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# *Gross Job Creation and Destruction: Microeconomic Evidence and Macroeconomic Implications\**

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## *1. Introduction*

Standard business cycle analysis focuses on the nature and propagation of aggregate shocks. High-frequency fluctuations in economywide output, productivity, and unemployment are typically modeled in an aggregate fashion that abstracts from sectoral and especially establishment-level heterogeneity and from frictions associated with reallocating resources across sectors and establishments. Allocative shocks and the resource reallocation process are typically associated with lower-frequency aggregate movements, if considered at all. This paper provides both theoretical motivation and empirical evidence for why this standard view is incomplete. We present evidence that fluctuations in the intensity of shifts in employment opportunities across establishments are intimately tied to aggregate fluctuations at business cycle frequencies.

Our analysis begins by documenting the magnitude and time-series behavior of gross job creation, gross job destruction, and gross job reallocation (the sum of creation and destruction) in the U.S. manufacturing sector over the 1972 to 1986 period. We rely on both quarterly and annual

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data. This measurement-intensive effort exploits a tremendously rich data set with approximately 860,000 annual observations and 3.4 million quarterly observations on 160,000 different manufacturing establishments. The data are longitudinal and include observations on all manufacturing establishments sampled in the Annual Survey of Manufactures between 1972 and 1986. The combination of establishment-level longitudinal data, high-frequency observations, a 15-year sample, and comprehensive coverage of the manufacturing sector provides an excellent basis for exploring the connection between the heterogeneity of establishment-level employment changes and aggregate fluctuations.

A key aspect of our analysis is its focus on gross job reallocation as opposed to gross worker flows. Previous studies have documented the tremendous gross worker flows across labor market states (i.e., employment, unemployment, out of the labor force) and high worker turnover rates. In the absence of evidence from longitudinal establishment data, it has been difficult to determine whether large gross worker flows primarily reflect temporary layoffs and recalls plus continual sorting and resorting of workers across a given set of jobs or, alternatively, whether a large portion of worker turnover is driven by gross job destruction and creation. Our measurement efforts enable us to quantify the contribution of gross job reallocation to worker reallocation and to examine the cyclic behavior of gross job reallocation.

The basic facts that emerge from our measurement efforts are striking. First, based on March-to-March establishment-level employment changes, we calculate that manufacturing's rates of gross job creation and destruction averaged 9.2% and 11.3% per year, respectively. The quarter-to-quarter rates of job creation and destruction are larger yet, averaging 5.37% and 5.62% on a quarterly basis. The impressive magnitude of gross job creation and destruction has been documented before, perhaps most convincingly at high frequencies by Leonard (1987) and at low frequencies by Dunne, Roberts, and Samuelson (1989).

A second basic fact is that most of the annual job creation and destruction and much of the quarterly creation and destruction represents persistent establishment-level employment changes. For example, 73% of the jobs created between March 1974 and March 1975 still existed in March 1976, and 72% of the jobs lost in the 1974–75 interval were still lost in March 1976. The average one-year persistence rates for annual job creation and destruction are 68% and 81%, respectively. Taken together, the heterogeneity and persistence of establishment-level employment changes implies large worker flows consequent to the reallocation of jobs across establishments.

A third basic fact is the importance of establishment births and deaths

in the process of job creation and destruction. Establishment deaths account for 25% of annual gross job destruction over the sample period, while establishment births account for 20% of annual gross job creation. More generally, establishment-level employment changes exhibit considerable discreteness.

A fourth basic fact is that the gross job reallocation rate (the sum of gross job creation and destruction rates) exhibits significant countercyclic time variation. The quarterly job reallocation rate for the manufacturing sector ranges from a low of 6.9% in 1979:1 to a high of 15.4% in 1975:1. The simple correlation between net employment growth and gross job reallocation for the manufacturing sector is  $-0.57$  using March-to-March changes and  $-0.51$  using quarter-to-quarter changes.

The magnitude and cyclic pattern of time variation in gross job reallocation immediately prompt several important and related questions: What factors drive the countercyclic time variation in gross job reallocation? Is this countercyclic time variation accounted for by aggregate, sectoral, or idiosyncratic effects? Does the countercyclic variation in gross job reallocation simply reflect familiar patterns of differential sectoral responses to business cycle fluctuations?

To address these questions, we develop a methodology for decomposing gross job reallocation into idiosyncratic, sectoral, and aggregate components. The results of applying our methodology are striking and consistent. The overwhelming bulk of time variation in gross job reallocation is accounted for by time variation in the idiosyncratic component. Aggregate-time effects and sector-time effects account for a small fraction of time variation in gross job reallocation. Furthermore, the idiosyncratic contribution to the gross job reallocation rate exhibits a strong pattern of countercyclic movements with respect to own-sector and total manufacturing net employment growth rates. These results hold in both annual and quarterly data and for every sectoral classification scheme we consider.

Motivated by these basic facts and the results of our decomposition exercise, we next present a theoretical model of employment reallocation and the business cycle. The model provides a structure that helps interpret the observed patterns of job creation and destruction and gauge their implications for aggregate fluctuations in output, productivity, and unemployment. The model focuses on the forces generating gross flows of workers and jobs across heterogeneous production sites. As the economy moves through time, some high-productivity job sites become less productive, while new ones are created from time inputs. The intensity of shifts in the pattern of employment opportunities across production sites fluctuates over time, so that the frictions associated with reallocating

resources influence the magnitude and character of economywide fluctuations. In addition to the time-varying intensity of allocative shocks, the economy we analyze is subject to aggregate shocks. Since the timing of worker and job reallocation is endogenous in the model, the pace of reallocation is influenced by both allocative and aggregate disturbances.

In this simple economy, several patterns emerge with respect to the predicted responses of job creation and job destruction to aggregate and allocative shocks. Adverse aggregate shocks tend to increase job destruction and decrease job creation. However, given the endogenous timing of reallocation, adverse aggregate shocks interact with frictions in the labor market to induce an accelerated pace of reallocation. We designate such accelerations or decelerations in the pace of reallocation induced by aggregate disturbances as reallocation timing effects.

In contrast to aggregate disturbances, an increased intensity of allocative shocks increases job destruction and *eventually* increases job creation. The lagged response of job creation to allocative shocks results from several factors that can operate separately or in combination. First, to the extent that the creation of new jobs and the reallocation of workers is time-consuming, the job creation response naturally lags the job destruction response. Second, any positive persistence to innovations in the intensity of allocative disturbances discourages immediate investment in the creation of new high-productivity jobs and in an improved allocation of workers across existing jobs. The mobility decision by the worker and the investment decision by the builder of a new production site represent investment in forms of specific capital. Under persistence, a positive innovation in the contemporaneous intensity of allocative disturbances means heightened uncertainty about the *ex post* returns to current investments in specific capital. This uncertainty effect of an innovation in the intensity of allocative disturbances depresses job creation contemporaneously, especially if the degree of uncertainty is expected to diminish in the future. Third (and outside the scope of our formal model), if there exist significant macroeconomic externalities associated either with external increasing returns or final goods demand spillover effects, then the initial increase in job destruction from an allocative shock can generate a temporary decrease in job creation. In sum, innovations in the intensity of allocative disturbances generate a contemporaneous increase in job destruction and an eventual increase in job creation but a positive, zero, or negative contemporaneous change in job creation.

Based on these theoretical results, we then turn to a more structured empirical investigation of job creation, destruction, and reallocation. We begin by considering an empirical characterization of the dynamics of job creation and destruction in terms of their response to aggregate

and allocative innovations. The methodology we use is adapted from Blanchard and Diamond's (1989) closely related investigation of unemployment and vacancy dynamics. In particular, we estimate the joint dynamics of job creation and destruction and use the theory to generate a set of identifying restrictions and recover innovations to the underlying allocative and aggregate shocks. We then trace out the dynamic effects of these innovations to evaluate their contributions to movements in job creation and destruction. Our main finding in this section is the large contribution that allocative shocks make to movements in job creation and destruction over short-, medium-, and long-forecast horizons. Further, the implied contribution of allocative shocks to movements in manufacturing employment growth is large over medium- and long-forecast horizons. These results contrast sharply with Blanchard and Diamond's conclusion that allocative shocks play a small role in the dynamics of unemployment and vacancies over short and medium horizons.

Various aspects of our theoretical analysis and a large body of existing research point to a potentially important relationship between the intensity of shifts in the pattern of employment opportunities and aggregate unemployment. Motivated by these factors, the last section of the paper investigates the relationship between our measures of gross job reallocation and unemployment. Our empirical investigation is closely related to the existing empirical literature on sectoral shifts in labor demand and unemployment. (See Davis and Haltiwanger (1989) for references.) This literature has struggled with difficult problems of measurement and causal inference. We are able to untangle some of these issues because (1) our measure of gross job reallocation captures shifts in the distribution of employment opportunities across establishments within sectors, and because (2) the establishment-level data enable us to decompose gross job reallocation into idiosyncratic, sectoral, and aggregate components.

We investigate the time-series relationship between unemployment and alternative job reallocation measures in simple regression models. Our basic measure of job reallocation in the regression analysis is the idiosyncratic component of total job reallocation. One set of alternative measures we consider involves a decomposition of the idiosyncratic component into a part associated with observed allocative shocks—taken to be movements in oil price growth rates—and a part associated with unobserved allocative shocks and/or reallocation timing effects. As a second alternative, we use the VAR model described above to decompose the moving average representation of gross job creation and destruction into the part driven by aggregate shocks and the part driven by allocative shocks. This decomposition leads directly to a gross job reallo-

ation series generated by aggregate shocks and one generated by allocative shocks.

Using quarterly data for these various measures, we find a strong positive effect of job reallocation on unemployment in all specifications we consider. Our results indicate that allocative disturbances have a statistically significant effect on unemployment both directly and through reallocation timing channels, but some specifications suggest that the direct contribution of allocative disturbances to unemployment movements is small.

## *2. Basic Facts about Gross Job Creation and Destruction*

### 2.1. THE LONGITUDINAL ESTABLISHMENT-LEVEL DATA SET

To measure gross job creation, gross job destruction, and gross job reallocation our study exploits annual and quarterly data on establishments in the Longitudinal Research Data file (LRD). The LRD is a comprehensive probability sample of establishments in U.S. manufacturing industries. An establishment is defined as a single physical location engaged in manufacturing activity. The only manufacturing establishments excluded from the sampling frame of the LRD are those with fewer than five employees. These establishments account for 1% of manufacturing employment, based on tabulations from either the Census of Manufactures or County Business Patterns.

The LRD is basically a series of contiguous five-year panels with annual and some quarterly data on manufacturing establishments, plus Census-year data on the universe of manufacturing establishments with more than five employees. Census years in the LRD are 1967, 1972, 1977, and 1982. Annual and quarterly data are available from 1972. From the Census-year universe, the Bureau draws a sample of establishments that are then surveyed during five successive years. This five-year panel, which commences two years after a Census year, comprises the sample of establishments that makes up the Annual Survey of Manufactures (ASM). New establishments are added to the panel as it ages to incorporate births and preserve the representative character of the panel. In 1977, the LRD included roughly 70,000 out of the 360,000 establishments in manufacturing industries. These sampled establishments accounted for 76% of manufacturing employment. The Data Appendix provides further information on the LRD. For a complete discussion of data quality issues pertaining to our use of the LRD, see Davis, Haltiwanger, and Schuh (1990).

One aspect of the sampling procedures in the LRD merits discussion at this juncture. With respect to the five-year ASM panels, establishments fall into three broad groups. As noted, the group containing establishments with fewer than five employees is excluded from the sampling frame. A second group of establishments is included in the panel with certainty. For the 1979–83 panel, for example, the certainty group includes all establishments with 250 or more employees during the 1977 Census year. This certainty threshold is lower in some industries, and many establishments are included with certainty based on other criteria. Taken as a whole, the certainty cases account for about two-thirds of manufacturing employment during the 1979–83 period. Establishments that fall into neither of the first two groups are sampled with probabilities proportional to a measure of size determined for each establishment from the preceding Census. Sampling probabilities for noncertainty establishments range from 1.000 to 0.005. Sample weights, equal to the reciprocal of the sampling probabilities, are used in the aggregation below.

Some, but not most, of the noncertainty establishments appear in contiguous panels. Thus, our ability to link establishment-level observations *across* panels ranges from excellent for large establishments to quite poor for the smallest. This observation implies that accurately measuring gross changes is more difficult in the first period of each panel (e.g., 1974:1, 1979:1, and 1984:1 for the quarterly changes). For the quarterly measures, we estimated the gross changes in the first period of each panel on the basis of the time-series relationship between continuing and noncontinuing establishments (see the Data Appendix for more details). For the annual measures, we opted for the simpler procedure of deleting the first year of each panel from our sample.

## 2.2. MEASUREMENT OF GROSS JOB CREATION, DESTRUCTION, AND REALLOCATION

We now introduce some notation and formally define our establishment growth rate measure and our measures of gross job creation, destruction, and reallocation. See Davis and Haltiwanger (1989) for a more detailed discussion of the measurement methodology.

We measure gross job creation by adding up employment growth at expanding and new establishments within the sector. Similarly, gross job destruction simply sums employment losses over shrinking and dying establishments within the sector. To express these measures as rates, we divide by a measure of sector size. Thus, gross job creation and destruction rates in sector  $s$  at time  $t$  are given by



$$POS_{st} = \sum_{\substack{e \in E_{st} \\ g_{et} > 0}} \left( \frac{x_{et}}{X_{st}} \right) g_{et}, \quad \text{and}$$

$$NEG_{st} = \sum_{\substack{e \in E_{st} \\ g_{et} < 0}} \left( \frac{x_{et}}{X_{st}} \right) |g_{et}|,$$

where  $E_{st}$  is the set of establishments in  $s$  at  $t$ ,  $x_{et}$  is the size of establishment  $e$  at  $t$ ,  $X_{st}$  the size of sector  $s$ , and  $g_{et}$  the growth rate of establishment  $e$  at  $t$ .

Our measure of establishment size at time  $t$  is simply the average of establishment employment at time  $t$  and  $t - 1$ . Sector size is defined analogously. We define  $g_{et}$  as the change in establishment employment from  $t - 1$  to  $t$ , divided by the measure of establishment size. This growth rate measure is symmetric about zero, and it lies in the closed interval  $[-2, 2]$  with deaths (births) corresponding to the left (right) endpoint. A virtue of this growth rate measure is that it facilitates an integrated treatment of births, deaths, and continuing establishments in the empirical analysis.  $g_{et}$  and the conventional growth rate measure are monotonically related and approximately equal for small growth rates.

To interpret our measures of gross job creation and destruction, two remarks are helpful. First, at quarterly and especially annual frequencies it seems apparent that changes in establishment-level employment are primarily driven by changes in desired establishment size rather than by temporary movements in the stock of unfilled positions. For this reason,  $POS_{st}$  and  $NEG_{st}$  directly reflect the reallocation of employment positions or jobs, and not the reallocation of workers. Of course, one motivation for our research is that the reallocation of jobs partly drives the reallocation of workers. Thus, the job reallocation concept in this paper differs from, but is related to, the worker turnover concepts considered by Lilien (1980), Hall (1982), Akerlof, Rose, and Yellen (1988), and others.

Second, since we observe only plant-level employment, we cannot determine whether a given level of employment in two different periods for the same plant represents the same or different employment positions. This observation and the point-in-time nature of the employment data imply that  $POS_{st}$  and  $NEG_{st}$  represent lower bounds on gross job creation and destruction.

We use the sum of  $POS_{st}$  and  $NEG_{st}$ ,  $SUM_{st}$ , to measure the gross job reallocation rate in sector  $s$  between  $t - 1$  and  $t$ .  $X_{st}SUM_{st}$  represents the gross change from  $t - 1$  to  $t$  in the number of employment positions at

establishments. To relate this measure to worker turnover, observe that  $X_{st}SUM_{st}$  also represents an upper bound on the number of workers who change jobs (or labor force status) in direct response to establishment-level employment changes. (The interpretation of  $X_{st}SUM_{st}$  as an upper bound is subject to the qualifications about the lower-bound nature of  $POS_{st}$  and  $NEG_{st}$  discussed above).  $X_{st}SUM_{st}$  represents an upper bound because some workers move from shrinking to growing establishments within sector  $s$  between  $t - 1$  and  $t$ . To obtain a lower bound, we eliminate the possibility of double-counting job losers who move directly to new jobs at expanding establishments in the same sector. That is,  $X_{st}MAX_{st} = X_{st}Max\{POS_{st}, NEG_{st}\}$  represents a lower bound on the number of workers who change jobs (or labor-force status) in direct response to job reallocation in sector  $s$ . In line with this discussion, we often refer to  $SUM_{st}$  and  $MAX_{st}$  as upper and lower bounds on the rate of worker reallocation driven by job reallocation. In interpreting these upper and lower bounds on worker reallocation associated with job reallocation, it is important to emphasize that the worker reallocation associated with job reallocation is itself a lower bound on total worker reallocation. As discussed in the introduction, worker reallocation reflects not only job reallocation but life-cycle turnover, job satisfaction, and match quality effects.

From a statistical viewpoint,  $SUM_{st}$  represents a size-weighted measure of the average absolute deviation of establishment growth rates about zero. Hence, like the variance of establishment growth rates,  $SUM_{st}$  is a summary measure of spread in the establishment growth rate density for sector  $s$  at time  $t$ . We focus on  $SUM_{st}$  because, unlike a variance statistic, it has a useful economic interpretation as the gross rate of change in the number of establishment-level employment positions, and because it has a simple connection to the economically meaningful concepts of gross job creation and destruction.

