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**GROSS JOB CREATION AND DESTRUCTION:  
MICROECONOMIC EVIDENCE AND  
MACROECONOMIC IMPLICATIONS\***

by

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### Abstract

This paper investigates the connection between the heterogeneity of establishment-level employment changes and aggregate fluctuations at business cycle frequencies. The empirical work exploits a rich data set with approximately 860,000 annual observations and 3.4 million quarterly observations on 160,000 manufacturing establishments to calculate rates of gross job creation, gross job destruction, and their sum, gross job reallocation. The central messages that emerge from the research in this paper are: (1) Establishment-level employment changes exhibit tremendous heterogeneity, even within narrowly defined sectors of the economy. This heterogeneity manifests itself in terms of high rates of gross job creation, destruction, and reallocation. Further, the magnitude of this heterogeneity varies significantly over time, most of the variation is due to time variation in the idiosyncratic component of establishment growth rates, and the variation is significantly countercyclical. (2) The theoretical model of employment reallocation and business cycles is suggestive of how both aggregate and allocative disturbances can drive fluctuations in job creation, job destruction, unemployment, productivity, and output. (3) The empirical analysis of the joint dynamics of job creation and job destruction supports 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.

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## I. 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 aggregative 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 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 fifteen-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. 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 high-productivity job sites 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 upon 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 result 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 (i) our measure of gross job reallocation captures shifts in the distribution of employment opportunities across establishments within sectors, and because (ii) 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 measures of gross job reallocation in simple regression models. For the regression analysis, our basic measure of job reallocation is the idiosyncratic component of total job reallocation. We also consider 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 third approach, 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 reallocation 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.

## II. Basic Facts about Gross Job Creation and Destruction

### *A. 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 Datafile (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 one percent 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 which 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 to 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 non-certainty 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 non-certainty 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 establishments. 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 non-continuing 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.

### B. 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,  $X_{st}MAX_{st} = X_{st}\text{Max}\{POS_{st}, NEG_{st}\}$  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 by job reallocation but by 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.

### *C. 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 in the manufacturing sector. Table 1 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 the various measures. Figure 1 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 the time series of box plots of the establishment growth rate density.) Evidently, this mean-translation effect is the 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 data, 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>

#### *D. Accounting for Time Variation in Job Destruction, Creation and Reallocation*

Consider the linear model for establishment-level growth rates

$$g_{et} = \tilde{g}_{et}^{ST} + g_{st} + g_t, \quad (1)$$

where  $g_t$  is the aggregate growth rate,  $g_{st}$  is the sector growth rate (deviated about the aggregate growth rate), and  $\tilde{g}_{et}^{ST}$  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,  $\tilde{g}_{et}^{ST}$ , 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  $\tilde{g}_{et}^{ST}$ .

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 the aggregate-time effects. This view encompasses a time-invariant, but possibly large,

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<sup>1</sup>Note that  $\text{COV}(NET_t, SUM_t) = V(POS_t) - V(NEG_t)$ . Thus, a negative correlation between  $NET_t$  and  $SUM_t$  means that the time-series variability of  $NEG_t$  exceeds that of  $POS_t$ . 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 than can be explained by aggregate-time and sector-time effects.

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 non-systematic 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,  $\widetilde{SUM}_t^{ST}$  measures the gross rate of

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

Now consider the identity

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

which implies the variance decomposition for gross job reallocation,

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

If the distribution over the  $\tilde{g}_{et}^{ST}$  is time-invariant, then the ratio of  $\text{Var}(\widetilde{SUM}_t^{ST})$  to  $\text{Var}(SUM_t)$  equals zero. Conversely, a large value for this ratio indicates that time variation in the cross-sectional variance (and higher moments) of  $\tilde{g}_{et}^{ST}$  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,  $\widetilde{SUM}_t^{ST}$  is immune to the criticisms that Abraham and Katz (1986) directed towards Lilien's (1982a) dispersion measure, because it accommodates arbitrary mean sectoral responses to aggregate disturbances. That is, conditional on the sectoral classification scheme,  $\widetilde{SUM}_t^{ST}$  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 industry sectoral classification.<sup>2</sup> The time-series variance of the raw measures appears in panel A. The next several 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 five percent of the time variation in annual gross job reallocation. If we attribute all of the covariance term to the aggregate-time and sector-time effects, they account for at most twelve percent of time variation in annual gross job reallocation. Panel C shows a similarly small contribution of aggregate-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 three percent 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. Further, 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

