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What's In a City?: Understanding the Micro-Level Employer Dynamics Underlying Urban Growth

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Abstract:

This paper synthesizes the literatures on labor dynamics and urban growth and agglomeration by presenting new evidence on the micro-level establishment dynamics of metropolitan areas. I explore how the patterns of job reallocation and entry and exit affect the growth and composition of these areas. I find that high-growth metropolitan areas have high rates of job and establishment turnover, primarily though higher rates of gross job creation and establishment entry, and have a relatively young distribution of establishments. Variations in the age distribution and differences in the entry and exit patterns of young establishments account for a sizeable portion of regional differences in labor dynamics and growth, even after controlling for regional differences in industry composition. These results suggest that variations in the age distribution and the dynamics that lead to such variations are important factors in understanding urban growth and agglomeration.

JEL Codes: E24, J63, R11
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1. Introduction

This paper aims to bridge the gap between the empirical literature on aggregate labor market dynamics and the literature on urban growth and agglomeration. For decades, economists have studied why cities exist, why some are larger than others, and why some grow faster than others. In recent years, researchers such as Glaeser et al. (1995) have explored how positive externalities, such as increasing returns and knowledge spillovers, may contribute to urban growth. The literature based on this approach is often motivated by endogenous growth models like those by Lucas (1988) and Romer (1986), since their implications are consistent with the factors economists believe underlie agglomeration.

The models, however, usually assume a representative agent in production, much like the real business cycle models that preceded them. Work by Dunne, Roberts, and Samuelson (1989a, 1989b), Davis and Haltiwanger (1990, 1992), and others have since shown that the economy has a distribution of heterogeneous agents continuously interacting in a dynamic environment. This depiction of the aggregate economy lends itself to models where micro-level frictions, idiosyncratic shocks, and underlying heterogeneity play a critical role; models of creative destruction (Caballero and Hammour, 1994), firm learning and selection (Jovanovic, 1982), and labor market search (Mortensen and Pissarides, 1994) are examples of such models.

In this paper, I use a relatively new source of establishment microdata to study the relationship between an employer's behavior and the growth of its metropolitan area. In doing so, I highlight the importance of firm and labor dynamics in accounting for regional differences in growth and agglomeration, and show how related models help explain urban growth. Existing urban empirical work often uses aggregated data to study the potential benefits of agglomeration. Many results suggest that firms are more productive when clustered within in a particular location (or industry and location). These are cited as evidence of positive external economies, which may stem from local factors (e.g., local government policies, comparative advantages in resources, a transport cost-minimizing location) or the co-location itself (e.g., the spillover of local innovations, savings from shared inputs, the sharing of built-up knowledge or "trade secrets" within a local industry). Yet, one may find more productive firms in a particular location (and hence evidence of agglomeration economies) for other reasons. For example, firms that are *ex ante* more productive may choose to locate in one city over another. Competition among firms may vary across areas and, through a process of entry and exit, less efficient firms may be selected out of the market, leaving relatively more productive firms in some areas through a greater lower-truncation of their firms' productivity distribution. These latter phenomena lend themselves to models of agglomeration that incorporate heterogeneity and constant churning. In fact, several recent studies have moved toward studying the returns to agglomeration at the micro-level (Henderson, 2003), the role of entry and exit in either reinforcing or weakening industry agglomeration (Dumais, Ellison, and Glaeser, 2002; Rosenthal and Strange, 2003).[1]

This paper differs from the above studies in that the focus is on variations in urban *growth* rather than agglomeration per se. I do this for two reasons. First, while there is much research on the causes of urban growth using aggregate data, there is little empirical work on its microfoundations. I use a rich source of longitudinal microdata

[1] Hyclak (1996) also has an earlier study of structural change in local labor markets using Dun & Bradstreet microdata.

from the Bureau of Labor Statistics (BLS) that allows a study of employment dynamics at a scope and level that was previously impossible.[2] Second, previous work on this topic, perhaps driven by the available data, has often focused on differences in industry composition (for example, through industry “shift-share” analyses). My data allow me to study the composition of a city’s establishments on a variety of different margins. For example, I can quantify how much variations in urban growth are due to variations in the establishment *age* distribution across cities.

I find that high-growth metropolitan areas have high rates of job reallocation—growing cities are more dynamic. This higher turnover comes more from greater variations among job-creating establishments rather than job-destroying establishments, reinforcing earlier findings by Eberts and Montgomery (1995). I also find that high-growth areas have higher establishment entry *and* exit rates, as well as a relatively small and young distribution of establishments. These results hold even after controlling for differences in industry, establishment size, and wages. In addition, regional variations in the age distribution preserve neither its mean nor its shape. Instead, high-growth areas have disproportionately higher shares of very young establishments and comparable shares of older establishments. These variations account for 44 percent of the differences in metropolitan growth (28 percent after controlling for industry). Nevertheless, there remain considerable variations in establishment growth and reallocation within age groups—high-growth areas have notably higher establishment growth and job reallocation among younger establishments. An analysis of entry and exit patterns shows

[2] Eberts and Montgomery (1995), Davis, Loungani, and Mahidhara (1997), and Schuh and Triest (2002) also document regional variations in labor dynamics using establishment microdata, though their studies are limited in varying degrees by data quality, sample scope (e.g., being limited to manufacturing), and the availability of various data items (e.g., measures of establishment age).

that a greater share of their entrants exit within five years and, conditional on survival, entrants' wage growth is higher within high-growth areas, suggesting that a "shakeout" process at young ages leaves these cities with a relatively smaller, but potentially more productive share of entrants within a given cohort.

One can draw several conclusions from these findings. First, urban agglomeration and growth are truly dynamic processes. Others (Henderson, Kuncoro, and Turner, 1995; Glaeser et al., 1992) have drawn similar conclusions with aggregate data, but this study depicts much more complex dynamics that determine a heterogeneous distribution of establishments within each city. Second, understanding regional variations in the establishment age distribution is an important part of understanding regional differences in growth, even more so than variations in industry mix. Finally, regional variations in establishment composition cannot fully explain the observed differences in growth across metropolitan areas, suggesting that location-specific characteristics, such as the concentration of human capital, remain as important factors as well.

The following section describes the data and methodology used throughout the paper. Section 3 presents the evidence. Section 4 discusses the theoretical implications of my results, and Section 5 concludes.

2. Data and Concepts

Access to a robust source of longitudinal establishment microdata is essential to this study. I employ the data BLS uses for its Business Employment Dynamics (BED) program, a relatively new source of statistics that measure quarterly gross job flows for the U.S. private sector. The data come from administrative records from state unemployment insurance (UI) programs, compiled for the Quarterly Census of

Employment and Wages (also known as the ES-202) program of the BLS, and are a virtual universe of all businesses.[3] To generate the BED estimates, the BLS links these records longitudinally over time.[4] The data are quarterly, and include an establishment's employment for each month, payroll for the quarter, and a variety of characteristics, such as industry, location (to the county level), organization (i.e., public versus private ownership, whether it is part of a multi-unit firm), and initial UI liability date (a proxy for age).

I use a sample of private sector establishments in 53 Metropolitan Statistical Areas (MSAs) and Primary Metropolitan Statistical Areas (PMSAs) across five U.S. states. I use only five states because of the attention to the data needed to identify true entrants and exits from temporary openings and closings, mergers and acquisitions, and administrative changes.[5] I choose my five states to satisfy several conditions. A state has to be relatively large and it has to contain multiple MSAs and PMSAs—this allows me to condition out state fixed effects where needed while preserving across-MSA variation (e.g., for estimating establishment age, where differences in state UI laws may affect reported initial liability dates.) Collectively, the states must also be somewhat representative of the U.S. in terms of employment growth, with regard to both the average rate and the variation across metro areas. I choose Colorado, North Carolina, Michigan, Ohio, and Pennsylvania; first two states represent the relatively high-growth cities of the South and West, while the latter three represent the lower-growth cities of the

[3] The self-employed and the military being the primary exceptions.
[4] More details about the BED and the record-linkage process can be found in the appendix, as well as in Pivetz, Searson, and Spletzer (2001) and Spletzer et al. (2004).
[5] I discuss my methodologies for identifying entrants and exits briefly in the appendix, and in more detail in my dissertation (Faberman, 2003).

Northeast and Midwest.[6] The resulting sample represents approximately 15 percent of all private employment and establishments in the U.S. and contains quarterly data from March 1992 through March 2000. The sample has 25.4 million observations of 1.43 million distinct establishments, with the average quarter having approximately 796,000 active establishments. Table 1 lists the sample's summary statistics for all state observations, observations in metropolitan areas only (i.e., the sample for this study), and the public BED estimates. The employment growth estimates are comparable; sample job flow estimates are somewhat lower because of the extra attention I give to entry, exit and record linkage. Summary statistics for each MSA are in Appendix Table A.1.

I measure quarterly employment at the third month of each quarter. *Gross job flows* are measures of net employment growth at the establishment level. *Job creation* is the sum of all gains at either expanding or opening establishments, while *job destruction* is sum of all losses at either closing or contracting establishments. The aggregate *net change* is simply the difference between job creation and job destruction. *Job reallocation*, a measure of the overall churning in a labor market, is the sum of job creation and destruction. One critique of the job reallocation measure is that it can be high simply because a labor market has a very high (or very low) net growth rate. An alternative measure is *excess reallocation*, which is job reallocation less the absolute value of the net change. Following the methodology of Davis, Haltiwanger and Schuh (1996), I translate net growth and the job flow measures into *rates* by dividing them by the average of the current and previous quarters' employment.

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[6] To maintain continuity of all metro areas in the sample, I also append data from five other states (Indiana, Kentucky, New Jersey, South Carolina, and West Virginia) where MSA or PMSA definitions cross state borders.

