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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 cities), 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 cities play an important role in the job matching process.

JEL Classification: J24, R23
Keywords: Job Search, Labor Market Matching, Agglomeration

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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

[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.

this process.[2] Yet, job search often takes place locally, implying that the number and types of employers located within a worker's county- or city-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

[2] None of the most prominent papers in this literature (e.g. Johnson (1978), Jovanovic (1979), McCall (1990), Sicherman 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).

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 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. Upon settling on an optimal production technique, firms can then move to markets in which similar producers have located and take advantage of localization economies.[5] 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 cities 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

[5]Localization economies refer to the gains in productivity associated with the geographic concentration of similar producers (usually defined by industry).

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 (conditional on making at least one) 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 helps to 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.

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. By confining the analysis to these workers, I can 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 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.

The final sample includes 1026 workers who make, on average, 4.34 job changes over the sample period.[7] 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.[8] The final sample identifies job changes in 349 local

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

[8]Metropolitan areas refer more specifically to metropolitan statistical areas (MSAs), primary metropoli-

markets, 190 of which are metropolitan areas.

Characteristics describing these local labor markets are derived from three primary sources: the Census Bureau's Population Estimates Program[9], the USA Counties 1998 on CD-ROM (U.S. Bureau of the Census (1999)) and 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 which allows me to compile a time series of population densities for all markets.[10] 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 1-digit industries.[11] Over the entire time frame, 207 3-digit industries appear.

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 4461 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

tan 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).

[9] These data are available at http://www.census.gov/popest/estimates.php.

[10] I assume a county's land area is given by its 1990 value.

[11] 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.

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 in light of the evidence on job search surveyed in the Introduction.

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 industry changes are represented by a binary variable, I follow two common approaches in the statistical analysis: a linear probability model (LPM) and a probit specification. Letting y_{im} represent an industry-change indicator for worker i of local market m, the LPM implies

$$\text{Prob}(y_{im} = 1|\mathbf{x}_{im}, z_m; \beta, \gamma) = \beta\mathbf{x}_{im} + \gamma z_m \qquad (1)$$

where $\mathbf{x}_{im}$ is a vector of personal covariates, including three educational attainment dummies (college graduate, some college or an associates 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.[12] The variable z_m represents the scale of a worker's local labor market, the measurement of which is described below.

Notice, because y_{im} is a binary variable, its expected value follows as

$$\mathrm{E}(y_{im}|\mathbf{x}_{im}, z_m; \beta, \gamma) = \beta\mathbf{x}_{im} + \gamma z_m$$

hence,

$$y_{im} = \beta\mathbf{x}_{im} + \gamma z_m + \epsilon_{im}$$

where ϵ is a mean zero stochastic element. Estimation of the LPM then proceeds by least squares where the standard errors are adjusted to account for the heteroskedasticity implied by the model.

With the probit, the probability that a worker experiences an industry change is specified as

$$\mathrm{Prob}(y_{im} = 1|\mathbf{x}_{im}, z_m; \beta, \gamma) = \Phi(\beta\mathbf{x}_{im} + \gamma z_m) \equiv \Phi_{im} \tag{2}$$

where all of the terms are the same as in (1), and $\Phi(\cdot)$ is the normal cumulative distribution function. The parameters are then chosen to maximize the sum of the log likelihoods over all observations, where the contribution from worker i of local market m is

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

[12] That is, for a worker's first job change, the covariates are evaluated at the beginning of his second job.

To quantify local market scale, z_m, 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.[13] 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.[14] As with the personal covariates, $\mathbf{x}$, each these scale variables, z_m, 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) and (2) in which all job changes, regardless of their places in a worker's labor market history, are pooled together. The resulting linear probability model and probit estimates appear in Tables 3A (for industry changes based on a 1-digit classification) and 3B (for changes based on a 3-digit classification). In each case, three specifications appear, one for each of the three measures of local market scale/diversity, z_m.

[13] Density is calculated as a weighted average over county-level population densities, where weights are given by county shares of a local market's total population.

