JOURNAL OF REGIONAL SCIENCE, VOL. 48, NO. 2, 2008, pp. 311–328

THE EFFECT OF URBANIZATION ON LABOR TURNOVER*

Miles M. Finney

Department of Economics and Statistics, California State University, Los Angeles, CA 90032. E-mail: mfinney@calstatela.edu

Janet E. Kohlhase

Department of Economics, University of Houston, Houston, TX 77204-5019. E-mail: jkohlhase@uh.edu

ABSTRACT. The paper empirically examines labor market matching as a source of urban agglomeration economies. We work from the hypothesis that job turnover leads to tighter labor matches and estimate the relationship between urbanization and the job mobility of young men. Using a panel from the National Longitudinal Survey of Youth, we find evidence that young men change jobs more frequently in their early career if they live in larger or in more educated urban areas. The sensitivity of the results to whether the young men were "movers" or "stayers" suggests the possible endogeneity of location.

1. INTRODUCTION

The standard rationale for urbanization is that the concentration of people and employment decreases the cost of market transactions. Recent research has expanded on this by conjecturing that urban labor markets generate human capital externalities that would not exist in less densely populated areas (Glaeser and Mare, 2001; Rauch, 1993; Moretti, 2004). A larger body of research has examined the possible advantages cities have in matching the skills of their workforce to local jobs (Helsley and Strange, 1990; Kim, 1987, 1990; Sato, 2001; Wheeler, 2001). Urban areas place a large number of people in close proximity to a large number of potential employers. The theory on the advantages cities may have in labor matching is a restatement of their principal rationale for existing: urbanization decreases the cost of making market transactions. Efficient labor matching should entail some job turnover by labor market participants at least in the initial stages of their career. The behavior of young job market participants attempting to obtain a good career match could be influenced by the degree of urbanization in the local labor market. This study examines the affect urbanization has on the job market activity of young men.

*The authors would like to thank Steven Craig, Adriana Kugler, Michael Lahr, the editor and three anonymous referees for helpful comments; Steven McClaskie and Audrey Light for information regarding the NLSY data set; and Michelle Ho for data assistance.

Received: February 2005; Revised: March 2007; Accepted: July 2007

Blackwell Publishing, Inc., 350 Main Street, Malden, MA 02148, USA and 9600 Garsington Road, Oxford, OX4 2DQ, UK.

Inferring the efficiency of urbanization by examining labor turnover hinges on the relationship labor mobility has with matching efficiency, and in turn, the effect urbanization has on labor mobility. The accepted view on labor mobility's effect on matching has been that although there is marked heterogeneity in mobility across young workers (Farber, 1994), wages grow with early career mobility as young workers experiment with job change, converging eventually to tighter matches (Topel and Ward, 1992; Bartel and Borjas, 1982). Recent research, however, has challenged this view. Light and McGarry (1998) present evidence that labor mobility decreases contemporaneous wage growth while Neumark (2002) finds future (adult) wage levels are inversely related with labor turnover during the initial years on the job market. Wheeler (2006) finds that workers in bigger cities experience faster wage growth due to job changes. His results provide contemporary evidence supporting the accepted view on the relationship between turnover and matching in the labor literature.

There is not necessarily a specific relationship between urbanization and mobility even if labor turnover reflects a move to better employment matches. Wheeler (2005) discusses how labor matching in urban areas may produce either a positive or an inverse relationship between urbanization and mobility. The increased number of choices open to those in more urbanized labor markets may give rise to a quicker convergence to tighter employment matches, suggesting less turnover. The cost of search and the possible uncertainty regarding match quality (Jovanovic, 1979), however, may induce a positive relationship between the size of the local labor market and job turnover. Urbanized areas may produce more efficient labor matches because they allow people to experiment with a greater variety of jobs.

The relationship urbanization has with labor turnover may depend on the stage of the individual's working career. Job turnover decreases with labor market experience (Topel and Ward, 1992; Neal, 1999; Farber, 1994). Wheeler (2005), analyzing job mobility over a longer time horizon, hypothesizes an inverse relationship between urbanization and turnover. We estimate the effect urbanization has on mobility in the first six years in the career of young males and hypothesize the expanded choices in more urbanized areas would increase turnover in this initial period.

Urbanization could affect job turnover not only by decreasing the physical distance to potential employment matches but also through reducing the cost of acquiring information about jobs. The social networks that arise among people living in the same area have been found to be an important source of job information (Corcoran, Datcher, and Duncan, 1980; Holzer, 1988; Granovetter, 1995). These networks would more readily grow within the dense populations associated with urbanization. Our primary indicators of urbanization are measures of metropolitan area population and density. Demographic characteristics of the populations residing in urban areas may also influence job turnover through their effect on job information. For example, metropolitan areas contain a disproportionate number of college-educated residents (Glaeser, 1999; Costa and

Kahn, 2000), a population found more likely to interact socially both informally and in terms of formal organizations (Putnam, 2001).

In this study, we examine the effect geography has on labor market activity. Location, however, is a choice variable and is potentially endogenous if residence itself is determined by labor market decisions. We approach this potential endogeneity by estimating separately the job mobility of those who move out of their urban area sometime during their early career and those who do not. We use data from the National Longitudinal Survey of Youth and hypothesize that, in addition to environmental influences, characteristics specific to the labor participants will partially determine job turnover. We control for such individual characteristics as ethnicity and marital status in estimating the probability of job turnover.

