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The Relationship Between the Establishment Age Distribution and Urban Growth

R. Jason Faberman*

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Abstract:

This paper presents new evidence on the relationship between a metropolitan area's employment growth and its establishment age distribution. I find that cities with a relatively younger distribution of establishments tend to have higher growth, as well as higher job and establishment turnover. Geographic variations in the age distribution account for 38 percent of the geographic differences in growth, compared to the 32 percent accounted for by variations in industry composition. Differences are disproportionately accounted for by entrants and young (5 years or younger) establishments. Furthermore, the relationship between age and growth is robust to controls for urban diversity and education. Overall, the results support a microfoundations view of urban growth, where the benefits of agglomeration affect firms not through some production externality but through a process that determines which firms enter, exit, and thrive at a given location.

JEL Codes: E24, J63, R11

Keywords: establishment age, urban growth and agglomeration, firm dynamics, job reallocation

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1. Introduction

What makes some cities grow faster than others is a question that has intrigued urban economists for decades. Most believe that cities exist to reap returns from the co-location of productive efforts. Many have argued that these benefits of agglomeration are reflected in localization economies (benefits attributed to the concentration of a particular industry), or urbanization economies (benefits attributed to industrial diversity). Alfred Marshall (1890) and Jane Jacobs (1969) were among the first to consider these notions. Contemporary work on this topic has extended their ideas to include the potential benefits of knowledge spillovers embodied in endogenous growth processes as in the models of Lucas (1988) and Romer (1986), since their implications are consistent with the factors economists believe underlie agglomeration.

In this paper, I depart from the conventional approach of relating agglomeration economies to growth and present new facts to help motivate a more microfoundations view of why some cities grow faster than others. In this sense, this paper is very much in the spirit of Duranton and Puga (2001), who model how a firm's location choice can depend on its point in its life-cycle; Wheeler (2001) and Andersson, Burgess, and Lane (2007), who show that the assortative matching of workers to firms is likely an important source of agglomeration economies; and Syverson (2004), who shows that increased product substitutability can increase average productivity through the exit of inefficient plants within densely clustered areas. It also builds upon recent work by Dumais, Ellison and Glaeser (2002), Henderson (2003), and Rosenthal and Strange (2003), who appeal to longitudinal microdata in various ways to get at the relationships between industry concentration, agglomeration economies, and firm performance, and Desmet and Rossi-

Hansberg (2007), who relate urban growth to industry age.[1] The paper has perhaps its strongest roots in the work of Eberts and Montgomery (1995), who document a positive relationship between job reallocation across establishments and city growth.

I present several new facts relating to the micro-behavior underlying urban growth. Similar to Eberts and Montgomery, I find that job reallocation and establishment entry and exit are all positively related to a city's employment growth rate. In other words, growing cities are more dynamic. Growing cities also tend to have a younger distribution of establishments, and within these cities, these young establishments are simultaneously more likely to grow and more likely to exit. Consequently, when I control for geographic variations in the establishment age distribution, much of these relationships disappear. Quantifying this result, I find that geographic variations in the age distribution account for at least as much of the cross-sectional differences in metropolitan employment growth (38 percent) as geographic variations in industry composition (32 percent), the source of plant/establishment heterogeneity most often studied in the agglomeration literature. Together, age and industry differences account for 54 percent of the variation in metropolitan growth.

Taking a closer look at the establishment age distribution, I find that in any given metropolitan area, the majority of its employment growth (66 percent) is accounted for by establishments aged 5 years or younger. This occurs because a) younger establishments make up a sizable portion of establishments in a metropolitan area, and b) establishments tend to exhibit the greatest growth and volatility early in their life-cycle. Variations in net entry and the growth of young establishments (aged 5 years or less) account for 61

[1] Similar studies include Hyclak (1996), Davis, Loungani, and Mahidhara (1997), and Schuh and Triest (2002). None of these studies, however, address the relationship between establishment age (or life-cycles)

percent of the variation in MSA growth, even though they account for only 23 percent of sample employment. Finally, through simple reduced-form regressions, I show that the relation of age to growth is robust to controls for other MSA characteristics, such as industrial diversity and the level of education. In fact, the converse does not hold – inclusion of average age in these regressions significantly alters the relations of diversity and education to growth.

These findings are a contribution in their own right, but more important, they suggest a subtle yet profoundly different approach to understanding agglomeration economies. Much of the literature to date has focused on how (or whether) city-specific externalities provide productive benefits to the firms that locate there. By highlighting the importance of varying life-cycle behavior across metropolitan areas, my findings suggest an alternative focus. Namely, rather than ask, "How does agglomeration affect the productive abilities of the firms within a particular city?" a more appropriate question is likely "How does agglomeration determine what types of firms survive and thrive within a particular city?" This subtlety produces two very different approaches to thinking about modeling and quantifying agglomeration economies, as well as two very different sets of policy questions and prescriptions for local economic development.

These findings also suggest a more microfoundations approach to studying agglomeration, much in the spirit of Duranton and Puga (2001), Acemoglu (1996) and others. They also suggest motivating theories that stress constant churning among heterogeneous agents. For example, such theories could involve a creative destruction process driven by underlying technological growth (e.g., Caballero and Hammour, 1994; Aghion and Howitt, 1992). They might also involve a process of firm learning and

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and urban growth.

selection where firms grow or exit based on what they learn about their productive abilities (e.g., Jovanovic, 1982; Ericsson and Pakes, 1995). Finally, they may involve frictions in the matching of workers to firms (e.g., Mortensen and Pissarides, 1994; Acemoglu, 1996; Wheeler, 2001) that depend on labor market thickness. In such cases, geographic variations in the underlying technology growth, learning process, or market thickness, respectively, can generate distributional differences across cities, which in turn can generate differences in urban growth.

Note that such theories depart from current theories of urban agglomeration highlighted by Glaeser et al. (1992), Henderson, Kuncoro, and Turner (1995), and Black and Henderson (1999), among others, in the sense that they do not attribute agglomeration economies to spillovers created through endogenous growth. Nevertheless, the above studies preserve many aspects of these studies in the sense that agglomeration economies – and their geographic variation – are necessary to generate some underlying processes of technology growth, firm learning or matching frictions to affect a city's composition, and ultimately, its growth. In this sense, my findings do not dispute the presence of agglomeration economies but motivate a refocus of research on agglomeration based more on its microfoundations than its aggregate outcomes.

