GROSS JOB CREATION, GROSS JOB DESTRUCTION, AND EMPLOYMENT REALLOCATION*

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This study measures the heterogeneity of establishment-level employment changes in the U. S. manufacturing sector over the 1972 to 1986 period. We measure this heterogeneity in terms of the gross creation and destruction of jobs and the rate at which jobs are reallocated across plants. Our measurement efforts enable us to quantify the connection between job reallocation and worker reallocation, to evaluate theories of heterogeneity in plant-level employment dynamics, and to establish new results related to the cyclical behavior of the labor market.

I. INTRODUCTION

This paper measures the heterogeneity of establishment-level employment changes in the U. S. manufacturing sector over the 1972 to 1986 period. We measure this heterogeneity in terms of the gross creation and destruction of jobs and the rate at which jobs are reallocated across plants. Our measurement efforts enable us to quantify the connection between job reallocation and worker reallocation, to evaluate theories of heterogeneity in plant-level employment dynamics, and to establish new results related to the cyclical behavior of the labor market.

Our empirical work exploits a tremendously rich data set with approximately 860,000 annual observations on 160,000 manufacturing establishments. The data are longitudinal and include observations on all manufacturing establishments sampled in the

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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 developing the implications of heterogeneity in establishment-level employment dynamics.

A key aspect of our study is its focus on gross job flows 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.[1] 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 re-sorting of workers across a given set of jobs or, alternatively, whether a large portion of worker turnover is driven by the destruction and creation of employment opportunities.

The results that emerge from our study 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 percent per year, respectively. We show that these figures reflect simultaneously high rates of job creation and destruction within narrowly defined sectors of the economy, e.g., four-digit industries. The impressive magnitude of gross job creation and destruction has been documented before, perhaps most convincingly at high sampling frequencies by Leonard [1987] and at low sampling frequencies by Dunne, Roberts, and Samuelson [1989b].

Summing the rates of gross job creation and destruction yields our measure of the job reallocation rate, i.e., the rate at which employment positions are reallocated across establishments. The high rates of job reallocation found in this paper indicate that the reshuffling of employment opportunities across plants is one of the most important reasons that workers change employers or transit between employment and joblessness. Combining information from the LRD and the Current Population Survey, we calculate bounds on the fraction of worker reallocation accounted for by job reallocation. Our calculations reveal that 35–56 percent of all worker reallocation between employers or between employment

1. See Clark and Summers [1979]; Abowd and Zellner [1985]; Poterba and Summers [1986]; Lilien [1980]; Hall [1982]; Darby, Haltiwanger, and Plant [1985]; Akerlof, Rose, and Yellen [1988]; and Blanchard and Diamond [1990].

and joblessness arises to accommodate shifts in the distribution of employment opportunities across work sites.

Two other findings documented below provide insight into the character of the worker reallocation associated with job reallocation. One finding is that most of annual job creation and destruction reflects persistent establishment-level employment changes. For example, 73 percent of the jobs created between March 1974 and March 1975 still existed in March 1976, and 72 percent of the jobs lost in the 1974–1975 interval were still lost in March 1976. The average one-year persistence rates for annual job creation and destruction are 68 percent and 81 percent, respectively. This persistence indicates that the bulk of annual job creation and destruction cannot be implemented by temporary layoff and recall policies. A second finding is that job destruction is highly concentrated: only 23 percent is accounted for by establishments that shrink by less than 20 percent over the span of a year. This finding indicates that the bulk of job destruction cannot be accommodated by normal rates of worker attrition. Taken together, the concentration and persistence results imply that job reallocation is typically associated with long-term joblessness or worker reallocation across employers.

The impressive magnitude of job reallocation and its bearing on worker reallocation lead us to inquire into the sources of heterogeneity in establishment-level employment changes. We document strong relationships between the intensity of job reallocation and observable plant characteristics like age, size, and ownership type (single-unit versus multi-unit firm). We also draw on several theories of plant-level heterogeneity and dynamics to identify reasons for simultaneous job creation and destruction within narrowly defined sectors of the economy. Guided by these theories, we quantify the contribution of various sources of heterogeneity to total job reallocation and to variation in job reallocation across groups of establishments defined in terms of industry, region, age, size, and ownership type.

One prominent theory of heterogeneity in plant-level employment dynamics stresses the selection effects associated with passive learning about initial conditions.[2] We develop a procedure for estimating the fraction of total job reallocation accounted for by this source of heterogeneity in plant-level employment dynamics.

2. See Jovanovic [1982], Lippman and Rumelt [1982], and Pakes and Ericson's [1990] version of the Jovanovic model.

The procedure combines information on the distribution of employment by plant age and the rate of job reallocation by plant age with simple and plausible identifying assumptions. Despite the attention that these theories have received in recent empirical work,[3] we find that passive learning about initial conditions accounts for only 11–13 percent of observed *levels* of job reallocation. In results more favorable to this type of theory, we find that learning about initial conditions accounts for roughly one third to one half of the *differences* in job reallocation rates across groups of plants defined in terms of industry, size, region, and ownership type.

Long traditions in labor and industrial economics view plants within industries, regions, or employer size classes as relatively homogeneous. Theories of vintage effects view plants as relatively homogeneous within age groups. These perspectives suggest an explanation for high rates of job reallocation as the natural consequence of continually occurring sector-specific shocks, where sectors are defined in terms of industry, region, size, or age. To evaluate this explanation, we compute the fraction of excess job reallocation accounted for by between-sector employment shifts. Excess job reallocation equals total job reallocation minus the minimum amount required to accommodate the net change in employment. Remarkably, we find that essentially none of the excess job reallocation in U. S. manufacturing is accounted for by employment shifts among two-digit industries, Census geographic regions, eight age classes, or five size classes. Even when we define sectors in terms of 450 four-digit manufacturing industries, between-sector employment shifts account for a mere 12 percent of excess job reallocation. Similar results hold when we define sectors in terms of both two-digit industry and either age, size, region, or ownership type.

The inability of either sectoral shock theories or theories that stress learning about initial conditions to account for observed rates of job reallocation leads us to the following conclusion: any successful explanation for the magnitude of job reallocation must also explain why simultaneously high rates of job creation and destruction occur among mature plants in narrowly defined sectors of the economy.

In addition to the cross-sectional results, another key finding is that the job reallocation rate exhibits significant countercyclic time variation. (Equivalently, job creation is less volatile over time

3. See Evans [1987a, b]; Hall [1987]; Dunne, Roberts, and Samuelson [1989a]; and Pakes and Ericson [1990].

than job destruction.) The March-to-March job reallocation rate for the manufacturing sector ranges from a low of 17 percent in 1980 to a high of 23 percent in 1975 and 1983. The simple correlation between net employment growth and the job reallocation rate is -0.57.

We carry out several empirical exercises designed to address the question of why the job reallocation rate fluctuates countercyclically. These exercises establish two important sets of results. First, the countercyclic behavior of job reallocation reflects time variation in the magnitude of idiosyncratic plant-level employment movements, not sectoral differences in the mean employment responses to aggregate disturbances. Second, patterns of time variation in job reallocation intensity differ sharply by plant age, size and ownership type. Job reallocation rates among young (0–9 years), small (1–249 employees), and single-unit plants exhibit no systematic relationship to the cycle. Job reallocation rates among older, larger, and multi-unit plants exhibit pronounced countercyclic patterns of variation.

These results enable us to discriminate between macroeconomic theories that cannot explain the observed cyclical behavior of job reallocation and theories that potentially can. We conclude that standard macroeconomic theories that specify homogeneous firms or homogeneous firms within sectors cannot account for the time variation in job reallocation intensity. Nor can cyclic movements in job reallocation intensity be explained by theories that treat the idiosyncratic component of firm-level employment behavior as orthogonal to the business cycle. As we discuss below, theories that stress the frictions associated with the reallocation of workers and jobs across employers imply potentially important interactions between aggregate employment growth and the pace of reallocation. Blanchard and Diamond [1989, 1990], Davis and Haltiwanger [1990], and Caballero [1990] develop theories of this sort that can explain some of the cyclical job flow findings in this paper.

We turn now to a description of the data and the gross job flow measures that we use in this study.

II. Data and Measurement

A. The Longitudinal Research Datafile

This study exploits annual, plant-level employment observations in the Longitudinal Research Datafile (LRD). The LRD sampling frame encompasses all U. S. manufacturing establishments with five or more employees. These establishments account for 99 percent of manufacturing employment, based on tabulations from either the Census of Manufactures or County Business Patterns.

The LRD is a series of contiguous five-year panels with annual data on many manufacturing establishments, plus Census-year data on the universe of manufacturing establishments. Census years in the LRD are 1967, 1972, 1977, and 1982; annual data are available from 1972 to 1986. From the Census-year universe, the Bureau draws a sample of establishments that are then surveyed during five successive years. This five-year panel, which commences two years after a Census year, comprises the sample of establishments that makes up the Annual Survey of Manufactures (ASM). New establishments are added to the panel as it ages to incorporate births and to preserve the panel's representative character. In 1977 the LRD included roughly 70,000 out of the 360,000 manufacturing establishments. These sampled establishments accounted for 76 percent of manufacturing employment.

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 1979–1983 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 1979–1983 period. Establishments that fall into neither of the first two groups are sampled with probabilities proportional to a measure of size determined for each establishment from the preceding Census. Sampling probabilities for noncertainty establishments range from 1.000 to 0.005. We use sample weights, equal to the reciprocals of the sampling probabilities, whenever we aggregate over establishments.

Some, but not most, of the noncertainty establishments appear in contiguous panels. Thus, our ability to link establishment-level observations *across* panels ranges from excellent for large establishments to quite poor for the smallest establishments. This observation implies that accurate measurement of gross employment changes is more difficult in the first year of each panel. While it is possible to construct continuous series for basic measures of job creation and destruction, and we have done so in Davis and Haltiwanger [1990], some of the cross-tabulations presented below cannot be constructed for the first year of a panel. Hence, we typically calculate the gross and net change measures reported in this paper from a sample that excludes 1974, 1979, and 1984.

Several key features of the LRD enable us to largely overcome the selection and measurement problems that have hampered most previous attempts to estimate gross rates of job creation and destruction from plant-level or firm-level data. In this regard, the LRD's key features are the comprehensive scope of its sampling frame for a major sector of the U. S. economy, large probability-based samples that minimize sampling error, the incorporation of births into ongoing panels, a careful distinction between firms and establishments, and a careful distinction between ownership transfers and the birth and death of establishments. Among U. S. studies on job creation and destruction, Dunne, Roberts, and Samuelson [1989b] provide the only other measurements based on a data set with similar virtues. Their work exploits the Census-year observations in the LRD to calculate five-year job creation and destruction rates.[4]

B. Measurement of Gross Job Creation, Destruction, and Reallocation

We now introduce some notation and define measures of establishment size and growth rate. We then plot the empirical growth rate density and relate it to job creation and destruction measures. We also describe the connection between these measures and measures of worker and job reallocation.