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<sup>2</sup>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 of gross job reallocation is countercyclic also holds up under the alternative sectoral classification schemes.

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 moves countercyclically.

#### *E. 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 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 co-movements 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  $\widetilde{SUM}_{st}^{ST}$  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

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<sup>3</sup>The finding of positive comovement across industries and negative comovement within industries may be linked to the recent ideas in the macro externalities literature (see, e.g., Cooper and Haltiwanger (1989)) that cross sector interactions exhibit complementarities while within sector interactions exhibit substitutibilities. More discussion of the role of macro externalities for the time patterns of job creation and destruction is provided below.

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 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.

#### *F. 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. Further, 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? (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.

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<sup>4</sup>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 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 because it indicates that our measured time variation in gross job creation and destruction is unlikely to be driven by 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  $FPOS_{tn}$  equal the fraction of newly-created jobs at time  $t$  that continue to exist through periods  $t + 1, t + 2, \dots, t + n$ . Define  $FNEG_{tn}$  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 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 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.

### *G. 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: (i) gross job reallocation exhibits considerable time variation, (ii) the idiosyncratic component of establishment-level employment changes explains virtually all of the time variation in gross job reallocation, and (iii) the idiosyncratic component of gross job reallocation exhibits significant countercyclic variation.

## III. Employment Reallocation and Business Cycles

### *A. A Prototype Model*

Motivated by the empirical findings in section II, 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 they produce zero otherwise. *Operational* high-productivity sites produce  $Y_H$  units when matched with one worker, where  $Y_H > Y_L > 0$ . For a high-productivity site to become operational 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; or (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

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

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 non-operational, 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 multi-good model.

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

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

where the Markov processes satisfy

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

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

### *B. 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

$$\begin{aligned}
 V(H, A, \sigma) = \max_{\theta \in [0, 1]} & \{AU[(1 - \sigma)Y_H H + (1 - H + \sigma H)(1 - \theta)Y_L] \\
 & + \beta E[V((1 - \sigma)H + \theta(1 - H + \sigma H), \tilde{A}, \tilde{\sigma})|A, \sigma]\}.
 \end{aligned}
 \tag{4}$$

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

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

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

*Proof:* The hypotheses of Theorems 9.6-9.8 and 9.10 in Stokey and Lucas (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

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

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  $\tilde{H}$ ,

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

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  $H$  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 of poorly-matched workers who move 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,

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

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  $(1 - \tilde{\sigma})$ .

### *C. 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: (i) investment in activities (i.e., reallocation) that yield improved future production possibilities are not measured as part of current output, and (ii) the tradeoff 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.

#### *D. 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 marginal 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.

#### *E. 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

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

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

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

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 multi-good 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.

#### IV. 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 job destruction.

Let  $Y_t = [POS_t, NEG_t]'$  be the vector composed of job creation and destruction. Further, 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:

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

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 III 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 innovation 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. Further, 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  $b_{0p}$  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 upon 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  $(b_{0p}, b_{0n})$  gives the other element of the pair. Accordingly, we assume  $b_{0n}$  is greater than one and then consider resulting pairs of the parameters such that (i)  $b_{0p}$  is less than one in absolute magnitude; (ii) 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: (i) zero correlation between aggregate and allocative innovations; (ii) both  $b_{0p}$  and  $b_{0n}$  are positive; (iii) aggregate innovations affect *POS* and *NEG* in opposite directions for at least  $k$  periods; and (iv) 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 job 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 own 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  $b_{0n}$  is greater than one and  $b_{0p}$  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  $b_{0n}$  equal to 1.0 implies a value of  $b_{0p}$  equal to 0.30 which is in the permissible range. As we increase the choice of  $b_{0n}$  the value of  $b_{0p}$  increases monotonically. At  $b_{0n} = 2.0$  the implied  $b_{0p} = 0.61$  and at  $b_{0n} = 3.3$  the implied  $b_{0p}$  just exceeds 1.0. Accordingly, in terms of these

identifying restrictions alone, the permissible range of the pair  $(b_{0n}, b_{0p})$  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  $b_{0p}$  is positive and monotonically increases with  $b_{0n}$ . That  $b_{0p}$  is positive suggests that 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). Further, the positive relationship between  $b_{0n}$  and  $b_{0p}$  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  $b_{0n}$  and  $b_{0p}$  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  $b_{0n} = 2.0$  with an implied value of  $b_{0p} = 0.61$ .

Figure 3 plots the impulse responses for the benchmark case. By construction, 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 job destruction around zero. Turning to allocative shocks, an allocative innovation generates a sharp increase in job destruction for 2-3 quarters 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 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.

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<sup>5</sup>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 values 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.

## V. 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 II show significant countercyclic variation in the idiosyncratic component of gross job reallocation. Our empirical results in section IV 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 to 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 II, 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.

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<sup>6</sup>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 addition of these regressors had little impact on the coefficients and standard errors of the idiosyncratic component.

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 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 (and 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,  $\widetilde{SUM}^{OIL}$ , and the part orthogonal to movements in the oil price growth rate,  $\widetilde{SUM} - \widetilde{SUM}^{OIL}$ . We interpret  $\widetilde{SUM} - \widetilde{SUM}^{OIL}$  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 non-oil 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 IV. 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,  $SUM^{AGG}$ .

<sup>7</sup>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 twelve-month interval. See the Data Appendix for more details.

<sup>8</sup>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 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 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.

## VI. Concluding Remarks

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

- (1) 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.
- (2) 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.

- (3) 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

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<sup>9</sup>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.

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.

- (4) 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.
- (5) Our analyses of the joint dynamics of job creation and destruction in section IV 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. Further, our unemployment regression results in section V 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 databases.

## Data Appendix

Most of the measures used in this paper are from the LRD described in section II.A. 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: 1st quarter (change from November of previous year to February of current year); 2nd quarter (change from February to May); 3rd quarter (change from May to August); 4th quarter (change from August to November). For a more complete description of the LRD, we refer the reader to Davis and Haltiwanger (1989) and Davis, Haltiwanger and Schuh (1990).

For the analysis in section V 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 number 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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TABLE 2  
Variance Ratios<sup>1,2</sup>

X -

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

<sup>1</sup>See text for explanation. Superscript definitions: I2 - 2-digit industry.

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

TABLE 3

## Comovements Between Net Job Growth and Adjusted Gross Job Reallocation

Summary Statistics on Time Series Correlation of  $NET_{st}$  with:

| Sector S:                                       | $\underline{SUM}_{st}$ | $\underline{SUM}_{st}^T$ | $\underline{SUM}_{st}^{ST}$ | $\underline{NET}_t$ |
|---|------------------------|--------------------------|-----------------------------|---------------------|
| <u>2-digit SIC</u>                              |                        |                          |                             |                     |
| 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                |
| <u>2-digit (continuing establishments only)</u> |                        |                          |                             |                     |
| 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                |
| <u>2-digit (quarterly measures)</u>             |                        |                          |                             |                     |
| 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.