Formally, let N_{jkt} denote the net growth rate for establishment *k* in MSA *j* in quarter *t*. The growth rate for the MSA at *t* is simply $N_{jt} = \sum_k \left(e_{jkt}/e_{jt}\right)N_{jkt}$, where e_{jkt} is the average of previous and current employment for establishment *k*. Similarly, MSA job creation, job destruction, job reallocation, and excess reallocation rates are (respectively),

$$
\begin{aligned}
C_{jt} &= \sum_k \frac{e_{jkt}}{e_{jt}} \max\{N_{jkt}, 0\} \\
D_{jt} &= \sum_k \frac{e_{jkt}}{e_{jt}} \left|\min\{N_{jkt}, 0\}\right|. \\
JR_{jt} &= C_{jt} + D_{jt} \\
XR_{jt} &= C_{jt} + D_{jt} - \left|N_{jt}\right|
\end{aligned}
\tag{1}
$$

Average earnings, W_{jkt}, are payroll divided average employment and are deflated by the Consumer Price Index to express them in real (1992) dollars. Establishment size is simply e_{jkt}. Establishment age is measured from the initial date of UI liability, which generally represents the start date of the establishment. Mean establishment age is about 10 years and the oldest UI accounts date back to 1936, so upper truncation of the age measure is of little concern. Missing values and state differences in liability dates are a concern, however, and I describe my methodology for dealing with these issues in the appendix.

3. Results

I begin the presentation of my results by noting the tremendous churning that occurs in all metropolitan areas. Table 1 shows that, on average, 7.3 percent of jobs are created and 6.7 percent of jobs are destroyed each quarter within the private sector of these areas, implying that the excess reallocation of these labor markets averages 13.4 percent of employment. There is substantial entry and exit each quarter as well, with the quarterly rates of each averaging 2.3 percent of establishments. The average establishment pays $6,453 each quarter in real earnings, employs 17.8 workers, and is 41.4 quarters (10.4 years) old.

3.1. Basic Relations across Metropolitan Areas

I now move on to the relationships between growth and other labor market variables. Figure 1 illustrates the unconditional relations of job flows, establishment size and establishment age with net growth across MSAs. For reference, each panel highlights the largest cities in the sample. Both job creation and job destruction vary positively with MSA growth. This is consistent with previous findings by Eberts and Montgomery (1995). In new evidence, average establishment size and age both vary negatively with growth. Variations in growth account for a sizeable portion (53 and 65 percent, respectively) of across-MSA variations in job creation and age. Together, the results imply that higher-growth MSAs have higher rates of job reallocation among smaller, younger establishments.

Table 2 presents the across-MSA correlations of job flows and establishment characteristics with net growth, earnings growth, average earnings, and average age. Across MSAs, job creation, destruction, and reallocation are positively related to growth and negatively related to age. The job flows have positive relations to earnings growth and negative relations to the earnings level, though most of these correlations are insignificant. Average establishment size is positively related to both age and earnings, consistent with earlier findings for the aggregate economy.[7] Entry and exit are both positively correlated with net growth, earnings growth, and the earnings level, and strongly negatively correlated with average age. The latter is also consistent with earlier findings. Across, MSAs, employment growth and earnings growth are positively correlated, while employment growth and the earnings level are uncorrelated. Job creation and job destruction highly correlated (with a coefficient of 0.94) across MSAs.

Taken together, these correlations suggest several things: i) many of the patterns found in the labor and firm dynamics literature (i.e., wages and size increase with age, job reallocation decreases with age, job creation and job destruction are positively correlated in the cross-section) are consistent with the cross-sectional evidence across metropolitan areas; ii) high-growth metropolitan areas are dynamic, with relatively high rates of job reallocation and establishment turnover, on average; and iii) the average age of a MSAs establishments is strongly related to nearly all of the labor market variables of interest.

3.2. Accounting for Establishment Characteristics

The results in Table 2 are unconditional relations. It is well known in the urban economics literature that establishment characteristics, particularly the industry composition, can vary widely and non-randomly across metropolitan areas (e.g., Ellison and Glaeser, 1997). In addition, the literature on firm and labor dynamics has found tremendous variations in job flows and establishment characteristics across industries (see Anderson and Meyer, 1994; Davis, Haltiwanger, and Schuh, 1996; Foote, 1998; and Burgess, Lane, and Stevens, 2000). Consequently, it is quite possible that across-MSA variations in characteristics such as industry composition explain much of the relations reported in Table 2.

To explore this hypothesis, I recalculate selected correlations controlling for a variety of characteristics (including industry). My controls condition out fixed effects for

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[7] See, for example, Dunne, Roberts and Samuelson (1989a, b) and Davis, Haltiwanger, and Schuh (1996).

each characteristic using regressions on pooled establishment-quarter observations. I then recalculate the correlations using the MSA means estimated from the residuals of these regressions.[8] In other words, for variable Y_j or net growth rate N_j the correlations are

(2) $$\rho\left(\hat{Y}_j^x, \hat{N}_j^x\right), \text{ with}$$

(3) $$\hat{Y}_j^x = \sum_k \theta_{kxj}\left(Y_{kxj} - \hat{\beta}_x\right) \text{ and } \hat{N}_j^x = \sum_k \theta_{kxj}\left(N_{kxj} - \hat{\gamma}_x\right),$$

where $\hat{\beta}_x$ and $\hat{\gamma}_x$ are the fixed effects coefficients for characteristic x, and θ_{kxj} is the appropriate weight.

My results are in Table 3. The top row of the table reports the unconditional correlations (identical to Table 2). The second row reports correlations conditional on 972 4-digit Standard Industrial Classification (SIC) industries. The across-MSA correlations of job creation and average age with net growth persist after controlling for industry; to a lesser extent, the correlation of size to growth persists as well. Correlations of job destruction and excess reallocation with net growth do not persist, however, suggesting that their unconditional positive correlations stem from high-growth MSAs having high-reallocation, high-turnover industries located there. In fact, the results suggest that, conditional on industry mix, high-growth cities actually have *lower* job destruction rates. The third row controls for the age distribution by conditioning out establishment age measured in quarters (giving 256 groups). The correlation between job creation and growth is again robust to the control, while the relations of job destruction, excess reallocation, and size become insignificant. Controlling for establishment size (using a quartic in employment levels) has little effect on the correlations. Controlling for

[8] Job flow and net growth rate regressions are weighted by average employment; establishment age and size

earnings (using a quartic in average earnings) only affects the relation of job destruction to growth notably. As one might expect, controlling for all characteristics (industry, age, size, earnings) alters the relations considerably, with only the relations of establishment size and age remaining significant and of the original sign. The correlation between job creation and growth remains positive, but is insignificant.

Overall, the results suggest that variations in industry composition do play a role in explaining the across-MSA correlations (particularly for job destruction and excess reallocation), but that variations in the age distribution are at least as important, and that some relations, notably the relations of job creation and average age to growth, persist even after applying a variety of controls.

3.3 The Importance of Entry, Exit, and the Age Distribution

The age distribution of establishments can vary widely across MSAs, as depicted in Figure 2. The figure shows the frequency distribution of pooled establishment age observations in MSAs ranking in the upper and lower quintiles of mean net growth.[9] One can see that the high-growth MSAs have a younger distribution, on average. Further, the younger distribution is not a leftward shift of the density function, but instead stems from a relatively high concentration of very young establishments (younger than 5 years) in these areas.

Differences in the age distribution account for a large part of the above correlations, and the relation of age to MSA growth is robust to a variety of controls,

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regressions are not.

[9] The quintiles are based on an establishment-weighted ranking; 11 MSAs are in the upper quintile and 16 MSAs are in the lower quintile, since the MSAs in the latter have fewer establishments. The specific MSAs in each group are noted in Appendix Table A.1.

leading one to ask, “Just how much do variations in the MSA age distribution account for variations in MSA labor dynamics?”

To answer this question, I perform a counterfactual exercise to obtain the values of net growth, job creation, job destruction and excess reallocation predicted from differences in the MSA age distribution alone, holding their values within each age constant across metropolitan areas. The predicted estimates answer the question, “What would MSA growth rates and job flows be if the only thing that mattered was establishment age?” One can write the actual estimate of variable Y_j, with $Y_j \in \{N_j, C_j, D_j, XR_j\}$, as

$$Y_j = \int Y_j(a) f_j(a) da \tag{3}$$

where $Y_j(a)$ is the mean value of Y in MSA j for establishments aged a and $f_j(a)$ is the density of establishments aged a in MSA j. Using this notation, the predicted estimate of Y_j is then

$$\hat{Y}_j = \int Y(a) f_j(a) da \tag{4}$$

where $Y(a)$ is the mean value of Y for all establishments aged a in the *sample*, and all other notations follows from before.

I obtain the predicted estimates for the variables noted above and then regress the actual values on the predicted estimates using OLS for the 53 MSA observations. The R-squared values from these regressions give the percentage of MSA variations due to differences in the age distribution alone. My results are in Table 4. The upper panel gives the percentages of variation explained as well as the correlations with MSA net growth implied by the predicted estimates. The lower panel reports the results of the exercise done with the residuals of the net growth and job flow rates after conditioning out industry fixed effects. The results suggest that MSA differences in the age distribution account for a large portion of the variations in labor dynamics, as well as the correlations of job flows to net employment growth. Differences in the age distribution alone account for 44 percent of the across-MSA variations in growth and 48 percent of the variations in job creation. They account for a smaller portion (12 percent) of the variations in job destruction and excess reallocation. Even after controlling for industry mix, differences in the age distribution still account for 28 percent of the variation in growth and 19 percent of the variation in job creation, but account for a negligible (2 percent) portion of the variations in job destruction and excess reallocation.

