for exploiting the BLS turnover data by allowing for a cyclically varying quit replacement rate. We splice the job flow series from the two sources based on their overlap from 1972 to 1981. Details of our data construction method and splicing technique appear in Appendix A.

The top two panels in Figure 1 display quarterly job creation and destruction rates from 1947:1 to 1988:4.[4] The dashed lines are constructed from BLS turnover data using a constant quit replacement rate of .85, as in Blanchard and Diamond. The solid lines show our spliced time series; they are identical to the LRD series from 1972:2 to 1988:4, and they incorporate a cyclically varying quit replacement rate in the use of the BLS turnover data during the earlier period.

The bottom panel in Figure 1 shows two quarterly time series for the net employment growth rate – one generated as the difference between the spliced creation and destruction rates displayed in the upper panels, and

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[4]To express the job flow measures as rates, we divide by the simple average of current employment and employment in the previous period.

another computed from BLS 790 data. The BLS 790 data draw on a separate establishment survey and are the source of the regularly published BLS establishment-based employment and wage estimates. Our spliced data closely mimic the BLS 790 series: the simple correlation between the two growth rates is .93, and the mean absolute difference between them is 0.7 percentage points over the 1947-88 sample (as compared to 0.6 percentage points in the 1972-88 LRD period). This close correspondence gives us confidence to proceed with the empirical analysis using our constructed job flow series.

In addition to job creation (POS_t) and destruction (NEG_t) rates, our empirical analysis considers two related time series: the net employment growth rate (NET_t) and the job reallocation rate (SUM_t), equal to the sum of the creation and destruction rates. This last measure is useful for evaluating the link between gross job flows and worker reallocation activity, for summarizing the heterogeneity in establishment-level employment changes, and for evaluating the success of theoretical models designed to explain cyclical variation in gross worker and job flows.

Figure 2a plots net and gross job flow rates for the U.S. manufacturing sector, and Table 1 summarizes important features of the data for three alternative sample periods. We compare the overall sample (1947:1-1988:4) to the LRD period (1972:2-1988:4) and to a period (1960:1-88:4) that we consider in multivariate systems that include monetary and oil shock measures.

One key feature of the data is the large magnitude of gross job flows. In an average quarter, the number of newly destroyed (newly created) manufacturing jobs equals 6.0% (6.0%) of manufacturing employment. Put together, the average quarterly rate of job reallocation over the 1947:1-1988:4

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period is 12.0%. We interpret this large magnitude to mean that the economy continually adjusts to a stream of allocative disturbances that cause large scale reshuffling of employment opportunities across locations.[5]

Strikingly, large scale job reallocation in manufacturing characterizes the entire post WWII period. The high pace of job reallocation in the 1950s is especially noteworthy, given recent concerns in the popular press about rising job insecurity (New York Times, 1996). The higher pace of job reallocation in the 1950s reflects a higher rate of job creation coupled with job destruction rates comparable to those in the 1970s and 1980s. In other words, the secular decline in the net employment growth rate primarily involved a decline in the job creation rate.

A second key feature of the data is the different cyclical properties of job creation and job destruction. Figure 2 reveals that recessions typically involve sharp increases in job destruction accompanied by milder declines in job creation. The cyclical asymmetry between job creation and destruction is more pronounced in the 1970s and the 1980s, but spikes in job destruction accompany every major contraction in the post WWII period.

For the long sample period, some of the simple correlations reported in the the lower panel of Table 1 are sensitive to whether the data are detrended. For example, the simple correlation between job reallocation and net employment growth is -0.23 in the unadjusted data and -0.52 in linearly detrended data. This sensitivity reflects lower frequency movements in net employment growth and job reallocation over the longer sample.

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[5]Large scale job reallocation is not peculiar to the manufacturing sector or the U.S. economy. See Davis, Haltiwanger and Schuh (1996) for further discussion and evidence.

B. Emerging Theories

A variety of theoretical models have emerged to interpret the cyclical behavior of gross job flows and related empirical phenomena.[6] All of these models postulate an economy subject to a continuous stream of allocative disturbances that create idiosyncratic variation in profitability across job sites or worker-job matches. The continuous stream of allocative disturbances generates the type of large scale job reallocation activity observed in the data.

Several different explanations have been proposed for the cyclical variation in gross job flows. First, time variation in the intensity of allocative disturbances can cause aggregate employment fluctuations accompanied by countercyclic movements in the job reallocation rate. Second, aggregate shocks can influence the timing of the job reallocation that ultimately arises from a steady stream of allocative shocks, leading to a bunching of job reallocation activity during downturns. Third, aggregate downturns may induce a shake-out of less efficient firms and establishments, contributing to aggregate contraction and increased heterogeneity in plant-level employment movements. Finally, when negative aggregate shocks are more severe (and less frequent) than positive aggregate shocks, the endogenous evolution of the employment distribution across plants can generate countercyclic variation in job reallocation intensity. We shall use these theories to specify identifying assumptions that enable us to (i) assess the relative importance of various driving forces behind aggregate fluctuations and (ii) draw inferences about the transmission channels through which observable disturbances drive aggregate fluctuations.

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[6]See Andolfatto (1996), Blanchard and Diamond (1989, 1990), Caballero (1992), Caballero and Hammour (1994), Davis and Haltiwanger (1990), Mortensen (1994), and Mortensen and Pissarides (1994).

III. Identification and Results in a Two-Variable System

A. The VAR Specification

Let Z_t represent a vector containing time-t values for the structural disturbances, and let $Y_t = [POS_t, NEG_t]$ be a vector containing observed values of the job creation and destruction rates. The job creation and destruction rates are linked to the net growth rate of employment by the identity, $NET_t \equiv POS_t - NET_t$.

We assume that the relationship between the structural disturbances Z_t and the observed outcomes Y_t has a linear moving average (MA) representation,

$$Y_t = B(L)Z_t, \quad B(0) = B_0, \tag{1}$$

where $B(L)$ is an infinite-order matrix lag polynomial.

Since the structural disturbances themselves are likely to be serially correlated, we write

$$Z_t = C(L)\epsilon_t, \quad C_0 = I, \tag{2}$$

where $C_0 = I$ is a normalization, and where $\epsilon_t = [\epsilon_{at}, \epsilon_{st}]'$ is the vector of white noise innovations to the structural disturbances. Here, the elements of ϵ_t correspond to the time-t values of innovations to the aggregate and allocative disturbances, respectively. Combining (1) and (2) yields

$$Y_t = A(L)\epsilon_t = B(L)C(L)\epsilon_t, \tag{3}$$

where, given our normalizations, $A_0 = B_0$. This representation of the system emphasizes that the observed dynamics of employment growth and the elements of Y_t reflect dynamic responses to the structural disturbances and the serial correlation properties of the disturbances.

When we estimate a VAR on Y_t, we do not immediately recover either the estimates of the matrix lag polynomial, $A(L)$, or the vector of

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innovations to the structural disturbances, ϵ_t. Instead, the estimated VAR yields

$$Y_t = D(L)\eta_t, \quad D(0) = I, \tag{4}$$

where $D(L)$ is an infinite-order matrix lag polynomial implied by the estimated coefficients in the VAR representation of Y_t, and where $\eta_t = [p_t, n_t]'$ is the vector of reduced-form innovations. Comparing (3) and (4) implies $\eta_t = B_0 \epsilon_t$ and $A(L) = D(L)B_0$, so that full knowledge of B_0 would enable us to recover estimates of both $A(L)$ and the innovations to the structural disturbances from the estimated VAR parameters. We could then proceed to evaluate the role played by the two types of disturbances as driving forces behind employment fluctuations.

Of course, the heart of the identification problem is that the time-series data on Y_t do not provide full knowledge of B_0. Thus, identifying the role played by the various disturbances requires additional, a priori information. Before spelling out our identifying assumptions, we introduce further notation. Let b_{ij} denote the element in the ith row and jth column of B_0, where $i = p, n$ and $j = a, s$. Likewise, let $A_{ij}(l)$ and $D_{ij}(l)$ denote the element in the ith row and jth column of the matrices describing responses at lag l to the structural innovations and the reduced form innovations, respectively. We use $\rho(x, y)$ to denote the correlation between x and y.

B. Minimal Identification Assumptions

Our approach to identification in this two-variable system (and in more complex systems) begins with a minimal set of identifying assumptions. The minimal set is consistent with a wide range of theoretical models and alternative views about business cycles. After examining the implications of the minimal set, we introduce more restrictive sets of assumptions.

The minimal set of identifying assumptions in the two-variable model is

(i) $b_{pa} = b_{ns} = 1$,

(ii) $b_{na} < 0$,

(iii) $b_{ps} > 0$,

(iv) $\rho(\epsilon_{at}, \epsilon_{st}) = 0$.

Assumption (i) is simply a normalization. Assumptions (ii) and (iii) reflect the assumed qualitative effects that aggregate and allocative disturbances have on the joint movement of job creation and destruction. That is, aggregate disturbances cause creation and destruction to move in opposite directions, while allocative disturbances cause creation and destruction to move in the same direction. In a sense, assumptions (ii) and (iii) are definitional and therefore should be widely accepted.[7]

Assumption (iv) imposes a zero covariance between the aggregate and allocative innovations. Zero covariance restrictions play a central role in most structural VAR models (see, e.g., Bernanke (1986), Blanchard and Quah (1989), Shapiro and Watson (1988)). Bernanke (1986, p. 52) justifies this type of restriction by arguing that since "these shocks are primitive, i.e., they do not have common causes, it is natural to treat them as approximately uncorrelated." This argument is not compelling in our context, because the allocative and aggregate innovations may represent different aspects of the same unobserved events. Fortunately, an alternative justification for (iv) is available.

To see the argument, consider as an example the impact of changes in military spending. Whether positive or negative, an innovation in military spending implies potentially important allocative effects. Furthermore, the aggregate consequences of these allocative effects likely depend primarily on the magnitude of the military spending innovation, not the direction. In contrast, the aggregate innovation aspect of military spending depends

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[7]Although, as we will see below, arguments can be made that allocative disturbances need not have a positive *contemporaneous* impact on job creation.

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crucially on the sign. In a large sample, the unobserved primitive shocks will be a random mixture of events like a positive military spending innovation and events like a negative military spending innovation. On balance, the correlation between the aggregate and allocative shocks associated with these primitive events will be approximately zero, so that restriction (iv) holds.

The equations $\eta_t = B_0 \epsilon_t$ imply three moment conditions that relate elements of the variance-covariance matrix of the reduced form innovations to parameters of B_0 and elements of the variance-covariance matrix of the structural innovations. Under restrictions (i) and (iv), there are four unknowns: the contemporaneous response coefficients, b_{na} and b_{ps}; and the standard deviations of the structural innovations, σ_a and σ_s. Hence, the system is underidentified on the basis of (i) and (iv) alone. However, the moment condition implied by (iv) yields a one-to-one mapping between b_{na} and b_{ps}; namely,

$$b_{ps} = \frac{\sigma_{pn} - b_{na}\sigma_p^2}{\sigma_n^2 - b_{na}\sigma_{pn}}.$$

Given this mapping, the qualitative restrictions embodied in (ii) and (iii) determine a locus of pairs, $\{b_{na}, b_{ps}\}$, that satisfy all four conditions. Furthermore, using the other two moment conditions, one can show that each value of b_{na} maps uniquely to values for σ_a and σ_s. Hence, while the minimal conditions do not achieve exact identification, they restrict the range of permissible values for the structural parameters.[8]

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[8]Reliance on this type of qualitative identifying information follows our 1990 work and is related to the identification strategy employed by Blanchard and Diamond (1989,1990). Other recent studies that exploit qualitative identifying information include King and Watson (1993) and Milhov (1995).

Figure 3 present results based on the minimal restrictions, a VAR lag length of four, and a 1948:1 to 1988:4 sample period.[9] Figure 3a depicts the relationship between b_{na} and b_{ps} that emerges from the estimation. There is an inverse and highly nonlinear relationship between b_{na} and b_{ps}. For b_{na} greater than than -0.95, b_{ps} is negative and thus violates (iii). As b_{ps} rises, b_{na} asymptotically approaches -2.3. Hence, the minimal restrictions require $b_{na} \in (-0.95, -2.3)$. Figure 3b shows how the standard deviations of the structural innovations vary with b_{na}. Over the permissible range for b_{na}, the standard deviation of allocative innovations varies from 20% larger than the standard deviation of aggregate innovations to essentially zero.

Figure 3c shows forecast-error variance decompositions for rates of employment growth and job reallocation intensity. Allocative innovations account for about 20% of the 4-step forecast-error variance in employment growth for b_{na} near -.95, less than 5% for b_{na} around 1.5, and close to 20% again for values of b_{na} around -2.3. For values of b_{na} that imply a larger effect of aggregate shocks on creation than destruction, allocative shocks dominate the 4-step and 16-step variability in employment. For example, at $b_{na} = -0.2$ allocative shocks account for more than 70% of the 4-step forecast-error variance. The 16-step variance decomposition for employment growth is qualitatively similar. Turning to job reallocation intensity, the fraction of variance explained by allocative innovations ranges from roughly 90% to 20% as b_{na} varies over the interval $(-.95, -2.3)$.

