THE WILLIAM DAVIDSON INSTITUTE
AT THE UNIVERSITY OF MICHIGAN BUSINESS SCHOOL

W.E. UPJOHN INSTITUTE
for Employment Research

Job Flows and Establishment Characteristics: Variations Across U.S. Metropolitan Areas

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William Davidson Institute Working Paper Number 609
September 2003

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August 2003

JEL Codes: E24, J63, R11

Keywords: job turnover, regional and urban growth, creative destruction, firm learning

Abstract:
This paper addresses the role played within metropolitan areas by heterogeneous agent models of constant churning. The evidence shows positive relationships between job turnover, young establishments, and metropolitan employment growth. Most areas, however, differ in their levels of job creation rather than job destruction. Results persist after controlling for regional differences in industry, but less so when controlling for differences in the establishment age distribution, and are consistent overall with standard models of creative destruction. Evidence from several entering cohorts, however, contradicts the vintage replacement process of creative destruction models. Namely, job destruction decreases as establishments age and there is no clear inverse relation between establishment entry rates and exit ages. These patterns are instead consistent with a turnover process seen in standard models of firm learning. Further evidence suggests that these patterns vary systematically with the overall employment growth of a region. Together, the results suggest that (i) processes of both creative destruction and firm learning may matter for local labor dynamics, but future models will have to reconcile with this new evidence, and (ii) intrinsic local factors, such as the "business climate", may affect the dynamics of both processes.

Acknowledgements
I would like to thank John Haltiwanger, Judy Hellerstein, Jim Spletzer, Ed Montgomery, and John Shea or helpful advice and guidance on this paper and earlier versions from my dissertation. I would also like to thank seminar participants at the Department of Economics at the University of Maryland, College Park, the Bureau of Labor Statistics, and the Center for Economic Studies at the Census Bureau for helpful comments on earlier versions. Any remaining errors are my own. The views expressed are solely my own and do not necessarily reflect the official positions or policies of the U.S. Bureau of Labor Statistics or the views of other staff members.

Introduction

Over the past 15 years, empirical work with firm and establishment microdata has underscored the importance of acknowledging the heterogeneity and dynamics that underlie macroeconomic behavior.[1] Consequently, heterogeneous-agent models with constant churning have become increasingly popular. These models often try to explain the cyclical behavior of employment and firm dynamics. Certain classes of models, such as those involving creative destruction or firm learning, are generally consistent with these empirical findings.[2] Existing tests, however, have almost exclusively used time-series data. To date, there has been little research using *cross-sectional* evidence to address these models.[3]

In this paper, I attempt to bridge this gap by presenting evidence on employment and establishment dynamics across a range of *metropolitan areas*. Doing so allows me to address cross-sectional implications of the models not readily testable in a time-series study. For example, models of creative destruction often posit that the pace of firm turnover is dependent on an exogenous rate of technology growth. Studying the empirical time-series of employment or establishment dynamics would quantify the pace of turnover, but not its variations with technology growth. Unless one can observe technology growth empirically, only a study across different economies (which presumably have differences in underlying productivity) can fully address such implications.

An important string of the related empirical literature examines the employment dynamics of firms that we now know simultaneously create and destroy many jobs each period. This literature focuses on the cyclical behavior of these employment dynamics, but it is not

[1] Examples include Davis and Haltiwanger (1990, 1992) and Dunne, Roberts, and Samuelson (1988, 1989a, 1989b).
[2] For examples of creative destruction models, see Aghion and Howitt (1992,1994), and Caballero and Hammour (1994, 1996). For examples of firm learning models, see Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995).
[3] The cross-sectional properties of these models have received little attention in the theoretical literature as well, though Hopenhayn (1992) is one notable exception who addresses some comparative statics within a firm learning framework.

exclusively devoted to firm life-cycle or business cycle dynamics. Studies exist that examine variations in these dynamics across industries, firm sizes, and firm ages.[4] However, very few studies document variation across *regions*.[5] Unlike industry, size, or age variations, regional differences can highlight variations across distinct labor markets. Thus, evidence across regions is well-suited to highlight the empirical facts related to the cross-sectional properties of the classes of models mentioned above.[6] I conduct my study of metropolitan areas using a rich sample of establishment microdata produced from administrative records by the Bureau of Labor Statistics. Doing so allows me to study employment and establishment dynamics in detailed ways not previously possible. Consequently, this paper provides several new stylized facts on these dynamics. Some of these facts are generally consistent with standard models of creative destruction and/or firm learning and selection, while others present new perspectives on these dynamics that future models will have to reconcile with.

In this study, I focus establishment and employment dynamics and their relation to the employment growth of an area. In doing so, I tacitly assume that regional differences in employment growth are a proxy for variations in the exogenous factors (such as the pace of technology growth or innovations in a creative destruction model) driving the classes of models I address. In my discussion, I show how other factors that may act as a proxy, such as the education level of an area's population, relate to the employment and establishment dynamics.

A first glance at the metropolitan data reveals three distinct findings over the sample period. First, the employment growth of an area is positively related to its job turnover. Second, most regional differences in job turnover stem from differences in job creation rather than job

[4] Davis and Haltiwanger (1999) have an extensive review of this research. Dunne , Roberts, and Samuelson (1989a, 1989b) and Davis, Haltiwanger, and Schuh (1996) provide detailed evidence of plant end employment dynamics in Manufacturing by plant age and size. Foote (1998) has a notable cross-industry study.

[5] These studies include Eberts and Montgomery (1995), and Dumais, Ellison, and Glaeser (2002).

[6] Ideally, one would want regional definitions that characterize separate economies. Studies across countries are appropriate, and there exists some work of this sort (see Baldwin, Dunne, and Haltiwanger,

destruction. Third, employment growth and the average age of establishments are negatively related across metropolitan areas. A decomposition exercise that indicates regional differences in industry mix can only account for a portion of these results. These findings are generally consistent with a creative destruction process whose *broadly defined* technology growth rate differs across regions. A second decomposition breaks out regional differences in job creation and destruction by establishment age. Differences occur both within and across age groups, so that regional differences in age distributions explain only a portion of the initial results. A study of entering cohorts reveals that entry and exit are higher in high-growth regions (again consistent with a creative destruction story), but there is no significant negative relation between the entry rate in an area and the age of its exiting establishments. In addition, the rate of job turnover, particularly job destruction, decreases as entrants age.[7] These latter two results contradict standard models of creative destruction, and instead reveal trends more consistent with a process of firm learning and selection. Moreover, the *pace* at which job turnover decreases with age varies across areas: areas with higher employment growth have higher initial levels of job turnover among their entrants, but the rate of turnover decreases relatively faster in these areas. This decrease is more evident in the rate of job creation then the rate of job destruction over the beginning of these entrants' life-cycle. While these results are generally consistent with firm learning models, there are new findings that must be reconciled in future theoretical work. In particular, job turnover does not decrease at a uniform pace across areas, and this is due mostly to differences in job creation. This contrasts with a model of learning and selection, since one would expect unobservable regional factors to affect the firm exit margin (which drives the selection process), and hence cause relatively greater regional variations in *job destruction*.

1998). Some studies have cross-country comparisons, but not in an analytical framework (see Davis and Haltiwanger, 1999, for an overview).

[7] This is also consistent with previous findings, such as Dunne, Roberts, and Samuelson (1989a, 1989b).

The following section provides a summary of the relevant empirical work, as well as a discussion of models that focus on creative destruction and firm learning processes. The data are described next, followed by the basic findings across metropolitan areas. Analyses for industry, age, and entering cohorts come next. The proceeding section discusses intrinsic factors and that could affect the dynamics of the creative destruction and learning processes. The final section draws conclusions.

Background

There has been considerable research on the gross flows of employment (i.e., job creation and job destruction). Dunne, Roberts, and Samuelson (1988, 1989a, 1989b) document the patterns of firm growth, entry, and exit within and across various categories, within manufacturing. Blanchard and Diamond (1990) document the trends of the flows of both jobs and workers (via hires and separations) using several data sources, both within and outside manufacturing. Davis and Haltiwanger (1990, 1992) use detailed longitudinal plant microdata to track the patterns of job creation and job destruction within manufacturing over the business cycle. Foote (1998) looks at firms across all industries in Michigan and documents differences in the cyclical behavior of industries. His main finding is that the cyclical behavior of manufacturing is quite different from the other industries. Anderson and Meyer (1994) and Burgess, Lane, and Stevens (2000) study both job flows and worker flows across all industries. Work on *regional* job flows is limited. Several researchers have studied local labor market dynamics through the net growth of employment. Blanchard and Katz (1992) study wage, unemployment, and employment dynamics in response to adverse shocks to labor demand across U.S. states. Davis, Loungani, and Mahidhara (1997) have a similar study for state responses to defense and oil shocks. Dumais, Ellison, and Glaeser (2002) have one of the few regional studies that appeals to firm-level dynamics within metropolitan areas. They use microdata on manufacturing plants to study how plant entry, exit, and growth relate to changes in local industry concentration. Eberts and Montgomery (1995) also study firm dynamics across regions. Their study is perhaps the most relevant of all to this paper, as they document the secular trends of job creation and destruction across areas, as well as the cyclical trends over time.

Several stylized facts from the above work are relevant to this study. First, there is a tremendous turnover of jobs every period, whether one looks at quarterly, annual, or longer frequencies. Second, the rates of job turnover vary greatly across industries, firm sizes, and firm ages. In particular, manufacturing tends to have the lowest job turnover, while seasonal industries, such as construction and retail, tend to have the highest.[8] Job turnover decreases with both firm age and firm size, so the greatest turnover occurs in the youngest and smallest firms. Firm exit also decreases with size and age. Third, there is tremendous heterogeneity in firm entry, exit, and growth outcomes even within industry, size, and age categorizations. Finally, studies find an inverse cyclical relation between turnover and growth—over time, periods of high turnover occur when employment growth is lowest. Foote (1998), however, shows that this finding may be unique to declining industries. Eberts and Montgomery (1995) document a similar cyclical trend, but find a positive pattern across states—areas with high growth are also areas with high turnover.

The empirical work done with national-level data has led to a focus on dynamic models that stress constant churning among heterogeneous agents. These models attempt to generate properties and implications consistent with the above findings. Several models have done well in replicating the observed patterns of entry, exit, job creation, job destruction, etc. The models focus more on their cyclical properties, however, consistent with the similar focus in the empirical literature. This is not to say, though, that these models do not have cross-sectional implications. Throughout this paper, I relate my empirical findings to both the well-studied and the less-studied implications of two classes of models: creative destruction and firm learning and

[8] This is evident with the data used in this study in my dissertation (Faberman, 2003).

selection. I do so to highlight how the existing models compare with the new stylized facts I present.

