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Job Flows and Productivity Dynamics: Evidence from U.S. Manufacturing

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Abstract

Through their influence on the cross-sectional distribution of productivity across firms and workers, job creation and destruction likely have an impact on the rate at which aggregate productivity changes over time. However, the nature of this effect is not, a priori, clear. While a broad consensus has emerged suggesting that job destruction enhances productivity by eliminating inefficient production units, theories disagree with regard to the effect of job creation. In particular, 'vintage-capital' theories of creative destruction suggest a positive influence since job flows are conjectured to represent the reallocation of labor from low- to high-productivity positions. Others suggest that job creation may, instead, represent the expansion of employment primarily along a low-skill (or low 'match-quality') dimension. In such a case, job creation would serve to lower aggregate productivity. This paper estimates the influence of job creation and destruction on total factor productivity (TFP) growth using annual data on 389 4-digit U.S. manufacturing industries over the period 1974-1993. As expected, the results reveal a positive association between job destruction and changes in TFP. Yet, they also indicate that, contrary to the creative-destruction view, job creation tends to have a negative effect on productivity growth.

*The views expressed herein are those of the author and do not represent the official positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

1 Introduction

The notion that sectoral productivity shocks underlie the flow of labor from one industry, producer, or region to another is a well established idea in both the macroeconomics and labor literatures.[1] However, while much of this work has focused on the response of job flows to changes in productivity, surprisingly little research has considered the reverse. That is, although productivity growth may influence the rates at which jobs are created and destroyed, do these creation and destruction rates, in turn, influence productivity?[2]

There is certainly ample reason to believe that they do. After all, much of the literature studying the determinants of job creation and destruction posit that, in response to some underlying shock (either technology- or demand-related), workers are reallocated across production units. This reallocation, in turn, affects the cross-sectional distribution of productivity across individual workers and producers and, thus, the aggregate productivity they engender.

Although there is some disagreement over the basic mechanisms underlying job destruction, there is a reasonably broad consensus regarding its conjectured impact on aggregate productivity. To be sure, virtually all studies suggest that job destruction takes place

[1] Examples include (among many others) Campbell and Fisher (2000), Davis and Haltiwanger (1999a, 1999b), Caballero et al. (1997), Davis et al. (1996), Caballero and Hammour (1994), Mortensen and Pissarides (1994), Lougani and Rogerson (1989), and Lilien (1982).

[2] To be fair, there is a large empirical literature linking productivity growth to job flows (see, for example, Davis and Haltiwanger (1999b, pp. 2762-2768) for a survey). Overwhelmingly, however, these studies (e.g. Baily et al. (1992), Baily et al. (1996), Foster et al. (1998)) approach the issue by conducting decompositions of aggregate productivity growth into components accounted for by plants belonging to various categories – e.g. expanding (including entering) establishments as opposed to contracting (including exiting) ones. This paper, by contrast, seeks to estimate the direct effects of job creation and destruction on productivity growth, accounting for their joint determination.

primarily among the most inefficient production arrangements in any given cross section. Merz (1999) and Den Haan et al. (2000), for example, examine models in which producers eliminate jobs in response to negative shocks to firm-worker 'match quality.' Caballero and Hammour (1994) study an environment in which decreases in the demand for an industry's output result in the elimination of the most inefficient production units in operation. In each of these instances, the act of destroying jobs serves to increase aggregate productivity by removing the bottom end of the micro-level productivity distribution.

Empirically, this rather straightforward conjecture has a fair amount of support. For example, in the context of firms, Baily et al. (1992), Griliches and Regev (1995), and Olley and Pakes (1996) have found that low productivity does indeed predict a producer's exit from the market. Evidence on the nature of job destruction implied by studies of individual work histories suggests a similar conclusion. Gibbons and Katz (1991), for instance, report that firms tend to target workers from the low end of the productivity distribution for layoffs when reducing total employment. Farber (1993) finds that, between 1982 and 1991, rates of job loss were higher among younger, less educated workers than among older, more educated ones.

The nature of job creation and its impact on productivity, by contrast, is somewhat less clear-cut. Indeed, some papers (e.g. Caballero and Hammour (1994), Mortensen and Pissarides (1994), and Hall (2000)) suggest that job creation represents the allocation of workers into new, technologically advanced (and, thus, high-productivity) work arrangements. When combined with the characterization of job destruction above, this line of reasoning suggests that, overall, job flows can be viewed as a manifestation of 'creative destruction.'

Evidence on this particular hypothesis, however, is somewhat mixed. While studies such as Baily et al. (1992) and Foster et al. (1998) find that the reallocation of workers from low- to high-productivity establishments contributes positively to aggregate productivity growth in U.S. manufacturing, Bowlus (1995) and Barlevy (2000) find that, on the whole, workers do not move into more productive positions during recessions, when rates of job destruction (thus, presumably, rates of productive reallocation) are especially high. Consequently, the extent to which job creation involves additions to the upper end of the job-productivity distribution remains uncertain.

In fact, other studies have taken a very different view of the matter, suggesting that job creation may, instead, reduce aggregate productivity. Merz (1999), for instance, explores an environment in which employment variation occurs primarily along a low match-quality margin. That is, when firms experience positive productivity shocks, they expand their employment by hiring predominantly low-wage (i.e. low-productivity) workers whereas given negative shocks to productivity, employment falls as these very same workers are laid off. In such an instance, because job creation involves the expansion of the lower tail of the worker productivity distribution, it confers a negative effect on aggregate efficiency.

Evidence reported by Solon et al. (1994), interestingly, is broadly consistent with this characterization of the labor market. Using data from the PSID, they find that the contribution of low-wage labor exhibits greater variation over the business cycle than high-wage labor. Thus, during recessions, low-wage workers are laid off in greater numbers than high-wage workers, whereas in expansionary periods, greater numbers of low-wage workers are hired. Assuming that low wages are indicative of low productivity, this evidence suggests that, by itself, job creation should reduce aggregate efficiency.

This paper attempts to evaluate these competing views of job flows by estimating the impact of job creation and job destruction on the growth of total factor productivity (TFP) using annual data on 389 4-digit manufacturing industries in the United States over the period 1974-1993. As a brief summary of the results, I find that, consistent with the consensus view, job destruction does indeed have a positive influence on TFP growth. Thus, on average, there certainly appears to be a cleansing aspect to the job-destruction process. However, contrary to the pure creative-destruction view, I also find that job creation tends to have a negative influence on productivity growth. As a consequence, the evidence favors the view that, on the whole, job creation and destruction represent employment changes along a predominantly low-skill/low-productivity margin as opposed to productive reallocation.

The remainder of the paper proceeds as follows. Section 2 presents a simple theoretical framework used to derive the hypothesized statistical relationship between job flows and TFP growth. The data and results from formal estimation of this relationship are then discussed in, respectively, Sections 3 and 4. Section 5 concludes.