What should be made of these results? First, they provide a clear message along one dimension: aggregate shocks are a major driving force

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[9]Dickey-Fuller and augmented Dickey-Fuller tests yield rejections of the null hypothesis of a unit root in both the job creation and destruction series. As a check on sensitivity of the results, we estimated VARs with deterministic time trends. We obtained similar results (for two-variable and larger VARs) identifying information include King and Watson (1993) and Milhov (1995).

behind fluctuations in net employment growth for every parameter combination consistent with the minimal identifying assumptions. Second, the minimal assumptions do not determine whether allocative innovations are an important driving force behind net employment fluctuations, nor do they determine whether either structural innovation is a dominant driving force behind fluctuations in job reallocation intensity. Third, the tradeoff in structural parameter values is interesting in its own right. In particular, *any* model that maintains roughly symmetric contemporaneous job creation and destruction responses to aggregate shocks implies, according to the empirical results, that allocative disturbances account for roughly 20% of the variation in net employment growth and most of the variation in job reallocation. Models with a disproportionate impact of aggregate shocks on job creation imply an even greater role for allocative disturbances as driving forces behind fluctuations in net employment growth and job reallocation intensity.[10]

C. Tighter Qualitative Restrictions

More precise inference requires stronger identifying information. Here, we draw upon the theories mentioned above to place tighter restrictions on b_{na} and b_{ps}. Theory supports the following refinements of (ii) and (iii):[11]

(ii)' $b_{na} \leq -1$,

(iii.a)' $|b_{ps}| \leq 1$.

(iii.b)' $A_{11}(l) > 0, 0 < m \leq l \leq M$

Assumption (ii)' restricts the contemporaneous job destruction response to an aggregate innovation. To understand the arguments for requiring $b_{na} \leq -1$, consider the impact of an aggregate disturbance in an

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[10]For an example of such a model, see the discussion of the "insulation effect" in Caballero and Hammour (1994).

[11]These are essentially the identifying assumptions we used in Davis and Haltiwanger (1990) for a 1972:2-86:4 LRD-based sample.

economy subject to a continuous stream of allocative disturbances. Two effects are important: First, since worker and job reallocation entail foregone production because of costs associated with search and moving, retraining, changes in the scale of operations, plant retooling and other factors, unfavorable (and temporary) aggregate disturbances increase the pace of reallocation. Second, since the reallocation of workers and jobs is time consuming, the contemporaneous increase in job destruction is larger than the contemporaneous decrease in job creation. Taken together, these two effects imply (ii)'. Davis and Haltiwanger (1990) and Mortensen (1994) develop dynamic equilibrium models that illustrate this effect.[12]

Assumption (iii.a)' restricts the contemporaneous job creation response to an allocative innovation to be smaller in magnitude than the contemporaneous destruction response. Two theoretical considerations underlie this restriction. First, the time-consuming nature of job and worker reallocation creates an asymmetry between the matching and separation processes in the

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[12]The properties of the two models differ somewhat in a manner that bears on assumption (ii)'. In Davis and Haltiwanger's model, recessions are a good time to reallocate because of a low opportunity cost of time, and, symmetrically, booms are a bad time to reallocate because of a high opportunity cost. In the Mortensen and Pissarides model, an adverse aggregate shock also induces a sharper contemporaneous response in job destruction. Job destruction rises sharply as the aggregate shock pushes a mass of jobs across a destruction threshold, but job creation responds more sluggishly because of the search process for forming new matches. However, a favorable aggregate shock does not induce a similarly asymmetric contemporaneous response of creation and destruction in their model. Our VAR specification fails to accommodate this sort of nonlinearity for unobservable allocative shocks, but section IV below allows observable oil shocks to generate different response patterns to positive and negative shocks.

labor market. Separations can occur instantaneously in response to new information that drives the surplus value of a job-worker match below zero, but the creation of new matches with positive surplus requires time. This asymmetry emerges clearly in search-theoretic models (Pissarides, 1985 and Mortensen, 1994) and in models that specify a simple time cost of moving (Davis and Haltiwanger, 1990). If the creation of job vacancies is itself time-consuming, then an allocative innovation temporarily depletes the stock of active vacancies, which can cause the number of newly-formed job-worker matches (i.e., job creation) to fall even as job destruction and unemployment rise.

Second, any sunk cost aspects of the investments required to create new vacancies and form new job-worker matches induce an option value for waiting on the part of both workers and firms. Waiting may reveal that the creation of a particular vacancy or the formation of a particular match is, ex post, undesirable. If the intensity of allocative disturbances is a positively serially correlated process, the incentive to wait increases in the wake of an allocative innovation (Davis and Haltiwanger, 1990).[13] Thus, the option value effect of an allocative innovation depresses job creation, even as the allocative disturbance disrupts existing matches and thereby boosts job destruction. This option value effect implies $b_{ps} < 1$ and, in principle, it could be large enough to push b_{ps} below zero.

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[13]Brainard and Cutler (1993) and Loungani, Rush and Tave (1990) use post-war quarterly data for the United States to construct time-series indexes of cross-industry variation in stock market rates of return. These indexes have a natural interpretation as proxies for the intensity of allocative disturbances. In appendix B, we report positive and statistically significant values for the first six autocorrelations of these indexes. This serial correlation evidence supports the empirical relevance of the option value effect discussed in the text.

One further remark about (iii.a)' underscores its appeal as an identifying assumption. Allowing for $b_{ps} > 1$ amounts to saying that the impact effect of an allocative innovation is to *increase* aggregate employment. This favorable short-run effect of an allocative innovation contravenes almost all of the literature – from Lilien (1982) through Blanchard and Diamond (1990) and more recent studies – on the aggregate consequences of allocative disturbances. Indeed, the chief controversy in this literature has been whether allocative disturbances cause recessions, not whether they cause booms. We infer, therefore, that (iii.a)' embodies a widely held view among economists who have investigated the aggregate consequences of allocative disturbances.[14]

Since we do not restrict the sign of b_{ps}, the refinement (iii.a)' actually relaxes one aspect of the original assumption (iii). However, we do require that allocative shocks ultimately raise job creation: assumption (iii.b)' requires that an allocative shock have a positive effect on job creation from m periods to M periods after the shock. In the analysis below, we set m=2 and M=16. As it turns out, this restriction never binds when we impose the remaining tighter qualitative restrictions.

Another way to motivate these tighter qualitative assumptions is to consider their relationship to standard representative agent macroeconomic models. Viewed from the latter perspective, the bounds at $b_{na} = -1$ and $b_{ps} = 1$ emerge as natural benchmarks. The assumption that $b_{na} = -1$

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[14]Assumption (iii.a)' does not deny that certain unusual allocative innovations might induce positive short-run employment responses, but it does require that such favorable allocative disturbances not predominate. Davis (1985) develops a theoretical model that admits both favorable and unfavorable allocative disturbances, and that also explains why favorable ones are relatively infrequent.

implies that job creation and destruction respond symmetrically (in opposite directions) to aggregate shocks. This presumed symmetry is consistent with the view that aggregate shocks primarily affect the first moment of the cross-sectional distribution of growth rates. Under this view, macroeconomists can appropriately abstract from the underlying microeconomic heterogeneity. The assumption $b_{ps} = 1$ implies that creation and destruction respond symmetrically to an allocative shock, so that the shock has no impact on aggregate employment. The short run neutrality of allocative shocks is consistent with the view implicit in representative agent models that aggregate fluctuations are entirely driven by aggregate shocks. Our tighter qualitative restrictions include these two benchmark assumptions as limiting cases. Thus, evaluating the nature of the results at these bounds – and determining whether both bounds can be satisfied simultaneously – helps evaluate the assumptions embodied in standard representative agent models.

The tighter restrictions yield a set of results summarized in the first two columns of Table 2. In addition to reporting forecast-error variance decompositions, Table 2 includes bootstrapped standard errors, but we defer a discussion of sampling uncertainty. The permissible range for b_{na} shrinks to (-1,-1.63), and the implied range for b_{ps} becomes (0.04,1). Over this range, the standard deviation of allocative shocks is 10% greater than that of aggregate shocks at $b_{na} = -1$ and approximately 60% as large at $b_{na} = -1.63$.

Over the range that satisfies the tighter qualitative restrictions, the 4-step forecast-error variance of net employment growth accounted for by allocative disturbances ranges from 15% for $b_{na} = -1$ to 3% for $b_{ps} = 1$. The corresponding range for the 16-step horizon is 20% to 5%. With respect to job reallocation intensity, the 4-step forecast-error variance accounted for by allocative disturbances ranges between 82% for $b_{na} = -1$ to 43% for $b_{ps} = 1$. The 16-step results are similar.

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In sum, the tighter qualitative restrictions considerably narrow the range of results, and one additional inference emerges quite clearly as a consequence of imposing the tighter qualitative restriction: allocative disturbances are a major driving force behind fluctuations in job reallocation intensity. Over the range of permissible parameter values, the variance of forecast errors in job reallocation accounted for by allocative innovations varies between approximately 40% and 80%. Despite these notes of success and tighter inferences along other dimensions, the identification analysis to this point leaves considerable imprecision regarding the relative importance of the two types of shocks. This imprecision prompts us to consider additional sources of identifying information.

Before proceeding to other types of identifying information, we construct historical decompositions of fluctuations in employment growth and job reallocation in order to examine the role of aggregate and allocative shocks in particular episodes. We generate the historical decompositions by feeding the estimated structural innovations and their first eight lags through the structural MA representation. The historical decompositions are intrinsically interesting, and they help to gauge whether the identifying assumptions produce sensible results.

Figures 4 and 5 depict historical decompositions for $b_{na} = -1$ and $b_{ps} = 1$, respectively, so that the reported results reflect the limiting cases at the boundaries of the tighter identifying assumptions. If aggregate shocks are restricted to have a symmetric contemporaneous effect on creation and destruction ($b_{na} = -1$), then according to Figure 4, allocative shocks play a dominant role in the fluctuations in job reallocation and a nontrivial role in the fluctuations in net employment growth. Interestingly, allocative shocks make the largest contribution to movements in employment growth during the downturns in the late 1950s and the early 1980s. If we restrict allocative shocks to a symmetric contemporaneous effect on creation and destruction ($b_{ps} = 1$), then according to Figure 5, allocative shocks play a major role in

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the fluctuations in job reallocation but only a miniscule role in employment fluctuations.

D. Long Run Neutrality Restrictions

Our qualitative identifying assumptions do not yield precise inferences about the importance of aggregate and allocative disturbances as driving forces. We can achieve greater precision by imposing additional restrictions on the two-variable VAR, or by bringing more information to bear through the use of other variables and attendant restrictions. One strategy we pursue involves long run neutrality restrictions of the sort emphasized by Blanchard and Quah (1989), Shapiro and Watson (1988), and King and Watson (1993). For the two variable system, we require one additional restriction to yield a just-identified system. In what follows, we consider in turn a number of alternative long run restrictions to achieve just-identification.

One reasonable long run restriction maintains that aggregate shocks have no permanent, *cumulative* effect on the extent of job reallocation. This restriction is consistent with the theories outlined in section II. It is also consistent with the view that aggregate disturbances play an important role in determining the timing of job reallocation activity, as stressed in some of the theories. As with the qualitative restrictions on b_{na} and b_{ps}, it is the decomposition of net employment changes that enables us to entertain this identifying assumption.

We consider two slightly different formal representations of this long run restriction. First, recall the short run restriction $b_{na} = 1$ discussed above. This restriction implies that aggregate shocks have symmetric contemporaneous effects on job creation and destruction and are thus contemporaneously neutral with respect to job reallocation. The direct long run analogue of this restriction is that aggregate shocks have long run symmetric effects on job creation and destruction, which implies long run neutrality of aggregate shocks on job reallocation. This neutrality condition translates

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into a joint restriction on the dynamic response functions of job creation and destruction:

$$(\text{v}) \quad \sum_{l=0}^{\infty}[A_{11}(l)+A_{21}(l)] = 0 \quad \Rightarrow \quad \sum_{l=0}^{\infty}[D_{11}(l)+D_{21}(l)]+b_{na}[D_{12}(l)+D_{22}(l)] = 0$$

While (v) is reasonable, it may be more appropriate to impose the long run restriction on *excess* job reallocation, defined as the difference between job reallocation and the absolute value of net employment growth. To appreciate the relevance of this concept, consider first a scenario with no heterogeneity among plants, so that plant-level employment fluctuations are driven by aggregate shocks. In this case, a positive aggregate shock causes equal increases in job reallocation and job creation but no change in job destruction, so that aggregate shocks have zero effect on excess job reallocation. While this scenario is artificial, extending its logic to a scenario with simultaneous job creation and destruction makes clear the attraction of a restriction on excess job reallocation. That is, suppose that aggregate shocks are accommodated entirely by fluctuations in job creation (e.g., via entry), so that a positive shock yields equal increases in employment, job creation and job reallocation.[15] As in the simpler scenario, the increase in job reallocation exactly equals the increase in job creation, so that excess job reallocation remains constant. Given the potential for this essentially mechanical connection between net employment growth and job reallocation, we consider an alternative restriction in which aggregate shocks have long run neutral effects on excess job reallocation:

$$(\text{v})' \quad \sum_{l=0}^{\infty} A_{11}(l)+A_{21}(l)-|A_{11}(1)-A_{21}(1)| = 0 \quad \Rightarrow \quad \sum_{l=0}^{\infty} D_{11}(l)+D_{21}(l)+$$

$$b_{na}[D_{12}(l)+D_{22}(l)] - |D_{11}(1)+D_{21}(1)-[b_{na}(D_{12}(1)+D_{22}(1))]| = 0.$$

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[15]The argument works the same if job destruction absorbs the entire effect of aggregate shocks.

Results for the two-variable system under (i), (iv) and (v) or (v)' appear in the fourth and fifth columns of Table 2, respectively. Imposing (v) results in $b_{na} = -0.74$, $b_{ps} = -0.14$ and a standard deviation of allocative shocks that is 33% larger than that for aggregate shocks. Imposing (v)' results in $b_{na} = -0.45$, $b_{ps} = -0.28$ and a standard deviation of allocative shocks that is 90% larger than that for aggregate shocks. In either form, this long run restriction yields results that are inconsistent with some component of either the minimal or the tighter qualitative restrictions. In particular, the results violate (iii) and (ii)'.