Central to models of creative destruction is a process of vintage replacement. Caballero and Hammour (1994, 1996), and Aghion and Howitt (1992, 1994) have representative depictions of these models. In a vintage replacement process, new firms enter with the latest innovation/technology. The competitive advantage this gives them (via greater productivity) allows them to outcompete older, outdated firms, who eventually exit. In the equilibrium of a creative destruction model, there is a continuous entry and exit of firms, as well as a steady-state distribution of firm vintages. An endogenous firm entry rate and firm exit age often characterize this equilibrium. A key parameter in this model (at least with respect to this paper) is the exogenous rate of technology growth, or innovation. When this rate is high, the entry rate is high, since the returns to entry are greater. In addition, firms exit at a younger age, since their technologies become obsolete at a relatively faster pace. This implies firm vintages are skewed more towards younger firms. Thus, higher rates of technology growth/innovations increase both entry and exit, and create a relatively younger distribution of firms. In broader terms, higher rates also increase job turnover—there is higher job creation among young entrants, and higher job destruction among older, exiting firms. In terms of entering cohorts (which will be important for the empirical results), all entrants are homogeneous with respect to technology, productivity, etc. Firm heterogeneity exists only through the distribution of firm vintages, with each cohort having a different (and fixed) technology level.

In models of firm learning, firms do not know their productive abilities *ex ante*, and must learn them over time from a noisy signal. Jovanovic (1982) presents a model where firms learn their true efficiency over time from a signal involving firm-specific cost shocks. Hopenhayn (1992) produces a similar model from which he draws steady-state implications. Ericson and Pakes (1995) have a model of active learning where firms can invest to improve their outcomes. These models focus mostly on firm life-cycle dynamics that occur within a cohort of entrants. In firm learning models, all entrants are heterogeneous, and do not know their true productive "type". Firms must form an expectation of their ability from repeated realizations of a signal, which is a function of both their true type and stochastic noise. Based on their expectations, firms choose to either grow, contract, or exit. Firms update their expectations each period, and as they do so, their beliefs converge toward their true abilities. Over time, the expectations of the least efficient firms fall below a critical threshold, and they exit. This creates a selection process, where the surviving establishments are those that were *ex ante* efficient. The models imply that, within a given cohort, job creation, job destruction, and firm exit will be highest when entrants are young. Their rates all decrease as a cohort ages. Firms do most of their learning early on. As beliefs converge, the rates of firm growth, contraction, and exit all decline. Note that this implication contrasts with standard creative destruction models, where job creation is high among entrants, but job destruction (and firm exit) is high among older firms.

Below, I relate my empirical work back to the implications of the above two classes of models. In doing so, I tacitly assume that regions can differ in the underlying growth of technology, innovations, productivity, etc. In other words, they differ in the factors that drive variations in a creative destruction (and possibly a firm learning) model.[9] I further assume that these factors are positively correlated with the employment growth of an area. For instance, these differences may stem from variations in the level of localized innovations. Jaffe, Trajtenberg, and Henderson (1993), through evidence on patent citations, show that innovation is highly localized, that the intensity of innovation varies geographically, and that the diffusion of these innovations to other areas is very slow. Differences may also stem from the amount of skilled labor in an area.[10] Glaeser, Scheinkman, and Shleifer (1995) show that the level of human capital

[9] The relation of a vintage replacement/creative destruction process to regional variations is not new. Varaiya and Wiseman (1978, 1981) have studies that attempt to relate the age of a metropolitan area to the growth of its Manufacturing employment.

[10] For example, Chari and Hopenhayn (1991) present a vintage replacement model where there are complementarities between firm vintage and human capital.

in a city is positively related to its growth.[11] In light of this evidence, I assume that regional variations in employment growth can act as a proxy for the unobservable differences in technology, innovation, etc. This assumption is consistent with the endogenous growth models of Romer (1986) and Lucas (1988), and even more plausible when one considers the correlations between growth and human capital I present in the Discussion.

In some sense, variations in the above factors are mostly relevant to the creative destruction rather than the firm learning models. The latter deal primarily with industry, or industry cohort, dynamics, so they rarely address factors relevant to an economy-wide framework, such as the economic growth. Exogenous factors can still affect the dynamics of a learning and selection process, though. Hopenhayn (1992) discusses how higher demand, lower entry costs, or higher fixed operating costs affect an industry's selection process, and the greater job turnover and firm distribution it generates. Hopenhayn and Rogerson (1993) show how firing costs can decrease the incentives to hire and fire, thus decelerating the selection process. Thus, while there are little theoretical priors that relate firm learning to variations in growth, there are precedents that suggest that learning may occur in different ways in different areas. In the Discussion, I argue that regional differences in the business "climate" (which would also affect growth) may affect the selection mechanism of a learning process, and may account for some of my findings.

Data

Access to a robust source of longitudinal establishment microdata is essential to this study. The data I employ come from the Longitudinal Database (LDB), a relatively new source

[11] In addition, Moretti (2002) finds evidence that a higher share of college-educated workers in a local industry increases its plants' productivity, while Acs and Armington (2003) find a positive relation between a region's college-educated share and establishment entry rates in the Service sector.

of establishment data created by the Bureau of Labor Statistics.[12] The LDB is a linked set of unemployment insurance (UI) administrative records from the ES-202 program of the BLS. These records represent the universe of all establishments (private and public, spanning all industries) with employment covered under a U.S. state's UI program. This coverage represents 98 percent of all employment, with the self-employed and the military being the primary exceptions.[13] The data are quarterly, and in the most recent quarter, the LDB includes over 8 million UI records. For this paper, the term "establishment" refers to a distinct UI record.[14] The data include monthly employment and quarterly payroll figures for each establishment. Most importantly, the data are linked across quarters to provide a complete longitudinal history for all records in the database. Pivetz, Searson, and Spletzer (2001) provide a detailed description of the linkage process. The data-generation process is a three-step procedure. It involves a State-level collection of data (for UI tax purposes, not necessarily for economic research), data processing by the ES-202 program, and record linkage, also done within the ES-202 program. The last procedure involves the greatest risk of mismeasurement, as missed linkages can dramatically overstate the number of opening and closing establishments, and consequently, the amount of job creation and job destruction. Linkages may be absent for a variety of reasons, including changes in corporate ownership, firm restructuring, and UI account restructuring. I summarize these issues and my methodology for dealing with them in my dissertation (Faberman, 2003). Suffice it to say, I take every precaution to minimize the amount of missed linkages in the sample of LDB data I use.

I employ a sample of private sector establishments in 53 Metropolitan Statistical Areas (MSA's) across five U.S. states. The scope of the LDB coupled with the attention required by

[12] Several other studies have appealed to the LDB (in various stages of its development) for research purposes. They include Card and Krueger (1998); Spletzer (2000); and Faberman (2001, 2002, 2003).
[13] See U.S. Bureau of Labor Statistics, (2002), p. 661, for details of exclusions.
[14] This is not always accurate. Some multi-unit firms do not report their establishments separately throughout the LDB's time series. The BLS has made efforts, such as the implementation of the "Multiple

data linkage issues make it difficult to study much more. Regardless, the current sample represents approximately 15 percent of all private employment and establishments in the U.S. It includes data from the metropolitan areas of Colorado, Michigan, North Carolina, Ohio, and Pennsylvania from March 1992 through March 2000.[15] The sample includes 1.43 million unique establishments. The average quarter has 14.8 million workers in approximately 796,000 active establishments. On average, MSA employment ranges from 24,000 (Jacksonville, NC) to 1.88 million (Philadelphia, PA-NJ). Table 1 reports quarterly summary statistics for my sample (derived from the LDB) and for the United States (derived from ES-202 macrodata.)

Methodology

I define gross job flows as employment changes due to establishment openings, closings, expansions, or contractions. In this study, "opening" establishments are those with positive employment in the current quarter of observation and either zero or missing employment reported for at least three prior quarters. Similarly, "closing" establishments are those with positive employment in the previous quarter and either zero or missing employment reported for three subsequent quarters. Expansions are net gains in employment at continuing establishments. Contractions are net losses in employment at continuing establishments. *Job creation* is the sum of jobs added at opening and continuing establishments. *Job destruction* is sum of jobs lost at closing and contracting establishments. Job turnover, or job reallocation, is the sum of job creation and job destruction. The rates of these statistics use the average of the current and previous quarters' employment levels as the denominator, just as in Davis, Haltiwanger and Schuh (1996). The employment growth rate is simply the difference between the job creation and job destruction rates. The paper reports both quarterly and annual job flows. Quarterly flows use

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Worksite Report", to mitigate this occurrence. Pivetz, Searson, and Spletzer (2001) and Faberman (2003) discuss this issue in more depth.

[15] The MSA's studied also include Primary Metropolitan Statistical Areas (PMSA's). If an MSA crosses State boundaries, its State affiliation is the location where the majority of its employment resides. For those MSA's who cross state boundaries outside the five states studied (namely Philadelphia, PA-NJ,

the third-month employment, while annual flows use March employment.[16] I do not seasonally adjust the quarterly flows, though they exhibit considerable seasonality. Wages are the total quarterly payroll (deflated with the Consumer Price Index to 1992 dollars) divided by average employment. When wage growth statistics are reported, they are done in analogous manner to employment growth—i.e., the average of the previous and current quarter's wage is used as the denominator. Establishment characteristics include their size (in workers) and age (in quarters). An establishment's age is based on its initial date of UI liability. The age variable must deal with both missing and sometimes incorrect (at least for the purposes of measuring age) liability dates. I deal with these as best as possible, and am confident that I have a reasonably good measure of establishment age. My exact methodologies are contained in my dissertation (Faberman, 2003).

Results

I begin this section focusing on the relationships of the establishment, employment and wage characteristics flows to employment growth. Table 2 lists the summary statistics for the entire sample, averaged across time. Employment grew at 0.6 percent quarterly, with total job reallocation of 13.9 percent. Job reallocation was 25 percent annually, indicating that 55 percent of quarterly reallocation was transitory. Wages were approximately $6,600 per quarter (in 1992 dollars) with quarterly growth of 0.5 percent. The average establishment had just under 19 workers and was approximately 11 years old.