Thus, variations in the age distribution play an important role in understanding urban growth, even after controlling for regional differences in industry mix, though there remains a sizeable portion of these variations unaccounted for. Differences in the MSA age distribution are an important and previously unexplored facet of urban growth, but they are not the whole story. Figure 3 illustrates this point. In panels (a) through (d), it shows the mean net growth rate, job creation rate, job destruction rate, and excess reallocation rate, respectively, as a function of age. It does so for the pooled observations for MSAs in the upper and lower quintiles of the growth rankings (as described previously). In each panel of the figure, the two groups have their greatest differences among their younger establishments (those aged 7 years or less). Among these establishments, high-growth MSAs have significantly higher growth and higher job flows.

Consequently, understanding regional differences among these younger establishments is crucial to understanding the relationship between the age distribution and the growth rate of a city, which implies that one must know how patterns of entry and exit vary across metropolitan areas. I take a subsample of establishments that enter between June 1992 and June 1995 and follow them for 5 years. To illustrate variations across MSAs, I compare entry and exit patterns between the MSAs in the upper and lower quintiles used above.

Table 5 lists the summary statistics for the entrant subsample. The sample contains nearly 2.9 million observations on 208,000 entrants. Entry in high-growth MSAs is notably higher than in low-growth MSAs—2.8 percent of all establishments as opposed to 2.0 percent. Exit rates are high in all areas, but entrants in high-growth MSAs have relatively greater attrition—49.7 percent of them exit within five years, as opposed to 46.7 percent in low-growth MSAs. Within the first five years, entrants in high-growth MSAs also have higher growth, excess reallocation, and average earnings (conditional on survival to quarter *t*, that is).

Figure 4 illustrates the differences in exit hazard rates for the two groups. Throughout the first five years after entry, establishments in high-growth MSAs have consistently higher hazard rates, though the difference with those in low-growth MSAs is only significant during the first 6 quarters of business. The lower panel of Figure 4 shows that the patterns are robust to controlling for industry differences. Figure 5 gives evidence that that the higher hazard rates in high-growth MSAs may translate into a greater selection of low-wage (and potentially low-productivity) establishments. Earnings begin somewhat higher in high-growth MSAs, and grow substantially faster in these areas—

32.1 percent versus 17.9 percent—than in the low-growth MSAs. Again, the results are robust to controlling for industry.

Taken together, the results suggest that variations in the age distribution are an important part of the observed differences in MSA growth. Differences in the growth and concentration of young establishments, driven by variations in entry, exit, and a potential selection mechanism, help generate these variations in the age distribution and thus also play an important role in generating differences in urban growth.

3.4 Employment Dynamics and Other Labor Market Characteristics

Entry, exit, and the age distribution of establishments are important, but what local factors account for their regional variations? To get at this question, I present basic evidence on the relationship of some local characteristics and labor market dynamics. Table 6 reports the correlations of growth, job flows, and establishment age, entry, and exit with a variety of MSA characteristics. City size, measured by either employment or population, has little relation to the variables of interest. The only exception is establishment exit, which is more likely in larger cities. The correlations of the selected variables with population growth mimic their relations to employment growth, as one might expect. A city's average unemployment rate is negatively correlated with employment growth, but essentially uncorrelated with job creation, job destruction, or job reallocation. Cities with high unemployment, though, have lower rates of entry and exit among a relatively older set of establishments. Lastly, cities with a relatively young (age 20-34) and educated (bachelors degree or more) population have higher growth and job reallocation among relatively young establishments with high rates of entry and exit, suggesting (as has been found before) that dynamic, high-growth cities are also high-human capital cities. On the surface, these relations are consistent with the evidence on growth dynamics from Blanchard and Katz (1992) and evidence on migration patterns from Topel (1986). The positive relation between the age and education of a city's population and the observed churning and establishment composition, however, lend a new facet to this line of research.

4. Theoretical Implications

The results suggest that the relationship between labor market churning and metropolitan growth stems primarily from regional variations in entry, exit, and the age distribution of establishments. Many current theories of urban growth, such as Black and Henderson (1999), assume that growth and agglomeration occur through scale economies that are external to the firm and localized knowledge spillovers. Externalities stemming from a greater concentration of human capital in an area lead all firms in that area to be more productive. My findings suggest that such a characterization of agglomeration economies is over-simplified. They instead suggest that a high concentration of human capital may affect firm productivity and urban growth through a composition effect on the distribution of a city's businesses. This composition effect not only drives entry into the local labor market, but also affects the process by which firms either grow or exit. My results are still consistent with localized knowledge spillovers as an underlying factor in urban growth and agglomeration. In fact, these spillovers may affect the dynamics and composition in important ways. Being able to adequately model the relationships of human capital and knowledge spillovers to growth in an environment of heterogeneity and constant labor market churning is thus vital to understanding the underlying causes of urban growth and agglomeration.

One approach in this spirit may be to incorporate a process of Schumpeterian "creative destruction" into a model of urban growth. Aghion and Howitt (1992) and Caballero and Hammour (1994) model such a process for the macroeconomy. In their models, exogenous technological innovation drives a process of vintage replacement, where new firms enter with the latest technology and are able to outcompete incumbents with older technologies. The steady state is characterized by a constant churning (stemming from the vintage replacement process) among a distribution of firms varying in their productivity based solely on age. In an urban setting, the pace of innovation may depend on knowledge spillovers stemming from the concentration of human capital. Cities with more human capital would then have greater entry and greater churning among a relatively young firm distribution—in such a setting, the opportunity cost of keeping the oldest firms in production is relatively high, inducing greater exit among them and thus shifting the distribution towards the younger firms.

Such a model of creative destruction would be consistent with much of the evidence in this paper, except that its exit occurs among the oldest firms, and in the data, it occurs mostly among younger firms. The "shakeout" observed in the data is instead consistent with a process of firm learning and selection depicted in models by Jovanovic (1982), Erickson and Pakes (1995) and others. In these models, firms vary in their *ex ante* productive abilities, which are unknown at entry. Firms learn their productivity by updating expectations over time—as expectations increase, firms grow and as they decrease, firms contract. If expectations fall below a threshold, the firm exits. Thus, average productivity increases over time through the self-selection, of low-productivity firms out of the market. Given that these models primarily focus on industry life-cycle dynamics (and not labor market dynamics), it is difficult to speculate on how local factors might affect urban growth through such a process. Some fruitful paths to explore include a model where local factors affect the distribution of *ex ante* productivities, the learning process through a greater speed of convergence, or the expectations threshold at which firms choose to exit. Baldwin and Okubo (2005) have a recent model that accounts for firm heterogeneity and models the processes by which sorting and selection into a particular area can generate the empirical findings attributed to urban agglomeration.

Finally, models of labor market search and matching may prove successful in explaining the empirical relations reported here. Such models assume that there are search frictions in the matching of workers to firms. Matches have an idiosyncratic component, which may be random or stem from a heterogeneous distribution of workers and firms. In the model of Mortensen and Pissarides (1994), workers meet firms through a matching function. Upon meeting, workers and firms enter a Nash bargaining process, and if the returns to each satisfy their reservation values, a match is made. Once matched, a worker and firm stay together unless an adverse shock lowers the match returns below some threshold. The heterogeneity and constant churning present in most search and matching models suggest that search frictions may account for some of my results, though, without more evidence on the relation between worker characteristics and establishment dynamics, it is difficult to speculate on how such a process would operate within a local labor market. Nevertheless, researchers have already made some headway on this approach, with Helsey and Strange (1990) and Wheeler (2001) each having models of labor market search within an urban framework.

5. Conclusions

This paper presents new evidence on the relations of labor market dynamics and establishment characteristics to urban growth using a rich new microdata source. I find that growing cities tend to have higher rates of both job creation and job destruction among a relatively younger distribution of establishments. This younger distribution occurs through more entry, and through a selection process that has greater exit, but also has survivors with relatively higher growth in their early years. Survivors in these cities also tend to have higher earnings growth than their counterparts. The regional variation in the age distribution that results accounts for a sizeable portion of the regional variation in employment growth. Much of this evidence is robust to regional variations in industry composition, implying that regional specializations in the production of a particular good cannot account for the observed patterns. Finally, I find that growing, dynamic cities tend to have a younger, more educated population.

These results suggest that regional dynamics stem from complex interactions among heterogeneous agents. Thus, the benefits of local characteristics such as knowledge spillovers and the concentration of human capital may not be as simple as a positive externality that benefits all local firms. Instead, these characteristics may alter the composition and dynamics of a heterogeneous distribution of firms, which in turn causes some cities to grow faster than others. Models of creative destruction, firm learning and selection, or labor market search may do well in accounting for the observed behavior of these dynamics. Further research, empirical and theoretical, will shed light on how these processes operate within an urban setting, and how they may affect the patterns of agglomeration.

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Appendix

A. Data Description and Record Linkage

This appendix describes the data and measurement in more detail. The UI administrative data used in this study cover nearly all private employment in the sample areas. The data have several advantages over other sources. First, they cover all industries; much of the previous research on firm and employment dynamics has focused solely on manufacturing, and used the Longitudinal Research Database of the Census Bureau. Second, they are a universe, and not a sample (covering 98 percent of employment) so save for the self-employed and military, there are no exclusions (thus avoiding potential selection bias) and there is a robust number of observations that allow analyses even within highly detailed categories. Finally, the BLS has an algorithm to link the data across time, providing a longitudinal history for each establishment.

