On the Driving Forces Behind Cyclical Movements in Employment and Job Reallocation

By Steven J. Davis and John Haltiwanger*

Theory restricts short-run job creation and destruction responses and cumulative employment and job reallocation responses to allocative and aggregate shocks. We formulate these restrictions and implement them for postwar data on U.S. manufacturing. Allocative shocks are the main driving force behind cyclical movements in job reallocation, but their contribution to employment fluctuations varies greatly across alternative identification assumptions. Also, the data compel one or both of the following inferences: aggregate shocks greatly alter the shape and not just the mean of the cross-sectional density of employment growth rates; allocative shocks cause short-run reductions in aggregate employment. (JEL C32, E32, J63)

What types of disturbances drive cyclical movements in aggregate employment? What do fluctuations in job reallocation activity tell us about the nature of cyclical movements in employment? These are basic questions in macroeconomics. 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 that bears on the answers. Our empirical implementation focuses on the U.S. manufacturing sector from the late 1940’s through the early 1990’s.

We seek especially to assess the role that allocative disturbances play in driving cyclical fluctuations in employment and job flows during the 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. 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 multidimensional 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 aggregate fluctuations, our analysis stresses how aggregate disturbances interact with a continual stream of allocative disturbances to further drive employment fluctuations. There has been a

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1 Daniel S. Hamermesh (1989), Robert Topel (1990), and Louis S. Jacobson et al. (1993) discuss costs that fall on workers. Valerie Ramey and Matthew Shapiro (1998) discuss capital reallocation costs. Davis et al. (1996 Ch. 5) provide a broad discussion of reallocation costs.
great deal of other work in this vein in recent years. The cornerstone of our empirical strategy for assessing 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, as we discuss below. We use these tighter 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.

A second virtue of the decomposition for 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 eventually the economy adjusts fully to an allocative disturbance. The paper proceeds as follows. Section I describes the data and briefly reviews several theories of job flows and employment fluctuations. Section II sets forth our VAR specification and develops several sets of identifying assumptions. Section III estimates the time-series model, implements the identifying assumptions, and discusses the resulting inferences about the nature of fluctuations in employment and job reallocation activity. Section IV states our conclusions.

I. Data and Theoretical Background

A. Measurement and Basic Facts


As Blanchard and Diamond (1990) point out, 3 Jeffrey Campbell and Kenneth 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 Danny Quah, 1989), identify the role of productivity shocks in business cycles (e.g., Robert G. King et al., 1991), and identify the effects of monetary policy disturbances (e.g., King and Mark W. Watson, 1992).
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 join the job flow series from the two sources based on their overlap from 1972 to 1981, as explained in the Appendix.4

The top two panels in Figure 1 display quarterly job creation and destruction rates from 1947:1 to 1993:4. The dashed lines are constructed from BLS turnover data using a constant quit replacement rate of 0.85, as in Blanchard and Diamond. The solid lines show our time series; they are identical to the LRD series from 1972:2 to 1993:4, 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 creation and destruction rates displayed in the upper panels, and 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 data closely mimic the BLS 790 series: the simple correlation between the two growth rates is 0.91, and the mean absolute difference between them is 0.6 percentage points over the 1947–1993 sample (as compared to 0.5 percentage points in the 1972–1993 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 and destruction rates (POS and NEG), our empirical analysis considers two related time series: the net employment growth rate (NET) and the job reallocation rate (SUM), 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 2 plots net and gross job flow rates for the U.S. manufacturing sector, and Table 1 summarizes important features of the data for two periods: the overall sample (1947:1–1993:4) and the LRD period (1972:2–1993:4). 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 percent (5.8 percent) of manufacturing employment. The average quarterly rate of job reallocation over the 1947:1–1993:4 period is 11.8 percent. 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.6

Perhaps surprisingly, large-scale job reallocation in manufacturing characterizes the entire post-World War II period. The high pace of job reallocation in the 1950’s is especially noteworthy, given recent concerns in the popular press about rising job insecurity (e.g., New York Times, 1996). The higher pace of job reallocation in the 1950’s reflects a higher rate of job creation coupled with job destruction rates comparable to those in the 1970’s and 1980’s. In other words, the secular decline in the 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 1970’s and the 1980’s, but spikes in job destruc-

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4 Our procedures are designed to measure job creation in the sense of newly filled employment positions. Blanchard and Diamond add the change in the vacancy rate to their measure of job creation to account for open, but unfilled, employment positions. We show elsewhere (Davis and Haltiwanger, 1998) that there is little difference between these two conceptually distinct job creation measures.

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

6 Large-scale job reallocation is not peculiar to the manufacturing sector or the U.S. economy. See Davis et al. (1996) for further discussion and evidence.
FIGURE 1. QUARTERLY JOB CREATION, JOB DESTRUCTION, AND EMPLOYMENT GROWTH RATES
VARYING TIME SERIES FOR U.S. MANUFACTURING
tion accompany every major contraction in the post-World War II period.