### 2.3. MAGNITUDE AND TIME VARIATION

Table 1 presents annual rates of gross job creation, gross job destruction, net employment growth, gross job reallocation, and a lower bound on worker reallocation associated with job reallocation. The annual measures are based upon March-to-March establishment-level employment changes. Manufacturing employment contracted during seven out of the eleven years in the sample. The most severe contraction occurred during 1975, when net and gross job destruction rates reached 10.0% and 16.6% of manufacturing employment. Net and gross job creation rates peaked in 1973 at 6.1% and 13.2% of employment. The lower bound on the worker reallocation rate varies from a low of 10.2% in 1980 to a high of 16.6% in 1975. The job reallocation rate ranges from 17.3% in 1980 to 23.3% in 1975.

Figure 1 plots quarterly rates of various measures. It illustrates that severe contractions typically involve sharp increases in gross job destruction and mild decreases in gross job creation. Accordingly, gross job reallocation rises during net contractions. In contrast, recoveries from contractions are characterized by sustained periods of slightly higher than average gross job creation and lower than average gross job destruction. Consequently, gross job reallocation is lower during periods of net expansion.

The average quarterly rate of job creation is 5.37%, while the average quarterly rate of job destruction is 5.62% (note: these rates are not annualized). Comparing the magnitudes of the quarterly and annual rates indicates that a nontrivial portion of the observed quarterly fluctuations in gross job creation and destruction are transitory. We return to a more direct measure of the degree of persistence of gross job creation and destruction below.

The simple correlations reported in Table 1 reveal a negative relationship between gross job creation and destruction in both annual and quarterly data. This pattern reflects the overall leftward shift in the establishment growth-rate density during economic downturns. (Davis and Haltiwanger (1989) portray the time series of box plots of the establishment growth rate density.) Evidently, this mean-translation effect is the

Figure 1 NET AND GROSS REALLOCATION RATES

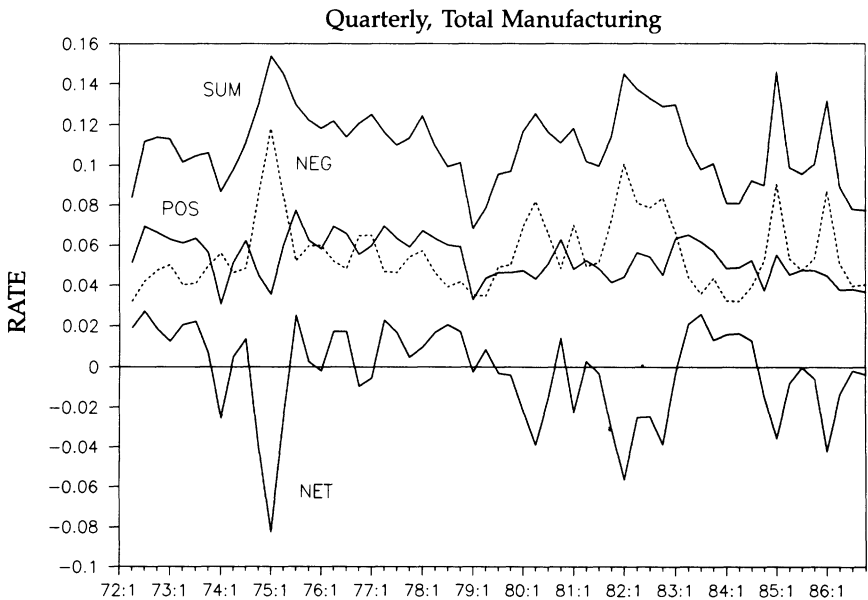


Table 1 SUMMARY STATISTICS ON JOB CREATION AND DESTRUCTION

	<i>Net and Gross Rates by Year for Total Manufacturing</i>				
	$POS_t$	$NEG_t$	$NET_t$	$SUM_t$	$MAX_t^1$
1973	0.132	0.061	0.071	0.194	0.133
1975	0.067	0.166	-0.100	0.233	0.166
1976	0.113	0.096	0.017	0.209	0.122
1977	0.112	0.096	0.018	0.206	0.117
1978	0.116	0.075	0.041	0.191	0.117
1980	0.080	0.093	-0.012	0.173	0.102
1981	0.070	0.118	-0.049	0.188	0.119
1982	0.064	0.152	-0.087	0.216	0.152
1983	0.086	0.142	-0.056	0.227	0.143
1985	0.084	0.117	-0.033	0.201	0.121
1986	0.088	0.132	-0.044	0.220	0.133
	<i>Net and Gross Rates by Quarter</i>				
	$POS_t$	$NEG_t$	$NET_t$	$SUM_t$	$MAX_t$
Mean	0.0537	0.0562	-0.0025	0.1098	0.0639
(Std. Dev.)	(0.0105)	(0.0183)	(0.0239)	(0.0190)	(0.0150)
<i>Pearson correlations<sup>2</sup></i>					
	Annual				
	$\rho(POS_t, NEG_t) = -0.864$				$\rho(NET_t, SUM_t) = -0.565$
	(0.001)				(0.07)
	Quarterly				
	$\rho(POS_t, NEG_t) = -0.221$				$\rho(NET_t, SUM_t) = -0.512$
	(0.092)				(0.0001)

<sup>1</sup>Size-weighted average of two-digit industry rates.

<sup>2</sup>Marginal significance levels in parentheses.

dominant change in the growth rate density in terms of the impact on gross job creation and destruction. However, this effect is much weaker in quarterly data than in annual, as indicated by comparing the reported correlations between  $POS_t$  and  $NEG_t$ .

Figure 1 suggests a negative relationship between net employment growth and gross job reallocation. The correlations between  $NET_t$  and  $SUM_t$  reported in Table 1 confirm this impression for both quarterly and annual data.

One important question raised by the results in Figure 1 and Table 1 runs as follows: How much of the time variation in gross job creation, destruction, and reallocation can be accounted for by simple mean translations of the establishment-level growth rate density and differential mean

sectoral responses to changes in the level of aggregate activity? To the extent these aggregate-time and sector-time effects account for the time variation in gross job creation, destruction, and reallocation, there would seem to be little remaining role for idiosyncratic establishment-level employment changes in explanations for aggregate labor market fluctuations. We now turn to a methodology for addressing this question.<sup>1</sup>

#### 2.4. ACCOUNTING FOR TIME VARIATION IN JOB DESTRUCTION, CREATION, AND REALLOCATION

Consider the linear model for establishment-level growth rates

$$g_{et} = \bar{g}_{et}^{ST} + g_{st} + g_{it} \quad (1)$$

where  $g_t$  is the aggregate growth rate,  $g_{st}$  is the sector growth rate (deviated about the aggregate growth rate), and  $\bar{g}_{et}^{ST}$  is the residual idiosyncratic component of the establishment growth rate. According to equation (1), each establishment's growth rate at  $t$  is the sum of an aggregate-time effect, a sector-time effect, and a time-varying idiosyncratic effect. Time variation in the realized aggregate and sectoral growth rates induce time variation in the location and shape of the density over the (size-weighted)  $g_{et}$ , thereby generating time variation in gross job creation, destruction, and reallocation. The cross-sectional variance and higher moments of the idiosyncratic component,  $\bar{g}_{et}^{ST}$ , also influence the shape of the growth rate density, thereby generating further time variation in gross job creation, destruction, and reallocation.

In terms of equation (1), a major objective of our empirical methodology is to apportion the time variation in gross job creation, destruction, and reallocation among three effects: (a) time variation in the realized values of  $g_t$ ; (b) time variation in the realized values of the  $g_{st}$ ,  $s = 1, \dots, S$ ; and (c) time variation in the realized cross-sectional variance and higher moments of the distribution over the  $\bar{g}_{et}^{ST}$ .

Several alternative views about the nature of aggregate fluctuations can be couched in terms of equations like (1). Prevailing views of the business cycle stress the role of aggregate disturbances as driving forces. The simplest version of this view implies that all time variation in gross job creation, destruction, and reallocation is driven by time variation in

1. Note that  $\text{COV}(\text{NET}_t, \text{SUM}_t) = \text{V}(\text{POS}_t) - \text{V}(\text{NEG}_t)$ . Thus, a negative correlation between  $\text{NET}_t$  and  $\text{SUM}_t$  means that the time-series variability of  $\text{NEG}_t$  exceeds that of  $\text{POS}_t$ . In what follows, we show that this empirical relationship is driven by the fact that gross job destruction increases more, and gross job creation falls less, during contractions that can be explained by aggregate-time and sector-time effects.

the aggregate-time effects. This view encompasses a time-invariant, but possibly large, cross-sectional variance of the idiosyncratic component of the  $g_{et}$ . We represent this pure aggregate shifts story by the hypothesis that the distribution over the  $\tilde{g}_{et}^T = g_{et} - g_t$  is time invariant.

A less simplistic characterization of prevailing views about the business cycle would recognize perennial differences in the timing and magnitude of sectoral responses to aggregate disturbances. These cross-sectoral differences in the responses to aggregate disturbances are an important element of traditional views about the business cycle. See Abraham and Katz (1986) on this point.

To capture this aspect of traditional views, we allow for completely unrestricted sectoral responses to aggregate disturbances and we consider several sectoral classification schemes. In particular, consider the hypothesis of a time-invariant distribution over the  $\tilde{g}_{et}^{ST}$ . Note that the sector-time effects,  $g_{st}$ , capture *any* systematic cross-sectoral differences in the mean sectoral response to aggregate disturbances. (Of course, they capture any nonsystematic differences as well.) Neither linearity, magnitude, nor timing restrictions are placed on the mean sectoral responses to aggregate disturbances under this interpretation of the  $g_{st}$ . The only restrictions placed on mean sectoral responses are those inherent in the sectoral classification scheme itself.

Given the above decomposition, our methodology is to measure the relative importance of these components for time variation in gross job creation, job destruction, and reallocation and, furthermore, to determine the nature of the covariation between the components. For example, from the distribution over the  $\tilde{g}_{et}^{ST}$ , we compute gross job creation, destruction, and reallocation rates adjusted for the aggregate-time and the sector-time effects:

$$\widetilde{POS}_t^{ST} = \sum_{e, g_{et} > 0} \frac{x_{et}}{X_t} (\tilde{g}_{et}^{ST}), \quad (2)$$

$$\widetilde{NEG}_t^{ST} = \sum_{e, g_{et} < 0} \frac{x_{et}}{X_t} (|\tilde{g}_{et}^{ST}|), \quad \text{and}, \quad (3)$$

$$\widetilde{SUM}_t^{ST} = \sum_e \frac{x_{et}}{X_t} |\tilde{g}_{et}^{ST}|. \quad (4)$$

The time-series movements in these adjusted measures reflect only the contributions of the idiosyncratic effects. From an economic perspective,

$\widetilde{SUM}_i^{ST}$  measures the gross rate of change in establishment-level employment positions due to idiosyncratic establishment-level employment behavior. From a statistical perspective,  $\widetilde{SUM}_i^{ST}$  equals the size-weighted average absolute deviation of establishment growth rates around the overall and sectoral means.

Now consider the identity

$$SUM_i = \widetilde{SUM}_i^{ST} + (SUM_i - \widetilde{SUM}_i^{ST}), \quad (5)$$

which implies the variance decomposition for gross job reallocation,

$$\text{Var}(SUM_i) = \text{VAR}(\widetilde{SUM}_i^{ST}) + \text{Var}(SUM_i - \widetilde{SUM}_i^{ST}) + 2\text{Cov}(\widetilde{SUM}_i^{ST}, SUM_i - \widetilde{SUM}_i^{ST}). \quad (6)$$

If the distribution over the  $\hat{g}_{et}^{ST}$  is time-invariant, then the ratio of  $\text{Var}(\widetilde{SUM}_i^{ST})$  to  $\text{Var}(SUM_i)$  equals zero. Conversely, a large value for this ratio indicates that time variation in the cross-sectional variance (and higher moments) of  $\hat{g}_{et}^{ST}$  accounts for much of the time variation in gross job reallocation. We interpret the covariance term as reflecting the part of time variation in gross job reallocation that cannot be unambiguously assigned to either the aggregate or sectoral and idiosyncratic effects.

We similarly decompose the variance of gross job creation and destruction rates along the lines of equations (5) and (6). Variance ratios provide information on the relative contribution of aggregate and idiosyncratic effects to time variation in job creation and destruction. The covariance terms indicate whether the idiosyncratic effects reinforce or counteract the aggregate and sectoral effects in terms of contributions to time variation in gross job creation and destruction.

Before turning to the results of the decomposition, one key point merits emphasis. As a measure of the intensity of shifts in the pattern of employment opportunities,  $\widetilde{SUM}_i^{ST}$  is immune to the criticisms that Abraham and Katz (1986) directed toward Lilien's (1982) dispersion measure, because it accommodates arbitrary mean sectoral responses to aggregate disturbances. That is, conditional on the sectoral classification scheme,  $\widetilde{SUM}_i^{ST}$  is a true measure of the idiosyncratic contribution to gross job reallocation. Accordingly, its comovement with net sectoral and aggregate growth provides direct evidence on the hypothesis that the idiosyncratic contribution to gross job reallocation is countercyclic.

Table 2 reports variance decompositions based on March-to-March establishment-level growth rates and quarterly establishment-level growth rates. All of the results reported in Table 2 are based on a two-digit

Table 2 VARIANCE RATIOS<sup>1,2</sup>  
X =

Panel		SUM	POS	NEG
A	$V(X_t)$	0.00033	0.00052	0.00107
	$V(X_t)$ (continuing establishments only)	0.00019	0.00039	0.00088
	$V(X_t)$ (quarterly)	0.0036	0.00011	0.00029
B	$V(\tilde{X}_t^{I2T})/V(X_t)$	0.876	0.136	0.068
	$V(X_t - \tilde{X}_t^{I2T})/V(X_t)$	0.044	1.395	0.658
	$2\text{COV}(\tilde{X}_t^{I2T}, X_t - \tilde{X}_t^{I2T})/V(X_t)$	0.079	-0.531	0.274
Continuing establishments only:				
C	$V(\tilde{X}_t^{I2T})/V(X_t)$	0.802	0.098	0.044
	$V(X_t - \tilde{X}_t^{I2T})/V(X_t)$	0.062	1.479	0.685
	$2\text{COV}(\tilde{X}_t^{I2T}, X_t - \tilde{X}_t^{I2T})/V(X_t)$	0.135	-0.577	0.272
Quarterly measures:				
D	$V(\tilde{X}_t^{I2T})/V(X_t)$	1.104	0.897	0.297
	$V(X_t - \tilde{X}_t^{I2T})/V(X_t)$	0.025	1.394	0.344
	$2\text{COV}(\tilde{X}_t^{I2T}, X_t - \tilde{X}_t^{I2T})/V(X_t)$	-0.129	-1.291	0.358

<sup>1</sup>See text for explanation. Superscript definitions: *I2* = two-digit industries.

<sup>2</sup> $V(\cdot)$  = Variance

industry sectoral classification.<sup>2</sup> The time-series variance of the raw measures appears in panel A. The next three panels report variance ratios corresponding to various empirical densities, as adjusted for aggregate-time and sector-time effects. The column headed *SUM* in Table 2 reports the variance ratios for gross job reallocation. According to Panel B, aggregate-time effects and sector-time effects unambiguously account for less than 5% of the time variation in annual gross job reallocation. If we attribute all of the covariance terms to the aggregate-time and sector-time effects, they account for at most 12% of time variation in annual gross job reallocation. Panel C shows a similarly small contribution of aggregate-

2. In Davis and Haltiwanger (1989) we also consider sectoral classifications based on four-digit industry, geographic region, two-digit industry and geographic region simultaneously, and establishment size class. Results based on these alternative sectoral classification schemes are very similar to results reported here. For example, even when we allow for one aggregate and 450 distinct 4-digit industry effects per year, the idiosyncratic component of gross job reallocation unambiguously accounts for 80% of the time variation in annual gross job reallocation. In addition, the result that emerges below in Tables 3 and 4 that the idiosyncratic component gross job reallocation is countercyclic also holds up under the alternative sectoral classification schemes.



time and sector-time effects to the gross job reallocation of continuing establishments (excluding births and deaths). Panel D reveals that the same pattern holds in the quarterly data where aggregate-time effects and sector-time effects account for less than 3% of the overall time variation in quarterly gross job reallocation. In contrast to the anemic role of aggregate-time effects and sector-time effects, idiosyncratic effects unambiguously account for 80% or more of the annual variability of gross job reallocation, regardless of whether we restrict the sample to continuers. Furthermore, the quarterly results indicate that the time variation in the idiosyncratic component equals 110% of the total variation in quarterly gross job reallocation.

We interpret these variance ratio results as a decisive rejection of the hypothesis that the normal pattern of sectoral responses to aggregate fluctuations can account for the significant time variation in gross job reallocation displayed in Table 1 and Figure 1. Instead, the time variation in gross job reallocation results overwhelmingly from time variation in the contribution of idiosyncratic effects. The results are especially striking in that our definition of idiosyncratic effects imposes neither linearity, magnitude, nor timing restrictions on the mean sectoral responses to aggregate disturbances.

Turning to the columns headed *POS* and *NEG* in Table 2, aggregate-time effects play a major role in accounting for fluctuations in job creation and destruction rates at both annual and quarterly frequencies. At annual frequencies, the variance of the idiosyncratic component of job creation amounts to only 10–14% of the variance of the raw job creation measure and the variance of the idiosyncratic component of the job destruction measure amounts to only 4–6% of the variance of the raw job destruction measure. In contrast, the idiosyncratic components play much larger roles in accounting for the quarterly variation in gross job creation and gross job destruction.

