Macroeconomic Dynamics, **11**, 2007, 175–201. Printed in the United States of America.
DOI: 10.1017.S1365100506060020

JOB FLOWS AND PRODUCTIVITY DYNAMICS: EVIDENCE FROM U.S. MANUFACTURING

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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. Although 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. If job flows represent the reallocation of labor from low- to high-productivity positions, job creation would boost productivity growth. If, instead, they represent changes in employment along a primarily low-skill dimension, the effect would be negative. This paper estimates the influence of job creation and destruction on total factor productivity (TFP) growth using annual data on four-digit U.S. manufacturing. As expected, the results reveal a positive association between job destruction and changes in TFP. Yet, they also indicate that job creation tends to have a negative effect on productivity growth.

Keywords: Productivity Growth, Job Flows, Creative Destruction, Job Matching

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, although 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

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https://doi.org/10.1017/S1365100507060026 Published online by Cambridge University Press

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 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. 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 described earlier, 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. Although 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

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(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 more than 300 four-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. On balance, then, the evidence favors the view that, on the whole, job creation and destruction represent employment changes along a predominantly low-skill/low-productivity margin rather than productive reallocation.

A more detailed look at the effects of job creation and destruction within continuing plants as opposed to the effects of plant births and deaths using two-digit data generates a similar conclusion. Although the results do not provide complete support for either theory, they do tend to be more consistent with the match-quality view of job flows than the pure creative destruction notion.

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 earlier, 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.

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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:

$$Y_{j,i,t} = \theta_{j,i,t}(K_{j,i,t})^{\alpha}\left[A_{j,i}^{(1)}\left(L_{j,i,t}^{(1)}\right)^{1-\alpha} + A_{j,i}^{(2)}\left(L_{j,i,t}^{(2)}\right)^{1-\alpha} + \cdots + A_{j,i}^{(N_{j,i,t})}\left(L_{j,i,t}^{(N_{j,i,t})}\right)^{1-\alpha}\right],\ 0 < \alpha < 1, \quad (\mathbf{1})$$

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 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:

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

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.

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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 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 nondecreasing 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. 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:

$$\begin{aligned} \mathrm{TFP}_{j,i,t} &= \frac{\theta_{j,i,t} K^{\alpha}\left[A_{j,i}^{(1)} L^{1-\alpha} + A_{j,i}^{(2)} L^{1-\alpha} + \cdots + A_{j,i}^{(N_{j,i,t})} L^{1-\alpha}\right]}{K^{\alpha} N_{j,i,t} L^{1-\alpha}} \\ &= \theta_{j,i,t} \frac{\sum_{w=1}^{N_{j,i,t}} A_{j,i}^{(w)}}{N_{j,i,t}}. \end{aligned} \tag{3}$$

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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:

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

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 reformulated in terms of rates of job creation, POS, and job destruction, NEG:

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

where the parameters $\gamma_C < 0$ and $\gamma_D > 0$ represent the influence of creation and destruction on productivity growth. Note, because producers either expand or contract (or neither), only one of the terms, $\mathrm{POS}_{j,i,t}$ or $\mathrm{NEG}_{j,i,t}$ can be nonzero 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:

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

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. On isolating each producer's

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index of efficiency, the logarithm of industry i's TFP can be approximated as a weighted sum over its constituent firm-level measures:

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

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 rewritten in a manner analogous to the decomposition considered by Baily et al. (1992):

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

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), whereas 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 important, 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

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higher productivity plants. Hence, $\gamma_C > 0$. Job destruction, by contrast, 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, although 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]

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 roughly 450 four-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]

Because the standard industrial classification (SIC) scheme changed in 1987, I consider two sample time frames. First, I look at the period 1974 to 1993 using 337 industries whose compositions did not change with the SIC revision.[11] Second, because dropping industries whose definitions changed involves eliminating a large fraction of the total sample (i.e., nearly a quarter) in a potentially nonrandom way, I also look at the 1974–1986 time period using 444 industries. Doing so involves dropping seven years of data but offers a more complete look at the population of manufacturing producers.

Two measures of TFP growth are reported by the MPD: a five-factor growth rate (capital, production worker hours, nonproduction workers, nonenergy materials, and energy) and a four-factor growth rate (energy and nonenergy materials are not treated separately).[12] Because the correlation across the two is extremely high (i.e., in excess of 0.99), I limit the analysis to the five-factor measure. Summary statistics for each of these variables—TFP growth, job creation, job destruction—appear in Table A.1 of the Appendix. Simple correlations and cross-correlations at various leads and lags are reported in Table A.2.