In Table 3, I examine how the statistics in Table 2 relate to employment growth across metropolitan areas. This will give an idea of whether the basic patterns of employment dynamics and establishment characteristics are consistent with the basic implications of the models listed previously. The table lists the coefficients from the regression of the MSA value of the listed variable (averaged across time) on the MSA's employment growth rate (also averaged across

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PMSA; Cincinnati, OH-KY-IN PMSA, Steubenville-Weirton, OH-WV MSA, and Charlotte-Gastonia-Rock Hill, NC-SC MSA) the relevant data from the outlying states are appended to the existing sample.

time) and the corresponding Pearson correlations. Job flows have quarterly and annual results reported. The regressions show a strong positive correlation between employment growth and job creation, with a correlation of 0.76 in the quarterly data and 0.90 in the annual data. Surprisingly, employment growth and *job destruction* also have a positive correlation, with values of 0.49 in the quarterly data and 0.36 in the annual data. Consequently, the correlations between employment growth and job reallocation are strong and positive as well. These findings are consistent with the across-State findings of Eberts and Montgomery (1995), and the across-industry results of Foote (1998) and Baldwin, Dunne, and Haltiwanger (1998). In addition, they are consistent with a process of creative destruction, where higher growth rates imply higher job turnover. An MSA's wage is uncorrelated with its employment growth, but its wage growth has a correlation of 0.39. High-growth MSA's tend to have smaller establishments on average, but the correlation is not strong. High-growth MSA's also tend to have younger establishments on average, and the correlation between employment growth and establishment age is a robust -0.66. The younger distribution of establishments is also consistent with a creative destruction process, since high-growth areas should have a younger exit age for its outdated establishments, and hence younger establishments on average. Thus, high-growth MSA's tend to have higher rates of both job creation and job destruction within relatively younger establishments.

Accounting for Differences in Industry Composition

There is significant heterogeneity in job flows and establishment characteristics across industries, as Table 4 illustrates.[17] More seasonal industries, such as agriculture, construction, and retail, exhibit relatively higher job turnover, and have smaller and younger establishments, while other industries, like manufacturing, have very low job turnover in larger, older establishments. In addition, the regional and urban economics literature documents significant differences in regional industry representation (for example, see Ellison and Glaeser, 1997).

[16] Pinkston and Spletzer (2002) discuss the methodology used for creating annual statistics with the LDB.

Therefore, it is plausible that the correlations reported in Table 3 are merely artifacts of regional differences in industry composition. To explore this hypothesis, I recalculate the correlations after conditioning out the effects of industry. Let X_{ij} denote one of the variables listed in the first column of Table 3 for the i^{th} industry in the j^{th} MSA. Let G_{ij} denote the employment growth rate similarly defined. Regressions controlling for the between-industry variation in each are

(1)
$$\begin{aligned} X_{ij} &= \delta_i + \varepsilon_{ij} \\ G_{ij} &= \mu_i + \eta_{ij} \end{aligned}$$

where δ_i and μ_i represent four-digit industry effects, and ε_{ij} and η_{ij} are error terms. The MSA values of the left-hand side variables independent of industry (denoted $\tilde{x}_j$ and $\tilde{g}_j$) are simply weighted sums of the residuals[18]. The share of the unconditional correlation due to industry is one minus the ratio of the conditional correlation (i.e., the correlation between $\tilde{x}_j$ and $\tilde{g}_j$) and the unconditional correlation.

Table 5 presents the results of this decomposition. Job flows are both quarterly and annual. The distinction between the two periods is important for this exercise, since seasonal trends in the quarterly data vary widely by industry. Comparing the contributions of between-industry effects across the two frequencies shows that seasonal fluctuations give them considerably more weight in the quarterly data. Thus, it may be more constructive to focus on the annual job flow results of this exercise. The exercise conditions out 972 four-digit industries for the 53 MSA's.

Industry differences account for 43 percent of the quarterly correlation between quarterly MSA employment growth and job creation, but only 14 percent of their annual correlation. Industry differences more than explain regional differences in job destruction. The relation between employment growth and job destruction switches from positive to negative when

[17] Similar across-industry findings appear in Anderson and Meyer (1994), Foote (1998), and Burgess, Lane, and Stevens (2000).

industry differences are controlled for. The relation between growth and job reallocation remains positive, with industry differences accounting for 79 percent of their quarterly correlation, and 47 percent of their annual correlation. Industry differences account for nearly all (91 percent) of the relation between a MSA's growth rate and the average size of its establishments. They account for a much smaller fraction (38 percent) of the relation between growth and average establishment age. In summary, industry differences account for a good deal of the relations observed between employment growth and job destruction and establishment size, but they account for much less of the relations between growth with establishment age, job creation, and overall job turnover. Note, however, that between-industry differences in job turnover and establishment age do not contradict a creative destruction model—differences in technological progress across industries are just as plausible as differences across regions.

Accounting for Differences in Age Distribution

Figure 1 illustrates the negative relation between job reallocation and establishment age, while Figure 2 illustrates the wide distribution of establishments across age categories.[19] Job turnover declines with age. At very young ages it is very high, representing as much as 50 percent of employment, but for older establishments, especially those over 20 years old, job turnover is low, representing only 10 percent of employment. The distribution of employment among establishments is remarkably uniform. About 20 percent of employment occurs in establishments aged 5 years or less. A similar amount of employment occurs in establishments of 20 years or older. The distribution of employment across establishments of differing age varies from region to region, however. As with industry, regional differences in job flows may be an artifact of differences in age distributions. Moreover, the models noted earlier have distinct

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[18] Residuals will either be weighted by employment (growth and job flows) or establishments (size and age), depending on the variable in question.

[19] Job reallocation is high for establishments less than one year old almost by definition. Entrants have both a growth and reallocation rate of 200 percent by the symmetric growth rate methodology. The rate reported for the first data point is considerably less than that, though, since its category also includes existing establishments one, two, or three quarters old.

implications for whether job flow variations should be primarily a between or within age-category phenomenon. Creative destruction models contain a vintage replacement process that creates differences in job reallocation primarily through differences in establishment age distributions (i.e., between-age variations.) In contrast, firm learning processes stress job turnover *within* a given age category, as firms within a given cohort respond to the uncertainty created by firm-level shocks to production. The evidence thus far (high correlations between MSA employment growth and high job reallocation and relatively younger establishments) favors a creative destruction process. If between-age differences accounted for the relationships seen in Table 3, it would lend further support to this process. If, however, job flows and growth were positively related independent of age (i.e., age distributions were essentially the same across areas, but the dynamics of establishments of the same age differed), then one would need to explore processes such as firm learning, which stress job turnover within age cohorts.

I categorize the sample by age and perform an analysis identical to the industry decomposition.[20] Rather than 972 four-digit industries, the decomposition uses 16 age categories.[21] Results of the decomposition are in Table 6. Between-age differences account for 43 percent of the quarterly correlation between MSA employment growth and job creation, but only 22 percent of the annual correlation. Like with industry differences, age-distribution differences over-account for the relations between employment growth and job destruction, with the quarterly correlation essentially zero, and the annual correlation -0.49. Variations in the age distribution account for 65 percent of the quarterly correlation between employment growth and job reallocation and 76 percent of their annual correlation. These findings are generally

[20] The age measure in the previous sections is adjusted for state-level differences, since there biases that can affect those results (see Faberman, 2003 for details). The measure used in this section is unadjusted, since my adjustment methodology distorts the age distribution within an area, making it incompatible with this exercise. Also, the nature of the decomposition forces me to deal with changes in UI account structures differently than in other exercises (also discussed in Faberman, 2003). Issues related to age measurement make estimates of job flows are somewhat higher, but this does not detract from the exercise.
[21] These categories group establishments by age at one-year intervals for ages 0 to 10 years and at two-year intervals for ages 10 to 20 years. A final category includes establishments 20 years and older.

supportive of the vintage replacement process seen in creative destruction models, but enough of the within-age category relationship between growth and turnover remains (between one-quarter and one-third) to warrant further exploration.

Entering Cohort Analysis

I explore within-age differences in job flows with an analysis of entering establishments. Theories of firm learning focus predominantly on entrants within the same industry and of the same cohort, and the dynamics that stem from their models occur primarily within cohorts. The following exercise focuses on entry, exit, growth, and job flow evidence for the first five years of an entering cohort's existence. Establishments enter between the second quarters of 1993 and 1995, providing nine distinct cohorts. Pooled together, they represent 177,373 starting establishments, making up 2.5 percent of active establishments and 0.7 percent of employment in a given quarter. I have 2,472,713 distinct observations on these entrants. I take extra care to ensure that the entrants are true births and not the re-opening of existing establishments, with the details of my sample creation in Faberman (2003).

Table 7 presents the sample means and correlations for various cohort statistics. The statistics are for the pooled sample of entrants within a particular MSA. The entry rate of establishments represents 2.5 of all establishments in a quarter, but *half* of these entrants exit within their first five years of existence. Those that exit do so in less than two years, on average. Total employment for each cohort declines over the first five years, but surviving establishments grow 26 percent in this period. The average wage of the cohort grows 20 percent. Entrants begin with 46 percent lower wages than the average wage for their MSA. After five years, their wage is only 17 percent lower. The first column of correlations represents the across-MSA correlation with the variable in the leftmost column with the MSA (total, not just the cohort) employment growth rate. The next two columns report the correlations with the entrants' share of MSA establishments and the average age of exiting establishments, respectively. The rates of both entry and exit are higher in MSA's with high employment growth. This is consistent with creative destruction models, as well as firm learning and selection models, since high-growth areas also have relatively younger establishments, and since the learning models predict higher turnover among younger firms. The age of exiting establishments, comparable to the "scrapping age" in creative destruction models (i.e., the age at which outdated firms shut down), is somewhat lower in these MSA's, but the correlation is not significant. As on might expect, cohort employment growth and surviving establishment growth are both positively correlated with MSA employment growth. Consistent with a creative destruction process, entry and exit rates have a strong positive correlation of 0.57. Entry and the exit age, however, are unrelated. This is in contrast to a creative destruction process, in which higher entry and a younger exit age occur together via a higher rate of technological change. MSA's with higher entry rates tend to have higher growth for their cohorts and their cohorts' survivors, in particular. In addition, MSA cohorts with higher overall and survivor growth had exits occur at a younger age, on average. Thus, while the overall relation between entry (or growth) and the exit age is essentially zero, the relation between cohort and survivor growth and the exit age is significantly negative. This may be consistent with regional differences in a firm learning process, and I discuss how this may be so below.