In both the annual and quarterly results, the reported covariances help link these findings together. For job destruction, the positive sign and nontrivial magnitude of the covariance terms indicate that idiosyncratic effects strongly reinforce the countercyclic fluctuations in gross job destruction associated with mean aggregate effects. For job creation, in contrast, the negative sign and nontrivial magnitude of the covariance terms indicate that idiosyncratic effects strongly counteract the procyclic fluctuations in job creation associated with mean aggregate effects. Taken together, the covariance terms from the *POS* and *NEG* decompositions explain why the idiosyncratic component dominates fluctuations in gross job reallocation. While *POS* falls and *NEG* rises during economic contractions, idiosyncratic effects counteract the fall in gross job creation

while reinforcing the rise in gross job destruction. Summing up the separate effects, gross job reallocation move countercyclically.

## 2.5. FURTHER RESULTS ON CYCLIC VARIATION IN GROSS JOB REALLOCATION

Having determined that idiosyncratic effects play a major role in the time variation of gross job creation, destruction, and reallocation, we now investigate the relationship of the idiosyncratic component of gross job reallocation to net job growth. For this purpose, we take net job growth to be an indicator of cyclical activity.

Table 3 summarizes the pattern of contemporaneous correlations between own-sector net job growth and various job reallocation measures. Although not shown here, results are similar for correlations between sectoral job reallocation measures and manufacturing net job growth. The basic pattern in Table 3 is clear: both raw and adjusted sectoral gross job reallocation measures fluctuate countercyclically. For example, defining sectors as two-digit industries and using annual changes, the size-weighted mean time-series correlation between net industry job growth and own-industry job reallocation equals  $-.51$ . Adjusting the empirical growth rate density for aggregate and sectoral effects yields a mean correlation of  $-.55$ . Furthermore, all twenty two-digit industries exhibit a negative time-series correlation between net job growth and the raw and adjusted job reallocation measures. A similar pattern prevails when

Table 3 COMOVEMENTS BETWEEN NET JOB GROWTH AND ADJUSTED GROSS JOB REALLOCATION  
Time Series Correlation of  $NET_{st}$  with:

	$SUM_{st}$	$\widetilde{SUM}_{st}^T$	$\widetilde{SUM}_{st}^{ST}$	$NET_t$
<i>2-digit SIC</i>				
Size-weighted Average Correlation	-0.51	-0.54	-0.55	0.87
# < 0/Total	20/20	20/20	20/20	0/20
Cross-sector Heterogeneity <sup>1</sup>	0.22	0.22	0.21	0.20
<i>2-digit (continuing establishments only)</i>				
Size-weighted Average Correlation	-0.53	-0.58	-0.56	0.86
# < 0/Total	18/20	19/20	19/20	0/20
Cross-sector Heterogeneity	0.24	0.22	0.25	0.12
<i>2-digit (quarterly measures)</i>				
Size-weighted Average Correlation	-0.37	-0.41	-0.42	0.72
# < 0/Total	17/20	17/20	17/20	0/20
Cross-sector Heterogeneity	0.26	0.25	0.29	0.20

<sup>1</sup>Cross-sector heterogeneity is measured by the size-weighted standard deviation of the sectoral correlations.

the sample is restricted to continuing establishments and for the quarterly results.

The last column of Table 3 reports correlations between individual industry and overall manufacturing net growth. Net employment changes in virtually every sector covary positively with total manufacturing employment changes. This correlation pattern is consistent with the positive cross-industry comovements typically found in the literature (e.g., Cooper and Haltiwanger (1990)). But, observing the large magnitudes of gross job creation and gross job destruction within sectors, substantial negative comovement across establishments and substantial positive comovements across industries in net employment growth operate simultaneously. Moreover, gross job reallocation (and in particular, the idiosyncratic component of gross job reallocation) is inversely related to net industry and aggregate employment changes. Thus, our results establish a link between the positive comovement across industries and the negative comovement within industries: during aggregate net contractions employment declines in all industries, while gross job reallocation rises within industries.<sup>3</sup>

To further investigate the pattern of comovement between gross job reallocation and net job growth, we examine OLS regressions of  $SUM_{st}^{ST}$  on sectoral and aggregate growth rates. The regressions include sector fixed effects to control for systematic cross-sectoral differences in the rate of job reallocation. Results appear in Table 4. For reasons described in more detail below, we do not impute a structural or causal interpretation to these regressions. Instead, we use them to gauge the magnitude and significance of the time-series covariance between gross job reallocation and net job growth, while controlling for permanent cross-sectoral differences in gross job reallocation.

Table 4 shows a statistically and economically significant inverse relationship between the idiosyncratic component of gross job reallocation and net job growth at both the aggregate and sectoral levels.<sup>4</sup> This relationship holds in both quarterly and annual data for aggregate growth, but the quarterly results indicate that holding aggregate growth constant

3. The finding of positive comovement across industries and negative comovement within industries may be linked to the recent ideas in the macroexternalities literature (see, e.g., Cooper and Haltiwanger (1989)) that cross-sector interactions exhibit complementarities, while within-sector interactions exhibit substitutabilities.
4. All standard errors and test statistics in Table 4 are based on White's heteroscedasticity-consistent covariance matrix estimator. Results based on the standard OLS covariance matrix estimator, and results based on WLS (weight proportional to the square root of the number of establishments in the sector) are in all essential respects identical.

Table 4 REGRESSION OF ADJUSTED GROSS JOB REALLOCATION ON OWN-SECTOR AND MANUFACTURING NET GROWTH<sup>1</sup>Dependent Variable:  $\widetilde{SUM}_{st}^{ST}$ 

	2-digit	2-digit (Continuing Establishments Only)	2-digit Quarterly Measures
<i>Regressor:</i>			
$g_{st}$	-0.221 (0.049) <sup>2</sup>	-0.174 (0.052)	0.074 (0.076)
$g_t$	-0.225 (0.024)	-0.203 (0.024)	-0.458 (0.043)
<i>Other Summary Statistics:</i>			
$R^2$ (including contribution of fixed effects)	0.78	0.75	0.49
$R^2$ (excluding contribution of fixed effects)	0.27	0.30	0.10
# Obs	220	220	1180
Difference in coefficient on $g_{st}$ and $g_t$ <sup>3</sup>	0.004 (0.946)	0.029 (0.448)	0.384 (0.000)
Mean ( $\widetilde{SUM}_{st}^{ST}$ )	0.202	0.156	0.113
Std. Dev. ( $\widetilde{SUM}_{st}^{ST}$ )	0.049	0.033	0.045
Mean ( $g_t$ )	-0.021	-0.021	-0.0025
Std. Dev. ( $g_t$ )	0.052	0.046	0.023
Mean ( $g_{st}$ )	-0.003	-0.001	-0.0007
Std. Dev. ( $g_{st}$ )	0.042	0.039	0.032

<sup>1</sup>All regressions include sector-fixed effects.<sup>2</sup>Heteroscedasticity-consistent standard errors in parentheses (using White correction).<sup>3</sup>Marginal significance level on chi-square test that coefficients are equal.

there is little additional covariation between industry net growth and the idiosyncratic component of gross job reallocation.

It is useful to place these findings alongside our earlier variance decomposition results. The variance decomposition results show that the great bulk of time variation in gross job reallocation is explained by idiosyncratic effects on the shape of the empirical growth rate density. The correlation and regression results show that the contribution of idiosyncratic effects to time variation in the shape of the density leads to large and systematic countercyclic variation in gross job reallocation. Taken together, these findings provide strong evidence that net aggregate and sectoral employment fluctuations are intimately related to

fluctuations in the intensity of shifts in employment opportunities across establishments.

## 2.6. THE CONCENTRATION AND PERSISTENCE OF GROSS JOB CREATION AND DESTRUCTION

The results above indicate that establishment-level employment changes exhibit tremendous heterogeneity, even within narrowly defined sectors of the economy. Furthermore, the heterogeneity in establishment-level employment changes is closely linked to sectoral and aggregate fluctuations. Two questions prompted by these findings are: (1) What is the role of plant births and deaths in the job-creation and destruction process? and (2) Do the measured high rates of job creation and destruction reflect transitory or persistent establishment-level employment changes? We take up these questions in turn in this section.

Gross job creation and destruction are distributed over establishments experiencing a range of expansion and contraction rates. To characterize the shape of this distribution, we partition gross job creation into three intervals: births, large continuing expanders (continuing establishments with annualized growth rates greater than or equal to 100%), and other continuing expanders. Similarly, we partition gross job destruction into three intervals: deaths, large continuing contractors (establishments with contractions greater than or equal to 50% at annualized rates), and other continuing contractors.

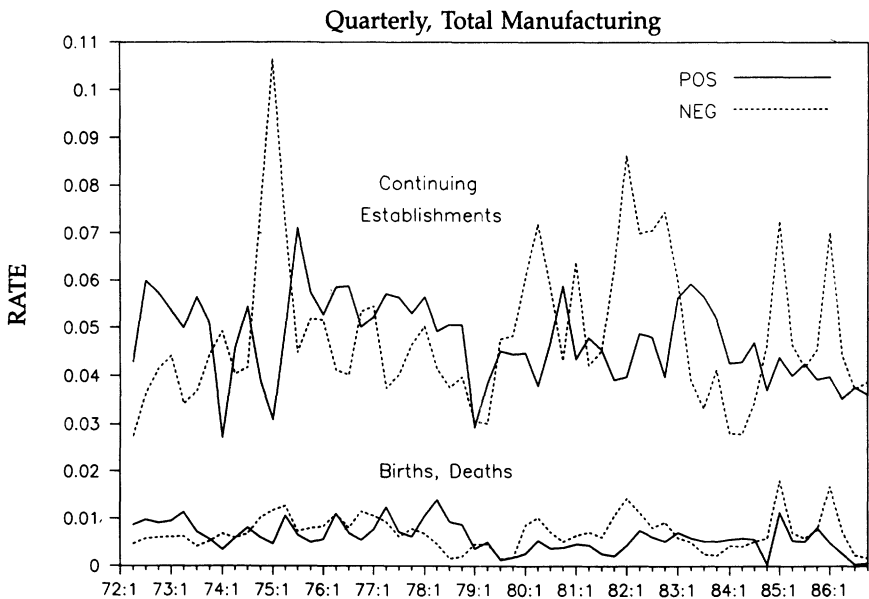
Table 5 reports job creation and job destruction partitioned into these intervals using the March-to-March annual changes. Figure 2 plots the partitioned job creation and destruction rates based on quarterly changes in establishment-level employment. Both Table 5 and Figure 2 reveal the significance of large discrete changes in accounting for job creation and destruction. For example, in 1975, expanding establishments with growth rates in excess of 100% by themselves accounted for a 2.1% gross job creation rate (recall that the total 1975 gross job creation rate was 6.7%). Similarly, in 1975, contracting establishments with contractions in excess of 50% by themselves accounted for a 6% gross job destruction rate (the total was 16.6%). Evidence of considerable discreteness in establishment-level employment changes raises questions about standard notions of smooth concave production technologies and convex adjustment costs.

Figure 2 illustrates that the time-series patterns of job creation and destruction depicted in Figure 1 hold for continuing establishments. This feature is important because it highlights the significant role of continuing establishments, and indicates that our measured time variation in gross job creation and destruction is unlikely to be driven by

Table 5 PARTITION OF GROSS JOB CREATION AND DESTRUCTION BY YEAR

$g_{et}$ scale:	<i>Job Creation Accounted for by establishments with growth rates in the interval:</i>			<i>Job Destruction Accounted for by establish- ments with growth rates in the interval:</i>		
	$[0, .666)$	$[\.666, 2)$	$[2, 2]$	$[0, -.666)$	$[-.666, -2)$	$[-2, -2]$
$G_{et}$ scale:	$[0, 1.00)$	$[1.00, \infty)$	$[\infty, \infty]$	$[0, -.50)$	$[-.50, -1.00)$	$[-1.00, -1.00]$
<i>Year:</i>						
1973	0.086	0.017	0.029	0.034	0.009	0.019
1975	0.036	0.012	0.019	0.106	0.032	0.028
1976	0.079	0.018	0.016	0.056	0.013	0.027
1977	0.074	0.017	0.020	0.045	0.015	0.034
1978	0.075	0.016	0.025	0.039	0.013	0.023
1980	0.062	0.012	0.006	0.061	0.018	0.013
1981	0.048	0.009	0.012	0.074	0.022	0.023
1982	0.043	0.011	0.010	0.088	0.026	0.038
1983	0.048	0.014	0.023	0.083	0.030	0.029
1985	0.057	0.011	0.016	0.061	0.022	0.035
1986	0.050	0.009	0.029	0.069	0.020	0.043

Figure 2 PARTITIONED POS AND NEG



errors in measuring the timing and magnitude of establishment births and deaths.

We now turn to the degree of persistence in the observed high rates of job creation and destruction. Since for total manufacturing the average quarterly rate of job creation (destruction) is 5.33% (5.62%) while, the average annual rate of job creation (destruction) is 9.2% (11.3%), we already suspect that some fraction of the observed quarterly creation and destruction is transitory. We measure persistence in job creation and destruction as follows: Let  $FPOS_{in}$  equal the fraction of newly created jobs at time  $t$  that continue to exist through periods  $t + 1, t + 2, \dots, t + n$ . Define  $FNEG_{in}$  analogously. Observe that these measures treat establishment-level employment changes as persistent only to the extent that they persist in every period over the  $n$ -period horizon.

Table 6 presents the persistence of annual job creation and destruction

Table 6 PERSISTENCE OF GROSS JOB CREATION AND DESTRUCTION

	<i>Annual Measures</i>							
	<i>Fraction of Job Creation in Year t that persists in Year:</i>		<i>Fraction of Job Destruction in Year t that persists in Year:</i>					
	<i>t+1</i>	<i>t+2</i>	<i>t+1</i>	<i>t+2</i>				
<i>Year:<sup>1</sup></i>								
1975	0.73	0.54	0.72	0.62				
1976	0.75	0.58	0.79	0.69				
1977	0.76	—	0.79	—				
1980	0.63	0.43	0.82	0.77				
1981	0.60	0.44	0.88	0.82				
1982	0.60	—	0.86	—				
1985	0.63	—	0.84	—				
	<i>Quarterly Measures</i>							
	<i>Fraction of Job Creation in Quarter t that persists in Quarter:</i>				<i>Fraction of Job Destruction in Quarter t that persists in Quarter:</i>			
	<i>t+1</i>	<i>t+2</i>	<i>t+4</i>	<i>t+8</i>	<i>t+1</i>	<i>t+2</i>	<i>t+4</i>	<i>t+8</i>
Time Series Mean	0.72	0.59	0.40	0.26	0.75	0.64	0.51	0.44
Time Series Standard Deviation	0.10	0.11	0.09	0.07	0.09	0.09	0.09	0.06

<sup>1</sup>These are the years for which the persistence measures can be calculated given the exclusion of 1974, 1979, and 1984 from the  $POS$ , and  $NEG$ , series.

over one- and two-year horizons and summary statistics on quarterly persistence measures over several horizons. Several notable results deserve highlighting. First, annual job creation and destruction are highly persistent. To take the most pronounced example, the one-year persistence rate for jobs destroyed between March 1980 and March 1981 is 88%, and the two-year persistence rate for these lost jobs is 82%. Second, about half of observed quarterly job creation and destruction persists for less than four quarters. However, the quarterly persistence measures imply that conditional on job creation or destruction persisting for a year, the probability is high that it will persist for a second year. Overall, Table 6 suggests that most of the March-to-March establishment-level employment changes and much of the quarterly changes represent a permanent reallocation of jobs.

## 2.7. SUMMARY OF BASIC FACTS

We conclude this section by highlighting the primary findings. Our measurement efforts document tremendous heterogeneity in establishment-level employment changes. These establishment-level employment changes are associated with large rates of gross job creation and destruction and, hence, large worker flows consequent to the reallocation of jobs across establishments. We find a substantial degree of discreteness and persistence in establishment-level employment changes underlying the gross creation and destruction of jobs. In terms of cyclical variation, job creation is strongly procyclical and job destruction is strongly countercyclical, as one would expect. However, job destruction increases by more and job creation decreases by less during net contractions than can be accounted for by mean aggregate and sectoral effects on the establishment-level growth rate density. This observation is closely related to our main findings: (1) gross job reallocation exhibits considerable time variation, (2) the idiosyncratic component of establishment-level employment changes explains virtually all the time variation in gross job reallocation, and (3) the idiosyncratic component of gross job reallocation exhibits significant countercyclic variation.

## 3. *Employment Reallocation and Business Cycles*

### 3.1. A PROTOTYPE MODEL

Motivated by the empirical findings in section 2, we develop a simple theoretical model of employment reallocation and the business cycle. Our intent is to provide some structure for interpreting the observed patterns of job creation and destruction and for gauging their implications for aggregate fluctuations in output, productivity, and unemployment.



Consider an economy that contains two types of production sites and a continuum of infinitely lived consumer-workers distributed over the unit interval. At the beginning of period  $t$ ,  $H_t$  workers are matched to high-productivity sites, while the remaining  $1 - H_t$  workers are matched to low-productivity sites. A fraction  $\sigma_t$  of the high-productivity sites revert to low productivity in period  $t$ . Low-productivity sites produce  $Y_L$  units of the consumption good when matched with one worker, and zero otherwise. *Operational* high-productivity sites produce  $Y_H$  units when matched with one worker, where  $Y_H > Y_L > 0$ . To become operational a high-productivity site requires one unit of time input by one worker.

