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Abstract

In finding a career, workers tend to make numerous job changes, with the majority of 'complex' changes (i.e. those involving changes of industry) occurring relatively early in their working lives. This pattern suggests that workers tend to experiment with different types of work before settling on the one they like best. Of course, since the extent of economic diversity differs substantially across local labor markets in the U.S. (e.g. counties and metro areas), this career search process may exhibit important differences depending on the size of a worker's local market. This paper explores this issue using a sample of young male workers drawn from the National Longitudinal Survey of Youth 1979 Cohort. The results uncover two rather striking patterns. First, the likelihood that a worker changes industries rises with the size and diversity of his local labor market when considering the first job change he makes. Second, however, this association gradually decreases as a worker makes greater numbers of job changes. By the time he makes his fourth change, the likelihood of changing industries significantly *decreases* with the scale and diversity of the local market. Both results are consistent with the idea that urban areas play an important role in the job matching process.

1 Introduction

The process by which young workers find careers typically involves years of search and experimentation, characterized by a lengthy series of job changes. In their study of the work histories of young men in the U.S., for example, Topel and Ward (1992) find that an average 40-year career involves approximately 10 job changes, with the majority (roughly two-thirds) occurring within the first 10 years. Because workers also tend to experience significant earnings growth over this period, the movement of workers from one job to another - at least during the early stages of their careers - appears to serve a mostly productive purpose.[1] As they change jobs, workers seem to learn about their abilities and preferences which, ultimately, enables them to settle into careers where their productivities are maximized.

One particularly important aspect of this search and learning process has been identified by Neal (1999) who, also using data on a sample of young male workers in the U.S., finds that a typical job history involves a series of 'complex' job changes (i.e. those that involve a change of both employer and either industry or occupation) during the early stages of an individual's working life, followed by a series of 'simple' changes (i.e. those involving only a change of employer) subsequently. This pattern suggests that workers tend to experiment with different types of work (e.g. manufacturing versus services), settle on the one they like the most, and then seek an optimal match with an employer within that particular line of work.

There is, however, little mention in either of these studies, or in the job search literature more generally, of how a worker's local labor market (e.g. county or city) may influence this process.[2] Yet, job search often takes place locally, implying that the number and types

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[1]Topel and Ward (1992) show that, over the course of a typical 40-year career, workers see their real wages double, with the majority of this growth again taking place within the first 10 years.

[2]None of the most prominent papers in this literature (e.g. Jovanovic (1979), McCall (1990), Sicherman

of employers located within a worker's county- or metropolitan area-of-residence may very well influence the extent to which he or she can engage in complex or simple changes.[3]

Moreover, research on spatial agglomeration has long argued that some basic features of a worker's local market - most notably, its sheer size - tend to enhance aggregate productivity, at least in part, by facilitating the firm-worker matching process.[4] The basic premise is rather simple: by allowing workers to experience different types of work with relative ease, large, economically diverse markets allow workers to learn more quickly about their abilities and preferences over jobs and, thus, settle into productive matches more quickly than workers in small, specialized markets.

Since Neal's (1999) evidence indicates that the matching process often involves a two-stage strategy - a series of complex changes followed by a set of simple changes - one might expect to see this pattern taking place to a greater extent in large, economically diverse local markets if agglomeration does, in fact, facilitate matching. That is, proximity to a wide array of jobs should allow workers to engage in greater experimentation early in their working lives. Yet, because they learn from this process, workers in large markets should also find optimal industry matches sooner and, accordingly, engage in less experimentation later on in their working lives. Empirically, then, the frequency of complex changes should be higher among workers in large markets than among workers in small markets when

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and Galor (1990)) delve into this matter.

[3]Anecdotal evidence suggests that many workers look for jobs within their immediate areas. Scott (1993), for example, finds that, among the (previously-employed) newly hired workers at Lockheed in southern California over the period 1980-1988 (135 workers), 60 percent had held jobs located within 30 miles of the plant just prior to being hired. Similarly, Hanson and Pratt (1988) report evidence from a survey of 600 households in Worcester, Massachusetts revealing that roughly two-thirds of the respondents located their present job *after* having established a place-of-residence in the area.

[4]This idea dates back at least to Marshall (1920) who suggested that the geographic concentration of firms and workers allows them to find one another relatively easily. For a recent survey of the matching-in-cities literature, see Duranton and Puga (2004).

considering a sample of 'early' job changes. In 'later' job changes, however, workers in large markets should make complex changes less frequently.

This idea is similar to the one proposed recently by Duranton and Puga (2001) who examine the location decisions of firms. They argue that producers tend to locate in economically diverse cities in the early stages of their lives, but then seek smaller, more concentrated markets later on. The rationale is straightforward. Early in its existence, a firm can choose to adopt one of many different technologies, but has little a priori knowledge of what its (idiosyncratic) optimal choice is. As a result, young firms tend to experiment with different production processes. This experimentation, Duranton and Puga (2001) argue, is especially easy in diverse cities because firms can observe a wide array of technologies as practiced by neighboring firms. Once they have settled on an optimal production technique, firms can then move to markets in which similar producers have located and take advantage of localization economies. Something similar may be happening among workers, at least during the initial search phase.

This paper examines the pattern of industry changes among young male workers drawn from the National Longitudinal Survey of Youth covering a collection of roughly 350 counties and metropolitan areas in the United States over the years 1978-1994. The results indicate that three measures of local market scale and economic diversity - population, population density, and an index of industrial heterogeneity - tend to be positively associated with the frequency of industry changes for the *first job change* that a worker is observed to make. This positive association, however, declines as a worker makes additional job changes so that, by the time he makes his fourth or higher-number job change, there is a significantly negative association between the scale of his local market and the likelihood of an industry switch.

Additionally, I find that workers in large markets tend to make fewer overall job changes

than workers in small markets. Assuming that a job change is indicative of the creation (and destruction) of an unproductive match, this finding suggests that, on the whole, spatial agglomeration may help create better matches.

The remainder of the paper proceeds as follows. The next section provides a description of the data and the statistical methods. Section 3 discusses the results. Section 4 offers some concluding remarks.

2   Data and Analytical Methods

2.1   The Data

Data on individual worker job histories are taken from the National Longitudinal Survey of Youth 1979 Cohort (NLSY79). The actual weekly records of each individual's labor force status come from the NLSY79 Work History files which identify, for each week beginning in January of 1978, whether a worker was employed or not and, if so, which job was held. Because the NLSY79 allows workers to report as many as five jobs held in a given week, many respondents are observed in more than one position at a particular time. To simplify the construction of a time series of job changes for each individual, I assume that a worker's job in a given week is the one at which he worked the most hours.

Following previous work (e.g. Neal (1999)), I examine only males from the cross-sectional sample of the NLSY79. This particular sample includes 3003 individuals who were between the ages of 14 and 21 as of December 31, 1978. Of these 3003, I keep only those respondents who were interviewed in every year to facilitate the construction of the work histories used in the analysis. In the raw NLSY79 Work History files, jobs are given codes depending on the interview year in which they were held. Hence, the same job may be given two (or more) distinct codes in the raw data. To impose consistency, I use the information in the NLSY79 main files that provides a link between jobs reported in adjacent years to create

a consistent set of job codes for each worker. Confining the sample to workers who were interviewed in each year helps to minimize the likelihood that a single job is treated as two or more different jobs.[5]

These individual work histories are supplemented with a variety of personal characteristics - including education, race, and marital status - which are also identified in the main NLSY79 files. Because my primary aim is to examine the career search process, I consider only post-education jobs. Jobs held prior to the completion of schooling tend to be temporary and may have little to do with a worker's ultimate selection of a career. Furthermore, because I am interested in examining the job changes a worker makes beginning with the first job he holds, I restrict the sample to individuals who are initially observed in school in 1978. Doing so allows me to identify with a fair amount of certainty the first several jobs a worker holds after completing school. Jobs are limited to full-time positions, defined as those involving at least 30 hours per week.