This linkage process is important, but also imperfect. The data are primarily used for UI tax collection, and there are many things firms can do (e.g., changes in corporate ownership, firm restructuring, and UI account restructuring) to complicate record linkage, causing missed links to occur. This falsely counts continuous records as openings and openings, thereby overstating entry, exit, and job flows. To ensure that my estimates of entry and exit are accurate as possible, I limit my sample to the five states noted in Section 2, and perform a manual review of all large employment changes (300 workers or more).[10] I use this review on top of the BLS methodology because of the large impact a single missed link can have on a regional analysis. For example, a missed link of a 5,000-employee establishment likely has a negligible effect on the national BED statistics, but

[10] I summarize my methodology in more detail in my dissertation (Faberman, 2003).

may have a tremendous effect on estimates for a small area like Greeley, CO (which is part of my sample). I also restrict my definition of entry and exit to those who enter the sample for the first time or leave permanently—in contrast, the BED data only estimate openings and closings, which include both temporary and permanent changes.

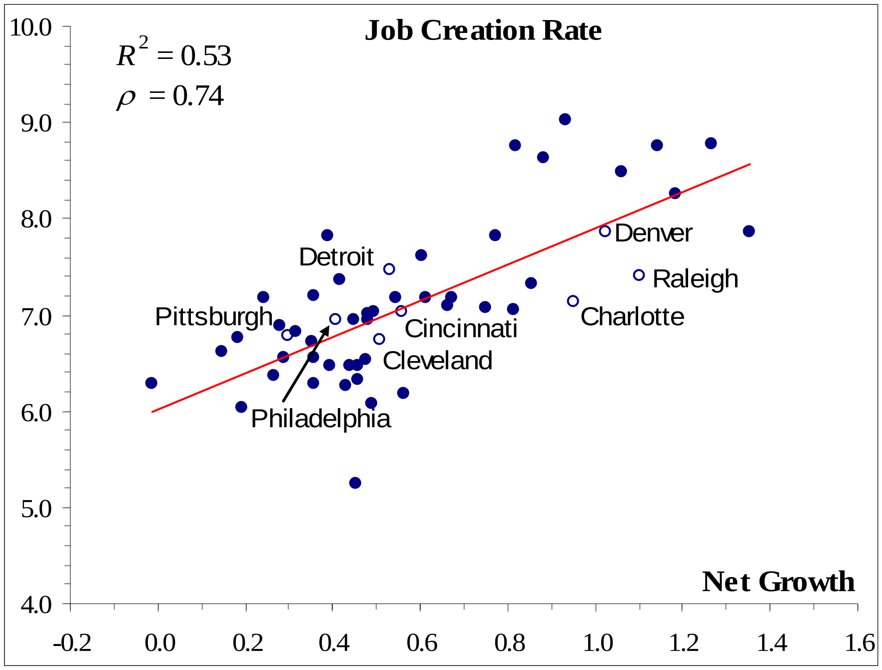
B. Measuring Establishment Age

The age variable, derived from an establishments initial date of UI liability must deal with two measurement concerns. First, nearly a third of observations at the beginning of the sample are missing their liability dates. Second, there are state differences in UI laws that appear to create state-specific differences in establishment age that persist even after a variety of controls. To deal with the first issue, I impute the missing ages using means calculated from state-industry-size class cells, which use 4-digit SIC industries and six size classes. These means are highly detailed, with nearly 20,000 cells estimated. Robustness checks of the data show that this imputation does not distort the establishment age distribution. For establishments that enter the sample with a missing age, I simply assign them an age of zero at entry.

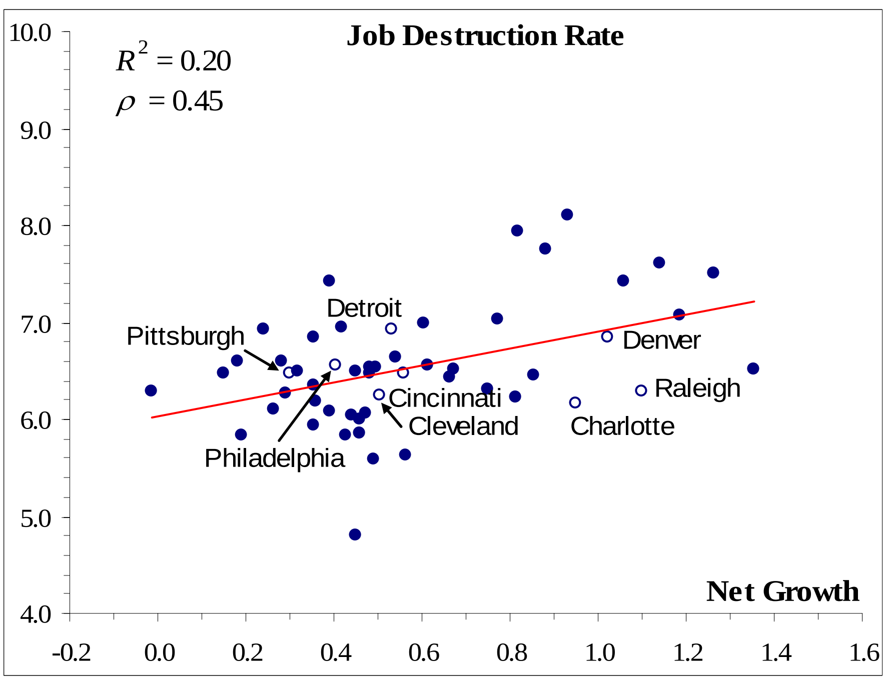
To deal with the second issue, I remove state fixed effects from the age variable (after imputations), controlling for a variety of other factors. To do so, I use the pooled establishment data to regress age on state fixed effects, with controls for quarter, industry, single versus multi-unit ownership, and a quartic each in employment level and average earnings. I then remove the state effects from establishments aged 3 years or more while preserving the sample mean—I choose this cutoff to avoid adjustments to a negative age and because the imputations already remove differences for many of the younger establishments. I use this adjusted age for all analyses throughout the paper.

Figure 1. MSA Labor Market Characteristics vs. Net Growth

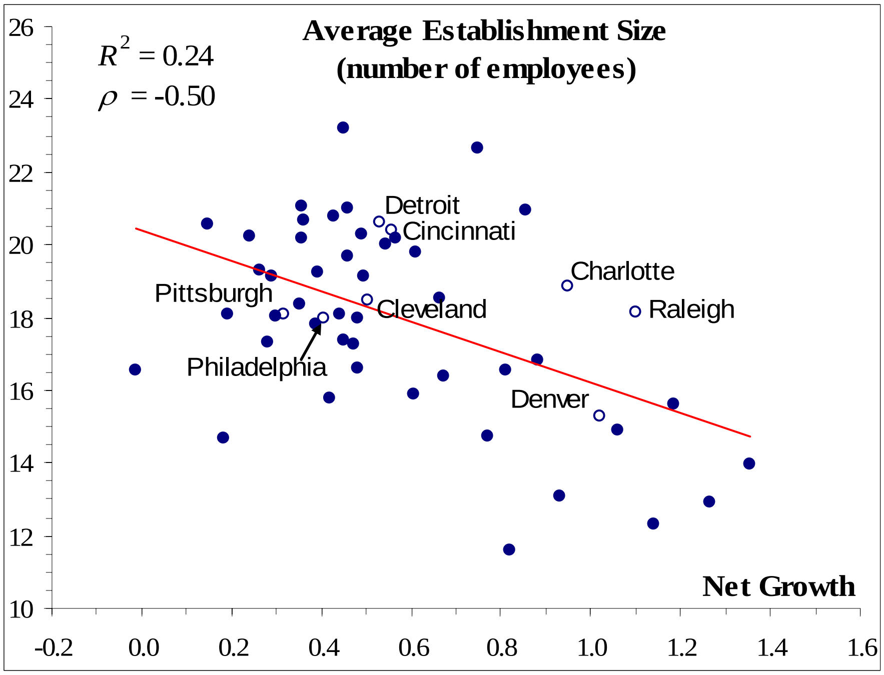
(*a*)



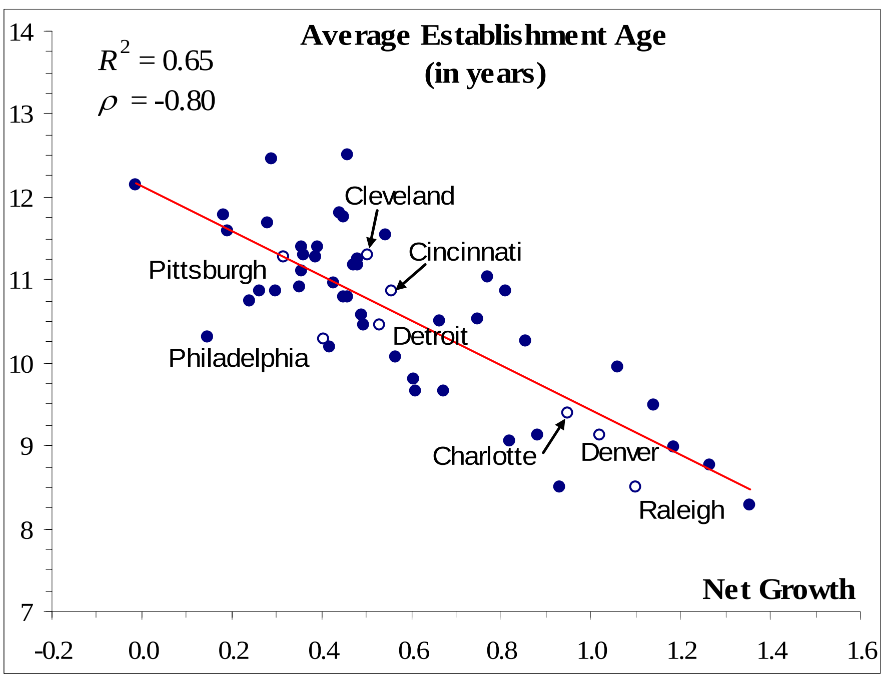
(*b*)