2 Theoretical Characterizations of TFP and Job Flows

This section develops a simple framework to explore the connection between job flows and total factor productivity growth. As noted above, two general approaches have been taken when examining this nexus. The first – the 'job match-quality' view (e.g. Merz (1999)) – suggests that both employment gains and losses involve jobs primarily situated at the bottom end of the productivity distribution. The second – the 'vintage-capital' approach (e.g. Caballero and Hammour (1994)) – views job creation and destruction as the means by which unproductive work arrangements are replaced by more productive ones. I consider each in turn.

2.1 Job Match Quality

Consider an economy comprised of many producers/firms, indexed by j, each of which belongs to an industry, indexed by i. In order to operate in any given time period t, a producer hires some number $N_{j,i,t} > 0$ of workers (the determination of which is described below) from a pool of available labor. Once assembled, this labor force then generates output, $Y_{j,i,t}$, given by

$$\begin{aligned} Y_{j,i,t} &= \theta_{j,i,t}(K_{j,i,t})^{\alpha}[A_{j,i}^{(1)}(L_{j,i,t}^{(1)})^{1-\alpha} + A_{j,i}^{(2)}(L_{j,i,t}^{(2)})^{1-\alpha} + \ldots \\ &+ A_{j,i}^{(N_{j,i,t})}(L_{j,i,t}^{(N_{j,i,t})})^{1-\alpha}],\ 0 < \alpha < 1, \end{aligned} \tag{1}$$

where $\theta_{j,i,t} > 0$ denotes a producer-specific random technology shock, $K_{j,i,t} > 0$ is the producer's endowment of physical capital, $L_{j,i,t}^{(w)} > 0$ is worker w's labor input, and $A_{j,i}^{(w)} > 0$ is worker w's time-invariant index of productivity (or match quality), all at time t. For the sake of simplicity, suppose that the producer's stock of physical capital is constant and that all workers supply the same quantity of labor input, L, inelastically at each point in time.[3]

Notice, although workers supply the same quantity of labor when hired, they do not all contribute equally to production. In particular, heterogeneity in the match-quality parameters, A – which, in practice, may derive from any of a host of individual characteristics including education, experience, or innate ability with respect to a particular job – implies that some workers are, quite simply, more productive than others. Because I am abstracting from labor market search decisions, I assume that these parameters are perfectly observable

[3]Note, these particular assumptions are not crucial since the ultimate object of interest, TFP, takes into account the effects of observable inputs (e.g. capital and labor hours) on output.

so that the producer knows the exact distribution of worker productivities when assembling a labor force. I also assume that the producer may hire any worker that it wants. The producer's problem, then, reduces to the choice of an optimal number of workers to hire at each point in time. To solve such a problem, consider first the specification of payoffs.

Workers in this framework are paid their marginal products, so that, in aggregate, labor receives $(1-\alpha)Y_{j,i,t}$ in each time period t. The producer, who owns the stock of physical capital, K, then receives the remainder, $\alpha Y_{j,i,t}$.[4] The producer's final payoff, I assume, is merely this residual part of output net of a worker coordination cost:

$$\alpha Y_{j,i,t} - g(N_{j,i,t}), \tag{2}$$

where $g' > 0$ and $g'' > 0$. This second term, $g(N_{j,i,t})$, is designed to capture the cost that a producer must, for instance, pay a manager to ensure that production proceeds smoothly. The fact that it is strictly increasing and convex in the number of workers hired reflects the notion that coordination becomes increasingly difficult as more and more workers are assembled (e.g. Williamson (1967), Becker and Murphy (1992)).[5]

The producer's problem, then, consists of choosing $N_{j,i,t}$ to maximize (2) conditional on knowledge of the technology shock, $\theta_{j,i,t}$. Doing so is straightforward. First, notice that the producer will always employ the most productive workers in the economy: for a given $N_{j,i,t}$, $\alpha Y_{j,i,t}$ strictly increases in the productivity index of each worker hired whereas

[4]This payoff scheme is analogous to a Nash bargaining solution which is common in matching models (e.g. Acemoglu (1996), Den Haan et al. (2000)). The results derived below hold for general firm-worker splits given by shares π and $1-\pi$, $\pi \in (0,1)$.

[5]The addition of the coordination cost also makes the producer's problem well-defined. Without it, optimal employment and the producer's payoff are both infinite.

the coordination cost is constant. As a result, when evaluating the payoff associated with a particular level of employment, $N_{j,i,t}$, the producer simply substitutes the $N_{j,i,t}$ highest values of A into (2). Optimal employment is then given by the value of $N_{j,i,t}$ that generates the highest quantity.

Based on this setup, we have the following intuitive result linking technology shocks and the producer's optimal employment.

Proposition: Optimal employment is non-decreasing in θ.

Proof: The term $\alpha Y_{j,i,t}$ is strictly increasing in the number of workers hired. Therefore, the amount by which an increase in the technology term, $\theta_{j,i,t}$, increases $\alpha Y_{j,i,t}$ increases in the number of workers hired. As such, the increase in the difference $\alpha Y_{j,i,t} - g(N_{j,i,t})$ in response to a rise in $\theta_{j,i,t}$ also increases in $N_{j,i,t}$, which implies that the optimal value of $N_{j,i,t}$ cannot decrease in response to a positive technology shock.

∎

Hence, as producers receive technology shocks, θ, the overall productivity of each worker's match, $\theta A^{(w)}$, changes, thus inducing potential changes in optimal employment.

Given that the most productive workers in the economy are employed at each point in time, changes in employment are accomplished by altering the number of relatively low match-quality jobs in operation. Thus, in response to a negative technology shock which reduces optimal employment by, say, P employees, a producer simply eliminates the P least productive matches.

The timing of the shock process and the producer's employment adjustment take the following form. At the beginning of each period, the technology shock is realized, implying an optimal employment level. Over the remainder of the period, the producer begins adjusting employment to meet this optimal level, which may take one or more periods to attain. In particular, the presence of certain labor market rigidities, such as contracts requiring producers to give workers notice that they will be fired (given a negative shock) or, if one allows for search considerations, finding and hiring workers that are desired (given a positive shock) may require producers to adjust employment only gradually.[6] Thus, each producer constantly reacts to values of θ as they are observed from one time period to the next.

From this basic characterization of employment and production, producer j's total factor productivity (TFP) can be expressed as follows:

$$\mathrm{TFP}_{j,i,t} = \frac{\theta_{j,i,t} K^{\alpha}[A_{j,i}^{(1)} L^{1-\alpha} + A_{j,i}^{(2)} L^{1-\alpha} + \ldots + A_{j,i}^{(N_{j,i,t})} L^{1-\alpha}]}{K^{\alpha} N_{j,i,t} L^{1-\alpha}} = \theta_{j,i,t} \frac{\sum_{w=1}^{N_{j,i,t}} A_{j,i}^{(w)}}{N_{j,i,t}} \tag{3}$$

That is, a firm's TFP is calculated by dividing output by the measured capital input, which, conditional on knowledge of α, is just K^{α} and the measured labor input, which is given by $N_{j,i,t} L^{1-\alpha}$ ($N_{j,i,t}$ workers, each of whom supplies L units of labor).[7] The resulting measure of TFP is the product of two terms: the technology shock and the average match quality of the workers hired. TFP growth is then given by taking log differences:

[6]Note, gradual adjustment would be consistent with the evidence reported by Stevens (1997) who finds that displaced workers suffer significant earnings losses in both the year prior to and year of displacement.