Finally, note that this paper also builds on a rich literature on firm and employment dynamics. For example, Dunne, Roberts and Samuelson (1989a, 1989b) present evidence on the entry, exit, and employment dynamics of manufacturing plants. Davis and Haltiwanger (1990, 1992) highlight the wide dispersion in plant-level employment growth rates, their differences across plant characteristics, and their variation over time. Others, such as Anderson and Meyer (1994) and Burgess, Lane, and

Stevens (2000) build on this research with additional evidence on the gross flow of workers both within and outside of manufacturing. This paper adds to this literature by presenting detailed regional evidence on employment and establishment dynamics.

The following section describes the concepts and data used. Section 3 presents the empirical results, and Section 4 concludes.

2. Data and Measurement

2.1 Data

For this study, I use microdata from the Business Employment Dynamics (BED) program of the Bureau of Labor Statistics (BLS). The BED is a relatively new data source that measures gross job flows for the U.S. private sector. The data are longitudinally linked administrative records for all establishments covered by state unemployment insurance (UI) programs. This makes the BED a virtual universe of all businesses.[2] The data are quarterly and include an establishment's employment for each month, payroll for the quarter, and a variety of characteristics, including 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 (my proxy for age).

My sample includes all private-sector establishments within 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 (which I describe in the appendix). Given this limitation, I

[2] The self-employed and certain nonprofits are the primary exceptions. More details about the BED and its record-linkage process can be found in the appendix, as well as in Pivetz, Searson, and Spletzer (2001) and Spletzer et al. (2004).

choose my five states to satisfy two main conditions. Collectively, I aim to ensure that the states are representative of the U.S. in terms of employment growth, with regard to both its means and its variation across metro areas. In addition, each 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 (namely, in measuring age) while preserving across-MSA variation in the variable. I choose Colorado, North Carolina, Michigan, Ohio, and Pennsylvania; the 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 Northeast and Midwest.[3] 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 observations statewide, observations in metropolitan areas only (i.e., the sample for this study), and for the national BED data.[4] The employment growth estimates are comparable, with the metropolitan area sample having slightly lower growth. Average earnings (detailed below) and average establishment size (in employees) are both somewhat higher in the sample, which is mostly due to the sample's relatively high share of manufacturing establishments and the fact that non-urban establishments tend to be smaller and pay lower wages.

[3] 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.
[4] I list the summary statistics for each MSA in Appendix Table A.1.

2.2 Measurement

Most measures used in this paper are straightforward. Employment is measured at the third month of each quarter. Earnings are the total payroll of an establishment divided by its employment, deflated using the consumer price index to 1992 dollars. Establishment entry rates are the percent of total establishments that are entrants, while exit rates are the percent of total establishments that exit. To measure gross job flows, I follow the methodology of Davis, Haltiwanger, and Schuh (1996). By definition, job flows are measures of net employment changes at the establishment level, summed up based on whether they added or shed jobs. *Job creation* is the sum of all gains at either entering or expanding establishments, while *job destruction* is the sum of all losses at either exiting or contracting establishments. These measures are different from measures of hires and separations because they do not capture the turnover of workers within an establishment. Table 1 illustrates that job churning is quite substantial, averaging nearly 8 percent of employment per quarter. The aggregate net change in employment is simply the difference between job creation and job destruction.

Following the methodology of Davis, Haltiwanger and Schuh, I express the net change and job flow measures as rates by dividing them by the average of the current and previous quarters' employment. The difference between the job creation rate (C_t) and the job destruction rate (D_t) is then a symmetric growth rate (g_t) bounded between -200 and 200 percent. A growth rate of -200 percent signifies an establishment exit, while a rate of 200 percent signifies an entrant. About 22 percent of job flows is due to entry and exit; the job gains and losses due to entry and exit, respectively, roughly cancel each other out each quarter. Aggregated job flow and growth rate statistics are simply averages of their establishment-level estimates weighted by the average employment measure.

Finally, I measure establishment age using the initial date of UI liability, which generally represents the start date of the establishment. The average establishment is 10.2 years old. The oldest UI accounts date back to 1936, so upper truncation of the age measure is not a concern. Missing values and differences in liability dates that may depend on state UI laws are a concern, however, and I describe my methodology for dealing with these issues in the appendix.

3. Results

3.1. Metropolitan-Level Evidence

I begin with evidence on the basic relationships among aggregate MSA statistics. Table 2 presents the across-MSA correlations of job flows, establishment entry and exit, and average establishment age and size with employment growth, average earnings and average age. The correlations are between the pooled MSA means of the listed variables. Much of the relationships reinforce the findings of previous research. Dunne, Roberts, and Samuelson (1989a, 1989b) and Davis and Haltiwanger (1990, 1992) show that job flows and exit rates decrease with establishment age. My correlations are consistent with these findings. Consistent with Eberts and Montgomery (1995), I find that both job creation and job destruction are positively correlated with net growth across MSAs. The same is true of both establishment entry and exit. Unlike previous research, I am able to relate MSA growth to the age distribution. When I do so, I find a strikingly strong correlation (-0.80) between MSA growth and the average establishment age – high-growth cities have relatively younger establishments, on average. Taken together, these correlations suggest that high-growth cities are dynamic environments with high rates of job reallocation and establishment turnover among a relatively young distribution of establishments.

For earnings, I find insignificantly negative relations between the job flows and earnings and essentially no relation between the average age and average earnings of a MSA. MSAs with higher earnings, however, have significantly higher exit.

Studies in the firm dynamics literature also show that there is a strong correlation between establishment age and establishment size, which is also reflected in my MSA correlations. This is not surprising, since the size of an establishment in many ways is a reduced-form expression of its age, since size is an outcome of establishment performance over its life-cycle. This is important to keep in mind, since it implies that many of the results of this paper, which focus on variations in a city's age distribution, most likely can be generalized for variations in a city's size distribution and thus are comparable to studies such as Holmes and Stevens (2002).

Average age is strongly correlated with metropolitan growth. This is a striking finding, but the average masks much of the heterogeneity and distributional differences that may exist across metropolitan areas. In Figure 1, I plot the (unweighted) density of establishments as a function of their age. I do so separately for pooled establishment observations grouped in the top and bottom quintiles of MSAs ranked by their employment growth to highlight the distributional differences between high- and low-growth metropolitan areas.[5] For both groups, the age distribution is largely exponential,

[5] 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. Note also that the employment-weighted age distributions, while having greater densities among older establishments, provide qualitatively similar results.

with the majority of establishments less than 8 years old. The age densities of the two MSA quintiles differ considerably. The greatest differences occur among the youngest establishments – MSAs in the upper growth quintile have a relatively greater density of establishments 3 years old or younger, 33.7 percent of their observations versus 26.0 percent of observations for the lower growth quintile. The differences between the two groups are greatest for establishments less than a year old. These establishments make up 11.3 percent of observations in the upper quintile, but only 7.2 percent of observations in the lower quintile. As one can guess, MSAs in the lower quintile have a larger density of older establishments, with establishments 17 years or older making up 19.1 percent of their observations, compared to 12.7 percent of observations in the upper quintile.