2. SAMPLE CONSTRUCTION

We focus our analysis on a sample of young males within the panel of the National Longitudinal Survey of Youth (NLSY), which follows a cohort of 12,868 youth, beginning in 1979. We construct a sample from a subset of 6,403 males surveyed yearly from 1979 to 1993. The sample details labor force attachment over time, post schooling. We construct six-year windows of continuous labor market attachment at the start of the respondents' working career. Many respondents transition from school to work by undertaking both activities over a period of time. In selecting the sample, the respondent is allowed to attend school within the window but not for consecutive years. The selected youth enters the sample over the first six-year period that satisfies the labor force attachment and schooling criteria. Our selection allows respondents to attend school during the period, possibly in relation to a particular job held, while specifying the youth is working or looking for work continuously over the period.

We further limit the sample to focus on urban areas. The sample consists of youth who reside within a metropolitan area at least initially within the six-year window. The sampled male had to be at least 18 years old at the start of the job window, which has starting dates that varied from 1979 to 1988. The above criteria eliminated 3,043 of the 6,403 in the original cohort. Among the respondents whose interview history allowed constructing a time series of labor force participation, those who were eliminated dropped out primarily because they lived exclusively in nonurban areas or were only sporadic participants in the labor market. All of the empirical models are estimated from subsets of the 3,360 respondents remaining in the sample.

3. DEPENDENT VARIABLE AND DATA

The dependent variable in each of the empirical models is constructed from jobs typically worked over 30 hours a week. The employment counts are measured as job starts as opposed to separations. A job start is identified as a job

TABLE 1: Characteristics of the Labor Market Participants and Metropolitan Areas

Variable	Mean (Std. Dev.)	Minimum	Maximum
Labor market participants			
Job starts (30+ hours/week)	3.81	0	21
	(2.83)		
Highest grade achieved (years)	12.53	3	20
	(2.42)		
Age	24.47	18	36
	(3.20)		
Experience (years)	4.35	0	15
	(2.58)		
Wage ($/hour)	$7.80	0	$230.76
	(5.92)		
Number of children in household	0.33	0	6
	(0.72)	—	—
Percent Non-Hispanic White	54.66	—	—
Percent Non-Hispanic Black	26.23	—	—
Percent married	30.73	—	—
	(46.14)	—	—
Metropolitan areas			
Unemployment rate	0.075	0.013	0.289
	(0.031)		
Population (in millions)	4.635	0.0617	18.8407
	(5.962)	—	—
Principal city density	5.814	0.276	16.28
(Thousands of persons/sq. mile)	(4.484)	—	—
Proportion college graduate	0.220	0.095	0.440
	(0.053)	—	—

Note: The statistics correspond to the 3,360 multiply-observed males in the sample.

appearing in the work history portion of NLSY that could not be traced to any employment originating in prior years. The NLSY data can account for up to five starts per year and allows for the possibility that a respondent held more than one job at a time.

In Table 1, the average sampled youth had 3.81 full-time job starts over the six-year window. The standard deviation for the variable measures only cross-sectional variation and is almost as large as the mean, indicating the large degree of variation in turnover across the sample. The remaining characteristics, except ethnicity, are averaged over the observed job window. The typical youth within the window was an unmarried high school graduate with some postsecondary education but no college degree, who had 4.35 years of work experience. The average age is 24 years but the range was substantial: the minimum at the start of the window is 18; the maximum age at the end is 36.

The cumulative work experience variable constructed from the NLSY includes employment in part- and full-time jobs including those held before the constructed job window. The respondent's wage is hourly earnings from the job held at the time of the yearly survey interview. For the small set of wage earners with simultaneous jobs, the wage represents the primary job employing the youth for the most hours (what the NLSY calls the CPS job).[1] The respondent's children are the total number, biological and adopted, living in the respondent's household.

The unit of observation for urban areas is the consolidated metropolitan statistical area (CMSA) or the metropolitan statistical area (MSA), defined as of the 1990 Census. The characteristics of the metropolitan areas are taken from the U.S. Census, except for the unemployment rate. Metropolitan area population is taken from yearly estimates produced by the Census.[2] The density of economic activity is measured by the population density of the principal cities making up the metropolitan areas. The Census provided biyearly population estimates for large U.S. cities up to 1990, annually afterwards. For nonestimated years, population data from the previous year are used. The yearly unemployment rate for each urban area is supplied by the NLSY. The median income and percent college graduate are taken from the 1990 Census and do not vary yearly. We also construct regional dummies based on the states in the nine Census Divisions.

4. STRATEGIES TO ESTIMATE LABOR MOBILITY

We measure labor mobility by observing yearly whether the sampled youth starts a new job and by calculating the cumulative number of jobs within the constructed career window. We use the probit specification to estimate the yearly probability of starting new employment and the negative binomial model to estimate the probability of accumulating a specific number of jobs in the early career.

The sample used for the probit models differs from that for the count-data specifications. Because of missing values for the year-specific variables, the number of times each individual is observed for the probit specifications may differ from the six observations specified within the job window. We estimate job start probabilities separately for the full sample, for those who at some point moved out of their urban area in their early career and those who did not. The sample for the count-data models, however, is restricted to respondents whose job count could be calculated in each of the six years and whose year specific covariates are observed at least in the first year of the career window. This was done to standardize the time period in which total jobs are summed. The

[1]The wage variable is derived by NLSY. The few instances of unusually large calculated wages were converted to missing values.