Cohort wage growth is positively correlated with both the entry rate and MSA employment growth. The wage an establishment begins with (relative to the MSA wage) is independent of both MSA growth and the entry rate, but the wages offered by those who survive 5 years (relative to the MSA wage) is positively related to both. None of the wage statistics are significantly related to the average exit age of establishments.

In my final exercise, I explore the relation between job flows, establishment age, and MSA employment growth through establishment-level regressions with the pooled sample of entrants. In doing so, I hope to see whether (i) job flows decrease with age, which would be consistent theoretically with firm learning and empirically with the work of Dunne, Roberts, and Samuelson (1989a, 1989b), but inconsistent with vintage replacement, (ii) the job flow-age relation varies across metropolitan areas, and if so, (iii) what the pattern of this variation may be. I again use the pooled sample of entrants, which gives me up to 20 quarters of observations for each establishment. I regress job flow variables, at the establishment level, on fixed effects for age (in quarters) and interactions between these fixed effects and the employment growth rate of their MSA, as well as the MSA growth rate alone and other controls. So far, I have presented evidence at the MSA-level that illustrates a positive relationship between job turnover and growth and a negative relationship between job reallocation and age. The logical next step explores whether differences in metropolitan employment growth affect the reallocation-age relationship. It may be possible that there is only a level effect: high growth MSA's have higher job turnover, and this essentially true for establishments regardless of their age. A positive coefficient on the MSA growth rate and jointly insignificant interaction effects would suggest that this is true. If, however, high-growth MSA's have disproportionately higher job reallocation among establishments of particular ages, I should observe positive interaction effects for those ages. Positive interaction effects would also introduce a facet of the learning and selection models yet to be explored. As stated earlier, these models focus primarily on cohorts within industries, and do not deal so much with the effect of variations in growth, technological or otherwise, on their implications. Positive interactions would suggest that growth (or other unobserved factors correlated with growth) has a significant effect on the dynamics of a learning and selection process.

The dependent variable is either the job creation, job destruction, or job reallocation rate. At the establishment level, job creation is the net employment change given a positive gain, while job destruction is the net employment change given a loss. Job reallocation is the absolute value of the net employment change. Let Y^c_{eijt} be one of these variables for establishment *e* in cohort *c* in industry *i* in MSA *j* aged *t* quarters. The full regression specification is

$$Y^s_{eijt} = \alpha^c + \mu_q + \beta G_j + \gamma_t D_{et} + \delta_i + \eta_t \left[D_{et} \cdot G_j \right] + \varepsilon^c_{eijt} . \quad (2)$$

The α^c control for cohort entry quarter, while the μ_q are quarter dummies that control for seasonal effects. The average quarterly MSA employment growth rate is G_j, the γ_t are age fixed effects, D_{et} is a matrix of establishment age dummies, the δ_i are 4-digit industry effects, and the η_t are coefficients from the interaction of the age effects with the MSA growth rate. I weight regressions by employment levels. Using this regression, I can obtain the fitted age-job flow relationship for an MSA with average growth rate $\overline{G}_j$. Conditioning out cohort, season, and industry effects makes the fitted value

$$\hat{\overline{Y}}_{jt} = \hat{\beta}\overline{G}_j + \hat{\gamma}_t + \hat{\eta}_t\overline{G}_j \,. \tag{3}$$

Figures 3 through 6 map out the $\hat{\overline{Y}}_{jt}$ over the five-year period using a centered 3×3 moving-average trend—this smoothes out any seasonality remaining after controlling for quarter-of-the-year. In all tables, two trends are fitted with G_j equal to 1.15 and 0.23 percent—these correspond to the MSA growth rates in the 90th and 10th percentiles, respectively. Figure 3 shows the relation between job reallocation and establishment age before I control for industry. Figures 4 through 6 depict the trend for the full regression specification (industry effects included) for job reallocation, job creation, and job destruction, respectively. The interaction coefficients, $\hat{\eta}_t$, and their significance for the latter three figures are reported in Table 8 for reference.

Figure 3, like Figure 1, shows job reallocation clearly decreases with age. The trends for a high-growth versus low-growth MSA show an interesting twist on this relationship. Job reallocation begins higher among entrants in high-growth areas. As cohorts age, however, the rate of reallocation decreases *faster* in the high-growth areas. By the fourth year, there is no significant difference in job reallocation between high and low-growth areas. In fact, the graph shows a crossing-point towards the end of the period, where the low-growth areas have higher turnover, though the interaction coefficients for these later quarters are insignificant. Figure 4 controls for industry effects and shows a qualitatively identical result. The only notable difference is the earlier occurrence of the crossing-point of the two trends, which happens about two years after entry. Figure 5 again portrays a qualitatively similar result, but this time for job creation. Job creation among entrants is greater in high-growth MSA's for the first two to three years of existence, but this difference dissipates by the fourth year. In Figure 6, a different trend is portrayed. Job destruction decreases with age. This decrease contrasts with a creative destruction process, since job loss and exit should be greatest among older, more technologically outdated firms, but this decrease is well-documented in previous work (e.g., Dunne, Roberts, and Samuelson (1989a, 1989b). Unlike in the previous figures, job destruction is higher within *low-growth* MSA's. In addition, the difference in slopes of the two trends is not nearly as distinct as with job reallocation or job creation. In fact, the interactions exhibit considerably less significance (as seen in the final column of Table 8) than those for either job creation or job reallocation. The difference in levels, however, is significantly greater in the low-growth areas—the coefficient on growth for this regression, $\hat{\beta}$, is -1.27 with a standard error of 0.30, and it stems from the same regression as the coefficients in the final column of Table 8.

This exercise suggests that the same intrinsic regional factors (which are correlated with employment growth) that affect the job turnover and establishment age distribution patterns relevant to a creative process may also be important to the establishment life-cycle dynamics relevant to a firm learning and selection process. The evidence in Figures 5 and 6 suggests that these factors are relatively more important for job creation rather than job destruction. While it might seem that the dynamics of firm learning models account for much of the above evidence, there are some results that these models must somehow address. The empirical life-cycle dynamics consistent with these models seem to vary with unobservable local factors, and cross-sectional variations such as this may be easily incorporated into future models. The most difficult result to reconcile may be that these variations matter more so for job creation than destruction. Key to this class of models is a selection mechanism by which inefficient firms exit an industry, so if local factors were to create variations in the dynamics of entrants' life-cycles, one would expect to observe these variations along the establishment exit and job destruction margins.

Discussion

My basic results present evidence consistent with a creative destruction process—areas with high employment growth (which I assume proxies for high technological growth) have higher rates of both job creation and job destruction among relatively younger establishments. Most of these relationships persist after controlling for differences in detailed industry classifications, with only exception being the positive correlation between job destruction and growth. I also find that areas with high employment growth have higher entry and exit, also consistent with creative destruction models. Between-age differences (those attributable to differences in the establishment age distribution) account for much of the relation between job turnover and regional growth. This is consistent with creative destruction models, since they imply that higher growth should produce a younger distribution of firms via an earlier firm exit age

Some of my more detailed results conflict with standard models of creative destruction. Most prominently, job destruction decreases rather than increases as entrants age, a reinforcement of previous empirical findings (e.g., Dunne, Roberts, and Samuelson, 1989a, 1989b). In addition, there is no clear negative relation between establishment entry rates and their average exit age—creative destruction models imply that greater entry and earlier exit should occur together in the steady-state when growth is higher. In addition, between one-quarter and one-third of the growth-reallocation relationship cannot be explained by regional between-age variations; between-age variations account for only 22 to 44 percent of the growth-job creation relationship, implying that the remaining variation is a within-cohort phenomenon. This contrasts with a creative destruction process, since the models assume (arguably in their most literal interpretation) that firms within a cohort are homogeneous, and that heterogeneity stems from firms of different vintages. The evidence from establishments within an entering cohort is instead more consistent with a firm learning and selection process. Notably, both job creation and job destruction decline as entrants age. Establishment entry and exit are positively correlated across areas, a finding consistent with both classes of models. Finally, exit occurs earlier rather than later in an entrant's life: when studying the first five years of their existence, the average age of an exiting establishment is about two years, and half the original cohort is gone by the end of the fifth year.

Interestingly enough, the dynamics observed as entrants age vary systematically in their *pace*—high-growth metropolitan areas have relatively higher job reallocation, mainly through higher job creation, among their youngest establishments. In addition, reallocation and creation rates decline with age *faster* in high-growth areas than in other areas. This is *not* true for job destruction, once I control for industry differences. Job destruction declines with age independent of area, but its variations across areas are also essentially independent of establishment age: *low-growth* metropolitan areas have higher rates of job destruction among their entrants, and this trend does not significantly differ by establishment age. This evidence introduces new stylized facts that learning and selection models must address. These models generally do not deal with whether the dynamics within entering cohorts can vary based on intrinsic factors of the economy (such as the pace of innovation or technology growth). My findings suggest these factors may indeed affect the life-cycle dynamics of firms. In addition, they do so in a way that may be inconsistent with the implications of a firm learning process. In particular, this process predicts that inefficient firms will eventually exit the market via a selection mechanism. Thus, one would expect the cross-sectional variations in such a process to occur through this mechanism (i.e., economies with different intrinsic attributes should have different firm exit thresholds), so that regional variations in intrinsic factors (which I assume are correlated with employment growth) would correspond with differences in job destruction. Instead, I find that these attributes are correlated with variations in *job creation*. Future models will have to reconcile how firm learning can differ across regions and create relatively greater variations along the job creation rather than destruction margin.

Underlying my empirical work is an assumption that high employment growth areas are also high technology growth areas, broadly defined. I originally posited that regional variations in innovations or technology growth are most important for models of creative destruction, since those models explicitly depend on an exogenous rate of technological change. My findings within entering cohorts, however, suggest that these factors (or other factors correlated with them) may also be important for models of firm learning. As I stated earlier, endogenous growth models such as Romer (1986) suggest that innovation drives growth, so that the greater the level of innovation the greater the rate of growth. Related to this is the model of Lucas (1988), which shows how high levels of human capital can have the same outcome. It is difficult to measure technological growth and innovation across metropolitan areas, but by using evidence from patent citations, Jaffe, Trajtenberg, and Henderson (1993) show that innovations are localized within metropolitan areas, and that the spatial diffusion of these innovations is slow, implying that regional variations in these innovations do in fact exist. And given models such as Chari and Hopenhayn (1991), who present a creative destruction model where the newest (and most productive) firm vintages require the most human capital, it is plausible to assume that the skill mix of a local labor force will affect growth, and hence the dynamics of the models addressed in this paper.