TABLE 4

Regression of Adjusted Gross Job Reallocation on Own-Sector  
and Manufacturing Net Growth

Dependent Variable:  $\bar{S}UM_{st}^{ST}$

Sector S:

| Regressor:   | <u>2-digit</u>                 | <u>2-digit<br/>(Continuing<br/>Establishments<br/>Only)</u> | <u>2-digit<br/>Quarterly<br/>Measures</u> |
|--|--------------------------------|---|---|
| $g_{st}$   | -0.221<br>(0.049) <sup>2</sup> | -0.174<br>(0.052)   | 0.074<br>(0.076)                          |
| $g_t$  | -0.225<br>(0.024)              | -0.203<br>(0.024)   | -0.458<br>(0.043)                         |
| Other Summary Statistics:  |                                |   |   |
| $R^2$ (including<br>contribution of<br>fixed effects)              | 0.78                           | 0.75  | 0.49                                      |
| $R^2$ (excluding<br>contribution of<br>fixed effects)              | 0.27                           | 0.30  | 0.10                                      |
| #Obs   | 220                            | 220   | 1180                                      |
| Difference in<br>coefficient on<br>$g_{st}$ and $g_t$ <sup>3</sup> | 0.004<br>(0.946)               | 0.029<br>(0.448)  | 0.384<br>(0.000)                          |
| Mean ( $\bar{S}UM_{st}^{ST}$ )                                     | 0.202                          | 0.156   | 0.113                                     |
| Std. Dev. ( $\bar{S}UM_{st}^{ST}$ )                                | 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.

TABLE 5

## Partition of Gross Job Creation and Destruction by Year

|       | Job Creation Accounted for<br>by establishments with growth<br>rates in the interval: |           |                   | Job Destruction Accounted for<br>by establishments with growth<br>rates in the interval: |             |                              |
|-------|---|-----------|-------------------|--|-------------|------------------------------|
|       | $g_{et}$ scale:   |           |                   |  |             |                              |
|       | [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] |
| Year: |   |           |                   |  |             |                              |
| 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                        |

TABLE 6

## Persistence of Gross Job Creation and Destruction

Annual Measures

| Year: <sup>1</sup> | Fraction of Job Creation<br>in Year t that persists<br>in Year: |            | Fraction of Job Destruction<br>in Year t that persists<br>in Year: |            |
|--------------------|---|------------|--|------------|
|                    | <u>t+1</u>  | <u>t+2</u> | <u>t+1</u>   | <u>t+2</u> |
| 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   | --         |

Quarterly Measures

|                                      | Fraction of Job Creation<br>in Quarter t that<br>persists in Quarter: |            |            |            | Fraction of Job Destruction<br>in Quarter t that<br>persists in Quarter: |            |            |            |
|--------------------------------------|---|------------|------------|------------|--|------------|------------|------------|
|                                      | <u>t+1</u>  | <u>t+2</u> | <u>t+4</u> | <u>t+8</u> | <u>t+1</u>   | <u>t+2</u> | <u>t+4</u> | <u>t+8</u> |
| Time Series Mean                     | 0.72  | 0.59       | 0.40       | 0.26       | 0.75   | 0.64       | 0.51       | 0.44       |
| Time Series<br>Standard<br>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  $POS_t$  and  $NEG_t$  series.

TABLE 7  
Variance Decompositions<sup>1</sup>

| <u>Variable</u> | <u>Quarters</u> | <u>Aggregate Innovations</u> | <u>Allocative Innovations</u> |
|-----------------|-----------------|------------------------------|-------------------------------|
| 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                          |
| 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                          |
|                 | 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                          |
| SUM             | 16              | 0.51                         | 0.49                          |
|                 | 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                         |                               |

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<sup>1</sup>Identification assuming  $b_n = 2.0$ .