I focus on the period 1978 to 1994 because interviews were conducted each year during this time frame. All subsequent interviews in the NLSY79 were conducted on an every-other-year basis beginning with 1996. Although interviewers do ask workers about their weekly activities in the time since the last interview, mapping personal characteristics to a weekly history is somewhat difficult because potentially time-varying characteristics such as county-of-residence and marital status are only identified at the time of the interview. Naturally, this difficulty becomes more pronounced as the time between interviews grows. I, therefore, only look at those years in which workers are interviewed on an annual basis.

Once I have compiled a weekly record of full-time jobs, job changes are identified from changes in the (consistent) job codes described above.[6] I make no distinction between

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[5]It also greatly helps with the tracking of each respondent's place-of-residence and the identification of geographic moves over time (see Appendix).

[6]Note, if a worker reports time away from a job, say due to a temporary layoff, but then returns to that

6

job changes that occur for different reasons (e.g. quit versus layoff), nor do I distinguish between changes that involve an intervening period of non-employment (unemployment or out of the labor force) and those that occur without any time away from employment. All types of transitions are treated identically in the analysis below.[7]

The final sample includes 1029 workers who make, on average, 4.35 job changes over the sample period.[8] Additional details about the construction of the work histories and the sample of job changes appear in the Appendix.

A worker's local labor market is identified from the information in the NLSY79 geocoded files covering each respondent's state- and county-of-residence. In particular, if a worker's county-of-residence does not belong to a metropolitan area (or if the metropolitan area only consists of a single county), I define his local labor market to be that county. If, on the other hand, a worker's county-of-residence belongs to a metropolitan area, the metropolitan area is assumed to be the local market.[9] The final sample identifies job changes in 349 local markets, 190 of which are metropolitan areas.

Characteristics describing these local labor markets are derived from four primary sources: (i) the Census Bureau's Population Estimates Program, (ii) the USA Counties

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job after a few weeks of unemployment, no job change is recorded. The worker is treated as having held a single job over this period.

[7]To the extent that quits and layoffs vary systematically with the business cycle (e.g. layoffs tend to be countercyclical; quits are somewhat procyclical - see Bleakley et al. (1999)), the analysis below partially accounts for differences in the frequency of industry switches by quit-layoff status by including the influence of two local business cycle measures on the likelihood of an industry change.

[8]The number of job changes ranges from a minimum of 1 to a maximum of 19, with a standard deviation of 3.34. Still, the median (3 changes) and 75th percentile (6 changes) indicate that much of the sample lies near the mean.

[9]Metropolitan areas refer more specifically to metropolitan statistical areas (MSAs), primary metropolitan statistical areas (PMSAs), and New England County Metropolitan Areas (NECMAs). Aggregation of counties to metropolitan areas is done using 1995 definitions. See U.S. Bureau of the Census (1999).

1998 on CD-ROM (U.S. Bureau of the Census (1999)), (iii) the Bureau of Labor Statistics' Local Area Unemployment Statistics, and (iv) County Business Patterns (CBP) files for the years 1978 to 1994. The first data set provides estimates of total resident population for each county in the U.S. for each year between 1978 and 1994. The second has information on county-level land area (for 1990) which allows me to compile a time series of population densities for all markets. The BLS data provide state-level unemployment rates for each year between 1978 and 1994 from which I estimate local market unemployment rates (see Appendix). The CBP files contain data on total employment in each county for industries at the four-digit (SIC) level which are used to construct a measure of industrial heterogeneity.

When looking at job changes, I consider industry changes at two different levels: an approximate 1-digit level and a 3-digit level. There are a total of 13 industries in the former categorization (see Appendix for a list), 207 in the latter.

Summary statistics describing the workers in the sample and some of the local market characteristics considered appear in Table 1. From these, it is evident that industry changes are quite common in this sample. Across the 4473 job changes, 65 percent involve a change of 1-digit industry while 81 percent involve a change of 3-digit industry. As shown in Table 2, this basic pattern holds throughout much of a worker's early job history. After grouping job changes into four categories - first change, second change, third change, fourth change or more - the frequencies remain above 60 percent for all four groups in the 1-digit classification and near 80 percent in the 3-digit classification. There is, however, some tendency for industry changes to become less frequent, at least when comparing the average over the first three job changes to the average across the fourth or more. This, of course, is exactly what one would expect if workers tend to find better industry matches over time.

Interestingly, when comparing metropolitan and non-metropolitan areas, some notable differences emerge. Most importantly, for first job changes, the frequency of industry

switches is higher within metropolitan areas than it is among non-metropolitan areas. However, this ordering gradually flips as we move through the sequence of jobs so that, by the time a worker makes a fourth job change or more, the likelihood that it involves a change of industry is lower in a metropolitan area than a non-metropolitan area. On the surface, this pattern is consistent with the hypothesis described above.

2.2 Statistical Methods

Because the fundamental object of interest is a binary indicator describing whether a job change involves a change of industry or not, I use a probit model to characterize the likelihood that such a change is made. Letting y_{imt} represent an industry-change indicator for worker i of local market m in year t, the probability that a worker changes industries follows as

$$\text{Prob}(y_{imt} = 1|\mathbf{x}_{imt}, \mathbf{z}_{mt}, \text{Scale}_{mt}; \beta, \delta, \mu_t, \gamma) = \Phi(\beta\mathbf{x}_{imt} + \delta\mathbf{z}_{mt} + \mu_t + \gamma\text{Scale}_{mt}) \equiv \Phi_{imt} \quad (1)$$

where $\mathbf{x}_{imt}$ is a vector of personal covariates, including three educational attainment dummies (college graduate, some college or an associate's degree, high school graduate), a quadratic in cumulative work experience, and indicators for marital status and race, all of which are evaluated at the beginning of a worker's new job. The vector, $\mathbf{z}_{mt}$, contains two indicators of the state of local market m's business cycle in year t: aggregate county/metropolitan area employment growth and the unemployment rate, both measured in the year in which the job change is observed. If changes of industry are particularly pronounced during, say, economic downturns, these quantities should help capture this effect. The term μ_t is a time dummy, intended to pick up any aggregate U.S. labor market effects on the likelihood of an industry shift (if, for example, certain years involved partic-

ularly large or small inter-industry employment shifts), and Scale_{mt} represents the scale of a worker's local labor market, the measurement of which is described below.

In a probit model, of course, $\Phi(\cdot)$ is the normal cumulative distribution function, and the parameters are chosen to maximize the sum of the log likelihoods over all observations, where the contribution from worker i of local market m in year t is

$$y_{imt}\log(\Phi_{imt}) + (1 - y_{imt})\log(1 - \Phi_{imt})$$

To quantify local market scale, I use three common metrics from the agglomeration literature: the logarithm of total resident population, the logarithm of population density, and a measure of industrial diversity. The last of these, diversity, is given by a 'Dixit-Stiglitz' index (Ades and Glaeser (1995)) based on a 4-digit (SIC) industrial breakdown. For local market m at time t,

$$\text{Diversity}_{mt} = \left(\sum_j \left(\frac{\text{Emp}_{jmt}}{\text{Emp}_{mt}} \right)^{\frac{1}{2}} \right)^2$$

where Emp_{jmt} denotes industry j's employment in market m at time t, and Emp_{mt} represents total employment in m at t. By construction, larger values of this index represent greater diversity. As with the personal covariates, $\mathbf{x}$, each these scale variables, Scale_{mt}, is set equal to its value at the beginning of a worker's new job for the purposes of estimation.

3 Results

3.1 Pooled Estimates

I begin with a simple specification of (1) in which all job changes, regardless of their places in a worker's labor market history, are pooled together. The resulting parameter estimates appear in Table 3, both for industry changes based on a 1-digit classification and those based on a 3-digit classification. In each case, three specifications appear, one for each of the three measures of local market scale.