[2]Population estimates are available from http://www.census.gov/popest/datasets.html.

count-data models estimate job mobility for the total designated sample and among nonmovers.

The probit specification exploits the panel nature of the data, which follows the young male workers yearly. The labor market participant derives utility from his primary employment, which, following Wooldridge (2002), can be expressed as,

$$y^*_{it} = \mathbf{x}_{it}\beta + \varepsilon_{it}, \quad i = 1, \ldots, n; t = 1, \ldots, \mathrm{T}, \tag{1}$$

where y^*_{it} is a latent variable representing respondent *i's* net benefits at period t. The vector $\mathbf{x}_{it}$ includes personal characteristics (for example, race and marital status), job specific variables, such as occupation and wage, location variables such as unemployment rate and population density, and a constant term. The model error term, ε_{it} is assumed independently drawn from a normal distribution.

The labor market participant will change primary employment in period t if an available job generates net benefits greater than what the worker receives at the current job. If more than one job has potentially greater benefits than his current employment, the worker will select that job yielding the greatest benefits. Define the unobserved net benefits for person i in period t, $\hat{y}_{it}$, to be the maximum net benefits over all job prospects (j) considered by the worker in time t, including the current job,

$$\hat{y}_{it} = \max(\hat{y}_{ijt}), \quad j = 1, 2, \ldots, J,$$

where J is the total number of jobs considered by the worker (which may or may not exhaust all possible openings). The decision-maker is assumed to know $\hat{y}_{it}$ with certainty at period t, although it may be known only ex post (Jovanovic, 1979). The observed outcome occurs when the labor market participant follows the rule in equation (2),

$$\begin{aligned} y_{it} &= 1 \text{ if } \hat{y}_{it} > \hat{y}_{i,currentjob,t}, \\ y_{it} &= 0 \text{ if } \hat{y}_{it} \leq \hat{y}_{i,currentjob,t}, \end{aligned} \tag{2}$$

where $y_{it} = 1$ indicates respondent i changed primary employment at time t.

Given that $\hat{y}_{it}$ is never fully observed by the researcher, and defining $\hat{y}_{it} \equiv y^*_{it}$, the probability of a job change, ($y_{it} = 1$) can be expressed, using equations (1) and (2), as,

$$\begin{aligned} \Pr(y_{it} = 1 \mid \mathbf{x}_{it}) &= \Pr(\varepsilon_{it} > -\mathbf{x}_{\mathrm{it}}\beta) \\ &= \Pr(\varepsilon_{it} < \mathbf{x}_{\mathrm{it}}\beta) \\ &= \Phi(\mathbf{x}_{\mathrm{it}}\beta). \end{aligned}$$

Under the probit specification, ε_{it} is assumed to be normally distributed and the probability of changing employment can be taken from the standard normal cumulative function, Φ.

The alternative count-data specification estimates total job turnover within the career window. The total number of job starts is assumed to reflect an aggregate of the utility maximizing decisions modeled above. The count-data specification is used because total job starts is a discrete variable. Using the negative binomial function, we estimate the probability the youth will acquire y number of jobs within the six-year window. Variation in total job starts across the sample is a function of the personal, job, and urbanization characteristics that determined the discrete decision estimated in the probit model. The negative binomial model is shown as,

$$f(y \mid \mathbf{x}) = \frac{\exp(-\lambda\nu)\lambda^{y}}{y!}, \tag{3}$$

where λ is a function of $\mathbf{x}$, representing the individual and urbanization covariates, and ν is a positive stochastic term that is independently distributed. Variation in y is determined by the observed heterogeneity across the sample (differences in λ) and by the unobserved ν. Equation (3) is a modification of the Poisson density.[3] The parameters within the equation are estimated using the negative binomial function after specifying that ν follows the gamma distribution (Cameron and Trivedi, 2001). The sign of the parameters, in linear specifications, can be interpreted as the same as the sign of the marginal effects.

5. RESULTS

Table 2 illustrates the negative binomial model determining cumulative job starts over the six-year windows for the sampled youth. The values of the regressor variables are set at the first year of each job window. The specifications in Table 2 covering the full sample include youth who at some point in their early career moved out of their urban area and those who did not. The "stayers" specifications show results for those who remained in the same urban area over the period.[4] For each sample, a model is presented with population and density entered either linearly or as a quadratic; and all models control for the nine Census Divisions.

We hypothesize that urbanization facilitates "job shopping" for employment matches inducing labor turnover. Population size and density, our primary indicators of urbanization, index the physical proximity to jobs, while the level of social interaction affecting job information flows is measured by the proportion of adults in the urban area with a college degree. We hypothesize that all three indicators of urbanization promote job mobility in the early career.

[3]The negative binomial model is often preferred over the Poisson due to the Poisson model's restriction that the mean of the dependent variable equal its variance. Our sample violates the equidispersion property. The mean number of job starts within the constructed windows (3.8) is less than half the variance (8.0). Statistical tests in the estimation of the negative binomial support the overdispersion specification.