[14] For example, a market with employment divided equally between two industries has an index of 2. A market with four equally sized industries has an index value of 4.

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. Relative to high school dropouts, workers with a college degree have a 4 to 6 percentage point lower probability of making an industry change, 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 relatively specialized in terms of the types of work they perform.

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 and estimation technique. Although most of the point estimates are negative, suggesting that cities 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) and (2) in which the association between local market scale/diversity and the frequency of industry shifts is permitted 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.[15] I then interact each of the three local market scale variables with indicators for these four groups and include them in the estimation.[16] The resulting coefficient estimates appear in Tables 4A and 4B for the, respectively, 1- and 3-digit industrial classification schemes. The coefficients from each of the personal characteristics have been suppressed since they do not differ substantially from what is reported in Tables 3A and 3B.

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 a worker has experienced increases. With all three measures of local market scale, the first job change carries a significantly positive coefficient, implying an increase in the probability that a job change will entail a change of industry. These associations, however, gradually decrease, turning negative by the third observed job

[15] These groups have, respectively, 1026, 822, 621, and 1992 observations. Results given below provide some justification for this grouping scheme.

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

change. By the time a worker makes his fourth job change, there is a significantly negative association between two of the measures - log population and diversity - and the likelihood of switching industries when changing jobs.[17] 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 2.9 percentage point increase in the likelihood that a worker's first job change will involve an industry switch.[18] 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 3.1 percentage point increase for first job changes, a 1.9 percentage point decrease for fourth changes or more) and diversity (a 4 percentage point increase for first changes, a 3 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 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.

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

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

Cheyenne in 1994 had a population of approximately 78000, with a density of 29 residents 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 4A suggest that the likelihood of an industry switch during a worker's first job change is 7 to 10 percentage points higher in Chicago than in Cheyenne. Among job changes made after the third, however, the probability of an industry switch is 5.5 to 8 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 2.2 percentage point increase in the probability of switching industries on a first job change and a 2.3 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 job changes likely contributes to the smaller estimated coefficients. Still, precisely the same qualitative pattern can be discerned from both the 1- and 3-digit results. 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 equations (1) and (2), 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.[19] The coefficients demonstrate that the dropoff does not continue in any substantial way beyond the fourth change, although there is a decrease in the coefficients among the eighth and ninth changes.[20] At the same time, there is little 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. The test statistics are reported in the final row of the table.[21]

Allowing for a more extensive array of job-change categories, therefore, does not 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.[22]

[19]There are 1026 first changes, 822 second changes, 621 third changes, 494 fourth changes, 400 fifth changes, 299 sixth changes, 227 seventh changes, 175 eighth changes, 116 ninth changes, 281 tenth changes or more. As before, the 10 indicators for job changes also appear in the estimating equations.

[20]For the sake of conciseness, the reported results are limited to the linear probability model estimates. The probit estimates were quite similar.

[21]This provides some justification for the use of only four job-change categories in the remainder of the paper.

[22]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.

3.3 Robustness

I now consider two basic modifications of the foregoing analysis - each of which looks at a particular subset of the total sample - in an attempt to gauge the robustness of the findings just reported. 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 1026 workers in the total sample is 4.34, 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 961 workers who make, on average, 3.76 job changes each.[23]

The second modification involves workers who, at some point during the sample time frame, move. Of the 1026 workers in the full sample, 417 are observed in more than one location between 1978 and 1994. Having workers move between markets could be somewhat problematic for the interpretation of the 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.[24] 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 both of these possibilities stand somewhat at odds with the evidence shown thus far[25], I attempt to address this matter by dropping all individuals for whom a move is

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

[24] Again, such a process would be analogous what Duranton and Puga (2001) find for young firms.

[25] Both scenarios suggest that large cities are places for industry shopping. Hence, the association between

observed at some point.[26] This leaves a total of 2352 job changes over 609 workers.