Several basic properties of the data deserve some mention. First, the contemporaneous correlation between job creation and job destruction across four-digit industries is only weakly negative, −0.05 (1974–93) and −0.13 (1974–86). These

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figures stand 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 correlations of the employment-share weighted averages of job creation and destruction in the present samples, −0.63 (1974–1993) and −0.74 (1974–1986). This result seems to suggest that simultaneous increases or decreases in creation and destruction occur more frequently within four-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.[13]

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 earlier. 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. Although, 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 four-digit industry level is significantly, negatively autocorrelated. Although 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.

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.[14]

For such a scenario to be plausible, naturally, TFP growth and job destruction would have to move together in some periods, whereas 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 both samples (1974–1993 and 1974–1986) of observations on $\{\Delta \ln \mathrm{TFP}_{i,t} - \Delta \ln \mathrm{TFP}_{i,t-1}\}$, $\{\mathrm{POS}_{i,t} - \mathrm{POS}_{i,t-1}\}$, and $\{\mathrm{NEG}_{i,t} - \mathrm{NEG}_{i,t-1}\}$, I find that TFP growth and the rate of job destruction either both increase or decrease roughly 46 percent of the time. TFP growth and job creation move in opposite directions in about 46 percent of the observations.[15]

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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 earlier, 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 instance are clear: job creation (destruction) will be positively (negatively) correlated with lagged TFP growth, whereas TFP growth will be negatively (positively) associated with lagged job creation (destruction). All, as it happens, are borne 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.[16]

Although 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 earlier.

3.2. Statistical Model

The theoretical characterization of productivity growth derived in Section 2,

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

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):

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

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, $\epsilon_{i,t}$.[17] The one-period growth rate of this average technology term can then be expressed as:

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

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

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

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

$$\Delta \ln \mathrm{TFP}_{i,t} = \mu + \rho_1 \Delta \ln \mathrm{TFP}_{i,t-1} + \gamma_C \mathrm{POS}_{i,t} - \gamma_C \rho_1 \mathrm{POS}_{i,t-1} + \gamma_D \mathrm{NEG}_{i,t} - \gamma_D \rho_1 \mathrm{NEG}_{i,t-1} + \epsilon_{i,t}, \quad (\mathbf{14})$$

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, $\mathrm{POS}_{i,t}$ and $\mathrm{NEG}_{i,t}$. Based on the job match-quality formulation, for example, an increase in $\epsilon_{i,t}$ signifies a positive shock to (average) industry productivity. Although this shock increases TFP, it also affects the extent to which firms are creating and destroying jobs because $\epsilon_{i,t}$ is itself the sum of firm-level technology terms that 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 (13) would, therefore, generate biased estimates of the creation and destruction effects, γ_C and γ_D.[18]

Consequently, to estimate (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 four-digit manufacturing 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.[19] 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 four-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

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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, pp. 10–11) offer a similar conclusion in their survey of the literature studying plant-level productivity, noting that, although productivity *levels* tend to be higher in large establishments, "it has been more difficult to find correlates of changes in productivity."[20] For these reasons, lagged plant size characteristics are not likely to be correlated with $\epsilon_{i,t}$.[21]

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 Tables A3 and A4 of the Appendix, which report correlations between creation and destruction rates and each of the three lagged plant-scale variables among the 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).[22] With 2SLS, the parameter vector, β, is chosen to minimize the following objective function:

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

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:

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

Here, Σ is an $(n \times n)$ covariance matrix of the error terms, $\epsilon_{i,t}$, and $(\mathbf{Z}'\Sigma\mathbf{Z})$ 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 Σ is some scalar multiple of the identity matrix—that is, when the errors are mutually uncorrelated and homoskedastic. In practice, however, because I base the GMM estimates on a heteroskedasticity-consistent specification of Σ, they will generally differ from the 2SLS estimates.[23]

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TABLE 1. Baseline parameter estimates