Table 9 presents statistics compiled from the 1990 and 2000 decennial censuses on demographic characteristics of the metropolitan areas in my sample, and their relation to employment growth, job reallocation, and average establishment age. I focus on the share of the population (aged 25 or older) with at least a college degree and the share of the population aged 20 to 34. The latter is more of a proxy for how much worker mobility (across jobs or areas) may play a role in my results.[22] My estimates for the 1990 census are adjusted so that all data correspond to the most recent classification of MSA definitions. The correlations across metropolitan areas are similar across censuses, illustrating the persistence in the shares of college educated and young workers in these areas over time. The correlations show that younger and college-educated workers tend to live in metropolitan areas with high employment growth, high rates of job reallocation, and relatively younger establishments. The results are all large in magnitude and significant. These results, coupled with my preceding findings, suggest that the level of human capital in an area may be an important exogenous factor for models of creative destruction and firm learning, though further research is needed on its relation to the models.

Other factors relating to the local "business climate" may also drive my findings. For example, Hopenhayn (1992) shows how variations in exogenous factors, such as entry costs, output demand changes, and fixed operating costs, can lead to variations in the selection process of a learning model, while Hopenhayn and Rogerson (1993) show how high firing costs can decrease turnover and employment growth. Whether it be variations in innovation, technology growth, human capital, or the costs of firm entry and operation, it is clear that differences exist that drive the observed regional variation in both establishment and employment dynamics. These variations may stem from differences in other aspects of a local business climate, such as public infrastructure, access to capital markets, local product market competition, or information spillovers stemming from firm agglomeration.

With respect to firm learning models, these factors may affect the pace of selection via regional differences in the "noisiness" of the signal by which firms learn about their abilities. These suggestions are purely speculative, and regional differences in the pace at which firms learn do not fully reconcile firm learning models with my evidence. These differences generate regional variations in firm life-cycle dynamics on both the job creation and destruction margins,

[22] In separate studies, Topel (1986) and Topel and Ward (1992) show that younger and more educated workers are the most mobile geographically and across different jobs.

but not exclusively along the creation margin, as is seen in Figures 5 and 6. It is still a worthwhile exploration. Figure 7 replicates the dynamics depicted by Jovanovic (1982, p. 650), but does so for two economies—one with a noisy learning process and one with a relatively smooth learning process. The figure illustrates the behavior of an efficient and inefficient firm within each economy. The thin lines represent their behavior within a noisy learning environment, while the thick lines represent their behavior in the smooth learning environment. When learning is less noisy, firm beliefs converge to their true value faster. The growth of productive firms and the exit of less successful firms occur quicker. This implies that turnover will be higher in the smoother learning environments among the youngest firms, but that this turnover will decrease faster as firms age in these environments. This is consistent with the patterns of job turnover evidenced in Figure 4, but not consistent with the more detailed breakout of turnover into its job creation and destruction components in Figures 5 and 6, respectively.

Conclusions

In this study, I present new stylized facts on employment and establishment dynamics across metropolitan areas using a new, rich source of establishment data. I relate these facts back to two classes of models that stress constant churning among heterogeneous firms: those of creative destruction and those of firm learning and selection. In doing so, I assume that the employment growth of a metropolitan area is correlated with its unobservable intrinsic factors, such as its rate of technological change. I find evidence in support of both models, but also find evidence in contrast to each model. High-growth metropolitan areas have higher rates of job creation and job destruction, as well as a relatively younger distribution of establishments. Most regional variations in employment dynamics (with the exception of job creation) are due to regional differences in the establishment age distribution. In addition, these areas have high entry and exit rates. These facts are all consistent with standard models of creative destruction. A substantial portion of the regional variations in job turnover (in job creation, in particular) occur within establishment cohorts, the pace of job destruction decreases rather than increases with age, and there is no clear negative relation between establishment entry rates and the age at which they exit. These findings run counter to a model of creative destruction. Evidence within nine cohorts of entrants indicates that both job creation and job destruction decrease with age, that half of all entrants exit within five years, and that establishments that exit do so within two years, on average. These findings are consistent with models of firm learning and selection. Again, however, I find other evidence that these models either do not explicitly address or runs counter to their implications. Namely, job reallocation, particularly job creation decreases with age and does so *faster* in high growth areas, suggesting that regions may vary in the *pace* of firm learning. This trend is not evident in job destruction, though, as regional variations in the firm exit thresholds of a selection mechanism would imply. The evidence suggests that region-specific factors (such as the rate of technological change, the labor skill mix, firm entry and operating costs, or the overall "business climate") may affect firm life-cycle dynamics in much the same way they affect the dynamics of a vintage replacement process. Future models wishing to characterize the churning and heterogeneity of labor markets will have to account for the possible effects of these factors, as well as the new stylized facts presented herein.

Bibliography

Acs, Zoltan J., and Armington, Catherine, 2003. "The geographic concentration of new firm formation and human capital: Evidence from the cities." Center for Economic Studies Working Paper 03-05.

Aghion, Philippe and Howitt, Peter, 1992. "A model of growth through creative destruction." *Econometrica* 60(2): 323-351.

Aghion, Philippe and Howitt, Peter, 1994. "Growth and unemployment." *Review of Economic Studies* 61: 477-494.

Anderson, Patricia and Meyer, Bruce R., 1994. "The extent and consequences of job turnover." *Brookings Papers on Economic Activity,* Microeconomics: 177-249.

Baldwin, John, Dunne, Timothy, and Haltiwanger, John, 1998. "A comparison of job creation and job destruction in Canada and the United States." *Review of Economics and Statistics* 80(3): 347-356.

Blanchard, Oliver J., and Diamond, Peter, 1990. "The cyclical behavior of the gross flows of U.S. workers." *Brookings Papers on Economic Activity, Vol. 2:* 85-143.

Blanchard, Oliver J., and Katz, Lawrence, 1992. "Regional Evolutions." *Brookings Papers on Economic Activity, Vol. 1:* 1-75.

Burgess, Simon, Lane, Julia I., and Stevens, David, 2000. "Job flows, worker flows, and churning." *Journal of Labor Economics* 18(3): 473-502.

Caballero, Ricardo J. and Hammour, Mohamad L., 1994. "The cleansing effect of recessions." *American Economic Review* 84(5): 1350-1368.

Caballero, Ricardo J. and Hammour, Mohamad L., 1996. "On the timing and efficiency of creative destruction." *Quarterly Journal of Economics* 111(3): 805-852.

Card, David, and Krueger, Alan B., 1998. "A reanalysis of the effect of the New Jersey minimum wage increase of the fast-food industry with *representative* payroll data." NBER Working Paper #6386.

Chari, V.V., and Hopenhayn, Hugo, 1991. "Vintage human capital, growth, and the diffusion of new technology." *Journal of Political Economy* 99(6): 1142-1165.

Davis, Steven and Haltiwanger, John C., 1990. "Gross job creation and destruction: Microeconomic evidence and macroeconomic implications." In *NBER Macroeconomics Annual* 5 (pp. 123-68). Cambridge, MA: National Bureau for Economic Research.

Davis, Steven and Haltiwanger, John C., 1992. "Gross job creation, gross job destruction and employment reallocation." *Quarterly Journal of Economics* 107(3): 819-63.

Davis, Steven and Haltiwanger, John C., 1999. "Gross job flows." In Orley Ashenfelter and David Card (eds.), *Handbook of Labor Economics, Volume 3* (pp. 2711-2805). Amsterdam: Elsevier Science.

Davis, Steven, Haltiwanger, John C., and Schuh, Scott, 1996. *Job Creation and Destruction.* Cambridge, MA: MIT Press.

Davis, Steven, Loungani, Prakash, and Mahidhara, Ramamohan, 1997. "Regional labor fluctuations: Oil shocks, military spending and other driving forces." University of Chicago, mimeo.

Dumais, Guy, Ellison, Glenn and Glaeser, Edward L., 2002. "Geographic concentration as a dynamic process." *Review of Economic Statistics* 84(2): 193-204.

Dunne, Timothy, Roberts, Mark J., and Samuelson, Larry, 1988. "Patterns of firm entry and exit in U.S. manufacturing industries." *RAND Journal of Economics* 19(4): 495-515.

Dunne, Timothy, Roberts, Mark J., and Samuelson, Larry, 1989a. "Plant turnover and gross employment flows in the U.S. manufacturing sector." *Journal of Labor Economics* 7(1): 48-71.

Dunne, Timothy, Roberts, Mark J., and Samuelson, Larry, 1989b. "The growth and failure of U.S. manufacturing plants." *Quarterly Journal of Economics* 104(4): 671-98.

Eberts, Randall W. and Montgomery Edward, 1995. "Cyclical versus secular movements in employment creation and destruction." NBER Working Paper #5162.

Ericson, Richard and Pakes, Ariel, 1995. "Markov-perfect industry dynamics: A framework for empirical work." *Review of Economic Studies* 62(1): 63-82.

Ellison, Glenn and Glaeser, Edward L., 1997. "Geographic concentration in U.S. manufacturing industries: A dartboard approach." *Journal of Political Economy,* 105(5): 889-927.

Faberman, R. Jason, 2001. "Job creation and job destruction within Washington and Baltimore." *Monthly Labor Review* 124(9): 24-31.

Faberman, R. Jason, 2002. "Job flows, establishment characteristics, and labor dynamics in the U.S. Rust Belt region." *Monthly Labor Review* 125(9): 3-10.

Faberman, R. Jason, 2003. "Employment and establishment dynamics in metropolitan areas." Unpublished Ph.D. dissertation, University of Maryland: College Park, MD.

Foote, Christopher, 1998. "Trend employment growth and the bunching of job creation and destruction." *Quarterly Journal of Economics* 113(3): 809-834.

Glaeser, Edward L., Scheinkman, Jose A., Shleifer, Andrei, 1995. "Economic growth in a cross-section of cities." *Journal of Monetary Economics* 36: 117-143.

Hopenhayn, Hugo, 1992. "Entry, exit, and firm dynamics in long run equilibrium." *Econometrica* 60(5): 1127-1150.