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

**B. Emerging Theories**

A variety of theoretical models have emerged to interpret the cyclical behavior of gross job flows and related empirical phenomena (see footnote 1). These models typically 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 job reallocation. 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 shakeout of less efficient firms and
TABLE 1—Net and Gross Job Flow Rates in the U.S. Manufacturing Sector

A. Summary Statistics (Percent of Employment)

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td></td>
<td>POS</td>
<td>NEG</td>
</tr>
<tr>
<td>Mean</td>
<td>5.8</td>
<td>6.0</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1.2</td>
<td>1.5</td>
</tr>
<tr>
<td>Minimum</td>
<td>3.8</td>
<td>2.9</td>
</tr>
<tr>
<td>Maximum</td>
<td>10.2</td>
<td>10.8</td>
</tr>
</tbody>
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B. Selected Contemporaneous Correlations

<table>
<thead>
<tr>
<th></th>
<th>p(POS, NET)</th>
<th>p(NEG, NET)</th>
<th>p(SUM, NET)</th>
<th>p(POS, NEG)</th>
<th>Sample period</th>
</tr>
</thead>
<tbody>
<tr>
<td>1947:Q1–1993:Q4</td>
<td>0.71</td>
<td>-0.82</td>
<td>-0.20</td>
<td>-0.17</td>
<td>47:1–93:4</td>
</tr>
<tr>
<td></td>
<td>0.69</td>
<td>-0.90</td>
<td>-0.49</td>
<td>-0.30</td>
<td>72:2–93:4</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th></th>
<th>p(POS, NET)</th>
<th>p(NEG, NET)</th>
<th>p(SUM, NET)</th>
<th>p(POS, NEG)</th>
<th>Sample period</th>
</tr>
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<tbody>
<tr>
<td>Linearly Detrended Data</td>
<td>0.82</td>
<td>-0.93</td>
<td>-0.50</td>
<td>-0.56</td>
<td>47:1–93:4</td>
</tr>
<tr>
<td></td>
<td>0.73</td>
<td>-0.93</td>
<td>-0.59</td>
<td>-0.43</td>
<td>72:2–93:4</td>
</tr>
</tbody>
</table>

establishments, contributing to aggregate contraction and increased heterogeneity in plant-level employment movements. Fourth, 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 draw on these theories to specify identifying assumptions that enable us to assess the relative importance of the driving forces.

II. Identification

A. The VAR Specification

Let \( Y_t = [POS_t, NEG_t]' \) be a vector containing observed values of the job creation and destruction rates. Also, let \( \varepsilon_t = [\varepsilon_{st}, \varepsilon_{sr}]' \) be a vector containing time-\( t \) innovations to the structural disturbances that drive the observed rates of creation and destruction.

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

\[
(1) \quad Y_t = B(L)\varepsilon_t, \quad B(0) = B_0, \]

where \( B(L) \) is an infinite-order matrix lag polynomial. Without loss of generality, we normalize the diagonal elements of \( B_0 \), the contemporaneous response matrix, to unity.

When we estimate a VAR on \( Y_t \), we do not immediately recover either the estimates of the matrix lag polynomial, \( B(L) \), or the vector of structural innovations, \( \varepsilon_t \). Instead, the estimated VAR yields

\[
(2) \quad Y_t = D(L)\eta_t, \quad D(0) = I, \]

where \( D(L) \) is an infinite-order matrix lag polynomial implied by the estimated coefficients in the VAR representation of \( Y_t \), and \( \eta_t = [p_t, n_t]' \) is the vector of reduced-form innovations. Comparing (1) and (2) implies \( \eta_t = B_0\varepsilon_t \) and \( B(L) = D(L)B_0 \), so that full knowledge of \( B_0 \) would enable us to recover estimates of both \( B(L) \) and the
structural innovations 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 structural disturbances requires additional, a priori information.

Before spelling out our identifying assumptions, we introduce additional notation. Let $b_{ij}$ denote the element in the $i$th row and $j$th column of $B_0$, where $i = p, n$, and $j = a, s$. Likewise, let $B_{ij}(l)$ and $D_{ij}(l)$ denote the element in the $i$th row and $j$th 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. Weak Restrictions on the Structural Parameter Range

Our approach to identification begins with a pair of weak restrictions that constrain the admissible range of the contemporaneous responses to the structural innovations. These weak restrictions are consistent with a wide range of theoretical models and alternative views about business cycles. We combine the weak restrictions on contemporaneous shock responses with a restriction on the covariance of the structural innovations:

1. $b_{na} < 0$,
2. $b_{ps} > 0$,
3. $\rho(e_{at}, e_{st}) = 0$.

Assumptions (i) and (ii) reflect the qualitative character of the effects that aggregate and allocative disturbances have on the response of job creation and destruction rates. That is, aggregate disturbances cause creation and destruction to move in opposite directions, while allocative disturbances cause them to move in the same direction. In a sense, assumptions (i) and (ii) are definitional and therefore should be widely accepted.7

Assumption (iii) 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., Ben S. Bernanke (1986), Matthew Shapiro and Watson (1988), and Blanchard and Quah (1989)]. 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 (iii) is available in our context.