[7]In formulating this expression for TFP, I assume that the match-quality parameters are not observed and, thus, are not accounted for by the researcher who calculates TFP. Although the distinction between production and non-production workers is accounted for in the TFP measure considered here (see Section 3.1), no other labor-quality adjustments are made.

$$\Delta\text{ln TFP}_{j,i,t} = \Delta\text{ln}\theta_{j,i,t} + \Delta\text{ln}\bar{A}_{j,i,t} \tag{4}$$

where $\bar{A}_{j,i,t} = \frac{1}{N_{j,i,t}} \sum_{w=1}^{N_{j,i,t}} A_{j,i}^{(w)}$.

Because the change in the average match quality over all workers within a firm depends directly on the extent to which the firm is expanding or contracting the number of workers that it employs (employment gains reduce $\bar{A}$, employment losses raise $\bar{A}$), TFP growth can be re-formulated in terms of rates of job creation, POS, and job destruction, NEG:

$$\Delta\text{ln TFP}_{j,i,t} = \Delta\text{ln}\theta_{j,i,t} + \gamma_C\text{POS}_{j,i,t} + \gamma_D\text{NEG}_{j,i,t} \tag{5}$$

where the parameters $\gamma_C < 0$ and $\gamma_D > 0$ represent the influence of creation and destruction on productivity growth. Note, since producers either expand or contract (or neither), only one of the terms, $\text{POS}_{j,i,t}$ or $\text{NEG}_{j,i,t}$ can be non-zero at a given point in time.

Now, because industry aggregates are merely weighted sums of firm-level measures, industry i's productivity growth follows as

$$\Delta\text{ln TFP}_{i,t} = \sum_j \omega_{j,i,t}\Delta\text{ln}\theta_{j,i,t} + \sum_j \omega_{j,i,t}(\gamma_C\text{POS}_{j,i,t} + \gamma_D\text{NEG}_{j,i,t}) \tag{6}$$

where $\omega_{j,i,t}$ denotes producer j's weight in the industry at t. This expression, of course, can then be written more compactly in terms of industry-level technology growth, job creation, and job destruction:

$$\Delta\ln\ \mathrm{TFP}_{i,t} = \Delta\ln\theta_{i,t} + \gamma_C\mathrm{POS}_{i,t} + \gamma_D\mathrm{NEG}_{i,t} \tag{7}$$

2.2 Vintage Capital

A second line of inquiry suggests that job flows embody creative destruction. That is, simultaneous job creation and destruction act as a mechanism by which inefficient production units are eliminated and more efficient ones established. This idea has been formalized, for example, by Caballero and Hammour (1994) who demonstrate that such a process can explain, among other things, the asymmetric patterns witnessed in the creation and destruction series.

The fundamental idea of that paper can be applied to a setting analogous to the one sketched above in the following manner. Let production of firm j of industry i at time t, $Y_{j,i,t}$, be given by the product of an efficiency term (TFP), $\theta_{j,i,t}$, and some function of a fixed amount of labor and capital. Upon isolating each producer's index of efficiency, the logarithm of industry i's TFP can be approximated as a weighted sum over its constituent firm-level measures:

$$\ln\ \mathrm{TFP}_{i,t} = \sum_{j\in\Omega_t} \omega_{j,i,t}\ln\theta_{j,i,t} \tag{8}$$

where, as before, $\omega_{j,i,t}$ is plant j's weight in the industry in period t, and Ω_t is the set of plants in operation during this period. Industry-level TFP growth then follows as

$$\Delta\ln \text{TFP}_{i,t} = \sum_{j\in\Omega_t} \omega_{j,i,t}\ln\theta_{j,i,t} - \sum_{j\in\Omega_{t-1}} \omega_{j,i,t-1}\ln\theta_{j,i,t-1} \tag{9}$$

which can be re-written in a manner analogous to the decomposition considered by Baily et al. (1992):

$$\begin{aligned} \Delta\ln \text{TFP}_{i,t} = \quad & \textstyle\sum_{j\in(\Omega_t\cap\Omega_{t-1})}(\omega_{j,i,t}\ln\theta_{j,i,t} - \omega_{j,i,t-1}\ln\theta_{j,i,t-1}) \\ & + \textstyle\sum_{j\in(\Omega_t\setminus\Omega_{t-1})} \omega_{j,i,t}\ln\theta_{j,i,t} \\ & - \textstyle\sum_{j\in(\Omega_{t-1}\setminus\Omega_t)} \omega_{j,i,t-1}\ln\theta_{j,i,t-1} \end{aligned} \tag{10}$$

Notice, the first term in this expression represents the change in the weighted log-productivity sum taken across continuing plants (i.e. those in operation at both $t-1$ and t); the second, the weighted log-productivity sum over plants entering at t, who (by assumption) utilize the most efficient technologies available; the third, the weighted log-productivity sum across plants exiting the market after period $t-1$, who (again, by assumption) utilize the least efficient technologies.

Given that all firms in operation employ a constant amount of labor, job creation and destruction in this framework are merely the products of entry and exit. Thus, the three terms on the right-hand-side of (10) can be expressed in a manner analogous to (7):

$$\Delta\ln \text{TFP}_{i,t} = \Delta\ln\theta_{i,t} + \gamma_C\text{POS}_{i,t} + \gamma_D\text{NEG}_{i,t}$$

The underlying source of job flows in Caballero and Hammour's (1994) model, other than purely exogenous rates of technological progress and producer obsolescence, are demand shocks. Increases in the demand for an industry's output result in decreases in the rate at which low-productivity producers are eliminated (as greater numbers of producers are required to accomodate the rise in demand), while decreases in demand do just the reverse. Although the magnitude of the response is somewhat smaller, demand shocks have the opposite effect on job creation. Positive (negative) shocks are met with modest increases (decreases) in the rate at which new production units are established.[8]

More importantly, consider the influence of job creation and destruction on TFP growth. Job creation in this formulation is clearly a benefit to industry productivity. As new producers are added, a larger share of industry output is accounted for by higher productivity plants. Hence, $\gamma_C > 0$. Job destruction, on the other hand, also serves a beneficial role as it represents the elimination of the most inefficient producers. Thus, because high rates of destruction also increase the weights assigned to the most efficient producers, $\gamma_D > 0$ as well.