For both modifications, the estimates appear in Table 6. Because the LPM and probit results were similar, I have suppressed the probit estimates in an effort to keep the presentation of the results concise. In general, both subsets of observations produce much the same qualitative pattern as the full sample. 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. In 8 of the 12 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. Among the subsample of workers with 10 or fewer job changes, for instance, only log population, log density, and diversity within a 1-digit industry classification are significantly associated with industry changes. The 3-digit results do not differ statistically from zero. Within the subsample of non-movers, none of the first job-change coefficients are significant.

On the other hand, the majority of coefficients among the fourth-or-more job-change category are still significant. Of the 12 total coefficients listed in the table, only 3 (all of which pertain to log density) are statistically negligible. 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 strong evidence that

scale and the frequency of industry changes ought to be uniformly positive regardless of how many job changes a worker has made.

[26] Simply adding an indicator variable describing whether a job change is also associated with a geographic move does not alter the results in Tables 4A and 4B substantially.

they are less likely to do so among later job changes.

3.4 Local Market Scale and the Frequency of Job Changes

While the evidence reported thus far seems to suggest that urban scale/diversity helps workers to settle into better industry matches, this finding does not necessarily imply that agglomeration helps to improve *firm-worker* matching. Workers in large markets may, for instance, make fewer industry changes after a certain point, but greater numbers of job changes total, suggesting that an optimal match with an *employer* may actually be somewhat more difficult to find in a large market.

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/diversity of his local labor market.[27] 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.

Nevertheless, 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

[27] Note, this analysis conditions on the fact that all workers in the sample have made at least one job change.

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?[28] Finding a negative association between local market scale/diversity and the frequency of job changes, therefore, should lend some additional support to 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[29] in which the probability that a worker has experienced n job changes, conditional on personal covariates $\mathbf{x}$, local market features z, and a stochastic element u, $f(n|\mathbf{x}, z, u)$ is specified as

$$f(n|\mathbf{x}, z, u) = \frac{(\lambda u)^n \exp(-\lambda u)}{n!} \tag{3}$$

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.[30] Integrating over the distribution of u then generates the following expression for the distribution of n conditional on $\mathbf{x}$ and z:

[28] 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 cities 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)).

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

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

$$f(n|\mathbf{x}, z) = \frac{\Gamma(\alpha + n)}{\Gamma(n+1)\Gamma(\alpha)} r^n (1-r)^\alpha \tag{4}$$

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 education[31] and race do not change, 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.[32] Results are reported in the first three columns of results in Table 7.

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 the features of a worker's local labor market, 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

[31] Recall, these are post-education jobs.

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

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 (417 of 1026), 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 7. 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.

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 total (conditional on making at least one), this evidence offers some support for the theory that agglomeration facilitates labor market matching through a learning process.

These results, however, represent 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 of a job provides some indication of the quality of the match, do workers in cities experience longer job durations than their rural counterparts? This type of analysis would likely represent a major improvement over what is presented with respect to total numbers of job changes in Section 3.4 above.

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 local markets? 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 cities, 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	1559056	2089048	3562	9064197
Population Density	1461.7	3411.2	2.5	26697.2
Dixit-Stiglitz Diversity Index	203.2	95.3	11.8	376.5

Note: Means taken across 4461 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	0.63	0.84	0.84	0.8
Second Job Change	0.68	0.68	0.67	0.83	0.83	0.82
Third Job Change	0.69	0.68	0.75	0.84	0.84	0.85
Fourth Job Change or More	0.62	0.61	0.66	0.77	0.76	0.81

Note: Means taken across 1026 first job changes, 822 second job changes, 621 third job changes, 1992 fourth or more job changes. Numbers of job changes in metropolitan areas are 820 first changes, 655 second changes, 490 third changes, 1547 fourth or more changes.