For the most part, the coefficient estimates demonstrate a number of well-known, or at least intuitive, results. Education, for example, tends to be negatively associated with changes of industry, at either level of aggregation, which is similar to what Neal (1998) finds. Relative to high school dropouts, workers with a bachelor's degree have a 3 to 7 percentage point lower probability of changing industries when they change jobs, whereas for workers with some education at the college level, the estimates suggest a probability that is 6 to 9 percentage points lower. These results are consistent with the idea that highly educated workers tend to be specialized in terms of the types of work they perform, perhaps because they possess relatively large stocks of specific human capital.

In addition, the probability that a worker switches industries decreases with cumulative work experience (on all jobs), although the positive sign on the quadratic term suggests that this association diminishes over time in magnitude. This finding suggests that, as workers spend more and more time in the workforce, they gradually settle into one particular line of work. Finally, workers who are married and white are also less likely to change industries when experiencing a change of employer. All of these associations are statistically significant at conventional confidence levels.

The coefficients on the three measures of local market size, by contrast, are uniformly insignificant across both levels of industrial aggregation. Although the majority of the point estimates are negative (especially among 1-digit changes), suggesting that metro areas may help to sort workers better into industries than smaller markets, none is sufficiently large in magnitude to allow this conclusion to be drawn with any real confidence.

3.2 Estimates by Job Number

A pooled specification, however, should not adequately capture the influence of labor market scale and diversity on a worker's pattern of industry changes. Recall, if agglomeration enhances the career search process, workers in diverse urban markets should make complex

changes more frequently in the early stages of their careers than workers in smaller markets because the costs associated with trying out different types of work are lower in large markets. Greater experimentation should then translate into workers finding optimal industry matches more quickly, and, as a consequence, making fewer industry changes later on.

To address this possibility, I re-estimate (1) allowing the association between local market scale and the frequency of industry shifts to differ depending on how many job changes have already occurred. Specifically, I allocate all job changes into one of four groups: first job changes, second job changes, third job changes, fourth job changes or more.[10] I then interact each of the three local market scale variables with indicators for these four groups and include them in the estimation.[11] The resulting coefficient estimates appear in Table 4. The coefficients from each of the personal characteristics have been suppressed since they do not differ substantially from what is reported in Table 3.

What is by far the most striking aspect of the results in the two tables is the decrease in the estimated population, density, and diversity associations with the frequency of industry shifts as the number of job changes that a worker has experienced increases. Among the 1-digit results, all three measures of local market scale produce significantly positive coefficients for the first job change, implying an increase in the probability that a job change involves a change of industry. These associations, however, gradually decrease, and turn negative by the third observed job change. By the time a worker makes his fourth job change, there is a significantly negative association between local market scale and the likelihood of an industry switch. Among 3-digit industries, the pattern is qualitatively similar, although there appears to be an increased likelihood of an inter-industry move during the

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[10]These groups have, respectively, 1029, 825, 622, and 1997 observations. Results given below provide some justification for this grouping scheme.

[11]The job-change indicators themselves are also included in the estimation to pick of any 'level' differences in the likelihood of an industry switch.

first *two* job changes, not just the first. This pattern may reflect an increased need for workers to experiment with different types of work in order to find an optimal match among a more detailed categorization of jobs. Nevertheless, by the time a worker makes his fourth or higher-number job change, the association becomes negative just as in the 1-digit results.[12] This is precisely what the hypothesis above suggested.

How sizable are these implied associations? Looking at the 1-digit industry results, a 1 standard deviation increase in log population correlates with a 3.1 percentage point increase in the likelihood that a worker's first job change will involve an industry switch.[13] For workers making their fourth transition or more, that same 1 standard deviation increase in log population is accompanied by a 2.9 percentage point drop in the likelihood of an industry change. The magnitudes are similar for density (a 3.2 percentage point increase for first job changes, a 1.9 percentage point decrease for fourth changes or more) and diversity (a 3.9 percentage point increase for first changes, a 3.4 percentage point decrease for fourth changes or more). These figures are not substantially different from the estimated associations with many of the personal covariates, including education, marital status, and race. Given the significance usually placed on these particular characteristics, the relationship between the features of a worker's local market and his pattern of industry changes appears to be economically important.

To put these figures into the context of some specific local markets, consider the implied differences in the frequency of 1-digit industry changes between observationally equivalent workers in the following two metropolitan areas: Cheyenne, Wyoming and Chicago, Illinois. Cheyenne in 1994 had a population of approximately 78000, with a density of 29 residents

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[12]Wald test statistics of the null hypothesis that the associations between scale and the likelihood of an industry change are equal for all four job-change categories appear in the final row of Table 4. In each case, I am able to reject this null at conventional confidence levels.

[13]The standard deviations of log population, log density, and diversity (divided by 1000) are roughly 1.8, 1.7, and 0.1.

per square mile, and a diversity index of 109. Chicago, by contrast, had a population of roughly 7.7 million, a density of more than 4100 residents per square mile, and a diversity index equal to 354. The point estimates from Table 4 suggest that the likelihood of an industry switch during a worker's first job change is 7.8 to 9.6 percentage points higher in Chicago than in Cheyenne. Among job changes made after the third, however, the probability of an industry switch is 5.4 to 8.3 percentage points lower in Chicago than in Cheyenne.

The magnitudes are somewhat more modest when considering 3-digit industry changes. A 1 standard deviation increase in log population, for instance, corresponds to a 2.5 percentage point increase in the probability of switching industries on a first job change and a 2 percentage point decrease in that same probability for fourth job changes or more. Part of the reason for this dropoff may be the relative frequency with which 3-digit industry changes occur in these data when compared to 1-digit changes. Recall, roughly 80 percent of all job changes involve a 3-digit industry change whereas 60 to 65 percent entail a change of 1-digit industry. The reduced variation in the extent of industry switches may contribute to the smaller estimated coefficients. Still, precisely the same qualitative pattern can be discerned from both the 1- and 3-digit results, at least when considering population and diversity as measures of scale. First jobs are more likely to involve industry switches in large markets, while later job changes, especially those beyond the third change, are less likely to do so.

Just how far does this pattern go? That is, if one were to look at, say, fourth, fifth, and sixth job changes, would the estimated coefficients continue to decline? Results from a more extensive specification of equation (1), in which I estimate a population, density, and diversity 'effect' for each of the first 9 job changes as well as a category for a worker's tenth change or more, appear in Table 5.[14] The coefficients demonstrate that the dropoff does not

[14]There are 1029 first changes, 825 second changes, 622 third changes, 495 fourth changes, 401 fifth

14

continue in any substantial way beyond the fourth change, although there is a discernible decrease in the coefficients among the eighth and ninth changes in the 1-digit results. At the same time, there is little overall tendency for the coefficients to rise significantly beyond the fourth job change. There is a small increase in the estimated associations among the sample of fifth job changes, but this increase does not appear to be part of any trend in the coefficients. In fact, Wald tests of the hypothesis that the coefficients on the last 7 job-change categories are equal largely fail to reject this null, providing some justification for the use of four job-change categories above. The test statistics are reported in the final row of the table.

Allowing for a more extensive array of job-change categories, therefore, does not seem to change the basic conclusion drawn above. The association between local market scale and the likelihood that a worker experiences a change of industry when switching jobs gradually decreases as that worker moves through his first several employment experiences. Across both industry levels and all three local market features, the associations are positive for the first 2 job changes (and mostly significant for the first job change). Among the remaining 8 job-change categories, only 9 of the 48 total coefficients are positive.[15]

3.3 Selection

A common concern in studies of location involves the non-randomness with which individuals are allocated geographically. In general, people choose where to live, and workers with certain characteristics may choose markets that differ with respect to size, density, and diversity from those selected by workers with different characteristics. This selection issue

changes, 300 sixth changes, 228 seventh changes, 176 eighth changes, 116 ninth changes, 281 tenth changes or more. As before, the 10 indicators for job changes also appear in the estimating equations.