At this level of abstraction, this time input can be interpreted in any of three ways without altering either the (complete markets) competitive equilibrium of the economy or the solution to an appropriate social planner's problem: (1) a worker's time cost of moving between production sites; (2) an adjustment cost, in the form of foregone production, associated with opening a new plant; and (3) an investment, in the form of foregone production, in match-specific capital by the worker and the site owner. Note that the first interpretation implies that unemployment is a direct consequence of employment reallocation.

Letting  $\theta_t$  denote the fraction of workers at low-productivity sites who move to high-productivity sites during period  $t$ , the law of motion governing  $H_t$  can be written

$$H_{t+1} = (1 - \sigma_t)H_t + \theta_t[1 - H_t + \sigma_t H_t], \quad t = 1, 2, \dots, \text{ given } H_1 = \bar{H}. \quad (1)$$

A consumer-worker derives utility  $A_t U(C_t)$  in period  $t$ , where  $A_t$  is a utility function shifter and  $C_t$  denotes consumption of the good. At time  $t$ , a worker chooses a contingency plan governing current and future mobility behavior to maximize the expected value of  $\sum_{t=1}^{\infty} \beta^{t-1} A_t U(C_t)$ , where the time discount factor  $\beta \in (0, 1)$ . The period utility function satisfies  $U'(C) > 0$ ,  $U''(C) < 0$ , and  $\lim_{C \rightarrow 0} U'(C) = \infty$ . Aggregate time- $t$  consumption equals

$$C_t = (1 - \sigma_t)H_t Y_H + [1 - H_t + \sigma_t H_t](1 - \theta_t)Y_L, \quad t = 1, 2, \dots \quad (2)$$

$A_t$  and  $\sigma_t$  index the stochastic disturbances that drive fluctuations in output, job creation and destruction, and other variables of interest in the model. We interpret the utility function shifter  $A_t$  as an aggregate demand disturbance, and we interpret  $\sigma_t$  as the intensity of allocative disturbances. We assume that the number of available high-productivity sites, operational plus nonoperational, always equals or exceeds the

number of workers. Thus, we can think of  $\sigma_t$  as both the rate at which existing high-productivity sites revert to low-productivity sites and the rate at which new high-productivity sites become available (although not necessarily operational). While our formulation treats idiosyncratic productivity disturbances as the ultimate cause of employment reallocation, it is clear that taste shocks could play the same role in a multigood model.

The  $A_t$  and  $\sigma_t$  driving processes evolve over time according to exogenous first-order Markov processes

$$F_A(\bar{A}|A) = \Pr(A_{t+1} \leq \bar{A} | A_t = A), \text{ and} \\ F_\sigma(\bar{\sigma}|\sigma) = \Pr(\sigma_{t+1} \leq \bar{\sigma} | \sigma_t = \sigma),$$

where the Markov processes satisfy

$$\frac{\partial F_A(\bar{A}|A)}{\partial A} \leq 0, \quad \frac{\partial F_\sigma(\bar{\sigma}|\sigma)}{\partial \sigma} \leq 0. \quad (3)$$

Equality in (3) corresponds to an i.i.d. process, and strict inequality corresponds to a process that exhibits persistence in the sense of first-order stochastic dominance.

Two further matters require discussion to complete the specification of this prototype model: opportunities for insuring idiosyncratic consumption risk, and the determination of wages. Idiosyncratic consumption risk arises because the nature of labor supply behavior (under interpretations (1) and (3) above of the friction in the model) potentially subjects each worker's output to the idiosyncratic productivity disturbance that impinges on his current work site. In what follows, we assume the existence of markets that permit complete insurance against idiosyncratic consumption risk. Since private information plays no role in the model, neither moral hazard nor adverse selection problems hamper the operation of insurance markets.

With respect to wages, the key issue is whether the wage-determination process leads to efficient mobility behavior. Interpretations (1) and (3) above of the friction in the model imply the existence of a surplus associated with a match between a worker and a production site. Efficient mobility behavior prevails in this prototype model if and only if workers at low-productivity sites share in any positive social surplus associated with movement to high-productivity sites.

What institutional features in the labor market would support efficient mobility behavior? Interpreting the friction as investment in match-

specific capital, efficient mobility behavior would be supported if site owners can precommit to a compensation contract when the match commences. This observation follows because workers are perfectly mobile *ex ante* under the match-specific investment interpretation of the friction. Under the time cost of moving interpretation of the friction, efficient mobility behavior would be supported if site owners can precommit to a compensation contract prior to the move by the worker. Under the adjustment cost interpretation of the friction, workers are perfectly mobile *ex post*, so that efficient mobility prevails even if the labor market operates as a period-by-period auction.

Departures from perfect consumption-risk sharing and efficient mobility probably play an important role in real-world labor market behavior and, hence, in the connection between employment reallocation and the business cycle. Here, we set these matters aside for two reasons. First, their analysis diverts attention from more basic connections between employment reallocation and business cycles—connections likely to be important whether or not fluctuations in output and employment reallocation represent fully efficient responses to underlying disturbances. In this regard, we note that the dynamic behavior of the economy is identical under each of the three quite different frictions described above—given perfect consumption-risk sharing and efficient mobility. Thus, the connections between employment reallocation and business cycles stressed in the prototype model are not tied to a narrow view of the frictions in the economy that interact with allocative disturbances, nor are they tied to a particular view about the nature of failures in labor or capital markets.

Second, the assumptions of efficient mobility and perfect consumption risk sharing greatly simplify the analysis. Together, perfect risk sharing and efficient mobility enable us to exploit the equivalence between competitive equilibrium outcomes and the solution to an appropriate social planner's problem. In this respect, our analytical approach is similar to Rogerson's (1987) analysis of employment fluctuations in general equilibrium environments characterized by risk sharing and labor-market frictions.

Our strategy for eliciting implications about the connection between employment reallocation and business cycles is as follows. We first formulate the social planner's problem for the model. The planner maximizes the discounted expected utility of a representative consumer-worker by choosing a contingency plan for  $\theta_t$ , subject to various constraints and laws of motion. We then analyze the effects of aggregate demand disturbances and the intensity of allocative disturbances on the planner's optimal choice of  $\theta_t$ . This analysis enables us to characterize the behavior of out-

put, productivity, unemployment, and employment reallocation in response to aggregate demand and allocative disturbances.

### 3.2. THE SOCIAL PLANNER'S PROBLEM

The social planner's problem has a recursive structure in this model, and we formulate it as a stationary discounted dynamic programming problem. Letting  $V(H, A, \sigma)$  denote the planner's value function under the optimal policy for employment reallocation, the optimality equation can be written as

$$V(H, A, \sigma) = \max_{\theta \in [0, 1]} \{AU[(1 - \sigma)Y_H H + (1 - H + \sigma H)(1 - \theta)Y_L] + \beta E[V((1 - \sigma)H + \theta(1 - H + \sigma H), \bar{A}, \bar{\sigma}) | A, \sigma]\}. \quad (4)$$

The law of motion for  $H$  and the resource constraint relating  $\theta$  to aggregate consumption are embedded in (4). An optimal policy for employment reallocation is a mapping  $\theta(H, A, \sigma) : [0, 1] \times [0, \infty) \times [0, 1] \rightarrow [0, 1]$  that maximizes the r.h.s. of (4).

In deriving the model's implications, the following proposition is useful:

*Proposition:*

- (a)  $V(H, A, \sigma)$  exists uniquely and is strictly concave in  $H$ .
- (b) There exists a unique, time-invariant optimal reallocation policy function  $\theta(H, A, \sigma)$ .
- (c) At an interior solution,  $V$  is continuously differentiable in  $H$  and satisfies

$$\frac{\partial V(H, A, \sigma)}{\partial H} = A(1 - \sigma)[Y_H - (1 - \theta)Y_L]U'(C) + \beta(1 - \sigma)(1 - \theta)E[\partial V(\bar{H}, \bar{A}, \bar{\sigma}) / \partial \bar{H} | A, \sigma], \quad (5)$$

where  $\bar{H} = (1 - \sigma)H + \theta(1 - H + \sigma H)$ .

*Proof:* The hypotheses of Theorems 9.6–9.8 and 9.10 in Stokey, Lucas, and Prescott (1989) hold.

Existence of a unique value function implies that we can treat the r.h.s. of (5) as a standard maximization problem. Differentiability of the value function implies that the optimal reallocation policy satisfies

$$Y_L AU'(C) = \beta E \left[ \frac{\partial V(\bar{H}, \bar{A}, \bar{\sigma})}{\partial \bar{H}} \mid A, \sigma \right] \quad (6)$$

at an interior solution. The l.h.s. of (6) represents the utility cost of foregoing one unit of current output to move one additional worker from

a low-productivity to a high-productivity site. The r.h.s. of (6) represents the discounted expected utility gains that result from an improved allocation of employment at the beginning of the next period. Thus, at an interior solution, the optimal reallocation policy equates the marginal utility loss associated with foregone current output to the discounted expected marginal utility gain associated with an improved future employment allocation.

It is helpful to rewrite the first-order condition in terms of  $H$  and  $\tilde{H}$ ,

$$Y_L AU'[(1 - \sigma)Y_H H + (1 - \tilde{H})Y_L] = \beta E \left[ \frac{\partial V(\tilde{H}, \tilde{A}, \tilde{\sigma})}{\partial \tilde{H}} \mid A, \sigma \right]. \quad (6')$$

From (1), choosing  $\theta$  is equivalent to choosing  $\tilde{H}$ . Thus, using the strict concavity of  $U$  and  $V$ , equation (6') implies that  $\tilde{H}$  is monotonically increasing in  $H$ . Equation (6') further implies that the optimal adjustment of  $\tilde{H}$  to a change in  $H$  ( $\Delta H$ ) satisfies  $|\Delta \tilde{H}| < |(1 - \sigma)(Y_H/Y_L)\Delta H|$ . It follows immediately that  $C$  is monotonically increasing in  $H$  at an interior solution for  $\theta$ . The aggregate resource constraint implies that  $C$  is monotonically increasing in  $H$  at corner solutions as well. The monotonicity properties of  $C$  and  $\tilde{H}$  can be understood as standard smoothing effects.  $H$  represents wealth in this model, so that a positive shock to wealth is spread between current consumption and future wealth.

However, neither the fraction nor the absolute number of poorly matched workers who move are necessarily monotonic in the fraction of workers currently matched to high-productivity sites. To see this point, let  $M = \theta(1 - H + \sigma H)$  be the number of workers who move. This definition and the law of motion yield

$$\frac{\partial M}{\partial H} = \frac{\partial \tilde{H}}{\partial H} - (1 - \sigma),$$

where we take the policy function to be differentiable for expositional convenience. The second term on the r.h.s. represents the direct effect of  $H$  on  $M$ : given  $\theta$ , an increase in  $H$  reduces  $M$ . The first term represents the consumption-smoothing response to increased  $H$ . To smooth consumption forward in time in response to a positive wealth shock, the social planner invests in an improved future allocation of workers. These two effects on  $M$  work in opposite directions. Similar remarks apply to  $\theta$ .

To better appreciate the investment aspect of reallocation in this model, combine equations (5) and (6) to obtain the Euler equation for aggregate consumption,

$$AU'(C) = \beta E[(1 - \bar{\sigma})(Y_H/Y_L)\tilde{A}U'(\tilde{C})|A, \sigma]. \quad (7)$$

The (stochastic) marginal rate of transformation between future and current consumption equals the productivity ratio,  $(Y_H/Y_L)$ , times the fraction of high-productivity sites that remain highly productive  $(1 - \bar{\sigma})$ .

### 3.3. THE EFFECTS OF AGGREGATE DISTURBANCES

Consider a transitory decline in aggregate demand,  $A$ . From the first-order condition and the concavity properties of  $U$  and  $V$ , this disturbance reduces  $C$  while increasing  $\theta$  and  $M$ . What features of the model yield this effect of aggregate demand disturbances on the pace of reallocation? The frictions in the model imply that reallocation involves foregone production, and temporarily depressed demand means that the marginal utility cost of foregone production is currently low. Hence, the pace of reallocation increases. Note that this effect becomes weaker to the extent that a decline in current aggregate demand portends lower future aggregate demand as well.

While this reallocation timing effect represents an efficient response to aggregate demand disturbances in the prototype model, we expect similar effects to arise in almost any model with endogenous timing of resource reallocation when such reallocation involves foregone production. The source of foregone production is not important for this reallocation timing effect—matching, learning on the job, time-consuming search and mobility, and firm costs of adjusting the labor force or scale of operations all imply that aggregate demand disturbances influence the timing of reallocation. To the extent that worker and job reallocation entail unemployment, aggregate demand disturbances working through this channel are the proximate cause of unemployment fluctuations, but allocative disturbances are the ultimate cause.

Aggregate demand disturbances, operating through reallocation timing channels, also cause measured productivity movements in the prototype model. Here, the nature of the friction in the model is important. Under the adjustment cost and match-specific investment interpretations of the friction, output per worker equals

$$Q_1 = (1 - \sigma)HY + (1 - H + \sigma H)(1 - \theta).$$

Under the time-cost of moving interpretation, output per worker equals

$$Q_2 = Q_1/(1 - \theta).$$

Hence, in response to a temporary aggregate demand disturbance,  $\partial Q_1/\partial A > 0$  and  $\partial Q_2/\partial A < 0$ . The procyclical productivity effect of aggregate

demand disturbances reflects two features of the model: (1) investment in activities (i.e., reallocation) that yield improved future production possibilities are not measured as part of current output, and (2) the trade-off between production for current consumption and investment in improved future production possibilities. The countercyclical productivity effect of aggregate demand disturbances reflects a simple selection effect. Adverse aggregate demand disturbances, for example, increase the number of low-productivity sites that become idle.

The reallocation timing effect is the only channel through which aggregate demand disturbances affect output, unemployment, and productivity in the prototype model. Below, we incorporate leisure into the model and discuss a second margin along which aggregate demand disturbances drive fluctuations.

#### 3.4. THE EFFECTS OF ALLOCATIVE DISTURBANCES

A transitory increase in  $\sigma$  is equivalent to a negative  $H$  shock in this model. From the preceding analysis, then, a temporary surge in the intensity of allocative disturbances decreases current consumption but has an ambiguous effect on the current pace of labor reallocation. The ambiguity reflects the consumption-smoothing motive discussed above.

Now consider the case where an innovation in current  $\sigma$  portends higher levels of future  $\sigma$  in the sense of (3). What are the implications of higher future  $\sigma$  for consumption and reallocation? Here, as well, there are offsetting effects. Under persistence, a positive innovation in the current  $\sigma$  implies a deterioration in the stochastic marginal rate of transformation between future and current consumption. The substitution effect associated with this deterioration leads to more current consumption and less current reallocation. This substitution effect will be particularly pronounced when the deterioration in the marginal rate of transformation is anticipated to be short-lived. The income effect associated with the deterioration in the marginal rate of transformation leads to less current consumption and more current reallocation. It is relatively more important for changes in the marginal rate of transformation anticipated to be long-lived.

In sum, the prototype model does not deliver unambiguous predictions about the contemporaneous responses of job reallocation to persistent or transitory shocks to the intensity of allocative disturbances. It does, however, suggest interesting dynamic responses of job destruction and creation to innovations in  $\sigma$ ; we return to this point below.

A word is in order about the concept of persistent allocative disturbances in the prototype model. These disturbances involve changes in the fraction of workers who are well matched and changes in the mar-

ginal rate of transformation between future and current consumption. This marginal rate of transformation change is a potentially important aspect of real-world allocative disturbances. One thinks, for example, of heightened uncertainty about the pattern of ex post returns to specific investments in the wake of the OPEC oil price shocks.

However, there is another reasonable concept of persistent allocative disturbances that has a quite different connection to the marginal rate of transformation. Consider a disturbance that increases the spread between  $Y_H$  and  $Y_L$ . If persistent, this allocative disturbance implies an *increase* in the stochastic marginal rate of transformation between future and current consumption. Hence, the substitution response to this persistent allocative disturbance leads to an immediate increase in job reallocation.

### 3.5. THE MODEL WITH LEISURE

When we introduce leisure into the model, we obtain another margin along which labor-market adjustments occur. We find this additional margin to be especially important when thinking about the dynamic response of job creation and destruction to allocative and aggregate disturbances.

Assume now that each person has three mutually exclusive uses of time: work, reallocation, and leisure. Denote the value of leisure by  $\epsilon$ . The utility function is separable between consumption and leisure and over time. Each person is subject to transitory and idiosyncratic disturbances to the value of leisure. The time-invariant distribution over  $\epsilon$  is described by a density function  $f(\epsilon)$  with continuous support on  $[0, B]$ . We assume  $B$  is sufficiently large as to guarantee that some leisure in each sector of the economy is always optimal. These assumptions generate a downward-sloping demand for leisure and interior choices for leisure in each sector. (An alternative approach would introduce transitory plant-specific productivity shocks to generate a downward sloping demand for labor in each sector.)