		Specification					
Sample	Parameter	AR(1)	AR(2)	AR(3)	AR(1)	AR(2)	AR(3)
1974–93	μ	−2.4	−1.5	−0.78	−2.5	−1.5	−1.1
		(1.7)	(0.54)	(0.41)	(1.8)	(0.7)	(0.6)
	ρ_1	0.01	−0.005	−0.02	0.003	−0.01	−0.01
		(0.06)	(0.02)	(0.02)	(0.07)	(0.03)	(0.03)
	ρ_2	—	−0.13	−0.11	—	−0.14	−0.11
			(0.01)	(0.01)		(0.02)	(0.02)
	ρ_3	—	—	−0.01	—	—	−0.01
				(0.01)			(0.02)
	γ_C	−0.35	−0.38	−0.32	−0.38	−0.35	−0.36
		(0.33)	(0.12)	(0.08)	(0.32)	(0.14)	(0.13)
	γ_D	0.51	0.43	0.35	0.54	0.41	0.41
		(0.42)	(0.12)	(0.09)	(0.41)	(0.15)	(0.14)
1974–86	μ	−2.4	−1.8	−0.33	−2.3	−1.8	−0.39
		(1.2)	(0.6)	(0.4)	(1.1)	(0.64)	(0.5)
	ρ_1	0.01	0.016	−0.02	−0.006	0.006	−0.02
		(0.05)	(0.02)	(0.02)	(0.05)	(0.03)	(0.03)
	ρ_2	—	−0.15	−0.13	—	−0.16	−0.14
			(0.01)	(0.01)		(0.02)	(0.02)
	ρ_3	—	—	−0.02	—	—	−0.03
				(0.02)			(0.02)
	γ_C	−0.16	−0.31	−0.18	−0.22	−0.3	−0.2
		(0.2)	(0.11)	(0.07)	(0.18)	(0.12)	(0.09)
	γ_D	0.34	0.38	0.19	0.37	0.37	0.22
		(0.26)	(0.12)	(0.07)	(0.23)	(0.12)	(0.09)
	Method	2SLS	2SLS	2SLS	GMM	GMM	GMM

Note: Nonlinear 2SLS and GMM estimates of parameters from (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, 6402, 6402, and 6064 industry-year observations for 1974–1993; 4704, 4704, and 4311 observations for 1974–1986 (i.e., the instruments series begin in 1974, the TFP growth and job-flow series begin in 1973). Standard errors are reported in parentheses.

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, many of the estimated autoregressive parameters, ρ, are negative (particularly at two lags), 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 raw productivity growth levels (Table A2). Although 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, although 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

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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, although a negative influence of job creation, on TFP growth. Statistically, in fact, the majority of the relationships are significant: of the twelve coefficients reported for each sample, only the parameters from the 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 eight percentage points), for example, is accompanied by a 1.5 to 4 percentage-point increase in TFP growth, on average, whereas a 1 standard-deviation rise in job creation (approximately five percentage points) is associated with one to two percentage-point decrease in TFP growth. Given that the overall standard deviation of the TFP growth series is about 7% in either sample, 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, although the coefficients in this case are now somewhat smaller—the estimated effects of a 1 standard-deviation change fall between 0.7 and 1.5 percentage points for destruction, 0.5 and 1 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 earlier, then, this baseline evidence tends to favor the job-matching perspective over the vintage capital view.[24]

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 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

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TABLE 2. Parameter estimates: Time effects included

		Specification					
Sample	Parameter	AR(1)	AR(2)	AR(3)	AR(1)	AR(2)	AR(3)
1974–93	μ	0.22	0.21	0.36	0.24	0.24	0.48
		(0.5)	(0.5)	(0.47)	(0.54)	(0.48)	(0.5)
	ρ_1	−0.03	−0.05	−0.05	−0.03	−0.05	−0.05
		(0.02)	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)
	ρ_2	—	−0.11	−0.1	—	−0.11	−0.09
			(0.01)	(0.01)		(0.02)	(0.02)
	ρ_3	—	—	−0.02	—	—	−0.02
				(0.01)			(0.02)
	γ_C	−0.19	−0.1	−0.16	−0.19	−0.1	−0.14
		(0.12)	(0.07)	(0.07)	(0.14)	(0.09)	(0.09)
	γ_D	0.2	0.1	0.14	0.2	0.11	0.13
		(0.11)	(0.06)	(0.06)	(0.14)	(0.08)	(0.09)
1974–86	μ	−2.2	−1.4	−1.2	−2.2	−1.4	−1.2
		(0.9)	(0.6)	(0.6)	(0.9)	(0.6)	(0.6)
	ρ_1	−0.01	−0.02	−0.02	−0.01	−0.02	−0.01
		(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)
	ρ_2	—	−0.13	−0.11	—	−0.13	−0.11
			(0.1)	(0.01)		(0.02)	(0.02)
	ρ_3	—	—	−0.01	—	—	−0.02
				(0.02)			(0.02)
	γ_C	−0.2	−0.13	−0.2	−0.21	−0.13	−0.21
		(0.17)	(0.09)	(0.09)	(0.17)	(0.1)	(0.11)
	γ_D	0.22	0.13	0.16	0.22	0.13	0.17
		(0.16)	(0.08)	(0.08)	(0.16)	(0.09)	(0.1)
	Method	2SLS	2SLS	2SLS	GMM	GMM	GMM