[15]Wald tests reported in the penultimate row of Table 5 soundly reject the null hypothesis that all 10 job-change coefficients are equal for all but one specification: log density among 3-digit industry changes.

is particularly problematic, for example, in studies of the urban wage premium. Workers in large metro areas, after all, may receive relatively high wages because they are inherently more productive than workers in smaller places, not because urban areas make them more productive.

There may very well be a selection issue to contend with here too. However, in assessing any potential bias in the results, two features of the data and results are worth highlighting. First, the NLSY79 is a sample of young workers. Again, at the beginning of the sample time frame, all respondents are between the ages of 14 and 21. Because young workers may not have had sufficient time and experience (e.g. learning about what they do well and where they can receive the most for doing it) to sort themselves geographically, the selection issue may not be as substantial as it would be for older workers.

Second, given the nature of the results, there would remain a significant association between urban scale and the likelihood of an industry change at some point in a worker's career, regardless of the nature of the selection mechanism. For example, if workers in big metro areas simply possess a lower propensity to change industries, the negative estimated influence of urban scale on the likelihood of an industry switch after the third job change would be an overstatement of the true effect. At the same time, however, the positive estimated influence of urban scale on the probability of an industry switch in the first (or even second) job change would be an *understatement* of the true effect. If, on the other hand, workers in large metro areas have chosen to locate there so they can experiment with different types of jobs, the positive coefficients observed for early job changes would be biased upward. Of course, the estimated negative influence of urban scale on the probability of a change-of-industry in later job changes would, in this case, be understated by the reported coefficients.

Both possibilities may still be consistent with a search and matching interpretation.

The notion that urban scale makes it increasingly likely for workers with an especially low propensity to change industries to do so early in their careers may indicate that the presence of greater opportunities to try different types of jobs encourages workers to experiment to a greater extent. In the opposite case, the idea that large, diverse markets reduce the frequency with which workers who are particularly likely to change industries actually do so later in their careers might indicate that they have been able to find productive matches relatively quickly in these environments.

3.4 Robustness

At this point, I consider two basic modifications of the foregoing analysis in an attempt to gauge the robustness of the findings. With the first, I attempt to eliminate the effects of highly mobile individuals on the results by looking only at those workers who experience 10 or fewer total job changes over the 1978-1994 period. Recall, although the mean number of job changes among the 1029 workers in the total sample is 4.35, the maximum is 19. Trimming the sample in this way is intended to remove some of the noisiest observations from the sample. Doing so leaves a total of 964 workers who make, on average, 3.76 job changes each.[16]

The second modification involves workers who, at some point during the sample time frame, move. Of the 1029 workers in the full sample, 419 are observed in more than one location between 1978 and 1994. The analysis so far has not accounted for the potential influence of these changes in location, yet there are clearly reasons why they might matter. To begin, geographic moves might be associated with an increased likelihood of changing industries, particularly if moves are associated with workers 'starting over.' Moreover, having workers move between markets may pose a problem for the interpretation of the

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[16]In this case, the median number of job changes is 3; the 75th percentile is 5; the standard deviation is 2.5.

results in the context of learning or experimentation in local markets. Workers may, for example, begin their working lives in a large, urban labor market where they try several different industries until finding the best one. They might then move on to a smaller market where they only make simple job changes. Similarly, workers who initially reside in small markets may have a series of jobs in only a single industry due to the lack of economic variety, but then try different sectors upon moving to a diverse urban market.

Although these latter two possibilities stand somewhat at odds with the evidence shown thus far in that they suggest that large metropolitan areas should be characterized by high rates of industry switching regardless of the number of jobs held previously, I attempt to address the issue of geographic moves in two ways. In the first, I keep the full sample of 4473 job changes and include dummies for whether a job change also entails an urban-to-urban, urban-to-rural, rural-to-urban, or rural-to-rural change in location.[17] In the second, I simply drop all individuals for whom a move is observed at some point during the sample time frame. Doing so leaves a total of 2354 job changes over 610 workers.

For all three modifications, the estimates appear in Table 6. In general, the coefficients demonstrate much the same pattern as what we have already seen. Nearly all of the associations across the two different industry levels are positive for the first job change and then gradually become negative as second, third, and fourth changes are experienced. Indeed, in 15 of the 18 specifications listed in the table, Wald tests reject (at conventional levels) the null hypothesis that all four job-change coefficients are equal.

There is, to be sure, some decrease in the magnitudes of the associations for first job changes, particularly among the sample of non-movers. None of the first job-change coefficients within that group are significant, although three of the second job-change coefficients are. On the other hand, the majority of coefficients among the fourth-or-more job-change

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[17]'Urban' refers to residence within a metropolitan area. A change of residence within a metropolitan area (or any other local market) is *not* counted as a move.

category are negative and significant. Of the 6 coefficients listed in the table among the sample of 610 non-movers, 5 are statistically less than zero. What is more, the magnitudes are actually somewhat larger than what was estimated from the full sample. Hence, although there may be less evidence in these results that workers are more likely to shift industries when making first job changes in large labor markets, there is still a fair amount of evidence that they are less likely to do so among later job changes.

3.5 Patterns by Educational Attainment

The extent to which individuals attempt to experiment with different types of work during their careers may depend on the amount of human capital they have accumulated. Workers with especially high levels of formal education, for example, may be focused on specific types of work and would, therefore, require fewer changes of industry. College graduates, then, might not conform to a similar pattern of industry switches over their careers as, say, high school graduates.

In this section, I explore this hypothesis a bit further by considering whether the estimated associations between local market scale and the prevalence of an industry switch at various points in a worker's job history differ across workers with different levels of schooling. To do so, I merely extend the regressions performed above by including interactions between the job change-local market scale variables and each of four education indicators: high school dropout, high school graduate, some college or an associate's degree, college graduate.[18] The results appear in Table 7.

Perhaps surprisingly, they reveal a similar qualitative pattern for nearly all four education groups. To be sure, the estimates are somewhat noisier and more variable than those

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[18]The regressions also include interactions between the education indicators and the job change indicators to capture any overall differences between the likelihood of an industry switch between differently educated workers at various points in their job histories.

reported previously (e.g. the coefficients on the scale-first job change interactions are negative for high school graduates). However, there remains evidence of a tendency for industry switches to be more frequent in large markets early on in a worker's career, but less frequent later on. In the vast majority of the education group-industry level pairings, the coefficients tend to drop as one moves from the first change to the fourth or more. Admittedly, fewer of the individual coefficients are now statistically significant, and only 9 of the 24 reported Wald statistics reject the equivalence of the four coefficients reported for each education group-industry level pairing. However, the results suggest that the industry switch-local market scale pattern established above holds to some degree across workers of all education levels.

In fact, formal tests (not reported) do not reveal substantial differences across the four groups. While the point estimates reveal some interesting findings (e.g., college graduates seem to be especially likely to change industries in large, economically diverse metro areas when making their first job changes, whereas high school graduates do not), Wald tests largely reject the notion that there are cross-education group differences. In only 3 of the 24 instances can I reject the hypothesis that a given industry change-local market size association (e.g. first changes by 1-digit industry and population, fourth changes by 3-digit industry and diversity) differs across all four groups. I interpret this evidence as an indication that the pooling of workers with different levels of formal schooling, as in the estimation above, is a reasonable approach.

3.6   Job Changes and Wage Growth

Although consistent with the idea that large, dense, diverse local markets facilitate job matching, the findings documented above provide little direct evidence on the productivity effects of local market scale. Indeed, if the extent of a worker's labor market influences his ability to identify and establish more productive matches over time through experimenta-

tion, we should observe faster wage growth through job changes in larger markets.