The social planner's optimality equation now becomes

$$\begin{aligned}
 V(H, A, \sigma) = & \text{Max}_{\theta, \epsilon_L, \epsilon_H} \{AU[(1 - \sigma)Y_H HF(\epsilon_H) + (1 - H + \sigma H)[F(\epsilon_L) - \theta]Y_L] \\
 & + (1 - \sigma)H \int_{\epsilon_H}^B \epsilon f(\epsilon) d\epsilon + (1 - H + \sigma H) \int_{\epsilon_L}^B \epsilon f(\epsilon) d\epsilon \\
 & + \beta E[V((1 - \sigma)H + \theta(1 - H + \sigma H), \bar{A}, \bar{\sigma}) | A, \sigma]\}.
 \end{aligned} \tag{8}$$

Here,  $F(\cdot)$  represents the cumulative distribution function over  $\epsilon$ .  $\epsilon_H$  and  $\epsilon_L$  denote the value of leisure for the the marginal workers in the high-



productivity and low-productivity sectors, respectively. Optimal behavior by the social planner is now characterized by the Euler equation (7) for aggregate consumption and the static first-order conditions

$$\epsilon_H = AY_H U'(C) \text{ and } \epsilon_L = AY_L U'(C). \quad (9)$$

According to equation (9), one effect of adverse aggregate demand disturbances is to increase job destruction at both types of plants as workers substitute into leisure. In line with our earlier analysis, this work-leisure substitution effect is reinforced in the low-productivity sector by the reallocation timing effect. Combining the two effects, then, suggests that adverse aggregate demand disturbances cause the largest job destruction rise in sectors that are already experiencing relatively low productivity (or relatively low demand in a multigood model).

With respect to allocative disturbances, an innovation in  $\sigma$  expands the low-productivity sector, thereby inducing greater substitution from work into leisure. Job destruction rises on account of this direct substitution effect. What happens along the other margin? If innovations in  $\sigma$  are persistent, the stochastic marginal rate of transformation falls, discouraging current reallocation activity (assuming that the substitution effect dominates). Hence, there is substitution from reallocation activity into leisure, which reinforces the direct substitution effect. Thus, in this model an innovation in  $\sigma$  causes a large contemporaneous increase in job destruction relative to the near-term increase in job creation. Near-term job creation may well fall. As the persistence effects of the innovation in  $\sigma$  die out over time, the marginal rate of transformation improves and job creation eventually rises.

It is useful to contrast the dynamic behavior of job creation and destruction induced by a  $\sigma$  innovation to their behavior under the alternative concept of an allocative disturbance. A mean-preserving spread in  $Y_H$  and  $Y_L$  encourages substitution out of leisure in both high-productivity and low-productivity sectors. In the high-productivity sector, the increase in  $Y_H$  reduces leisure because of the direct substitution effect identified above. For the low-productivity sector, the increase in the ratio ( $Y_H/Y_L$ ) improves the stochastic marginal rate of transformation, thereby causing substitution from leisure into reallocation activity. Combining the effects in the two sectors implies that a mean-preserving spread disturbance leads to a large near-term increase in job creation as well as increased gross job destruction among low-productivity plants. If there are no time costs of reallocation, then the increase in job creation is immediate.

In sum, job creation, job destruction, and unemployment are likely to

exhibit significantly different patterns of response to the two types of allocative disturbances. The key distinction between the two types of allocative disturbances involves their contrasting implications for the stochastic marginal rate of transformation. We think that a failure to clearly make this distinction is a shortcoming of the existing sectoral shifts literature.

Real-world events with allocative consequences are likely to entail elements of both  $\sigma$  innovations and innovations in the spread between  $Y_H$  and  $Y_L$ . It is our sense that recent U.S. experience with allocative disturbances like oil price shocks more closely resembles a  $\sigma$  innovation than a mean-preserving spread disturbance. Some historical events are perhaps closer to a mean-preserving spread disturbance. For example, the shift to a wartime production economy upon U.S. entry into World War II may well have reduced uncertainty about the ex post pattern of returns to investment in specific capital and, thus, increased the stochastic marginal rate of transformation.

#### *4. The Dynamic Effects of Aggregate and Allocative Shocks on Gross Job Creation and Destruction*

Our theoretical analysis suggests how observed dynamics of gross job creation and destruction can be interpreted as responses to aggregate and allocative shocks. In this section of the paper, we construct a vector autoregressive representation of these dynamics. Following closely the methodology developed by Blanchard and Diamond (1989), we then estimate the VAR, identify the aggregate and allocative shocks based on guidance from theory, trace out their dynamic effects, and evaluate the relative contribution of these shocks to job creation and destruction.

Let  $Y_t = [POS_t, NEG_t]'$  be the vector composed of job creation and destruction. Furthermore, using notation similar to that used in the theory above, let  $Z_t = [a_t, \sigma_t]'$  represent a vector containing aggregate and (the intensity of) allocative shocks, respectively. One can interpret our theory as yielding the following specification:

$$Y_t = B(L)Z_t, \quad B(0) = B_0,$$

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

The shocks themselves are likely to be serially correlated. We capture this by

$$Z_t = C(L)\epsilon_t, \quad C_0 = I,$$

where  $\epsilon_t = [\epsilon_{at}, \epsilon_{\sigma t}]'$  is the vector of white noise innovations to the shocks and  $C_0 = I$  is a normalization. Combining these two equations yields:

$$Y_t = A(L)\epsilon_t = B(L)C(L)\epsilon_t$$

where, given the above normalizations,  $A_0 = B_0$ . In writing down the system this way, one observes that  $A(L)$  reflects both the dynamics of the job creation and destruction responses to the shocks as well as the dynamics of the shocks themselves (see Blanchard and Diamond (1989) for further discussion).

When we estimate a VAR on  $Y_t$ , we do not immediately recover either the estimates of  $A(L)$  or the vector of innovations to aggregate and allocative disturbances. Instead, the VAR estimation yields:

$$Y_t = D(L)\eta_t, D(0) = I$$

where  $\eta_t = [p, n]'$  is a vector of reduced-form innovations. From this set of equations we have  $\eta_t = B_0\epsilon_t$  and  $A(L) = D(L)B_0$ , so that, if we know  $B_0$ , we can recover estimates of both the innovations to the shocks and  $A(L)$  from the estimates of the VAR.

The problem of course is that we do not know  $B_0$ . But we can rely on restrictions implied by the theory to place bounds on  $B_0$ . In particular, explicitly writing out the relationship between the reduced-form innovations and the innovations to aggregate and allocative shocks we have:

$$p = b_{0p}\epsilon_{\sigma t} + \epsilon_{at}$$

$$n = \epsilon_{\sigma t} - b_{0n}\epsilon_{at}$$

where we normalize the aggregate innovation to yield a one-for-one change in the reduced-form innovation to job creation and the allocative innovation to yield a one-for-one change in the reduced-form innovation to job destruction.

The theory presented in Section 3 provides the following guidance: Given the normalization, a positive aggregate innovation should increase job creation and reduce job destruction. Hence,  $b_{0n}$  is positive. Moreover, to the extent that reallocation is time-consuming, reallocation timing effects induced by aggregate shocks imply that the magnitude of the contemporaneous change in job destruction is greater than the contemporaneous change in job creation. Hence,  $b_{0n}$  is greater than one. Now, consider a positive innovation in  $\sigma$ , the intensity of allocative disturbances. Given the normalization, a positive reallocation innova-

tion increases job destruction contemporaneously and increases job creation, typically with a lag.

To the extent that job creation increases contemporaneously the response is less than the response of job destruction. Furthermore, increases in uncertainty associated with persistent innovations in  $\sigma$  or aggregate increasing returns may cause job creation to fall initially. If job creation does fall, the response is again proportionately smaller in magnitude than the response of job destruction. Taken together, these considerations suggest that  $b_{op}$  could be either zero, positive, or negative but, in any case, less than one in absolute value. Finally, regardless of the initial effect, positive reallocation innovations eventually generate an increase in job creation over some intermediate horizon.

Based on these theoretical considerations, we achieve identification of  $B_0$  as follows: First, we assume that the aggregate and allocative innovations are uncorrelated. It is our sense that if one interprets the underlying aggregate and allocative shocks as representing the ultimate sources of variability and any resulting covariation as part of the propagation process, then this assumption is a reasonable one.

Observe that in combination with the zero-correlation assumption, knowledge of one element of the pair  $(b_{op}, b_{on})$  gives the other element of the pair. Accordingly, we assume  $b_{on}$  is greater than one and then consider resulting pairs of the parameters such that (1)  $b_{op}$  is less than one in absolute magnitude and (2) the impact of an allocative innovation generates an increase in job creation after  $m$  periods and for at least  $M$  periods.

Before proceeding to the results of the estimation of the VAR and the subsequent identification, it is helpful to contrast the identifying assumptions we have made relative to the identifying assumptions made by Blanchard and Diamond (1989) in their characterization of aggregate unemployment and vacancy dynamics. Roughly, translating their identifying assumptions to job creation and destruction yields the following restrictions: (1) zero correlation between aggregate and allocative innovations; (2) both  $b_{op}$  and  $b_{on}$  are positive; (3) aggregate innovations affect *POS* and *NEG* in opposite directions for at least  $k$  periods; and (4) allocative innovations affect *POS* and *NEG* in the same direction for at least  $k$  periods. Thus, there is considerable potential overlap between Blanchard and Diamond's set of identifying assumptions and our own preferred set.

The key differences are that we attempt to capture explicitly both the impact of potential reallocation timing effects and the possibility that the initial effect of an allocative innovation on job creation may not be positive. Note that as an important basis of comparison, in what follows we also examine the implications of the Blanchard and Diamond identifying

assumptions for the dynamics of job creation and destruction. We now proceed to the estimation.

We estimate a VAR on job-creation and -destruction rates using quarterly data for the period 1972:2 to 1986:4. Using four lags, F tests reject the null hypothesis that lags are jointly insignificant at the 1% level in each regression. Lags of job destruction (creation) are jointly significant at the 1% (5%) level in the job-creation (-destruction) regression. Analysis of the economic dynamics implied by the estimated VAR depends on our identifying assumptions to which we now turn.

Imposing the restrictions that  $b_{on}$  is greater than one and  $b_{op}$  is less in absolute magnitude than one generates candidate pairs of these two parameters as follows: Recall that knowledge of one of the two parameters implies a value for the other, given the estimated variance-covariance matrix of the reduced-form innovations to the VAR. Choosing  $b_{on}$  equal to 1.0 implies a value of  $b_{op}$  equal to 0.30, which is in the permissible range. As we increase the choice of  $b_{on}$  the value of  $b_{op}$  increases monotonically. At  $b_{on} = 2.0$  the implied  $b_{op} = 0.61$  and at  $b_{on} = 3.3$  the implied  $b_{op}$  just exceeds 1.0. Accordingly, in terms of these identifying restrictions alone, the permissible range of the pair  $(b_{on}, b_{op})$  is  $(1.0, 0.30)$  to  $(3.3, 1.0)$ .

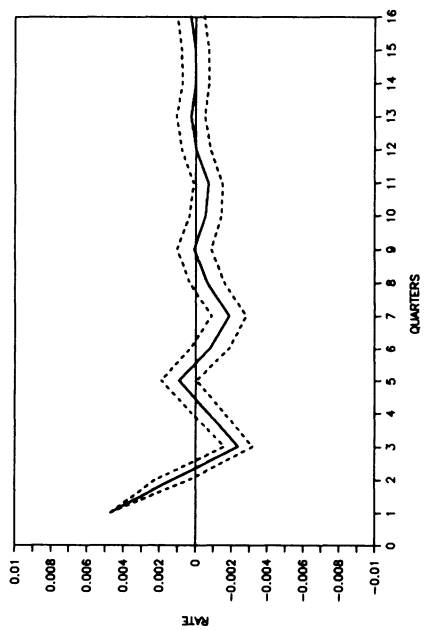
A couple of remarks are useful at this stage. First, it is interesting that over the relevant range  $b_{op}$  is positive and monotonically increases with  $b_{on}$ . That  $b_{op}$  is positive suggests the data support an orthogonalization of the reduced-form innovations into a component that generates contemporaneous negative comovement between job creation and destruction (i.e., the aggregate innovation) and another component that generates contemporaneous positive comovement (i.e., the allocative innovation). Furthermore, the positive relationship between  $b_{on}$  and  $b_{op}$  indicates that in order to increase the influence of an allocative innovation on job creation, the data require increasing the influence of an aggregate innovation on job destruction.

We also imposed restrictions on the dynamic responses to the innovations. However, we find that the pattern of impulse-response functions is remarkably invariant to variation of the parameter pair and that the pattern satisfies our identifying restrictions over the permissible range of parameters (letting  $m = 0$  and without imposing a tight restriction on  $M$ ). Note, further, that our permissible range of  $b_{on}$  and  $b_{op}$  satisfy the Blanchard and Diamond restrictions and that the dynamic responses satisfy their restrictions for  $k = 2.0$ . Given this invariance, we focus our attention in most of what follows on a benchmark case of  $b_{on} = 2.0$  with an implied value of  $b_{op} = 0.61$ .

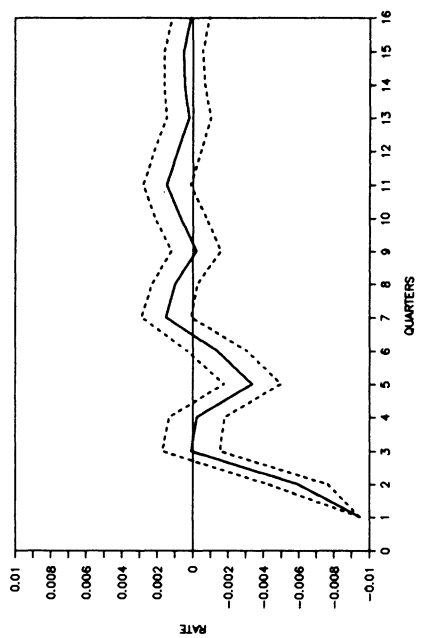
Figure 3 plots the impulse responses for the benchmark case. By con-

Figure 3 IMPULSE-RESPONSE FUNCTIONS

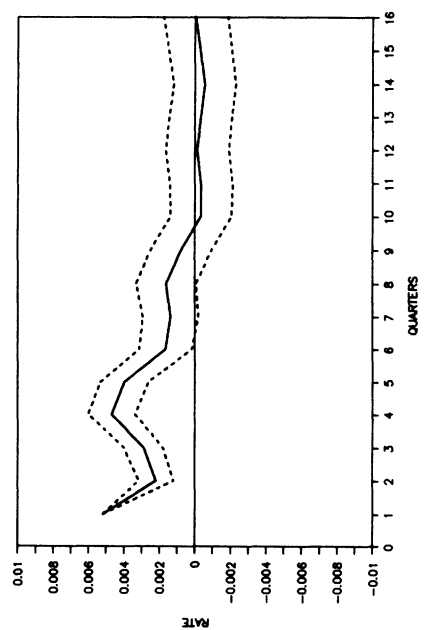
POS—AGGREGATE



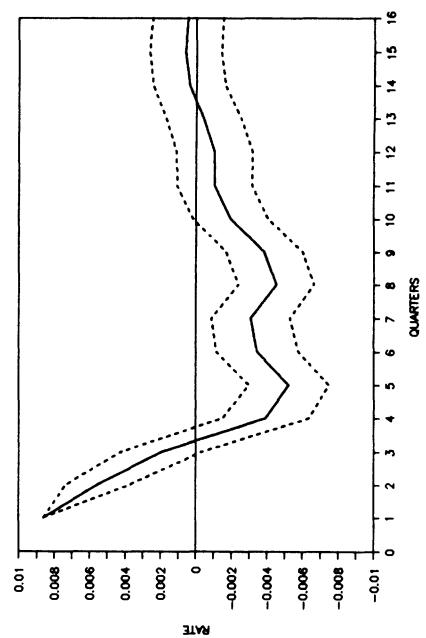
NEG—AGGREGATE



POS—ALLOCATIVE



NEG—ALLOCATIVE



struction, aggregate innovations generate an immediate increase in job creation and a decrease in job destruction. Analogously, allocative innovations generate an immediate increase in both job creation and destruction. Aggregate innovations generate relatively transitory effects on job creation and destruction. After about three quarters, an aggregate innovation generates oscillatory behavior in both job creation and destruction around zero. Turning to allocative shocks, an allocative innovation generates a sharp increase in job destruction for two to three quarters

Table 7 VARIANCE DECOMPOSITIONS<sup>1</sup>

<i>Variable</i>	<i>Quarters</i>	<i>Aggregate Innovations</i>	<i>Allocative Innovations</i>
POS	1	0.45	0.55
	2	0.43	0.57
	3	0.43	0.57
	4	0.33	0.67
	6	0.29	0.71
	8	0.31	0.69
	16	0.30	0.70
NEG	1	0.55	0.45
	2	0.54	0.46
	3	0.54	0.46
	4	0.50	0.50
	6	0.45	0.55
	8	0.41	0.59
	16	0.40	0.60
NET	1	0.95	0.05
	2	0.92	0.08
	3	0.92	0.08
	4	0.72	0.28
	5	0.60	0.40
	6	0.57	0.43
	7	0.56	0.44
	8	0.53	0.47
	16	0.51	0.49
SUM	1	0.10	0.90
	2	0.15	0.85
	3	0.15	0.85
	4	0.15	0.85
	5	0.16	0.84
	6	0.17	0.83
	7	0.17	0.83
	8	0.16	0.84
	16	0.16	0.84

<sup>1</sup>Identification assuming  $b_{0n} = 2.0$ .

and a sustained increase in job creation over several quarters. This pattern is consistent with the notion that it is costly in terms of time to reallocate jobs and workers.

Decompositions of forecast-error variances for the benchmark identifying assumptions appear in Table 7. The striking result is the large contribution of allocative shocks to both job creation and destruction at all forecast horizons. Moreover, for both job creation and destruction, the contribution of allocative shocks rises at longer horizons. Using the identities relating job creation and destruction to gross job reallocation and net employment growth, we also decomposed the implied variance of the forecast errors of the latter measures into components driven by aggregate and allocative shocks. The results from this exercise are also reported in Table 7. Perhaps not surprisingly, allocative shocks are the predominant source of variation in gross job reallocation at all horizons. More striking is the result that allocative shocks play an important role in explaining the variance of net growth at medium and long horizons. Overall, the results in Table 7 stand in stark contrast with Blanchard and Diamond's finding of a relatively anemic role for allocative shocks in the forecast-error variance decompositions of unemployment and vacancies at both short- and medium-run horizons.