Table 3A: Industry Changes and Urban Scale

1-Digit Pooled Estimates

	LPM			*Probit*		
	I	*II*	*III*	*I*	*II*	*III*
College	-0.06	-0.064	-0.062	-0.064	-0.066	-0.064
	(0.025)	(0.025)	(0.025)	(0.027)	(0.027)	(0.027)
Some College	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09
	(0.025)	(0.025)	(0.025)	(0.027)	(0.027)	(0.027)
High School	-0.004	-0.003	-0.003	-0.004	-0.003	-0.004
	(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
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Experience Squared	0.004	0.004	0.004	0.004	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Married	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Non-White	0.04	0.04	0.04	0.04	0.04	0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log Population	-0.004	–	–	-0.003	–	–
	(0.004)			(0.004)		
Log Density	–	-0.0005	–	–	-0.0003	–
		(0.004)			(0.004)	
Diversity	–	–	-0.056	–	–	-0.05
			(0.08)			(0.08)

Note: 4461 observations. Dependent variable is indicator for 1-digit industry change. Probit 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. Standard errors are given in parentheses.

Table 3B: Industry Changes and Urban Scale

3-Digit Pooled Estimates

	LPM			*Probit*		
	I	*II*	*III*	*I*	*II*	*III*
College	-0.04	-0.037	-0.035	-0.036	-0.037	-0.035
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Some College	-0.065	-0.065	-0.065	-0.064	-0.064	-0.064
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
High School	0.02	0.02	0.02	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	-0.0006	-0.0006	-0.0006
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Experience Squared	0.005	0.005	0.005	0.005	0.005	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Married	-0.024	-0.023	-0.024	-0.023	-0.022	-0.023
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Non-White	0.04	0.04	0.04	0.04	0.04	0.04
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Log Population	-0.0002	–	–	0.0006	–	–
	(0.003)			(0.003)		
Log Density	–	0.002	–	–	0.003	–
		(0.003)			(0.004)	
Diversity	–	–	-0.028	–	–	-0.013
			(0.06)			(0.06)

Note: 4461 observations. Dependent variable is indicator for 3-digit industry change. Probit 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. Standard errors are given in parentheses.

Table 4A: Industry Changes and Urban Scale

By Job Number

1-Digit Estimates

	LPM			*Probit*		
	I	*II*	*III*	*I*	*II*	*III*
First Change*	0.016	–	–	0.016	–	–
Log Population	(0.008)			(0.008)		
Second Change*	0.008	–	–	0.008	–	–
Log Population	(0.009)			(0.009)		
Third Change*	-0.01	–	–	-0.011	–	–
Log Population	(0.01)			(0.011)		
Fourth Change*	-0.016	–	–	-0.016	–	–
Log Population	(0.006)			(0.006)		
First Change*	–	0.018	–	–	0.018	–
Log Density		(0.009)			(0.009)	
Second Change*	–	0.006	–	–	0.006	–
Log Density		(0.009)			(0.01)	
Third Change*	–	-0.006	–	–	-0.007	–
Log Density		(0.01)			(0.012)	
Fourth Change*	–	-0.011	–	–	-0.011	–
Log Density		(0.006)			(0.006)	
First Change*	–	–	0.38	–	–	0.39
Diversity			(0.16)			(0.16)
Second Change*	–	–	0.18	–	–	0.19
Diversity			(0.17)			(0.18)
Third Change*	–	–	-0.13	–	–	-0.14
Diversity			(0.19)			(0.21)
Fourth Change*	–	–	-0.34	–	–	-0.33
Diversity			(0.11)			(0.11)
Wald Test	4.18	2.71	5.25	12.28	8.07	15.48
	(0)	(0.04)	(0)	(0)	(0.04)	(0)

Note: 4461 observations. Dependent variable is indicator for 1-digit industry change. Probit 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 Tables 3A and 3B 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).