We measure the size of establishment e at time t, denoted by x_{et}, as the simple average of establishment employment at time t and $t-1$. Sector size is defined analogously. We define the time-t growth rate of establishment e, denoted by g_{et}, as the change in establishment employment from $t-1$ to t, divided by x_{et}. 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 measure is that it facilitates an integrated treatment of births, deaths, and continuing establish-

4. Davis and Haltiwanger [1989] discuss the weaknesses in other data sets that have been used in U. S. studies of job creation and destruction. For a full discussion of data quality issues pertaining to our use of the LRD, see Davis, Haltiwanger, and Schuh [1990].

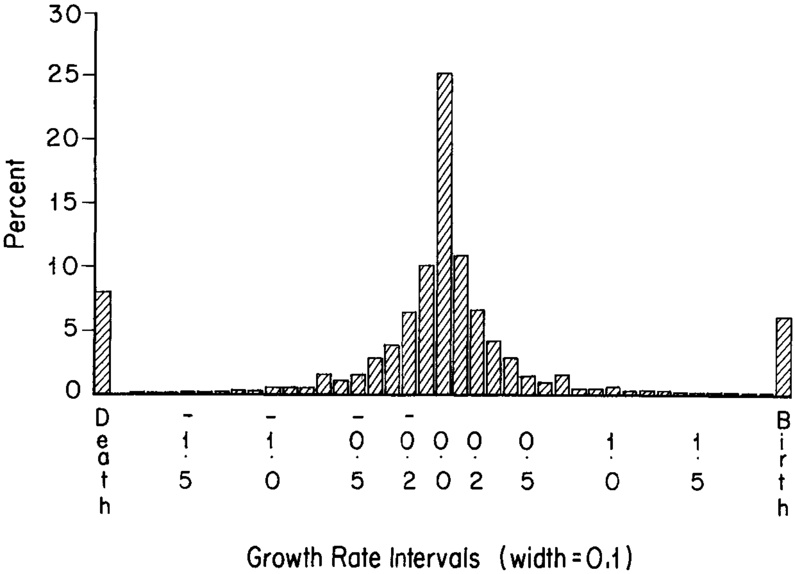

FIGURE Ia
Unweighted Growth Rate Distribution

ments in the empirical analysis. The g measure is monotonically related to the conventional growth rate measure, and the two measures are approximately equal for small growth rates.[5]

Figures Ia and Ib plot frequency distributions for the establishment growth rate observations in our eleven-year sample. Figure Ia depicts the shape of the empirical density over the 677,000 annual observations on g_{et}. Figure Ib depicts the shape of the empirical density over the size-weighted observations on g_{et}. Both the weighted and unweighted densities are slightly asymmetric with central peaks in the interval surrounding zero and endpoint spikes corresponding to births and deaths.

On an unweighted basis, 25 percent of all manufacturing establishments experienced a growth rate in the interval $(-0.05,0.05)$, and 46 percent experienced a growth rate in the interval $(-0.15,0.15)$. Births and deaths account for 14 percent of annual growth rate observations on manufacturing establishments. The mass of the size-weighted distribution is much more concentrated about the center and much less concentrated in the

5. Let G be the change in employment divided by lagged employment, i.e., the conventional growth rate measure. The two growth rate measures are linked by the identity $G \equiv 2g/(2-g)$.

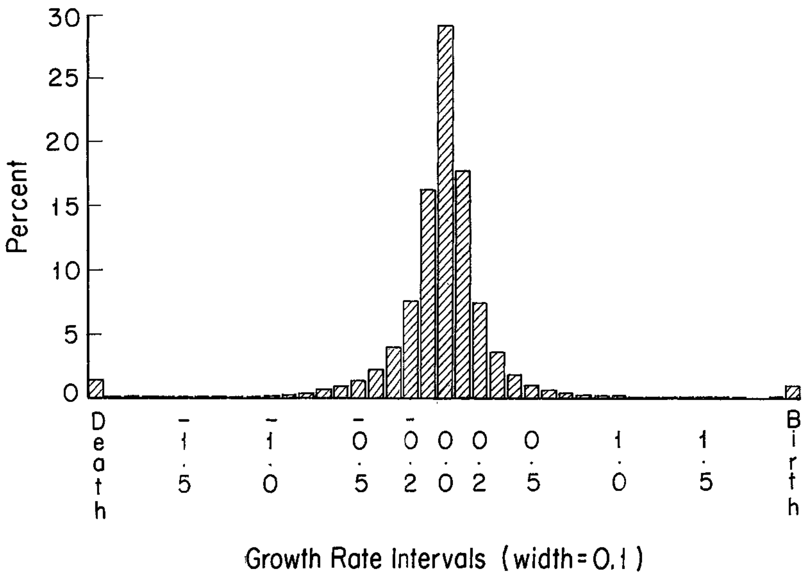

FIGURE Ib
Size-Weighted Growth Rate Distribution

tails. On a size-weighted basis, 29 percent of the annual growth rate observations fall in the interval (−0.05,0.05), and 63 percent fall in the interval (−0.15,0.15). Births and deaths account for only 2.4 percent of all size-weighted growth rate observations.[6] Evidently, establishment turnover and employment volatility are sharply declining functions of establishment size in our sample, a result that is consistent with work by Evans [1987a, b]; Hall [1987]; Dunne, Roberts, and Samuelson [1989a, b]; and others.

The gross job flow measures investigated in this paper have a simple relationship to the size-weighted frequency distribution of establishment growth rates. We calculate gross job creation by summing employment gains at expanding and new establishments within a sector. Similarly, we calculate gross job destruction by summing employment losses at shrinking and dying establish-

6. Two caveats should be borne in mind when interpreting this aspect of the size-weighted density. First, our size metric (x_{et}) assigns only half as much weight to observations on births and deaths as would a more conventional size metric. For example, if we were to ask what fraction of current employment is located at establishments born within the past year, the birth category would appear twice as important as in Figure Ib. Second, although births and deaths account for a small fraction of size-weighted establishment growth rate observations, they account for a large fraction of gross job reallocation. We return to this point in subsection III.C.

ments within a sector. To express these measures as rates, we divide by sector size. Introducing some additional notation, we can write gross job creation and destruction rates in sector s at time t as

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

where E_{st} is the set of establishments in s at t.[7] As these formulas indicate, the size-weighted frequency distribution determines the weight to attach to each growth rate value in the calculation of job creation and destruction rates.

Two remarks are helpful in thinking about our job creation and destruction measures. First, it seems apparent that year-to-year changes in establishment-level employment are largely induced 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. We spell out the contribution of job reallocation to worker reallocation in subsection III.C.

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 true job creation and destruction rates.

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. $X_{st}SUM_{st}$ equals the gross change from $t - 1$ to t in the number of employment positions at establishments. In terms of the frequency distribution, the job reallocation rate SUM_{st} can be thought of as the size-weighted mean of the absolute value of establishment growth rates.

To relate job reallocation to worker reallocation, observe that $X_{st}SUM_{st}$ represents an upper bound on the number of workers

7. Sample weights are suppressed in these formulas to reduce notational clutter.

who change jobs or switch between employment and nonemployment in response to establishment-level employment changes.[8] $X_{st}SUM_{st}$ represents an upper bound because some workers move from shrinking to growing establishments within sector s between $t-1$ and t. To obtain a lower bound, we eliminate the possibility of double counting job losers who move directly to new jobs at expanding establishments in the same sector. That is, $X_{st}MAX_{st} = X_{st}max\ \{POS_{st},NEG_{st}\}$ represents a lower bound on the number of workers who change jobs or employment 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 worker reallocation rate required to accommodate job reallocation. When interpreting these upper and lower bounds, it is important to recognize that the worker reallocation associated with job reallocation is itself a lower bound on total worker reallocation. Worker reallocation reflects life-cycle, career path, job satisfaction, and match quality considerations as well as job reallocation.

III. Some Elementary Facts about Job Creation and Destruction

This section of the paper lays out some elementary facts about job creation and destruction behavior in the U. S. manufacturing sector. We relate these facts to the magnitude and character of the worker reallocation associated with job reallocation. These facts also set the stage for the analysis in the succeeding sections of the paper.

A. Magnitude and Time Variation

Table I presents annual rates of job creation and destruction, net employment growth, job reallocation, and a lower bound on the worker reallocation required to accommodate job reallocation. The figures in Table I and elsewhere in this paper are based on March-to-March changes in establishment-level employment.

The central fact captured by Table I is the phenomenon of simultaneous job creation and destruction. Every year of the sample exhibits both job creation and job destruction rates that exceed 6 percent of manufacturing employment. In 1973, when manufacturing employment expanded by a robust 7 percent on net,

8. 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.

TABLE I
NET AND GROSS RATES BY YEAR, MANUFACTURING SECTOR

Year	POS_t	NEG_t	NET_t[a]	SUM_t	MAX_t
1973	0.132	0.061	0.071	0.194	0.133
1975	0.067	0.166	−0.100	0.233	0.166
1976	0.113	0.096	0.017	0.209	0.122
1977	0.112	0.096	0.018	0.206	0.117
1978	0.116	0.075	0.041	0.191	0.117
1980	0.080	0.093	−0.012	0.173	0.102
1981	0.070	0.118	−0.049	0.188	0.119
1982	0.064	0.152	−0.087	0.216	0.152
1983	0.086	0.142	−0.056	0.227	0.143
1985	0.084	0.117	−0.033	0.201	0.121
1986	0.088	0.132	−0.044	0.220	0.133

Pearson correlations:[b]
$\rho(POS_t, NEG_t) = -0.864$ (0.001) $\rho(NET_t, SUM_t) = -0.565$ (0.07)

a. $NET_t \equiv POS_t - NEG_t$ is the net employment growth rate.
b. Marginal significance level in parentheses.

the gross job destruction rate was 6 percent. In 1975, when manufacturing employment shrank by a dramatic 10 percent, the gross job creation rate was 7 percent.

The last two columns in Table I point out the reallocation of jobs and workers associated with simultaneous job creation and destruction. The job reallocation rate ranges from 17.3 percent in 1980 to 23.3 percent in 1975. Substantial worker reallocation is required to accommodate job reallocation of this magnitude. The lower bound on the required rate of worker reallocation ranges from 10.2 percent of employment in 1980 to 16.6 percent in 1975. Thus, the heterogeneity of establishment-level employment movements illustrated in Figures I translates into a large amount of worker reallocation.