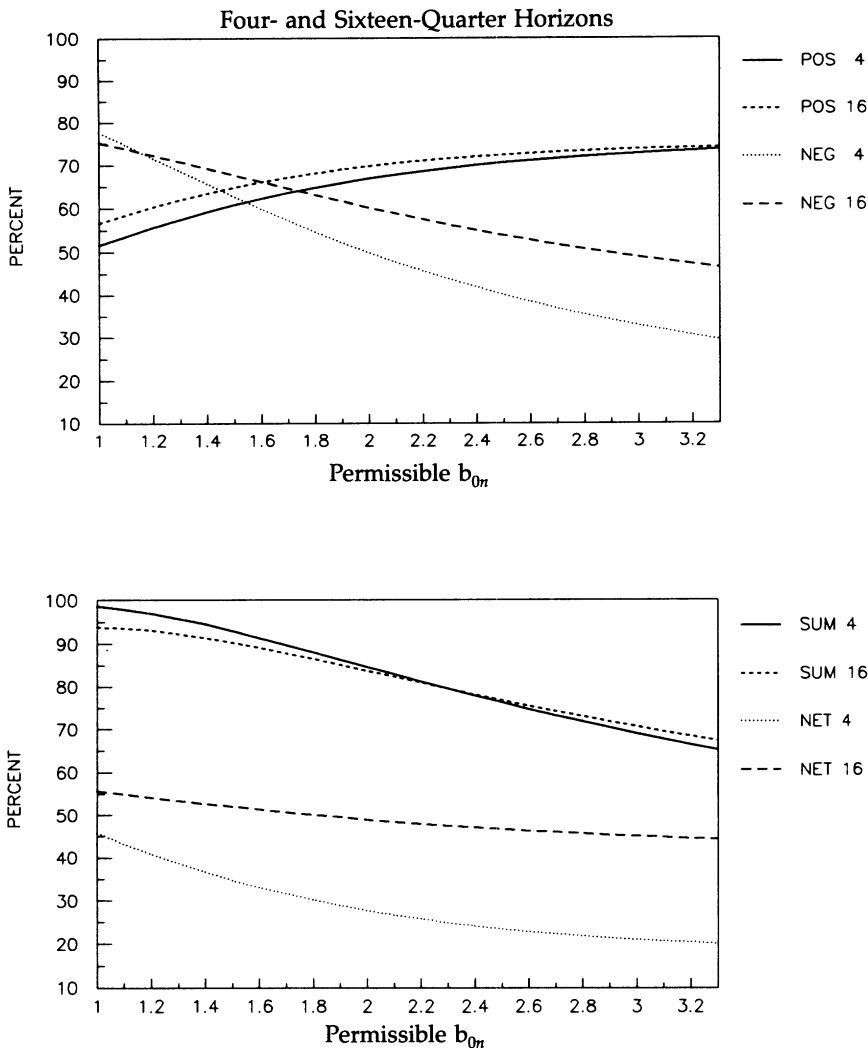
This finding of a strong role for allocative shocks, even at high frequencies, is robust to alternative parametric restrictions. The top panel of Figure 4 plots the contribution of allocative shocks to the variance of job creation and destruction at 4 and 16 quarter horizons as the choice of  $b_{0n}$  varies. For low values of  $b_{0n}$  (which in turn imply low values of  $b_{0p}$ ), the contribution of allocative shocks to job destruction exceeds 70% at both 4 and 16 quarter horizons and the contribution to job creation exceeds 50% at these same horizons. For high values of  $b_{0n}$  (implying high values of  $b_{0p}$ ), the contribution of allocative shocks to job creation exceeds 70% at 4 and 16 quarter horizons and the contribution to job destruction exceeds 30% at the 4 quarter horizon and 40% at 16 quarters.<sup>5</sup>

This same exercise is repeated for gross job reallocation and net employment growth in the lower panel of Figure 4. For low values of  $b_{0n}$ , the contribution of allocative shocks to job reallocation exceeds 90% at both 4 and 16 quarter horizons and the contribution to net employment growth

5. The pattern depicted in Figure 4 extends beyond the boundaries imposed by our identifying assumptions. For example, choosing  $b_{0n} = 4.0$  implies a  $b_{0p} = 1.2$ . For this parameter pair, the contribution of allocative shocks at 4 and 16 quarter horizons to job creation (job destruction) is 74% and 75% (24% and 42%), respectively. At the other extreme, a value of  $b_{0n} = 0.1$  implies a  $b_{0p} = 0.03$ . For this parameter pair, the contribution of allocative shocks at 4 and 16 quarter horizons to job destruction (job creations) is 78% and 95% (31% and 36%), respectively.



Figure 4 PROPORTION OF VARIANCE DUE TO ALLOCATIVE SHOCKS



exceeds 40% at these same horizons. For high values of  $b_{0n}$ , the contribution of allocative shocks to job reallocation exceeds 65% at both 4 and 16 quarter horizons and the contribution to net employment growth exceeds 20% at 4 quarters and 40% at 16 quarters. Simply put, allocative shocks contribute substantially to the variation of job creation, destruction, and reallocation at all horizons and to net employment growth at all forecast horizons of at least one year.

## 5. Gross Job Reallocation and Unemployment

Our theoretical analysis points to a potentially important relationship between changes in the intensity of job reallocation and aggregate unemployment fluctuations. Our findings in section 2 show significant countercyclic variation in the idiosyncratic component of gross job reallocation. Our empirical results in section 4 indicate that allocative shocks play a large role in the dynamics of job creation and destruction at high and low frequencies. Motivated by these considerations and much previous research, we now investigate the empirical relationship between changes in the intensity of job reallocation and unemployment.

Table 8 reports regressions of unemployment on various measures of gross job reallocation. The dependent variable is the quarterly, seasonally unadjusted total-manufacturing unemployment rate (see the data appendix for details). The first specification simply relates the unemployment rate to the raw gross job reallocation rate. For all estimation methods considered (OLS, AR2, and First Difference), we find a positive and statistically significant relationship between the unemployment rate and both the contemporaneous and the lagged gross job reallocation rate. The magnitude of the coefficients indicate that a one standard deviation increase in gross job reallocation is associated with a contemporaneous increase in the unemployment rate of .64 to 1.05 percentage points and an increase of .50 and 1.14 percentage points in the next period. This first specification controls only for a linear time trend.

The second specification considers the relationship between the idiosyncratic component of gross job reallocation and the unemployment rate. Here, we control for mean aggregate effects and differential mean sectoral responses to aggregate disturbances. The results are similar to the results with the raw reallocation measure.<sup>6</sup> While this similarity is not surprising in view of the decomposition results in Section 2, we interpret the regressions as supporting the view that allocative shocks play an important role in unemployment fluctuations—either directly as a driving force, or indirectly through reallocation timing effects.

We now consider two separate decompositions of gross job reallocation in the unemployment regressions. Both decompositions have a two-fold motivation. The first motivation is to isolate different types of time

6. We also examined specifications where we included a distributed lag on the difference between the raw and idiosyncratic component of the gross job reallocation rate as an additional regressors. The parameter estimates for these additional estimates were erratic (sometimes positive, sometimes negative) and mostly insignificant. Note further that the addition of these regressors had little impact on the coefficients and standard errors of the idiosyncratic component.

Table 8 THE RELATIONSHIP BETWEEN UNEMPLOYMENT AND GROSS JOB REALLOCATION  
 Dependent Variable: Total Manufacturing Unemployment Rate

	<i>Mean</i> ( <i>Std. Dev.</i> )	<i>Estimation Method:</i> <sup>1</sup>		
		OLS	AR2	FD <sup>2</sup>
$UN_t$	0.077 (0.025)			
Specification:				
$SUM_t$	0.110 (0.02)	0.525 (0.131)	0.333 (0.084)	0.319 (0.081)
$SUM_{t-1}$	—	0.568 (0.130)	0.275 (0.084)	0.253 (0.079)
$R^2$	—	0.66	0.86	0.29
D.W.	—	0.63	1.94	1.73
$\widetilde{SUM}_t$	0.115 (0.02)	0.488 (0.122)	0.333 (0.071)	0.324 (0.070)
$\widetilde{SUM}_{t-1}$	—	0.567 (0.124)	0.235 (0.071)	0.232 (0.068)
$R^2$	—	0.64	0.87	0.33
D.W.	—	0.57	1.95	1.64
$\widetilde{SUM}_t^{OIL}$	0.114 (0.012)	0.569 (0.189)	0.369 (0.105)	0.343 (0.107)
$\widetilde{SUM}_{t-1}^{OIL}$	—	0.434 (0.204)	0.100 (0.105)	0.118 (0.107)
$\widetilde{SUM}_t - \widetilde{SUM}_t^{OIL}$	0.000 (0.016)	0.466 (0.155)	0.310 (0.083)	0.323 (0.083)
$\widetilde{SUM}_{t-1} - \widetilde{SUM}_{t-1}^{OIL}$	—	0.638 (0.151)	0.296 (0.082)	0.290 (0.080)
$R^2$	—	0.64	0.88	0.36
D.W.	—	0.55	1.89	1.57
$SUM_t^{AGG}$	0.111 (0.008)	1.03 (0.295)	1.258 (0.166)	1.250 (0.158)
$SUM_{t-1}^{AGG}$	—	0.987 (0.292)	0.486 (0.166)	0.537 (0.158)
$SUM_t^{ALL}$	0.110 (0.017)	0.325 (0.126)	0.131 (0.068)	0.152 (0.004)
$SUM_{t-1}^{ALL}$	—	0.326 (0.131)	0.138 (0.068)	0.182 (0.064)
$R^2$	—	0.75	0.92	0.66
D.W.	—	0.46	2.13	1.75

<sup>1</sup>Sample period: 1972:2–1986:4. All equations include a constant: OLS and AR2 include a linear time trend. Standard errors in parentheses.

<sup>2</sup>FD = First Difference.

variation in gross job reallocation, so that we can investigate whether the unemployment response to the various types of variation is consistent with the theory and with our interpretation of the previous regression. The second motivation is to investigate whether allocative disturbances are the proximate driving force behind unemployment fluctuations or, alternatively, whether the results of the previous regression reflect reallocation timing effects. Our two decompositions rely on different types of identifying assumptions.

Our first approach is based on the identifying assumption that oil price shocks affect manufacturing unemployment through their allocative effects (not through their reallocation timing effects). In line with this assumption, we decompose the idiosyncratic component of gross job reallocation into the part associated with oil price growth rate movements,  $SUM^{OIL}$ , and the part orthogonal to movements in the oil price growth rate,  $SUM - SUM^{OIL}$ . We interpret  $SUM - SUM^{OIL}$  as reflecting the reallocation timing effects of aggregate disturbances and the effects of unobserved allocative disturbances. The decomposition is accomplished via an auxiliary regression relating the idiosyncratic component of gross job reallocation to a distributed lag on a polynomial in real oil-price growth rates.<sup>7</sup> The third panel of Table 8 reports the results using this decomposition.<sup>8</sup> The results indicate that both the oil and nonoil components of job reallocation have a positive and significant effect on the unemployment rate. The estimated effects are similar to those in the previous regressions.

Our second decomposition is based on the VAR model estimated in Section 4. Using the decomposition of the moving average representation of job creation and destruction implied by the estimated VAR and the benchmark identifying assumptions, we constructed the job reallocation series generated by allocative shocks,  $SUM^{ALL}$ , and the job reallocation series generated by aggregate shocks,  $SUM^{AGG}$ .

The fourth panel of Table 8 reports the results of using this decomposition. The results indicate that both the aggregate and allocative components of job reallocation have a positive and significant effect on the unemployment rate. However, here we find a larger quantitative role for

7. Specifically, we regressed the idiosyncratic component of gross job reallocation on the current and two lags of a third-order polynomial in oil price growth rates. The oil price growth rate is calculated over a 12-month interval. See the Data Appendix for more details.

8. We use a two-step estimation procedure here but have not adjusted the standard errors to account for the first-step estimation. Appropriate caution needs to be used in interpreting the standard errors.

the component of job reallocation driven by aggregate shocks in explaining variation in unemployment.<sup>9</sup>

The results based on the two alternative decompositions of gross job reallocation support the interpretation we gave to the regression of unemployment on the idiosyncratic component of gross job reallocation. In terms of this interpretation, the decomposition-based results point to a major role for reallocation timing effects for explaining unemployment fluctuations during our sample period. The results are also largely consistent with a significant but relatively small direct influence of allocative disturbances.

## 6. Concluding Remarks

To conclude, we offer our interpretation of the five main messages to emerge from the research in this paper.

First, as an empirical matter, there is tremendous heterogeneity of establishment-level employment changes. Associated with the establishment-level employment changes are large rates of gross job creation, destruction, and reallocation.

Second, the magnitude of heterogeneity varies significantly over time and in a way that is intimately related to aggregate fluctuations. Furthermore, the time variation in this heterogeneity cannot be accounted for by differences in mean sectoral responses to aggregate disturbances. Stated differently, it is time variation in the importance of the idiosyncratic component that accounts for the comovement between manufacturing employment growth and the magnitude of heterogeneity in establishment-level employment changes.

These are the raw facts. They seem hard to argue with. Interpretations of the facts leave more room for disagreement, but the following considerations weigh heavily in our own thinking about useful directions for research on labor market dynamics and business cycles.

Third, there are nontrivial costs associated with job loss, worker reallocation, and specific capital formation (see Topel (1990) and references therein). Careful analysis of these costs and their implications underlies many of the successes in search, matching, and human capital theories of labor market dynamics. Combined with the raw facts, the significance of these costs indicates that the frictions associated with the reallocation of jobs and workers play a major role in business cycle fluctuations. We are doubtful that a satisfactory understanding of aggregate fluctuations will emerge from theories that ignore these frictions.

9. The magnitude of the relevant coefficients are sensitive to the choice of  $b_{0n}$ . Low values of  $b_{0n}$  lead to substantially greater effects of  $SUM^{ALL}$  on unemployment.

Fourth, our model of employment reallocation and business cycles is suggestive of how both aggregate and allocative disturbances can drive fluctuations in job creation and destruction, unemployment, productivity, and output. Different types of allocative disturbances have different effects on the return to investments in specific capital and, hence, different implications for the dynamic response of job creation and destruction. The simplicity of the model suggests that it can be successfully extended to incorporate a stochastic search technology and investments in specific physical capital. The model can also be integrated with the neoclassical growth model that serves as the analytical framework for most of the research in the real business cycle literature. Simple forms of aggregate-increasing returns are easily introduced into the basic model.

Fifth, and last, our analysis of the joint dynamics of job creation and destruction in section 4 support the view that allocative disturbances were a major driving force behind movements in job creation, job destruction, job reallocation, and net employment growth in the U.S. manufacturing sector during the 1972 to 1986 period. Furthermore, our unemployment regression results in section 5 suggest that allocative disturbances, both directly and via reallocation timing effects, played an important role in explaining unemployment fluctuations over this period. Whether these findings hold up for other sectors, time periods, and countries awaits further research and the development of additional longitudinal establishment-level data bases.

### *Data Appendix*

Most of the measures used in this paper are from the LRD described in section 2.1. The annual gross employment-change measures are based on March-to-March establishment-level changes in total employment. The quarterly gross change employment measures are based on quarterly establishment-level changes in production worker employment. Quarterly changes here refer to: first quarter (change from November of previous year to February of current year); second quarter (change from February to May); third quarter (change from May to August); and fourth quarter (change from August to November). For a more complete description of the LRD, see Davis and Haltiwanger (1989) and Davis, Haltiwanger, and Schuh (1990).

For the analysis in Section 5 we used the following additional series: The total manufacturing unemployment rate is measured from CPS monthly seasonally unadjusted data on number of workers employed and unemployed by industry. The monthly unemployment rate for total manufacturing is measured as the ratio of the number unemployed to

the sum of the number employed and unemployed. The quarterly unemployment rate used in the analysis is the average over the current and previous two months of the quarter (using the above dating of quarters).

The monthly oil price data are from CITIBASE. The real price of oil is measured as the nominal price of crude oil (series PW561) deflated by the producer price index (series PW) (both are seasonally unadjusted). The 12-month real growth rate series used in the regressions is based on this series using the dating convention described above.

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## *Comment*

KATHARINE G. ABRAHAM

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When a progress report on this work was presented at the summer meeting of the NBER Economic Fluctuations group last summer, much of both the formal and the informal discussion centered on data quality issues. My initial reaction, too, was to be concerned about the underpinnings of Davis and Haltiwanger's numbers. The Census Bureau's Longitudinal Research Datafile (LRD) is a largely unexploited resource, which means the potential pitfalls associated with using it are not well understood. Having subsequently had the opportunity to talk at some length with both Davis and Haltiwanger about the LRD and the procedures they followed in working with it, however, I have been persuaded that their numbers do indeed measure what it is claimed they do. Davis and Haltiwanger's job creation and job destruction series should ultimately prove to be of considerable value to other researchers. They certainly have my admiration for undertaking the rather overwhelming task of putting them together.

Perhaps the most striking feature of the results reported in the paper is the enormous dispersion in establishments' employment growth rates, even within narrowly defined sectors. This finding, which is similar to those reported in earlier work by Leonard (1987) and by Dunne, Roberts, and Samuelson (1989), raises significant questions about research on a wide range of topics based on the assumption of the existence of a "representative firm" or that takes the industry as an appropriate unit of analysis.