In a related paper, Wheeler (2006), I explore this implication using the same NLSY79 sample employed here. In particular, I examine the association between the same three measures of market scale - population, density, diversity - and two measures of wage growth: growth experienced on a particular job (within-job growth) and growth experienced when a worker moves from one job to another (between-job growth). The findings indicate that, conditional on a host of person-specific covariates such as education and work experience, there is little association between within-job growth and local market scale. Workers in large, urban markets do not see their wages grow faster on particular jobs than comparable workers in small markets.

Between-job wage growth, however, shows a significantly positive association with all three scale measures. Based on the magnitudes of the estimates, a 1 standard deviation increase in population, density, or diversity tends to be accompanied by a 1 percentage point increase, roughly, in the wage change a worker experiences when he changes jobs. This magnitude turns out to be quite large, representing approximately 16 percent of the mean wage change observed when workers in this sample change jobs. These findings, of course, can be interpreted along the lines of what Jovanovic (1979) and Topel and Ward (1992) find: that workers tend to find better matches over time, and that the extent of the local labor market facilitates this process. Moreover, they suggest that the pattern of industry switches documented in this paper is an important aspect of this mechanism.

3.7 Local Market Scale and the Frequency of Job Changes

One final question that I investigate is whether workers in larger local markets actually make fewer job changes overall. If the extent of a worker's labor market really enhances his or her ability to find a good match, we should see workers in such markets making fewer job changes overall.

In this section, I delve into this matter by evaluating whether the total number of job changes a worker experiences increases or decreases with the scale of his local labor market. A negative association, for example, would indicate that, conditional on features like cumulative work experience and education, workers in larger markets experience fewer job changes, suggesting that larger labor markets ultimately allow workers to find better firm-worker matches.

Admittedly, this empirical exercise is somewhat tenuous because the same conclusion could be drawn from finding a *positive* association between local market scale and the number of job changes. Finding an optimal match, after all, may require many job changes. Hence, workers in large markets may be better matched to their jobs than observationally equivalent workers in smaller markets, but simply require greater numbers of job changes in order to find those better matches.

Still, while a positive association could just as easily be interpreted as indicating that larger markets create *less* productive matches, it would be more difficult to interpret a negative association in this way. Again, if workers leaving jobs signifies poor match quality, why would fewer job changes be an indication of less efficient matching?[19] Finding a negative association between local market scale and the frequency of job changes, therefore, should lend some additional support to the idea that agglomeration facilitates the creation of productive matches.

Because the dependent variable in this case, the number of job changes, constitutes the count of a particular event, I estimate a negative binomial regression[20] in which the

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[19]One could argue, of course, that workers in large, diverse markets have fewer outside options, thereby forcing them to remain in unproductive matches. Existing evidence, however, suggests that finding work is actually somewhat *easier* in large, diverse markets. In particular, diverse metropolitan areas tend to have lower rates of frictional unemployment (Simon (1988)), and workers in large cities tend to experience shorter unemployment durations (Alperovich (1993), Gan and Zhang (2004)).

[20]Results from a Poisson regression are qualitatively similar to those reported here. However, the fact

probability that a worker has experienced n job changes, conditional on personal covariates $\mathbf{x}$, local market size z, and a stochastic element u, $f(n|\mathbf{x}, z, u)$ is specified as

$$f(n|\mathbf{x}, z, u) = \frac{(\lambda u)^n \exp(-\lambda u)}{n!} \qquad (2)$$

where the term λ is modeled as a linear function of $\mathbf{x}$ and z. These variables are the same as those considered in the analysis above. As is common in the estimation of count models, the stochastic element, u, is assumed to have a gamma distribution.[21] Integrating over the distribution of u then generates the following expression for the distribution of n conditional on $\mathbf{x}$ and z:

$$f(n|\mathbf{x}, z) = \frac{\Gamma(\alpha + n)}{\Gamma(n+1)\Gamma(\alpha)} r^n (1-r)^\alpha \qquad (3)$$

where α is a parameter of the gamma distribution (to be estimated), $r = \frac{\lambda}{\lambda + \alpha}$, and $\Gamma(\cdot)$ is the gamma function. The likelihood function describing the sample then follows as the product of (4) taken across all workers.

One estimation issue associated with equation (4) deserves to be mentioned at this point: not all of the covariates are constant for each individual. While race and education do not change (these are post-education jobs), cumulative work experience and the size and diversity of the local labor market tend to be different on different jobs. To estimate the model, I set each worker's personal and labor market characteristics equal to their values at the beginning of their last observed job.[22] Results are reported in the first three columns of results in Table 8.

that variance of the job-change distribution is nearly 3 times the mean suggests that the Poisson provides an inappropriate statistical representation of these data.

[21] See Greene (2000, pp. 886-887).

[22] At least for cumulative work experience, this is sensible practice. After all, correlating the number of

Looking at the personal covariates, many of the associations are quite reasonable, at least in an intuitive sense. Higher levels of education are associated with fewer job changes, whereas the number of changes tends to rise with cumulative work experience. In addition, workers who are married and white tend to experience fewer job changes in the sample.

As for the coefficients on market scale, all are negative and statistically significant. Hence, consistent with the idea that agglomeration generates better firm-worker matches, the results indicate that workers in large, dense, or diverse markets make, on average, fewer total numbers of job changes conditional on their personal characteristics.

A similar result emerges when the sample is confined to workers who are not observed changing labor markets at any point during the 1978-1994 period. Although dropping all movers does eliminate a large fraction of the full sample (419 of 1029), it again provides a tighter link between a worker's history of job changes and the features of his labor market. Those results appear in the final three columns of Table 8. While the coefficient magnitudes in this case are somewhat smaller than what was observed for the full sample, the coefficients on log population, log density, and diversity all remain negative.

It should be noted that these results are based upon the same sample of workers used in the remainder of the paper. Hence, these findings should be interpreted as being conditional on making at least one job change. As it turns out, when I add the 52 workers from the NLSY79 who are observed in only one job between 1978 and 1994, I arrive at similar results. The resulting coefficients (standard errors) on log population, log density, and diversity are -0.017 (0.011), -0.022 (0.012), and -0.32 (0.2) among both movers and non-movers; -0.007 (0.02), -0.013 (0.017), and -0.11 (0.3) among non-movers alone.

job changes a worker has experienced with the total length of time he has spent working is a meaningful exercise. Correlating the total number of job changes with the amount of experience acquired only through part of his labor market history is not.

4 Conclusion

The idea that urban agglomeration facilitates the creation of productive firm-worker matches has been discussed at least since Marshall (1920). However, while a sizable body of theoretical work has studied the issue, very little empirical research has explored the topic.

This paper has examined the pattern of job changes among young male workers, looking at the frequency of industry changes in markets of varying sizes and degrees of economic diversity. Again, the results indicate that industry changes occur more often in large, diverse local markets than in small, specialized ones within a sample of first job changes. Once a worker has held several jobs, however, this positive relationship becomes significantly negative. Given that workers in large markets also tend to experience fewer job changes overall, the evidence is broadly consistent with the theory that agglomeration facilitates labor market matching through a learning process.

Several implications might be drawn from these results. First, and most obviously, a significant part of the urban wage premium - which most studies find to be the result of increased productivity in large cities (e.g. Glaeser and Mare (2001)) - may come directly through the job matching process. Second, metropolitan areas have long been populated by relatively young individuals. Although some have interpreted this result as a manifestation of young workers seeking diverse environments where they can acquire human capital (e.g. Glaeser (1999), Peri (2002)), the analysis here suggests that young workers may flock to metropolitan areas to find a career. Third, while urban areas have long been seen as engines of national economic growth through their influence on technological change and human capital accumulation (e.g. Lucas (1988), Black and Henderson (1999)), they should also be viewed as a fundamental element in the efficient functioning of national labor markets. Finally, and more speculatively, it is possible that the success of programs aimed at helping workers to find stable employment may depend, in part, on the extent of the local market.