Allocative shocks are an important driving force behind net employment growth fluctuations and a dominant one for job reallocation fluctuations under these long run restrictions. Under (v) allocative shocks account for 33% of the variance of the 4-step forecast error for net employment growth, while under (v)' allocative shocks account for 55%. In either case, they account for more than 90% of the 4-step forecast-error variance of job reallocation.

Another reasonable long run restriction maintains that allocative disturbances have no permanent effect on the level of employment. This neutrality restriction captures the idea that eventually the economy fully adjusts to an allocative disturbance. The long run neutral impact of allocative shocks on employment translates into a joint restriction on the dynamic re-

sponse functions of job creation and destruction:[16]

$$\text{(vi)} \quad \sum_{l=0}^{\infty}[A_{12}(l)-A_{22}(l)] = 0 \quad \Rightarrow \quad \sum_{l=0}^{\infty} b_{ps}[D_{11}(l)-D_{21}(l)]+[D_{12}(l)-D_{22}(l)] = 0$$

Results for the two-variable system under (vi) appear in the third column of Table 2. Imposing (vi) results in $b_{na} = .15$, $b_{ps} = -.46$, and a standard deviation of the allocative shock more than twice the standard deviation of an aggregate shock. Thus, this long run restriction also yields results that violate the qualitative restrictions. In particular, these results violate (ii), (iii) and (ii)'.

Allocative shocks play a dominant role under this neutrality restriction. They account for approximately 85% of the variance of the forecast error of net employment growth at both 4- and 16-step horizons. They account for more than 70% of the forecast-error variance for job reallocation.

In short, the results for the long run restrictions widen rather than narrow the range of plausible inferences. In the next subsection, we discuss the imprecision in inferences generated by specification uncertainty relative to that generated by sampling error.

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[16] Assumption (vi) says that the sequence of net job growth rate responses to an allocative disturbance sums to zero over a sufficiently long horizon. If we were measuring growth rates as log changes, this restriction would imply a long run employment effect of exactly zero. Instead, we measure the growth rate of x as $2\Delta x_t/(x_t + x_{t-1})$. This growth rate measure is identical to the log change up to a second-order Taylor series expansion, which implies that the approximation is extremely accurate for growth rates of the size that occur in our sample.

E. Sampling Error Versus Specification Uncertainty

The preceding analysis highlights how inferences about driving forces differ across plausible sets of identifying assumptions. It is useful to compare the consequences of this specification uncertainty with the uncertainty induced by sampling variation. As noted above, Table 2 presents the forecast-error variance decompositions with standard errors for the net job growth rate and job reallocation rate under alternative identifying assumptions.[17]

Across the different specifications, the fraction of the 4-step forecast-error variance for net job growth accounted for by allocative shocks ranges from 0.03 to 0.84. This very wide range dwarfs the standard errors of these estimates for any given specification. Overall, the results indicate that the importance of allocative shocks as a driving force behind employment fluctuations is estimated precisely for a given specification, while varying greatly across specifications.

The standard errors are notably larger under the long run restrictions for reasons suggested by the lower panel of Figure 3. In the neighborhood implied by the long run restrictions, small changes in the structural parameters generate large changes in the variance decompositions. In this neighborhood, modest uncertainty about the reduced form parameter estimates generates relatively large uncertainty about the role of allocative shocks as a driving forces behind employment fluctuations.

Turning now to job reallocation, specification uncertainty yields relatively modest variation in the fraction of job reallocation accounted for by allocative shocks. For the variance decomposition of job reallocation, sampling error is also relatively modest but large enough that the modest difference in results across specifications may not be statistically different.

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[17]We computed approximate standard errors by Monte Carlo simulation with 1000 replications.

In summary, allocative disturbances emerge as an important driving force behind fluctuations in job reallocation intensity across all specifications we considered. In contrast, specification uncertainty makes it difficult to draw precise inferences about the role of allocative shocks as driving forces behind net employment movements, unless one has a strong preference for a particular set of identifying assumptions within the class we considered. This ambiguity is one factor that motivates our consideration of larger systems in the next section.

IV. Identification and Results in a Five-Variable System

A. An Expanded VAR Specification

Incorporating observable disturbances into the VAR provides a richer environment for identifying the roles of various driving forces. In the context of an expanded VAR, we investigate two related questions. First, how does the inclusion of observable disturbances affect the role of unobserved aggregate and allocative disturbances? Second, how much explanatory power do observable disturbances have for net and gross job flows? To address these questions, we consider a five-variable VAR specification that contains the job creation rate, job destruction rate, a monetary policy/credit shock variable, an oil price index, and the absolute change in the oil index.

As indicators of shocks in monetary policy and credit intermediation, we considered four measures: a credit mix variable, measured as the ratio of bank loans to the sum of bank loans and commercial paper; the spread $(SPREAD)$ between the six-month commercial paper rate and the six-month treasury bill rate; the federal funds rate; and the spread between the 10-year constant maturity government bond rate and the federal funds rate. Each measure has been featured in one or more recent papers that investigate the impact of monetary policy and credit market conditions on

the economy.[18] None of these variables have been used in the literature as reliable indicators of monetary policy or credit market conditions prior to 1959 or 1960, and for good reason: financial markets changed dramatically in the post WWII era as the federal funds, treasury bill and commercial paper markets grew dramatically. For this reason, we follow the recent literature and estimate the five-variable system on a sample from 1960:1-1988:4. We report results using the *SPREAD* variable. All four variables generate similar results and yield considerable predictive power for job creation and destruction. The *SPREAD* and credit mix variables yield virtually identical results, and they have greater predictive power for creation and destruction rates than either the federal funds rate or the long-short spread.

Recent work by Hooker (1996a,b) and Hamilton (1996) raises questions about the appropriate measure of oil price shocks. Hamilton argues for an oil shock measure that filters out price declines and price increases that merely offset recent past declines. In a similar vein, Davis (1987) argues that allocative disturbances (including oil shocks) cause more adverse aggregate outcomes when they reinforce, rather than reverse, recent past disturbances.

We are sympathetic to these arguments, and we construct an oil shock index accordingly. Our index equals the log of the following ratio: the current real oil price divided by a weighted average of prices in the prior 20 quarters with weights that sum to one and decline linearly to zero. We measure the real price as the nominal price of crude petroleum deflated by the producer price index. We include the oil shock index and its absolute change in the multivariate VAR systems below.[19]

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[18]See Bernanke and Blinder (1992), Friedman and Kuttner (1992), Kashyap, Wilcox and Stein (1993), and Stock and Watson (1989).

[19]We also generated results using a more traditional measure of the real oil price growth rate. Specifically, we calculated the time-t real oil price growth rate as the twelve-month log difference for the middle month of quarter t

Figure 2b plots time series for the oil shock index, its absolute change, and the spread between the six-month commercial paper rate and the six-month Treasury bill rate. Three major oil shock episodes – two increases and one decrease – stand out clearly. The two oil price increases are accompanied by large increases in the quality spread, but the persistence and volatility of movements in the two shock indexes differ in both episodes. In two episodes that were not accompanied by important oil price movements, the quality spread also rose in the middle 1960s and early 1970s.

B. Identification

Let $Y_t = [POS_t, NEG_t, CREDIT_t, OIL_t, ABS_t]'$ be a vector containing observed values of the job creation rate, job destruction rate, the interest rate quality spread, the oil shock index, and the absolute change in the index. Let $\epsilon_t = [\epsilon_{at}, \epsilon_{st}, \epsilon_{ct}, \epsilon_{ot}, \epsilon_{mt}]'$ where the elements of ϵ_t correspond to the time-t values of innovations to the aggregate, allocative, credit, and two oil disturbances, respectively. Also, let $\eta_t = [p_t, n_t, c_t, o_t, m_t]'$ be the vector of reduced-form innovations. Let b_{ij} denote the element in the ith row and jth column of B_0, where $i = p, n, c, o, m$ and $j = a, s, c, o, m$.

It is helpful to explicitly write out the contemporaneous relationship between the reduced-form and structural innovations with some of our basic identifying assumptions incorporated:

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and included this measure and its absolute value in multivariate VARs. The results using the more traditional oil shock measures are quite similar to our reported results, *if* we end the sample in 1985:4, but the oil shock index described in the text yields a much larger role for oil shocks in samples that extend to 1988:4. Thus, as in recent work by Hooker and Hamilton, the choice among alternative reasonable oil shock measures matters greatly only for samples that extend beyond 1985. Regarding other shocks in our multivariate VARs, we obtain similar results under both approaches to measuring oil shocks.

$$p = \epsilon_a \quad + \quad b_{ps}\epsilon_s \qquad\qquad\qquad + \quad b_{po}\epsilon_o \quad + \quad b_{pm}\epsilon_m \quad \text{(5.a)}$$

$$n = b_{na}\epsilon_a \quad + \quad \epsilon_s \qquad\qquad\qquad\quad + \quad b_{no}\epsilon_o \quad + \quad b_{nm}\epsilon_m \quad \text{(5.b)}$$

$$c = b_{ca}\epsilon_a \quad + \quad b_{cs}\epsilon_s \quad + \quad \epsilon_c \quad + \quad b_{co}\epsilon_o \quad + \quad b_{cm}\epsilon_m \quad \text{(5.c)}$$

$$o = \qquad\qquad\qquad\qquad\qquad\qquad\qquad\quad \epsilon_o \qquad + \quad b_{om}\epsilon_m \quad \text{(5.d)}$$

$$m = \qquad\qquad\qquad\qquad\qquad\qquad b_{mo}\epsilon_o \quad + \quad \epsilon_m \qquad \text{(5.e)}$$

Time subscripts are suppressed for notational convenience.

In this system, we take the oil innovations, ϵ_o and ϵ_m, to be exogenous relative to the other innovations. For now, we do not impose any causal ordering within the subsystem involving ϵ_o and ϵ_m. The fraction of the forecast-error variance of job creation, job destruction and credit accounted for by the joint impact of these two innovations is invariant to causal orderings within the oil subsystem.

The specification of equation of (5.c) is unrestricted. This reflects the view that movements in monetary policy and credit variables often respond in a passive, systematic manner to developments in the real side of the economy. The inclusion of the ϵ_c term in (5.c) allows for the possibility that some innovations in the credit variable reflect exogenous monetary policy events.

In this specification, aggregate and allocative disturbances reflect the decomposition of the reduced form innovations to job creation and destruction *after* exogenous oil innovations are taken into account. In contrast, contemporaneous credit innovations are not included in (5.a) and (5.b), reflecting the view that money-credit innovations take some time to have an impact.

Note that the specification in (5) does not constrain the behavior of the oil and monetary policy disturbances to have an aggregate or allocative character. Thus, we do not prejudge the question of how these disturbances influence employment fluctuations. Instead, we rely on the estimated historical decompositions and impulse response functions to assess whether oil

and monetary disturbances affect employment primarily through allocative or aggregate channels.

Further identifying assumptions in terms of zero covariance restrictions and qualitative or long run restrictions must be imposed to identify the structural parameters. The zero covariance restriction assumptions that we make in this context are:[20]

(vii) $\rho(\epsilon_a, \epsilon_s) = \rho(\epsilon_a, \epsilon_c) = \rho(\epsilon_a, \epsilon_o) = \rho(\epsilon_a, \epsilon_m) = 0$

(viii) $\rho(\epsilon_s, \epsilon_c) = \rho(\epsilon_s, \epsilon_o) = \rho(\epsilon_s, \epsilon_m) = 0$

(ix) $\rho(\epsilon_c, \epsilon_o) = \rho(\epsilon_c, \epsilon_m) = 0$

Define $p' = p - b_{po}\epsilon_o - b_{pm}\epsilon_m$ and $n' = n - b_{no}\epsilon_o - b_{nm}\epsilon_m$. The zero covariance restrictions together with (5) enable us to identify the variance-covariance matrix of p' and n'. This implies a subsystem of (5) that can be written

$$p' = \epsilon_a + b_{ps}\epsilon_s \qquad (5.a)'$$

$$n' = b_{na}\epsilon_a + \epsilon_s \qquad (5.b)'$$

This subsystem is identical in structure to the two-variable system considered in section III. Accordingly, identification of this subsystem proceeds as in the two-variable system. Specifically, we consider in turn: (1) minimal qualitative identification restrictions (the analogues of (i)-(iv) from section III.B); (2) tighter qualitative restrictions on the contemporaneous response to aggregate and allocative shocks (replacing the analogues of (ii) and (iii) with (ii)', (iii.a)' and (iii.b)' from section III.C); (3) the neutrality restriction that aggregate shocks have no cumulative effect on (excess) job reallocation; (4) the neutrality restriction that allocative shocks have no long run employment effect.

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[20]For the purpose of investigating the joint effect of ϵ_o and ϵ_m, we need not specify an assumption regarding $\rho(\epsilon_o, \epsilon_m)$.

C. Results for the Five Equation System

Figure 6 reports the tradeoff for the b_{na} and b_{ps} parameters in the underidentified system. As in the two-variable system, there is an inverse and highly nonlinear relationship between b_{na} and b_{ps}. The minimal restrictions require require $b_{na} \in (-0.76, -3.67)$. Under the tighter qualitative restrictions, the permissible range for b_{na} shrinks to (-1,-2.02), and the implied range for b_{ps} becomes (0.12,1). These ranges for the key contemporaneous response parameters are quite similar to the ones obtained in the two-variable system under the tighter qualitative restrictions, and they carry similar implications. Thus, if one maintains the view that aggregate shocks have contemporaneously symmetric (i.e., opposite) effects on job creation and destruction ($b_{na} \approx -1$), one is also driven to the view that allocative shocks have disproportionately large contemporaneous effects on job destruction and, hence, that allocative shocks contemporaneously reduce aggregate employment. Alternatively, if one maintains the view that allocative shocks have no contemporaneous effect on aggregate employment ($b_{ps} \approx 1$), then one is driven to the view that aggregate shocks have disproportionately large contemporaneous effects on job destruction.