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 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 (iii) holds. Even though we believe that this identifying assumption is reasonable, particularly with a long sample period, we shall also consider the sensitivity of our results to relaxing (iii).

Writing out the equations $\eta_t = B_0 e_t$, we have

$$p_t = e_{at} + b_{ps} e_{st},$$

$$n_t = b_{na} e_{at} + e_{st}.$$

This system implies three moment conditions that relate elements of the covariance matrix of the reduced-form innovations to parameters of $B_0$ and elements of the covariance matrix of the structural innovations.

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7Although, as we will see below, arguments can be made that allocative disturbances need not have a positive contemporaneous impact on job creation.
Making use of the covariance restriction (iii), these second moment conditions are

\[ \sigma_p^2 = \sigma_a^2 + b_p^2 \sigma_s^2, \]
\[ \sigma_n^2 = b_{na} \sigma_a^2 + \sigma_s^2, \]
\[ \sigma_{ps} = b_{na} \sigma_a^2 + b_{ps} \sigma_s^2, \]

where \( \sigma_p^2, \sigma_n^2, \) and \( \sigma_{ps} \) comprise the elements of the reduced-form covariance matrix. There are four unknowns on the right side of these moment conditions: the contemporaneous response coefficients, \( b_{na} \) and \( b_{ps} \), and the standard deviations of the structural innovations, \( \sigma_a \) and \( \sigma_s \). Hence, restriction (iii) by itself implies a one-dimensional underidentification of the VAR system.

Combining the moment conditions yields a one-to-one mapping between \( b_{na} \) and \( b_{ps} \), namely,

\[ b_{ps} = \frac{\sigma_{ps} - b_{na} \sigma_p^2}{\sigma_n^2 - b_{na} \sigma_{ps}}. \]

Given this mapping, the inequality restrictions (i) and (ii) determine a locus of pairs, \( \{ b_{na}, b_{ps} \} \), that satisfy all three identifying assumptions. Furthermore, one can easily show that each value of \( b_{na} \) maps uniquely to values for \( \sigma_a \) and \( \sigma_s \). Hence, while the inequality conditions do not achieve exact identification, they restrict the range of permissible values for the structural parameters. Looking ahead to Figure 3, which we construct from the estimated VAR, the permissible parameter values under (i) and (ii) lie to the left of the solid vertical line at \( b_{na} = -0.87 \) and to the right of \( b_{na} = -2.5 \).

### C. Tighter Restrictions on the Structural Parameter Range

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

(i)' \( b_{na} \leq -1 \),
(ii.a)' \( |b_{ps}| \leq 1 \),
(ii.b)' \( \sum_{l=1}^{M} B_{11}(l) > 0 \), for all \( m \) such that \( 2 \leq m \leq M \).

Assumption (i)' restricts the contemporaneous job destruction response to an aggregate innovation to be at least as large as the contemporaneous creation response. To understand the arguments for requiring \( b_{na} \leq -1 \), consider the impact of an aggregate disturbance in an economy subject to a continuous stream of allocative disturbances. Two effects are important: First, since worker and job reallocation entail forgone 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 (i)'.

Davis and Haltiwanger (1990) and Mortensen (1994) develop dynamic equilibrium models that illustrate this effect.9

Assumption (ii.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

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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 studies that exploit qualitative identifying information in a VAR context are King and Watson (1992) and Ilian Milhov (1995).

9 The properties of the two models differ somewhat in a manner that bears on assumption (i)'. 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.
Figure 3. Identification Results for $\rho = 0$
and worker reallocation creates an asymmetry between the matching and separation processes in the 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 (Christopher Pissarides, 1985; 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). In this way, the option value effect of an allocative innovation depresses job creation, even as the 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.

Table 2 provides some evidence regarding this option value effect. The table draws on Prakash Loungani et al. (1990, 1991) and Lael Brainard and David Cutler (1993), who use postwar 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. The table shows positive and statistically significant values for the first six autocorrelations of these indexes, which supports the empirical relevance of the option value effect discussed above.
One further remark about (ii.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 David 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 (ii.a)' embodies a widely held view among economists who have investigated the aggregate consequences of allocative disturbances.\(^{10}\)

Since we do not restrict the sign of \( b_{ps} \), the refinement (ii.a)' actually relaxes one aspect of the original assumption (ii). However, we do require that allocative shocks ultimately raise job creation: in fact, (ii.b)' requires that an allocative shock has a positive cumulative effect on job creation at every horizon from 1 to \( M - 1 \) periods after the initial impulse. In the analysis below, we set \( M = 16 \). As it turns out, this restriction never binds in our data set when we impose the remaining tighter restrictions.