[4]"Movers" are kept within the full sample but not separately modeled. For the youth who moved, the urban covariates would reflect their labor market characteristics only for the period they remained in their initial urban area.

TABLE 2: Negative Binomial Model Estimating the Number of Jobs Acquired Over Six-Year Job Market Interval

Variable	Full Sample	Full Sample	Stayers	Stayers
Personal characteristics				
Non-Hispanic White	0.1353*	0.1366*	0.0751	0.0774
	(0.0495)	(0.0496)	(0.0585)	(0.0586)
Black	0.1947*	0.1927*	0.1049	0.1049
	(0.0556)	(0.0556)	(0.0655)	(0.0654)
Highest grade achieved	−0.0530*	−0.0541*	−0.0556*	−0.0560*
	(0.0082)	(0.0082)	(0.0099)	(0.0100)
Married	−0.0060	−0.0048	−0.0568	−0.0537
	(0.0592)	(0.0593)	(0.0722)	(0.0725)
Experience	−0.0616*	−0.0587*	−0.0573*	−0.0541*
	(0.0118)	(0.0116)	(0.0140)	(0.0137)
Wage	−0.0208*	−0.0207*	−0.0306*	−0.0309*
	(0.0074)	(0.0074)	(0.0081)	(0.0081)
Children	0.0638	0.0601	0.0866**	0.0836**
	(0.0421)	(0.0418)	(0.0500)	(0.0499)
Metropolitan area characteristics				
Unemployment rate	0.2796	0.2231	1.3180	1.2395
	(0.7994)	(0.7966)	(0.9425)	(0.9358)
Population	0.0131**	0.0361	0.0201*	0.0555*
	(0.0068)	(0.0226)	(0.0079)	(0.0266)
Population squared	—	−0.0022	—	−0.0030
		(0.0016)		(0.0020)
Principal city density	−0.0115	−0.0745*	−0.0210**	−0.0891*
	(0.0112)	(0.0341)	(0.0128)	(0.0403)
Density squared	—	0.0049**	—	0.0053**
		(0.0026)		(0.0031)
Proportion college grad	0.9453*	0.7174	1.5876*	1.2153*
	(0.4810)	(0.5217)	(0.5854)	(0.6324)
Constant	2.0621*	2.2273*	1.9003*	2.0929*
	(0.1690)	(0.1821)	(0.2067)	(0.2222)
Observations	1,782	1,782	1,418	1,418
Log likelihood	−3,974.85	−3,972.55	−3,110.39	−3,108.68
Pseudo-R^2	0.028	0.028	0.028	0.029

Notes: The sample is restricted to those who had calculated job count observations in each of the six years of the constructed job window. Covariates are measured at the beginning of the six-year window. Dummy variables indicating region, based on nine census divisions, are included in the models but are not shown. Robust standard errors are given in parentheses. *Significant at the 5 percent level, **significant at the 10 percent level.

Table 2 indicates that the three covariates are significant determinants of labor turnover. Labor market participants living in larger, more educated urban areas change jobs more frequently in their early career. The results suggest urban size entered linearly is more appropriate than the quadratic specification of

TABLE 3: Expected Number of Jobs by Urbanization Measures

Evaluated at:	Full Sample	Stayers
Means of the covariates	3.4855	3.3555
	(3.259, 3.7121)	(3.0893, 3.6217)
Urban size		
Large	3.5247	3.5028
Small	3.1567	2.8444
Difference	0.3681	0.6584
	(−0.0669, 0.8030)	(0.1101, 1.2067)
Principal city density		
High	3.4289	3.2546
Low	3.9364	3.9099
Difference	−0.5075	−0.6552
	(−1.0324, −0.0174)	(−1.2291, −0.0814)
Educational achievement		
High	3.5646	3.4868
Low	3.3995	3.2149
Difference	0.1651	0.2719
	(0.0677, 0.3978)	(−0.0005, 0.5443)

Notes: Based on estimates from the quadratic job count model in Table 2. High values are based on the 75th percentile of the covariate, and low values are based on the 25th percentile for each sample. All other covariates are held at their mean. Numbers in parentheses are 95 percent confidence intervals.

population. Population density entered quadratically appears more appropriate in the full sample. Contrary to expectations, an increase in urban density decreases turnover; the quadratic model, however, indicates this effect over only an initial range of population density. The estimated marginal effects for the variable in the full sample indicate a relationship that turns positive once density exceeds 7,650 persons per square mile, roughly the 73rd percentile in the distribution of population density.[5]

Table 3 shows how the expected number of job changes in the six-year window differ for high and low values of the urbanization measures. We use the 75th and 25th percentiles for each sample as the high and low values of the measures, holding the remaining covariates to their sample mean. The results indicate only a moderate difference in predicted job count between the mean of the urbanization variables and their high values. The difference in predicted job count between the high and low values of the covariates, however, is more substantial.

The positive relationship urban size has with turnover indicates the increased choices larger areas present to young entrants into the labor market. Urban density has an inverse relationship with job turnover over a range

[5]The marginal effects from the negative binomial and probit models are not shown.

within which most urban areas fall. The inverse relationship found for density is consistent with Wheeler's (2005) hypothesis that urbanization decreases the turnover needed to converge to an efficient job match. Wheeler (2005), using a specification that enters population size and density in separate regressions, finds that both population size and density inversely correlate with mobility.