Note: Nonlinear 2SLS and GMM estimates of parameters from (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, 6402, 6402, and 6064 industry-year observations for 1974–1993; 4704, 4704, and 4311 observations for 1974–1986 (i.e., the instruments series begin in 1974, the TFP growth and job-flow series begin in 1973). Standard errors are reported in parentheses.

for changes in the utilization of both capital and labor.[25] Because 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 (13) the contemporaneous values of the growth rate of hours per worker among production

https://doi.org/10.1017/S1365100507060026 Published online by Cambridge University Press

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, by contrast, do enter significantly and [following Klenow's (1998) evidence] with the expected signs: industries with greater capital intensity tend to experience faster 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 important, the job-destruction and creation parameters remain, respectively, positive and negative, exhibiting roughly the same magnitudes as those from Table 2. Although 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 in the 1974–1993 sample, two in the 1974–1986 sample), the results certainly appear to reinforce the basic conclusion drawn earlier.

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 A5 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, whereas 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 $\text{POS}_{i,t}$ and $\epsilon_{i,t}$ could produce a positive estimate for a truly negative coefficient (γ_C), whereas a negative association between $\text{NEG}_{i,t}$ 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 earlier, 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, whereas 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, by contrast, is somewhat more difficult to reconcile with this presumed correlation pattern. Consider, for example, a negative shock

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TABLE 3. Parameter estimates: Time effects, hours per worker growth, capital and labor shares included

		Specification					
Sample	Parameter	AR(1)	AR(2)	AR(3)	AR(1)	AR(2)	AR(3)
1974–93	μ	−1.2	−1.1	−1.1	−1.3	−1.2	−0.9
		(0.7)	(0.6)	(0.6)	(0.9)	(0.7)	(0.8)
	ρ_1	−0.04	−0.06	−0.06	−0.03	−0.05	−0.06
		(0.02)	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)
	ρ_2	—	−0.12	−0.11	—	−0.11	−0.1
			(0.01)	(0.01)		(0.02)	(0.02)
	ρ_3	—	—	−0.03	—	—	−0.02
				(0.01)			(0.02)
	γ_C	−0.18	−0.09	−0.15	−0.19	−0.1	−0.13
		(0.12)	(0.07)	(0.07)	(0.16)	(0.09)	(0.09)
	γ_D	0.26	0.15	0.18	0.27	0.16	0.17
		(0.13)	(0.06)	(0.06)	(0.17)	(0.09)	(0.1)
	Hours per worker	0.0003	0.002	−0.002	−0.0001	0.001	−0.003
	Growth	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
	Capital share	0.07	0.07	0.07	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	−0.07
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
1974–86	μ	−4.7	−3.4	−3.5	−4.7	−3.3	−3.5
		(1.8)	(0.9)	(0.9)	(1.9)	(1)	(1.1)
	ρ_1	−0.006	−0.02	−0.02	−0.01	−0.02	−0.02
		(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)
	ρ_2	—	−0.13	−0.11	—	−0.13	−0.11
			(0.01)	(0.01)		(0.02)	(0.02)
	ρ_3	—	—	−0.02	—	—	−0.02
				(0.02)			(0.02)
	γ_C	−0.25	−0.14	−0.21	−0.26	−0.15	−0.23
		(0.2)	(0.09)	(0.1)	(0.22)	(0.11)	(0.12)
	γ_D	0.34	0.21	0.24	0.34	0.21	0.25
		(0.22)	(0.09)	(0.09)	(0.22)	(0.1)	(0.11)
	Hours per worker	0.03	0.02	0.02	0.03	0.02	0.02
	Growth	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Capital share	0.09	0.09	0.1	0.1	0.09	0.1
		(0.03)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
	Labor share	−0.08	−0.07	−0.08	−0.08	−0.08	−0.08
		(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
	Method	2SLS	2SLS	2SLS	GMM	GMM	GMM

Note: Nonlinear 2SLS and GMM estimates of parameters from (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, 6402, 6402, and 6064 industry-year observations for 1974–1993; 4704, 4704, and 4311 observations for 1974–1986 (i.e., the instruments series begin in 1974, the TFP growth and job-flow series begin in 1973). Standard errors are reported in parentheses.