Table 4B: Industry Changes and Urban Scale

By Job Number

3-Digit Estimates

	LPM			*Probit*		
	I	*II*	*III*	*I*	*II*	*III*
First Change*	0.012	–	–	0.013	–	–
Log Population	(0.007)			(0.007)		
Second Change*	0.014	–	–	0.016	–	–
Log Population	(0.007)			(0.008)		
Third Change*	0.002	–	–	0.002	–	–
Log Population	(0.008)			(0.009)		
Fourth Change*	-0.013	–	–	-0.011	–	–
Log Population	(0.005)			(0.005)		
First Change*	–	0.01	–	–	0.011	–
Log Density		(0.007)			(0.008)	
Second Change*	–	0.013	–	–	0.015	–
Log Density		(0.008)			(0.008)	
Third Change*	–	0.007	–	–	0.008	–
Log Density		(0.009)			(0.01)	
Fourth Change*	–	-0.008	–	–	-0.007	–
Log Density		(0.005)			(0.005)	
First Change*	–	–	0.23	–	–	0.26
Diversity			(0.13)			(0.14)
Second Change*	–	–	0.22	–	–	0.25
Diversity			(0.14)			(0.15)
Third Change*	–	–	0.02	–	–	0.01
Diversity			(0.16)			(0.18)
Fourth Change*	–	–	-0.27	–	–	-0.22
Diversity			(0.1)			(0.09)
Wald Test	4.44	2.44	4.3	13.23	7.54	12.6
	(0)	(0.06)	(0)	(0.02)	(0.06)	(0)

Note: 4461 observations. Dependent variable is indicator for 3-digit industry change. Probit 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 Tables 3A and 3B 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).

Table 5: Industry Changes and Urban Scale

Extended Specification by Job Number

	Log Population	Log Density	Diversity	Log Population	Log Density	Diversity
First Change	0.016	0.018	0.38	0.012	0.01	0.23
	(0.008)	(0.009)	(0.16)	(0.007)	(0.007)	(0.13)
Second Change	0.008	0.006	0.18	0.014	0.013	0.22
	(0.009)	(0.009)	(0.17)	(0.007)	(0.008)	(0.14)
Third Change	-0.01	-0.006	-0.13	0.002	0.007	0.02
	(0.01)	(0.01)	(0.2)	(0.008)	(0.009)	(0.16)
Fourth Change	-0.018	-0.029	-0.46	-0.013	-0.016	-0.35
	(0.012)	(0.013)	(0.23)	(0.009)	(0.01)	(0.19)
Fifth Change	0.015	0.03	0.27	-0.004	0.006	-0.09
	(0.013)	(0.014)	(0.25)	(0.01)	(0.01)	(0.21)
Sixth Change	-0.021	-0.012	-0.39	-0.019	-0.016	-0.34
	(0.015)	(0.016)	(0.29)	(0.014)	(0.015)	(0.27)
Seventh Change	-0.008	-0.001	-0.26	0.002	0.013	-0.05
	(0.02)	(0.02)	(0.34)	(0.016)	(0.017)	(0.31)
Eighth Change	-0.04	-0.039	-0.87	-0.024	-0.021	-0.68
	(0.02)	(0.02)	(0.36)	(0.017)	(0.019)	(0.33)
Ninth Change	-0.037	-0.025	-0.56	-0.031	-0.035	-0.43
	(0.023)	(0.025)	(0.45)	(0.023)	(0.023)	(0.42)
Tenth Change	-0.031	-0.015	-0.53	-0.012	-0.002	-0.12
or More	(0.014)	(0.016)	(0.28)	(0.012)	(0.01)	(0.23)
Industry Level	1-Digit	1-Digit	1-Digit	3-Digit	3-Digit	3-Digit
Wald Test	2.49	2.34	2.78	1.77	1.4	1.8
	(0)	(0.01)	(0)	(0.07)	(0.18)	(0.06)
Wald Test of	1.63	2.24	1.51	0.46	0.97	0.59
Last 7 Coefficients	(0.13)	(0.04)	(0.17)	(0.84)	(0.44)	(0.74)

Note: Dependent variables are indicators for 1- and 3-digit industry changes. Linear probability model estimates of coefficients on interactions between log population, log density, and diversity with indicators for job-change number. Heteroskedasticity-consistent standard errors are given in parentheses. Estimating equations also include all variables considered in Tables 3A and 3B 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).