Another way to motivate these tighter inequality restrictions is to consider their relationship to standard representative agent models. Viewed from this perspective, the bounds at \( b_{na} = -1 \) and \( b_{ps} = 1 \) emerge as natural benchmarks. The assumption that \( b_{na} = -1 \) implies that job creation and destruction respond symmetrically (in opposite directions) to aggregate shocks. This symmetry is consistent with the view that aggregate shocks affect mean plant-level growth but have little effect on the shape of the cross-sectional growth rate distribution. This view suggests that macroeconomists can safely abstract from the underlying microeconomic heterogeneity for the purposes of explaining aggregate employment fluctuations. 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 inequality restrictions include these two benchmark assumptions as limiting cases. Thus, examining the results at these bounds—and determining whether both bounds can be satisfied simultaneously—helps evaluate the assumptions embodied in representative agent models of economic fluctuations.

D. Neutrality Restrictions

The inequality restrictions do not fully identify the VAR system. We can achieve greater precision in some of our inferences by imposing additional restrictions on the VAR system, or by bringing more information to bear through the use of other variables and attendant restrictions. Here, we pursue neutrality restrictions similar to the long-run sort emphasized by Shapiro and Watson (1988), Blanchard and Quah (1989), and King and Watson (1992).\(^11\)

Given the covariance restriction (iii), we require one additional restriction to yield a just-identified system. In what follows, we consider in turn a number of alternative restrictions on the cumulative response behavior of creation and destruction to achieve just-identification.

One reasonable neutrality restriction maintains that aggregate shocks have no effect on cumulative job reallocation in the long run. This restriction is consistent with the theories outlined in Section I. 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 employment changes that enables us to entertain this identifying restriction.

\(^{10}\) Assumption (ii.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.

\(^{11}\) We consider larger VAR systems in the working paper version of this paper (Davis and Haltiwanger, 1996), and we consider implications related to cross-sectoral shock response variation in a panel VAR setup in Davis and Haltiwanger (1999).
We consider two slightly different formal representations of this neutrality 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 analog of this restriction is that aggregate shocks have symmetric effects on cumulative creation and destruction, which implies long-run neutrality of aggregate shocks on job reallocation. This neutrality condition translates into a joint restriction on the dynamic response functions of job creation and destruction:

\[
(iv) \sum_{l=0}^{\infty} [B_{11}(l) + B_{21}(l)] = 0
\]

\[
\Rightarrow \sum_{l=0}^{\infty} [D_{11}(l) + D_{21}(l)] + b_{na} [D_{12}(l) + D_{22}(l)] = 0.
\]

While (iv) is reasonable, it may be more appropriate to impose the 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 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.\(^{12}\)

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 employment growth and job reallocation, we consider an alternative restriction in which aggregate shocks have neutral effects on cumulative excess reallocation:

\[
(iv') \sum_{l=0}^{\infty} B_{11}(l) + B_{21}(l)
\]

\[
- |B_{11}(l) - B_{21}(l)| = 0
\]

\[
\Rightarrow \sum_{l=0}^{\infty} D_{11}(l) + D_{21}(l)
\]

\[
+ b_{na} [D_{12}(l) + D_{22}(l)]
\]

\[
- |D_{11}(l) + D_{21}(l)|
\]

\[
- [b_{na} (D_{12}(l) + D_{22}(l))] = 0.
\]

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 response functions of job creation and destruction.\(^{13}\)

\[
(v) \sum_{l=0}^{\infty} [B_{12}(l) - B_{22}(l)] = 0
\]

\[
\Rightarrow \sum_{l=0}^{\infty} b_{px} [D_{11}(l) - D_{21}(l)]
\]

\[
+ [D_{12}(l) - D_{22}(l)] = 0.
\]

\(^{12}\) The argument works the same if job destruction absorbs the entire effect of aggregate shocks.

\(^{13}\) Assumption (v) 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 \( 2 \Delta x/(x_i + x_{i-1}) \). 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.
III. Empirical Results

A. Weak Restrictions on the Structural Parameter Range

Figure 3 presents results for an estimated VAR in the job creation and destruction rates using a lag length of four and a sample period that runs from 1948:1 to 1993:4. The top panel depicts the negative and highly nonlinear relationship between $b_{na}$ and $b_{ps}$ that emerges from the estimation. For $b_{na}$ greater than $-0.87$, $b_{ps}$ is negative and thus violates (ii). As $b_{ps}$ rises, $b_{na}$ asymptotically approaches $-2.5$. Hence, the minimal restrictions require $b_{na} \in (-2.5, -0.87)$. The middle panel 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 percent larger than the standard deviation of aggregate innovations to essentially zero.

The bottom panel of Figure 3 shows forecast-error variance decompositions for rates of employment growth and job reallocation intensity. Allocative innovations account for about 20 percent of the 4-step forecast-error variance in employment growth for $b_{na}$ near $-0.87$, less than 5 percent for $b_{na}$ around $-1.5$, and close to 20 percent again for values of $b_{na}$ around $-2.5$. The 16-step variance decomposition is qualitatively similar. Turning to job reallocation intensity, the fraction of variance explained by allocative innovations ranges from roughly 90 percent to 20 percent as $b_{na}$ varies over the interval $(-2.5, -0.87)$.