Imposing the restriction that aggregate shocks have no long run effect on job reallocation yields $b_{na} = -1.60$ and $b_{ps} = 0.53$. Imposing the alternative form of this restriction on excess job reallocation yields $b_{na} = -1.29$ and $b_{ps} = 0.29$ Hence, moving to a many-shock specification yields results that simultaneously satisfy the qualitative restrictions and one of the long run neutrality restrictions suggested by theory (under either form). However, results for the restriction that allocative shocks have no long run employment effect still violate some of the qualitative restrictions. This long run neutrality restriction implies $b_{na} = -0.44$ and $b_{ps} = -.13$.

The forecast-error variance decompositions for net employment growth and job reallocation appear in Figures 7a-7d and Tables 3 and 4 under alternative identification assumptions for the subsystem (5.a)' and (5.b)'. The contributions of oil and money-credit innovations to the variance decomposition are invariant to the identification of this subsystem (i.e., the system is block recursive).

Consider, first, the impact of the observable disturbances. Both oil and credit innovations play important roles in accounting for the forecast-error variances of net and gross job flows. With respect to employment growth, oil and credit shocks jointly account for 34% of the forecast-error variance at a 4-step horizon and 44% at a 16-step horizon. Credit shocks alone account for 30% of the forecast-error variance of net employment growth at a 4-step horizon. The contribution of oil shocks rises at longer horizons. With respect to job reallocation, oil and credit jointly account for 13% of the 4-step variance and 34% of the 16-step variance. Again, credit has a greater impact than oil at a 4-step horizon, while oil becomes more important at the 16-step horizon.

Second, consider the role of the unobserved aggregate and allocative disturbances. Under the tighter qualitative restrictions, unobserved aggregate shocks are unambiguously an important driving force for employment fluctuations, and unobserved allocative shocks are unambiguously an important driving force for job reallocation fluctuations. Under the long run restriction that they have netural effects on job reallocation or excess job reallocation, aggregate shocks account for about 60% of employment movements at the 4-step horizon and about 50% at the 16-step horizon. In contrast, under long run employment neutrality of allocative shocks, aggregate shocks account for a modest fraction of employment fluctuations at the 4-step and 16-step horizons.

Figures 8 and 9 present 8-quarter historical decompositions for employment growth and job reallocation. We display results for the unobserved

aggregate and allocative shocks at the boundaries of the tighter qualitative restrictions. The decompositions for oil and credit shocks are invariant to the assumptions used to separately identify the unobserved shocks.

Oil shocks played a prominent role in the employment contractions of 1974-75 and 1981-82. Otherwise, the contribution of oil shocks is quite modest, and, in particular, the steep price decline in 1986 had little effect on employment. These results clearly point away from the symmetric response to positive and negative price changes predicted by aggregative theories and towards the type of asymmetric response predicted by theories that stress a role for the allocative aspects of oil shocks.

Money-credit shocks played a prominent role in employment growth fluctuations over the period from 1968 to 1980, including the recessions of 1970 and 1974-75, but they played little role in the deep contraction of 1981-82. Unobserved aggregate shocks played an important role in every cyclical employment episode of the sample period (for both b_{na} specifications), except for the sharp contraction of 1974-75. Unobserved allocative shocks played a small role in employment fluctuations throughout the sample period, except for a large contribution to the contraction of 1980 under the $b_{na} = -1$ specification.

Regarding job reallocation, the contribution of oil price shocks is greatest during the mid 1970s and early 1980s. The contribution of credit shocks is greatest during the cyclical increases in job reallocation in the early and mid 1970s. Unobserved allocative shocks play an important role throughout the sample period, while unobserved aggregate shocks play a modest one.

These results suggest that oil shocks, and to a lesser extent money-credit shocks, operate through a mixture of aggregate and allocative channels. That is, both observable shocks contribute substantially to the cyclical variation in employment growth and job reallocation intensity. The results

also indicate that the contribution of the various observable and unobservable shocks to employment fluctuations and job reallocation differ greatly among business cycle episodes.

D. Sampling Error Vs. Specification Uncertainty

Tables 3 and 4 show how specification uncertainty and sampling variation affect the inferences we draw about the driving forces behind fluctuations in employment growth and job reallocation. The central features of Table 3 mirror closely the pattern of results in the two-variable system. As before, specification uncertainty generates a wide range of results regarding the contribution of unobserved shocks to employment fluctuations. However, the range of results are tighter than in the two-equation system, and there is less inconsistency between results under the qualitative restrictions and the long run neutrality restrictions. Standard errors of the variance decompositions are also somewhat smaller in the five-variable system, so that specification uncertainty rather than sampling variation remains the main obstacle to inference.

As in the two-variable system, the variance decomposition results for the job reallocation rate are substantially less sensitive to specification uncertainty. Under all of the restrictions considered, allocative disturbances account for a large fraction of movements in job reallocation, especially at shorter horizons.

E. The Dynamic Response to Oil and Money-Credit Shocks

Figure 10 displays the dynamic response of employment growth and job flow rates to structural oil and money-credit shocks. The block-recursive nature of the structural VAR implies that (i) the response functions are insensitive to the identification of the unobserved allocative and aggregate

shocks, and (ii) the credit shock response function is insensitive to assumptions involving the oil shock subsystem. In principle, the MA representation that underlies the oil shock response functions depends on assumptions about b_{mo}, b_{om} and $\rho(\epsilon_o, \epsilon_m)$ in equation (5), but the reduced-form innovations in the oil shock index and its absolute change are nearly uncorrelated $(\rho(o, m) = -.10)$, so that assumptions about these structural parameters matter little. In practice, we derive the MA representation by placing the oil index ahead of its absolute change in the causal ordering; i.e., we set $b_{om} = \rho(\epsilon_o, \epsilon_m) = 0$.

We generate response functions for positive and negative oil price shocks by simultaneously perturbing the two structural oil innovations, ϵ_o and ϵ_m. We perturb ϵ_o up or down by one standard deviation, and we perturb ϵ_m by an amount that satisfies the identity linking the oil shock index to its absolute change. We then trace out the response functions implied by the MA representation of the structural VAR.

The results in Figure 10 show a large adverse response to a positive oil price shock and very little response to a negative one. Job destruction rises sharply and employment growth declines sharply in the aftermath of a positive oil shock, while job creation declines modestly. Peak responses occur five quarters following the shock and involve an employment growth rate roughly three-fourths of a percentage point below its baseline value. The asymmetric responses to positive and negative oil price shocks differ dramatically from the approximately symmetric responses predicted by the aggregative models of Finn (1991), Kim and Loungani (1992), Rotemberg and Woodford (1996) and others. We expect to see just this sort of asymmetry if oil shocks affect the economy through a mixture of allocative and aggregate channels, because these channels are reinforcing for a positive shock but offsetting for a negative shock.

To pursue this interpretation, we isolate the effects of the absolute change shock in the upper right panel of Figure 10. This picture reveals

important effects of the absolute change shock, including a peak employment growth response roughly one-third of a percentage point below its baseline value. In addition, the absolute change shock accounts for 53% of the sixteen-step forecast-error variance attributed to oil shocks in Table 3. These results reinforce the historical decomposition evidence of a nonlinear relationship between oil shocks and employment, and they are consistent with theories that stress a role for the allocative aspects of oil shocks.

Yet, one feature of the response functions fails to neatly fit our earlier characterization of an allocative shock: job creation remains at or below its baseline value for two years following a pure absolute change shock rather than rising in its near-term aftermath. Thus, while the historical decomposition, the forecast-error variance decomposition and the dynamic response functions deviate sharply from the symmetry prediction of aggregative models, the dynamic response functions do not fit a simple characterization of oil price changes as a mixture of pure aggregate and pure allocative shocks.

In contrast, the money-credit response functions neatly fit our earlier characterization of an aggregate shock: job destruction lies above and job creation lies below baseline values for two years following the shock. A unit standard deviation shock to the quality spread causes a peak employment growth decline one year later of more than half a percentage point. The greater sensitivity of job destruction means that job reallocation rises in the aftermath of an adverse money-credit shock.

V. Concluding Remarks

Several conclusions emerge from our analysis of employment fluctuations and gross job flows in the U.S. manufacturing sector. We state the most important ones here.

First, our analysis shows that the data do not simultaneously accommodate two views embodied in representative agent macro models. One view holds that aggregate shocks primarily affect the first moment of the

cross-sectional growth rate density but do not greatly alter its shape. A second view holds that allocative shocks do not have important short-run effects on aggregate employment. According to our analysis, specifications that maintain the first view imply that allocative shocks have disproportionately large contemporaneous effects on job destruction and, hence, reduce aggregate employment. Specifications that maintain the second view imply that aggregate shocks have disproportionately large contemporaneous effects on job destruction and, hence, alter the shape of the cross-sectional growth rate density.

As a related point, our results reveal that any theory of employment fluctuations that attributes a predominant role to aggregate shocks must entail an equal or disproportionately large contemporaneous effect of such shocks on job destruction. This result emerges clearly whether or not we include observable oil and money-credit shocks in the VARs.

Second, across a broad range of plausible identifying assumptions and VAR specifications, allocative shocks consistently play the main role in driving fluctuations in job reallocation intensity. This finding suggests that time variation in the intensity of allocative disturbances will be an essential element in successful theories of gross job flow dynamics.

Third, the results favor a many-shock characterization of cyclical employment fluctuations in which oil shocks, money-credit shocks, and unobserved aggregate shocks all act as important driving forces. Forecast-error variance decompositions and historical decompositions of employment fluctuations provide direct evidence for a many-shock characterization. Over the 1960-1988 period, oil shocks account for an estimated 17 (4) percent of sixteen-step (four-step) forecast-error variance of employment growth, and money-credit shocks account for 27 (30) percent.[21] Unobserved aggregate

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[21]These and other inferences involving the oil and money-credit shocks do not depend on how we identify the unobserved aggregate and allocative

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shocks account for the lion's share of the remaining movements in employment growth for all but one of the identification schemes we considered.[22]

The historical decompositions indicate that the operative driving force(s) differs greatly among business cycle episodes. Oil shocks play major roles in the employment contractions of the middle 1970s and early 1980s, but only a modest role at other times. Money-credit shocks play important roles in several episodes between 1968 and 1980 but little role in most other episodes, including the deep 1981-82 contraction. Unobserved aggregate shocks play important roles in several episodes with the notable exception of the 1974-75 recession. In terms of driving forces, business cycle episodes are not all alike.

Fourth, the effects of oil shocks on employment and gross job flows are highly nonlinear. Positive oil price shocks cause sharp adverse responses in job creation, job destruction and employment growth. Negative price shocks, in contrast, cause little effect. This characterization emerges quite clearly in comparisons between oil shock episodes in historical decompositions and in comparisons of dynamic response functions to negative and positive oil shocks. The dynamic response functions also show large adverse employment growth and job destruction responses to the absolute change component of *any* oil price shock, whether up or down. A forecast-error

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disturbances. Rather, they follow from the assumption that oil shocks are exogenous with respect to other variables in the VAR, and the assumption that the exogenous component of money-credit shocks has no within-quarter effect on job creation and destruction.

[22]The exceptional case maintains that allocative shocks have no long run effect on employment. This identifying assumption produces the inference that aggregate shocks play a minor role in driving movements in employment growth.

variance decomposition attributes over half of the oil shock role to the absolute change effect. These results deviate sharply from the approximately symmetric response predicted by aggregative models of economic fluctuations. They are more consistent with the view that oil shocks affect the economy through a mixture of aggregate and allocative channels.

Finally, the dynamic response functions for money-credit shocks fit a natural and simple definition of aggregate shocks whereby job creation and job destruction respond in opposite directions. An adverse money-credit shock causes a rise in job destruction and decline in job creation that peaks after one year and persists for two years. Job destruction is considerably more sensitive than job creation, so that the shock increases job reallocation. Thus, for both unobserved aggregate shocks and for the observed "aggregate" money-credit shock, job destruction responds more sharply than job creation.

Appendix A. Constructing the Job Flow Time Series

For 1972:2 to 1988:4, we use the job creation (POS) and job destruction (NEG) measures developed by Davis, Haltiwanger and Schuh (1996). For 1947:1 to 1972:1, we construct time series from monthly BLS data on accessions, layoffs and quits. We use a simple regression model to adjust the BLS-based series to allow for a cyclically varying quit replacement rate and to splice them to the LRD series.

Let Q, L and A denote quarterly quit, layoff and accession rates, which we compute by cumulating the corresponding monthly rates in the BLS turnover data. As noted by Blanchard and Diamond (1990), the BLS turnover data exhibit pronounced and time varying seasonality. Following their lead, we apply the Census X11 seasonal adjustment procedure to Q, L, A, POS and NEG.

Next, we compute job creation and destruction rates from the quarterly time series according to

$$POS = A - \theta Q, \quad \text{and}$$

$$NEG = L + (1 - \theta)Q,$$

where θ denotes the quit replacement rate. No direct observations on the time series of quit replacement rates are available. Blanchard and Diamond (1990, Appendix D) rely on evidence in a 1973 survey of job-seeking methods to support an assumption of $\theta = .85$. We adopt this value for θ to generate the "BLS turnover" series in the top two panels of Figure 1, but it does not affect our final job creation and destruction time series.

Aside from our lack of direct observations on the quit replacement rate, other considerations point to sources of either measurement error in the BLS-based series or discrepancies between the BLS-based and LRD-based series. The quarterly LRD series reflect changes over three-month

intervals of point-in-time employment measures, whereas the BLS series reflect cumulated flows during the quarter. Thus, for example, the BLS series capture temporary layoff spells that end in recall within the quarter, whereas the LRD series do not. Sampling frames for the two data sources also differ. The LRD is a mandatory national probability sample that excludes only the smallest establishments, whereas the BLS series reflect a voluntary survey that over-represents large establishments.