Thus, there are clear compositional differences between high- and low-growth MSAs in terms of where their establishments are in the life-cycle, with the greatest differences among the youngest establishments. How much these compositional differences account for differences in MSA growth is a question I address below. Before doing so, though, it is important to highlight the differences in growth, job flows and exit that exist between high- and low-growth MSAs among establishments of the same age (i.e., independent of the age distribution). Figure 2 presents these differences in four panels, and the variation in these dynamics within age cohorts is substantial. The first panel illustrates net employment growth (as its quarterly rate) as a function of age for establishments in the upper and lower growth quintiles of MSAs. Growth is higher for observations in the upper quintile regardless of age, though the differences are significant only for the very young (less than 2 years old), and those between 5 and 20 years old. Growth rates decline with age, a finding consistent with the evidence in the firm dynamics literature, though it is nonmonotonic. Growth eventually becomes negative. It starts to rise in later years but is never statistically different from zero. Comparing the two quintiles, the results suggest that establishments in the upper growth quintile of MSAs continue to grow for 2 years longer (7 years versus 5 years), on average, than establishments in the lower growth quintile of MSAs. Keep in mind, though, that this is a difference "on average." As exit rates in the last panel of this figure suggest, differences in selection between the two groups may drive some of this result.

The next two panels of Figure 2 illustrate the quarterly job creation and job destruction rates, respectively, as a function of age for each quintile. Again, consistent with previous research on firm dynamics, job flows decline with age. Both job creation and job destruction begin higher for observations in the upper growth quintile, but also fall *faster* as establishments age. This results in a crossing point for both job flows where their rates become higher for older establishments in the lower growth quintile of MSAs. This pattern is more pronounced for job creation than for job destruction. Job flows are significantly higher for establishments in the upper growth quintile when they are 7 years old or younger. Job flows are significantly higher for establishments in the lower growth quintile when they are 28 years old or older. This suggests that younger establishments tend to be more turbulent in high-growth MSAs, while older establishments tend to be more turbulent in low-growth MSAs.

The last panel of Figure 2 shows that establishment exit rates (measured as averages of quarterly values) generally decline with age. Exit rates, like job flows, begin higher but fall faster in the upper quintile of MSAs. Exit rates in this group are significantly higher for establishments up to 7 years of age. Exit rates are higher in the lower quintile, however, for establishments between 9 and 15 years of age.[6] For older establishments, there is no significant difference in exit rates between the two growth quintiles. While the differences in exit rates seem small, their cumulative effects for a given cohort can be substantial. For example, the estimates from Figure 2 imply that by their fifth year, 50 percent of the establishments in a cohort of the upper growth quintile will have shut down, but only 43 percent of a cohort in the lower growth quintile will have shut down.

3.2 The Age Distribution, Industry Composition, and Growth

The comparison of high-growth and low-growth MSAs reveals that there are clear differences in their establishment age distribution but that there also exist variations in growth and establishment dynamics within cohorts. In this section, I quantify the contribution of geographic differences in the age distribution to geographic variations in MSA growth. I compare it to the contribution of geographic differences in industry composition as a benchmark because its variation across cities is the basis for many of the empirical proxies for localization economies (the benefits of industrial concentration) and urbanization economies (the benefits of industrial diversity) used in the urban economics literature. This approach allows me to simultaneously quantify the importance of the age distribution and relate it to the most common variation exploited in the empirical work on urban growth. Using industry variation as a benchmark is also useful because research on labor dynamics (e.g., Anderson and Meyer, 1994; Davis, Haltiwanger, and Schuh, 1996; Foote, 1998; and Burgess, Lane, and Stevens, 2000) suggests that job and establishment turnover varies widely by industry in addition to age.

[6] There is some concern that the nonmonotonicity observed in exit rates (as well as the age distribution in Figure 1) stems from my imputation of missing age data. I perform several robustness checks on the

In addition, recent research by Desmet and Rossi-Hansberg (2007) highlights the relationship *industry* age has to urban growth. Therefore, a question arises as to whether variations attributed to differences in the age distribution are not simply reduced-form outcomes of differences in industry composition – i.e., one might think that entrants and growing young establishments are concentrated in younger, growing industries.

I highlight the contributions of age and industry differences in two exercises. The first examines the correlations with MSA growth observed in Table 2 after conditioning out variations in the age distribution and industry composition. To estimate these correlations, I first obtain the residuals from separate regressions of the growth rate, job creation rate, job destruction rate, and exit rate on a set of 260 quarterly age dummy variables. Regressions are employment-weighted for the growth and job-flow variables. I repeat the exercise with separate regressions for the same variables plus the entry rate and age on a set of 972 four-digit SIC industry dummy variables, and repeat it again with separate regressions on both the age and industry dummies. Next, I aggregate the residuals for each dependent variable to the MSA level (weighting each appropriately). Finally, I calculate the correlations between these aggregate estimates across the 53 MSAs in my sample.

The results are in Table 3, with the unconditional correlations from Table 2 listed in the top row. The next row shows that when I control for MSA differences in the age distribution, the positive correlations that job destruction and exit have with MSA growth essentially disappear. The correlation between job creation and growth, however, remains positive and significant. I obtain similar results when I instead control for MSA differences in industry composition, though the relation between job destruction and

imputation approach, however, and neither the exit rates nor the distributions change much.

growth becomes insignificantly negative in this case. Controlling for industry, however, does little to alter the correlations of the entry rate or average MSA age to growth, suggesting that it is not that high-growth MSAs have a greater representation of growing industries, which in turn happen to have more entrants and younger, growing establishments. Instead, high-growth MSAs have more entrants and younger establishments independent of industry composition. The final row of Table 4 lists the correlations with growth controlling for both age and industry. Job creation remains positively correlated with growth, but this is only significant at the 10 percent level. In addition, when I control for both industry and age differences across MSAs, both job destruction and exit become significantly negatively related to MSA growth.