We distinguish between the full sample and "stayers" to address the possible endogeneity of location resulting from residence being determined by unobserved characteristics of the respondents related to labor market activity. Location endogeneity could bias the estimated effect the urbanization characteristics have on job mobility.[6] Although the direction of this bias is ambiguous, under reasonable assumptions the bias is likely to be positive. For example, youth may migrate to (or elect to remain in) more urban labor markets due to unobserved characteristics related to finding a tighter job match. From our hypothesis on early career mobility, the self-selection would lead to an overestimate of the effect urbanization has on job turnover. The linear specifications in Table 2 for "stayers," a sub-sample for which location is assumed not be a choice variable, produce estimated effects for each of the urbanization variables that are larger (in absolute value) than in the full sample inconsistent with the expected bias.[7] The urbanization effects are larger for "stayers" also in the quadratic specifications at least over the initial range of population and density. To examine further the possible endogeneity, we now compare the count-data specifications to probit models that account for labor market behavior within the six-year windows.

The probit specifications in Table 4 estimate the yearly probability of job change for the full sample and separately for "movers" and "stayers."[8] The inferences drawn from the models are largely consistent with the negative binomial results. The primary indicators of urbanization, population size and density, both significantly determine job mobility in the quadratic specification for the full sample. The two covariates generate opposing effects in the linear specifications in Table 4, as in the count-data models. In the quadratic specifications, the opposing signs for each variable's two-parameter estimates indicate decay in the variables' marginal effect, found also in the count-data models. The estimated marginal effect population density has on job turnover in the probit model turns positive, however, at a smaller density level, approximately the

[6]The effect geography has on job market behavior could be estimated in a two stage selection model in which location choice is first determined. The individual choice sets would have to be modeled however, which is extremely difficult to determine.

[7]Geography is potentially endogenous even among youth observed to have remained in the same area over the six-year window. Conversely, location is not necessarily endogenous for those who had moved. If the location choice were determined by factors unrelated to labor market behavior, the urbanization covariates would be exogenous within the models.

[8]Each of the probit specifications includes a lagged wage variable, causing the first year's observation of each respondent to drop out. Each youth is observed a maximum of five times.

TABLE 4: Probit Model Results for Employment Mobility

Variable	Full Sample	Full Sample	Movers	Movers	Stayers	Stayers
Personal characteristics						
Non-Hispanic White	0.1547*	0.1543*	0.2346*	0.2387*	0.1137*	0.1140*
	(0.0445)	(0.0446)	(0.0883)	(0.0887)	(0.0517)	(0.0518)
Black	0.1436*	0.1364*	0.3411*	0.3357*	0.1032**	0.0983**
	(0.0495)	(0.0495)	(0.1038)	(0.1039)	(0.0564)	(0.0564)
Interval-year	−0.0404*	−0.0411*	−0.0378	−0.0403	−0.0441*	−0.0445*
	(0.0116)	(0.0115)	(0.0257)	(0.0257)	(0.0131)	(0.0131)
Highest grade achieved	−0.0337*	−0.0335*	−0.0444*	−0.0449*	−0.0399*	−0.0398*
	(0.0080)	(0.0080)	(0.0151)	(0.0150)	(0.0093)	(0.0094)
Married	−0.1645*	−0.1687*	−0.0767	−0.0812	−0.1950*	−0.1974*
	(0.0350)	(0.0350)	(0.0723)	(0.0723)	(0.0404)	(0.0404)
Experience	−0.0985*	−0.0978*	−0.0619*	−0.0622*	−0.1030*	−0.1023*
	(0.0097)	(0.0097)	(0.0199)	(0.0198)	(0.0110)	(0.0110)
Wage_{t-1}	−0.0341*	−0.0344*	−0.0474*	−0.0479*	−0.0309*	−0.0312*
	(0.0064)	(0.0064)	(0.0088)	(0.0088)	(0.0076)	(0.0077)
Children	0.0371**	0.0393**	0.0417	0.0398	0.0444**	0.0464*
	(0.0216)	(0.0216)	(0.0426)	(0.0428)	(0.0249)	(0.0249)

Continued

TABLE 4: Continued

Variable	Full Sample	Full Sample	Movers	Movers	Stayers	Stayers
Metropolitan area characteristics						
Unemployment rate	−2.2218*	−2.3015*	−2.7828**	−2.5533**	−2.0783*	−2.1731*
	(0.7135)	(0.7137)	(1.4396)	(1.4351)	(0.8349)	(0.8351)
Population	0.0072	0.0641*	−0.0018	0.0698**	0.0118**	0.0544*
	(0.0058)	(0.0197)	(0.0123)	(0.0377)	(0.0067)	(0.0233)
Population squared	—	−0.0042*	—	−0.0047**	—	−0.0032*
		(0.0013)		(0.0025)		(0.0016)
Principal city density	−0.0015	−0.0759*	0.0276	−0.0271	−0.0088	−0.0674*
	(0.0096)	(0.0271)	(0.0188)	(0.0523)	(0.0113)	(0.0318)
Density squared	—	0.0057*	—	0.0042	—	0.0045*
		(0.0020)		(0.0038)		(0.0023)
Proportion college grad	−0.1040	−0.6702	−1.1930**	−1.7285**	0.2111	−0.2539
	(0.4035)	(0.4400)	(0.6790)	(0.7140)	(0.5008)	(0.5561)
Constant	1.2697*	1.5122*	1.5979*	1.7850*	1.2245*	1.4228*
	(0.2104)	(0.2213)	(0.4040)	(0.4235)	(0.2522)	(0.2657)
Observations	12,224	12,224	2,385	2,385	9,782	9,782
Individuals	3,054	3,054	630	630	2,367	2,367
Log likelihood	−7,620.92	−7,613.42	−1,510.64	−1,508.06	−5,974.77	−5,971.45
Pseudo-R^2	0.0567	0.0576	0.0830	0.0846	0.0559	0.0564