Davis and Haltiwanger's objective in this paper, however, is not simply to document the existence of heterogeneity across establishments, but to use information on job creation and job destruction to shed light on the relationship between allocative disturbances and macroeconomic fluctuations. From that perspective, the key finding of the paper's first section is the existence of a strong negative correlation between SUM—their measure of the dispersion in employment growth rates across manufacturing establishments, and NET—the net rate of growth in manufacturing employment. Later in the paper, they also report that higher values of SUM are associated with higher manufacturing unemployment rates. Davis and Haltiwanger interpret the findings that greater dispersion in employment growth rates across establishments is associated with slower net manufacturing employment growth and higher manufacturing unemployment as evidence that allocative distur-



bances that shift labor demand across establishments make an important contribution to economic fluctuations at business cycle frequencies, either directly or indirectly through what they term the reallocation timing effect.

In principle, the negative correlation between SUM and NET, and the positive relationship between SUM and the manufacturing unemployment rate, could reflect the influence of aggregate developments of the sort hypothesized by conventional single-factor business cycle models. If, for example, slowly growing manufacturing industries also tended to be more cyclically responsive, such models would imply that the dispersion of employment growth rates across establishments should rise during cyclical downturns. Perhaps not surprisingly, given that their analysis is restricted to the manufacturing sector, Davis and Haltiwanger are quickly able to rule out this explanation for the patterns they observe. Changes in the distribution of mean employment growth rates across manufacturing industries account for little of the time-series variation in the dispersion of employment growth rates across establishments, and the dispersion of establishment growth rates not of industry-specific time-period effects ( $\text{SUM}$ ) has almost exactly the same negative correlation with NET, and almost exactly the same positive association with the manufacturing unemployment rate as the unadjusted dispersion nature.

These results have an interesting family resemblance to earlier findings, some fairly well known but others less so, based on sectoral employment data. In an important and provocative paper, Lilien (1982a) proposed the following measure of sectoral shifts:

$$\sigma_t = \left[ \sum_{i=1}^n \frac{E_{it}}{E_t} (\Delta \ln E_{it} - \Delta \ln E_t)^2 \right]^{1/2}, \quad (1)$$

where  $N$  equals the number of sectors,  $E_{it}$  represents employment in sector  $i$  in period  $t$ , and  $E_t$  represents aggregate period  $t$  employment. This measure captures the dispersion of employment growth rates across industries and is thus analogous to Davis and Haltiwanger's SUM measures. The existence of a positive relationship between  $\sigma$  and the aggregate unemployment rate, the analogue to Davis and Haltiwanger's findings concerning the associations between SUM and NET and between SUM and the manufacturing unemployment rate, lead Lilien to conclude that allocative shocks that shifted labor demand from some sectors to others might have been responsible for a substantial fraction of all cyclical variation in U.S. unemployment during the postwar period.

Abraham and Katz (1986) criticized this interpretation of Lilien's re-

sults, arguing that, because industries with slow trend-growth rates also tend to be especially cyclically sensitive, aggregate shocks could also have produced a positive association between  $\sigma$  and the unemployment rate. They interpret the fact that  $\sigma$  is positively correlated with the unemployment rate, but negatively correlated with the normalized help-wanted index (a job-vacancy rate proxy) as evidence for an aggregate disturbance interpretation of Lilien's findings.

A natural strategy for dealing with the Abraham and Katz criticism is to purge sectoral employment growth rates of the systematic influence of aggregate fluctuations, and then to examine the relationship between the dispersion of the employment growth rate residuals and unemployment. Following Lilien (1982b), suppose that the employment growth rate in sector  $i$  can be represented as:

$$\Delta \ln E_{it} = \gamma_{1i} + \gamma_{2i}t + \phi_t A_t + \epsilon_{it} \quad (2)$$

where  $E$  represents employment,  $t$  is a time trend;  $A$  is a vector of aggregate demand variables—including the current and lagged values of unanticipated money-supply growth and a time-fixed effect common across all sectors;  $\epsilon$  is a first-order autoregressive error term; and the  $\gamma$ 's and  $\phi$  are parameters to be estimated. Define:

$$\sigma_t = \left[ \sum_{i=1}^N \frac{E_{it}}{E_t} \left( \frac{\hat{\epsilon}_{it}^2}{\hat{\sigma}_i} \right) \right]^{1/2}, \quad (3)$$

where  $N$  equals the number of sectors,  $E_{it}$  equals employment in sector  $i$  in period  $t$ ,  $E_t$  equals aggregate period  $t$  employment,  $\hat{\epsilon}_{it}$  equals the estimated innovation in the error term  $\epsilon_{it}$ , and  $\hat{\sigma}_i$  is the estimated variance of the  $\hat{\epsilon}_i$ 's. This  $\bar{\sigma}$  measure can be thought of as the analogue to  $\bar{S}\bar{U}\bar{M}$  in Davis and Haltiwanger's analysis.

Somewhat surprisingly, given the inclusion of time-period fixed effects in (2),  $\bar{\sigma}$  not only has a positive association with the unemployment rate, but a negative association with the normalized help-wanted index (Abraham and Katz 1985). In other words, there appears to be a negative association between the residual dispersion in sectoral employment growth rates, net of the systematic influence of aggregate conditions, and aggregate conditions themselves. These results can be thought of as the analogue to Davis and Haltiwanger's findings that  $\bar{S}\bar{U}\bar{M}$  is negatively related to NET and positively related to the manufacturing unemployment rate.

The two sets of results just described, the Davis-Haltiwanger findings

based on establishment-level data and the Lilien-Abraham-Katz results based on industry-level data, strike me as nicely complementary. Taken together, they may provide an important clue about the relationship between allocative shocks and aggregate fluctuations that could not be gleaned from either taken separately. One possible interpretation of these results is that they reflect the direct influence of allocative shocks on aggregate activity, attributable to hiring that lags behind firing when demand shifts occur. An alternative interpretation, very close in spirit to the reallocation timing interpretation offered by Davis and Haltiwanger, is that shakeouts affecting weak establishments and weak sectors tend to occur primarily during downturns in aggregate economic activity. Thus far I have said nothing about the sources or nature of allocative shocks. This is something that neither the paper, nor the literature more generally, is very specific about. Insofar, however, as there is no compelling reason to think that allocative shocks that affect the distribution of employment demand across establishments within particular sectors should necessarily affect the distribution of employment demand across sectors, or vice versa, the similarity between the Davis-Haltiwanger and Lilien-Abraham-Katz results arguably lends support to the view that both reflect the concentration of needed business adjustments during periods of weak aggregate demand rather than the direct affects of allocative shocks.

One caveat to be attached to both sets of findings is that their sensitivity to the choice of employment dispersion measure has not been fully explored. Given the absence of any theoretical justification for choosing any one particular dispersion measure over another, it would be reassuring to know that the patterns reported are not an artifact of a particular choice. More generally, a weakness of the essentially descriptive work described thus far is the absence of any formal structure for disentangling the separate influences of allocative and aggregate shocks.

The second empirical part of Davis and Haltiwanger's paper contains a more formal effort to characterize the dynamics of job creation and job destruction during a VAR methodology that very closely parallels that used by Blanchard and Diamond (1989) to study the evolution of job vacancies, unemployment, and the labor force. While this approach has the advantage that it can generate estimates of the underlying shocks driving observable variables such as job creation and job destruction, or vacancies and unemployment, its implementation requires some fairly strong assumptions. Two assumptions shared by the Davis-Haltiwanger and Blanchard-Diamond papers strike me as particularly important. First, both papers assume that allocative shocks and aggregate shocks are uncorrelated with one another. In fact, many shocks may have both allocative and aggregate consequences. The oil shocks

of the 1970s, for example, may fall into this category. Second, both papers assume that there is only one type of allocative shock. In fact, there may be different types of allocative shocks, each with its own unique time-series properties.<sup>1</sup>

Because the Davis-Haltiwanger and Blanchard-Diamond approaches are so similar, however, these sorts of methodological problems seem unlikely to account for the dramatic differences in the two papers' findings. Whereas Blanchard and Diamond found that sectoral shocks explain almost none of the time-series variation in either job vacancies or unemployment, Davis and Haltiwanger find that such shocks explain a substantial fraction of the time-series variation in both job creation and job destruction. Given the importance of understanding the respective contributions of allocative and aggregate shocks to the dynamic behavior of the economic system, some effort to reconcile these two sets of results seems called for.

One obvious difference between the two papers is that, whereas Blanchard and Diamond used data for the whole economy, Davis and Haltiwanger use data for the manufacturing sector only. It is not obvious, however, how this difference could account for the relatively greater importance of allocative shocks in Davis and Haltiwanger's results. Unfortunately, because available data permit neither the replication of the Blanchard-Diamond analysis for the manufacturing sector alone nor the replication of the Davis-Haltiwanger analysis for the whole economy, this must at present remain an unanswered question.<sup>2</sup>

A second difference between the two papers is that Blanchard and Diamond's results are based on data for the 1952 through 1988 time period, while Davis and Haltiwanger use data only for the years from 1972 through 1986. Again, however, it is unclear how this difference might have affected the two papers' respective conclusions. On the one hand, one might think the years from 1972 through 1986 were a period during which the economy suffered from a series of unusually significant allocative shocks, so that such shocks played a relatively more important role over the period represented in Davis and Haltiwanger's analysis than over the longer period represented in Blanchard and Diamond's equations. On the other hand, the Davis and Haltiwanger period included more than its share of recession years, which might have

1. Yellen (1989) offers an insightful and more thorough critique of the Blanchard and Diamond paper. Many of the points she makes apply to the Davis and Haltiwanger paper as well.
2. The Blanchard-Diamond analysis requires information on job vacancies; no job vacancy proxy is available for the manufacturing sector. Davis and Haltiwanger's job creation and job destruction data are not available outside of manufacturing.

made aggregate shocks look more important than they would have had the analysis covered a longer time period. The obvious way to resolve this issue would be to replicate the Blanchard-Diamond analysis for the shorter period for which the Davis-Haltiwanger data are available.

A third difference between the two papers is that, whereas Blanchard and Diamond used seasonally adjusted data, Davis and Haltiwanger use seasonally unadjusted data. One might ask whether the use of adjusted or unadjusted data is a better choice. My own inclination is to think that, because seasonal demand movements may produce quite different responses than other, less predictable movements in either relative or aggregate demand, their effects ought to be modeled separately or, perhaps as a second-best alternative, be removed from the data before analysis begins.

The more pertinent question for present purposes, however, is how the use of seasonally unadjusted data affects the estimated relative importance of allocative and aggregate shocks. In essence, the answer to this question depends on the relationship between the seasonal components of job creation (POS) and job destruction (NEG). If the seasonal components of POS and NEG are positively correlated, an analysis based on seasonally unadjusted data will assign relatively greater importance to allocative shocks than would an otherwise identical analysis based on seasonally adjusted data; if the seasonal components in POS and NEG are negatively correlated, an analysis based on seasonally unadjusted data will assign relatively greater importance to aggregate shocks. The information presented in the Davis and Haltiwanger paper does not make it obvious to me whether the seasonal components in POS and NEG are positively or negatively correlated, so that I cannot tell whether their use of seasonally unadjusted data helps to explain the difference between their findings and those reported by Blanchard and Diamond.<sup>3</sup> This is, however, something that would be easy to investigate.

A more fundamental difference between the two papers is that, whereas Blanchard and Diamond used data on labor market stocks (vacancies and unemployment), Davis and Haltiwanger use data that comes closer to capturing labor market flows (job creation and job destruction, defined as the sum of net changes in employment at establishments that grew and the sum of net changes in employment at establishments that shrank between one quarter and the next). Although both papers talk about vacancies and unemployment, on the

3. The fact that the negative correlation between POS and NEG reported in Table 1 is weaker in quarterly than annual data is consistent with the seasonal components in these series being positively correlated, but could also simply reflect the presence of greater noise in the quarterly series.

one hand, and job creation and job destruction, on the other, as though they are much the same thing, in fact there is good reason to think that the effects of both allocative and aggregate shocks on labor market stocks might be quite different than their effects on the corresponding labor market flows.

Think first about the effects of an aggregate shock that leads to a decrease in the rate of job creation and an increase in the rate of job destruction. A consequence of the decline in vacancy inflows and increase in unemployment inflows produced by such an aggregate shock is that the vacancy to unemployment ratio will fall. This, in turn, will affect both vacancy and unemployment durations. Standard matching models imply that a decline in the vacancy to unemployment ratio will lead to job vacancies being filled more quickly than they otherwise would have been, and to unemployed people remaining without a job longer than they otherwise would have. Since the stock of vacancies is the product of the vacancy inflow rate and average vacancy duration, this implies that a negative aggregate shock can be expected to reduce the stock of vacancies proportionately more than it reduces the vacancy inflow rate. By similar reasoning, a negative aggregate shock can be expected to raise the stock of unemployment proportionately more than it raises unemployment inflows. A positive aggregate shock should, by the same logic, have proportionately larger effects on vacancy and unemployment stocks than on the corresponding vacancy and unemployment inflows.

The analysis of an allocative shock is somewhat more complex, primarily because the effects of such a shock on the vacancy to unemployment ratio, and thence on vacancy and unemployment durations, cannot be determined unambiguously. Consider, for example, the effects of an allocative shock that raises both the rate of job creation (vacancy inflows) and the rate of job destruction (unemployment inflows). Whether the initial effect of these increased inflows is to raise or lower the vacancy to unemployment ratio depends on whether the increase in vacancy inflows is larger or smaller relative to the initial stock of vacancies than is the increase in unemployment inflows to the initial stock of unemployment. Davis and Haltiwanger believe that allocative shocks raise vacancy inflows less than unemployment inflows, at least initially, but the stock of vacancies is also typically much smaller than the stock of unemployed persons (see Abraham 1983). This means that an allocative shock might either decrease or increase the vacancy to unemployment ratio. A reasonable guess might be that, on average, allocative shocks have no effect on the vacancy to unemployment ratio, so that they do not affect average vacancy and unemployment durations. This would imply that, again on

average, allocative shocks have the same proportional effects on vacancy and unemployment stocks as on job creation and job destruction.<sup>4</sup>

The discussion thus far leads to two conclusions. First, there is good reason to believe that aggregate shocks have a larger proportional affect on vacancy and unemployment stocks than on job creation and job destruction. Second, it is at least reasonable to suppose that the proportional effects of allocative shocks on vacancy and unemployment stocks are roughly equal to their effects on job creation and job destruction. The implication is that we should expect aggregate shocks to explain relatively more, and allocative shocks relatively less, of the variation in vacancies and unemployment studied by Blanchard and Diamond than of the variation in job creation and job destruction studied by Davis and Haltiwanger.

A further consideration is that, even if allocative shocks always have the same effects on job creation (vacancy inflows) and job destruction (unemployment inflows), they will not always have the same effects on vacancy stocks and unemployment stocks. This is because vacancy and unemployment stocks are the product of inflow rates and durations; vacancy and unemployment durations depend on the vacancy to unemployment ratio; and the effect of a given allocative shock on the vacancy to unemployment ratio depends on the initial stocks of vacancies and unemployment, which may vary considerably from one point in time to another. It seems possible that, even if allocative shocks had generally similar effects on vacancies and unemployment as on job creation and job destruction, the former might be more difficult to identify in the data than the latter. All this suggests that the distinction between the behavior of stocks and the behavior of flows may provide at least a partial explanation for the differences between the Davis-Haltiwanger and the Blanchard-Diamond results.

Neither I nor its authors would conclude that the Davis-Haltiwanger paper has closed the ongoing debate over the respective contributions of allocative and aggregate shocks to macroeconomic fluctuations. Their paper has, however, certainly introduced important new evidence that any future research on this subject will have to take into account.

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4. Note that the implicit model here is one in which allocative shocks affect only the inflows of vacancies and unemployment, and not the fit between vacant jobs and unemployed persons. A more complex characterization of allocative shocks could well lead to a different conclusion.

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## Comment

ROBERT M. TOWNSEND

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One enjoys this paper by Davis and Haltiwanger for the three things it tries to accomplish: (1) it is explicit about microeconomic underpinnings for macroaggregate phenomena; (2) it goes out and gathers new evidence, specifically that beyond aggregate employment and unemployment statistics there is great turbulence in employment at the level of manufacturing establishments; and (3) it begins to set up explicit prototypes with these microunderpinnings, built up around the evidence. My best tribute to this work is to take seriously the prototypes that are suggested. I try to do this in three ways. First, I argue that the prototypes can be made more operational, that it is possible to compute entire solutions paths. Second, the prototypes can be made more realistic; crucial missing features can be added. Third, and related, I complain that the authors themselves do not take this class of models seriously enough. They shy away from an explicit analysis of policy, yet there are various key social issues that cry out for a research program that is not unrelated to that envisioned by the authors.

I begin by describing the first, basic prototype model of the paper, so that we have a clear picture of the economy envisioned by the authors. Basic computational issues can be addressed as well in this simple framework. Next, following the authors, I add labor supply, though the model here is an alternative envisioned by the authors but not analyzed by



them. Here, there are firm specific shocks to labor demand, not household specific shocks to labor supply. In either setup with labor supply the complication is to retain the “representative consumer” construct even though there is explicit diversity across firms or households. But this can be done in the space of fractions or lotteries. At the same time, that space facilitates computation. Finally, I show that the prototype economy with labor supply can accommodate information and incentive problems. This will lead to a discussion of some policy issues.