Hopenhayn, Hugo and Rogerson, Richard, 1993. "Job turnover and policy evaluation: A general equilibrium analysis." *Journal of Political Economy* 101(3): 915-938.

Jaffe, Adam B., Trajtenberg, Manuel, and Henderson, Rebecca, 1993. "Geographic localization of knowledge spillovers as evidenced by patent citations." *Quarterly Journal of Economics* 108(3): 577-598.

Jovanovic, Boyan, 1982. "Selection and the evolution of industry." *Econometrica* 50(3): 649-670.

Lucas, Robert, 1988. "On the mechanics of economic development." *Journal of Monetary Economics* 22(1): 3-42.

Moretti, Enrico, 2002. "Human capital spillovers in manufacturing: Evidence from plant-level production functions. " NBER Working Paper #9316.

Pinkston, Joshua C., and Spletzer, James R., 2002. "Annual measures of job creation and job destruction created from quarterly ES-202 microdata." *2002 Proceedings of the Annual Statistical Association* [CD-ROM]. Alexandria, VA: American Statistical Association, 3311-3316.

Pivetz, Timothy R., Searson, Michael A., and Spletzer, James R., 1999. "Measuring job flows and the life cycle of establishments with BLS longitudinal establishment microdata." unpublished working paper, Bureau of Labor Statistics.

Romer, Paul M., 1986. "Increasing returns and long run growth." *The Journal of Political Economy*, 94(5): 1002-1037.

Spletzer, James R., 2000. "The contribution of establishment births and deaths to employment growth." *Journal of Business and Economic Statistics* 18(1): 113-126.

Topel, Robert H., 1986. "Local labor markets." *Journal of Political Economy,* 94(3), part 2: S111-S143.

Topel, Robert H., and Ward, Michael P., 1992. "Job mobility and the careers of young men." *Quarterly Journal of Economics,* 107(3): 441-479.

U.S Bureau of Labor Statistics, 2002. *Employment and Wages Annual Averages, 2001*. Washington, DC: Bureau of Labor Statistics, Bulletin 2554.

Varaiya, Pravin and Wiseman, Michael, 1978. "The age of cities and the movement of manufacturing employment, 1947-72." *Papers of the Regional Science Association* 41: 127-140.

Varaiya, Pravin and Wiseman, Michael, 1981. "Investment and employment in manufacturing in U.S. metropolitan areas 1960-1976." *Regional Science and Urban Economics* 11: 431-469.