Notes: Dummy variables indicating individual years and nine census regions are included in the models but are not shown. *Significant at the 5 percent level, ** significant at the 10 percent level.

69th percentile for the variable in the full sample.[9] The covariate measuring the proportion college educated falls out of significance across models except for "movers."

Comparing the probit results for "stayers" to "movers" in Table 4, the quadratic specifications indicate population is a significant determinant of job mobility among "movers" while both population size and density influence those who remain in same area in their early career. If location is considered endogenous for the youth who relocated during the career window, the comparison of the population point estimates in the quadratic model points to the possible bias in urbanization effects. At least within the lower range of population size, the estimated relationship between urban size and the probability of job change is larger among "movers" than "stayers." While both relationships decay as population grows, the unsquared population term is substantially larger in the "movers" specification.

The results for both the count-data and probit specifications imply the size and density of the local labor market influence the job behavior of youth who remain in the same urban area in their early career. The difference in sign between the two urbanization measures (in their linear form) suggest they are accounting for different aspects of urbanization's effect on mobility; urban size indicating the pool of choices open to labor market entrants and density indexing the cost of job access. Results in the count-data model also suggest the effect an area's education level has on the flow of job information. We draw these inferences assuming youth labor markets are primarily local. While this assumption is not directly tested, evidence such as Yankow's (2003) finding that over 85 percent of job turnover among young males is intra-county suggests it is not unreasonable. We also find some evidence indicating possible location endogeneity among "movers."

The mean difference in labor mobility between the two groups is shown in Table 7. Those who moved at some point in their early career started more jobs on average each year than those who did not. The difference between "movers" and "stayers," statistically significant in all but the first year, grows in the first four of the six years. While the number of job starts falls continuously over time for both groups, "movers" in the last year of their observed career window exhibit a larger average number of starts than "stayers" had by their third year.

The probabilities of job change calculated from the quadratic probit model indicate that a change in urban size has only a moderate affect on the probability of job turnover. In Table 5, a standard deviation change in urban population increases the "movers" probability of job change by 1.6 percentages points; the "stayers" probability changes by less than a percentage point. The effects are

[9]For the full sample, the marginal effects for the quadratic probit specifications indicate the estimated effect urban size has on the probability of job change becomes negative where the metropolitan area population goes beyond 7.7 million residents. Population density has a positive effect beyond the density level of 6,612 per square mile.

TABLE 5: Job Change Probability Estimates Conditional on the Urbanization Characteristics

Evaluated at the:	Full Sample	Movers	Stayers
Mean of the covariates	0.3781	0.4807	0.3489
	(0.3563,0.3998)	(0.4432,0.5182)	(0.3231,0.3747)
Mean + 1SD in population	0.3717	0.4966	0.3518
	(0.3298,0.4135)	(0.4191,0.5741)	(0.3018,0.4018)
Mean + 1SD in density	0.4060	0.5322	0.3619
	(0.3604,0.4515)	(0.4615,0.6028)	(0.3056,0.4182)
Mean + 1SD in percent college	0.3656	0.4429	0.3444
	(0.3422,0.3891)	(0.3981,0.4877)	(0.3172,0.3717)

Notes: Based on estimates from the quadratic probit model in Table 4. The job change probabilities are calculated holding all variables, other than the illustrated urbanization covariate, constant at their means. The 95 percent confidence intervals are in parentheses.

TABLE 6: New Job Probabilities by Year within the Six-Year Interval

	Proportion Who Made at Least One New Job Start:		
Year in job interval	Full sample	Movers	Stayers
First year	0.8226	0.8409	0.8162
	(0.0075)	(0.0159)	(0.0086)
Second	0.5167	0.5943	0.4925
	(0.0093)	(0.0201)	(0.0105)
Third	0.4276	0.5236	0.4013
	(0.0091)	(0.0205)	(0.0102)
Fourth	0.3774	0.4807	0.3515
	(0.0089)	(0.0205)	(0.0098)
Fifth	0.350	0.4407	0.3263
	(0.0087)	(0.0204)	(0.0096)
Sixth	0.3433	0.4095	0.3221
	(0.0088)	(0.0206)	(0.0098)

Notes: The sample consists of 3,054 respondents but the number used to calculate the above statistics varied by year due to missing values for the job count variable. The values in parentheses are the standard errors of the calculated sample proportions.

substantially smaller than, for example, the yearly decrease in the probability of job change over the first four years (see Table 6). The effect for changes in population from the linear probit specification (not shown) indicates a similar pattern. The estimated effects of density are larger and more sensitive to specification. The marginal effect population density has on job mobility is estimated to turn positive in the quadratic probit model at a density level not far above the mean. This effect is reflected in Table 5, in which "movers" and "stayers" increase their probability of job change if they reside in an urban area with a density one standard deviation above the mean.