One other noteworthy fact emerges from Table I: the pace of job reallocation exhibits significant countercyclic time variation.[9] The range of variation in job reallocation over the eleven years of the sample is six percentage points. The simple correlation between the net job growth rate and the job reallocation rate equals −0.57. Given the magnitude of job reallocation and its countercyclic pattern of variation, one is led naturally to inquire about the

9. Note that the job reallocation rate, SUM_t, is negatively correlated with NET_t if, and only if, $\text{var}(NEG_t)$ exceeds $\text{var}(POS_t)$.

connection between the pace of job reallocation and aggregate employment fluctuations. We take up this inquiry in Section V.

B. Cross-Industry Variation

Table II presents average annual net and gross job flow measures for the manufacturing sector and each two-digit industry. The industry figures are X_{it}-weighted averages of the eleven annual industry observations, and the figures for the manufacturing sector are X_i-weighted averages of the industry figures.

Employment contracted in every two-digit manufacturing industry over the sample period (1972–1986, exclusive of 1974, 1979, and 1984). Annual net contraction rates range from 0.2

TABLE II
NET AND GROSS RATES BY INDUSTRY, SIZE-WEIGHTED AVERAGES[a]

Industry:	*POS*	*NEG*	*NET*	*SUM*	*MAX*	*SUM* − |*NET*|
Food (20)	0.089	0.104	−0.015	0.193	0.108	0.169
Tobacco (21)	0.058	0.082	−0.024	0.140	0.090	0.098
Textile (22)	0.074	0.110	−0.036	0.185	0.124	0.121
Apparel (23)	0.116	0.156	−0.040	0.272	0.168	0.207
Lumber (24)	0.129	0.160	−0.031	0.288	0.188	0.202
Furniture (25)	0.101	0.121	−0.019	0.222	0.143	0.157
Paper (26)	0.063	0.078	−0.015	0.141	0.089	0.105
Printing (27)	0.091	0.087	−0.004	0.178	0.099	0.158
Chemicals (28)	0.068	0.080	−0.013	0.148	0.089	0.118
Petroleum (29)	0.066	0.091	−0.025	0.157	0.100	0.114
Rubber (30)	0.107	0.118	−0.011	0.225	0.143	0.163
Leather (31)	0.091	0.144	−0.053	0.235	0.152	0.166
Stone, clay, and glass (32)	0.093	0.123	−0.031	0.216	0.136	0.160
Primary metals (33)	0.059	0.114	−0.054	0.173	0.126	0.094
Fabricated metals (34)	0.095	0.120	−0.025	0.215	0.137	0.156
Nonelectric machinery (35)	0.096	0.121	−0.025	0.217	0.141	0.152
Electric machinery (36)	0.097	0.109	−0.011	0.206	0.130	0.152
Transportation (37)	0.094	0.099	−0.006	0.193	0.123	0.140
Instruments (38)	0.093	0.093	−0.002	0.186	0.112	0.149
Miscellaneous (39)	0.108	0.145	−0.037	0.253	0.156	0.193
Total manufacturing	0.092	0.113	−0.021	0.205	0.129	0.152
Size-weighted cross-industry standard deviation	0.016	0.21	0.015	0.034	0.023	0.028

Cross-industry:[b] $\rho(POS,NEG) = 0.764$ (0.0001) $\rho(NET,SUM) = -0.347$ (0.135)

a. Size-weighted average based on annual values with t = 1973–1986 (excluding 1974, 1979, 1984).
b. Marginal significance levels in parentheses.

percent in Instruments to 5.4 percent in Primary Metals. The manufacturing sector as a whole declined at a rate of 2.1 percent per year. Despite pervasive net contractions, every two-digit industry experienced significant gross job creation. Average March-to-March gross job creation rates range from 5.8 percent in Tobacco to 12.9 percent in Lumber and Wood Products. March-to-March gross job destruction rates range from 7.8 percent in Paper to 16.0 percent in Lumber and Wood Products. In the manufacturing sector as a whole, gross job creation and destruction rates averaged 9.2 percent and 11.3 percent, respectively.

The annual average job reallocation rate shows considerable cross-industry variation, ranging from 14.0 percent in Tobacco to 28.8 percent in Lumber and Wood Products. The lower bound on the rate of worker reallocation required to accommodate observed job reallocation ranges from 8.9 percent in Chemicals and Paper to 18.8 percent in Lumber and Wood Products. For the manufacturing sector as a whole, the lower (upper) bound on the required rate of worker reallocation equals 12.9 percent (20.5 percent) of employment per year.

The final column of Table II shows that simultaneous job creation and destruction is an important phenomenon in every two-digit manufacturing industry. This column reports average industry rates of excess job reallocation, i.e., the mean difference between total job reallocation and the minimum job reallocation required to accommodate net employment changes. The excess job reallocation rate varies from 9.8 percent to 20.6 percent across two-digit industries. The size-weighted average of the two-digit industry excess job reallocation rates equals 15.2 percent of employment. These striking facts, and their bearing on worker reallocation, provide strong motivation for an inquiry into the underlying sources of the establishment-level heterogeneity responsible for simultaneous job creation and destruction. We take up this inquiry in Section IV.

C. The Connection to Total Worker Reallocation

The preceding results indicate that a substantial fraction of total worker reallocation is demand driven in the sense of being induced by shifts in the distribution of employment opportunities across work sites. To quantify this statement, we now compare the total number of persons who switch jobs or employment status to the number of switches required to accommodate the reallocation of jobs.

Recall that our job reallocation figures are based on employment changes over a twelve-month interval. A meaningful comparison requires a consistent measure of total worker reallocation. With this observation in mind, we calculate total worker reallocation as the sum of two pieces. The first piece is the number of persons who have job tenure of twelve months or less. Based on the Current Population Survey (CPS), Hall [1982, p. 317] reports that this number is 28.2 percent of employment in 1978. The second piece is the number of currently jobless persons who were employed twelve months earlier. Summing these two pieces yields the total number of persons who currently have a different job or employment status than they had twelve months earlier.

To calculate the second piece of total worker reallocation, we tabulated March-to-March gross worker flows from the CPS. Gross worker flows refer to the number of persons who report a change in labor force status—employed, unemployed, or out of the labor force—between survey dates. Using the March-March matched files of the CPS, we obtained the 3×3 matrix of gross flows, F, for fifteen pairs of years between 1968 and 1987. Since reporting errors are known to cause a substantial upward bias in the measured flows, we adjusted the F matrices following Poterba and Summers [1986]. Letting Q denote the 3×3 matrix of classification error probabilities, the measured and true gross flows satisfy the relationship $F = Q'F^*Q$, where F^* denotes the true flows. Obtaining $\hat{Q}$ from Table III in Poterba and Summers, we estimate the true gross flow matrix in year t as $\hat{F}_t = (\hat{Q}^{-1})'F_t\hat{Q}^{-1}$. Collapsing unemployment and out of the labor force into a single category, we then calculate the yearly number of transitions from employment to joblessness as a percentage of employment. Averaging this transition rate over the fifteen years, we estimate the number of currently jobless persons who held a job twelve months earlier as 8.6 percent of employment.[10]

Summing the two pieces, total worker reallocation equals $28.2 + 8.6 = 36.8$ percent of employment in a typical year. From Table II the amount of worker reallocation required to accommodate job reallocation is bounded between 12.9 and 20.5 percent of employment in a typical year. Hence, taking the ratio of the job reallocation figures to the total worker reallocation figure, we

10. Carrying out an identical set of calculations, but obtaining $\hat{Q}$ from Table VI in Abowd and Zellner [1985], we estimate the number of currently jobless persons who held a job twelve months earlier as 9.9 percent of employment. The corresponding figure unadjusted for classification error is 11.2 percent of employment.

calculate that 35–56 percent of total worker reallocation arises to accommodate shifts in the distribution of employment opportunities across work sites. Simply put, job reallocation accounts for a major fraction of worker reallocation.[11]

Two observations provide further perspective on the magnitude of job reallocation's contribution to worker reallocation. First, our calculations neglect secondary waves of worker reallocation initiated by job creation and destruction. For example, a person who quits an old job in favor of a newly created job potentially creates a chain of further quits as other workers reshuffle across the new set of jobs. It follows that the direct plus indirect contribution of job reallocation to worker reallocation exceeds the figure derived above.

Second, a certain amount of worker reallocation inevitably arises from life-cycle considerations as old workers retire and young workers enter the workforce. If the typical person works 45 years, then retirement and initial labor force entry directly cause transitions between employment and nonemployment equal to roughly 4.4 percent of the workforce in a typical year. It follows from our figure for total worker reallocation that simple life-cycle effects account for roughly 12 percent of worker reallocation. After accounting for job reallocation and life-cycle effects, the residual amount of worker reallocation equals 11.9–19.5 percent of employment, or 33–53 percent of all worker reallocation. This component of worker reallocation reflects temporary exits from the workforce and the sorting and re-sorting of workers across existing jobs for a variety of reasons.

We conclude this discussion with a caveat. Recall that our job and worker reallocation figures are based on changes between two points in time twelve months apart. Carrying out similar calcula-

11. Three sources of potential bias in our calculations merit discussion. First, Hall's job tenure figure understates worker mobility (for our purposes), because it does not include workers who, within the past twelve months, transferred between plants owned by the same employer. Second, nonmatch rates in the March-March CPS matched files may differ systematically by change in employment status. We are unaware of direct evidence on this point, but the margin-error adjustments in Abowd and Zellner [1985] for nonmatches in month-to-month CPS gross flows data indicate that this problem is trivial for employment-to-jobless flows. Using the appropriate entries in the top row of their Table IV, the margin-error adjustments reduce the transitions from employment to joblessness by only 1 percent of the corresponding unadjusted flow. Third, our job reallocation figures are based on the manufacturing sector only. According to Leonard's [1987, Table 6.6] tabulations for Wisconsin, annual job reallocation rates are 28 percent higher in nonmanufacturing than in manufacturing. Thus, Leonard's results suggest that the numerator of our calculated ratio significantly understates the job reallocation rate in the economy as a whole.

tions for data based on, say, monthly sampling would place greater emphasis on seasonal disturbances and other factors that lead to transitory flows of workers and jobs. To the extent that these factors disproportionately affect worker or job flows, a different calculation of job reallocation's contribution to worker reallocation would emerge.

D. Concentration and Persistence

The high rates of job reallocation reported in Tables I and II prompt two further factual questions. First, what role do plant births and deaths play in the creation and destruction of jobs? Or, to restate the question in a more general way, how are job creation and destruction distributed by establishment growth rate? Second, do the high rates of job creation and destruction reported in Tables I and II reflect primarily transitory or persistent establishment-level employment changes? We address these questions in turn.