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to industry i's demand. Because overall demand is now lower, the extent of job creation should fall, whereas 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.

4.3. Job Flows in Continuing Plants versus Births and Deaths

One difficulty involved with the interpretation of these results in the context of the job matching and vintage capital theories stems from the fact that these two explanations are 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. Because the data used thus far quantify aggregate job flows—that is, those involving contributions from continuing establishments as well as the influence of births and deaths—the results reported above reflect some average effect across these underlying pieces.

Furthermore, 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. As such, the results do not necessarily imply that the vintage capital view of job creation and destruction is invalid. Indeed, it may simply be that, in these aggregate data, the positive effect associated with plant births is outweighed by the negative effect of creation among stayers. In order to explore this possibility, however, data in which creation and destruction have been decomposed into different types (i.e., continuing versus births and deaths) would be required.

Although this information is not available at the four-digit level in the Davis et al. (1996) data, it is available at the two-digit level. Hence, I can provide at least a cursory look at any potential differences in how different types of job creation and destruction influence productivity growth among this coarser grouping of industries. To do so, I consider the following simple exercise. Using 19 sectors[26] over the 1974–1993 period, I estimate two different versions of (13). First, I estimate it as before (using the same three instruments) so that the resulting parameters, γ_C and γ_D, can be compared with the four-digit estimates. Second, I decompose creation into the sum of gains among continuing plants and gains from births, destruction into losses from continuing plants and losses due to deaths, and enter each of these four terms into (13) with its own coefficient.[27] In both cases, TFP growth is constructed as an employment-share weighted average of the constituent four-digit TFP growth rates for each two-digit sector.[28]

The primary complication associated with this decomposed version of (13), of course, is that there are now four endogenous regressors rather than two. Because I only use three instrumental variables in the previous analysis, I need to find at least

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TABLE 4. Two digit results: Effects of overall job flows and flows from continuing plants versus births-deaths

Parameter	Specification			Time effects?	Hours per worker growth?	Capital and labor shares?
	AR(1)	AR(2)	AR(3)			
γ_C	−0.44	−0.2	−0.25	Yes	No	No
	(0.26)	(0.18)	(0.2)			
γ_D	0.49	0.23	0.27	Yes	No	No
	(0.26)	(0.18)	(0.19)			
γ_{CC}	0.01	0.05	−0.02	Yes	No	No
	(0.19)	(0.14)	(0.14)			
γ_{CB}	−1.4	−1.02	−0.61	Yes	No	No
	(0.7)	(0.6)	(0.45)			
γ_{DC}	0.32	0.31	0.33	Yes	No	No
	(0.19)	(0.13)	(0.16)			
γ_{DD}	0.44	0.1	−0.06	Yes	No	No
	(0.36)	(0.28)	(0.24)			
γ_C	−0.34	−0.11	−0.01	Yes	Yes	Yes
	(0.25)	(0.2)	(0.17)			
γ_D	0.45	0.13	0.01	Yes	Yes	Yes
	(0.3)	(0.21)	(0.18)			
γ_{CC}	0.09	0.06	−0.03	Yes	Yes	Yes
	(0.18)	(0.13)	(0.14)			
γ_{CB}	−1.3	−0.86	−0.56	Yes	Yes	Yes
	(0.76)	(0.59)	(0.45)			
γ_{DC}	0.23	0.27	0.32	Yes	Yes	Yes
	(0.2)	(0.12)	(0.15)			
γ_{DD}	0.33	0.02	−0.07	Yes	Yes	Yes
	(0.33)	(0.26)	(0.23)			

Note: GMM estimates of parameters from (13). γ_C (γ_D) represents the estimated effect of job creation (job destruction) on TFP growth; γ_{CC} is the effect of creation among continuing plants; γ_{CB} is the effect of creation from new births; γ_{DC} is the effect of destruction among continuing plants; γ_{DD} is the effect of destruction from deaths. The AR(1), AR(2), AR(3) specifications use, respectively, 361, 342, and 323 industry-year observations. Standard errors are reported in parentheses.