My second exercise addresses how much variation in the age distribution (and in industry composition) can account for variations in net growth alone. To get at this question, I decompose the employment growth rate to reflect its between-group and within-group variations. I repeat the exercise to account for age, industry and age and industry jointly, so my "groups" are either establishment cohorts (by age, in quarters), 4-digit industries, or age cohorts by 4-digit industry.

I represent the MSA growth rate as the weighted average of its pooled components summed across *k* groups: $g_j = \sum_k \theta_{kj} g_{kj}$, where θ_{kj} is the employment share of group *k* within MSA *j* and g_{kj} is the net growth rate for this group. Note that g_{kj} is simply the weighted average growth rate for all observations within the group. With some manipulation, one can rewrite g_j as

(1) $$g_j = \sum_k \theta_{kj} g_k + \sum_k \theta_k g_{kj} + \left\{ \sum_k (\theta_{kj} - \theta_k)(g_{kj} - g_k) - \bar{g} \right\}.$$

The first term is the between-group effect and is the term of interest for this exercise. It estimates the MSA growth rate predicted from holding the growth rate within each group constant at its group mean for the sample (g_k) and only allowing the employment shares to vary across MSAs. The within-group effect (second term) does the opposite—it estimates the MSA growth rate predicted from holding group employment shares constant at their sample values (θ_k) and allowing the growth rate to vary. The final term is a cross-product, where $\bar{g}$ is the mean growth rate for the sample. After calculating each component for each MSA in the sample, I estimate the percent of the across-MSA variance in the growth rate each component explains.

Table 4 reports the results. The first row reports that differences in the age distribution account for 37.6 percent of the across-MSA variation in growth rates. The next row reports that differences in industry composition account for 31.8 percent of the across-MSA variation in growth rates, which is a sizable percentage, but smaller than the fraction accounted for by age differences. Results in the third row suggest that more than half (53.8 percent) of the differences in MSA growth are explained by differences in the joint industry-age distribution of establishments. Thus, metropolitan differences in the age distribution are at least as important as metropolitan differences in industry composition for accounting for the geographic variation in employment growth.

3.3 Establishment Life-Cycles and Metropolitan Growth

If age is at least as important as industry in accounting for differences in urban growth, then the next logical question is: which part of the age distribution matters most? Research in urban economics that has stressed the importance of industry differences for growth has often studied whether particular industries (e.g., high-tech sectors) disproportionately contribute to growth because there are obvious local policy implications that stem from this question. Examining the contribution of establishments of a particular age – or equivalently, at a particular point in their life-cycle – can provide analogous implications for local planning policy.

To quantify the contributions to growth of establishments of a particular age, I split the sample into three categories: entrants and exits, continuing establishments aged 5 years or younger, and continuing establishments older than 5 years. I then break out aggregate MSA growth into its components attributable to each category. Let g_j again denote the aggregate growth rate of MSA of j over its pooled observations, and let θ_{ej} denote the employment share of observation e in MSA j. I can then write the growth rate as the sum of its components as follows,

(2) $$g_j = \sum_{e \in EN,EX} \theta_{ej} g_{ej} + \sum_{e \in YOUNG} \theta_{ej} g_{ej} + \sum_{e \in OLD} \theta_{ej} g_{ej} .$$

Here, "EN, EX" represents observations of entrants and exits, "YOUNG" represents observations of continuous establishments up to 5 years old, and "OLD" represents observations of continuous establishments older than 5 years. Dividing a component by g_j yields its percent contribution to the aggregate growth rate.

In Table 5, I report the results of this exercise for the full sample, for MSAs ranked in the upper quintile of growth and for MSAs ranked in the lower quintile of growth. I also report the share of employment within each category as well as the percentage of the across-MSA variation in growth rates accounted for by each component. Young establishments (aged 0-5 years) make up 22.3 percent of the sample's employment but account for 65.4 percent of its employment growth. Similarly, net entry (gains by entrants less losses by exits) accounts for 9.4 percent of growth, even though entrants and exits account for less than 0.8 percent of sample employment. Within high-growth MSAs, net entry accounts for a larger fraction, 19.4 percent, of aggregate growth, mostly through high entry rates among these MSAs. Among low-growth MSAs, young establishments account for nearly all growth (87.0 percent). This is mostly because older establishments have a mean growth rate close to zero, making their contribution negligible, regardless of their employment share.

The last row of Table 5 reports the percentage of the across-MSA variance in growth rates accounted for by the across-MSA variation in each component. While young establishments have the largest contribution to aggregate growth, their contribution to *the variance* of growth across MSAs is somewhat smaller than the contribution of older establishments. The percentage of variance explained by younger establishments remains larger than their share of employment, though. This is also true of net entry – entrants and exits account for only 0.8 percent of employment, but 26.3 percent of the across-MSA variance in employment growth. Thus, geographic differences in the growth across all three categories drive observed variations in MSA growth, but net entry and younger establishments account for highly disproportionate shares of the variation. Differences in the age distribution important for explaining differences in MSA growth, and the contribution of these differences appear concentrated (at least in relative terms) among entering, exiting, and relatively young establishments.

3.4 Establishment Age and MSA Characteristics

My final exercise examines the importance of establishment age relative to other labor market characteristics. I do so through OLS regressions of the MSA employment growth rate on the MSA's average establishment age and selected characteristics. The goals are to compare the explanatory power of average age to other, previously studied MSA characteristics and to see whether controlling for these characteristics significantly diminishes the explanatory power of establishment age.

I choose as my labor market characteristics MSA size (measured as the log of the 1990 population), the MSA unemployment rate, the fraction of the MSA population with at least a bachelor's degree, and MSA industrial diversity. For my diversity measure, I use the negative of a normalized Herfindahl index.[7] Save for the negative sign, it is identical to the diversity measure used by Henderson (2003) and is defined as

$$D_j \equiv -\sum_i (\theta_{ij} - \theta_i)^2 .$$

In words, the diversity measure is the sum of square differences between the employment share of industry *i* in MSA *j* and the employment share of industry *i* for the full sample. The closer the value is to zero, the more industrial diversity an MSA has. This variable measures the effects urban diversity, as described by Jacobs (1969), has on MSA growth. The population variable measures the effect city size has on growth. The unemployment rate controls for local labor market conditions, while the population share with at least a college degree measures how much of an effect the local level of human capital has on MSA growth. I run my regressions for the MSA job creation, job destruction, entry and exit rates, in addition to the growth rate, to highlight the relationships for the underlying dynamics.