Gross job creation and destruction are distributed over establishments experiencing the full range of expansion and contraction rates. Figure II displays the distributions of job creation and destruction over this range. The right half of Figure II plots the fraction of job creation accounted for by establishments experienc-

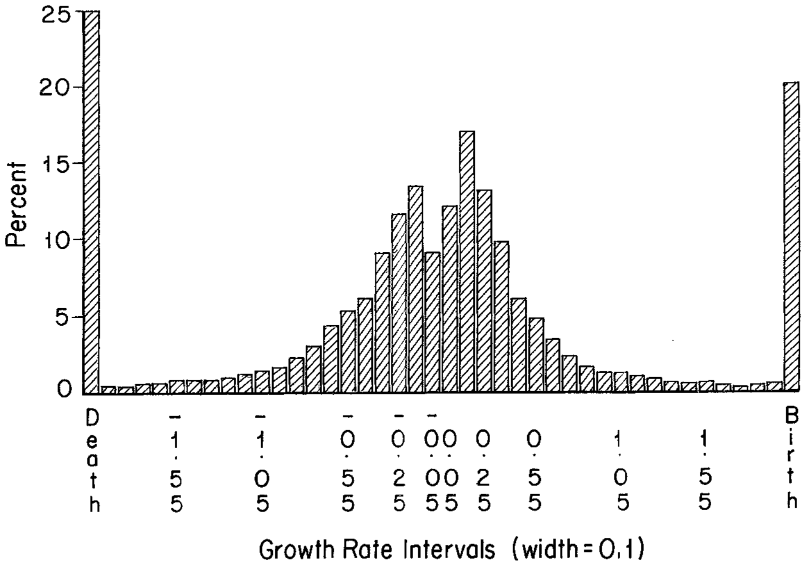

FIGURE II
Job Creation and Destruction Partitioned by Establishment Growth Rate

ing growth rates in the intervals [0,0.1], [0.1,0.2] . . . , [1.9,2.0]. A final category shows the fraction of job creation accounted for by establishment births. The left half of Figure II provides a symmetric partition of gross job destruction.

Figure II highlights two noteworthy aspects of job creation and destruction. First, both large discrete changes and smaller incremental changes account for significant fractions of job creation and destruction. Establishments experiencing modest growth rates ($|g| < 0.20$) account for 29 percent of job creation and 23 percent of job destruction. Establishments experiencing dramatic growth rates ($|g| > 1.0$) account for 28 percent of job creation and 34 percent of job destruction. Births (deaths) alone account for 20 percent (25 percent) of job creation (destruction).[12]

Second, Figure II reveals a mild asymmetry between the distributions of job creation and destruction by establishment growth rate. Relative to job creation, job destruction exhibits greater concentration at establishments that experience dramatic growth rates. This aspect of job creation and destruction behavior provides modest support for theories of plant-level employment dynamics that generate greater lumpiness in employment contraction than employment expansion.

We now turn to the persistence of the March-to-March establishment-level employment changes that underlie our annual job creation and destruction measures. The persistence question is especially pertinent to an assessment of the character of worker reallocation associated with job reallocation. To the extent that job creation and destruction represent short-lived establishment-level employment changes, these changes can be implemented largely through temporary layoffs and recalls. To the extent that establishment level employment changes are persistent, they must be associated with long-term joblessness or worker reallocation across plants.

In thinking about how to measure persistence, we stress that our focus is on the persistence of the typical newly created or newly destroyed job. This focus is distinct from a focus on the persistence of the typical existing job (e.g., Dunne and Roberts [1989]) or the persistence of establishment size (e.g., Leonard [1987]). In line

12. An earlier version of this paper reports partitions of job creation and destruction by year and partitions by two-digit industry. These more detailed results show that the important role of dramatic establishment-level employment changes illustrated in Figure II is pervasive across industries and years. For example, the fraction of job destruction accounted for by establishment deaths ranges from 14–36 percent across years and 15–35 percent, on average, across two-digit industries.

TABLE III
PERSISTENCE RATES FOR JOB CREATION AND DESTRUCTION[a]

Year[b] (t)	$FPOS_{t1}$	$FPOS_{t2}$	$FNEG_{t1}$	$FNEG_{t2}$
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	0.62	—	0.84	—
Simple mean	0.67	0.50	0.81	0.73

a. $FPOS_{tn}$ ($FNEG_{tn}$) is the fraction of jobs created (destroyed) between March of year $t - 1$ and March of year t that persists through March of year $t + n$.
b. Given the ASM panel structure, the persistence measures can be calculated for all plants only in the indicated years.

with our focus, we measure persistence as follows. Let $FPOS_{t1}$ denote the fraction of newly created jobs in March of year t that continue to be present in March of year $t + 1$.[13] Also, let $FPOS_{t2}$ denote the fraction of newly created jobs in March of year t that are present in March of year $t + 1$ *and* March of year $t + 2$. Define $FNEG_{tn}$ analogously.

Table III reports the persistence measures for a set of base years determined by the life-cycle of the ASM panels. The key fact captured by the table is the highly persistent nature of the establishment-level employment movements underlying annual job creation and destruction. To take the most pronounced example, the one-year persistence rate for jobs destroyed between March 1980 and March 1981 is 88 percent, and the two-year persistence rate for these lost jobs is 82 percent. The average one-year persistence rates for newly created and newly destroyed jobs are 68 percent and 81 percent, respectively.[14]

These facts on concentration and persistence shed further

13. Let EMP_{et} denote time-t employment at establishment e. Newly created jobs at e in t equal $EMP_{et} - EMP_{e,t-1}$, assuming positive growth. If $EMP_{e,t+1} \geq EMP_{et}$, then all of these newly created jobs are present in $t + 1$. If $EMP_{e,t+1} \leq EMP_{e,t-1}$, then none of the newly created jobs are present in $t + 1$. If $EMP_{e,t+1} \in [EMP_{e,t-1}, EMP_{et}]$, then $EMP_{e,t+1} - EMP_{e,t-1}$ of the newly created jobs are present in $t + 1$. Carrying out this calculation for all growing establishments in t and dividing the result by POS_t yields $FPOS_{t1}$.

14. Table III may appear inconsistent with Lilien's [1980, Table III] estimates that 60–78 percent of manufacturing layoffs ended in recall during the years 1965 to 1976. The apparent discrepancy is resolved by recalling Lilien's estimate [1980, Figure I] that 92 percent of manufacturing unemployment spells ending in recall last three months or less. Most of these short-duration temporary layoffs are not counted in our calculations on March-to-March establishment-level employment changes.

light on the connection between job reallocation and worker reallocation. Since only 23 percent of job destruction is accounted for by establishments that shrink by less than 20 percent over the span of a year, the bulk of job destruction cannot be accommodated by normal rates of worker attrition. Since annual job creation and destruction primarily reflect persistent establishment-level employment changes, the bulk of annual job creation and destruction cannot be implemented by temporary layoff and recall policies.

IV. Explanations for Simultaneous Job Creation and Destruction

The preceding section established that job reallocation is large in magnitude and that it accounts for a large fraction of worker reallocation. This section investigates the sources of establishment-level heterogeneity that lead to simultaneous job creation and destruction within industries. We first draw on theories of plant-level heterogeneity and dynamics to identify potential driving forces behind simultaneous job creation and destruction. We then quantify the contribution of various sources of heterogeneity to total job reallocation and to variation in job reallocation among groups of establishments defined in terms of industry and other observable characteristics.

A. Theories of Heterogeneity That Explain Simultaneous Job Creation and Destruction

One prominent theory of heterogeneity in plant-level employment dynamics stresses the selection effects associated with passive learning about initial conditions. In this type of theory, plants face ex ante uncertainty about certain cost parameters or their efficiency level. A plant's underlying efficiency level cannot be directly observed but is learned over time through the process of production. A plant that accumulates favorable information about its efficiency expands and survives, whereas a plant that accumulates sufficiently unfavorable information exits. Well-articulated theories of this sort include Jovanovic [1982], Lippman and Rumelt [1982], and Pakes and Ericson's [1990] version of the Jovanovic model. Much of the empirical analysis in recent studies of firm-level and plant-level employment dynamics is explicitly couched in terms of this type of theory [Evans, 1987a, b; Hall, 1987; Dunne, Roberts, and Samuelson, 1989a; Pakes and Ericson, 1990].

As a stand-alone theory, passive learning about initial conditions cannot explain perpetual plant turnover within an industry. Eventually, plants learn their underlying efficiency level and decide whether to exit or remain indefinitely. The transitory, idiosyncratic cost disturbances present in the Jovanovic model generate transitory, plant-level employment fluctuations that continue indefinitely, but the existence of sunk costs associated with entry and exit insures that the set of surviving plants eventually becomes fixed in the absence of some other type of disturbance. Hence, we view passive learning and selection as a mechanism that magnifies the job reallocation and plant turnover response to other disturbances. For example, learning about initial conditions might explain why growing industries experience job destruction associated with plant deaths.

The replacement of old, outmoded plants by new, technologically superior plants provides another reason for the coexistence of job creation and destruction [Dunne, Roberts, and Samuelson, 1989b; Bresnahan and Raff, 1990]. Pursuing this theme, Ericson and Pakes [1989] and Pakes and Ericson [1990] develop a theory of firm and industry dynamics in which investment outcomes involve idiosyncratic uncertainty. The stochastic outcomes of an individual plant's investments, coupled with competitors' investment outcomes, determine the probability distribution over future profitability streams. A plant's investment outcome may improve its position relative to competitors, thus leading to expansion, or it may involve a relative deterioration, thus leading to contraction and, possibly, exit. Investment in the Ericson-Pakes model thus entails elements of active learning and selection. Unlike the passive learning and selection model of Jovanovic [1982], the Ericson-Pakes model builds in an explanation for perpetual entry and exit: the outside industry or competitors stochastically, but exogenously, advance along an efficiency path. Hence, the active learning theory embeds technical change into a rich model of plant-level heterogeneity and selection.

Another class of theories stresses differences in initial conditions, or uncertainties about future conditions, that lead firms to commit to different factor intensities and production techniques [Lambson, 1991]. These differences in turn lead to heterogeneity in plant-level responses to common cost and demand shocks.

Finally, even plants that produce identical products with identical technologies can face idiosyncratic cost disturbances. As examples, energy costs and tax burdens are often heavily influenced by local conditions. Exogenous, idiosyncratic cost disturbances lead to contraction at some plants and, simultaneously, expansion at other plants [Hopenhayn, 1989]. In Davis and Haltiwanger [1990] we develop a general equilibrium model of employment reallocation and job turnover driven by exogenous, idiosyncratic cost disturbances. Demand disturbances could clearly play the same role.