This paper, however, represents only a very modest step in the empirical analysis of this issue. Indeed, there are many additional features of worker job histories that could be explored to evaluate it further. For example, do jobs created in large urban markets last longer than those created in smaller markets? Following Jovanovic (1979), if the length of time a worker remains on a job provides some indication of the quality of the match, do workers in urban labor markets experience longer job durations than their rural counterparts? This type of analysis would likely represent an improvement over what is presented with respect to total numbers of job changes in Section 3.7.

Further analysis could also explore periods in which individuals are not working. In particular, do workers tend to experience longer or shorter periods of unemployment in large metro areas? Although previous work has examined the relationship between average unemployment duration and city size (e.g. Alperovich (1993) and Gan and Zhang (2004)), I am unaware of any micro-level studies looking at the length of time young workers in markets of varying sizes spend between jobs during the early stages of their careers. Given the relative scarcity of empirical work on the topic of labor market matching in local labor markets, these (and other) questions would be worthwhile to pursue.

Table 1: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
College	0.19	0.39	0	1
Some College	0.19	0.39	0	1
High School	0.49	0.5	0	1
Cumulative Weeks of Work Experience	220.4	164.6	2	823
Married	0.32	0.47	0	1
Non-White	0.18	0.39	0	1
1-Digit Industry Changes	0.65	0.48	0	1
3-Digit Industry Changes	0.81	0.39	0	1
Population	1556281	2087040	3562	9064197
Population Density	1458.5	3407.2	2.5	26697.2
Dixit-Stiglitz Diversity Index	203.1	95.3	11.8	376.5

Note: Means taken across 4473 observed job changes.

Table 2: Frequency of Industry Changes

	1-Digit			3-Digit		
	All	Metro Areas	Non-Metro Areas	All	Metro Areas	Non-Metro Areas
First Job Change	0.67	0.68	0.62	0.84	0.84	0.81
Second Job Change	0.68	0.68	0.66	0.83	0.83	0.81
Third Job Change	0.69	0.68	0.75	0.84	0.84	0.86
Fourth Job Change or More	0.62	0.61	0.66	0.77	0.76	0.81

Note: Means taken across 1029 first job changes, 825 second job changes, 622 third job changes, 1997 fourth or more job changes. Numbers of job changes in metropolitan areas are 822 first changes, 656 second changes, 490 third changes, 1552 fourth or more changes.

Table 3: Industry Changes and Urban Scale

Pooled Estimates

	1-Digit			3-Digit		
	I	II	III	I	II	III
College	-0.06*	-0.07*	-0.06*	-0.03	-0.03	-0.03
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Some College	-0.09*	-0.09*	-0.09*	-0.06*	-0.06*	-0.06*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
High School	-0.005	-0.004	-0.005	0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Experience	-0.0005*	-0.0005*	-0.0005*	-0.0005*	-0.0005*	-0.0005*
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Experience Squared	0.004*	0.004*	0.004*	0.005*	0.005*	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Married	-0.06*	-0.06*	-0.06*	-0.02*	-0.02*	-0.02*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Non-White	0.04*	0.04*	0.04*	0.04*	0.04*	0.04*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Employment Growth	0.07	0.07	0.07	0.18	0.19	0.18
	(0.19)	(0.18)	(0.18)	(0.15)	(0.15)	(0.15)
Unemployment Rate	0.004	0.004	0.004	0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
Log Population	-0.003	–	–	0.001	–	–
	(0.004)			(0.003)		
Log Density	–	-0.0002	–	–	0.003	–
		(0.004)			(0.004)	
Diversity	–	–	-0.05	–	–	-0.006
			(0.08)			(0.06)

Note: 4473 observations. Dependent variable is indicator for 1- or 3-digit industry change. Coefficients are reported as marginal effects, evaluated at the mean values of the covariates. The coefficients on experience squared and the diversity index have been multiplied by 10000 and 1000. Time effects are included throughout. Standard errors are given in parentheses. An asterisk (*) denotes statistical significance at 10 percent or better.

Table 4: Industry Changes and Urban Scale

By Job Number

	1-Digit			3-Digit		
	I	*II*	*III*	*I*	*II*	*III*
First Change*	0.017*	–	–	0.014*	–	–
Log Population	(0.008)			(0.007)		
Second Change*	0.01	–	–	0.018*	–	–
Log Population	(0.009)			(0.008)		
Third Change*	-0.01	–	–	0.003	–	–
Log Population	(0.01)			(0.009)		
Fourth Change or More*	-0.016*	–	–	-0.011*	–	–
Log Population	(0.006)			(0.005)		
First Change*	–	0.019*	–	–	0.012	–
Log Density		(0.009)			(0.007)	
Second Change*	–	0.008	–	–	0.017*	–
Log Density		(0.01)			(0.008)	
Third Change*	–	-0.006	–	–	0.008	–
Log Density		(0.011)			(0.009)	
Fourth Change or More*	–	-0.011*	–	–	-0.007	–
Log Density		(0.006)			(0.005)	
First Change*	–	–	0.39*	–	–	0.27*
Diversity			(0.16)			(0.14)
Second Change*	–	–	0.22	–	–	0.28*
Diversity			(0.18)			(0.15)
Third Change*	–	–	-0.13	–	–	0.02
Diversity			(0.21)			(0.18)
Fourth Change or More*	–	–	-0.34*	–	–	-0.23*
Diversity			(0.11)			(0.09)
Wald Test	13.1	8.6	16.6	15.1	8.6	14.2
	(0.004)	(0.04)	(0)	(0.002)	(0.03)	(0.003)

Note: 4473 observations. Dependent variable is indicator for 1- or 3-digit industry change. Coefficients are reported as marginal effects, evaluated at the mean values of the covariates. Standard errors are given in parentheses. Estimating equations also include all variables considered in Table 3 as well as indicators for job-change number. 'Wald Test' reports statistic from test of the null that all four job-change coefficients are equal (p-value under the null in parentheses). An asterisk (*) denotes statistical significance at 10 percent or better.

Table 5: Industry Changes and Urban Scale

Extended Specification by Job Number

	Log Population	Log Density	Diversity	Log Population	Log Density	Diversity
First Change	0.017*	0.018*	0.39*	0.014*	0.012	0.39*
	(0.008)	(0.009)	(0.16)	(0.007)	(0.007)	(0.16)
Second Change	0.01	0.007	0.22	0.018*	0.017*	0.22
	(0.009)	(0.01)	(0.18)	(0.008)	(0.008)	(0.18)
Third Change	-0.01	-0.006	-0.13	0.003	0.008	-0.13
	(0.01)	(0.012)	(0.21)	(0.009)	(0.01)	(0.21)
Fourth Change	-0.017	-0.029*	-0.45*	-0.012	-0.015	-0.44*
	(0.012)	(0.013)	(0.23)	(0.01)	(0.01)	(0.24)
Fifth Change	0.014	0.03*	0.26	-0.004	0.006	0.26
	(0.013)	(0.014)	(0.25)	(0.01)	(0.01)	(0.25)
Sixth Change	-0.02	-0.011	-0.35	-0.015	-0.012	-0.35
	(0.015)	(0.016)	(0.29)	(0.012)	(0.012)	(0.29)
Seventh Change	-0.008	-0.001	-0.28	0.002	0.01	-0.28
	(0.017)	(0.018)	(0.32)	(0.01)	(0.01)	(0.32)
Eighth Change	-0.04*	-0.04*	-0.9*	-0.02	-0.017	-0.9*
	(0.02)	(0.02)	(0.37)	(0.014)	(0.015)	(0.37)
Ninth Change	-0.039*	-0.028	-0.6	-0.026	-0.03	-0.6
	(0.02)	(0.025)	(0.44)	(0.02)	(0.02)	(0.44)
Tenth Change	-0.03*	-0.015	-0.55*	-0.011	-0.0006	-0.55*
or More	(0.015)	(0.016)	(0.29)	(0.012)	(0.012)	(0.29)
Industry Level	1-Digit	1-Digit	1-Digit	3-Digit	3-Digit	3-Digit
Wald Test	22.8	20.9	25.5	17.2	13.5	25.5
	(0.007)	(0.01)	(0.002)	(0.05)	(0.14)	(0.002)
Wald Test of	9.87	13.03	9.1	2.54	5.7	9.1
Last 7 Coefficients	(0.13)	(0.04)	(0.17)	(0.86)	(0.45)	(0.17)

Note: Dependent variable is indicator for 1- or 3-digit industry change. Probit estimates of coefficients on interactions between log population, log density, and diversity with indicators for job-change number. Standard errors are given in parentheses. Estimating equations also include all variables considered in Table 3 as well as indicators for job-change number. 'Wald Test' reports statistic from test of the null that all ten job-change coefficients are equal (p-value under the null in parentheses). 'Wald Test of Last 7 Coefficients' reports statistic from test of the null that the coefficients on the fourth through tenth-or-more groups are equal (p-value in parentheses). An asterisk (*) denotes statistical significance at 10 percent or better.