To splice the series together and to allow for a cyclically varying quit replacement rate in the expressions above, we fit the following regression models to quarterly data for the overlap period from 1972:2 to 1981:1:

$$POS = \alpha_0 + \alpha_1 A + \alpha_2 Q + \alpha_3 Q \cdot Y + \epsilon_p,$$

$$NEG = \beta_0 + \beta_1 L + \beta_2 Q + \beta_3 Q \cdot Y + \epsilon_n,$$

where POS and NEG are LRD values, Y is a cyclical indicator, ϵ_p and ϵ_n are error terms, and the parameter vector (α, β) minimizes the sum of squared residuals. We tried several cyclical indicators, and the quarterly manufacturing employment growth rate implied by the BLS turnover data delivered the best fit. We obtained virtually identical results with the unemployment rate as a cyclical indicator.

Using the estimated regression parameters (α, β) and the quarterly values for A, L and Q, we generated the 1947:1-1972:1 values for our spliced and adjusted time series and joined them to the 1972:2-1988:4 LRD values.

Appendix B

Table B.1
Serial Correlation in the Dispersion of Industry Stock Returns
Quarterly Data, U.S. Economy

$$\text{Dispersion Measure} = \left[\sum_{i=1}^{I} w_{it}(r_{it} - r_t)^2 \right]^{1/2}$$

where: w_{it} is the weight for industry i at time t,

r_{it} is a stock market rate of return measure for i at t,

r_t is an average market rate of return measure at t

Data Sources and Summary Descriptions

Source	Loungani-Rush-Tave, 1990	Brainard-Cutler, 1991	Loungani-Rush-Tave, 1991
Sample Period	49:Q3 to 87:Q4	49:Q3 to 91:Q2	49:Q4 to 85:Q1
Industry Rate of Return Measure	Raw Rate of Return	Component orthogonal to S&P Composite Index	Component orthogonal to base money growth, govt. purchases, comm. paper/bill rate spread, S&P 500
# of Industries	60	18-44	60
Weighting By	Avg. Emp.	Current Emp.	Avg. Employment

Autocorrelations

Lag			
1	.51**	.43**	.48**
2	.18*	.36**	.11
3	.21**	.44**	.18*
4	.22**	.33**	.18**
5	.28**	.37**	.24**
6	.28**	.36**	.24**

Notes:
 (i) "*" ("**") indicates that the correlation differs from zero at the 5% (1%) significance level in a two-tailed test.
 (ii) The Brainard-Cutler dispersion measure is not transformed by taking the square root of the weighted sum.

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Table 1
Net and Gross Job Flow Rates in the
U.S. Manufacturing Sector

A. Summary Statistics (% of Employment)
1947:Q1-1988:Q4 (Spliced data)

Statistic	POS	NEG	NET	SUM
Mean	6.0	6.0	0.0	12.0
St. Dev.	1.2	1.5	2.1	1.7
Minimum	3.8	2.9	-5.9	7.9
Maximum	10.2	10.8	6.8	16.2

1960:Q1-1988:Q4 (Spliced data)

Statistic	POS	NEG	NET	SUM
Mean	5.6	5.8	-0.2	11.4
St. Dev.	0.9	1.3	1.7	1.5
Minimum	3.8	3.6	-5.9	7.9
Maximum	8.0	9.7	2.8	15.2

1972:Q2 - 1988:Q4 (LRD data)

Statistic	POS	NEG	NET	SUM
Mean	5.2	5.6	-0.4	10.8
St. Dev.	0.8	1.4	1.8	1.4
Minimum	3.8	3.6	-5.9	7.9
Maximum	7.5	9.7	2.8	14.6

B. Selected Contemporaneous Correlations

(Spliced Data)

ρ(POS, NET)	ρ(NEG,NET)	ρ(SUM,NET)	ρ(POS,NEG)	Sample Period
0.73	-0.84	-0.23	-0.24	47:1-88:4
0.63	-0.85	-0.37	-0.12	60:1-88:4
0.71	-0.91	-0.52	-0.35	72:2-88:4

(Linearly Detrended Spliced Data)

ρ(POS, NET)	ρ(NEG,NET)	ρ(SUM,NET)	ρ(POS,NEG)	Sample Period
0.83	-0.94	-0.52	-0.58	47:1-88:4
0.74	-0.93	-0.59	-0.44	60:1-88:4
0.76	-0.94	-0.65	-0.49	72:2-88:4

Table 2
Forecast-Error Variance Decompositions for Net and Gross Flows
Two-Variable System, Spliced Data
1948:Q1-1988:Q4

A. Fraction of Variance of Net Job Growth Rate Fluctuations due to Allocative Shocks[a]
Identification Assumption

Forecast Horizon	Qualitative Restrictions[b]		Long Run Restrictions[c]		
	$b_{na}=-1$ $b_{ps}=0.04$	$b_{na}=-1.63$ $b_{ps}=1$	$b_{aa}=0.15$ $b_{ps}=-0.46$	$b_{na}=-0.74$ $b_{ps}=-0.14$	$b_{na}=-0.45$ $b_{ps}=-0.28$
1 quarter	0.22 (0.06)	0.00 (0.00)	0.93 (0.27)	0.43 (0.15)	0.66 (0.22)
4	0.15 (0.06)	0.03 (0.04)	0.84 (0.27)	0.33 (0.12)	0.55 (0.20)
8	0.20 (0.07)	0.05 (0.04)	0.86 (0.26)	0.38 (0.12)	0.58 (0.18)
16	0.20 (0.07)	0.05 (0.04)	0.86 (0.26)	0.38 (0.12)	0.59 (0.18)

B. Fraction of Variance of Job Reallocation Rate Fluctuations due to Allocative Shocks[a]

Forecast Horizon	Qualitative Restrictions[b]		Long Run Restrictions[c]		
	$b_{na}=-1$ $b_{ps}=0.04$	$b_{na}=-1.63$ $b_{ps}=1$	$b_{na}=0.15$ $b_{ps}=-0.46$	$b_{na}=-0.74$ $b_{ps}=-0.14$	$b_{na}=-0.45$ $b_{ps}=-0.28$
1 quarter	1 (0.00)	0.78 (0.03)	0.48 (0.33)	0.95 (0.07)	0.81 (0.16)
4	0.82 (0.07)	0.43 (0.08)	0.79 (0.26)	0.92 (0.03)	0.94 (0.05)
8	0.84 (0.07)	0.45 (0.10)	0.78 (0.26)	0.93 (0.03)	0.94 (0.05)
16	0.87 (0.07)	0.50 (0.11)	0.74 (0.27)	0.94 (0.03)	0.93 (0.05)

Notes:

[a] Standard errors are in parentheses.

[b] The two indicated b_{na} values represent the lower and upper bounds of the range of values that satisfy the tighter qualitative restrictions.

[c] The first column reports results under the assumption that allocative shocks have symmetric long run effects on creation and destruction; that is, allocative shocks have no long run effect on net employment. The second column reports results under the assumption that aggregate shocks have symmetric (opposite) long run effects on creation and destruction; that is, aggregate shocks have no long run effect on job reallocation. The third column reports results under the assumption that aggregate shocks have no long run effect on excess job reallocation.

Table 3
Forecast-Error Variance Decompositions for the Net Growth Rate
Five-Variable System, Spliced Data,1960:Q1-1988:Q4

A. Under Tighter Restrictions[a]

Fraction of Forecast-Error Variance Due to:

Forecast Horizon	Oil	Credit	Aggregate $(b_{na}=-1)$ $(b_{ps}=0.1153)$	Allocative $(b_{na}=-1)$ $(b_{ps}=0.1153)$	Aggregate $(b_{na}=-2.023)$ $(b_{ps}=1)$	Allocative $(b_{na}=-2.023)$ $(b_{ps}=1)$
1 quarter	0.00	0.00	0.73	0.27	1.00	0.00
	(0.02)	(0.00)	(0.02)	(0.01)	(0.02)	(0.00)
4	0.04	0.30	0.51	0.16	0.66	0.01
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.01)
8	0.17	0.27	0.42	0.14	0.55	0.01
	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)	(0.01)
16	0.17	0.27	0.41	0.16	0.55	0.02
	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)	(0.01)

B. Under Long Run Identification Assumptions[b]

Fraction of Forecast-Error Variance Due to:

Forecast Horizon	Aggregate $b_{na}=-0.4448$ $b_{ps}=-0.1298$	Allocative $b_{na}=-0.4448$ $b_{ps}=-0.1298$	Aggregate $b_{na}=-1.601$ $b_{ps}=0.5296$	Allocative $b_{na}=-1.601$ $b_{ps}=0.5296$	Aggregate $b_{na}=-1.285$ $b_{ps}=0.2854$	Allocative $b_{na}=-1.285$ $b_{ps}=0.2854$
1 quarter	0.37	0.62	0.96	0.04	0.87	0.13
	(0.07)	(0.07)	(0.03)	(0.02)	(0.06)	(0.05)
4	0.28	0.38	0.65	0.02	0.60	0.07
	(0.04)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)
8	0.23	0.33	0.54	0.02	0.50	0.07
	(0.04)	(0.03)	(0.03)	(0.01)	(0.03)	(0.02)
16	0.22	0.35	0.53	0.03	0.48	0.08
	(0.04)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)

[a]Standard errors in parentheses.

[b] In the lower panel: the first two columns reflect the assumption that allocative shocks have no long run effect on employment; the middle two columns reflect the assumption that aggregate shocks have no long run effect on job reallocation; the rightmost two columns reflect the assumption that aggregate shocks have no long run effect on excess job reallocation.
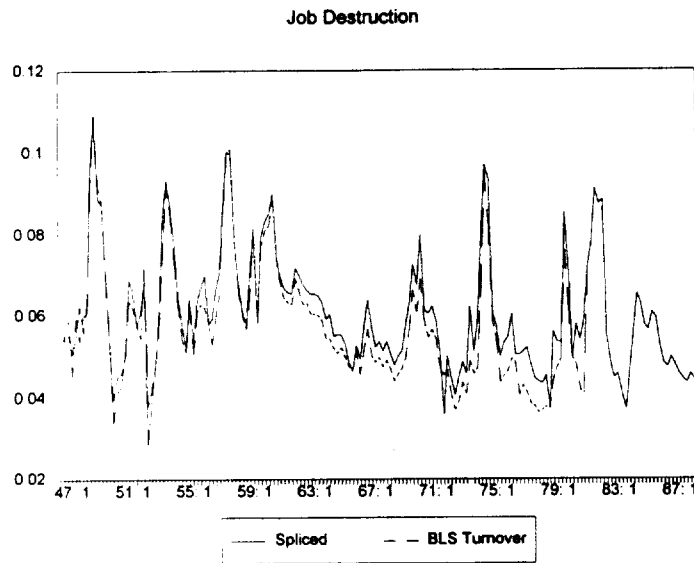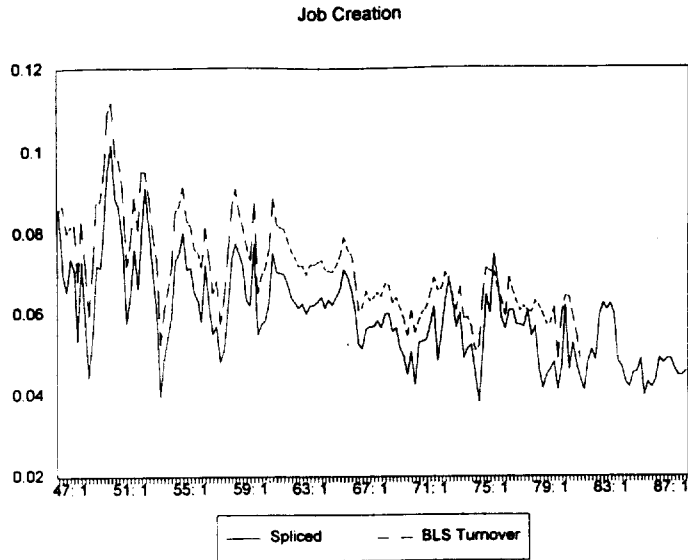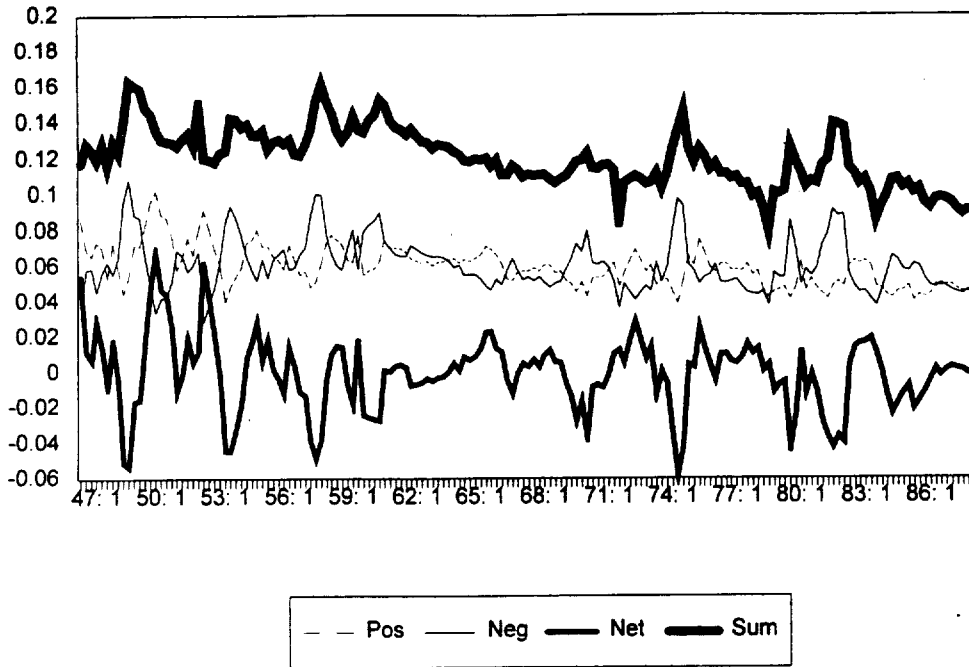
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Table 4
Forecast-Error Variance Decompositions for the Job Reallocation Rate
Five-Variable System, Spliced Data,1960:Q1-1988:Q4