(*c*)

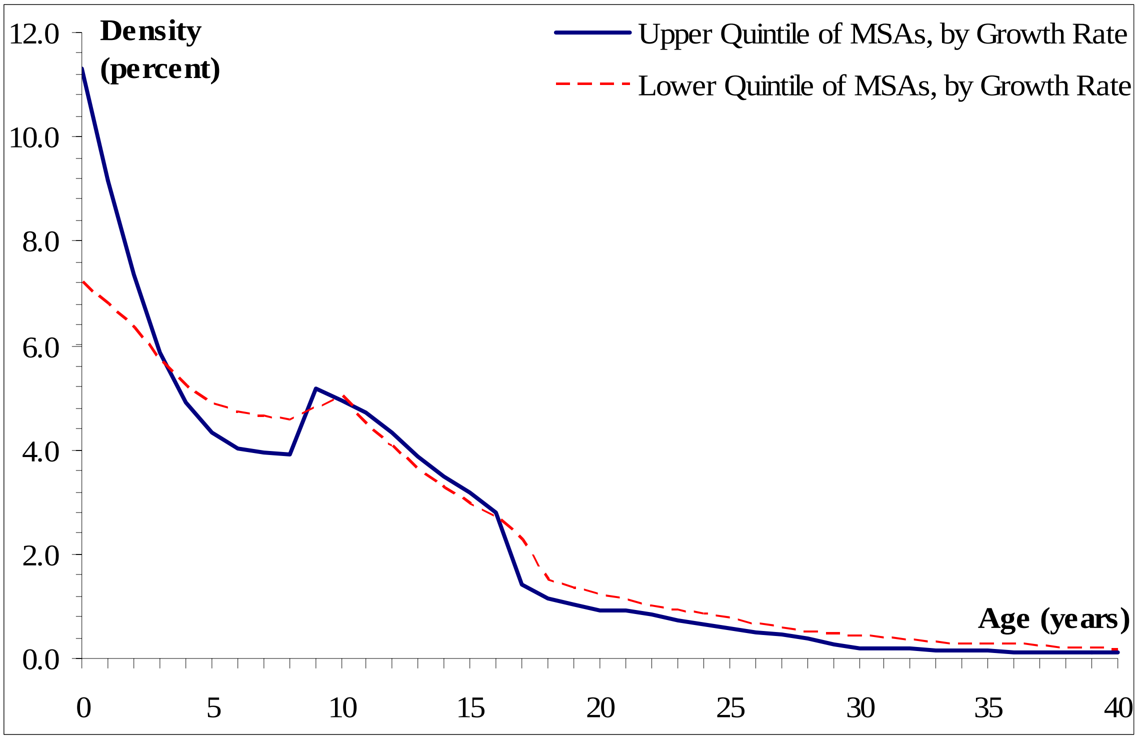


(*d*)



Note: Figures are scatter plots of mean MSA values of listed variables versus the mean MSA growth rate. Larger MSAs are highlighted and the solid line represents the OLS trend relation, with R-squared and correlation coefficient values listed.

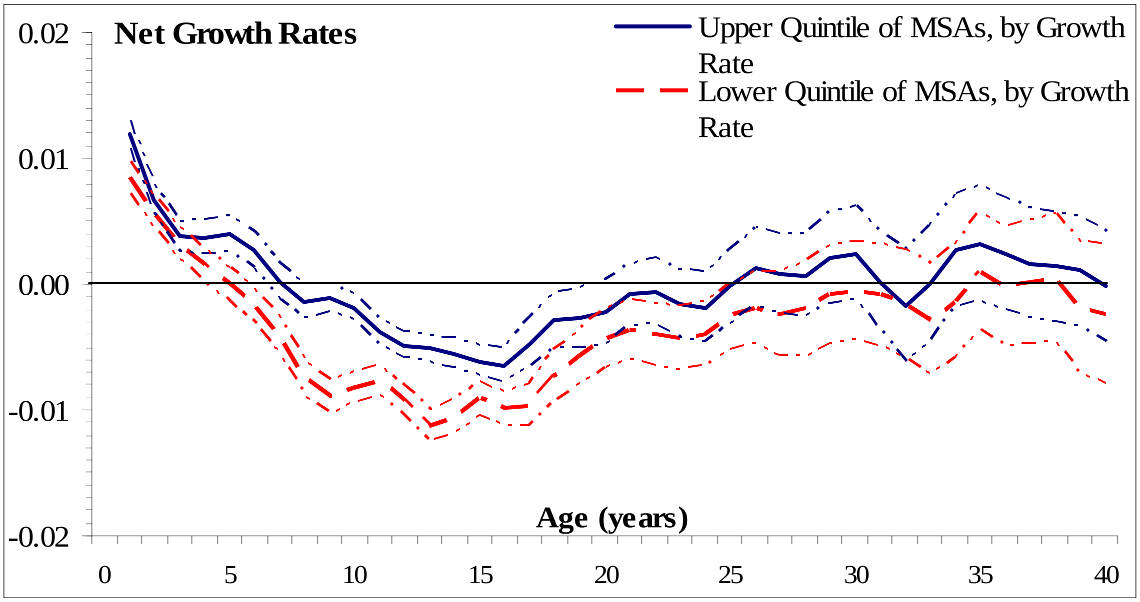
Figure 2. Establishment Age Densities for High- and Low-Growth MSAs



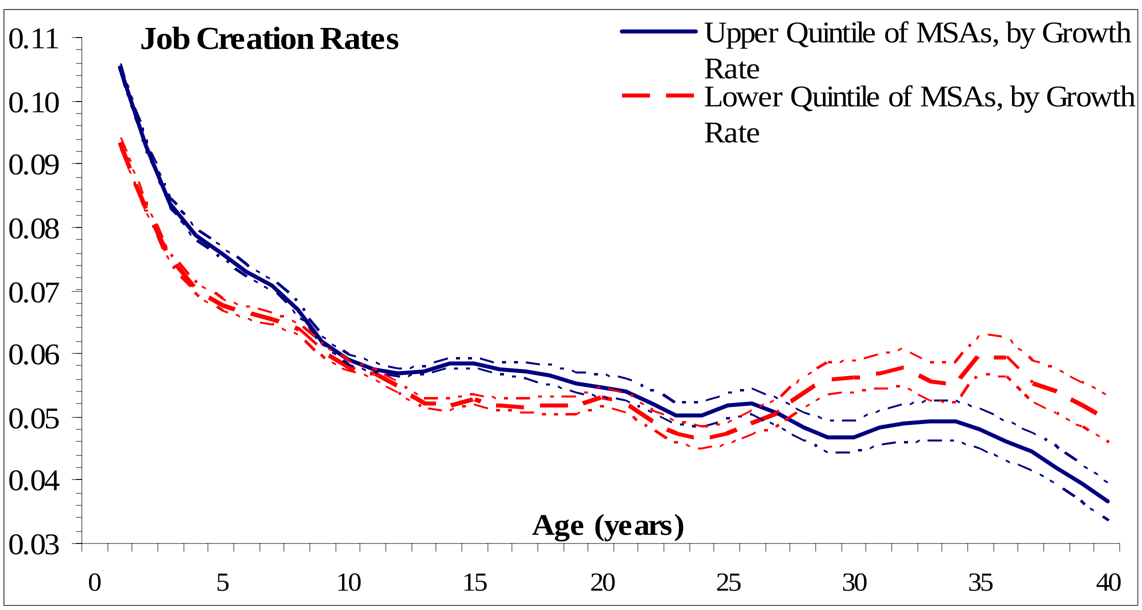
Note: Figure plots the frequency distributions of establishment age for the pooled observations of high- and low-growth MSAs. "High-growth" MSAs are those whose average growth rates rank in the top quintile of the 53 MSAs in the sample; "low-growth" MSAs are those who rank in the bottom quintile.

Figure 3. Employment Dynamics versus Age, High- and Low-Growth MSAs

(*a*)



(*b*)