Notice, while these particular implications regarding the direct effects of job flows on productivity are straightforward, evaluating the overall effect of a demand shock on an industry's rate of TFP growth is more complicated. That is, whether a positive shock to demand (say, associated with an expansionary period) generates greater or lower productivity growth is not clear-cut. A rise in demand, for instance, may be associated with more job creation but less job destruction, thereby leaving the overall change in TFP ambiguous. Moreover, although the TFP of each continuing plant does not change in Caballero and Hammour's (1994) formulation, permitting it to do so would further complicate the change in productivity emanating from a change in demand.[9]

[8] For a rigorous characterization of the response of job creation and destruction to demand shocks, see Caballero and Hammour (1994).

[9] Hence, as they carefully note (p. 1365), this formulation does not necessarily imply a particular cyclical

3 Data and Statistical Methods

3.1 Productivity and Job-Flow Data

The productivity data used in the analysis are taken from the NBER Manufacturing Productivity Database (MPD), which reports annual rates of TFP growth for more than 400 4-digit industries between 1958 and 1996. The job-creation and destruction data, which are defined as total employment gains and losses, respectively, expressed as percentages of total industry employment, are reported by Davis et al. (1996) over the period 1973 to 1993.[10] To maintain a balanced panel of industries for the entire 1973-1993 period, I eliminate all industries for which the 1972 and 1987 SIC codes do not match. The resulting sample consists of 389 industries.

Two measures of TFP growth are reported by the MPD: a 5-factor growth rate (capital, production worker hours, non-production workers, non-energy materials, and energy) and a 4-factor growth rate (energy and non-energy materials are not treated separately).[11] Since the correlation across the two is extremely high (i.e., in excess of 0.99), I limit the analysis to the 5-factor measure. Summary statistics for each of these variables – TFP growth, job creation, job destruction – appear in Table A1 of the Appendix. Simple correlations and cross-correlations at various leads and lags are reported in Table A2.

Several basic properties of the data deserve some mention. First, the contemporaneous correlation between job creation and job destruction across 4-digit industries is only weakly negative, -0.06. This figure stands in contrast to the one reported by Davis et al. (1996, p. 33) for aggregate manufacturing over the period 1973-1988, -0.75, and to the correlation

pattern for productivity with respect to expansions and recessions.

[10] John Haltiwanger has generously provided these data online at www.bsos.umd.edu/econ/haltiwanger.

[11] For further information about the MPD, see Bartelsman and Gray (1996).

of the employment-share weighted averages of job creation and destruction in the present sample, -0.67. This result seems to suggest that simultaneous increases or decreases in creation and destruction occur more frequently within 4-digit industries than within aggregate manufacturing itself. It also indicates that, at this level of aggregation, these two series are relatively independent. Both may, therefore, enter feasibly into a single regression equation.[12]

Second, TFP growth is positively correlated with contemporaneous job creation (POS), but negatively correlated with contemporaneous job destruction (NEG). This feature, of course, can be interpreted in terms of both hypotheses discussed above. Positive technology shocks, for instance, may induce producers to expand their payrolls, thus generating an increase in both creation and TFP growth. Similarly, a rise in demand may induce greater job creation which, in turn, may raise overall productivity as especially productive jobs are established. While in both cases, job destruction would decrease, thereby mitigating any increase in productivity growth, it is certainly possible to observe productivity growth moving (on average) with creation but against destruction.

Third, just as Baily et al. (1992) find among individual manufacturing establishments, TFP growth at the 4-digit industry level is significantly, negatively autocorrelated. While Baily et al. (1992) suggest that this mean-reverting tendency can be interpreted in terms of a model in which there are random shocks to productivity levels (i.e. higher-than-average shocks in one period tend to be followed by smaller shocks subsequently), it should be noted that it is also compatible with the job-matching formulation above with *persistent* shocks to technology.

[12] That is, identifying the separate effects of creation and destruction on productivity growth should not be impaired by an excessively high degree of collinearity between them.

Suppose that, given a negative technology shock at t which persists for two periods, producer j adjusts its employment to the new (lower) optimal level in periods t and $t+1$. Again, various labor market rigidities may necessitate a gradual transition of employment levels over time. In period t, there would be a negative contemporaneous correlation between TFP growth and job destruction as long as the initial decrease in $\theta_{j,i,t}$ outweighed the increase in the average match quality $\bar{A}_{j,i,t}$ as low productivity workers are released. In the following period, however, as job destruction continues, TFP will begin rising.[13]

For such a scenario to be plausible, naturally, TFP growth and job destruction would have to move together in some periods while TFP growth and job creation would have to move in opposite directions some of the time. As it turns out, the data indicate that both happen roughly half of the time. Using the 7780 industry-year observations for $\{\Delta \ln \text{TFP}_{i,t} - \Delta \ln \text{TFP}_{i,t-1}\}$, $\{\text{POS}_{i,t} - \text{POS}_{i,t-1}\}$, and $\{\text{NEG}_{i,t} - \text{NEG}_{i,t-1}\}$, I find that TFP growth and the rate of job destruction either both increase or decrease in 46 percent of the observations. At the same time, TFP growth and job creation move in opposite directions about 46 percent of the time.[14]

In terms of the implied correlations, this example suggests that the contemporaneous correlation between job creation and TFP growth as well as that between job destruction and TFP growth will be given by a mixture of positive and negative values. As mentioned above, on net, such a correlation could very well be positive for job creation and negative for job destruction (as in the data). At one lag, however, the implied relationships in this particular

[13] The fact that each job-flow series is positively autocorrelated (see Table A2) is certainly compatible with the notion of persistent shocks and gradual adjustment.

[14] Although they study labor productivity, these findings are similar to those of Baily et al. (1996, p. 267) who find that over half of all expanding plants experience productivity declines whereas over half of all contracting plants experience productivity increases.

instance are clear: job creation (destruction) will be positively (negatively) correlated with lagged TFP growth, while TFP growth will be negatively (positively) associated with lagged job creation (destruction). All, as it happens, are born out empirically.

What is more, TFP growth itself will be negatively autocorrelated as a direct consequence of the job flows that are induced by the underlying (persistent) technology shocks: productivity gains induce job creation which generates future losses; productivity losses induce job destruction which generates future gains. Thus, random shocks – as in Baily et al. (1992) – are not necessary for mean reversion.[15]

While intriguing, none of these casual statistics provide any direct evidence on how either job-flow series influences TFP growth. Hence, at this point, I turn to the formal estimation of the models sketched above.