What should be made of these results? First, they provide a clear message along one dimension: aggregate shocks are a major driving force behind fluctuations in employment growth for every parameter combination consistent with the weak inequality restrictions. Second, the weak restrictions do not pin down whether allocative are a trivial or moderately important driving force behind employment fluctuations, nor do they determine which structural shock is the dominant driving force behind fluctuations in job reallocation intensity. Third, the trade-off 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 percent of the variation in employment growth and most of the variation in job reallocation. Models with a disproportionately large impact of aggregate shocks on job creation ($b_{na} > -1$) imply an even greater role for allocative disturbances as driving forces behind fluctuations in employment growth and job reallocation intensity.\footnote{For an example of such a model, see the discussion of the “insulation effect” in Caballero and Hammour (1994).}

The trade-off identified by the admissible \{b_{nat}, b_{ps}\} pairs allows us to assess whether, in light of the data, certain views about labor-market fluctuations can be consistently held. In particular, the results in Figure 3 show that some views cannot be consistently held. Under the view that allocative shocks have little impact effect on employment growth, one cannot also hold the view that aggregate shocks have no effect on job reallocation intensity. Alternatively, under the view that aggregate shocks have little impact effect on job reallocation, one cannot hold the view that allocative shocks have no important effect on employment growth. Thus, the data preclude views that sever the connection between cyclical fluctuations in employment growth and job reallocation. Either aggregate shocks play an important role in driving both employment growth and job reallocation intensity, or allocative shocks play an important role in driving both (or both shocks play an important role in driving both outcome variables).

B. Tighter Restrictions on the Structural Parameter Range

The tighter inequality restrictions yield a set of results summarized in the first two columns of Table 3. In addition to reporting forecast-error variance decompositions, Table 3 includes \footnote{Dickey-Fuller and augmented Dickey-Fuller tests yield rejections of the null hypothesis of a unit root in both the creation rate and the destruction rate. As a sensitivity check, we also estimated VARs allowing for deterministic time trends in the creation and destruction rates and obtained results similar to those reported in the text.}
### TABLE 3—FORECAST-ERROR VARIANCE DECOMPOSITIONS FOR NET AND GROSS FLOW RATES
**TWO-VARIABLE SYSTEM, 1948:Q1–1993:Q4**

#### A. Fraction of Variance of Net Job Growth Rate Fluctuations due to Allocative Shocks

<table>
<thead>
<tr>
<th>Identification Assumption</th>
<th>Qualitative restrictions</th>
<th>Neutrality restrictions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$b_{na} = -1$</td>
<td>$b_{na} = -1.63$</td>
</tr>
<tr>
<td></td>
<td>$b_{ps} = 0.1$</td>
<td>$b_{ps} = 1$</td>
</tr>
<tr>
<td>Forecast Horizon</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 quarter</td>
<td>0.20</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>4</td>
<td>0.13</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>8</td>
<td>0.16</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>16</td>
<td>0.17</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.04)</td>
</tr>
</tbody>
</table>

#### B. Fraction of Variance of Job Reallocation Rate Fluctuations due to Allocative Shocks

<table>
<thead>
<tr>
<th>Identification Assumption</th>
<th>Qualitative restrictions</th>
<th>Neutrality restrictions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$b_{na} = -1$</td>
<td>$b_{na} = -1.63$</td>
</tr>
<tr>
<td></td>
<td>$b_{ps} = 0.1$</td>
<td>$b_{ps} = 1$</td>
</tr>
<tr>
<td>Forecast Horizon</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 quarter</td>
<td>1</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>4</td>
<td>0.80</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.08)</td>
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<tr>
<td>8</td>
<td>0.81</td>
<td>0.45</td>
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<tr>
<td></td>
<td>(0.07)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>16</td>
<td>0.84</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.10)</td>
</tr>
</tbody>
</table>

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*Standard errors are in parentheses.

The two indicated $b_{na}$ values represent the lower and upper bounds of the range of values that satisfy the tighter qualitative restrictions (i)' and (ii)'.

The first column reports results under identifying assumption (v) that allocative shocks have equal effects on cumulative creation and destruction—in other words, that allocative shocks have no long-run effect on the level of employment. The second column reports results under assumption (iv) that aggregate shocks have opposite, equal-size effects on cumulative creation and destruction—in other words, that aggregate shocks have no long-run effect on the level of job reallocation. The third column reports results under assumption (iv)' that aggregate shocks have no long-run effect on the level of excess job reallocation.

The permissible range for $b_{na}$ shrinks to $(-1, -1.63)$, and the implied range for $b_{ps}$ becomes $(0.1, 1)$. Over this range, the standard deviation of allocative shocks is 10 percent greater than that of aggregate shocks at $b_{na} = -1$ and approximately 60 percent as large at $b_{na} = -1.63$.

Over the range that satisfies the tighter inequalities, the 4-step forecast-error variance of employment growth accounted for by allocative disturbances ranges from 13 percent for $b_{na} = -1$ to 3 percent for $b_{ps} = 1$. The corresponding range for the 16-step horizon is 17 percent to 5 percent. With respect to job reallocation intensity, the 4-step forecast-error variance accounted for by allocative disturbances ranges between 80 percent for $b_{na} = -1$ to 44 percent for $b_{ps} = 1$. The 16-step results are similar.