A. Under Tighter Restrictions[a]

</div>

Fraction of Forecast-Error Variance Due to:

Forecast Horizon	Oil	Credit	Aggregate $(b_{na}=-1)$ $(b_{ps}=0.1153)$	Allocative $(b_{na}=-1)$ $(b_{ps}=0.1153)$	Aggregate $(b_{na}=-2.023)$ $(b_{ps}=1)$	Allocative $(b_{na}=-2.023)$ $(b_{ps}=1)$
1 quarter	0.01	0.00	0.00	0.99	0.27	0.73
	(0.02)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
4	0.034	0.10	0.04	0.83	0.33	0.51
	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)
8	0.13	0.16	0.03	0.67	0.25	0.46
	(0.045)	(0.02)	(0.00)	(0.03)	(0.03)	(0.03)
16	0.18	0.16	0.07	0.59	0.20	0.46
	(0.05)	(0.02)	(0.01)	(0.04)	(0.02)	(0.04)

<div align="center">

B. Under Long Run Identification Assumptions[b]

</div>

Fraction of Forecast-Error Variance Due to:

Forecast Horizon	Aggregate $b_{na}=-0.4448$ $b_{ps}=-0.1298$	Allocative $b_{na}=-0.4448$ $b_{ps}=-0.1298$	Aggregate $b_{na}=-1.601$ $b_{ps}=0.5296$	Allocative $b_{na}=-1.601$ $b_{ps}=0.5296$	Aggregate $b_{na}=-1.285$ $b_{ps}=0.2854$	Allocative $b_{na}=-1.285$ $b_{ps}=0.2854$
1 quarter	0.13	0.87	0.12	0.87	0.03	0.96
	(0.05)	(0.06)	(0.03)	(0.04)	(0.03)	(0.04)
4	0.05	0.81	0.21	0.65	0.11	0.76
	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)
8	0.08	0.62	0.14	0.56	0.07	0.64
	(0.03)	(0.05)	(0.01)	(0.04)	(0.02)	(0.04)
16	0.14	0.52	0.12	0.54	0.08	0.58
	(0.04)	(0.06)	(0.01)	(0.04)	(0.01)	(0.04)

[a]Standard errors in parentheses.

[b]In the lower panel: the first two columns reflect the assumption that allocative shocks have no long run effect on employment; the middle two columns reflect the assumption that aggregate shocks have no long run effect on job reallocation; the rightmost two columns reflect the assumption that aggregate shocks have no long run effect on excess job reallocation.

Figure 1

Job Creation

Spliced   — — BLS Turnover

Job Destruction

Spliced   — — BLS Turnover

BLS and Spliced Net Employment Growth

Spliced   - - - BLS 790
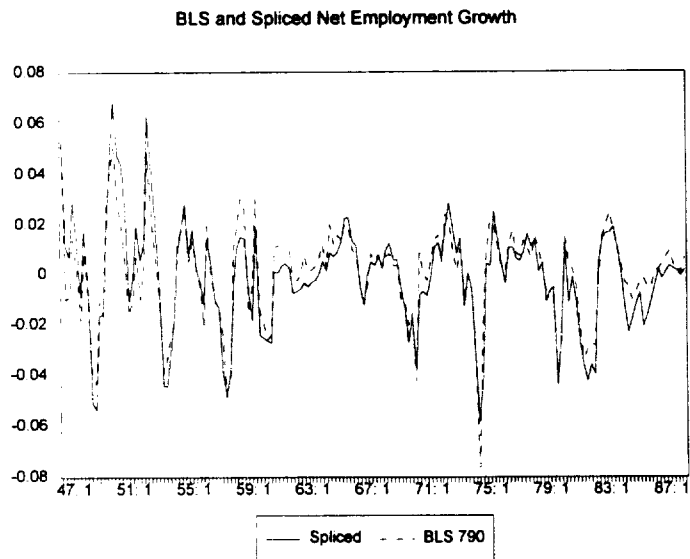
Figure 2

Gross and Net Job Flows
Spliced Data

- – Pos   —— Neg   ▬▬ Net   ▬▬▶ Sum

Oil Indices and Quality Spread


—— Oil Index   ▬▬ Abs Chg (Oil Index)   – – Quality Spread
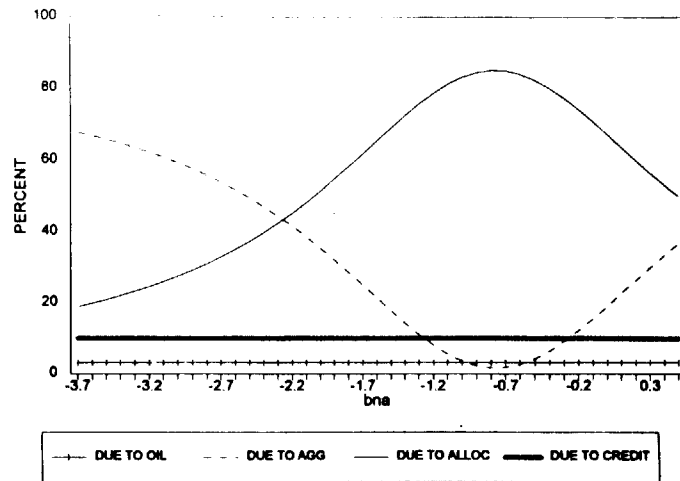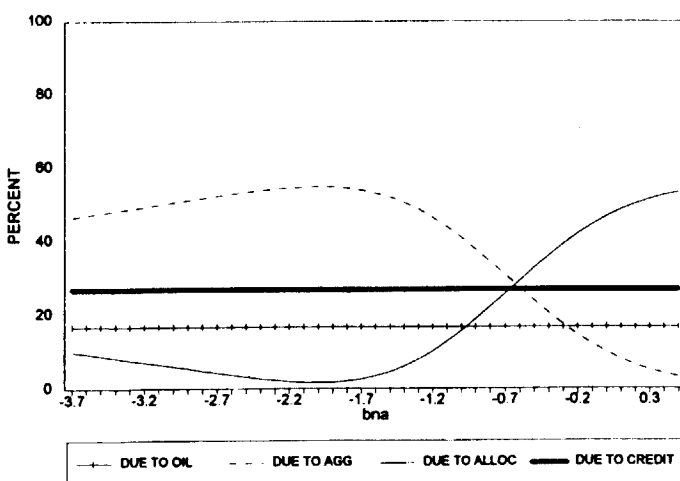
Figure 3

Implications of Identification
for Key Parameters

Implications of Identification
for Key Parameters

Std (Allocative) — — Std (Aggregate)

Percent of Net Growth and Job
Reallocation Due to Allocative Shocks

Net (4 Step) — — Sum (4 Step) - - - Net(16 Step) —— Sum (16 Step)
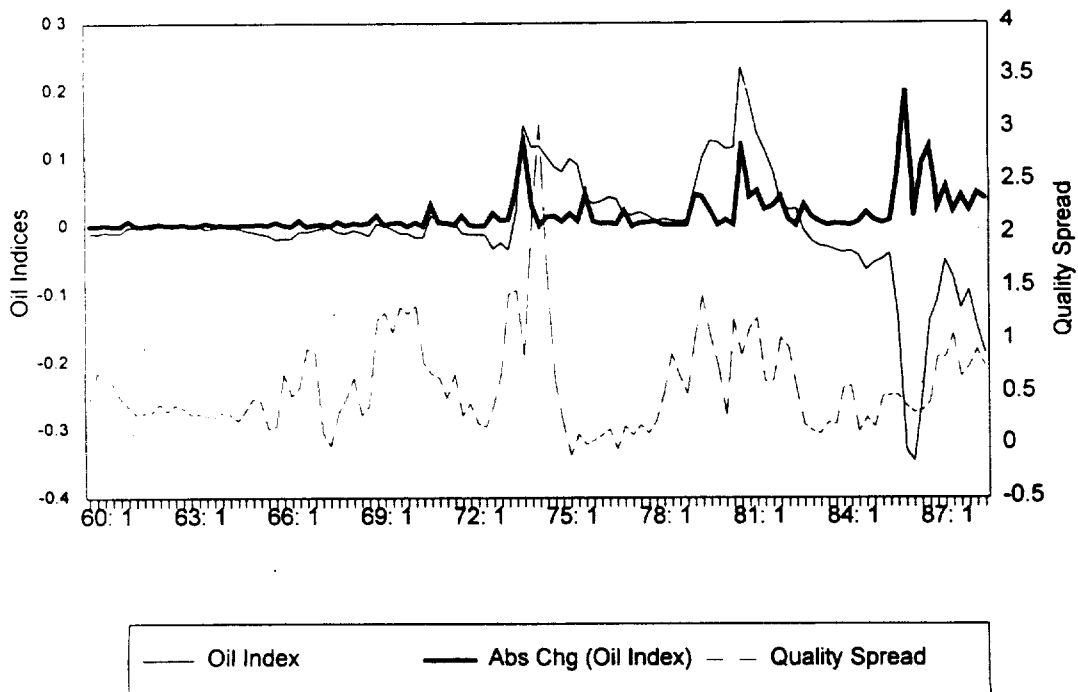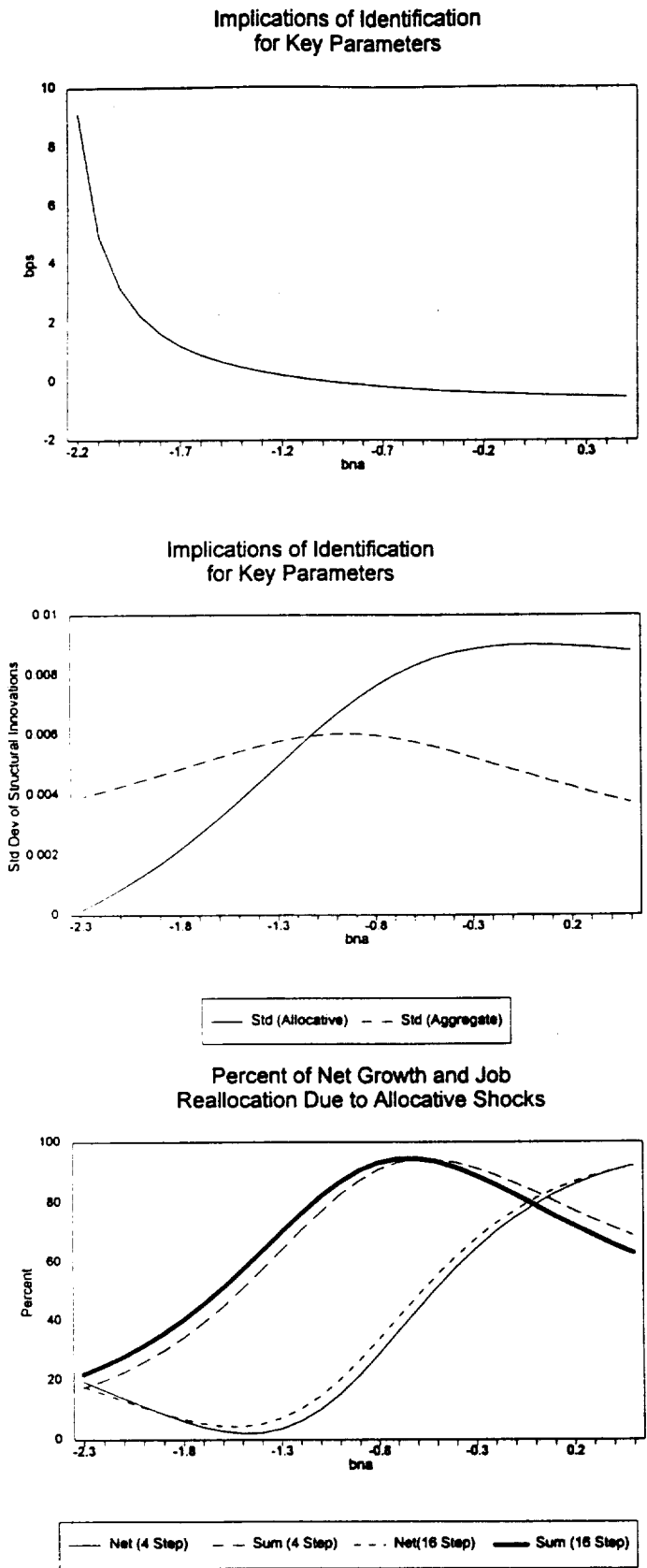
Figure 4