TABLE 8

## The Relationship Between Unemployment and Gross Job Reallocation

Dependent Variable: Total Manufacturing Unemployment Rate

|   | Mean<br>(Std. Dev.) | Estimation Method: <sup>1</sup> |                  |                        |
|---|---------------------|---------------------------------|------------------|------------------------|
|   |                     | <u>OLS</u>                      | <u>AR2</u>       | <u>FD</u> <sup>2</sup> |
| $UN_t$                                    | 0.077<br>(0.025)    |                                 |                  |                        |
| Specification:                            |                     |                                 |                  |                        |
| $SUM_t$                                   | 0.110<br>(0.02)     | 0.525<br>(0.131)                | 0.333<br>(0.084) | 0.319<br>(0.081)       |
| $SUM_{t-1}$                               | --                  | 0.568<br>(0.130)                | 0.275<br>(0.084) | 0.253<br>(0.079)       |
| $R^2$                                     | --                  | 0.66                            | 0.86             | 0.29                   |
| D.W.                                      | --                  | 0.63                            | 1.94             | 1.73                   |
| $\bar{SUM}_t$                             | 0.115<br>(0.02)     | 0.488<br>(0.122)                | 0.333<br>(0.071) | 0.324<br>(0.070)       |
| $\bar{SUM}_{t-1}$                         | --                  | 0.567<br>(0.124)                | 0.235<br>(0.071) | 0.232<br>(0.068)       |
| $R^2$                                     | --                  | 0.64                            | 0.87             | 0.33                   |
| D.W.                                      | --                  | 0.57                            | 1.95             | 1.64                   |
| $\bar{SUM}_t^{OIL}$                       | 0.114<br>(0.012)    | 0.569<br>(0.189)                | 0.369<br>(0.105) | 0.343<br>(0.107)       |
| $\bar{SUM}_{t-1}^{OIL}$                   | --                  | 0.434<br>(0.204)                | 0.100<br>(0.105) | 0.118<br>(0.107)       |
| $\bar{SUM}_t - \bar{SUM}_t^{OIL}$         | 0.000<br>(0.016)    | 0.466<br>(0.155)                | 0.310<br>(0.083) | 0.323<br>(0.083)       |
| $\bar{SUM}_{t-1} - \bar{SUM}_{t-1}^{OIL}$ | --                  | 0.638<br>(0.151)                | 0.296<br>(0.082) | 0.290<br>(0.080)       |
| $R^2$                                     | --                  | 0.64                            | 0.88             | 0.36                   |
| D.W.                                      | --                  | 0.55                            | 1.89             | 1.57                   |

TABLE 8 (cont.)