In sum, the tighter qualitative restrictions narrow the range of results considerably, and one

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16 We computed approximate standard errors by Monte Carlo simulation with 1,000 draws using the procedures described in Chapter 10 of the RATS manual (Thomas A. Doan, 1992).
additional inference emerges quite clearly: 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 ranges from 44 to 80 percent.

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 employment growth. Interestingly, allocative shocks make the largest contribution to movements in employment growth during the downturns in the late 1950’s and the early 1980’s. 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 the fluctuations in job reallocation but only a miniscule role in employment fluctuations.

C. Neutrality Restrictions

The fourth and fifth columns in Table 3 report results under the restriction that aggregate shocks have no long-run effect on total and excess job reallocation, respectively. Imposing (iv) yields $b_{na} = -0.68$, $b_{ps} = -0.12$, and a standard deviation of allocative shocks that is 33 percent larger than that for aggregate shocks. In either form, this long-run restriction yields results that are inconsistent with some component of either the weaker or the tighter qualitative restrictions. In particular, the results violate (ii) and (i)’.

Allocative shocks are an important driving force behind employment growth fluctuations and a dominant one for job reallocation fluctuations under these long-run restrictions. Allocative shocks account for 34 percent of the variance of the 4-step forecast error for employment growth under (iv) and 54 percent under (iv)’. In either case, they account for more than 90 percent of the 4-step forecast-error variance of job reallocation.

Results under the assumption that allocative shocks have no long-run effect on the employment level appear in the third column of Table 3. Imposing (v) results in $b_{na} = 0.03$, $b_{ps} = -0.41$, 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 (i), (ii), and (i)’.

Allocative shocks play a dominant role under this neutrality restriction as well. They account for approximately 80 percent of the variance of the forecast error of employment growth at both 4- and 16-step horizons. They account for more than 80 percent of the forecast-error variance for job reallocation.

In summary, the long-run neutrality restrictions imply that allocative shocks are a major driving force behind fluctuations in both employment growth and job reallocation intensity. In this respect, the neutrality restrictions select very different sets of shocks than the ones implied by the qualitative restrictions.

D. Dynamic Shock Responses

Depending on the identifying assumptions, we obtain a wide range of inferences regarding the relative importance of aggregate and allocative shocks in accounting for employment movements. We now consider the impulse response functions of job creation and destruction under alternative identifying assumptions. For this purpose, we focus on the extremes in Table 3. That is, we consider the impulse response functions under the specifications in Table
Figure 4. Historical Decompositions for $b_{na} = -1.0$
A. Decomposition of Net Employment Growth
For $b_{ps} = 1.0$

B. Decomposition of Job Reallocation
For $b_{ps} = 1.0$

Figure 5. Historical Decompositions for $b_{ps} = 1.0$
that yield the largest and the smallest contributions of allocative shocks to the forecast-error variance of employment growth at a 4-step horizon. The specification that yields the largest role for allocative shocks at a 4-step horizon is the one that maintains no long-run effect on the level of employment. The specification that yields the smallest contribution of allocative shocks at four steps maintains symmetric impact effects on creation and destruction.

Figure 6 displays the response functions for unit standard deviation impulses. The upper panels reflect the identifying assumption that allocative shocks have symmetric impact effects on creation and destruction. Under this assumption, an aggregate impulse has relatively large effects. The impact effect dissipates in about one year and more rapidly for creation than destruction. The impact of an allocative impulse on job destruction dissipates rapidly, but the effect on creation is sustained for several quarters. A unit size allocative shock has relatively small effects on creation and destruction in any event.

The lower panels reflect the assumption that allocative disturbances have a zero long-run effect on employment. In this case, the short-run effects of an allocative impulse are quite large. An allocative impulse produces an immediate increase in job destruction and an immediate, more modest, decrease in creation. Five quarters later, the impact on destruction has largely dissipated. In contrast, the effect on creation dissipates in only three quarters after impact and then turns mildly positive for several quarters. The lower left panel shows that an adverse aggregate impulse produces no immediate impact on destruction but a negative impact on creation. Destruction effects are positive and creation effects are negative for roughly one year after impact.
One cannot help but notice the similarity between the dynamic responses to an aggregate shock in the upper left panel and to an allocative shock in the lower right panel. Evidently, accounting for the creation and destruction dynamics in the data calls for some driving force that produces an immediate increase in job destruction, a simultaneous but smaller decrease in creation, the gradual dissipation of the destruction response over the following year, and the reversal of the creation impact from one to two and one-half years out. Alternative identifying assumptions, all of which hold some claim to plausibility, lead to very different interpretations of this driving force.

E. Sensitivity to the Zero Covariance Assumption

To this point, we have followed standard practice by maintaining a zero correlation between the underlying structural disturbances in our VAR system. Section II, subsection B argues for the plausibility of this covariance restriction in our setting. However, one can certainly craft reasonable theories that deliver a nonzero correlation between the "primitive" aggregate and allocative disturbances.