3.2 Statistical Model

The theoretical characterization of productivity growth derived in Section 2,

$$\Delta \ln \text{ TFP}_{i,t} = \Delta \ln \theta_{i,t} + \gamma_C \text{POS}_{i,t} + \gamma_D \text{NEG}_{i,t}$$

provides the basis for the statistical analysis that follows. I begin by specifying the structure of the average technology growth term $\Delta\ln\theta_{i,t}$ as a stationary AR(P) process, designed to capture any autocorrelation in the underlying shocks (i.e. technology or demand shifts)

$$\Delta \ln \theta_{i,t} = \sum_{s=1}^{P} \rho_s \Delta \ln \theta_{i,t-s} + \xi_{i,t} \tag{11}$$

[15]Indeed, one could also rationalize mean reversion in TFP growth with persistence in the *growth rate* of technology, $\Delta\ln\theta$, as long as job creation and destruction adjust slowly (i.e. an increase in technology growth at t which persists through $t+1$ induces a small increase in creation at t, but a large increase at $t+1$).

where the term $\xi_{i,t}$ is the sum of two elements: an overall constant, μ, and a white-noise term specific to industry i at time t, $\epsilon_{i,t}$.[16] The one-period growth rate of this average technology term can then be expressed as

$$\Delta \text{ln}\theta_{i,t} = \frac{\xi_{i,t}}{1 - \rho_1 L - \rho_2 L^2 - \ldots - \rho_P L^P} = \frac{\mu + \epsilon_{i,t}}{1 - \rho(L)} \tag{12}$$

where L denotes the lag operator, so that the equation describing TFP growth above becomes

$$\begin{aligned} \Delta\text{ln TFP}_{i,t} &= \mu + \rho(L)\Delta\text{ln TFP}_{i,t} + (1 - \rho(L))\gamma_C \text{POS}_{i,t} \\ &+ (1 - \rho(L))\gamma_D \text{NEG}_{i,t} + \epsilon_{i,t} \end{aligned} \tag{13}$$

So, for example, an AR(1) representation of the technology process results in the following specification

$$\begin{aligned} \Delta\text{ln TFP}_{i,t} &= \mu + \rho_1 \Delta\text{ln TFP}_{i,t-1} + \gamma_C \text{POS}_{i,t} - \gamma_C \rho_1 \text{POS}_{i,t-1} \\ &+ \gamma_D \text{NEG}_{i,t} - \gamma_D \rho_1 \text{NEG}_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{14}$$

[16] It should be noted that if $\text{ln}\theta_{i,t}$ follows a stationary autoregression in *levels*, this representation in differences will involve an MA(1) error instead of white noise. However, since none of the estimated specifications reported in Tables 1-3 produced residuals with significant first-order autocorrelation, I proceed under the assumption that (11) is valid.

which involves the estimation of four parameters: μ, ρ_1, γ_C, and γ_D.

The difficulty associated with estimating this equation, of course, is the endogeneity of the contemporaneous job-flow terms, $\text{POS}_{i,t}$ and $\text{NEG}_{i,t}$. Based on the job match-quality formulation, for example, an increase in $\epsilon_{i,t}$ signifies a positive shock to (average) industry productivity. While this shock increases TFP, it also affects the extent to which firms are creating and destroying jobs since $\epsilon_{i,t}$ is itself the sum of firm-level technology terms which determine employment changes. Similarly, a shock to demand in the vintage-capital formulation influences both the extent of job creation and destruction as well as the term $\epsilon_{i,t}$ through its influence on the weights $\omega_{j,i,t}$ of the continuing plants. A negative demand shock, for instance, may decrease creation and increase destruction and, simultaneously, increase the weighted average productivity over continuing plants. Simple nonlinear least squares (NLLS) estimation of equation (13) would therefore generate biased estimates of the creation and destruction effects, γ_C and γ_D.[17]

Consequently, to estimate equation (13), I turn to the use of instrumental variables. As instruments for the two endogenous job-flow series, I utilize three variables describing an industry's plant-size distribution: the logarithm of the average number of workers per plant, the percentage of all establishments with at least 500 employees, and the percentage of all establishments with fewer than 50 employees, all lagged one period. Hence, these three 'average plant-scale' variables at time t instrument for an industry's job creation and destruction between t and $t+1$.

Annual data on establishment counts by employment size categories for 4-digit man-

[17] For the purpose of comparison, NLLS estimates of the creation and destruction parameters for each of the specifications considered below appear in Table A4 of the Appendix.

ufacturing is taken from annual County Business Patterns (CBP) files produced by the Bureau of the Census. From these data, the percentage of plants employing fewer than 50 employees and those employing 500 or more are readily computed.[18] The average number of workers per plant is calculated, quite simply, as the ratio of total industry employment to the number of establishments. It should be noted that, because the CBP 4-digit industry codes changed substantially between 1973 and 1974, I have dropped the 1973 data and focused on the 1974-1993 time period.

Are these variables plausible as instruments for the two job-flow series? Instrumental variables, of course, must satisfy two criteria. First, they must be exogenous with respect to, in this case, total factor productivity growth. Second, they must be correlated with job creation and destruction.

To begin, lagged features of an industry's establishment size distribution are certainly not determined by subsequent productivity growth. Hence, there are no simultaneity problems associated with these variables. Moreover, existing studies of plant-level productivity indicate that lagged establishment size characteristics are themselves unlikely to be the central determinants of TFP growth. Baily et al. (1992), for example, find that plant size – measured by total employment – is not a significant predictor of TFP growth in their sample of manufacturing establishments. Foster et al. (1998, p. 10-11) offer a similar conclusion in their survey of the literature studying plant-level productivity, noting that, while productivity *levels* tend to be higher in large establishments, "it has been more difficult to find

[18]The size categories (in terms of employees) reported in the U.S. Summary data files include the following: 1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, 1000 or more. Casual experimentation indicated that the proportions of establishments situated in the (combined) 1-49 and 500 or more groupings were particularly correlated with creation and destruction.

correlates of changes in productivity."[19] For these reasons, lagged plant size characteristics are not likely to be correlated with $\epsilon_{i,t}$.[20]

At the same time, measures of average establishment size tend to be highly correlated with rates of job creation and destruction. Davis et al. (1996), for instance, document a strong inverse association between average establishment size – measured directly by employment as well as indirectly through average wage earnings and capital intensity – and both job-flow series. A similar result is shown in Table A3 of the Appendix, which reports correlations between creation and destruction rates and each of the three lagged plant-scale variables among the 389 industries considered here. Clearly, as industries organize their activity around establishments with greater numbers of employees, average rates of job creation and destruction fall dramatically.

4 Results

4.1 Baseline Estimates

Estimation of (13) is performed in two ways: (nonlinear) two-stage least squares (2SLS) and generalized method-of-moments (GMM).[21] With 2SLS, the parameter vector, β, is chosen

[19] For example, they note that while Dunne (1994) finds that large plants are more likely to adopt 'advanced' technologies (e.g. CAD/CAM) which may help to rationalize their high productivity levels, Doms et al. (1997) find that the growth of average labor productivity is only weakly connected to the adoption of these technologies.

[20] In the data used here, the raw correlations of TFP growth with the logarithm of average plant size, percentage of plants with at least 500 workers, and percentage with fewer than 50 workers (all lagged one period) are small: -0.026, -0.018, and 0.017. Only the first of these values differs statistically from zero at 10 percent significance.