The decrease over time in the mean number of starts shown in Table 7 suggests youth converge over time to more efficient employment matches. Topel

TABLE 7: Average Number of Job Starts by Year Within the Six-Year Interval

Year in job Interval	Full Sample	Movers	Stayers
First year	1.2460	1.2652	1.2333
	(0.0186)	(0.0424)	(0.0208)
Second	0.7342	0.8569	0.6938
	(0.0166)	(0.0381)	(0.0184)
Third	0.5748	0.7138	0.5343
	(0.0146)	(0.0344)	(0.0159)
Fourth	0.5155	0.7092	0.4673
	(0.0145)	(0.0377)	(0.0153)
Fifth	0.460	0.6153	0.4193
	(0.0134)	(0.0347)	(0.0142)
Sixth	0.4545	0.5817	0.4159
	(0.0136)	(0.0354)	(0.0146)

Notes: The sample consists of 3,054 respondents but the number used to calculate the above statistics varied by year due to missing values for the job count variable. The values in parentheses are the standard errors of the calculated sample means.

and Ward (1992) find that a substantial proportion of lifetime job change occurs in the first few years of a career. The probit specifications in Table 4 also indicate that the probability of job change declines intertemporally within the six-year window. The interval-year variable in Table 4 indexes the specific period within the six-year window the respondent is in. The inverse relationship is statistically significant within the full model and specifically for "stayers."

The probit and count-data results for many of the individual characteristics of the youth are intuitive and are consistent with previous findings on the determinants of labor turnover. Both models suggest youth with more years of education and labor market experience exhibit less early career turnover. The point estimates for both covariates are negative and statistically significant for the full sample and across sub-samples for both models. Farber (1994) finds similar evidence on the relationship between education and labor turnover. The affect labor market experience has on mobility is well established in the labor literature (Topel and Ward, 1992; Farber, 1994; Neal, 1999). In specifying the six-year window, we allow youth to continue going to school although not for consecutive years. The highest grade achieved, in addition to job experience, may vary intertemporally in the probit specifications.

An increase in wage is associated with a decrease in job turnover in the probit and count-data specifications. The covariate is lagged one year in the probit models and takes on the value established at the start of the job window in the count-data specifications. The point estimates for the covariate are negative and significant across specifications. These results follow Topel and Ward

(1992), which also finds job mobility decreases as the wage rises.[10] The probit specifications also indicate that young participants in the labor market start jobs less frequently in metropolitan areas with higher unemployment rates. The inverse relationship between unemployment rate and mobility is highly significant in the "stayers" probit specifications, and at the 10 percent level among "movers." The covariate is not statistically significant in the count-data specifications.

Results from the full sample suggest Black and Non-Hispanic White youth who live in urban areas generally change jobs more often than Hispanic youth, holding other factors constant. The result is found in both the probit and negative binomial specifications. The effects for ethnicity are less precisely estimated among "stayers." Both specifications indicate marriage decreases job turnover although the relationship is statistically significant only in the probit models. Surprisingly, the number of children living in the household is associated with increases labor market instability. The point estimate for the covariate is positive and significant for "stayers" across models and in the full sample in the probit.

6. CONCLUSION

We test the hypothesis that the productivity advantage of cities derives partially from greater coordination in urban labor markets. We examine the labor market activity of young urban men using the hypothesis that turnover in the early career reflects a move to tighter labor matches. We find that larger urban areas are associated with greater labor mobility in the early career. Urbanization affords young workers the opportunity to try various jobs in search of a closer match. The effect urbanization has on job mobility is found primarily for those who remain in the same area. We find that density induces turnover but only among the more densely populated labor markets. The level of education in an area, affecting the flow of information on jobs, also induces turnover, at least within the count-data specifications. Our empirical findings for young workers support the theories suggesting urban areas are wealthier because of their advantage in labor matching.

REFERENCES

Bartel, Ann P. and George J. Borjas. 1981. "Wage Growth and Labor Turnover," in Sherwin Rosen (ed.), *Studies in Labor Markets*. Chicago: University of Chicago Press, pp. 65–90.

[10]The one-period lagged wage may yet be endogenous given lags between the decision to start new employment and the actual job start. The probit models may be controlling for returns to labor by the included human capital variables (e.g., experience, education). Appendix A illustrates the quadratic probit specifications excluding wage. The point estimates for experience, education as well as the interval-year variable increase substantially in absolute value. The urbanization effects are largely unchanged.

Cameron, A. Colin and Pravin K. Trivedi. 2001. "Essentials of Count Data Regression," in Badi H. Baltagi (ed.), *A Companion to Theoretical Econometrics*. Oxford: Blackwell Publishers, pp. 331–348.

Corcoran, Mary. E., Linda Datcher, and Greg Duncan. 1980. "Most Workers Find Jobs through Word of Mouth," *Monthly Labor Review*, 103, 33–35.

Costa, Dora. L. and Matthew E. Kahn. 2000. "Power Couples: Changes in the Locational Choice of the College Educated, 1940–1990," *Quarterly Journal of Economics*, 115, 1287–1315.