Table 6: Robustness Checks

Modification	Variable	First Change	Second Change	Third Change	Fourth Change or More	Industry Level	Wald Test
10 Changes or Fewer	Log Population	0.016*	0.01	-0.01	-0.017*	1-Digit	10.9
		(0.009)	(0.01)	(0.01)	(0.007)		(0.01)
	Log Density	0.019*	0.005	-0.007	-0.015*	1-Digit	8.6
		(0.009)	(0.01)	(0.01)	(0.008)		(0.04)
	Diversity	0.38*	0.21	-0.14	-0.39*	1-Digit	15.2
		(0.17)	(0.19)	(0.22)	(0.14)		(0.002)
	Log Population	0.012*	0.016*	-0.001	-0.008	3-Digit	9.1
		(0.007)	(0.008)	(0.009)	(0.006)		(0.03)
	Log Density	0.011	0.013	0.004	-0.004	3-Digit	3.7
		(0.008)	(0.008)	(0.01)	(0.006)		(0.3)
	Diversity	0.25*	0.25*	-0.05	-0.24*	3-Digit	10.8
		(0.14)	(0.15)	(0.18)	(0.11)		(0.01)
Move Indicators	Log Population	0.013	0.006	-0.013	-0.019*	1-Digit	12.3
		(0.009)	(0.009)	(0.011)	(0.006)		(0.006)
	Log Density	0.016*	0.005	-0.008	-0.013*	1-Digit	8.1
		(0.009)	(0.01)	(0.01)	(0.006)		(0.04)
	Diversity	0.34*	0.17	-0.18	-0.38*	1-Digit	15.8
		(0.17)	(0.18)	(0.21)	(0.12)		(0.001)
	Log Population	0.013*	0.018*	0.003	-0.011*	3-Digit	14.6
		(0.007)	(0.008)	(0.009)	(0.005)		(0.002)
	Log Density	0.011	0.017*	0.008	-0.006	3-Digit	8.2
		(0.008)	(0.008)	(0.01)	(0.005)		(0.04)
	Diversity	0.26*	0.28*	0.02	-0.23*	3-Digit	13.7
		(0.14)	(0.15)	(0.18)	(0.09)		(0.003)

Table 6 Continued

Modification	Variable	First Change	Second Change	Third Change	Fourth Change or More	Industry Level	Wald Test
Non-Movers Only	Log Population	-0.004	0.003	-0.022	-0.026*	1-Digit	4.7
		(0.01)	(0.01)	(0.015)	(0.009)		(0.19)
	Log Density	-0.003	0.005	-0.011	-0.016*	1-Digit	2.1
		(0.01)	(0.01)	(0.015)	(0.009)		(0.55)
	Diversity	0.09	0.2	-0.34	-0.53*	1-Digit	8.4
		(0.21)	(0.25)	(0.29)	(0.17)		(0.04)
	Log Population	0.005	0.024*	-0.007	-0.018*	3-Digit	13.02
		(0.009)	(0.01)	(0.01)	(0.007)		(0.005)
	Log Density	0.005	0.025*	0.001	-0.008	3-Digit	6.95
		(0.009)	(0.01)	(0.01)	(0.007)		(0.07)
	Diversity	0.15	0.55*	-0.15	-0.35*	3-Digit	15.7
		(0.17)	(0.2)	(0.23)	(0.13)		(0.001)

Note: Dependent variable is indicator for 1- or 3-digit industry change. Probit estimates of coefficients on interactions between log population, log density, and diversity with indicators for job-change number. 3628 job-change observations for the '10 changes or fewer' specification; 4473 for the specification including four geographic move indicators (urban-urban, urban-rural, rural-urban, rural-rural); 2354 observations for 'non-movers only' specification. Standard errors are given in parentheses. Estimating equations also include all variables considered in Table 3 as well as indicators for job-change number. 'Wald Test' reports statistic from test of the null that all four job-change coefficients are equal (p-value under the null in parentheses). An asterisk (*) denotes statistical significance at 10 percent or better.

Scale Variable	Education Group	First Change	Second Change	Third Change	Fourth Change or More	Industry Level	Wald Test
Log Population	Dropout	0.03*	0.015	-0.002	-0.027	1-Digit	4.8
		(0.018)	(0.02)	(0.03)	(0.02)		(0.19)
Log Population	High School	-0.015	0.014	-0.001	-0.023*	1-Digit	2.4
		(0.02)	(0.02)	(0.02)	(0.013)		(0.49)
Log Population	Some College	0.021	0.012	-0.027*	-0.01	1-Digit	7
		(0.014)	(0.015)	(0.016)	(0.01)		(0.07)
Log Population	College	0.1*	-0.04	-0.037	-0.015	1-Digit	7.97
		(0.04)	(0.04)	(0.034)	(0.014)		(0.05)
Log Population	Dropout	0.002	0.013	-0.004	-0.032*	3-Digit	4.2
		(0.02)	(0.017)	(0.02)	(0.016)		(0.23)
Log Population	High School	-0.004	0.007	0.011	-0.015	3-Digit	2.47
		(0.015)	(0.016)	(0.019)	(0.01)		(0.48)
Log Population	Some College	0.029*	0.022*	0.005	-0.002	3-Digit	7.38
		(0.012)	(0.012)	(0.013)	(0.006)		(0.06)
Log Population	College	0.035	-0.022	-0.04*	-0.002	3-Digit	5.07
		(0.031)	(0.03)	(0.02)	(0.01)		(0.17)
Log Density	Dropout	0.035*	0.011	-0.024	-0.039*	1-Digit	7.61
		(0.019)	(0.021)	(0.027)	(0.022)		(0.05)
Log Density	High School	-0.01	0.012	-0.005	-0.017	1-Digit	1.25
		(0.02)	(0.023)	(0.03)	(0.013)		(0.74)
Log Density	Some College	0.029*	0.016	-0.03*	-0.001	1-Digit	7.69
		(0.015)	(0.016)	(0.018)	(0.008)		(0.05)
Log Density	College	0.053	-0.036	-0.029	-0.001	1-Digit	3.06
		(0.045)	(0.035)	(0.03)	(0.014)		(0.38)
Log Density	Dropout	0.001	0.01	-0.013	-0.032*	3-Digit	3.66
		(0.02)	(0.016)	(0.02)	(0.017)		(0.3)
Log Density	High School	-0.008	0.014	0.018	-0.011	3-Digit	2.56
		(0.016)	(0.018)	(0.02)	(0.01)		(0.47)
Log Density	Some College	0.037*	0.02	-0.002	-0.0001	3-Digit	7.33
		(0.013)	(0.014)	(0.02)	(0.007)		(0.06)
Log Density	College	-0.003	-0.018	-0.022	0.017	3-Digit	3.51
		(0.03)	(0.027)	(0.022)	(0.011)		(0.32)