[21] This discussion follows chapters 10 and 11 of Greene (2000).

to minimize the following objective function:

$$(\epsilon(\beta)'\mathbf{Z})(\mathbf{Z}'\mathbf{Z})^{-\mathbf{1}}(\mathbf{Z}'\epsilon(\beta)) \tag{15}$$

where $\epsilon(\cdot)$ is an $(n \times 1)$ vector of residuals associated with parameter vector β, $\mathbf{Z}$ is an $(n \times g)$ matrix of instrumental variables, n is the number of (industry-year) observations, and g the number of instruments (here, equal to three). GMM, by contrast, selects the vector of parameters to solve a similar, but slightly more general minimization problem:

$$(\epsilon(\beta)'\mathbf{Z})(\mathbf{Z}'\mathbf{\Sigma}\mathbf{Z})^{-\mathbf{1}}(\mathbf{Z}'\epsilon(\beta)) \tag{16}$$

Here, $\mathbf{\Sigma}$ is an $(n \times n)$ covariance matrix of the error terms, $\epsilon_{i,t}$, and $(\mathbf{Z}'\mathbf{\Sigma}\mathbf{Z})$ represents the estimated $(g \times g)$ covariance matrix of the model's moment conditions $\mathbf{Z}'\epsilon(\beta)$, scaled by n^2.

These two objective functions, of course, coincide when $\mathbf{\Sigma}$ is some scalar multiple of the identity matrix – that is, when the errors are mutually uncorrelated and homoskedastic. In practice, however, since I base the GMM estimates on a heteroskedasticity-consistent specification of $\mathbf{\Sigma}$, they will generally differ from the 2SLS estimates.[22]

Results for each of three lag lengths describing $\Delta\ln\theta_{i,t}$ – AR(1), AR(2), AR(3) – appear in Table 1. Two features are particularly noteworthy. First, we can see that the estimated autoregressive parameters, ρ, are significantly negative throughout, implying that the shock process, $\Delta\ln\theta_{i,t}$ (i.e. the 'residual' element of TFP growth after removing the effects of job creation and destruction) follows an autocorrelation pattern similar to one characterizing the

[22]The specification of the error matrix follows that of White (1980) so that $(\mathbf{Z}'\mathbf{\Sigma}\mathbf{Z})$ in (16) is estimated as $\sum_{i=1}^{n} \hat{\epsilon}_i^2 \mathbf{z}_i \mathbf{z}_i'$ where $\mathbf{z}_i$ is the $(g \times 1)$ vector of instruments for observation i.

raw productivity growth levels (Table A2). While not completely surprising, this result does offer some evidence on the role of employment variation in generating a mean-reverting TFP growth series. In particular, while job creation and destruction may certainly contribute to a negative autocorrelation pattern in productivity growth (as described in Section 3.1), the evidence does not support the idea that job flows themselves provide a complete explanation for this pattern. Independent of the effects of job creation and destruction, TFP growth is negatively autocorrelated.

Second, the estimates reveal a positive influence of job destruction, while a negative influence of job creation, on TFP growth. Statistically, in fact, nearly all of the relationships are significant: of the twelve coefficients, only the job-creation parameters, γ_C, from the two AR(1) specifications are indistinguishable from zero at conventional significance levels. Moreover, the magnitudes of the coefficients also suggest economically significant effects. Based on the point estimates, a 1 standard-deviation increase in job destruction (roughly 7 percentage points), for example, is accompanied by a 2 to 3.5 percentage-point increase in TFP growth, on average, whereas a 1 standard-deviation rise in job creation (approximately 6 percentage points) is associated with 2 to 2.5 percentage-point decrease in TFP growth. Given that the overall standard deviation of the TFP growth series across all industry-years is about 7 percent, these estimated effects are substantial.

Of course, one reason for these large magnitudes may be that this first specification of the model does not account for the potential influence of exogenous time effects on productivity growth. In particular, if they are correlated with the two job-flow series, the creation and destruction parameters given in Table 1 may simply be reflecting the influence of these time effects.

To examine this possibility, I estimate (13) with year dummies included. The resulting parameter estimates appear in Table 2. Notice, while the coefficients in this case are now somewhat smaller – the estimated effects of a 1 standard-deviation change fall between 0.7 and 1.3 percentage points for destruction, 0.6 and 0.9 percentage points for creation – and, unfortunately, not as consistently significant across all specifications, they still suggest the same qualitative pattern. Job creation serves to reduce productivity growth, job destruction acts to boost it. Given the two characterizations of the job flows-productivity growth nexus described above, then, this baseline evidence tends to favor the job-matching perspective over the vintage-capital view.[23]

4.2 Robustness: Factor Utilization and Intensity

Empirically, TFP has proved to be an elusive concept due to the likely influence of unobserved inputs on measured output. In particular, variations in factor utilization have been shown to play a large role in the dynamic properties of Solow-residual type measures of technological progress, such as those reported in the MPD (e.g. Burnside et al. (1993) and Shapiro (1993)). Furthermore, because factor utilization is largely unobservable, this concern has plagued studies of productivity dynamics for years.

A recent paper by Basu and Kimball (1997), however, suggests a simple correction that can be performed to account for variable capital and labor utilization. Assuming that firms

[23]These results may also offer some insight into why the observed association between establishment size and TFP growth tends to be weak in studies of plant-level data (e.g. Baily et al. (1992)). Large plants tend to experience lower rates of job destruction (hence slower productivity growth) as well as job creation (hence faster productivity growth). Given a cross section of expanding and shrinking plants, little overall correlation may emerge between size and productivity growth. This mechanism would also imply that the dispersion of productivity growth is higher in smaller plants (due to higher job-flow rates) which is broadly consistent with the evidence reported by Dunne et al. (1989).

are cost minimizers and price takers in factor markets and that the only cost of increasing the work-week of capital is the compensation of workers for a shift premium, changes in hours per worker can be used to proxy for changes in the utilization of both capital and labor.[24] Since the NBER MPD reports total numbers of production workers and production worker hours for each industry in each year, this correction is readily implemented.

Additionally, Klenow (1998) finds that rates of total factor productivity growth vary significantly with respect to capital and labor intensity. Specifically, capital intensive industries seem to experience faster rates of TFP growth than labor intensive ones, at least over fairly long time horizons. As a consequence, some correction for the extent of capital and labor intensity across industries may be required.

Following these observations, I include as exogenous regressors into equation (13) the contemporaneous values of the growth rate of hours per worker among production workers, the share of capital in total output, and the share of labor in total output. These shares are calculated as in Klenow (1998) who defines an industry's labor share as its total payroll divided by its total value of shipments, materials share as total materials cost (including energy) divided by the total value of shipments, and capital share as the residual after subtracting these first two from unity.

The resulting parameter estimates appear in Table 3. Beginning with the three correction terms, we can see that hours per worker growth appears to play little role, at least after having conditioned on all other variables appearing in the model. Capital and labor shares, on the other hand, do enter significantly and (following Klenow's (1998) evidence) with the expected signs: industries with greater capital intensity tend to experience faster

[24]Basu and Kimball (1997) find that allowing for increased capital utilization to generate a second cost, faster depreciation, does not greatly alter their productivity calculations.