Decomposition of Net Employment Growth
bna=-1.0
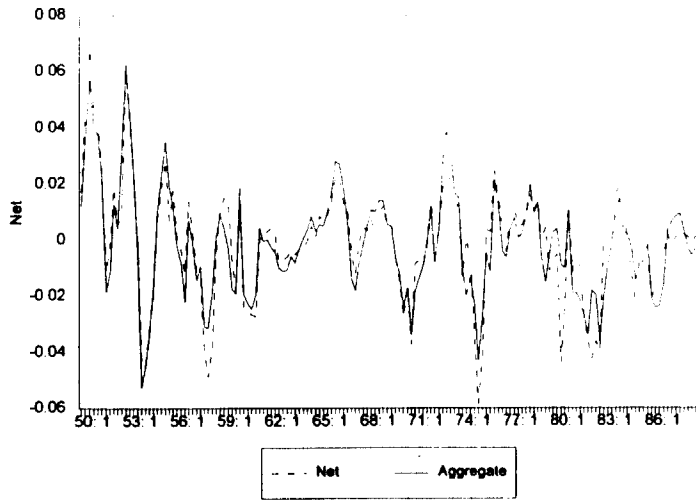
Decomposition of Net Employment Growth
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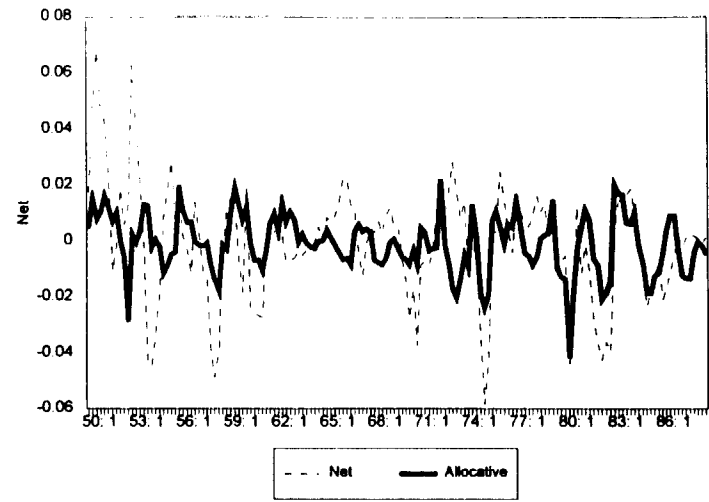
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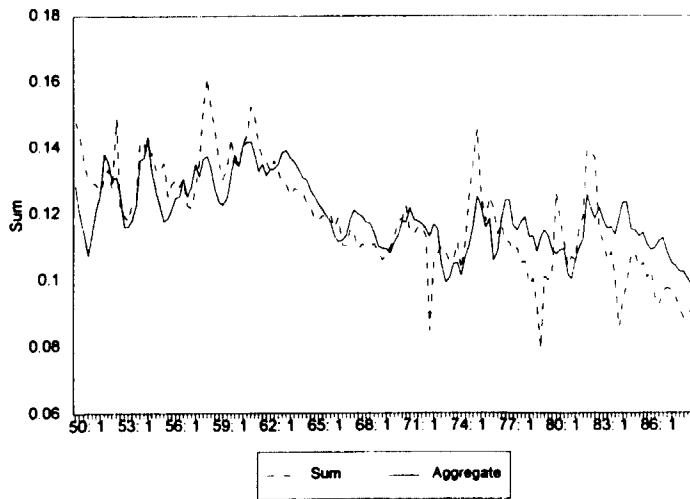
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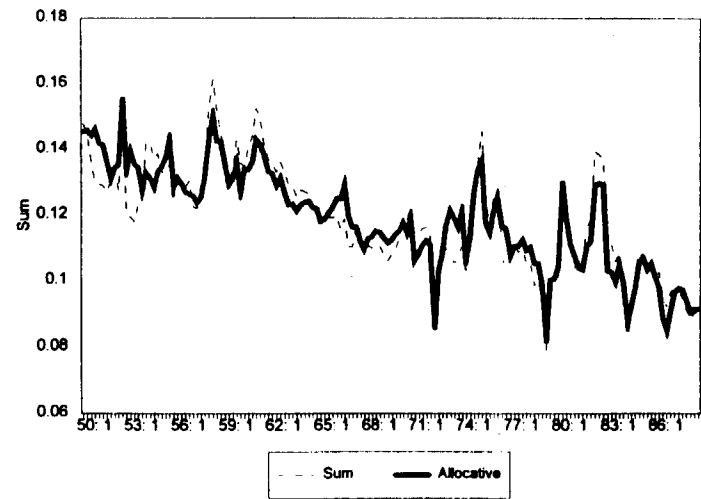
Figure 5

Decomposition of Net Employment Growth
bps =1
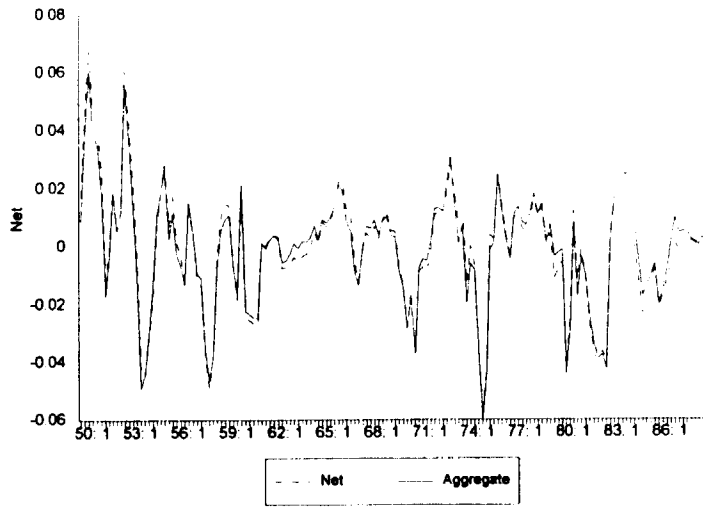
Decomposition of Net Employment Growth
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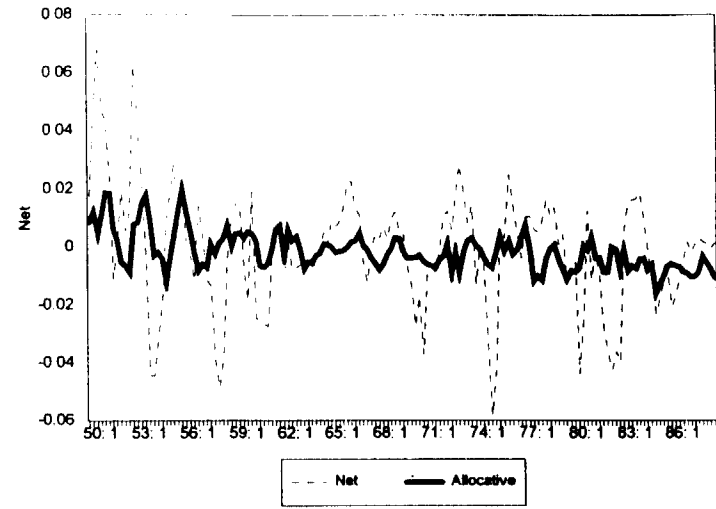
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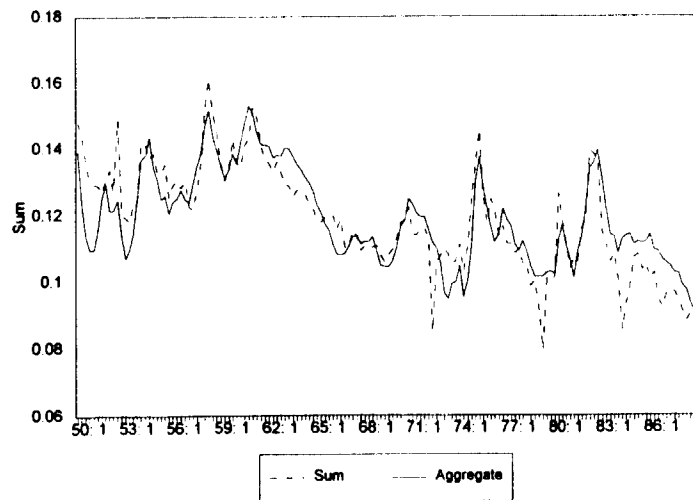
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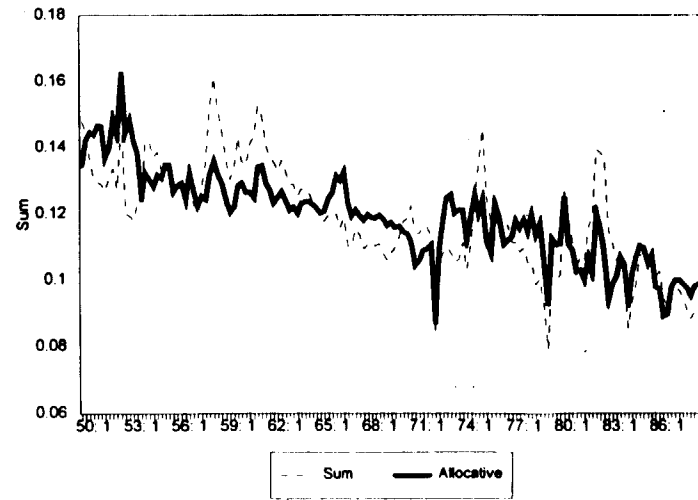
Figure 6

IMPLICATIONS OF IDENTIFICATION
FOR KEY PARAMATERS
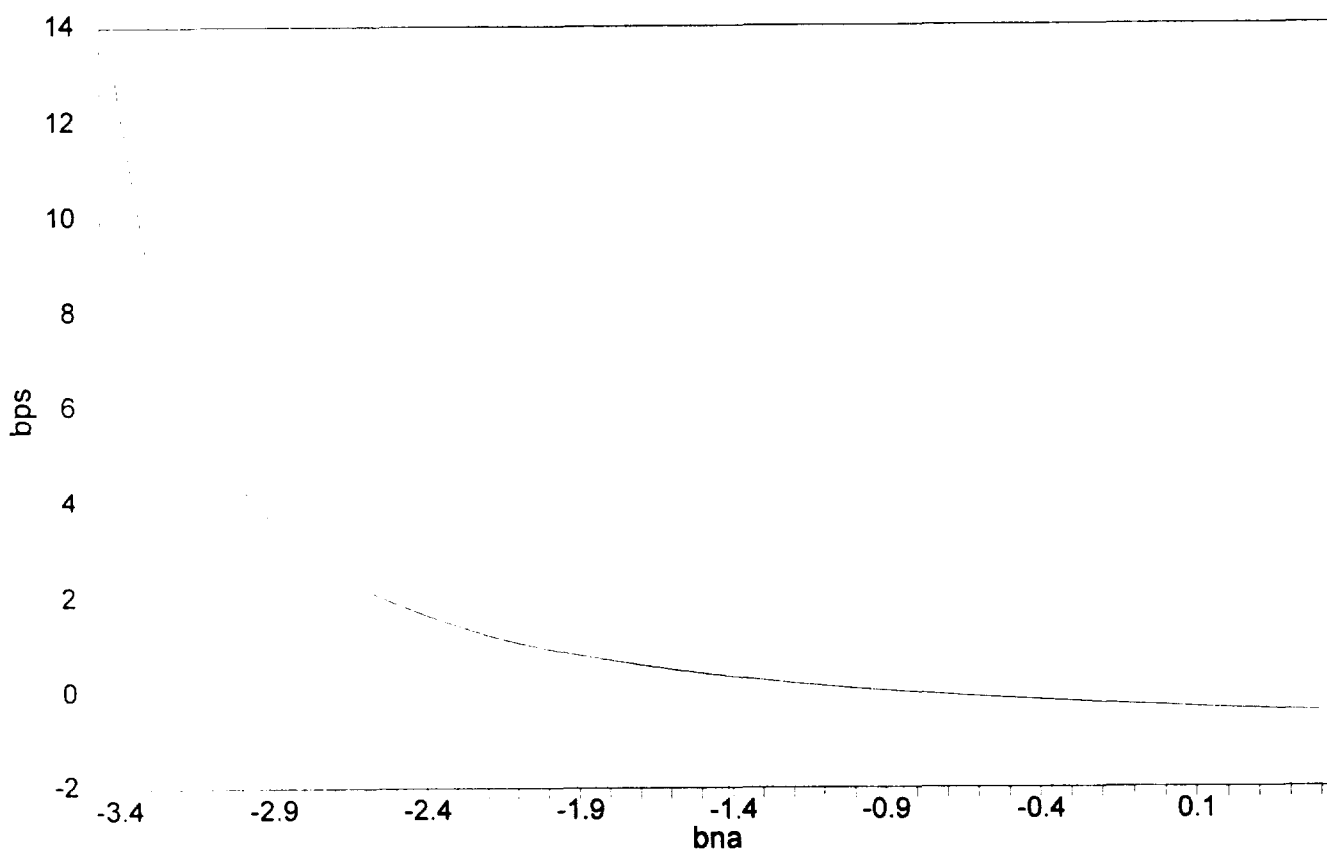
Figure 7

VARIANCE DECOMPOSITION OF NET
4-STEP HORIZON
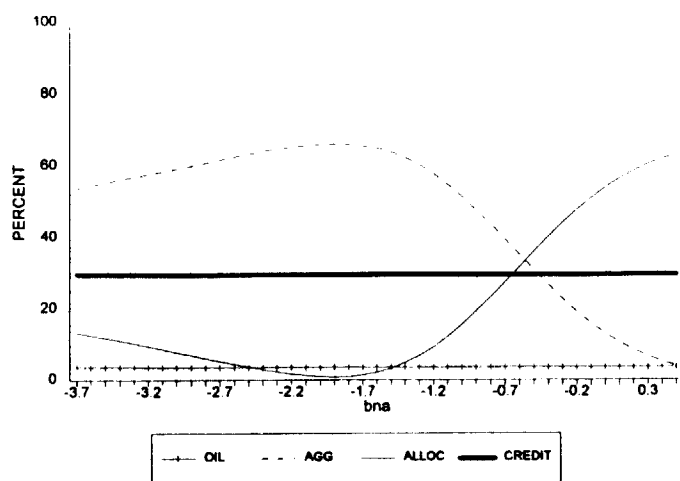
VARIANCE DECOMPOSITION OF SUM
4-STEP HORIZON