The preceding remarks identify several theories or factors that plausibly account for simultaneously large job creation and destruction rates within narrowly defined sectors of the economy. While a full assessment of each theory is beyond the scope of a single paper, we exploit several observable plant characteristics to quantify the contribution of some potentially important factors to job reallocation. In addition to industry, the observable plant characteristics we consider are plant age, size, geographic region, and ownership type (single plant versus multiplant firms). We interpret these plant characteristics as observable correlates of technical change, choice of production technique, differences in initial conditions, location-specific disturbances, organizational scale, and the progressive resolution of uncertainty about initial conditions.

B. Variation by Region, Size, Age, and Ownership Type

Table IV displays net and gross job flow rates cross-tabulated by plant size, age, ownership type, and geographic region. The rightmost column reports the distribution of manufacturing employment by plant characteristic. Except for plant age, the figures in Table IV represent average annual rates over the eleven years in our sample. Since our ability to construct detailed age categories is greatest in the last year of complete panels, we report averages of 1978 and 1983 values for the age figures.

According to Table IV, every region except the Mountain region experienced net job loss over the sample period. The variation in net job loss rates is quite small across plants of different average sizes and ownership types. In contrast, net job loss rates vary greatly by plant age. Young plants grow rapidly on average, while older plants shrink on average.

The gross job flow measures exhibit strong patterns of variation within each grouping of plants in Table IV. The western regions exhibit noticeably higher job reallocation rates than the rest of the country. Job reallocation rates for single-unit plants are half again as large as reallocation rates for plants operated by multi-unit firms. Job reallocation rates decline sharply with average establishment size, ranging from 14 percent at plants with 1000+ employees to 30 percent at plants with 1–99 employees.

TABLE IV

NET AND GROSS RATES BY TYPE OF PLANT[a]

	Size[b]					
No. of employees	*POS*	*NEG*	*NET*	*SUM*	*MAX*	Share[c]
1–99	0.140	0.164	−0.023	0.304	0.180	0.246
100–249	0.099	0.120	−0.021	0.219	0.133	0.185
250–499	0.086	0.105	−0.019	0.191	0.120	0.162
500–999	0.070	0.093	−0.023	0.163	0.106	0.134
1000+	0.060	0.078	−0.019	0.138	0.090	0.273
	Age					
Age in years	*POS*	*NEG*	*NET*	*SUM*	*MAX*	Share
Births						0.008
1	0.270	0.206	0.064	0.476	0.299	0.018
2	0.169	0.167	0.003	0.336	0.200	0.015
3	0.139	0.117	0.022	0.257	0.148	0.015
4–5	0.133	0.134	−0.001	0.267	0.154	0.045
6–10	0.120	0.121	−0.001	0.240	0.135	0.143
11–14	0.102	0.111	−0.010	0.213	0.123	0.110
15+	0.065	0.097	−0.033	0.162	0.103	0.645
	Ownership type					
Firm operates:	*POS*	*NEG*	*NET*	*SUM*	*MAX*	Share
Multiple mfg. plants	0.080	0.103	−0.023	0.184	0.115	0.768
A single mfg. plant	0.131	0.146	−0.016	0.277	0.170	0.232
	Geographic region					
Census region	*POS*	*NEG*	*NET*	*SUM*	*MAX*	Share
New England	0.090	0.108	−0.018	0.198	0.122	0.073
Middle Atlantic	0.085	0.121	−0.036	0.205	0.127	0.175
South Atlantic	0.079	0.111	−0.032	0.190	0.126	0.238
E. South Central	0.092	0.107	−0.015	0.198	0.122	0.068
W. South Central	0.092	0.101	−0.009	0.193	0.117	0.154
E. North Central	0.091	0.107	−0.016	0.198	0.124	0.070
W. North Central	0.105	0.115	−0.010	0.220	0.134	0.077
Mountain	0.118	0.114	0.005	0.232	0.138	0.026
Pacific	0.118	0.128	−0.009	0.246	0.149	0.120

a. Figures are size-weighted averages of eleven annual values, except for age group figures. Age group figures are size-weighted averages of 1978 and 1983 values.

b. A plant's size is measured as its mean number of employees over all sample observations with positive employment.

c. Group share of total employment, using the size metric described in the text.

The most dramatic variation in gross job flow rates involves plant age. For plants that are one-year old in the base year, the annual job reallocation rate averages a remarkable 48 percent.[15] The job reallocation rate drops off rapidly to 26 percent by age three, and it declines further to 16 percent for plants that are at least fifteen years old. Unreported results reveal that this sharp relationship between plant age and the job reallocation rate is pervasive across two-digit industries, regions, size classes, and ownership types.

These facts about variation in job reallocation rates by plant characteristic are consistent with the existing literature on heterogeneity in firm dynamics. Our measure of dispersion and our scheme for weighting establishment-level observations differ from previous studies, but sharp declines in employment volatility with plant size and age are robust findings in the literature. In seeking explanations for simultaneous job creation and destruction, the especially sharp and pervasive relationship between job reallocation and plant age impels one toward theories that can also explain this fact. Theories based on passive learning and selection suggest an interpretation of this fact as the natural outcome of a progressive resolution of uncertainty about initial conditions. In the next subsection we quantify the extent to which this type of theory can explain the magnitude of job reallocation and the variation in job reallocation rates across industries, regions, plant size classes, and plant ownership types.

C. Quantifying the Role of Passive Learning about Initial Conditions

Consider the following counterfactual question: how much would gross job reallocation be diminished if selection effects associated with passive learning about initial conditions were absent from the economic environment determining firm dynamics? We provide an answer to this question by bringing some simple identifying assumptions to bear on the age-related information in Table IV.

Identifying Assumptions and Methodology. If plants accumulate information over time about an unknown, but time-invariant, cost parameter, then the posterior distribution eventually converges in probability to the true value. Assume that this conver-

15. This figure is not inflated by including reopenings of previously idled plants. As the LRD enables us to track reopenings of older plants, their contribution to job creation and reallocation is allocated to the appropriate plant age category.

gence process is largely complete within n years of plant birth. This is our central identifying assumption. It follows from this assumption that none of the job reallocation among mature plants (age $\geq n$) reflects selection effects associated with learning about initial conditions.

Now, consider how we might exploit this identifying assumption to answer the counterfactual question. Besides the passive learning mechanism, many factors contribute to simultaneous job creation and destruction within industries or sectors of the economy. Except as described below, we assume that these other factors have age-neutral effects on job reallocation rates. This assumption means that these other factors generate the same base job reallocation rate for younger and older plants. Thus, as our second identifying assumption, we take the "base" reallocation rate to be age invariant.

Combining the two identifying assumptions, the fraction of job reallocation caused by passive learning and selection is

$$(1)\quad P = \left[\sum_{a<n} x(a)[r(a) - r(\text{age} \geq n)]\right] \Big/ rX = \left[\sum_{a<n} \frac{x(a)}{X}[r(a) - r(\text{age} \geq n)]\right] \Big/ r,$$

where $x(a)/X$ is the ath age group's share of sectoral employment, $r(a)$ is the job reallocation rate of age group a, and r denotes the sectoral job reallocation rate. The term $r(\text{age} \geq n)$, equal to the measured job reallocation rate among mature plants, represents the base rate of job reallocation assumed to be age invariant. Thus, the formula attributes all job reallocation in excess of the base amount to learning about initial conditions.

Besides passive learning, other factors can lead to age-nonneutral effects on the job reallocation rate. In particular, long-run net growth generates age-nonneutral effects on job reallocation rates.[16] For this case, the adjustment of (1) is straight-

16. Consider an industry equilibrium similar to the one articulated by Jovanovic. Suppose that industry demand and employment grow at a constant rate through time. Job reallocation among mature plants arises because of the transitory, idiosyncratic cost disturbances present in the Jovanovic model. Among younger plants, however, job reallocation also arises because of selection effects associated with learning about initial plant conditions. Thus, along the stationary growth path for the industry, new plants continuously enter to accommodate net industry expansion and to replace the employment losses at dying plants. Given diminishing returns at the plant level, net long-run industry growth occurs entirely through the entry of new plants rather than through higher job creation rates among existing plants.

forward and given by

$$(2) \qquad P = \left[\sum_{a<n} \frac{x(a)}{X} [r(a) - r(\text{age} \geq n)] - g \right] \Big/ r,$$

where g denotes the net sectoral employment growth rate. This alternative formula counts all job reallocation in excess of the base amount and the amount required to accommodate net expansion as arising from selection effects due to learning about initial conditions.

The appropriate adjustment is less clear for a contracting industry or sector, because contraction is likely to occur through shrinkage (and death) among plants of various ages. Taking these considerations into account, we modify our second identifying assumption by assuming that (a) net contraction has age-neutral effects on the reallocation rates, and (b) net expansion has the age-nonneutral effects described above. In line with this modification, the empirical results below estimate the fraction of job reallocation due to passive learning and selection as

$$(3) \qquad P = \left[\sum_{a<n} \frac{x(a)}{X} [r(a) - r(\text{age} \geq n)] - \max\{g,0\} \right] \Big/ r.$$

Two additional remarks about equation (3) are in order. First, factors other than net growth conceivably lead to age-nonneutral effects on the job reallocation rate. These factors potentially bias our estimate of passive learning's contribution to total job reallocation.[17] To the extent that these age-nonneutral factors reflect transitory or industry-specific disturbances, their impact on the calculation of P for the entire manufacturing sector will be negligible. To the extent that some unspecified factor systematically causes higher job reallocation rates among young plants, our estimate of passive learning's contribution will be upwardly biased.

Second, sunk costs associated with plant entry imply that transitory fluctuations in industry demand will be largely accommodated by the expansion and contraction of existing firms. The industry response to these disturbances is unlikely to involve a sharply age-nonneutral response in job reallocation rates. Hence, we interpret g in equations (2) and (3) as the long-run net growth

17. Age-nonneutral disturbances to employment growth rates, as opposed to reallocation rates, do not bias the estimate of passive learning's contribution. For example, a technological innovation that causes an equal rise in gross job destruction among mature plants and in gross job creation among young plants has offsetting effects on the calculation of P in (1)–(3).

rate. Empirically, we estimate g as the average annual employment growth rate in our sample for the industry or sector.

Empirical Results. We implement equation (3) using pooled sample data from 1978 and 1983, the only years for which we can tabulate the $r(a)$ function by the detailed age categories in Table IV. Carrying out the calculations for $n = 4$ years, we find that selection effects associated with learning about initial conditions account for 11 percent of job reallocation in the U. S. manufacturing sector. Repeating the calculations under the assumption that plants completely learn their underlying efficiency level by age six, learning about initial conditions explains 13 percent of job reallocation in the manufacturing sector. The key finding contained in these results is that learning about initial conditions explains only a small fraction of job reallocation.

This finding is unlikely to be overturned by reasonable modifications of our procedure or identifying assumptions. Table IV indicates why: nearly nine tenths of manufacturing employment is located at plants more than six years old, yet these plants exhibit substantial job reallocation rates. Learning about initial conditions is not a plausible explanation for high job reallocation rates among these plants.