My results are in Table 6. For each dependent variable, I report the results of three regressions. The first is the univariate regression on average establishment age alone. The

[7] The population measure and the fraction of the population (age 25 or older) with at least a bachelor's degree come from the 1990 decennial census. The unemployment measure is the mean of the monthly

second regression is on the four MSA characteristics. The third regression includes both the age and MSA characteristics variables. I also include a regression of average age on the MSA characteristics to illustrate how the variables interact. The first set of regressions shows that average age has a significantly negative relationship to growth, as well as job creation, job destruction, establishment entry, and establishment exit. The coefficient on growth implies that a one-standard-deviation decrease in the average establishment age of an MSA relates to a 0.11 percentage point increase in its employment growth rate, about 19 percent of its mean. The second set of results report the coefficients from the regressions on MSA characteristics. Urban diversity measures are significant for all dependent variables, but of the wrong sign, implying less growth, lower job flows, and less entry and exit in diverse areas.[8] Diversity is also positively related to average age. The unemployment rate is negatively related to growth and establishment entry, though insignificantly so. It is positively related to job flows and establishment exit, as well as average establishment age. MSA size has no significant relation to any of the variables save for establishment exit, with which it is positively related. The fraction of the population that is college-educated exhibits the strongest relations to the variables of interest. It has a significantly positive relation to growth, job flows, entry and exit, and it is negatively related to average age.

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estimates from the BLS Local Area Unemployment Statistics. The diversity measure is calculated directly from the sample.

[8] The literature on the effect of urban diversity on MSA or establishment outcomes is mixed. For example, Glaeser et al. (1992) find a positive relationship to MSA growth, but Henderson, Kuncoro, and Turner (1995) and Henderson (2003) find insignificant effects on manufacturing plant productivity. Part of the discrepancy might be because diversity matters only for particular industries, such as R&D, which is consistent with the model of diverse "nursery cities" that Duranton and Puga (2001) put forth. Consistent with this notion, I find positive but insignificant relations for urban diversity when I use the growth rate in manufacturing rather than the growth rate for all industries as the dependant variable.

Several notable things occur when I include both average age and the MSA characteristics. First and most important, the inclusion of MSA characteristics has a negligible effect on the relationship between average age and growth. In fact, they do little to alter the relationship between average age and any of the dependent variables. Instead, the coefficients on some MSA characteristics change considerably. In particular, the coefficient on urban diversity decreases in absolute value and loses significance, and the coefficient on the fraction of the population that is college-educated decreases and loses significance as well. This occurs across all specifications. There is little change in the coefficients for unemployment or MSA size.

To summarize, the negative relationship between establishment age and MSA growth is robust to the inclusion of a variety of MSA characteristics, including measures of unemployment, MSA size, urban diversity and education. Moreover, the relations of urban diversity and education to growth – notions cited in numerous urban studies as important for city growth – are substantially affected when I control for establishment age. This occurs because diverse cities have significantly older establishments and relatively educated cities have significantly younger establishments. Thus, not only do geographic differences in the age distribution account for a sizable fraction of the variations in urban growth, but they also strongly relate to other factors long thought to drive urban agglomeration and growth.

4. Conclusions

In this paper, I show that geographic differences in the establishment age distribution account for a sizeable portion of the observed variation in employment growth across metropolitan areas. I show these differences to be at least as important as geographic differences in industry composition, which is the margin of metropolitan variation most urban economists study in some form or another when trying to explain differences in cities' growth. Variation in cities' age distributions proves important because it captures differences in establishment behavior over their life-cycles. For example, I find a positive correlation between both job turnover and growth and establishment turnover and growth because fast-growing cities tend to have younger, more volatile establishments. I also find that geographic differences in the fraction of employment at young establishments and in the employment dynamics of these young employers account for much of the correlation between growth and the age distribution. Finally, I find that the relationship between growth and establishment age is robust to controls for a variety of urban characteristics. In fact, a metropolitan area's average establishment age is strongly related to its industrial diversity and the education of its workforce.

These findings do not provide a definitive answer for what drives differences in growth among cities. They do, however, suggest a fundamentally different way of approaching the question – one based on the microfoundations of the life-cycle behavior of firms and its interaction with urban characteristics, such as industrial diversity and the stock of human capital, often attributed to driving differences in urban agglomeration. Some existing work (e.g., Duranton and Puga, 2001; Henderson, 2003; Moretti, 2004) has already moved toward gaining a micro-level understanding of these characteristics. Future research in this vein can provide a deeper understanding of the evolutions of urban agglomeration. Along similar lines, this paper focuses solely on the relationship between age distribution and growth, though the nature of regional differences in industry concentration (i.e., localization economies) and firm productivity is also of economic interest. Understanding how firm behavior over the life-cycle affects or even drives these differences is another fruitful path of research. Research along these lines is already underway, at least with respect to firm entry and exit (e.g., Dumais, Ellison and Glaeser, 2002; Rosenthal and Strange, 2003). Future work in this vein will also provide a microfoundations-based understanding of the nature and dynamics of urban agglomeration.

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 (even within the urban literature) has focused solely on manufacturing. Second, they are a universe and not a sample (covering 98 percent of employment), thus avoiding potential selection bias with 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 closings, thereby overstating entry, exit, and job flows. To ensure that my estimates of entry and exit are as 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).[9] 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 will likely have a tremendous effect on turnover 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 estimate only openings and closings, which include both temporary and permanent changes.

B. Measuring Establishment Age

The age variable, derived from an establishment's initial date of UI liability must deal with two measurement concerns. First, nearly a third of the observations at the beginning of the sample are missing their liability dates. Second, state differences in UI laws 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 for incumbent establishments at the beginning of the sample period 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

[9] I summarize my methodology in more detail in my dissertation (Faberman, 2003). I focus only on large changes because a) they are relatively easy to identify, and the chances of identifying a false positive link is

establishments that enter the sample with a missing age after the start of the sample, 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 previous imputations already remove differences for many of the younger establishments. I use this adjusted age for all analyses throughout the paper.

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very low, and b) they have a much larger impact on the turnover estimates.