Figure 1.
Job Reallocation by Age Category, All Metropolitan Areas

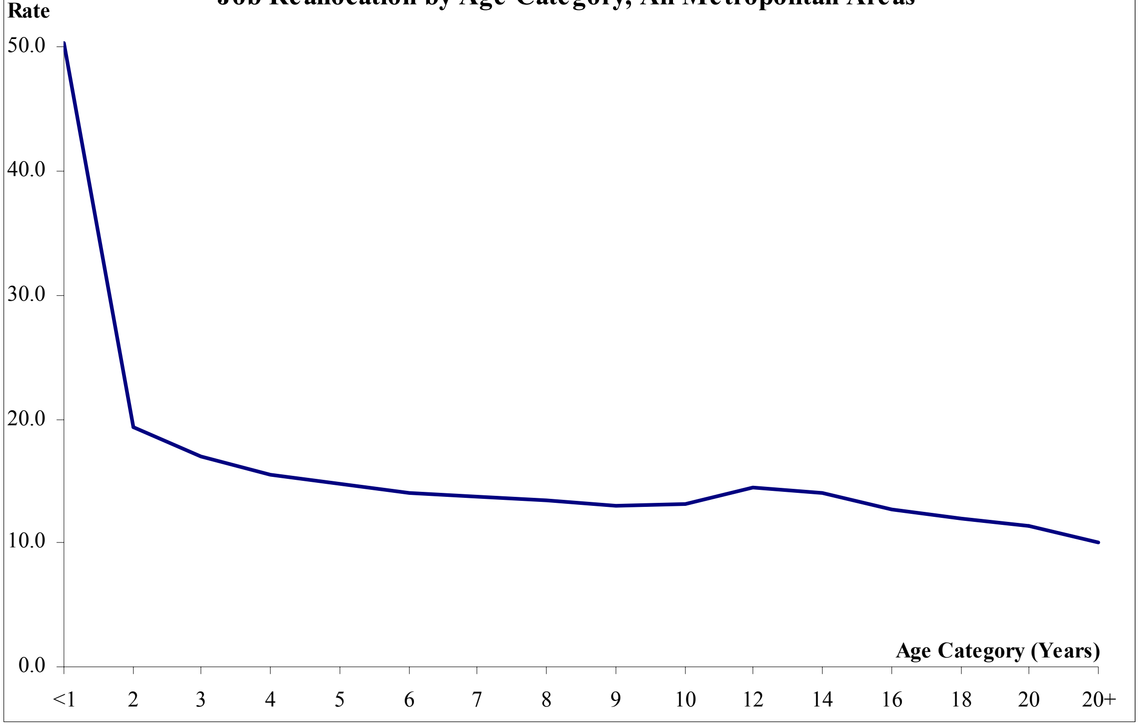


Figure 2.
Employment Distributions by Age Category, All Metropolitan Areas

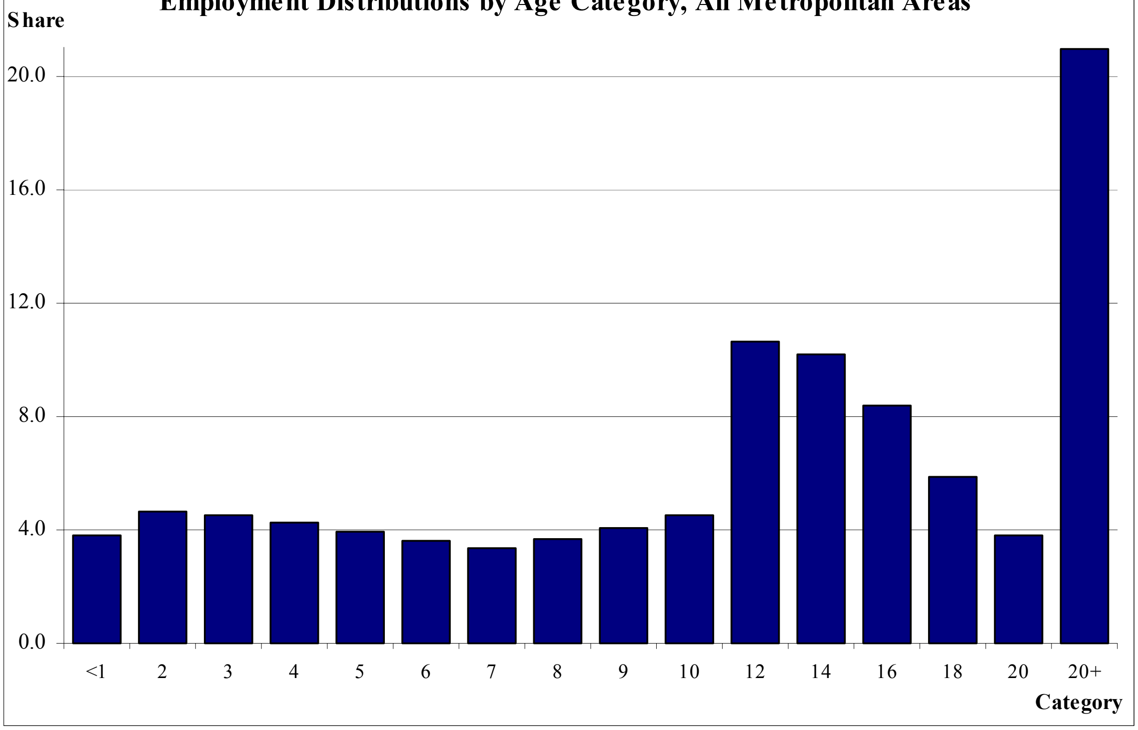


Figure 3.
Reallocation and Age - MSA Interactions, No Industry Effects

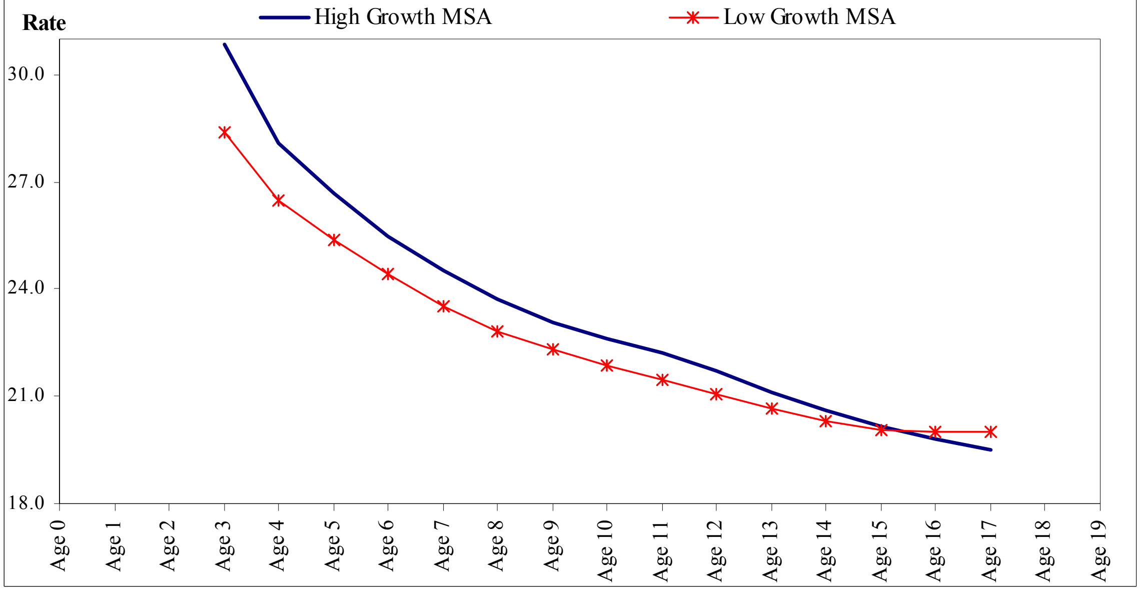


Figure 4.
Reallocation and Age - MSA Interactions and Industry

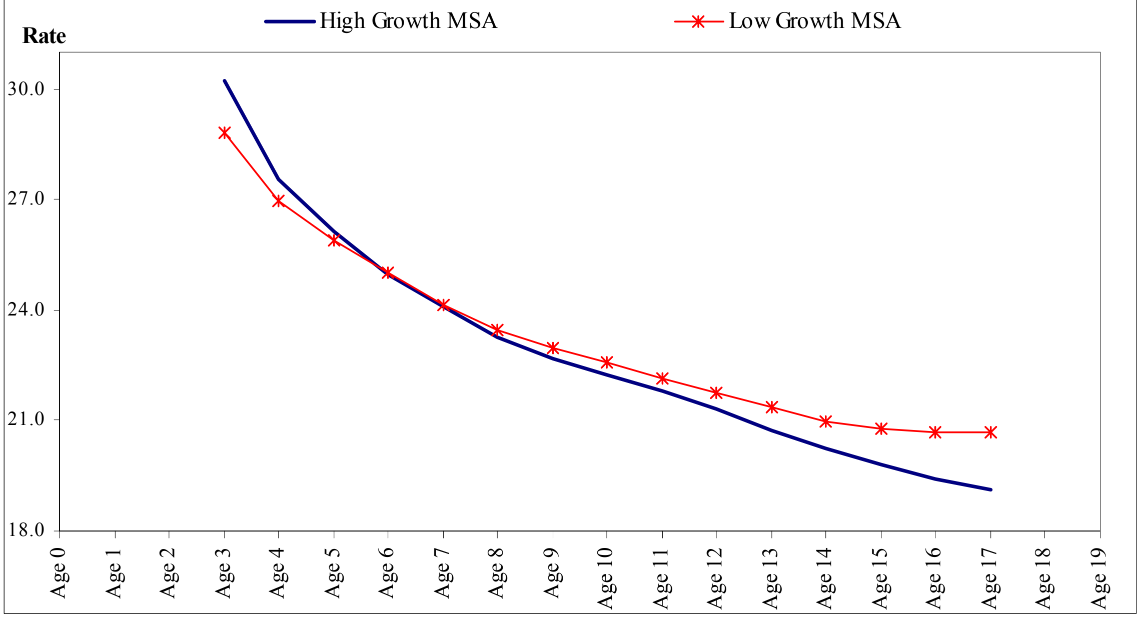


Figure 5.
Job Creation and Age - MSA Interactions and Industry

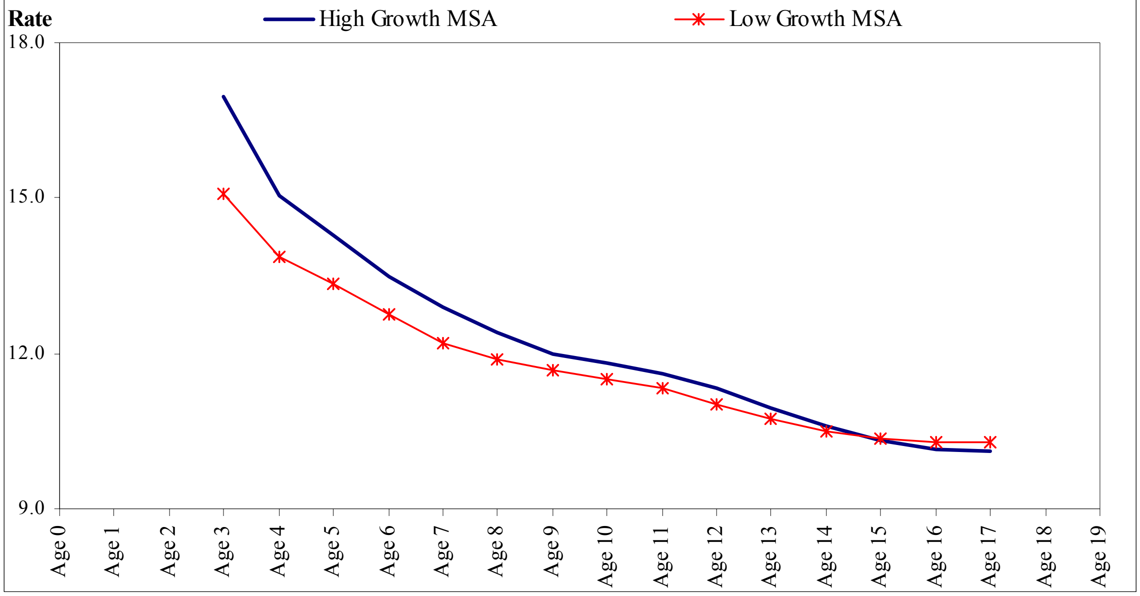


Figure 6.
Job Destruction and Age - MSA Interactions and Industry

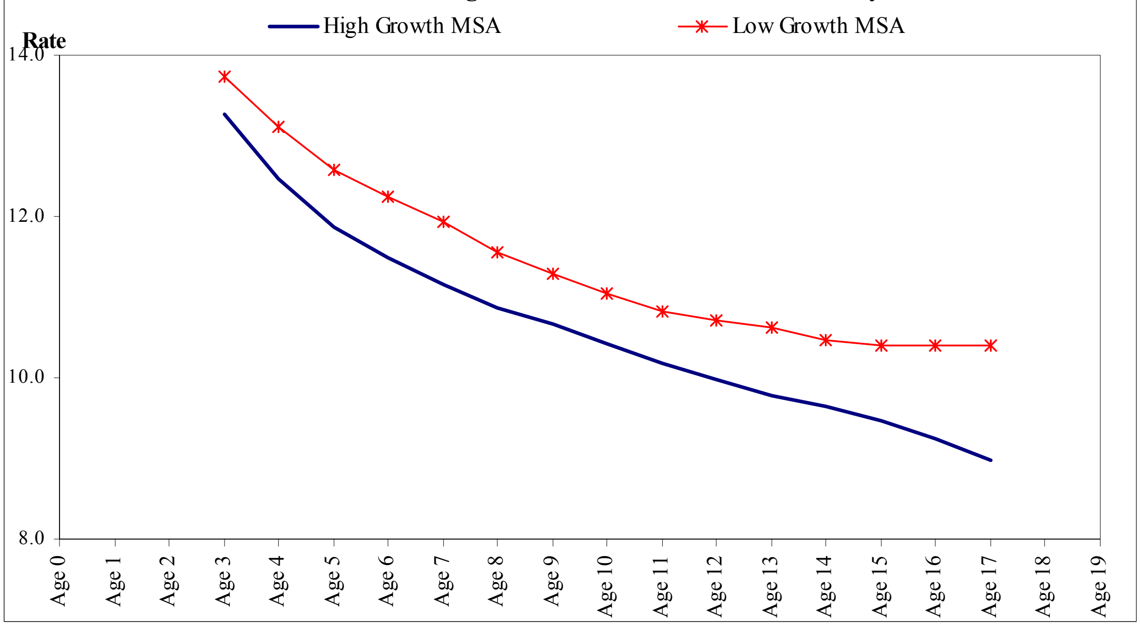
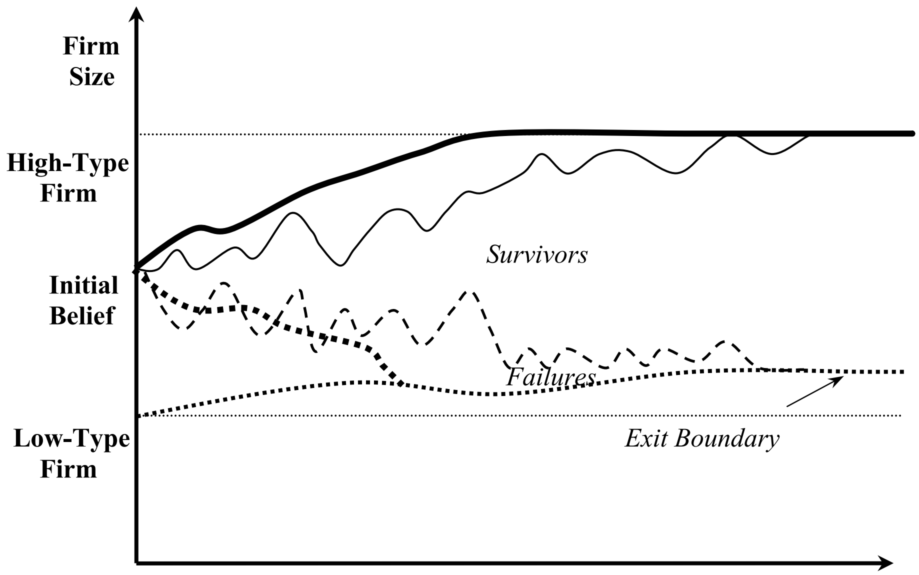


Figure 7.

Evolution of Firm Beliefs in Two Environments of Differing Signal Noise



Notes: The thick solid and dashed lines represent the size paths of a productive and less productive firm, respectively, in an environment with little signal noise. The thin solid and dashed lines represent the size paths of a productive and less productive firm, respectively, in a noisy learning environment. The thick dotted line represents the threshold at which firms will no longer find it profitable to operate. The figure is an adaptation from Jovanovic, 1982 (p. 650).

TABLE 1.
SUMMARY STATISTICS: LDB SAMPLE AND U.S. TOTALS, PRIVATE SECTOR EMPLOYMENT

	LDB Sample		*United States*	
Variable	**Mean**	**Std. Deviation**	**Mean**	**Std. Deviation**
Employment (thousands)	14,798	---	99,148	---
Employment growth rate (percent)	0.58	1.95	0.67	1.81
Wages (1992 dollars)	$ 6,625	350	$ 6,470	369
Wage growth rate (percent)	0.48	7.27	0.51	7.65

Notes: Sample statistics represent the quarterly means and standard deviations from March 1992 to March 2000. Results for the LDB sample are for all private employment in the metropolitan statistical areas of Colorado, Michigan, North Carolina, Ohio, and Pennsylvania. Results for the United States are from aggregate tabulations of ES-202 data.

TABLE 2.
SUMMARY STATISTICS: LDB SAMPLE

	Quarterly Tabulations		*Annual Tabulations*	
Variable	**Mean**	**Std. Deviation**	**Mean**	**Std. Deviation**
Employment (thousands)	14,798	---	14,521	---
Employment growth rate (percent)	0.58	2.05	2.2	0.73
Wages (1992 dollars)	$6,625	350	6,594	355
Wage growth rate (percent)	0.48	7.27	1.9	2.98
Job creation rate (percent)	7.25	1.00	13.6	0.34
Job destruction rate (percent)	6.67	1.14	11.4	0.47
Job reallocation rate (percent)	13.92	0.91	25.0	0.38
Average establishment size (in workers)	18.8	0.27	---	---
Average establishment age (in quarters)	43.5	1.74	---	---

Notes: Quarterly and annual means are from March1992 to March 2000, for the full sample of metropolitan areas. Annual statistics represent the March to March employment and wage dynamics. Annual reporting of wages is kept in quarterly values. Results are not seasonally adjusted.