The small contribution of learning to the level of job reallocation does not preclude a large role for learning in the cross-sectoral variation in job reallocation rates (Tables II and IV). For example, selection effects associated with learning about initial conditions might play a more important role among small establishments than among large establishments. Selection effects associated with uncertain imitability à la Lippman and Rumelt [1982] are likely to be more important for single-plant than for multiplant firms, because technology transference between plants within a firm is relatively easy. Other things equal, selection effects associated with learning about initial conditions will be more important in rapidly growing sectors than in mature or contracting sectors.

To investigate cross-sectoral differences in the importance of learning about initial conditions, we implemented equation (3) for each two-digit industry, geographic region, size class, and ownership type. The (unreported) results show considerable cross-sectoral variation in the fraction of job reallocation explained by learning about initial conditions, although learning never explains more than one fifth of sectoral job reallocation. Learning about initial conditions is relatively important in the western states, among small plants, and among plants owned by a single-unit firm. As indicated in Table IV, these sectors also display high total rates of job reallocation. Thus, our implementation of (3) on detailed sectors suggests that cross-sectoral differences in learning about initial conditions account for part of the observed cross-sectoral differences in job reallocation rates.

Table V quantifies the ability of the passive learning story to explain cross-sectoral differences in job reallocation rates. The first row of the table reports the cross-sectoral standard deviation of job reallocation rates for alternative sectoral classification schemes. The next two rows present estimates of the fraction of the cross-sectoral variance in job reallocation rates explained by the passive learning story. In computing these estimates, we rely on equation (3) to compute sectoral job reallocation rates net of the estimated contribution of learning about initial conditions.

The Table V results indicate that differences in the importance of learning about initial conditions explain a major portion of observed cross-sectoral differences in job reallocation rates. Learning about initial conditions explains one third or more of the variation in job reallocation rates among two-digit industries and census geographic reasons. Learning explains over half of the variation in job reallocation rates among plants of differing sizes and between single-unit and multi-unit plants.

TABLE V
ESTIMATED FRACTION OF CROSS-SECTORAL VARIATION IN JOB REALLOCATION RATES DUE TO LEARNING ABOUT INITIAL CONDITIONS

	Sector classification by:			
	Industry	Region	Size	Ownership
Cross-sectoral standard deviation of job reallocation rates	0.042	0.026	0.056	0.050
Fraction of cross-sectoral variance explained by learning about initial conditions, assuming $n = 4$	0.32	0.39	0.51	0.56
Fraction of cross-sectoral variance explained by learning about initial conditions, assuming $n = 6$	0.36	0.48	0.57	0.62

a. All table entries are based on the pooled sample data for 1978 and 1983.
b. Rows two and three report the quantity $1 - (\tilde{V}/V)$. V is defined as the cross-sectoral variance of job reallocation rates. $\tilde{V}$ is defined as the cross-sectoral variance of adjusted job reallocation rates. The adjusted sectoral reallocation rate equals the observed rate minus the contribution of learning as estimated from equation (3).

In terms of explaining job reallocation behavior, we can summarize the empirical performance of the passive learning story as follows. Learning about initial conditions provides a plausible explanation for the sharp and pervasive relationship between job reallocation rates and plant age. This aspect of our results confirms closely related findings by Evans [1987a, b]; Hall [1987]; and Dunne, Roberts, and Samuelson [1989a]. In addition, Table V indicates that the passive learning story also explains much of the cross-sectoral variation in job reallocation intensity. These results lead us to conclude that the passive learning story is quite useful for interpreting variation in job reallocation intensity across different types of plants.

On the more fundamental matter of explaining the overall magnitude of job reallocation, the passive learning story is far less successful. Learning about initial conditions accounts for a small portion, 11–13 percent, of total job reallocation and only a slightly larger fraction of excess job reallocation. This result prompts us to investigate another potential explanation for high rates of excess job reallocation.

D. Quantifying the Role of Between-Sector Employment Shifts

Disturbances that cause a reshuffling of employment among different sectors or groups of plants generate simultaneous job creation and destruction. This simple point immediately raises two questions: what fraction of excess job reallocation can be explained by the reshuffling of employment among groups of plants defined in terms of interesting observable characteristics? And which observable plant characteristics are most useful in accounting for excess job reallocation?

We address these questions by decomposing excess job reallocation for the manufacturing sector, and for each two-digit industry, into two components.[18] One component represents the contribution of reshuffling employment among sectors, and the other component represents the contribution of excess job reallocation within sectors. The component of excess job reallocation due to between-sector employment shifts is given by

$$\sum_{s=1}^{S} |\text{Net Employment Change in } s| - |\text{Overall Net Employment Change}|,$$

18. Dunne, Roberts, and Samuelson [1989b] exploit an equivalent decomposition in their analysis of gross job flows over five-year intervals.

where s indexes sectors. The component due to excess job reallocation within sectors is given by

$$\sum_{s=1}^{S} (\text{Job Reallocation in } s - |\text{Net Employment Change in } s|).$$

Table VI reports the results of decomposing excess job reallocation for sectoral classification schemes defined in terms of plant

TABLE VI
FRACTION OF EXCESS JOB REALLOCATION DUE TO BETWEEN-GROUP EMPLOYMENT SHIFTS

Means of 1978 and 1983 values for total manufacturing

Group Type	Age	Size	Region	Ownership	2-digit ind.	4-digit ind.	All ex ind.[b]	All[a]
Number	8	5	9	2	20	450	720	14400[c]
	0.06	0.00	0.00	0.00	0.01	0.12	0.15	0.39

Means of 1978 and 1983 values by two-digit industry

Group type	Age	Size	Region	Ownership	All[b]
No. of groups	8	5	9	2	720
Industry					
Food	0.13	0.01	0.01	0.00	0.36
Tobacco	0.12	0.03	0.05	0.01	0.62
Textiles	0.18	0.01	0.01	0.03	0.39
Apparel	0.20	0.11	0.10	0.02	0.46
Lumber	0.01	0.00	0.02	0.00	0.36
Furniture	0.08	0.03	0.04	0.00	0.45
Paper	0.12	0.08	0.08	0.00	0.43
Printing	0.08	0.06	0.05	0.00	0.39
Chemicals	0.06	0.00	0.00	0.00	0.39
Petroleum	0.26	0.07	0.21	0.00	0.65
Rubber	0.16	0.12	0.01	0.00	0.48
Leather	0.12	0.03	0.06	0.01	0.52
Stone, clay, glass	0.04	0.00	0.02	0.00	0.39
Primary metals	0.07	0.01	0.05	0.00	0.31
Fabricated metals	0.05	0.00	0.00	0.00	0.23
Nonelectric mach.	0.12	0.00	0.00	0.00	0.31
Electric machinery	0.10	0.00	0.02	0.00	0.33
Transportation	0.09	0.00	0.01	0.00	0.35
Instruments	0.11	0.00	0.02	0.00	0.50
Miscellaneous	0.20	0.05	0.05	0.06	0.56

a. Based on a grouping of plants by age, size, region, ownership type, and two-digit industry simultaneously.
b. Based on a grouping of plants by age, size, region, and ownership type simultaneously.
c. Approximately 11,000 group cells are nonempty.

age, size, region, ownership type, and industry. Each entry in Table VI reports the fraction of excess job reallocation explained by between-sector employment shifts for the indicated sectoral classification.

The most remarkable aspect of Table VI is the inability of between-sector employment shifts to account for excess job reallocation. According to the top panel, employment shifts among plants of different ages, sizes, regions, ownership types, and two-digit industries account for virtually none of the excess job reallocation in the manufacturing sector as a whole. Cutting sectors much more finely by defining them in terms of age, size, region, and ownership simultaneously, between-sector employment shifts account for only 15 percent of excess job reallocation. Employment shifts among the 450 four-digit manufacturing industries account for a mere 12 percent of excess job reallocation. Even when we define sectors in terms of all five plant characteristics simultaneously, between-sector employment shifts account for only 39 percent of excess job reallocation.[19] The industry-level decompositions in the second panel of Table VI carry the same basic message as the top panel, although the age-based classification scheme consistently yields the most successful accounting for excess job reallocation.

The results in Table VI argue strongly against the view that high rates of excess job reallocation arise primarily because of sectoral disturbances or economywide disturbances with differential sectoral effects. Instead, Table VI argues that excess job reallocation is fundamentally a phenomenon related to plant-level heterogeneity in labor demand. Learning about initial conditions is one reason for plant-level heterogeneity in labor demand, but we found that this story has limited ability to explain the magnitude of job reallocation. Theories that stress active learning and selection among young and old plants [Ericson and Pakes, 1989], theories that stress endogenous precommitment to heterogeneous production technologies [Lambson, 1990], and theories that stress exogenous plant-specific cost or demand disturbances [Hopenhayn, 1989; Davis and Haltiwanger, 1990] all seem consistent with the results in Table VI. Investigation into the ability of these theories to explain high rates of excess job reallocation must await further research.

19. To appreciate the level of detail captured by this classification scheme, we remark that the average nonempty "sector" contains only about five sampled plants.

V. Accounting for Time Variation in Job Reallocation Intensity

Table I showed that the pace of job reallocation exhibits significant countercyclic variation in our sample. For example, between the business cycle trough in 1975 and the peak in 1980 the job reallocation rate fell by six percentage points. This cyclical pattern is confirmed in subsequent research that relies on data for other time periods, sectors, and countries. Blanchard and Diamond [1990] demonstrate a close relationship between our job creation and destruction figures and appropriately adjusted measures of job turnover in the BLS manufacturing turnover series. They find that their related job reallocation measure fluctuates countercyclically over the 1958 to 1981 period. Based on BLS establishment level data, Bronars [1990] finds significant countercyclical variation in the job reallocation rate for every one-digit industry group in the United States over the 1972–1989 period. Tabulations in Baldwin and Gorecki [1990, Table 3.5] reveal countercyclic job reallocation behavior in the Canadian manufacturing sector during the 1970 to 1981 period. Regev [1990] reports countercyclical variation in job reallocation rates for Israel during the 1980s.

These empirical results point to a close relationship between the business cycle and the intensity of job reallocation, but they do not address the question of why the job reallocation rate fluctuates countercyclically. In view of the links between job reallocation and worker reallocation, an answer to this question will provide insight into the source and nature of aggregate labor market fluctuations. To address the question of why job reallocation moves countercyclically, we first address two simpler questions: how much of the time variation in job reallocation is accounted for by mean translations of the establishment-level growth rate density and differential mean sectoral responses to aggregate disturbances? And, how does the cyclical behavior of job reallocation differ by industry type, plant size, age, and ownership type? Drawing on our answers to these questions, we then discriminate between macroeconomic theories that cannot explain the observed cyclical behavior of job reallocation and theories that potentially can.