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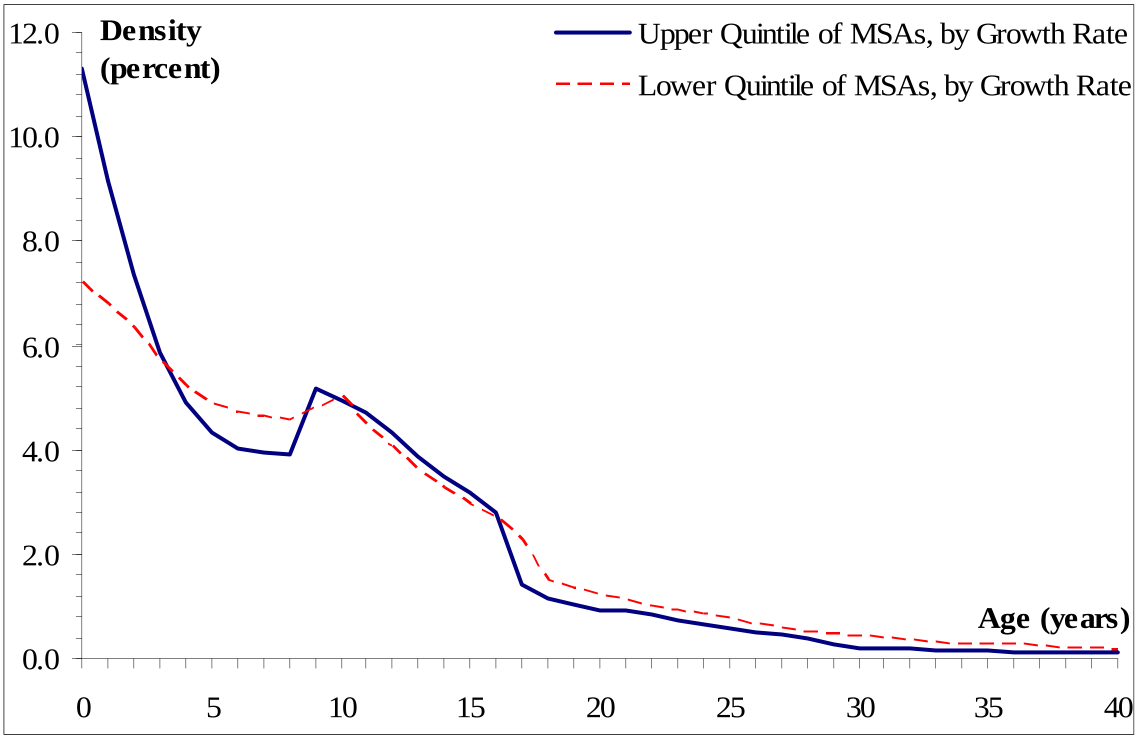
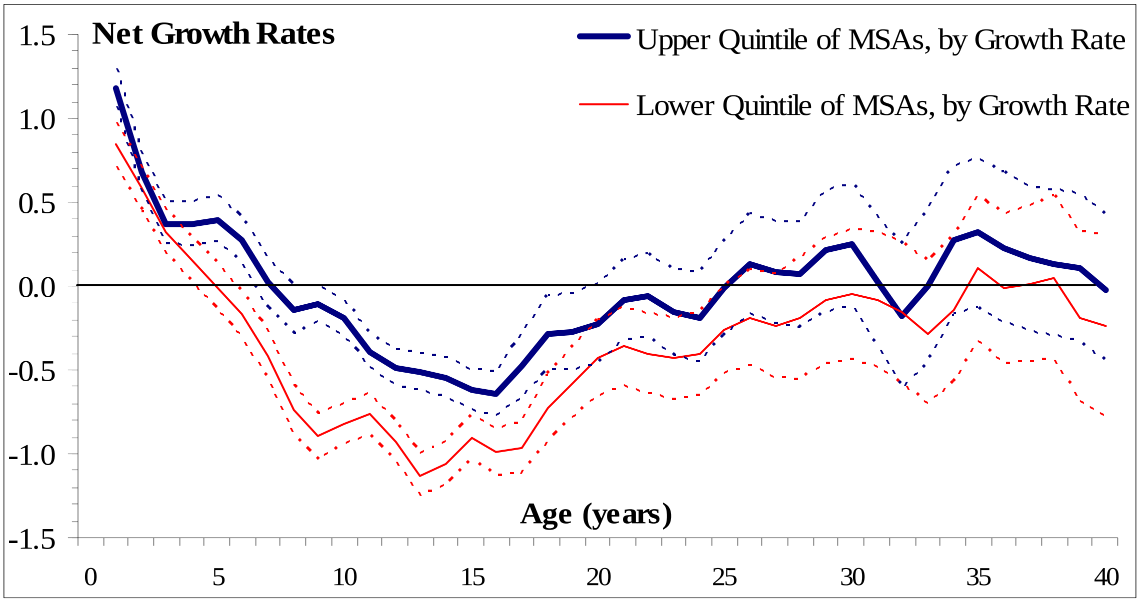
Figure 1. Establishment Age Densities for High- and Low-Growth MSAs



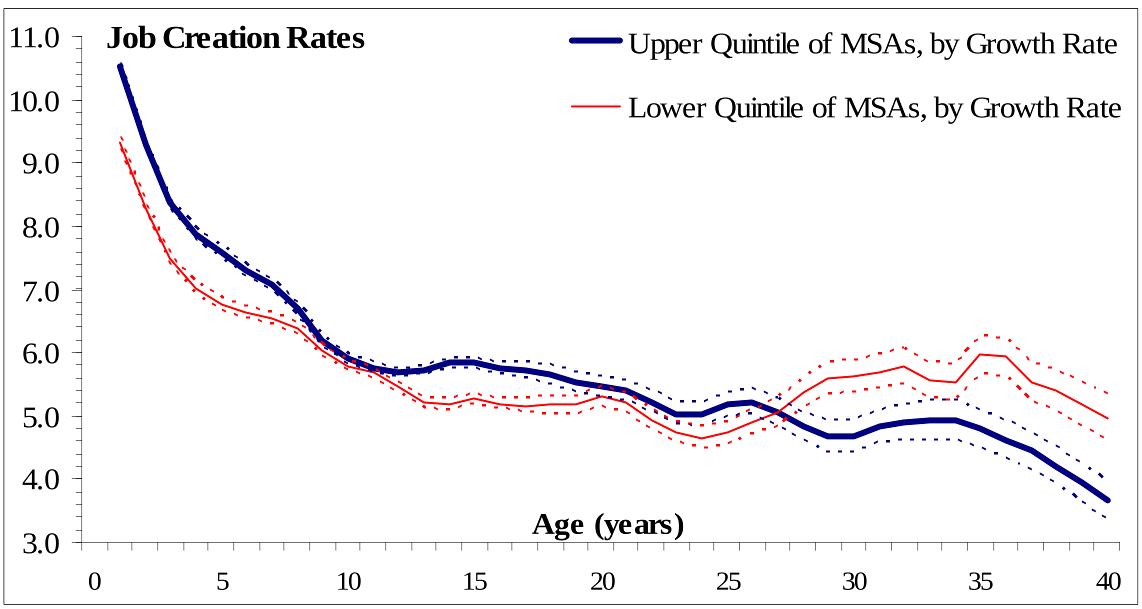
Note: Figure plots the frequency distributions of establishment age for the pooled observations of high- and low-growth MSAs. “High-growth” MSAs are those whose average growth rates rank in the top quintile of the 53 MSAs in the sample; “low-growth” MSAs are those who rank in the bottom quintile.