one additional instrument in order to estimate a creation effect from continuing establishments (γ_{CC}), a creation effect from births (γ_{CB}), a destruction effect from continuing establishments (γ_{DC}), and a destruction effect from deaths (γ_{DD}). I do so by exploiting a more detailed set of characteristics from the establishment size distributions for each industry. In particular, I use the following seven variables, all of which are lagged one period as before: average plant size and the proportion of plants with 1 to 4, 5 to 9, 10 to 19, 20 to 49, 50 to 99, and 100 to 249 employees.[29]

The results of two separate specifications, one that includes time effects and one in which I also add hours per worker growth and the capital and labor shares of total output, appear in Table 4. In an effort to be concise, I have only reported the GMM results. To begin, consider the estimated effects of overall creation and

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destruction, γ_C and γ_D. Although the majority of the estimates are insignificant, the signs and magnitudes of the coefficients are similar to what the four-digit data produced. Hence, at either level of aggregation, creation has an apparently negative effect on productivity growth, whereas destruction has a positive effect.

Looking at the separate influences of creation through continuing establishments as opposed to births, it is apparent that there is a difference between the two.[30] Job creation among continuers appears to have very little impact on TFP growth. All estimates of γ_{CC} have small magnitudes and are statistically negligible. By contrast, the estimated effect of employment gains stemming from births, γ_{CB}, tends to be large and negative. Three of the six estimates reported in the table are significant. Evidently, much of the negative effect of job creation on TFP growth among two-digit industries appears to be driven by startups rather than continuing plants. As noted later, such findings stand at odds with both the vintage capital and job matching formulations.

For destruction, there also appears to be a difference between the effects of the two types of flows.[31] Although most of the values of the destruction-through-deaths parameter, γ_{DD}, are positive, none are significant. The estimated effect from continuing plants, γ_{DC}, also tends to be positive, but the majority of the estimated parameters in this case (five of six) are statistically significant. Interestingly, this finding is broadly consistent with the results of Gibbons and Katz (1991), who find an important difference 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 with the latter, both high- and low-quality matches may be involved. This line of reasoning implies that job destruction associated with continuing establishments may actually involve a larger boost to productivity than destruction emanating from plant closures. This is precisely what the results in Table 4 seem to indicate.

What do these findings suggest with regard to the vintage capital and job matching theories outlined in Section 2? According to the vintage capital view of job flows, one would expect the birth and death parameters, γ_{CB} and γ_{DD}, to be positive. Statistically, neither one is. On the contrary, γ_{CB} tends to be strongly negative. The implication from the job match-quality view is that the effect of creation among continuers, γ_{CC}, should be negative, but the effect of destruction among continuers, γ_{DC}, ought to be positive. Although there is little evidence of the former, there is relatively strong evidence of the latter. Thus, between these two theories, the job matching explanation is, again, more consistent with the findings, yet these data are not overwhelmingly supportive of either view.

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.

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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, whereas negatively associated with job creation. This relationship holds at both the two- and four-digit levels but is particularly strong among four-digit industries. Between the two theoretical characterizations of employment variation surveyed, such evidence is more consistent with the job match-quality view than with the vintage capital (or pure creative-destruction) perspective.

A cursory look into the effects of different types of job flows offers some mixed results but a similar basic conclusion. Within two-digit manufacturing, job creation through plant births tends to be negatively associated with productivity growth, whereas destruction through deaths is only weakly associated with TFP growth. Neither result provides much evidence in favor of the vintage capital notion. Although the estimated impact of creation in continuing plants is weak, the effect of destruction in existing plants is quite strong. This latter finding, of course, is consistent with the job match-quality view.

Needless to say, these issues require a great deal more research. This paper has only taken a somewhat rudimentary look at the effect of job flows on productivity growth. Given the fundamentally micro-level nature of the theories discussed here, future work examining plant-level data (including data on individual workers at each establishment), rather than industry aggregates as employed here, would be of tremendous importance in gaining additional insight into these matters.

NOTES

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), Loungani 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—for example, 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.

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.

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 here 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.

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 before 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 nonproduction workers is accounted for in the TFP measure considered here (see Section 3.1), no other labor-quality adjustments are made.

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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 pattern for productivity with respect to expansions and recessions.

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

11. This is accomplished using the correspondence between the two systems provided by the NBER. I use only those industries whose 1987 composition matches completely with the 1972 composition (i.e., the 1972–1987 and 1987–1972 shares both equal 1). I begin the series at 1974 because the instrumental variables employed in the analysis below begin in 1974.