A. An Accounting Framework

Consider the linear model for establishment-level employment growth rates,

$$g_{et} = \tilde{g}_{et}^{ST} + g_{st} + g_t, \tag{4}$$

where g_t is the manufacturing growth rate, g_{st} is the sector growth rate (deviated about g_t), and $\tilde{g}_{et}^{ST}$ is the residual idiosyncratic component of the establishment growth rate. According to equation (4), 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 the job flow measures.

Several alternative views about the nature of aggregate fluctuations can be couched in terms of equations like (4). 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 reflects variation in the aggregate-time effects. This view encompasses a time-invariant, but possibly large, cross-sectional variance of the idiosyncratic component. 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 incorporate differences in the timing and magnitude of sectoral responses to aggregate disturbances. Systematic cross-sectoral differences in the responses to aggregate disturbances are an important element of traditional views about the business cycle [Abraham and Katz, 1986].

To capture this aspect of traditional views, we allow for completely unrestricted sectoral responses to aggregate disturbances. In particular, consider the hypothesis of a time-invariant distribution over the $\tilde{g}_{et}^{ST}$. In view of (4) the sector-time effects g_{st} capture *any* systematic or nonsystematic cross-sectoral differences in the mean response to aggregate disturbances. 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.

Based on the decomposition in (4), we measure the relative importance of aggregate, sectoral, and idiosyncratic components for time variation in job creation, destruction, and reallocation. We also measure the covariation between the components. To see our procedure, consider the distribution over the $\tilde{g}_{et}^{ST}$, from which we compute job creation, destruction, and reallocation rates adjusted for aggregate-time and sector-time effects:

$$\widetilde{POS}_t^{ST} = \sum_{e,\tilde{g}_{et}>0} \frac{x_{et}}{X_t} (\tilde{g}_{et}^{ST}), \tag{5}$$

$$\widetilde{NEG}_t^{ST} = \sum_{e,\tilde{g}_{et}<0} \frac{x_{et}}{X_t} (|\tilde{g}_{et}^{ST}|), \tag{6}$$

and

$$\widetilde{SUM}_t^{ST} = \sum_{e} \frac{x_{et}}{X_t} |\tilde{g}_{et}^{ST}|. \tag{7}$$

Time variation in these adjusted measures reflects only the contributions of the idiosyncratic effects. Thus, $\widetilde{SUM}_t^{ST}$ measures the gross rate of change in the number of establishment-level employment positions as a result of idiosyncratic establishment-level employment movements. 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,

$$SUM_t = \widetilde{SUM}_t^{ST} + (SUM_t - \widetilde{SUM}_t^{ST}), \tag{8}$$

which implies the variance decomposition for gross job reallocation,

$$\operatorname{var}(SUM_t) = \operatorname{var}(\widetilde{SUM}_t^{ST}) + \operatorname{var}(SUM_t - \widetilde{SUM}_t^{ST}) + 2\operatorname{cov}(\widetilde{SUM}_t^{ST}, SUM_t - \widetilde{SUM}_t^{ST}). \tag{9}$$

If the distribution over the $\tilde{g}_{et}^{ST}$ is time-invariant, then the ratio of $\operatorname{var}(\widetilde{SUM}_t^{ST})$ to $\operatorname{var}(SUM_t)$ 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 and sectoral effects or to the idiosyncratic effects.

We also decompose the variance of job creation and destruction rates along the lines of (8) and (9). Variance ratios provide information on the relative contribution of aggregate/sectoral versus idiosyncratic effects to time variation in job creation and destruction. The covariance terms indicate whether the idiosyncratic effects reinforce or counteract the impact of aggregate and sectoral effects on job creation and destruction rates.

B. Results

Table VII decomposes the time-series variance of annual job reallocation, creation, and destruction rates using several sectoral classification schemes. According to the first row of the first panel, aggregate and sectoral effects account for 4.2–10.5 percent of the time variation in job reallocation, depending on the classification scheme. Assigning all of the covariance term to the aggregate and sectoral effects, they still account for no more than 20 percent of time variation in annual job reallocation rates. These results show

TABLE VII
DECOMPOSITION OF TIME-SERIES VARIANCE OF JOB REALLOCATION, CREATION, AND DESTRUCTION

	Sectoral classification scheme						
	Total mfg.	4-digit	2-digit	2-digit, size	2-digit, age	2-digit, owner	2-digit, region
# of sectors	1	450	20	100	40	40	180
Fraction of job reallocation (SUM_t) variance accounted for by							
(a) Sectoral/agg. mean effects	0.03	0.105	0.044	0.044	0.042	0.051	0.053
(b) Idiosyncratic effects	1.026	0.797	0.876	0.816	0.879	0.838	0.917
2cov(a,b)	−0.056	0.098	0.079	0.140	0.078	0.111	0.030
Fraction of job creation (POS_t) variance accounted for by							
(a) Sectoral/agg. mean effects	1.44	1.318	1.395	1.431	1.388	1.459	1.385
(b) Idiosyncratic effects	0.16	0.124	0.136	0.142	0.138	0.149	0.142
2cov(a,b)	−0.60	−0.442	−0.531	−0.573	−0.526	−0.609	−0.526
Fraction of job destruction (NEG_t) variance accounted for by							
(a) Sectoral/agg. mean effects	0.63	0.705	0.658	0.726	0.664	0.680	0.665
(b) Idiosyncratic effects	0.079	0.062	0.068	0.063	0.067	0.066	0.071
2cov(a,b)	0.287	0.233	0.274	0.211	0.288	0.254	0.264

a. Entries in the top panel are based on the variance decomposition in equation (9). Each entry reports the ratio of the indicated term on the right side of (9) to the term on the left side. Entries in the second and third panels are based on analogous variance decompositions for job creation and destruction.

b. Size, region, and ownership sectors are defined as in Tables IV and V.

c. There are two age groups: young plants (0–9 years) and old plants (10+ years).

that time variation in the structure of mean employment growth rates across regions, detailed industries, plant size classes, age groups, and ownership types account for remarkably little of the time variation in job reallocation. The flip side of the same coin is that idiosyncratic effects account for 80 percent or more of the variability in annual job reallocation rates.

Thus, Table VII finds that only 4–20 percent of the time variation in job reallocation rates can be accounted for by mean translations of the growth rate density and differential mean sectoral responses to aggregate disturbances. This finding refutes the hypothesis that some systematic pattern of sectoral responses to aggregate disturbances can account for the significant time variation in gross job reallocation displayed in Table I. Instead, the time variation in gross job reallocation results overwhelmingly from time variation in the magnitude of idiosyncratic effects. This result is especially striking in that our narrow definition of idiosyncratic effects imposes neither linearity, magnitude, nor timing restrictions on the mean sectoral responses to aggregate disturbances.

The second and third panels of Table VII shed further light on the time-series behavior of gross job reallocation. These panels indicate that aggregate-year effects play a dominant role in accounting for time variation in job creation and destruction rates. The variance of the idiosyncratic component of job creation amounts to only 12–16 percent of the overall variance of job creation, and the variance of the idiosyncratic component of job destruction amounts to only 6–8 percent of the overall variance of job destruction. The covariance results for job creation and destruction link their behavior to the behavior of job reallocation. For job destruction the positive sign and large magnitude of the covariance terms indicate that idiosyncratic effects strongly reinforce the countercyclic movements in gross job destruction associated with aggregate mean effects. For job creation, in contrast, the negative sign and large magnitude of the covariance terms indicate that idiosyncratic effects strongly counteract the procyclic fluctuations in job creation associated with aggregate mean effects. Taken together, the covariance terms from the *POS* and *NEG* decompositions explain how the idiosyncratic component dominates fluctuations in 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.

We turn now to a more detailed accounting for time variation in job reallocation intensity. Table VIII provides information on the cyclical behavior of sectoral job reallocation rates. The top panel shows that whether we define sectors in terms of industry, region, size, age, or ownership type, movements in adjusted sectoral job reallocation rates are predominantly countercyclical. For example, all twenty of the two-digit manufacturing industries show countercyclic movements in the adjusted job reallocation rates. Unreported results are similar for the raw job reallocation rate, but adjusted job reallocation rates show a stronger and more pervasive countercyclical pattern than the raw rate. Thus, rather than providing an explanation for countercyclical fluctuations in job reallocation, sectoral differences in mean growth rates actually mitigate the countercyclicality of job reallocation.

The bottom panel of Table VIII shows how the cyclical behavior of job reallocation varies by type of sector. Countercyclic movements in job reallocation rates are more pronounced for larger plants, older plants, multi-unit plants, and plants that produce durable goods.

The results by plant age and size are especially striking. Segregating plants into groups of young (0–9 years) and old (10+

TABLE VIII

CYCLICAL BEHAVIOR OF SECTORAL JOB REALLOCATION RATES: TIME-SERIES CORRELATIONS BETWEEN NET_{ST} AND $\widetilde{SUM}_{st}^{ST}$

By alternative sectoral classification schemes

	Total mfg.	4-digit	2-digit	2-digit, size	2-digit, age	2-digit, owner	2-digit, region
Size-weighted avg. correlation	−0.64	−0.36	−0.55	−0.41	−0.50	−0.45	−0.42
(# < 0)/total	1/1	360/450	20/20	87/100	29/40	31/40	152/177

For particular sector types

			Two-digit industry by					
	Durable	Nondur.	Small	Large	Young	Old	Single	Multi
Size-weighted avg. correlation	−0.65	−0.40	−0.20	−0.63	0.06	−0.71	−0.19	−0.53
(# < 0)/total	10/10	10/10	33/40	38/40	9/20	20/20	11/20	20/20

a. Each entry summarizes the simple correlations between the net job growth rate and the adjusted job reallocation rate for the indicated classification scheme or sector type. Results are similar for the correlations between the net job growth rate and the unadjusted job reallocation rate.

b. "Small" refers to the 40 sectors with plants in the 0–99 and 100–249 size classes. "Large" refers to the 40 sectors with plants in 500–999 and 1000+ size classes.

years), and then interacting with two-digit industry, yields 40 industry-by-age sectors. For the twenty sectors representing older plants, the size-weighted average correlation between rates of net sectoral growth and adjusted gross job reallocation equals −0.71. In sharp contrast, the younger plant sectors show no systematic relation between net job growth and job reallocation. These results reveal that the countercyclicality of job reallocation rates entirely reflects greater heterogeneity in the establishment-level employment movements of mature plants during contractions. A similar characterization of cyclical movements in job reallocation rates holds in terms of small versus large plants. Cross-classifying on two-digit industry and our five size classes yields 100 industry-by-size sectors. The average correlation between net sectoral growth and adjusted job reallocation for the 40 large plant sectors is −0.63. In contrast, the average correlation for the 40 small plant sectors is only −0.20.