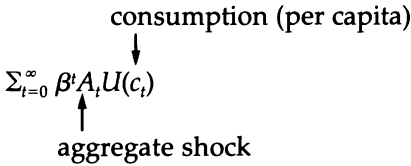
The basic state variable of the simplest prototype is  $H_t$ , the fraction of workers matched to high-productivity sites at the very beginning of date  $t$ . There is one worker per site, and output if produced there, assuming the high-productivity status is retained would be  $Y_H$ . Fraction  $1 - H_t$  workers are matched with low-productivity sites at the very beginning of date  $t$ , and output if produced there, assuming the worker stays, would be  $Y_L$ . At the next instant of date  $t$ , though, fraction  $\sigma_t$  of the high-productivity sites become low-productivity sites (fraction  $1 - \sigma_t$  of the high-productivity sites remain high). This then forces a decision about  $\theta_t$ , the fraction of workers at low-productivity sites who are to abandon production and move onward to high-productivity sites, arriving at the very beginning of date  $t + 1$ . All this notation can be understood, then, by law of motion of state variable  $H_t$ , namely,

$$\begin{array}{c}
 \text{old lows at } t \quad \text{new lows} \\
 \phantom{H_{t+1} = (1-\sigma_t)H_t + \theta_t[1-H_t + \sigma_t H_t].} \quad \downarrow \quad \downarrow \\
 H_{t+1} = (1-\sigma_t)H_t + \theta_t[1-H_t + \sigma_t H_t]. \quad (1) \\
 \phantom{H_{t+1} = (1-\sigma_t)H_t + \theta_t[1-H_t + \sigma_t H_t].} \quad \uparrow \quad \uparrow \\
 \text{remaining} \quad \text{fraction of those who move} \\
 \text{high at } t \quad \text{at } t \text{ to high sites at } t+1
 \end{array}$$

To retain feasibility there must be a shadow, “unused” high-productivity site for every low-productivity site in the model. That is, it must be feasible to reallocate all workers in low-productivity sites to as yet unused high-productivity sites. For example, imagine there are 10 high-productivity sites at the beginning of date  $t$ , and 15 low-productivity sites. Among the highs, three revert to low productivity in the next instant; these sites are, in effect, “reallocated” to the low-productivity sector, though the movement is in the sense of accounting, not locations. In the low-productivity sector itself, four sites are to be abandoned. The four released workers from these abandoned sites are destined for the “shadow” high sector, consisting now of 15 old shadow highs plus the new three shadow highs. Note that the model thus has a symmetric, “bad news, good news” aspect. Shocks  $\sigma_t$  that turn high-productivity sites into low-productivity sites also create new high-

productivity opportunities elsewhere. Hence the term, “reallocation shocks”  $\sigma_t$ .

Each and every household in the economy maximizes a discounted time-separable utility function.



Here  $A_t$  is an aggregate demand shock at date  $t$ ; when it is high it adds to the utility of consumption  $c_t$ . Note that all households are identical in preferences  $U(\cdot)$ , shocks  $A_t$ , and discount rate  $\beta$ . Different households may have different names, but they are to be treated alike nonetheless. The task then is to find a symmetric Pareto optimum.

For per capita consumption  $c_t$  to be feasible it must satisfy the resource constraint, that output from operational high-production sites and operational low-production sites sum to it, namely:

$$c_t = (1 - \sigma_t)H_t \cdot Y_H + [1 - H_t + \sigma_t H_t](1 - \theta_t)Y_L. \tag{2}$$

↓ producing high      ↓ not moving so producing low

The prototype can thus be summarized by a functional equation:

$$V(H_t, \sigma_t, A_t) = \max_{\theta_t} \{AU(c_t) + \beta E V[H_{t+1}, \sigma_{t+1}, A_{t+1}]\}. \tag{3}$$

Utility is maximized by choice of  $\theta_t$  at each date  $t$ , conditioned on the state variable  $H_t$ , reallocation shock  $\sigma_t$ , and aggregate shock  $A_t$ . Equation (2) can be substituted into  $c_t$  at date  $t$  and law of motion (1) for  $H_{t+1}$  can be embedded into future  $V(\cdot)$ .

Davis and Haltiwanger do some comparative static exercises on this model, asking what happens at date  $t$  (only) conditioned on shocks  $\sigma_t$  and  $A_t$ . Outcomes from some of the experiments can be signed, but some cannot. The obvious suggestion, though, is to compute the full dynamic stochastic equilibrium. This can be done in two ways.

First, imagine that  $H_t$  can take on a finite though large number of values. Also, let  $\sigma_t$  and  $\theta_t$  take on at most finite number of values as well, and suppose these are such that given a finite set of potential values of  $H_t$ , the set of values  $H_{t+1}$  is the same set of potential values. This grid technique has been used successfully by Sargent (1979) in a different

context. In any event, with  $A_t$  finite as well, value function  $V(\cdot)$  is then a finite dimensional vector. One need only make an initial guess for  $V$  on the right-hand side of (3); solve the maximum problem in (3) for  $\theta_t$  given each  $H_t$ ,  $\sigma_t$ , and  $A_t$  combination; substitute the maximized solution into the objective function of (3); solve for  $V$  on the left-hand side; and finally iterate with this as a new guess for  $V$  on the right-hand side. This method of computing the value function  $V$  converges, and at the converged solution the method will dictate a choice of  $\theta_t$  as a function of  $H_t$ ,  $\sigma_t$ , and  $A_t$ . This policy rule will be fully optimal for the explicit infinite horizon stochastic dynamic program.

An alternative technique has been pursued by Coleman (1987) in a different context. Imagine  $H_t$  can take on a continuum of values after all. Then go to first-order equation 7, p. 23.

$$A_t U'(c_t) = \beta E[(1 - \sigma_{t+1})(Y_H/Y_L)A_{t+1}U'(c_{t+1})|A_t, \sigma_t]. \quad (4)$$

Take a guess for next period's policy function by naming a value for  $\theta_{t+1}$  at each of a *finite* number of values for  $H_{t+1}$  and given  $\sigma_{t+1}$  and  $A_{t+1}$ . Interpolation, connecting the dots as it were, describes a policy function over the entire range of  $H_{t+1}$ . Now solve first-order condition (4) for each  $\sigma_t$  and  $A_t$  at each of the finite number of values for  $H_t$ , finding the maximizing value of  $\theta_t$ . This, with interpolation as above, gives a policy function for the next iteration. In other contexts, such as Coleman's, this numerical technique converges fast and is not sensitive to the number of grid points of  $H_t$  used for interpolation.

The point is that after choosing parameters for utility functions, discount rates, shock process, and the like, one can simulate entire dynamic paths. One just takes random draws off the supposed stochastic processes for  $A_t$  and  $\sigma_t$  and substitutes these into the compound optimal policy function. With these one can generate all time series and thus get explicit vector autoregressions without the need for identifying assumptions. Innovations in the stochastic processes for  $\sigma_t$  and  $A_t$  are directly linked to innovations in all derived, economic variables. Innovation experiments can trace out all relevant dynamics. I confess to being very curious about what these paths would look like.

Having solutions in hand, however, would beg some further important issues. In particular, what are the key features of the model and of the data that one is trying to match. The model as it stands literally has only job destruction and new job creation, because labor is as yet inelastic. Related, people either work or search; employment in this broader sense is constant. Finally, the model has a strong persistence characteris-

tic: new high-productivity jobs are as likely to crash as old ones. I'm not sure this last feature is matched in the data. The first two features definitely are not.

Troubled by some of these features, Davis and Haltiwanger add labor supply to the model, with utility for leisure entering linearly and subject to a stochastic shock. Here, let us take a somewhat different route, allowing a (common) concave nonseparable utility function for consumption and leisure but supposing output in each plant is random, even across plants in the high- (or low-) productivity sectors.

The revised model must distinguish different labor supply numbers across different households, distinguished at least by sector and search status. So let the utility functions and allocations take the form

$$AU(c, T - a_H) \quad AU(c, T - a_L) \quad AU(c, T - S)$$

in the high- and low-productivity sectors and in search status mode, respectively. Here  $T$  is a common time endowment,  $a_H$  is hours for each worker in operational high-productivity sites,  $a_L$  is hours for each worker in operational low-productivity sites, and  $S$  is a fixed number of hours lost for those engaged in "search" or reallocation.

A priori every one is to be treated equally. Initially, then, one would just maximize the sum of all agents' utilities. But as the economy evolves, people move around. In particular,  $\theta_t$  represents the fraction of households in the low-productivity sector who move, changing the count of the number of households in each sector. Still, one can also let  $\theta_t$  be the *probability* that it will be moved from the point of view of a household in the low-productivity sector. Then I have verified that the equal-weight Pareto optimum with utility over the explicit dynamic paths can be reduced into looking like the value function of a representative consumer. Namely,

$$V(H_t, \sigma_t, A_t) = \underset{a_{HT}, a_{LT}, \theta_t}{Max} \{ (H_t - \sigma_t H_t) AU(c, T - a_H) + (1 - H_t + \sigma_t H_t) [\cdot] + \beta EV(H_{t+1}, \sigma_{t+1}, A_{t+1}) \} \tag{5}$$

where

movers



$$[\cdot] = [(1 - \theta_t) AU(c, T - a_L) + \theta_t AU(c, T - S)]$$



fraction not moving conditioned on being in low sector

(6)

subject to law of motion (1) and to a resource constraint

$$c = (1 - \sigma_t) H_t f(a_{Ht}) \quad + \quad (1 - H_t + \sigma_t H_t)(1 - \theta_t) f(a_{Lt}).$$

$\downarrow$   
 output from highs

$\downarrow$   
 output from lows

A problem with the value function (5) as it is written is that moving is a lumpy decision variable. A household is to move or not, though one can see from dot expression in (6) that the random variable  $\theta_t$  smooths over this decision at the household level. Similarly, one is either in one sector or another, or in the search mode, and this may be “lumpy” because labor supply decisions vary over the three states. In short, the programming problem is not concave. But, this can be remedied by appropriate use of fractions or randomization.

In particular, let  $\pi_H(a, q, c)$  denote the fraction of households in the high-productivity sector who are to be assigned labor action  $a$ , who are to suffer output  $q$  (recall this is random), and to receive consumption  $c$ . Of course, output is determined by nature, probabilistically. That is, let  $\bar{\pi}_H(q|a)$  denote the fraction of households in the high-productivity sector getting output  $q$  when action  $a$  is taken. To respect this one can impose a simple linear equality on endogenous choice variables  $\pi_H(a, q, c)$ , namely:

$$\sum_c \pi_H(a, q, c) = \text{Prob}(a, q) = \bar{\pi}_H(q|a) \sum_{q,c} \pi_H(a, q, c). \tag{7}$$

For the low-productivity sector let  $\pi_L(a, q, c|m=0)$  denote the fraction of households assigned labor action  $a$ , suffering output  $q$ , and getting consumption  $c$ , conditioned on not moving,  $m=0$ . Also, one can impose a constraint like (7) for  $\pi_L(a, q, c)$ . Finally, let  $\pi_m(c|m=1)$  denote the fraction of movers getting consumption  $c$ , and let  $\pi(m-1)=\theta$  denote the fraction of agents moving, the already familiar random variable  $\theta$ . From the individual household’s point of view, *all* the fractions represent probabilities.

With this notation the program for the determination of an equal weight Pareto optimum is to choose

$$\pi_{Ht}(a, q, c), \pi_{Lt}(a, q, c|m=0), \pi_{mt}(c|m=1), \theta_t = \pi(m-1).$$

To maximize:

$$V(H_t, \sigma_t, A_t) = \{ (H_t - \sigma_t H_t) [\sum_{a,q,c} AU(c, T-a) \pi_{Ht}(a, q, c)] + (1 - H_t + \sigma_t H_t) [\cdot] + \beta EV[H_{t+1}, \sigma_{t+1}, A_{t+1}] \} \tag{8}$$

where

$$[\cdot] = [\pi(m=0) \sum_{a,q,c} AU(c, T-a) \pi_{Lt}(a, q, c|m=0) + \pi_t(m=1) \sum_c AU(c, T-S) \pi_{mt}(c|m=1)]$$

subject to (7) and its analogue for  $\pi_{L_t}(\cdot)$  and to a resource constraint, namely, consumption = output:

$$H_t(1 - \sigma_t) \sum_{a,q,c} (c - q) \pi_{H_t}(a, q, c) + (1 - H_t + \sigma_t H_t) [\pi_t(m=0) \sum_{a,q,c} (c - q) \pi_{L_t}(a, q, c | m=0) + \pi_t(m=1) \sum_{c} \pi_{m_t}(c | m=1)] = 0. \quad (9)$$

A strategy for computing solutions to this program is suggested by what we have done before. Like  $H_t$  take on a finite number of values as before. Then take a guess for  $V$  on the right-hand side of (8). Next, fix decision variable  $\theta_t = \pi_t(m=1)$  at some arbitrary value. At this point, one can solve the program above as a linear program. That, among other things, is one of the virtues of the lottery program. Finally, one can check all the others of a finite number of possible values for decision  $\theta_t$ . Picking the best decision delivers a new guess for value function  $V$ . One then should be able to iterate as before.

At this point we should ask a basic question: Do we really believe this prototype captures important features of the U.S. economy? That is, should we take solutions to the prototype seriously? Three objections come readily to mind.

First, the data is about employment in the manufacturing sector only, whereas in the United States there has been a trend away from manufacturing toward the service sector. This is more than apparent in inner-city neighborhoods like those of Chicago where unemployment has increased and incomes have decreased.

Second, job matching is modeled here as a simple one-period lag. There is no search per se and no variation in search unemployment. Nothing much about the search process feeds back to the individual decision problem. Frictions in the labor market, emphasized by Blanchard and Diamond (1989), are missing from the model (though one can begin to think up obvious remedies, while retaining the basic prototype).

Third, the model makes a strong prediction about consumption profiles in the population at a point: they are completely flat. A household's consumption is independent of which sector it is in. At most per capita consumption fluctuates over time with the state of the aggregate economy.

I am not inclined to believe this third feature of the model, the so-called full-insurance implication. A model with private information on labor effort seems much more appealing a priori, something that would make household consumption fluctuate with household income. This would give households an incentive to work hard by penalizing households who suffer low outputs. Indeed, a related prototype of Phelan (1989) is essentially the model here with one sector only and no aggre-

gate shocks. Essentially, one need only add an incentive constraint to induce households to take action  $a$  over any other action  $\bar{a}$ , namely,

$$\sum_{q,c,w'} \{U(c,t,a) + \beta w'\} \pi_i(a,q,c,w')$$

$$\geq \sum_{q,c,w'} \{U(c,T-\bar{a}) + \beta w'\} \pi_i(\bar{a},q,c,w') [\bar{\pi}(q|\bar{a})/\pi(q|a)] \quad (10)$$

for all actions  $a$  and  $\bar{a}$  in some set  $A$ , with  $w'$  as expected utility from next period on.

Phelan's model delivers a nontrivial, nonflat distribution of consumption and labor supply in the population. Related, it delivers time variation in consumption and labor efforts for each household, as households are rewarded or penalized for high and low outputs. In other words, it delivers a nontrivial level of gross employment changes and gross consumption changes at the microlevel even without aggregate shocks. Finally, average productivity is lower than in the analogue model with no incentive problem, in the model without (10).

A two-sector model with private information would force one to come to grips with some basic informational issues. One can imagine, for example, that labor effort remains unobserved as in the private information prototype above, but that the identity of one's sector as well as aggregate shocks  $\sigma_t$  and  $A_t$  are fully observed. But one guesses for that information specification that consumption fluctuations would not be closely linked to sector-specific shocks  $\sigma_t$ . That is, being moved from one sector to another would not necessarily cause a household's consumption to fluctuate beyond the effect that publicity observed variables have on everyone. Yet we see in PSID data the effect documented by Cochrane (1989): workers who experience layoffs with protracted job search are those who experience diminished growth in consumptions.

If the identity or productivity of one's plant or sector is private information, along with labor effort, then productivity shocks  $\sigma_t$  would not be so well insured. Still, in the determination of an information-constrained optimum one would search ruthlessly for all random variables that might be revealing of these productivity shocks. Can anything much be inferred from firms "nearby," distinguished by location or production line? Davis and Haltiwanger suggest the answer may be no, that most of the fluctuations at the establishment level are idiosyncratic. This could be one of their most important findings.

An extended private information prototype would guide one in how

to measure and quantify idiosyncratic and common components, would guide one in attempts to answer the question of whether there is any local, product line, or sector-specific information that is utilized or could be utilized to alleviate incentive problems. Indeed, we can ask whether observed fluctuations in employment and consumption are informationally constrained efficient. It is conceivable that the answer may be no, that unemployment insurance and other schemes might be modified in such a way as to reduce incentive problems. If so it seems this could increase average production and consumption, and reduce fluctuations in leisure and consumption. This possibility is something Pigou (1929) took seriously in his early treatment of industrial fluctuations. It is something one is led to naturally from consideration of the microunderpinnings for macroeconomic phenomena.

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## Discussion

Martin Eichenbaum suggested that seasonal shocks were allocative shocks, so that the authors should leave them in the empirical work. He also wondered whether the model implies a linear VAR structure like the authors estimated.

Peter Diamond noted that the discrete sampling of data made it hard to infer flows of workers and vacancies from data on job creation and destruction. He also suggested that job creation need not lag behind job destruction if the allocation is in response to a positive productivity shock. Finally, he suggested similar government policies can have aggregate and allocative effects so that just differentiating between the types of shocks did not yield any implications about optimal government policy.

Ben Bernanke suggested that data on accessions and separations



would be useful to add because they provide information on worker flows in addition to the flow of jobs. Davis replied that they were interested in the flow of jobs in addition to the flow of workers.

Davis closed by noting that the authors planned in future work to examine the sources of heterogeneity within a sector in more detail.