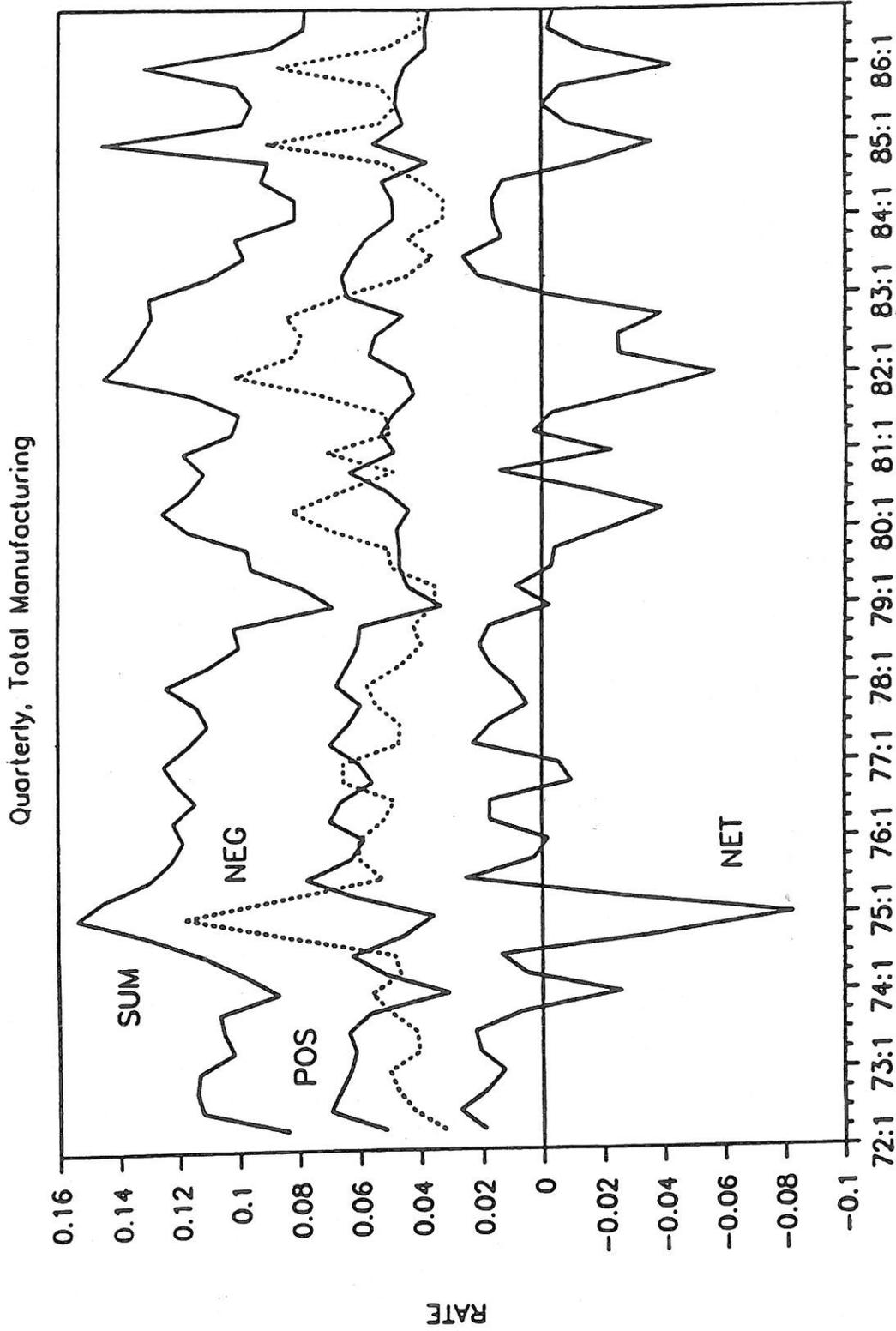
|                                   | Mean<br>(Std. Dev.) | <u>OLS</u>       | <u>AR2</u>       | <u>FD</u> <sup>2</sup> |
|-----------------------------------|---------------------|------------------|------------------|------------------------|
| SUM <sub>t</sub> <sup>AGG</sup>   | 0.111<br>(0.008)    | 1.03<br>(0.295)  | 1.258<br>(0.166) | 1.250<br>(0.158)       |
| SUM <sub>t-1</sub> <sup>AGG</sup> | --                  | 0.987<br>(0.292) | 0.486<br>(0.166) | 0.537<br>(0.158)       |
| SUM <sub>t</sub> <sup>ALL</sup>   | 0.110<br>(0.017)    | 0.325<br>(0.126) | 0.131<br>(0.068) | 0.152<br>(0.004)       |
| SUM <sub>t-1</sub> <sup>ALL</sup> | --                  | 0.326<br>(0.131) | 0.138<br>(0.068) | 0.182<br>(0.064)       |
| R <sup>2</sup>                    | --                  | 0.75             | 0.92             | 0.66                   |
| D.W.                              | --                  | 0.46             | 2.13             | 1.75                   |