TFP growth; those with greater labor intensity tend to experience slower growth.

As for the remainder of the parameters, the estimated values are similar to those reported in Tables 1 and 2. The autoregressive coefficients, for instance, remain negative and display the same pattern with a particularly strong AR(2) term. More importantly, the job-destruction and creation parameters remain, respectively, positive and negative, exhibiting roughly the same magnitudes as those from Table 2. While not all of the coefficient estimates are significant in this case (e.g. only one of the job-creation terms, γ_C, differs statistically from zero at conventional levels), the results certainly appear to reinforce the basic conclusion drawn above.

It is worthwhile at this point to compare these instrumental-variables (IV) estimates of the effects of job creation and destruction, given in Tables 1-3, with those derived from the estimation of (13) by nonlinear least squares (NLLS), which are summarized in Table A4 of the Appendix. Looking at the two sets of estimates, the differences are striking. In particular, based on the NLLS coefficients, job creation appears to have a positive impact on TFP growth while job destruction has an apparently detrimental effect.

To the extent that one trusts the 2SLS and GMM results, naturally, this distinction suggests that contemporaneous creation and destruction are, respectively, positively and negatively associated with the stochastic error term. That is, only a positive association between $\mathrm{POS}_{i,t}$ and $\epsilon_{i,t}$ could produce a positive estimate for a truly negative coefficient (γ_C), while a negative association between $\mathrm{NEG}_{i,t}$ and $\epsilon_{i,t}$ generates a negative estimate for a truly positive coefficient (γ_D). Given the two characterizations of job flows and productivity growth sketched above, the job-matching framework, I hold, better accounts for this conjectured correlation structure.

Indeed, following the framework of Section 2.1, a positive shock to industry i's average

TFP growth (i.e. a rise in $\epsilon_{i,t}$) will generate an increase in contemporaneous job creation, while contemporaneous job destruction falls. Hence, the job match-quality formulation implies that NLLS estimate of γ_C (γ_D) will be positively (negatively) biased.

The vintage-capital notion, on the other hand, is somewhat more difficult to reconcile with this presumed correlation pattern. Consider, for example, a negative shock to industry i's demand. Because overall demand is now lower, the extent of job creation should fall, while the amount of job destruction should rise. This process, in turn, increases the average TFP taken over continuing establishments, $\theta_{i,t}$, because a higher rate of destruction eliminates a larger part of the bottom end of the plant-level productivity distribution. Interpreting this result as an increase in the stochastic term $\epsilon_{i,t}$, the resulting correlations with creation and destruction are, respectively, negative and positive. In such an instance, the IV estimates would possess the same signs as those of the NLLS estimates.

5 Conclusion

Because job creation and destruction influence the cross-sectional distribution of productivity across existing employment relationships, job flows likely affect the rate at which aggregate productivity changes. This paper has offered evidence in support of this notion.

To recap, the findings indicate that, after accounting for the endogeneity of the job-flow series, TFP growth tends to be positively associated with job destruction while negatively associated with job creation. As a consequence, between the two theoretical characterizations of employment variation surveyed, the evidence is more consistent with the 'job match-quality' view than with the 'vintage-capital' (or pure creative-destruction) perspective.

Such a conclusion, however, should not be taken as a suggestion that the vintage-capital notion of job creation and destruction is invalid. Indeed, the job-matching and vintage-capital explanations tend to be targeted at fundamentally different aspects of the creation and destruction process. As described in Section 2, the former involves the variation of employment within continuing establishments whereas the latter characterizes job flows in terms of entry and exit. It is certainly possible, of course, that both theories are correct.

To be sure, since I am unable to differentiate empirically between job flows occurring in continuing establishments and those generated by establishment births and deaths (at least at the 4-digit level of aggregation), the results here are likely capturing some average effect across the two types. Because the majority of employment gains and losses in U.S. manufacturing take place among continuing plants (Davis et al. (1996)), it is logical that the evidence would favor the job-matching framework.

Of course, given the potential importance of the distinction between employment variation accounted for by stayers as opposed to plant births and deaths, further investigation into this issue seems warranted. Indeed, while distinguishing between the two types of job creation may seem particularly important (i.e. creation through plant births may enhance productivity, creation in existing plants may reduce it) so may differentiating between the two types of job destruction.

In particular, Gibbons and Katz (1991) argue that a crucial difference may exist between workers who are displaced from continuing plants and those who are laid off due to plant closures. With the former, layoffs are likely to consist of predominantly low-quality firm-worker matches, whereas in the latter, both high- and low-quality matches may be involved. This line of reasoning suggests that job destruction associated with continuing establishments may actually involve a larger boost to productivity than destruction emanating from plant closures. Exploring this distinction would be an interesting exercise for future work.

Table 1: Baseline Parameter Estimates

Parameter	*Specification*					
	AR(1)	AR(2)	AR(3)	AR(1)	AR(2)	AR(3)
μ	-2.3	-1.8	-0.83	-2.1	-1.7	-1.02
	(1.03)	(0.5)	(0.37)	(1.02)	(0.6)	(0.48)
ρ_1	-0.01	-0.01	-0.04	-0.02	-0.01	-0.03
	(0.04)	(0.02)	(0.02)	(0.05)	(0.03)	(0.03)
ρ_2	–	-0.13	-0.11	–	-0.14	-0.12
		(0.01)	(0.01)		(0.02)	(0.02)
ρ_3	–	–	-0.02	–	–	-0.02
			(0.01)			(0.02)
γ_C	-0.29	-0.4	-0.28	-0.3	-0.34	-0.29
	(0.23)	(0.12)	(0.08)	(0.21)	(0.13)	(0.1)
γ_D	0.45	0.48	0.33	0.44	0.43	0.35
	(0.27)	(0.12)	(0.08)	(0.26)	(0.14)	(0.11)
Method	2SLS	2SLS	2SLS	GMM	GMM	GMM

Note: Nonlinear 2SLS and GMM estimates of parameters from equation (13). γ_C (γ_D) represents the effect of job creation (job destruction) on TFP growth. The AR(1), AR(2), AR(3) specifications use, respectively, 7391, 7391, and 7002 industry-year observations (i.e. the instruments series begin in 1974, the TFP growth and job-flow series begin in 1973). Standard errors are reported in parentheses.