TABLE 3.
RELATIONS BETWEEN LABOR MARKET CHARACTERISTICS AND EMPLOYMENT GROWTH

Independent Variable	Coefficient on Growth	R^2	Implied Correlation
Job Creation Rate (Quarterly)	1.894** (0.226)	0.58	0.76**
Job Creation Rate (Annual)	1.242** (0.087)	0.80	0.90**
Job Destruction Rate (Quarterly)	0.894** (0.226)	0.24	0.49**
Job Destruction Rate (Annual)	0.242** (0.087)	0.13	0.36**
Job Reallocation Rate (Quarterly)	2.789** (0.451)	0.43	0.65**
Job Reallocation Rate (Annual)	1.485** (0.173)	0.58	0.77**
Wages (1992 Dollars)	-247.0 (354.6)	0.01	-0.09
Wage Growth Rate	0.265** (0.089)	0.15	0.39**
Average Establishment Size	-1.880* (0.838)	0.09	-0.30*
Average Establishment Age	-5.625** (0.906)	0.43	-0.66**

N = 53

Notes: Results are from regressions of the listed variable on the net employment growth rate. Variables represent their quarterly or annual averages (from March 1992 to March 2000) for 53 MSA's. Standard errors are in parentheses.
** denotes significance at the 1 percent level. * denotes significance at the 5 percent level.

TABLE 4.
JOB FLOWS AND ESTABLISHMENT CHARACTERISTICS BY ONE-DIGIT INDUSTRY, QUARTERLY AVERAGES

Industry	Employment (thousands)	Employment Growth	Job Creation	Job Destruction	Job Reallocation	Average Establishment Size	Average Establishment Age
Agriculture, Forestry, and Fishing	143.5	1.3 (20.9)	18.8 (12.0)	17.5 (9.79)	36.3 (6.52)	8.7 (0.76)	36.7 (2.09)
Mining	29.1	-0.6 (4.04)	7.0 (2.26)	7.6 (2.62)	14.6 (2.77)	16.3 (0.59)	49.3 (4.19)
Construction	747.4	1.4 (8.17)	13.8 (5.19)	12.4 (3.48)	26.2 (3.36)	9.1 (0.54)	39.2 (1.32)
Manufacturing	3,278.6	0.06 (0.84)	4.2 (0.56)	4.1 (0.68)	8.3 (0.92)	56.8 (0.54)	57.6 (4.31)
Transportation & Utilities	838.3	0.6 (1.46)	5.9 (0.64)	5.3 (1.22)	11.3 (1.30)	29.0 (0.46)	41.5 (0.80)
Wholesale Trade	915.7	0.5 (1.05)	6.3 (0.53)	5.8 (0.90)	12.0 (1.04)	12.5 (0.35)	47.1 (2.53)
Retail Trade	3,171.9	0.5 (4.13)	8.6 (1.93)	8.1 (2.48)	16.7 (1.66)	17.6 (0.53)	41.2 (1.96)
Finance, Insurance, and Real Estate	974.6	0.4 (1.14)	5.8 (0.86)	5.4 (0.93)	11.2 (1.38)	14.2 (0.38)	47.2 (0.91)
Services	4,698.8	0.9 (1.40)	7.8 (1.00)	6.9 (0.66)	14.7 (0.96)	17.0 (0.40)	42.2 (1.47)

Notes: Statistics are tabulated from the full sample of metropolitan areas. Standard deviations are in parentheses. All statistics represent quarterly averages from March 1992 to March 2000.

TABLE 5.
ACROSS-MSA CORRELATIONS WITH EMPLOYMENT GROWTH, ACCOUNTING FOR INDUSTRY

Variable	*Correlations* Unconditional	*Correlations* Conditional on Industry	Percent of Correlation Due to Industry
Job Creation Rate (Quarterly)	0.76**	0.44**	42.7
Job Creation Rate (Annual)	0.90**	0.78**	13.5
Job Destruction Rate (Quarterly)	0.49**	-0.21	142.8
Job Destruction Rate (Annual)	0.36**	-0.31*	185.2
Job Reallocation Rate (Quarterly)	0.65**	0.14	79.2
Job Reallocation Rate (Annual)	0.77**	0.41**	46.7
Average Establishment Size	-0.30*	-0.03	90.5
Average Establishment Age	-0.66**	-0.40**	37.8

N = 53

Notes: Results are the Pearson correlations of the listed variable with the on the employment growth rate. Variables represent their quarterly or annual averages (from March 1992 to March 2000) for 53 MSA's.
** denotes significance at the 1 percent level. * denotes significance at the 5 percent level.

TABLE 6.
ACROSS-MSA CORRELATIONS WITH EMPLOYMENT GROWTH, ACCOUNTING FOR AGE

Variable	*Correlations* Unconditional	*Correlations* Conditional on Age	Percent of Correlation Due to Age
Job Creation Rate (Quarterly)	0.74**	0.42**	43.2
Job Creation Rate (Annual)	0.87**	0.68**	22.2
Job Destruction Rate (Quarterly)	0.45**	-0.01	101.7
Job Destruction Rate (Annual)	0.27	-0.49**	285.6
Job Reallocation Rate (Quarterly)	0.62**	0.22	64.5
Job Reallocation Rate (Annual)	0.71**	0.17	75.9

N = 53

Notes: Results are the Pearson correlations of the listed variable with the on the net employment growth rate. Variables represent their quarterly averages (from March 1992 to March 2000) for 53 MSA's.
** denotes significance at the 1 percent level. * denotes significance at the 5 percent level.

TABLE 7.
ACROSS-MSA CORRELATIONS OF ENTERING COHORT STATISTICS

	Sample Mean	*Correlation with…*		
		MSA Net Growth	**Entrant Share**	**Exit Age**
Entrant's share of MSA establishments (percent)	2.49 (0.44)	0.82** [0.000]	1.00 [---]	0.06 [0.655]
Share of entrants exited after 5 years (percent)	49.5 (2.48)	0.33* [0.017]	0.57** [0.000]	0.20 [0.155]
Average establishment age at exit (quarters)	7.82 (0.30)	-0.15 [0.284]	0.06 [0.655]	1.00 [---]
Cohort 5-year net employment growth rate	-0.88 (7.54)	0.39** [0.004]	0.31* [0.026]	-0.28* [0.040]
Net employment growth rate of survivors only	26.3 (8.11)	0.54** [0.000]	0.44** [0.001]	-0.44** [0.001]
Cohort wage growth rate	20.4 (6.37)	0.60** [0.000]	0.56* [0.000]	-0.07 [0.606]
Entrant initial wage/MSA wage	0.54 (1.15)	-0.04 [0.765]	-0.13 [0.335]	-0.13 [0.336]
Entrant 5^{th}-year wage/MSA wage	0.83 (1.15)	0.52** [0.000]	0.40** [0.003]	-0.21 [0.138]
N = 53				

Notes: Results are the Pearson correlations of the listed variable with the on the net employment growth rate. Variables represent statistics for a pooled sample of entrants in 53 MSA's. The sample means (and standard deviations) are unweighted across the MSA's. "MSA Net Growth" refers to the mean net employment growth rate of the MSA; "Entrant Share" refers to the entrant's share of MSA establishments; and "Exit Age" refers to the average establishments' age at which exit occurs.

** denotes significance at the 1 percent level. * denotes significance at the 5 percent level.

TABLE 8.
MSA GROWTH INTERACTIONS WITH THE AGE-JOB FLOW RELATION FOR ENTRANTS

	Dependent Variable		
Age	**Job Reallocation Rate**	**Job Creation Rate**	**Job Destruction Rate**
1 quarter	7.868**	7.148**	0.719*
2 quarters	3.478**	2.636**	0.842**
3 quarters	2.987**	2.380**	0.607
4 quarters	1.808**	0.754**	1.055**
5 quarters	1.702**	1.452**	0.250
6 quarters	2.175**	2.220**	-0.045
7 quarters	1.510**	0.684*	0.826**
8 quarters	1.125**	0.607*	0.518
9 quarters	1.818**	1.328**	0.490
10 quarters	1.073**	0.567	0.506
11 quarters	1.409**	0.663*	0.745*
12 quarters	1.188**	0.500	0.688
13 quarters	1.756**	1.469**	0.287
14 quarters	0.282	0.611*	-0.329
15 quarters	0.671	-0.058	0.729*
16 quarters	0.921*	0.095	0.826**
17 quarters	-0.040	0.771**	-0.811*
18 quarters	-0.799	0.326	-1.125**
19 quarters	-0.819	-0.112	-0.706
R^2	0.384	0.547	0.031

Notes: Estimates are coefficients on the interaction of the mean MSA growth rate with establishment age. They come from employment-weighted establishment-level regressions of the listed variable on the above interactions, year of entry effects, establishment age effects, 4-digit industry effects, and the mean growth rate of the establishment's MSA. Regressions use 2,472,713 quarterly observations on 177,373 active establishments entering between the March 1993, and June 1995.
** denotes significance at the 5 percent level. * denotes significance at the 10 percent level.

TABLE 9.
METROPOLITAN AREA EDUCATION AND AGE STATISTICS

	Share of Population Aged 25+ With at Least a B.A.		***Share of Population Aged 20-34 Years***	
	1990	**2000**	**1990**	**2000**
Sample mean	19.8	25.0	24.8	20.9
Across-MSA Correlation with…				
Employment Growth	0.58 [0.000]	0.61 [0.000]	0.45 [0.001]	0.54 [0.000]
Job Reallocation	0.36 [0.009]	0.36 [0.008]	0.40 [0.003]	0.48 [0.000]
Average Establishment Age	-0.75 [0.000]	-0.77 [0.000]	-0.59 [0.000]	-0.62 [0.000]

Notes: Statistics are from the 1990 and 2000 decennial censuses. The table reports the sample means with Pearson Correlations across the 53 MSA's and their *p*-values (in brackets). All correlations are significant at the 1 percent level and 1990 statistics are calculated so that they are consistent with 2000 MSA definitions.

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