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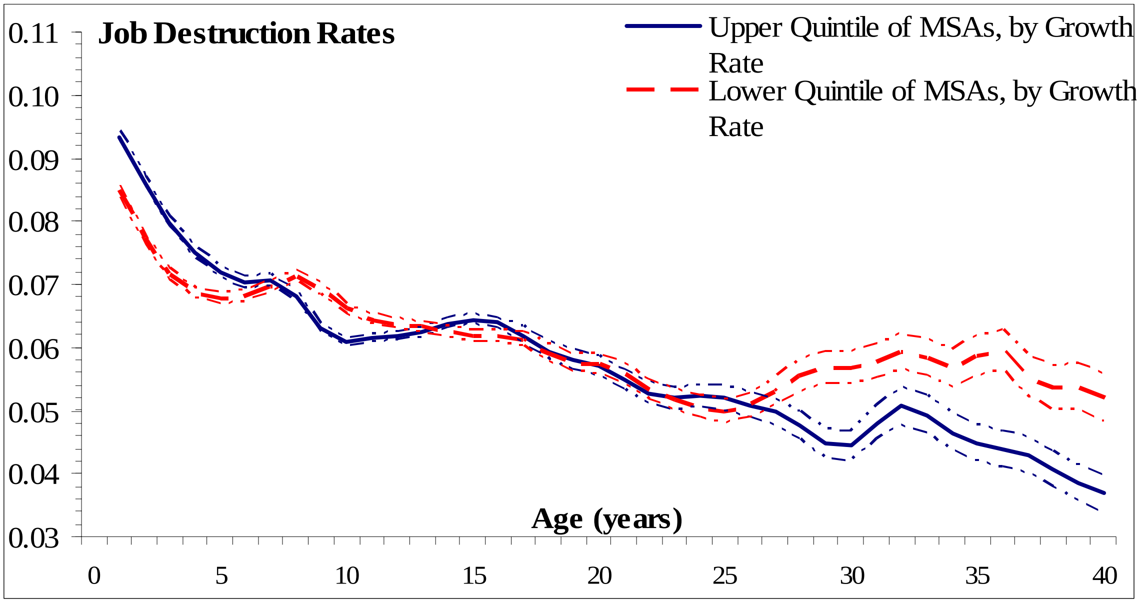
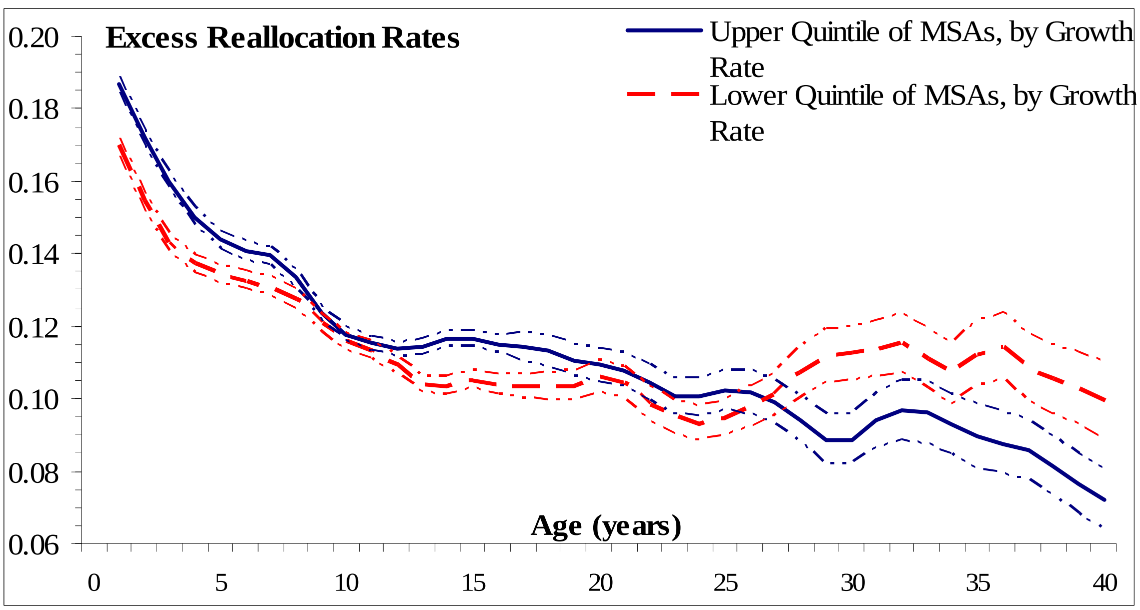


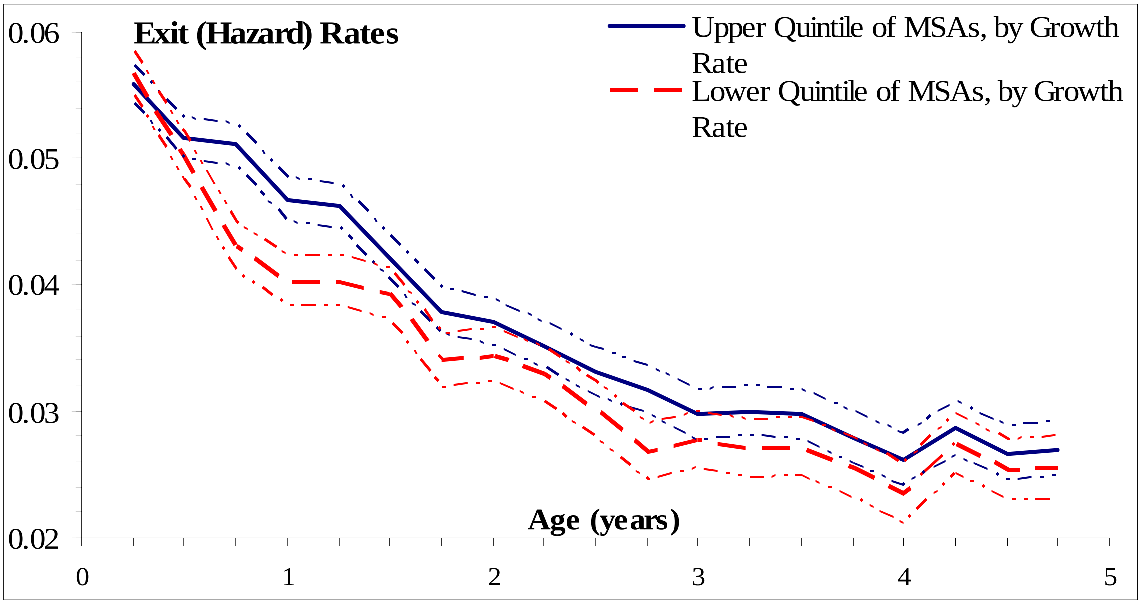
(*d*)



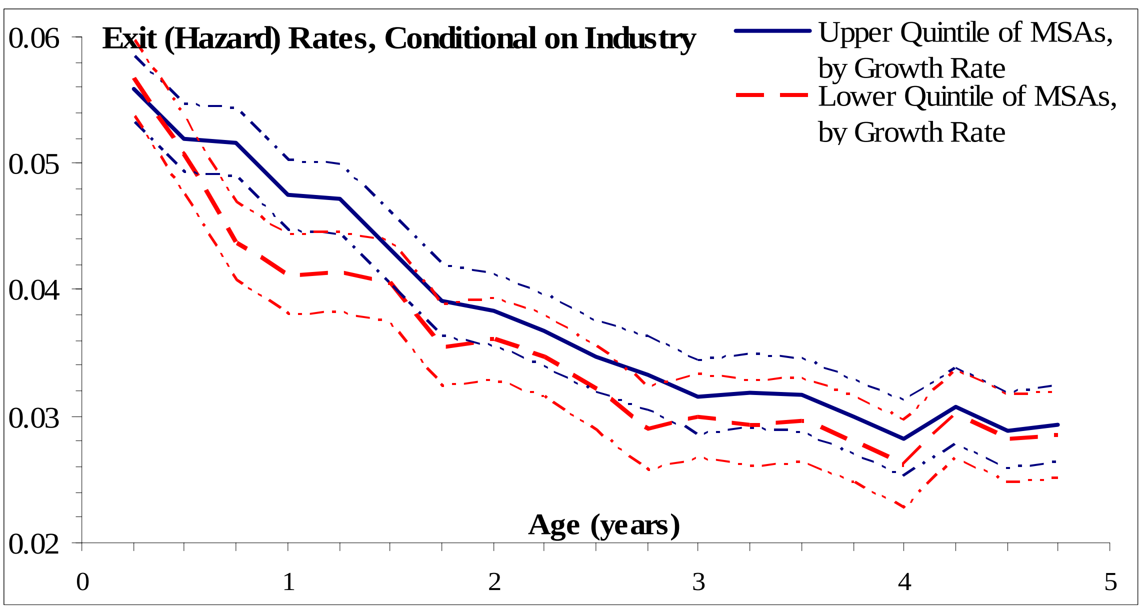
Note: Figures plot the growth and job flow rates as a function of establishment age for the pooled observations of high- and low-growth MSAs. "High-growth" MSAs are those whose average growth rates rank in the top quintile of the 53 MSAs in the sample; "low-growth" MSAs are those who rank in the bottom quintile. Functions are smoothed for each series using a centered, 3-year (i.e., across establishment years, as opposed to across time) moving average. Thin dotted lines represent 95 percent confidence intervals.

Figure 4. Hazard Rates of Entrants for the First 5 Years of Existence, High- and Low-Growth MSAs

(*a*)



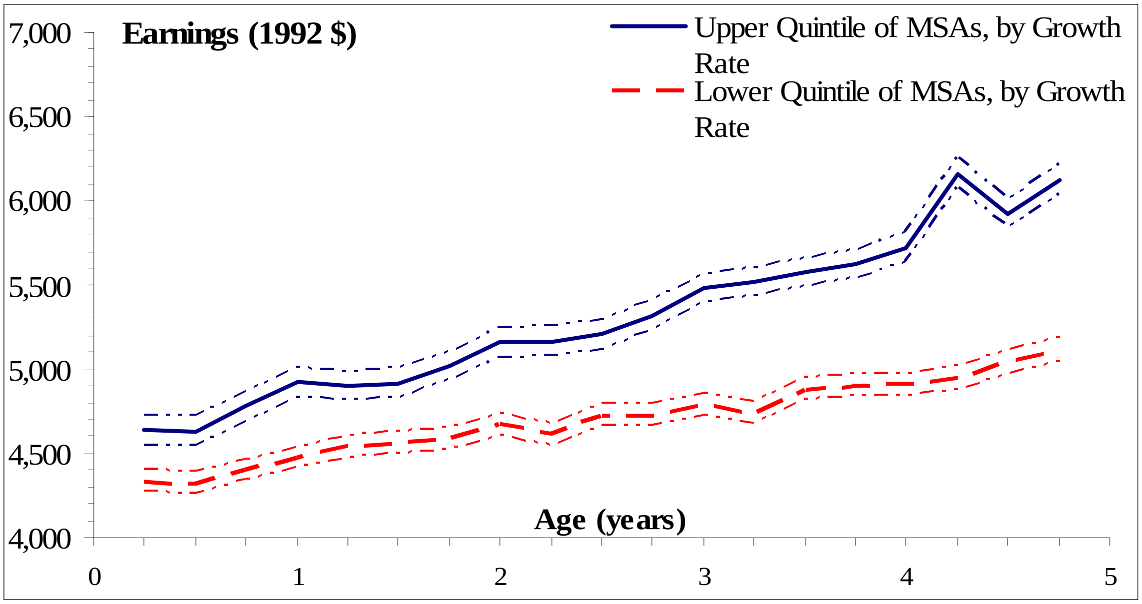
(*b*)