Table 7 Continued

Scale Variable	Education Group	First Change	Second Change	Third Change	Fourth Change or More	Industry Level	Wald Test
Diversity	Dropout	0.5	0.29	-0.21	-0.62	1-Digit	5.28
		(0.35)	(0.39)	(0.56)	(0.39)		(0.15)
Diversity	High School	-0.17	0.24	0.08	-0.52*	1-Digit	3.07
		(0.37)	(0.42)	(0.49)	(0.25)		(0.38)
Diversity	Some College	0.5*	0.22	-0.41	-0.17	1-Digit	6.99
		(0.27)	(0.28)	(0.32)	(0.15)		(0.07)
Diversity	College	2.03*	-0.44	0.14	-0.23	1-Digit	7.53
		(0.8)	(0.63)	(0.58)	(0.25)		(0.06)
Diversity	Dropout	0.04	0.16	-0.34	-0.73*	3-Digit	5.13
		(0.29)	(0.32)	(0.5)	(0.3)		(0.16)
Diversity	High School	-0.19	0.06	0.06	-0.39*	3-Digit	2.15
		(0.3)	(0.32)	(0.4)	(0.19)		(0.54)
Diversity	Some College	0.6*	0.45*	0.1	-0.06	3-Digit	8.14
		(0.24)	(0.24)	(0.28)	(0.12)		(0.04)
Diversity	College	0.64	-0.2	0.07	0.024	3-Digit	1.25
		(0.59)	(0.49)	(0.39)	(0.2)		(0.74)

Note: 4473 observations. Dependent variable is indicator for 1- or 3-digit industry change. Probit estimates of coefficients on interactions between log population, log density, and diversity with indicators for job-change number and educational attainment. Standard errors are given in parentheses. Estimating equations also include all variables considered in Table 3 as well as indicators for job-change number interacted with educational attainment. 'Wald Test' reports statistic from test of the null that all four job-change coefficients are equal (p-value under the null in parentheses). An asterisk (*) denotes statistical significance at 10 percent or better.

Table 8: Frequency of Job Changes and Local Market Scale

Negative Binomial Regression Results

	I	II	III	I	II	III
College	-0.73*	-0.73*	-0.73*	-0.77*	-0.77*	-0.77*
	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)	(0.08)
Some College	-0.42*	-0.42*	-0.42*	-0.47*	-0.47*	-0.47*
	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)	(0.09)
High School	-0.29*	-0.29*	-0.29*	-0.28*	-0.28*	-0.28*
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
Experience	0.005*	0.005*	0.005*	0.004*	0.004*	0.004*
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Experience Squared	-0.04*	-0.04*	-0.04*	-0.035*	-0.035*	-0.035*
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
Married	-0.11*	-0.12*	-0.11*	-0.1*	-0.1*	-0.1*
	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)
Non-White	0.05	0.04	0.04	0.11*	0.11*	0.11*
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Log Population	-0.017*	–	–	-0.011	–	–
	(0.01)			(0.015)		
Log Density	–	-0.022*	–	–	-0.015	–
		(0.012)			(0.016)	
Diversity	–	–	-0.34*	–	–	-0.21
			(0.2)			(0.29)
Sample	Full	Full	Full	Non-Movers	Non-Movers	Non-Movers

Note: 1029 observations in the full sample; 610 observations in the sample of non-movers. Dependent variable is the number of job changes. The coefficients on experience squared and the diversity index have been multiplied by 10000 and 1000. Standard errors are given in parentheses. An asterisk (*) denotes statistical significance at 10 percent or better.

A Appendix

A.1 National Longitudinal Survey of Youth 1979 Data

Data on individual work histories are derived from the geocoded files of the National Longitudinal Survey of Youth 1979 (NLSY79). As noted in the text, the sample of jobs is limited to full-time positions (i.e. involving at least 30 hours per week), for which industry codes are identified, and which are held after all schooling is completed. Because these post-education jobs must be numbered (i.e. first job, second job, third job), I only include those workers who report having initially been in school at the 1979 interview (i.e. their work histories beginning in January of 1978 initially code them as being in school). This procedure helps ensure that the job numbers I assign to each worker's job history are reasonably accurate. Workers not initially observed in school may have had an entire history of jobs not identified in the survey.

The sample is restricted to individuals for whom an interview is conducted each year (1979-1994) to help ensure a correct coding of geographic location and other covariates which are only observed on interview dates (e.g. marital status). Workers who have missing values for their places-of-residence in any year are dropped unless all of the identified locations are the same. In these cases, I assume that the missing locations are the same as the identified locations. As described in the text, places-of-residence are identified by the information provided at each interview and then mapped forward in time (as is marital status). This means that a change in a worker's place-of-residence (or marital status) from one year to the next is assumed to begin on the new interview date. There is, however, one important exception to this procedure. In the event that a worker reports a new place-of-residence, but the job held in that new residence is reported to have started at some date prior to the interview, I assume the worker's place-of-residence changed at the beginning of that job. Marital status and place-of-residence in the year 1978 are assumed to be the same as what is reported at the 1979 interview.

As mentioned before, confining the sample to workers who are identified in every year also facilitates matching job codes across years. Because the same job may be reported with a different job code in different years (e.g. the second job held in the year 1990 may be the same as the first job held in 1991), the NLSY79 provides a correspondence between jobs reported in the current interview year and whether these jobs were reported in the previous interview year. This information allows me to create a consistent set of job codes across years thereby eliminating the likelihood of treating a change in a job code within the same job as a job change.

Workers sometimes report changes in industry while on the same job. To ensure that each job falls into a single industrial grouping, I follow Neal (1999) and edit the codes where within-job industry changes have been reported. In particular, I assume that a job's

industry is given by the code the worker first reports for it. Jobs for which industry codes are missing are dropped from the sample.

Once I have constructed a complete weekly array of jobs, I identify job changes as points where the job codes change. Hence, if a job involves a worker moving in and out of employment, say due to temporary layoffs, no job change is recorded over this period. A job change requires the movement into another position. With job changes identified, jobs are numbered based on their position in the sequence. Cumulative weeks of work experience is calculated as a running total of all weeks in which a worker reports having a full-time job.

The 1-digit industrial breakdown runs as follows: (1) agriculture, forestry, fisheries; (2) mining; (3) construction; (4) durable manufacturing; (5) nondurable manufacturing; (6) transportation, communications, utilities; (7) wholesale trade; (8) retail trade; (9) finance, insurance, real estate; (10) business and repair services; (11) personal, entertainment, recreation services; (12) professional and related services; (13) public administration.

A.2   Additional Data Details

Local market population density is calculated as a weighted average of county-level densities across all counties belonging to the market. A county's weight in the calculation is given by its share of total local market population. This particular density measure helps to mitigate somewhat the problems generated by metropolitan areas containing extremely large, but relatively unpopulated, counties such as some of those in the western United States.

The industry coverage in the County Business Patterns files is reasonably complete. Excluded are workers in railroads, agricultural production, and most government. Due to disclosure restrictions, County Business Patterns does not always identify employment figures at the county level for all industries, especially those at the four-digit (SIC) level. Where the data are suppressed, one of the following employment ranges is given: 0 to 19, 20 to 99, 100 to 249, 250 to 499, 500 to 999, 1000 to 2499, 2500 to 4999, 5000 to 9999, 10000 to 24999, 25000 to 49999, 50000 to 99999, 100000 or more. The largest of these intervals did not appear in any of the data used here. To construct the Dixit-Stiglitz diversity index, I impute all undisclosed employment figures as the midpoint of the reported range. Total local market employment is estimated as the sum over industry-level employments so that, within each market, industry shares sum to 1.

The unemployment rate for a local market is estimated as a weighted average of the state-level rates taken across all states in which the local market lies. Only some metropolitan areas lie in more than one state. The weights are given by shares of the local market population residing in each state. Because the state unemployment series runs annually beginning in 1976, while the county unemployment series begins in 1990, I use the former in estimating local area unemployment.

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