In some theories of informational spillovers, aggregate shocks trigger the release of accumulated pieces of private information that bear on the desired allocation of jobs, workers, and capital. In this way, an aggregate shock can induce a contemporaneous increase in the intensity of allocative shocks. Building on earlier work by Andrew Caplin and John Leahy (1994), Schivardi (1997) carefully develops this point in a dynamic equilibrium model of reallocation activity with informational spillovers. In this model, an adverse aggregate shock can accelerate exit decisions, but the exit actions also reveal unfavorable private information that induces other firms to exit. The resulting surge in exits brings a spike in job destruction and, by freeing up workers, an increase in job creation. Hence, Schivardi’s model delivers a negative correlation between aggregate shocks and the intensity of allocative shocks. One can also imagine theories in which favorable aggregate shocks trigger new investment actions by some firms that, in turn, reveal useful information about the desired reallocation of other firms’ jobs and capital, so that aggregate shocks covary positively with the intensity of allocative shocks at a primitive level.

Motivated by these ideas, we consider the implications of relaxing (iii) to allow for an arbitrary correlation, \( \rho(\varepsilon_{at}, \varepsilon_{st}) \). The analog to equation (3) becomes

\[
\rho(\sigma_n^2 - 2b_{na}\sigma_{pn} + b_{na}^2\sigma_{p}^2)^{1/2}(\sigma_p^2 - 2b_{ps}\sigma_{pn} + b_{ps}^2\sigma_{p}^2)^{1/2} \nonumber \]

\[
= (1 + b_{na}b_{ps})\sigma_{pn} - b_{ps}\sigma_p^2 - b_{na}\sigma_n^2. \nonumber
\]

For a given value of \( \rho \), (4) delivers a one-to-one correspondence between the structural parameters \( b_{na} \) and \( b_{ps} \), as before. In the absence of systematic empirical evidence on the matter, we considered a range of negative and positive values for \( \rho(\varepsilon_{at}, \varepsilon_{st}) \).

Figures 7 and 8 show selected results for \( \rho = -0.3 \) and \( \rho = 0.3 \), respectively. The left-hand panels show structural parameter combinations that satisfy (4) for \( b_{na} < 0 \) — dashed vertical lines indicate restrictions (i)' and (ii)'. The right-hand panels show variance decomposition results for parameter values that satisfy these restrictions.

Because the structural disturbances are correlated, the forecast-error variance decompositions involve \( \sigma_n^2 \) and \( \sigma_p^2 \), as before, and the covariance between the structural innovations. Hence, a portion of the forecast-error variance cannot be unambiguously attributed to either allocative or structural disturbances. For this reason, we report the fraction of the variance attributed to allocative disturbances in the upper right panels of Figures 7 and 8 and the fraction accounted for by the covariance in the lower right panels. Aggregate disturbances account for the remaining fraction.

The results in Figures 7 and 8 support three inferences. First, the choice of \( \rho \) influences the size of the admissible parameter space along
other dimensions. For example, when we widen the structural parameter space to consider negative values of $\rho$, the admissible $(b_{na}, b_{ps})$ locus shrinks. For $\rho = -0.3$, $b_{na}$ is restricted to lie in $(-1.19, -1.0)$ under the tighter qualitative restrictions. For $\rho = -0.45$, the admissible locus shrinks to a single point, $(b_{na} = -1, b_{ps} = 1)$. And, for $\rho < -0.45$, the data are inconsistent with restrictions (i)' and (ii)'. In contrast, positive values of $\rho$ enlarge the space of admissible $(b_{na}, b_{ps})$ values. Large, positive values for $\rho$ further cloud the inference process by leading to a large role for the covariance term in the variance decompositions, as shown in the lower right panel of Figure 8.

Second, departures from the covariance restriction (iii) have some bearing on the quantitative character of the results. To see this point, consider the results at the benchmark $b_{na} = -1$. For $\rho = 0$, allocative shocks account for 13 percent of the variation in employment fluctuations at a 4-step horizon (Table 3 and Figure 3). For $\rho = 0.3$, allocative shocks account for 33 percent of the employment variation (Figure 8). And, for $\rho = -0.3$, allocative shocks account for only 2 percent (Figure 7). In short, if we assume a higher value for $\rho(\varepsilon_{a}, \varepsilon_{s})$ for fixed values of the other structural parameters, the identification analysis tells us to attribute a greater role to allocative disturbances as driving forces behind employment fluctuations.

Third, even for $\rho = -0.3$, allocative shocks play the dominant role in driving the fluctuations in job reallocation intensity over the range of $(b_{na}, b_{ps})$ values implied by the tighter qualitative restrictions. They also play a major role in this regard for $\rho = 0.3$. In this respect, relaxing the zero covariance restriction (iii) does not alter the inference that allocative shocks play a major or dominant role in driving the cyclical fluctuations in job reallocation intensity.
F. Sampling Error Versus Specification Uncertainty

The preceding analysis highlights how inferences about driving forces and impulse response functions vary with the identifying assumptions. It is instructive to compare this specification uncertainty to the uncertainty induced by sampling variation. As noted above, Table 3 presents the forecast-error variance decompositions with standard errors for the employment growth rate and job reallocation rate under alternative identifying assumptions.