Table 2: Parameter Estimates

Time Effects Included

	Specification					
Parameter	AR(1)	AR(2)	AR(3)	AR(1)	AR(2)	AR(3)
μ	0.12	0.13	0.29	0.19	0.18	0.42
	(0.47)	(0.43)	(0.43)	(0.47)	(0.44)	(0.44)
ρ_1	-0.05	-0.06	-0.07	-0.05	-0.06	-0.07
	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
ρ_2	–	-0.12	-0.11	–	-0.12	-0.1
		(0.01)	(0.01)		(0.02)	(0.02)
ρ_3	–	–	-0.04	–	–	-0.03
			(0.01)			(0.02)
γ_C	-0.14	-0.09	-0.12	-0.15	-0.09	-0.11
	(0.1)	(0.06)	(0.06)	(0.12)	(0.07)	(0.07)
γ_D	0.18	0.11	0.12	0.18	0.11	0.11
	(0.1)	(0.05)	(0.05)	(0.12)	(0.07)	(0.07)
Method	2SLS	2SLS	2SLS	GMM	GMM	GMM

Note: Nonlinear 2SLS and GMM estimates of parameters from equation (13). γ_C (γ_D) represents the effect of job creation (job destruction) on TFP growth. The AR(1), AR(2), AR(3) specifications use, respectively, 7391, 7391, and 7002 industry-year observations (i.e. the instruments series begin in 1974, the TFP growth and job-flow series begin in 1973). Standard errors are reported in parentheses.

Table 3: Parameter Estimates

Time Effects, Hours Per Worker Growth,

Capital and Labor Shares Included

Parameter	*Specification*					
	AR(1)	AR(2)	AR(3)	AR(1)	AR(2)	AR(3)
μ	-1.38	-1.28	-1.31	-1.43	-1.3	-1.06
	(0.68)	(0.57)	(0.56)	(0.82)	(0.68)	(0.7)
ρ_1	-0.05	-0.07	-0.07	-0.05	-0.07	-0.07
	(0.02)	(0.01)	(0.01)	(0.04)	(0.03)	(0.03)
ρ_2	–	-0.13	-0.11	–	-0.12	-0.11
		(0.01)	(0.01)		(0.02)	(0.02)
ρ_3	–	–	-0.04	–	–	-0.03
			(0.01)			(0.02)
γ_C	-0.16	-0.08	-0.12	-0.17	-0.09	-0.11
	(0.11)	(0.06)	(0.06)	(0.14)	(0.07)	(0.07)
γ_D	0.25	0.16	0.17	0.27	0.16	0.16
	(0.11)	(0.05)	(0.05)	(0.15)	(0.07)	(0.08)
Hours Per Worker	0.006	0.004	-0.003	0.005	0.005	-0.003
Growth	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Capital Share	0.07	0.07	0.08	0.07	0.07	0.07
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Labor Share	-0.07	-0.07	-0.08	-0.07	-0.07	-0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Method	2SLS	2SLS	2SLS	GMM	GMM	GMM

Note: Nonlinear 2SLS and GMM estimates of parameters from equation (13). γ_C (γ_D) represents the effect of job creation (job destruction) on TFP growth. The AR(1), AR(2), AR(3) specifications use, respectively, 7391, 7391, and 7002 industry-year observations (i.e. the instruments series begin in 1974, the TFP growth and job-flow series begin in 1973). Standard errors are reported in parentheses.

Appendix

Table A1: Summary Statistics, 1973-1993

Variable	Mean	Standard Deviation	Minimum	Maximum
$\Delta\ln$ TFP$_{i,t}$	0.21	6.9	-62.1	89.9
POS$_{i,t}$	8.7	5.9	0	200
NEG$_{i,t}$	10.7	7.1	0	115.1

Note: Values represent percentages. $\Delta\ln$ TFP is growth of 5-factor TFP; POS is the rate of job creation; NEG is the rate of job destruction.

Table A2: Simple Correlations

TFP Growth and Job Flows, 1973-1993

	$\Delta \ln \text{TFP}_{i,t}$	$\text{POS}_{i,t}$	$\text{NEG}_{i,t}$
$\Delta \ln \text{TFP}_{i,t}$	1	0.08	-0.1
		(0)	(0)
$\Delta \ln \text{TFP}_{i,t-1}$	-0.06	0.05	-0.11
	(0)	(0)	(0)
$\Delta \ln \text{TFP}_{i,t-2}$	-0.13	-0.03	-0.004
	(0)	(0.01)	(0.72)
$\Delta \ln \text{TFP}_{i,t-3}$	-0.03	-0.003	-0.03
	(0.01)	(0.78)	(0.02)
$\text{POS}_{i,t}$	0.08	1	-0.06
	(0)		(0)
$\text{POS}_{i,t-1}$	-0.03	0.24	0.1
	(0.006)	(0)	(0)
$\text{POS}_{i,t-2}$	-0.05	0.15	0.17
	(0)	(0)	(0)
$\text{POS}_{i,t-3}$	0.01	0.17	0.17
	(0.45)	(0)	(0)
$\text{NEG}_{i,t}$	-0.1	-0.06	1
	(0)	(0)	
$\text{NEG}_{i,t-1}$	0.08	0.29	0.3
	(0)	(0)	(0)
$\text{NEG}_{i,t-2}$	0.07	0.29	0.17
	(0)	(0)	(0)
$\text{NEG}_{i,t-3}$	-0.003	0.21	0.19
	(0.82)	(0)	(0)

Note: P-values under the null of zero correlation are reported in parentheses.

Table A3: Simple Correlations

Lagged Plant Size Variables and Job Flows, 1974-1993

	POS	NEG	Log Employment Per Plant	Percent $\geq$ 500 Workers
POS	1	–	–	–
NEG	-0.06 (0)	1	–	–
Log Employment Per Plant	-0.29 (0)	-0.21 (0)	1	–
Percent $\geq$ 500 Workers	-0.21 (0)	-0.16 (0)	0.79 (0)	1
Percent $<$ 50 Workers	0.27 (0)	0.17 (0)	-0.83 (0)	-0.61 (0)

Note: Correlations of average plant size characteristics at time t with job creation and destruction between t and $t+1$ for $t = 1974$ to 1992. P-values under the null of zero correlation are reported in parentheses.

Table A4: NLLS Parameter Estimates

Specification	$\hat{\gamma}_C$	$\hat{\gamma}_D$	Time Effects?	Hours Per Worker Growth?	Capital and Labor Shares?
AR(1)	0.09	-0.08	No	No	No
	(0.01)	(0.01)			
AR(2)	0.08	-0.09	No	No	No
	(0.01)	(0.01)			
AR(3)	0.08	-0.09	No	No	No
	(0.01)	(0.01)			
AR(1)	0.06	-0.08	Yes	No	No
	(0.01)	(0.01)			
AR(2)	0.05	-0.09	Yes	No	No
	(0.01)	(0.01)			
AR(3)	0.06	-0.1	Yes	No	No
	(0.01)	(0.01)			
AR(1)	0.07	-0.07	Yes	Yes	Yes
	(0.01)	(0.01)			
AR(2)	0.06	-0.07	Yes	Yes	Yes
	(0.01)	(0.01)			
AR(3)	0.07	-0.09	Yes	Yes	Yes
	(0.01)	(0.01)			

Note: Nonlinear least squares estimates of parameters from equation (13). $\hat{\gamma}_C$ ($\hat{\gamma}_D$) represents the estimated effect of job creation (job destruction) on TFP growth. The AR(1), AR(2), AR(3) specifications use, respectively, 7780, 7391, and 7002 industry-year observations. Standard errors are reported in parentheses.

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