Figure 2. Employment Dynamics versus Age, High- and Low-Growth MSAs

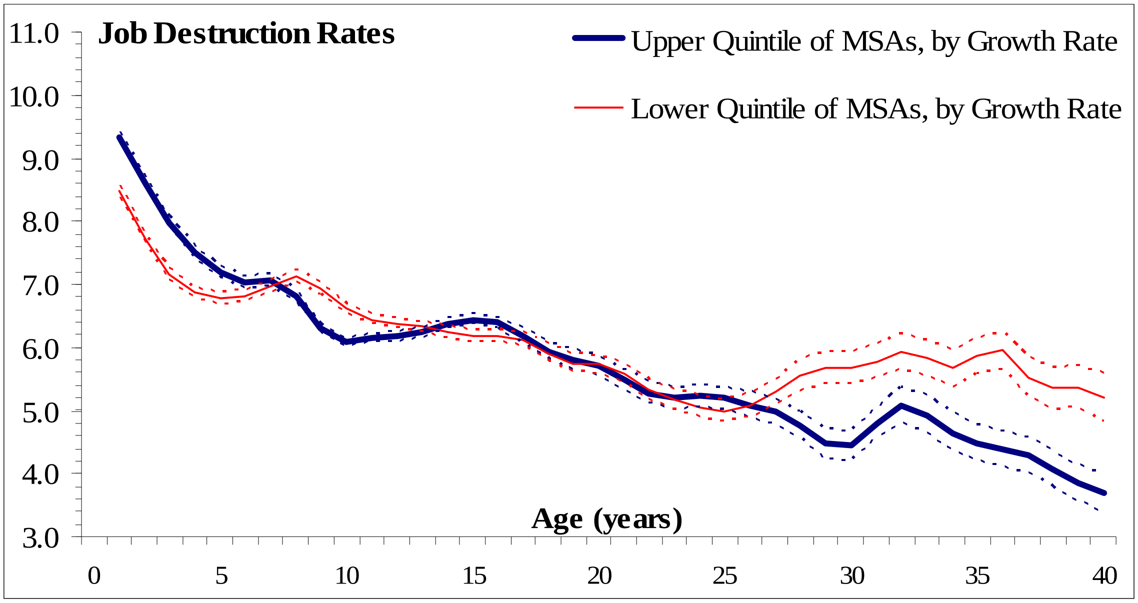
(*a*)



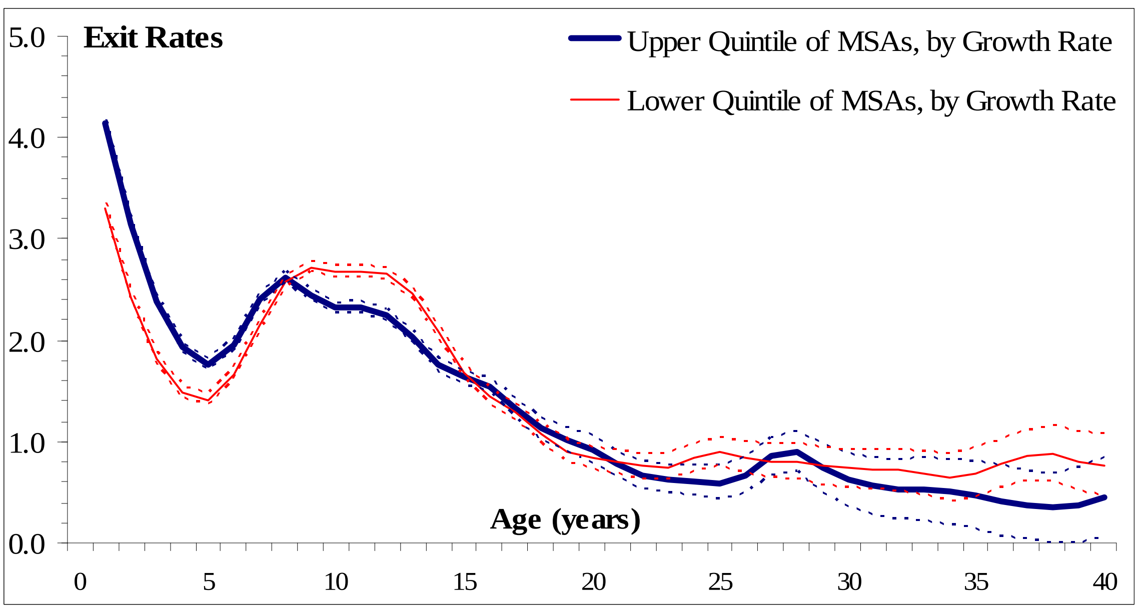
(*b*)



(*c*)



(*d*)



Note: Figures plot the growth, job flow, and establishment exit 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.

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

	Sample (MSA observations only)	Sample (MSA and non-MSA observations)	National BED Data
Employment Growth Rate	0.58 [1.92]	0.62 [2.04]	0.67 [1.86]
Average Earnings (1992 Dollars)	6,695 [420]	6,453 [398]	6,484 [455]
Average Establishment Size (no. of employees)	18.66 [0.25]	17.79 [0.22]	16.36 [0.24]
Manufacturing Average Share of Employment	0.222	0.234	0.186

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 are tabulated from microdata. Standard deviations are in brackets.