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 fairly 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 force behind employment fluctuations.

Turning now to job reallocation, specification uncertainty yields more modest variation in the fraction of job reallocation accounted for by allocative shocks. For the variance decomposition of job reallocation, sampling error is also modest but large enough that the modest difference in results across specifications may not be statistically different.
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 employment movements, unless one prefers a particular set of identifying assumptions within the class we considered.

IV. Concluding Remarks

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

First, across a wide range of identifying assumptions, allocative disturbances consistently play a dominant or co-equal role as driving forces behind fluctuations in job reallocation intensity. This finding implies that time variation in the intensity of allocative disturbances will be an essential element in successful theories of gross job flow dynamics, at least within the class of linear models.

Second, our analysis yields no clear-cut inference regarding the relative importance of allocative disturbances as driving forces behind cyclical employment movements. Across alternative plausible identifying assumptions, the contribution of allocative shocks to employment fluctuations varies greatly. It may be difficult to construct a completely compelling argument that strongly favors particular identifying assumptions within the set we consider. For readers who bring sharp priors to the data, our identification analysis shows how these priors map into particular conclusions about the relative importance of allocative and aggregate disturbances as driving forces behind employment fluctuations.

Third, our identification analysis shows that certain views about the nature of business cycles cannot be sustained in the face of the data. In particular, we show that the data do not simultaneously accommodate the following two views. One view holds that aggregate disturbances 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 disturbances do not have important short-run effects on aggregate employment. According to our analysis, specifications that maintain the first view imply that allocative disturbances have disproportionately large contemporaneous effects on job destruction and, hence, reduce aggregate employment. Specifications that maintain the second view imply that aggregate disturbances trigger large responses in the intensity of job reallocation activity.

In addition, because factor reallocation activity is costly (see footnote 1), the second view pushes us to conclude that reallocation activity acts as an important propagation mechanism for business-cycle impulses. Under either view, then, we reach the conclusion that the labor-market reallocation process plays an important role in cyclical employment fluctuations.\textsuperscript{18}

Fourth, the long-run neutrality restrictions that we consider—that allocative disturbances have no permanent effect on the level of employment, or that aggregate disturbances have no cumulative effect on the extent of job reallocation—imply a very different story about employment fluctuations than the qualitative identifying restrictions. Adopting either of these neutrality restrictions as an identifying assumption leads to the inference that allocative disturbances play a major, or even dominant, role as driving forces behind employment fluctuations. In contrast, the qualitative restrictions imply a much more modest role for allocative disturbances.

In our view, the qualitative restrictions reflect the basic nature of allocative and aggregate disturbances, whereas the long-run neutrality restrictions pertain to theoretical implications that hold in many models. It follows that the contrasting implications of the qualitative restrictions and the neutrality restrictions convey an important note of caution for research on the connection between reallocation activity and business cycles. In particular, while it may be convenient to embed one or both of these neutrality restrictions into a formal model, it is far from innocuous to impose that structure when bringing the theory to bear on the data.

Finally, as a methodological observation, we

\textsuperscript{18} Hall (1999) reaches the same conclusion by a rather different route.
note that it is straightforward to embed any of the identification strategies we consider in this paper into larger VAR systems with more outcome variables and additional shocks. We show how to accomplish this in the working paper version of this study (Davis and Haltiwanger, 1996).

APPENDIX: CONSTRUCTING THE JOB FLOW TIME SERIES

For 1972:2 to 1993:4, we use the job creation (POS) and job destruction (NEG) measures developed by Davis et al. (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 join 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

$$\begin{align*}
\text{POS} &= A - \theta Q, \\
\text{NEG} &= L + (1 - \theta)Q,
\end{align*}$$

where $\theta$ 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 $\theta = 0.85$. We adopt this value for $\theta$ 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 overrepresents large establishments.

To joint 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:

$$\begin{align*}
\text{POS} &= \alpha_0 + \alpha_1 A + \alpha_2 Q + \alpha_3 Q \cdot X + \epsilon_p, \\
\text{NEG} &= \beta_0 + \beta_1 L + \beta_2 Q + \beta_3 Q \cdot X + \epsilon_n,
\end{align*}$$

where POS and NEG are LRD values, $X$ is a cyclical indicator, $\epsilon_p$ and $\epsilon_n$ are error terms, and the parameter vector $(\alpha, \beta)$ 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 with an $R^2$ value of 0.64 in the POS regression and 0.91 in the NEG regression. We obtained virtually identical results with the unemployment rate as a cyclical indicator.

Using the estimated regression parameters $(\alpha, \beta)$ and the quarterly values for $A$, $L$, and $Q$, we generated the 1947:1–1972:1 values for POS and NEG and joined them to the 1972:2–1993:4 LRD values.

REFERENCES