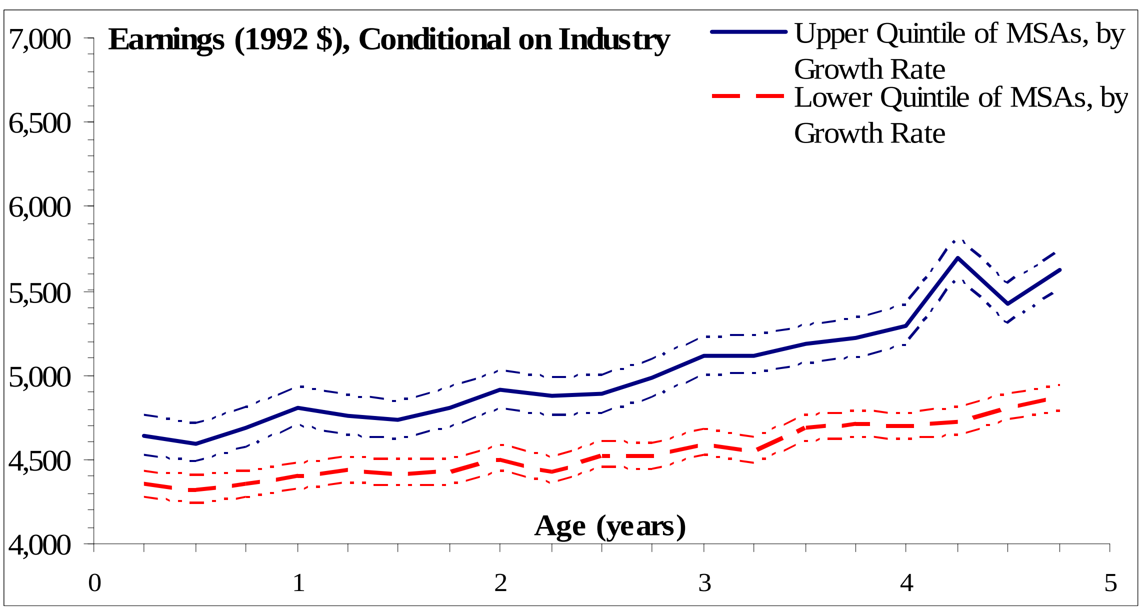
Note: Figures plot establishment exit (i.e., hazard) rates as a function of establishment age for the pooled observations of high- and low-growth MSAs. "High-growth" MSAs are those whose average growth rates rank in the top quintile of the 53 MSAs in the sample; "low-growth" MSAs are those who rank in the bottom quintile. Thin dotted lines represent 95 percent confidence intervals. The top panel depicts the unconditional functions, while the bottom panel depicts the functions conditional on 4-digit industry classification.

Figure 5. Earnings of Entrants for the First 5 Years of Existence, High- and Low-Growth MSAs

(*a*)



(*b*)



Note: Figures plot wages (in 1992 dollars) as a function of establishment age for the pooled observations of high- and low-growth MSAs. "High-growth" MSAs are those whose average growth rates rank in the top quintile of the 53 MSAs in the sample; "low-growth" MSAs are those who rank in the bottom quintile. Thin dotted lines represent 95 percent confidence intervals. The top panel depicts the unconditional functions, while the bottom panel depicts the functions conditional on 4-digit industry classification.

Table 1. Sample Statistics, Quarterly Means and Variation, 1992:2 – 2000:1

	Sample (MSA observations only)	Sample (MSA and non-MSA observations)	BED (public data)
Job Creation Rate	7.0 [1.0]	7.3 [1.2]	8.2 [0.9]
Job Destruction Rate	6.5 [1.0]	6.7 [1.0]	7.5 [1.1]
Net Growth Rate	0.6 [1.9]	0.6 [2.0]	0.7 [1.9]
Average Earnings (1992 Dollars)	6,695 [420]	6,453 [398]	---
Average Establishment Size (no. of employees)	18.7 [0.2]	17.8 [0.2]	---
Average Establishment Age (no. of quarters)	41.4 [1.8]	41.4 [1.7]	---
Entry Rate	2.2 [0.3]	2.3 [0.3]	---
Exit Rate	2.2 [0.4]	2.3 [0.4]	---

Notes: Sample MSA statistics are for the 53 MSAs within CO, MI, NC, OH, and PA (with appended data from 5 other states, where required by MSA definition). Sample MSA and non-MSA data includes all observations within the 5 noted states, plus the appended observations. BED statistics come directly from publicly available data. Standard deviations are in brackets.

Table 2. Across-MSA Correlations, Selected Statistics

	Net Growth	Earnings Growth	Average Earnings	Average Age
Job Creation Rate (C_j)	0.74 [0.00]	0.31 [0.03]	-0.18 [0.21]	-0.66 [0.00]
Job Destruction Rate (D_j)	0.45 [0.00]	0.16 [0.25]	-0.23 [0.10]	-0.47 [0.00]
Job Reallocation Rate (JR_j)	0.62 [0.00]	0.25 [0.07]	-0.20 [0.15]	-0.59 [0.00]
Excess Reallocation Rate (XR_j)	0.45 [0.00]	0.16 [0.25]	-0.23 [0.10]	-0.47 [0.00]
Average Establishment Size	-0.50 [0.00]	-0.11 [0.45]	0.44 [0.00]	0.44 [0.00]
Average Establishment Age	-0.79 [0.00]	-0.66 [0.00]	-0.08 [0.59]	1.00 [---]
Entry Rate	0.89 [0.00]	0.52 [0.00]	0.14 [0.31]	-0.89 [0.00]
Exit Rate	0.57 [0.00]	0.55 [0.00]	0.49 [0.00]	-0.70 [0.00]

$\rho(C_j, D_j)$ =	0.94 [0.00]	ρ(Net Growth, Earnings) =	0.00 [0.99]	ρ(Net Growth, Earnings Growth) =	0.47 [0.00]

Notes: Statistics are Pearson correlations with the variable noted in each column. Correlations use the pooled mean statistics for 53 MSAs. *p*-values are reported in brackets.

Table 3. Across-MSA Correlations, Conditional on Establishment Characteristics

	$\rho(C_j, N_j)$	$\rho(D_j, N_j)$	$\rho(XR_j, N_j)$	$\rho(Size_j, N_j)$	$\rho(Age_j, N_j)$
Unconditional Correlation	0.74 [0.00]	0.45 [0.00]	0.45 [0.00]	-0.50 [0.00]	-0.79 [0.00]
Controlling for Industry	0.41 [0.00]	-0.22 [0.11]	-0.01 [0.95]	-0.30 [0.03]	-0.70 [0.00]
Controlling for Age	0.52 [0.00]	0.14 [0.31]	-0.08 [0.56]	-0.17 [0.23]	---
Controlling for Size	0.65 [0.00]	0.27 [0.05]	0.45 [0.00]	---	-0.80 [0.00]
Controlling for Earnings	0.65 [0.00]	0.12 [0.39]	0.29 [0.03]	-0.66 [0.00]	-0.53 [0.00]
Controlling for All	0.19 [0.18]	-0.64 [0.00]	-0.53 [0.00]	-0.54* [0.00]	-0.27* [0.06]

Note: Correlations are for the pooled MSA means of residual values of the listed variables after conditioning out the listed characteristic(s). Industry controls are 946 4-digit SIC industries, age controls are yearly age categories from 0 to 64 years, size controls are a quartic of employment, and wage controls are a quartic of wages. * The correlation with size excludes the quartic in size, and the correlation with age excludes the age effects.

Table 4. Accounting for Variations in MSA Age Densities

	$\boldsymbol{N_j}$	$\boldsymbol{C_j}$	$\boldsymbol{D_j}$	$\boldsymbol{XR_j}$
Pct. of across-MSA variation accounted for by differences in age densities	43.7	47.8	12.3	12.3
Across-MSA correlation with *Net* predicted by age density differences	1.00	0.87 [0.00]	0.46 [0.00]	0.46 [0.00]
Pct. of across-MSA variation accounted for by differences in age densities, conditional on industry	28.4	19.3	1.7	1.9
Across-MSA correlation with *Net* predicted by age density differences, conditional on industry	1.00	0.94 [0.00]	0.46 [0.00]	0.87 [0.00]

Note: Percentages are R-squared values from the OLS regression of the actual (upper panel) or conditional (lower panel) MSA pooled mean on the pooled mean predicted by the MSA age distribution, holding values within each age constant. Correlations are across MSAs and use the predicted mean values. See text for further details.

Table 5. Entrant Statistics, First 5 Years of Existence, High- vs. Low-Growth MSAs

	All Entrants	Entrants of High-Growth MSAs	Entrants of Low-Growth MSAs
Total Entrants	207,916	56,347	37,594
Share of Establishments	2.3	2.8	2.0
Total Exits After 5 Years	99,837	28,021	17,563
Share of Entrants	48.0	49.7	46.7
Average Net Growth Rate	4.97	5.15	4.86
Average Excess Reallocation Rate	19.6	20.9	19.8
Average Earnings(1992 $)	5,177	5,357	4,770
Total Observations	2,938,461	755,088	536,414

Note: Statistics are for a subsample of all establishments who entered between June 1992 and June 1995. "High-growth" MSAs are those whose average growth rates rank in the top quintile of the 53 MSAs in the sample; "low-growth" MSAs are those who rank in the bottom quintile.