Farber, Henry S. 1994. "The Analysis of Interfirm Worker Mobility," *Journal of Labor Economics*, 12, 554–593.

Glaeser, Edward. L. 1999. "Learning in Cities," *Journal of Urban Economics*, 46, 254–277.

Glaeser, Edward. L. and David C. Mare. 2001. "Cities and Skills," *Journal of Labor Economics*, 19, 316–342.

Granovetter, Mark S. 1995. *Getting a Job: A Study of Contacts and Careers*, 2nd ed. Chicago: University of Chicago Press.

Helsley, Robert W. and William. C. Strange. 1990. "Matching and Agglomeration Economies in a System of Cities," *Regional Science and Urban Economics*, 28, 189–212.

Holzer, Harry J. 1988. "Search Method Use by Unemployed Youth," *Journal of Labor Economic*s, 6, 1–20.

Jovanovic, Boyan. 1979. "Job Matching and the Theory of Turnover," *Journal of Political Economy*, 87, 972–990.

Kim, Sunwoong. 1987. "Diversity in Urban Labor Markets and Agglomeration Economies," *Papers of the Regional Science Association*, 62, 57–70.

———. 1990. "Labor Heterogeneity, Wage Bargaining, and Agglomeration Economies," *Journal of Urban Economics*, 28, 160–177.

Light, Audrey and Kathleen McGarry. 1998. "Job Change Patterns and the Wages of Young Men," *Review of Economics and Statistics*, 80, 276–286.

Moretti, Enrico. 2004. "Workers' Education, Spillovers and Productivity: Evidence from Plant-Level Production Functions," *American Economic Review*, 94, 656–690.

Neal, Derek. 1999. "The Complexity of Job Mobility among Young Men," *Journal of Labor Economics*, 17, 237–261.

Neumark, David. 2002. "Youth Labor Markets in the United States: Shopping Around vs. Staying Put," *Review of Economics and Statistics*, 84, 462–482.

Putnam, Robert D. 2001. *Bowling Alone: The Collapse and Revival of American Community*, New ed. New York: Simon and Shuster.

Rauch, James E. 1993. "Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities," *Journal of Urban Economics*, 104, 869–895.

Sato, Yasuhiro. 2001. "Labor Heterogeneity in an Urban Labor Market," *Journal of Urban Economics*, 50, 313–337.

Topa, Giorgio. 2001. "Social Interactions, Local Spillovers and Unemployment," *Review of Economic Studies*, 68, 261–295.

Topel, Robert H. and Michael P. Ward. 1992. "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics*, 107, 439–479.

Wheeler, Christopher H. 2001. "Search, Sorting, and Urban Agglomeration," *Journal of Labor Economics*, 19, 879–899.

———. 2005. "Local Market Scale and the Pattern of Job Changes Among Young Men," working paper.

———. 2006. "Cities and the Growth of Wages among Young Workers: Evidence from the NLSY," *Journal of Urban Economics*, 60, 162–184.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Massachusetts: MIT Press.

Yankow, Jeffrey J. 2003. "Migration, Job Change, and Wage Growth: A New Perspective on the Pecuniary Return to Geographic Mobility," *Journal of Regional Science*, 43, 483–516.

APPENDIX A: Probit Model of Employment Mobility without Lagged Wage Covariate

Variable	Full sample	Movers	Stayers
Personal characteristics			
Non-Hispanic White	0.1221*	0.2258*	0.0774**
	(0.0398)	(0.0815)	(0.0459)
Black	0.1165*	0.3023*	0.0749
	(0.0445)	(0.0942)	(0.0504)
Interval-year	−0.1400*	−0.1315*	−0.1453*
	(0.0091)	(0.0201)	(0.0103)
Highest grade achieved	−0.0501*	−0.0701*	−0.0529*
	(0.0067)	(0.0129)	(0.0079)
Married	−0.1925*	−0.1040	−0.2233*
	(0.0324)	(0.0660)	(0.0373)
Experience	−0.1582*	−0.1220*	−0.1645*
	(0.0084)	(0.0177)	(0.0094)
Children	0.0324	0.0388	0.0399**
	(0.0207)	(0.0407)	(0.0239)
Metropolitan area characteristics			
Unemployment rate	−2.1274*	−2.4713*	−1.9441*
	(0.6368)	(1.2581)	(0.7441)
Population	0.0635*	0.0707*	0.0563*
	(0.0178)	(0.0345)	(0.0210)
Population squared	−0.0041*	−0.0041**	−0.0034*
	(0.0012)	(0.0023)	(0.0014)
Principal city density	−0.0800*	−0.0479	−0.0709*
	(0.0249)	(0.0475)	(0.0292)
Density squared	0.0058*	0.0042	0.0048*
	(0.0018)	(0.0034)	(0.0021)
Proportion college grad	−0.7792**	−1.6909*	−0.4050
	(0.4034)	(0.6513)	(0.5096)
Constant	2.9009*	2.9346*	2.8962*
	(0.1638)	(0.3147)	(0.1976)
Observations	15,574	3,054	12,434
Individuals	3,131	646	2,399
Log likelihood	−9,448.88	−1,853.89	−7,446.67
Pseudo-R^2	0.1214	0.1193	0.1275

Notes: Dummy variables indicating individual years and regions are included in the models but are not shown. *Significant at the 5 percent level, **significant at the 10 percent level.