12. For further information about the MPD, see Bartelsman and Gray (1996).

13. 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.

14. 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.

15. 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.

16. Indeed, one also could 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 $t + 1$).

17. It should be noted that if $\ln \theta_{i,t}$ follows a stationary autoregression in *levels*, this representation in differences will involve an MA(1) error instead of white noise. However, because 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.

18. For the purpose of comparison, NLLS estimates of the creation and destruction parameters for each of the specifications considered below appear in Table A.5 of the Appendix.

19. 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, 1,000 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.

20. For example, they note that although 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.

21. 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: −0.03, −0.02, and 0.02 (1974-93); −0.02, −0.01, 0.01 (1974-86). Only the first of these values (average employment in the 1974–1993 sample) differs statistically from zero at 10% significance.

22. This discussion follows Chapters 10 and 11 of Greene (2000).

23. The specification of the error matrix follows that of White (1980), so that $(\mathbf{Z}'\Sigma\mathbf{Z})$ 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.

24. These results also may 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 also would 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).

25. 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.

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26. The data of Davis et al. (1996) combine SIC 20 (Food and Kindred) and SIC 21 (Tobacco) for the vast majority of years. In the analysis, I treat these combined industries as a single sector.

27. Although strong, the correlations between the two types of creation, 0.29, and the two types of destruction, 0.38, do not seem excessively high for the purposes of estimating the separate effects of each type of job flow series.

28. Similar results were obtained using value-added weights. All of the additional regressors used earlier were created by aggregating four-digit data in the NBER MPD to the two-digit level.

29. Experimentation indicated that this combination of variables produced the most "reasonable" results, at least in the sense that (i) they produced estimates of γ_C and γ_D that were similar to what the three instruments used earlier produced and (ii) the estimated values of the parameters on the growth of hours per worker and the capital share were positive, the value of the labor share parameter was negative.

30. Technically, Wald tests only reject the hypothesis that γ_{CC} and γ_{CB} are equal in two of the six instances.

31. Statistically, however, Wald tests do not reject the equality of γ_{DD} and γ_{DC} in any of the cases.

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APPENDIX

TABLE A.1. Summary statistics

Sample	Variable	Mean	Standard deviation	Minimum	Maximum
1974–93	$\Delta \ln \text{TFP}_{i,t}$	0.24	6.8	−62.2	89.9
	$\text{POS}_{i,t}$	8.5	5.2	0	67.1
	$\text{NEG}_{i,t}$	11.1	7.8	0	200
1974–86	$\Delta \ln \text{TFP}_{i,t}$	0.08	6.9	−52.6	50.9
	$\text{POS}_{i,t}$	8.9	5.3	0	51.5
	$\text{NEG}_{i,t}$	11.6	7.7	12.4	115.1

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

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TABLE A.2. Simple correlations: TFP growth and job flows

	1974–93 Sample			1974–86 Sample		
	$\Delta \ln TFP_{i,t}$	$POS_{i,t}$	$NEG_{i,t}$	$\Delta \ln TFP_{i,t}$	$POS_{i,t}$	$NEG_{i,t}$
$\Delta \ln TFP_{i,t}$	1	0.09	−0.1	1	0.1	−0.13
		(0)	(0)		(0)	(0)
$\Delta \ln TFP_{i,t-1}$	−0.06	0.07	−0.11	−0.03	0.08	−0.12
	(0)	(0)	(0)	(0.04)	(0)	(0)
$\Delta \ln TFP_{i,t-2}$	−0.13	−0.04	−0.004	−0.15	−0.04	−0.01
	(0)	(0)	(0.77)	(0)	(0.01)	(0.72)
$\Delta \ln TFP_{i,t-3}$	−0.02	−0.01	−0.03	−0.02	0.001	−0.02
	(0.14)	(0.36)	(0.02)	(0.28)	(0.92)	(0.13)
$POS_{i,t}$	0.09	1	−0.05	0.1	1	−0.13
	(0)		(0)	(0)		(0)
$POS_{i,t-1}$	−0.04	0.31	0.11	−0.03	0.29	0.1
	(0)	(0)	(0)	(0.06)	(0)	(0)
$POS_{i,t-2}$	−0.05	0.22	0.19	−0.06	0.19	0.19
	(0)	(0)	(0)	(0)	(0)	(0)
$POS_{i,t-3}$	0.01	0.22	0.19	−0.03	0.2	0.21
	(0.29)	(0)	(0)	(0.03)	(0)	(0)
$NEG_{i,t}$	−0.1	−0.05	1	−0.13	−0.13	1
	(0)	(0)		(0)	(0)	
$NEG_{i,t-1}$	0.08	0.34	0.28	0.08	0.34	0.27
	(0)	(0)	(0)	(0)	(0)	(0)
$NEG_{i,t-2}$	0.06	0.33	0.16	0.08	0.33	0.14
	(0)	(0)	(0)	(0)	(0)	(0)
$NEG_{i,t-3}$	−0.004	0.25	0.18	−0.001	0.23	0.18
	(0.77)	(0)	(0)	(0.93)	(0)	(0)