Table 6. Across-MSA Correlations of Labor Market Dynamics to Selected Labor Market Characteristics

	N_j	C_j	D_j	XR_j	Age_j	$Entry_j$	$Exit_j$
MSA Avg. Net Growth Rate	1.00	0.74 [0.00]	0.45 [0.00]	0.45 [0.00]	-0.79 [0.00]	0.89 [0.00]	0.57 [0.00]
MSA Size (Avg. Employment)	0.01 [0.96]	-0.06 [0.68]	-0.08 [0.57]	-0.08 [0.57]	-0.09 [0.53]	0.10 [0.47]	0.44 [0.00]
MSA 1990 Population	-0.05 [0.70]	-0.06 [0.66]	-0.06 [0.69]	-0.06 [0.69]	-0.05 [0.74]	0.05 [0.75]	0.41 [0.00]
Population Growth, 1990-2000	0.70 [0.00]	0.49 [0.00]	0.29 [0.04]	0.29 [0.04]	-0.64 [0.00]	0.71 [0.00]	0.42 [0.00]
Average Unemployment Rate	-0.56 [0.00]	-0.15 [0.28]	0.08 [0.54]	0.08 [0.55]	0.59 [0.00]	-0.49 [0.00]	-0.31 [0.02]
Share of 1990 Populated Aged 20-34	0.42 [0.00]	0.45 [0.00]	0.37 [0.01]	0.37 [0.01]	-0.58 [0.00]	0.40 [0.00]	0.30 [0.02]
Share of 1990 Population 25 or Older with at Least a College Degree	0.63 [0.00]	0.44 [0.00]	0.25 [0.07]	0.25 [0.07]	-0.69 [0.00]	0.68 [0.00]	0.65 [0.00]

Notes: Statistics are Pearson correlations with the variable noted in each column. Unless a specific year is noted, correlations use the mean statistics for 53 MSAs (March 1992 – March 2000). *p*-values are reported in brackets.

Appendix Table A.1 Quarterly Mean Statistics for Sample MSAs

Metro Area	E_j (000s)	C_j	D_j	N_j	$Size_j$	Age_j	W_j	$Entry_j$	$Exit_j$
Akron, OH PMSA	264.0	6.9	6.5	0.5	18.0	11.2	6,376	2.1	2.1
Allentown-Bethlehem MSA[2]	227.3	6.7	6.4	0.4	18.3	10.9	6,429	2.0	2.1
Altoona, PA MSA	47.2	6.5	6.1	0.5	17.3	11.2	4,907	1.8	1.9
Ann Arbor, MI PMSA	211.5	7.2	6.6	0.6	19.8	9.7	7,072	2.2	2.2
Asheville, NC MSA	85.6	7.2	6.5	0.7	16.4	9.7	5,240	2.5	2.2
Benton Harbor, MI MSA[2]	59.1	7.8	7.4	0.4	17.8	11.3	5,850	1.9	2.1
Boulder, CO PMSA[1]	123.3	7.9	6.5	1.4	14.0	8.3	7,453	3.1	2.6
Canton, OH MSA	151.4	6.5	6.0	0.4	18.1	11.8	5,708	1.9	1.9
Charlotte-Gastonia, NC-SC MSA[1]	635.9	7.1	6.2	1.0	18.9	9.4	6,769	2.7	2.3
Cincinnati OH-KY-IN PMSA	669.5	7.0	6.5	0.6	20.4	10.9	6,763	2.2	2.2
Cleveland-Lorain, OH PMSA	945.4	6.7	6.2	0.5	18.5	11.3	6,783	2.1	2.1
Colorado Springs, CO MSA[1]	170.2	8.3	7.1	1.2	15.6	9.0	5,984	3.0	2.6
Columbus, OH MSA[1]	643.1	7.3	6.5	0.9	20.9	10.3	6,352	2.4	2.3
Dayton, OH MSA[2]	383.2	6.6	6.2	0.4	20.7	11.3	6,447	2.0	2.1
Denver, CO PMSA[1]	854.9	7.9	6.8	1.0	15.3	9.1	7,310	2.8	2.6
Detroit, MI PMSA	1,742.4	7.5	6.9	0.5	20.6	10.4	8,143	2.1	2.3
Erie, PA MSA[2]	110.0	6.5	6.1	0.4	19.2	11.4	5,690	1.8	2.0
Fayetteville, NC MSA	71.6	7.6	7.0	0.6	15.9	9.8	4,777	2.2	2.1
Flint, MI PMSA[2]	147.4	6.6	6.5	0.1	20.5	10.3	7,550	2.0	2.3
Ft. Collins, CO MSA[1]	81.0	8.8	7.5	1.3	12.9	8.8	5,820	2.8	2.3
Goldsboro, NC MSA	33.1	7.0	6.2	0.8	16.6	10.9	4,601	2.0	1.9
Grand Junction, CO MSA	35.6	8.7	7.6	1.1	12.3	9.5	4,952	2.6	2.1
Grand Rapids-Muskegon, MI MSA	462.1	7.1	6.3	0.7	22.7	10.5	6,372	2.0	2.0
Greeley, CO PMSA[1]	49.1	8.5	7.4	1.1	14.9	10.0	5,462	2.4	2.1
Greensboro-Winston Salem, NC MSA	543.0	6.2	5.6	0.6	20.2	10.1	5,956	2.2	2.1
Greenville, NC MSA[1]	42.7	8.6	7.8	0.9	16.8	9.1	4,922	2.3	2.0
Hamilton, OH MSA	97.1	7.1	6.4	0.7	18.5	10.5	6,302	2.2	2.1
Harrisburg, PA MSA	260.9	6.3	5.9	0.5	21.0	10.8	6,080	2.0	2.1
Hickory-Morganton, NC MSA	152.6	5.3	4.8	0.5	23.2	10.8	5,141	1.9	1.8
Jackson, MI MSA	46.6	6.9	6.5	0.4	17.4	11.7	6,130	1.8	1.9
Jacksonville, NC MSA	23.9	8.8	7.9	0.8	11.6	9.1	3,577	2.4	2.2
Johnstown, PA MSA[2]	69.0	6.8	6.6	0.2	14.7	11.8	4,734	1.8	1.9
Kalamazoo-Battle Creek, MI MSA[2]	173.7	7.2	6.8	0.4	21.1	11.1	6,295	1.8	2.0
Lancaster, PA MSA	184.8	6.1	5.6	0.5	20.3	10.6	5,907	2.0	2.0
Lansing, MI MSA	157.0	7.0	6.5	0.5	19.1	10.4	6,199	2.0	2.1
Lima, OH MSA	64.4	6.5	6.0	0.5	19.7	12.5	5,778	1.8	1.8

(continued on next page)

Appendix Table A.1 (continued)

Metro Area	E_j (000s)	C_j	D_j	N_j	$Size_j$	Age_j	W_j	$Entry_j$	$Exit_j$
Mansfield, OH MSA[2]	67.1	6.6	6.3	0.3	19.1	12.5	5,483	1.8	2.0
Philadelphia, PA-NJ PMSA	1,877.4	7.0	6.6	0.4	18.0	10.3	7,402	2.1	2.5
Pittsburgh, PA MSA[2]	903.1	6.8	6.5	0.3	18.1	11.3	6,516	1.9	2.1
Pueblo, CO MSA	39.7	7.8	7.0	0.8	14.7	11.0	4,819	2.1	2.0
Raleigh-Durham, NC MSA[1]	465.5	7.4	6.3	1.1	18.1	8.5	6,673	2.8	2.3
Reading, PA MSA[2]	141.4	6.3	5.9	0.4	20.2	11.4	6,368	1.9	2.0
Rocky Mount, NC MSA[2]	56.0	7.2	6.9	0.2	20.2	10.7	5,282	2.0	2.0
Saginaw-Bay City, MI MSA[2]	145.9	6.4	6.1	0.3	19.3	10.9	6,957	1.8	1.9
Scranton-Wilkes-Barre, PA MSA[2]	231.1	6.8	6.5	0.3	18.0	10.9	5,228	1.9	2.1
Sharon, PA MSA	39.7	7.0	6.5	0.5	16.6	11.3	5,216	2.0	2.1
State College, PA MSA	39.8	7.4	7.0	0.4	15.8	10.2	4,947	2.0	2.0
Steubenville-Weirton, OH MSA[2]	42.2	6.3	6.3	0.0	16.5	12.1	5,921	1.8	2.0
Toledo, OH MSA	259.0	7.2	6.6	0.5	20.0	11.5	6,147	2.0	2.1
Williamsport, PA MSA[2]	44.7	6.0	5.8	0.2	18.1	11.6	5,114	1.8	2.0
Wilmington, NC MSA[1]	77.4	9.0	8.1	0.9	13.1	8.5	5,328	3.0	2.4
York, PA MSA	141.4	6.3	5.8	0.4	20.8	11.0	6,058	2.0	2.1
Youngstown, OH MSA[2]	206.5	6.9	6.6	0.3	17.3	11.7	5,900	1.9	2.0

Notes: Estimates are the pooled mean statistics for each MSA. Employment levels are in thousands. Job flow and net growth rates are percentages of employment. "Size" refers to the average establishment size, in employees. "Age" refers to average establishment age, in years. Earnings are for a quarter and expressed in 1992 dollars. Entry and exit rates are percentages of establishments.

1. Ranked in the (establishment-weighted) upper quintile of MSA growth.
2. Ranked in the (establishment-weighted) upper quintile of MSA growth.