It is helpful to place the results in the bottom panel of Table VIII alongside the variance decomposition results in Table VII. The variance decomposition results show that the great bulk of time variation in job reallocation cannot be accounted for by sectoral differences in mean responses to cyclical impulses. The bottom panel of Table VIII indicates that the bulk of time variation in job reallocation can be accounted for by especially sharp countercyclical job reallocation movements among sectors made up of older, larger, and multi-unit plants.

While the results in Table VIII provide insight into the basic pattern of time variation in sectoral job reallocation rates, they provide little information about the magnitude of the covariances between net overall and sectoral growth rates, on the one hand, and sectoral job reallocation rates, on the other hand. To investigate the covariance structure, we regress the adjusted sectoral reallocation rates defined by (7) on net sectoral and manufacturing growth rates plus interactions of these net rates with age, size, and ownership dummies. The regressions also contain sectoral fixed effects to control for permanent sectoral differences in the intensity of job reallocation.

Table IX summarizes the regressions and reports key results. Column (1) of the top panel, for example, regresses adjusted industry-level job reallocation rates on industry fixed effects and two time-varying covariates: g_t and g_{st}. These covariates are highly significant (t-statistics greater than five in absolute value), and they account for 27 percent of the time variation in industry job

TABLE IX
REGRESSIONS OF ADJUSTED SECTORAL JOB REALLOCATION RATES ON OWN-SECTOR AND MANUFACTURING NET GROWTH RATES

Dependent variable in regressions: adjusted sectoral job reallocation rates
Summary of regressions and goodness-of-fit measures

	Sectoral classification scheme			
	2-digit industry	Industry by age	Industry by size	Industry by ownership
Regression number	(1)	(2)	(3)	(4)
# of observations	220	440	1100	440
# of sectoral fixed effects	20	40	100	40
# of other regressors	2	4	6	4
Regression R^2	0.78	0.78	0.53	0.75
Fraction of time-series variation explained by other regressors	0.27	0.08	0.05	0.11

Estimated responses (×100) of sectoral job reallocation rates

Sector type:	Ind.	Young	Old	Small	Med.	Large	Single	Multi
Response to a one st. dev. decline in:								
Mfg. net growth rate	−1.15	−0.13	−1.82	−0.18	−1.51	−1.38	0.20	−1.46
	(0.12)	(0.39)	(0.14)	(0.60)	(0.21)	(0.17)	(0.25)	(0.13)
Own net growth rate	−0.24	0.11	−0.26	0.55	−0.13	−0.38	−0.16	−0.23
	(0.05)	(0.19)	(0.06)	(0.79)	(0.10)	(0.07)	(0.10)	(0.13)
Based on regression #:	(1)	(2)	(2)	(3)	(3)	(3)	(4)	(4)

a. In regression (1) "other regressors" refers to g_t, the manufacturing net growth rate, and g_{st}, the own-sector net growth rate deviated about g_t. Relative to regression (1): regression (2) adds interactions of these variables with one age-group dummy; regression (3) adds interactions with two size-class dummies; and regression (4) adds interactions with one ownership-type dummy.

b. The "Fraction of time-series variation explained by other regressors" equals the R^2 from a regression of the deviations about sectoral fixed effects on the time-varying "Other regressors."

c. In computing the estimated responses in the bottom panel, a one standard deviation increase in the own-sector net growth rate is measured as the size-weighted average of the time-series standard deviations of sectoral growth rates. This measure isolates the magnitude of time-series variation in the g_{st}.

d. Heteroskedasticity-consistent standard errors are in parentheses.

reallocation rates. The bottom panel summarizes the implications for the covariance structure. Here, we use the regression to estimate the response of adjusted job reallocation rates to one standard deviation increases in g_t and g_{st}. Based on regression (1), for example, a one standard deviation decline in the manufacturing (own-industry) net growth rate is associated with an increase in sectoral job reallocation rates of 1.15 (0.24) percentage points. Relative to regression (1), regressions (2)–(4) add the age, size, and ownership interaction terms, respectively.

Two main results stand out in Table IX.[20] First, large movements in sectoral job reallocation rates are associated with movements in total manufacturing employment growth rather than movements in own-sector employment growth. This result occurs primarily because the average time-series standard deviation of g_{st} is small relative to the standard deviation of g_t. The regression coefficients on g_t and g_{st} differ significantly only for old plants in regression (2).

Second, the covariation between the manufacturing employment growth rate and sectoral job reallocation rates is much larger among old plants than among young plants, among medium-sized and big plants than among small plants, and among multi-unit plants than among single-unit plants. Indeed, there is no evidence of statistically significant covariation between manufacturing or own-sector net employment growth and rates of job reallocation among younger, smaller, and single-unit plants. There is clear evidence of large and highly significant covariation between manufacturing employment growth and rates of job reallocation among older, larger and multi-unit plants.

A similar, but less pronounced, pattern emerges with respect to the covariation between own-sector employment growth and sectoral job reallocation rates. Point estimates indicate greater negative covariation between own-sector employment growth and job reallocation rates among older, larger, and multi-unit plants. These differences are statistically significant at the 5 percent level except for the comparison between multi-unit and single-unit plants. The negative covariation between own-sector employment growth and job reallocation rates is highly statistically significant for old and large plants.

C. Interpretation of Cyclical Findings

We have established the following cyclical facts: (1) job reallocation rates fluctuate countercyclically; this pattern is pervasive across industries and regions. (2) The countercyclic behavior of job reallocation reflects time variation in the magnitude of idiosyncratic plant-level employment movements, not sectoral differences in the mean employment responses to aggregate disturbances. (3) Job reallocation rates among young (0–9 years), small (1–249 employees), and single-unit plants exhibit little or no systematic

20. The main results in Table IX are unaffected if we use the raw job reallocation rates as dependent variables in the regressions.

relationship to the cycle. (4) Job reallocation rates among older, larger, and multi-unit plants exhibit pronounced countercyclic patterns of variation.

What classes of macroeconomic models can explain these facts? It is useful, and perhaps easier, to first identify important classes of models that cannot explain these facts: (i) models that specify or treat all firms as homogeneous. (ii) Sectoral models of the business cycle that specify homogeneous firms within sectors. Examples include simple versions of the model described by Lilien [1982], in which sectoral disturbances drive aggregate fluctuations, and the model described by Abraham and Katz [1986], in which aggregate disturbances drive differential sectoral responses. (iii) Sectoral or aggregate models that treat the idiosyncratic component of firm-level employment behavior as orthogonal to the business cycle. This class includes models that specify a cyclically invariant natural rate of unemployment as in Phelps et al. [1970], Hall [1979], and Johnson and Layard [1986].

We stress that appending idiosyncratic establishment-level shocks to simple sectoral or aggregate models is not sufficient to explain our cyclical findings. Idiosyncratic establishment-level shocks clearly generate an underlying rate of gross job reallocation within sectors, but they do not necessarily generate a relationship between aggregate fluctuations and the pace of job reallocation. This point is nicely made by Caballero [1990]. He posits an asymmetry in firm-level hiring and firing costs in a model that accommodates aggregate and idiosyncratic labor demand disturbances. His adjustment cost specification implies a higher time-series variance in job destruction rates than in job creation rates at the firm level. This feature of the microeconomic structure in Caballero's model is consistent with the pattern displayed in our Figure II. If this firm-level result carried over to the aggregate level, it would provide an explanation for countercyclic variation in job reallocation rates. However, Caballero shows that the asymmetry in firm-level job creation and destruction behavior is smoothed away by aggregation when firms exhibit idiosyncratic components to their employment movements. Empirically, we have seen that the idiosyncratic components are large and pervasive.

To explain our findings requires a macroeconomic model that generates simultaneous job creation and destruction within narrowly defined sectors *and* countercyclical rates of job reallocation within sectors. Progress along these lines is made in recent work by Blanchard and Diamond [1989, 1990], Davis and Haltiwanger

[1990], and Caballero [1990]. These authors specify alternative models that allow both common aggregate and idiosyncratic allocative shocks to influence establishment-level employment dynamics. The models differ in the frictions that they ascribe to the process of reallocating workers and jobs across establishments, but in each model labor market frictions imply potentially important interactions between aggregate employment growth and the pace of reallocation.

These models identify four types of potentially important interactions between the pace of job reallocation and the stage of the business cycle. First, time-series fluctuations in the intensity of allocative shocks can cause aggregate employment fluctuations, as well as countercyclic movements in the job reallocation rate. Second, aggregate shocks can influence the timing of the job reallocation that ultimately arises from allocative shocks, and thereby lead to a bunching of job reallocation activity during downturns.[21] Third, aggregate downturns may induce a shakeout of less efficient firms and establishments, leading to both aggregate contraction and increased heterogeneity in plant-level employment movements. Fourth, if negative aggregate shocks are more severe (and less frequent) than positive aggregate shocks, then the endogenous evolution of the cross section distribution over plant-level employment growth can generate countercyclic variation in job reallocation intensity.

In light of the findings reported in this paper, disentangling these and other connections between aggregate activity and the pace of job reallocation is an important area for future research. None of the interpretations of countercyclic job reallocation intensity offered by Blanchard and Diamond, Davis and Haltiwanger, and Caballero incorporate an explanation for the findings in this paper related to pronounced differences in the magnitude and cyclicality of job reallocation intensity by plant age, size, and ownership type.

VI. CONCLUSION

This study paints a sharp picture of gross job flow behavior in U. S. manufacturing industries. Gross rates of job creation and destruction are remarkably large: they amount to roughly 10

21. Darby, Haltiwanger, and Plant [1985] and Davis [1987] also discuss this reallocation timing effect.

percent of manufacturing employment in a typical year. The phenomenon of simultaneously high rates of job creation and destruction is pervasive across industries and across groups of plants defined in terms of plant age, size, region, and ownership type. In large part, the gross job flows that we measure reflect establishment-level employment changes that are highly persistent and concentrated at plants experiencing sharp expansion or contraction.

The magnitude and character of gross job flows bear directly on the reasons for gross worker flows in the labor market. Combining longitudinal information from household and establishment surveys, we calculate that the reallocation of employment opportunities across establishments accounts for 35–56 percent of all worker reallocation between employers or between employment and joblessness.

The magnitude and cyclical variability of gross job flows differs systematically across plants with different observable characteristics. On average, job reallocation rates are substantially higher among younger, smaller, and single-unit plants. At the same time, job reallocation rates among these plants show no systematic cyclical variation; whereas job reallocation rates among older, larger, and multi-unit plants show pronounced countercyclic variation.

This paper provides partial explanations for several aspects of gross job flow behavior. Further research designed to explain gross job flow behavior and to develop its implications for labor market dynamics, for the evolution of firms and industries, and for the nature of business cycles merits a high priority.

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