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

TABLE A.3. Simple correlations: Lagged plant size variables and job flows, 1974–1993 sample

	POS	NEG	Log employment per plant	Percent ≥ 500 workers
POS	1	—	—	—
NEG	−0.05	1	—	—
	(0)			
Log employment	−0.17	−0.1	1	—
per plant	(0)	(0)		
Percent ≥ 500	−0.24	−0.13	0.83	1
workers	(0)	(0)	(0)	
Percent < 50	0.3	0.15	−0.48	−0.62
workers	(0)	(0)	(0)	(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.

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TABLE A.4. Simple correlations: Lagged plant size variables and job flows, 1974–1986 sample

	POS	NEG	Log employment per plant	Percent ≥ 500 workers
POS	1	—	—	—
NEG	−0.13	1	—	—
	(0)			
Log employment	−0.17	−0.14	1	—
per plant	(0)	(0)		
Percent ≥ 500	−0.25	−0.17	0.83	1
workers	(0)	(0)	(0)	
Percent < 50	0.31	0.16	−0.5	−0.63
workers	(0)	(0)	(0)	(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 1985. P-values under the null of zero correlation are reported in parentheses.

TABLE A.5. NLLS parameter estimates

Sample	Specification	$\hat{\gamma}_C$	$\hat{\gamma}_D$	Time effects?	Hours per worker growth?	Capital and labor shares?
1974–93	AR(1)	0.11	−0.09	No	No	No
		(0.02)	(0.01)			
	AR(2)	0.1	−0.08	No	No	No
		(0.02)	(0.01)			
	AR(3)	0.1	−0.08	No	No	No
		(0.02)	(0.01)			
	AR(1)	0.07	−0.09	Yes	No	No
		(0.02)	(0.01)			
	AR(2)	0.07	−0.08	Yes	No	No
		(0.02)	(0.01)			
	AR(3)	0.07	−0.09	Yes	No	No
		(0.02)	(0.01)			
	AR(1)	0.09	−0.07	Yes	Yes	Yes
		(0.02)	(0.01)			
	AR(2)	0.09	−0.07	Yes	Yes	Yes
		(0.02)	(0.01)			
	AR(3)	0.09	−0.08	Yes	Yes	Yes
		(0.02)	(0.01)			
1974–86	AR(1)	0.11	−0.11	No	No	No
		(0.02)	(0.01)			
	AR(2)	0.1	−0.1	No	No	No
		(0.02)	(0.01)			
	AR(3)	0.09	−0.11	No	No	No
		(0.02)	(0.01)			

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TABLE A.5. Continued

Sample	Specification	$\hat{\gamma}_C$	$\hat{\gamma}_D$	Time effects?	Hours per worker growth?	Capital and labor shares?
	AR(1)	0.07	−0.11	Yes	No	No
		(0.02)	(0.01)			
	AR(2)	0.07	−0.1	Yes	No	No
		(0.02)	(0.01)			
	AR(3)	0.08	−0.13	Yes	No	No
		(0.02)	(0.01)			
	AR(1)	0.09	−0.09	Yes	Yes	Yes
		(0.02)	(0.01)			
	AR(2)	0.09	−0.09	Yes	Yes	Yes
		(0.02)	(0.01)			
	AR(3)	0.09	−0.11	Yes	Yes	Yes
		(0.02)	(0.01)			

Note: Nonlinear least squares estimates of parameters from (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, 6402, 6402, and 6064 industry-year observations for the 1974–1993 sample; 4704, 4704, and 4311 industry-year observations for the 1974–1986 sample. Standard errors are reported in parentheses.

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