VARIANCE DECOMPOSITION OF NET
16-STEP HORIZON

VARIANCE DECOMPOSITION OF SUM
16-STEP HORIZON
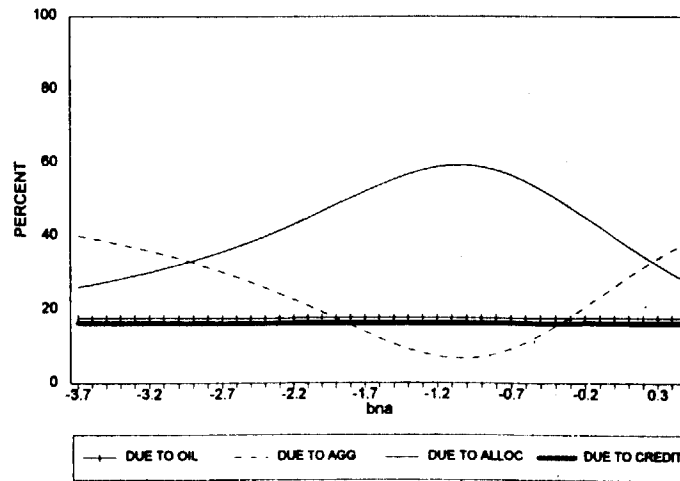
Figure 8

Decomposition of NET
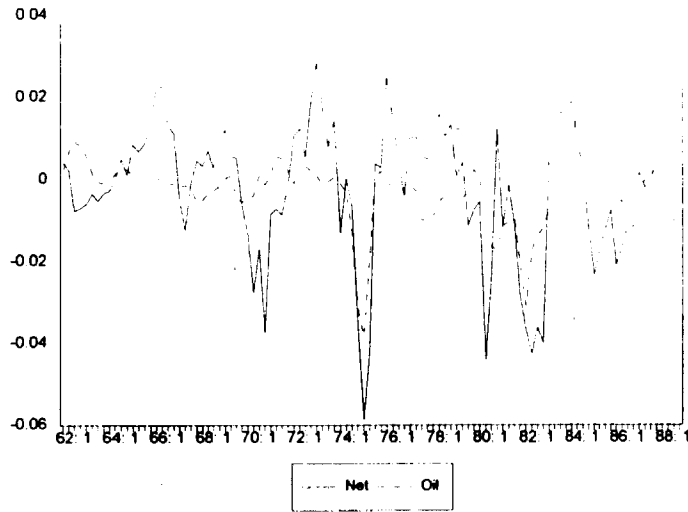
Decomposition of NET
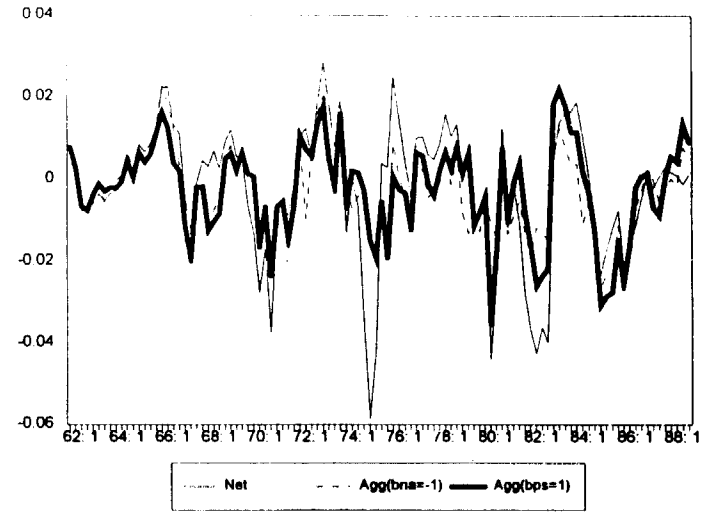
Decomposition of NET
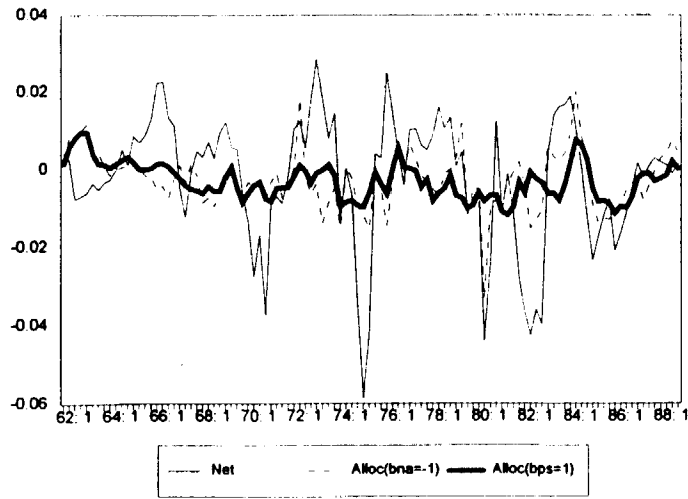
Decomposition of NET
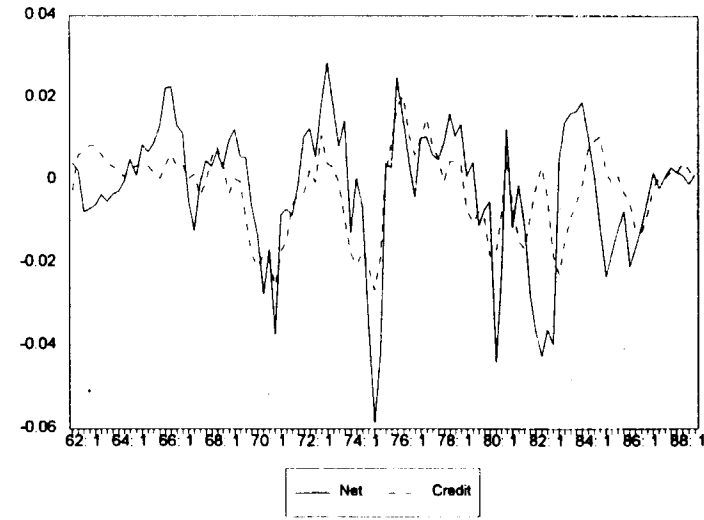
Figure 9

Decomposition of SUM

Decomposition of SUM
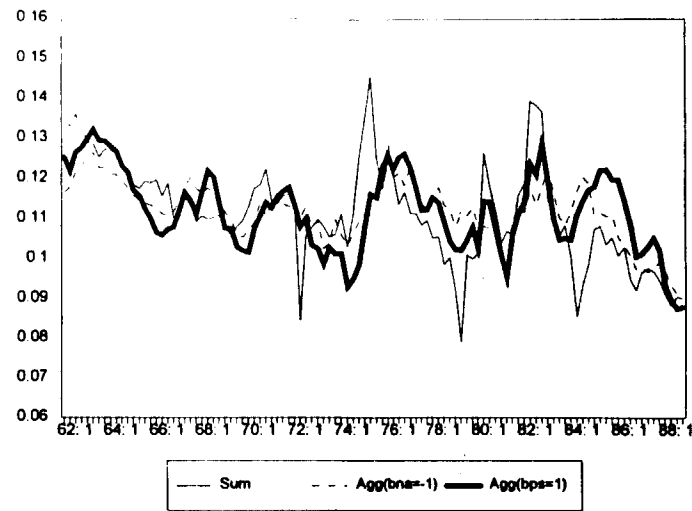
Decomposition of SUM
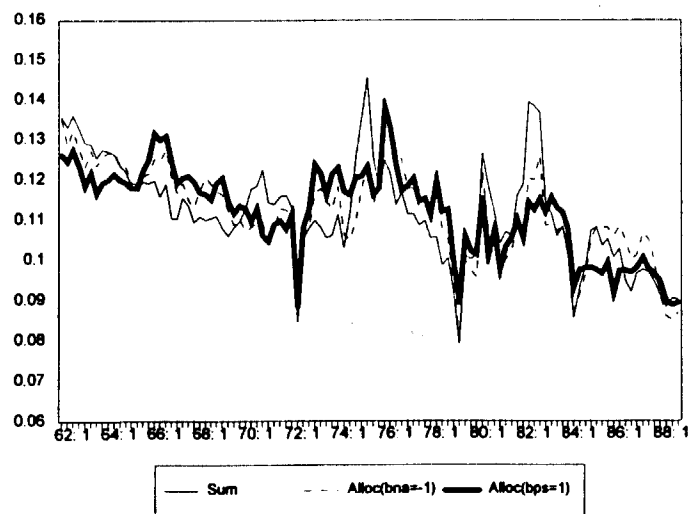
Decomposition of SUM
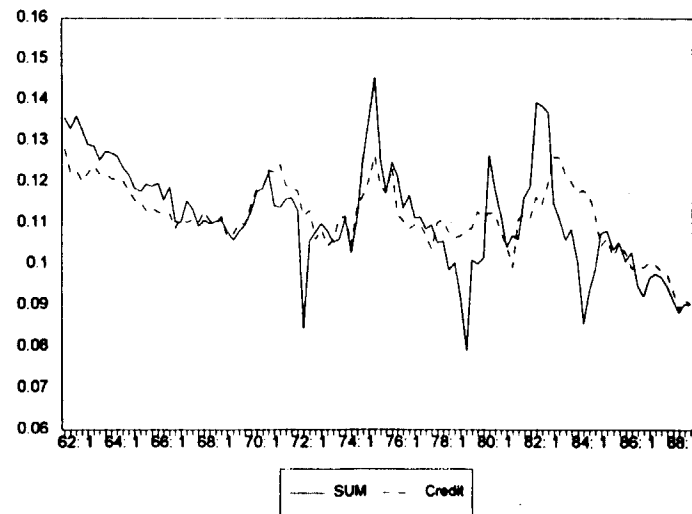
Figure 10

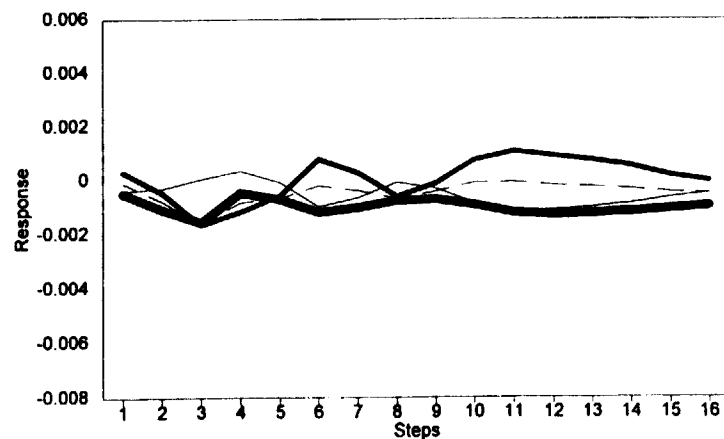### Response to Positive Unit Standard Deviation Oil Shock
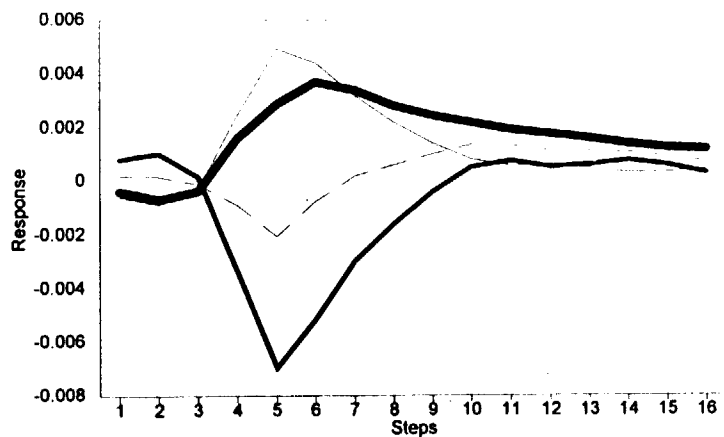
Legend: POS NEG NET SUM

Response to a Unit Standard Deviation Oil Shock: Absolute Change Only
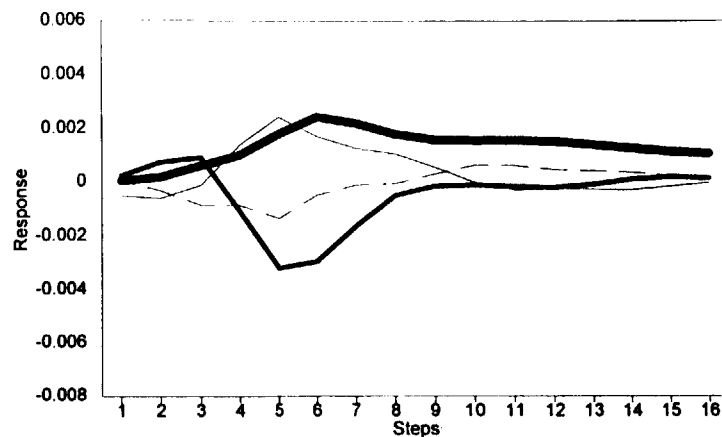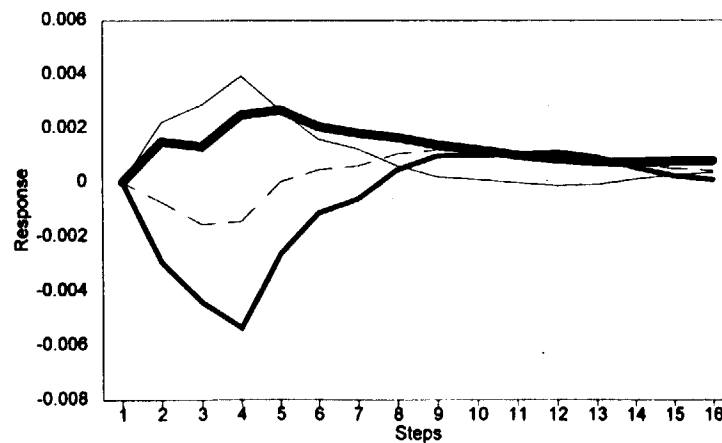

Legend: POS NEG NET SUM

Response to a Negative Unit Standard Deviation Oil Shock

Legend: POS NEG NET SUM

Response to a Unit Standard Deviation SPREAD Shock

Legend: POS NEG NET SUM