Table 2. Across-MSA Correlations with Employment Growth, Earnings and Age

	Net Growth (g_j)	Avg. Earnings (w_j)	Average Age (a_j)
Job Creation Rate	0.74 [0.00]	-0.18 [0.21]	-0.66 [0.00]
Job Destruction Rate	0.45 [0.00]	-0.23 [0.10]	-0.47 [0.00]
Entry Rate	0.89 [0.00]	0.14 [0.31]	-0.89 [0.00]
Exit Rate	0.53 [0.00]	0.49 [0.00]	-0.70 [0.00]
Average Establishment Age	-0.80 [0.00]	-0.08 [0.59]	1.00 [---]
Average Establishment Size	-0.50 [0.00]	0.44 [0.00]	0.44 [0.00]
$\rho(C_j, D_j) =$ 0.94 [0.00]		$\rho(g_j, w_j) =$ 0.00 [0.99]	

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

	Correlation of MSA the Growth Rate with MSA:				
	Job Creation	Job Destruction	Entry	Exit	Average Age
Unconditional Correlation	0.74 [0.00]	0.45 [0.00]	0.89 [0.00]	0.53 [0.00]	-0.79 [0.00]
Controlling for Age	0.52 [0.00]	0.14 [0.31]	---	-0.05 [0.73]	---
Controlling for Industry	0.41 [0.00]	-0.22 [0.11]	0.81 [0.00]	0.17 [0.21]	-0.70 [0.00]
Controlling for Industry and Age	0.24 [0.09]	-0.38 [0.01]	---	-0.34 [0.01]	---

Note: Correlations are for the pooled MSA means of residual values of the listed variables after conditioning out the listed characteristic(s). Industry controls use 946 4-digit SIC industries and age controls use yearly age categories from 0 to 64 years.

Table 4. Accounting for Across-MSA Variations in Employment Growth

	Between-Group Component	Within-Group Component	Cross-Product
Percent accounted for by variations in the age distribution	37.6	56.7	5.7
Percent accounted for by variations in industry composition	31.8	160.3	-92.1
Percent accounted for by jointly by variations in the age distribution and industry composition	53.8	73.2	-27.0

Note: Percentages are the share of the across-MSA variance in employment growth accounted for by across-MSA variations between groups (i.e., differences due to across-MSA variations in the age distribution and/or industry mix), differences within groups (i.e., differences across MSAs within age cohorts and/or industries) and a cross-product term. See text for further details.

Table 5. Contributions to Employment Growth and its Across-MSA Variation

	Net Entry	Continuing Establishments Aged ≤ 5 Years	Continuing Establishments Aged > 5 Years
Percent of Growth Accounted for by...			
Full Sample	9.6	65.4	25.0
Upper Growth Quintile of MSAs	19.4	53.7	26.9
Lower Growth Quintile of MSAs	8.9	87.0	4.1
Employment Shares Accounted for by...			
Full Sample	0.0077	0.2234	0.7688
Upper Growth Quintile of MSAs	0.0082	0.2318	0.7600
Lower Growth Quintile of MSAs	0.0073	0.2135	0.7792
Percent of Across-MSA Variation in Growth Accounted for by the Variation of...	26.3	35.0	38.7

Note: The upper panel reports the percent contribution of each of the three categories (entrants and exits, continuers 5 years old or younger, continuers over 5 years old) to the listed group's mean growth rate. The contribution is measured as the category's growth rate multiplied by its employment share for the group. The middle panel reports the employment shares used in the previous calculations. The lower panel reports the percent of the across-MSA variance in net growth accounted for by the variations in each category's contribution to growth.

Table 6. MSA-Level Regressions of Labor Dynamics on Age and Selected Labor Market Characteristics

Dependent Variable:	**Net Growth**	**Job Creation**	**Job Destruction**	**Entry**	**Exit**	**Average Age**
			OLS Regressions: Average Age Alone			
Average Age [x 100][1]	-0.060* (0.006)	-0.132* (0.020)	-0.071* (0.018)	-0.077* (0.005)	-0.033* (0.005)	---
R-squared	.65	.46	.23	.81	.50	
			OLS Regressions: Select MSA Characteristics			
Urban Diversity (D_j)	-0.469* (0.134)	-1.615* (0.391)	-1.146* (0.327)	-0.742* (0.138)	-0.270* (0.081)	947.91* (135.06)
Unemployment Rate	-0.039 (0.029)	0.209* (0.086)	0.247* (0.072)	-0.021 (0.030)	0.053* (0.018)	20.75 (29.57)
log(1990 Pop.) [x 100][1]	-0.024 (0.033)	-0.071 (0.097)	-0.047 (0.081)	0.047 (0.034)	0.089* (0.020)	-47.31 (33.64)
Fraction of Pop. College-Educated	0.025* (0.006)	0.082* (0.016)	0.056* (0.014)	0.037* (0.006)	0.022* (0.004)	-38.72* (5.62)
R-squared	.61	.50	.40	.68	.62	.77
			OLS Regressions: Average Age and Select MSA Characteristics			
Average Age [x 100][1]	-0.045* (0.013)	-0.135* (0.037)	-0.091* (0.033)	-0.070* (0.011)	-0.037* (0.007)	---
Urban Diversity (D_j)	-0.047 (0.171)	-0.334 (0.497)	-0.287 (0.437)	-0.077 (0.144)	0.079 (0.093)	---
Unemployment Rate	-0.029 (0.027)	0.237* (0.077)	0.266* (0.068)	0.035 (0.022)	0.060* (0.014)	---
log(1990 Pop.) [x 100][1]	-0.045 (0.031)	-0.135 (0.089)	-0.089 (0.078)	0.013 (0.026)	0.071* (0.017)	---
Fraction of Pop. College-Educated	0.008 (0.007)	0.029 (0.020)	0.021 (0.018)	0.010 (0.006)	0.008* (0.004)	---
R-squared	.69	.61	.48	.83	.76	

Note: The table reports the coefficients from the regression of the dependent variable listed in each column on the variables listed in each row. Standard errors are in parentheses. Observations are pooled MSA variables (N = 53). The upper panel reports the results of the regression of each variable on the MSA average establishment age alone. The middle panel reports the results of the regression of each variable on a set of MSA characteristics. The lower panel reports the results of the regression of each variable on both age and the MSA characteristics.

1. Coefficient estimates are multiplied by 100 for reporting ease.

* Denotes significance at the 5 percent level.

Appendix Table A.1 Quarterly Mean Statistics for Sample MSAs

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

(continued on next page)

Appendix Table A.1 (continued)

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

Notes: Estimates are the pooled mean statistics for each MSA. Employment levels are in thousands. Job flow (job creation, C_j and job destruction, D_j) and net growth rates (g_j) are percentages of employment. Average earnings (w_j) are for a quarter and expressed in 1992 dollars. "Size" refers to the average establishment size, in employees. Entry (EN_j) and exit (EX_j) rates are percentages of establishments. "Age" refers to average establishment age, in years.

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