Table 6: Robustness Checks

Modification	Variable	First Change	Second Change	Third Change	Fourth Change	Industry Level	Wald Test
10 Changes or Fewer	Log Population	0.015	0.008	-0.01	-0.017	1-Digit	3.5
		(0.009)	(0.009)	(0.01)	(0.007)		(0.01)
	Log Density	0.017	0.003	-0.008	-0.015	1-Digit	2.79
		(0.009)	(0.01)	(0.01)	(0.008)		(0.04)
	Diversity	0.35	0.17	-0.14	-0.41	1-Digit	4.84
		(0.17)	(0.18)	(0.2)	(0.14)		(0)
	Log Population	0.011	0.013	-0.001	-0.01	3-Digit	2.58
		(0.007)	(0.008)	(0.008)	(0.006)		(0.05)
	Log Density	0.009	0.01	0.003	-0.005	3-Digit	1
		(0.007)	(0.008)	(0.009)	(0.007)		(0.39)
	Diversity	0.21	0.19	-0.05	-0.28	3-Digit	3.17
		(0.13)	(0.15)	(0.17)	(0.12)		(0.02)
Non-Movers Only	Log Population	-0.004	0.003	-0.021	-0.024	1-Digit	1.44
		(0.01)	(0.01)	(0.013)	(0.009)		(0.23)
	Log Density	-0.004	0.005	-0.011	-0.014	1-Digit	0.54
		(0.01)	(0.01)	(0.014)	(0.009)		(0.66)
	Diversity	0.07	0.2	-0.34	-0.49	1-Digit	2.62
		(0.21)	(0.24)	(0.27)	(0.17)		(0.05)
	Log Population	0.003	0.021	-0.005	-0.019	3-Digit	3.79
		(0.009)	(0.01)	(0.01)	(0.007)		(0)
	Log Density	0.002	0.021	0.001	-0.009	3-Digit	1.85
		(0.009)	(0.01)	(0.01)	(0.007)		(0.14)
	Diversity	0.1	0.48	-0.14	-0.39	3-Digit	4.67
		(0.16)	(0.2)	(0.22)	(0.14)		(0)

Note: Dependent variables are indicators for 1- and 3-digit industry changes. Linear probability model estimates of coefficients on interactions between log population, log density, and diversity with indicators for job-change number. 3616 job-change observations for the '10 changes or fewer' specification; 2352 observations for 'non-movers only' specification. Heteroskedasticity-consistent standard errors are given in parentheses. Estimating equations also include all variables considered in Tables 3A and 3B 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).

Table 7: Frequency of Job Changes and Local Market Scale

Negative Binomial Regression Results

	I	*II*	*III*	*I*	*II*	*III*
College	-0.72	-0.72	-0.72	-0.77	-0.77	-0.77
	(0.07)	(0.07)	(0.07)	(0.1)	(0.1)	(0.1)
Some College	-0.42	-0.42	-0.42	-0.47	-0.47	-0.47
	(0.07)	(0.07)	(0.07)	(0.1)	(0.1)	(0.1)
High School	-0.3	-0.3	-0.3	-0.28	-0.28	-0.28
	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)	(0.08)
Experience	0.005	0.005	0.005	0.004	0.004	0.004
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0006)
Experience Squared	-0.04	-0.04	-0.04	-0.035	-0.035	-0.035
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Married	-0.11	-0.12	-0.11	-0.1	-0.1	-0.1
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
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	-0.02	–	–	-0.013	–	–
	(0.01)			(0.015)		
Log Density	–	-0.023	–	–	-0.017	–
		(0.012)			(0.016)	
Diversity	–	–	-0.38	–	–	-0.24
			(0.2)			(0.29)
Sample	Full	Full	Full	Non-Movers	Non-Movers	Non-Movers

Note: 1026 observations in the full sample; 609 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.

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 identifed 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.

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.

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.

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