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

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

# FIGURE 1 NET AND GROSS REALLOCATION RATES Quarterly, Total Manufacturing



**FIGURE 2**  
**PARTITIONED POS AND NEG**  
 Quarterly, Total Manufacturing

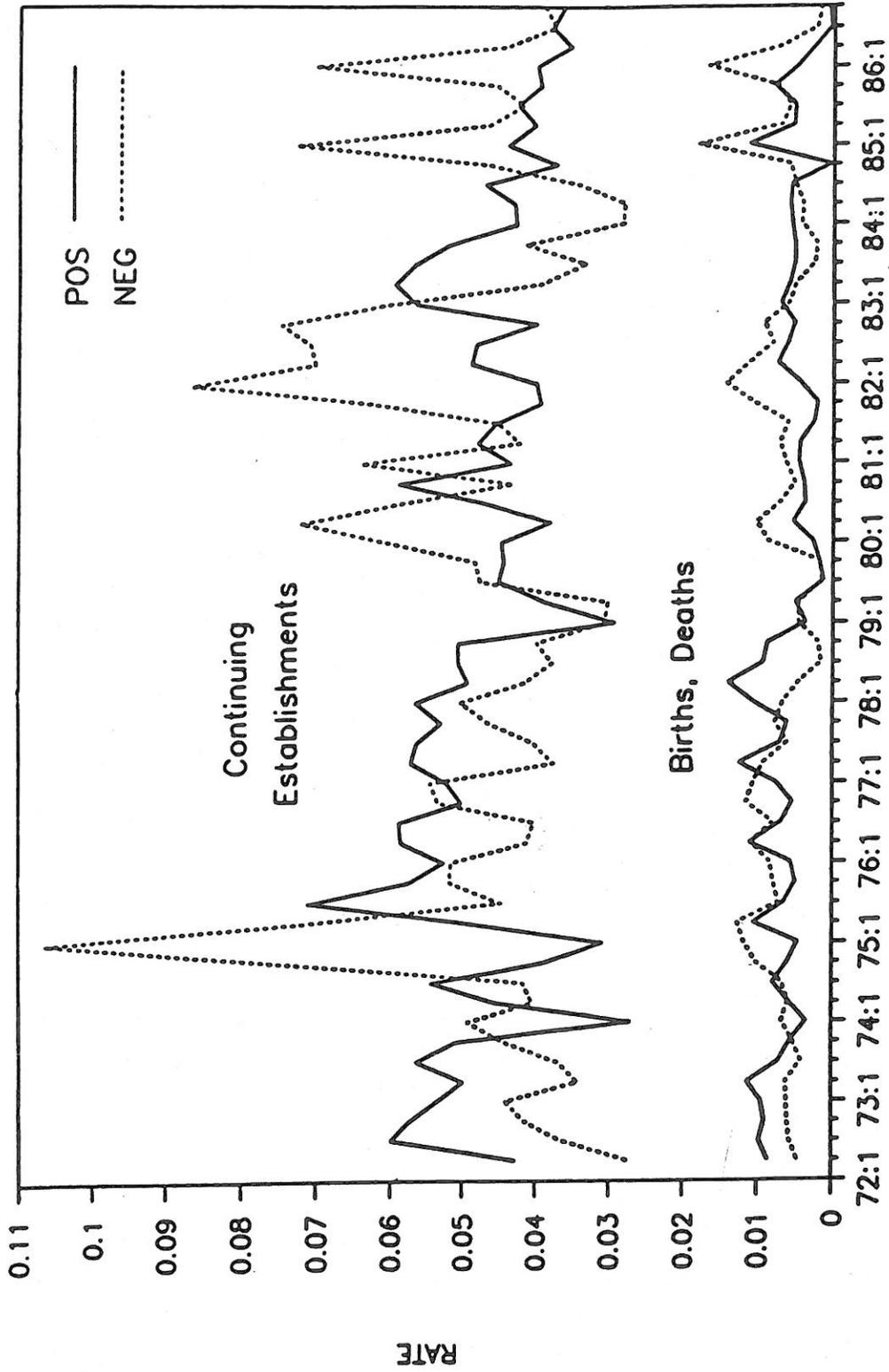


FIGURE 3  
 IMPULSE RESPONSE FUNCTIONS

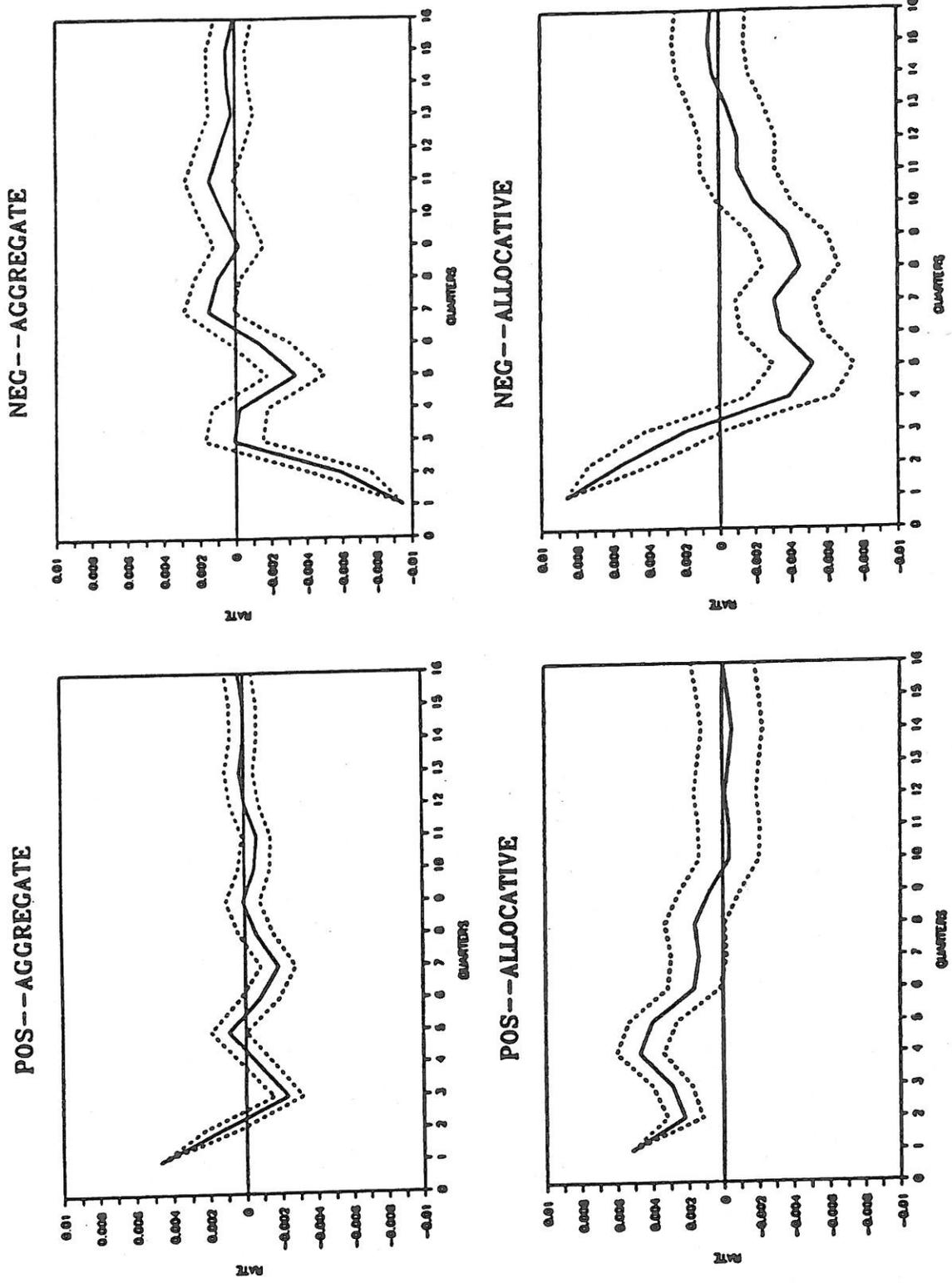


FIGURE 4

# PROPORTION OF VARIANCE DUE TO ALLOCATIVE SHOCKS

Four and Sixteen Quarter Horizons

