Landing a Job in Urban Space:
The Extent & Effects of Spatial Mismatch

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Abstract
This paper emphasizes the spatial nature of the job search process and analyzes the effects of job accessibility on search duration. Unique measures of accessibility to turnover-induced job availability and accessibility to employment opportunities generated by employment growth are developed. The results provide strong support of the spatial mismatch hypothesis, and indicate that job search behavior/outcomes are affected by the interaction of the degree of residential location constraints facing the job seeker and the searcher's proximity to employment opportunities. Simulation results show that black's greater sensitivity to local labor market demand conditions contribute significantly to the black-white gap in search durations. Racial differences in the distribution of job accessibility account for one-fourth of the black-white gap in the hazard of successfully completing a job search, and the cumulative effect of racial differences in all the spatial search-related variables accounts for half the overall black-white gap.

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I. Introduction

The increasing decentralization of employment, especially amongst low-skill jobs, that has occurred in U.S. metropolitan areas over the past 30 years has been well documented (Kasarda 1985, 1995; Hughes and Sternberg 1992). Yet, low-income households, particularly minorities, are largely residentially confined to the central city because of lack of affordable suburban housing, exclusionary zoning, and discrimination (Yinger 1986, 1995). Consequently, their residential location decisions are not very responsive to changes in the geographic distribution of employment opportunities. In addition, public transit routes, originally designed to transport suburban residents to the central city, are now outmoded and inadequate to reach today's sprawling suburban job growth areas.

The ways less-educated individuals search for work, as well as the costs associated with search, have implications for the effects of increased suburbanization of low-skilled employment. Are individuals expanding their search geographically in response to the decentralization of employment? This paper will analyze job search behavior and its effects on search duration, to investigate how access to employment opportunities affects the labor market outcomes of less-educated individuals. I use a search theoretic framework to analyze the mechanisms through which a worker's location affects his/her return to human capital. My analysis uses data from three large metropolitan areas, Los Angeles, Atlanta, and Boston.

Kain (1968) was the first to propose the relationship between residential segregation and labor market outcomes, commonly referred to as the "Spatial Mismatch Hypothesis" (SMH). The SMH proposes that involuntary housing segregation acts to disadvantage poor inner-city workers' labor market outcomes by isolating them from labor market opportunities. Kain's original formulation applied only to blacks. However, given the trend of increasing residential segregation by class (Massey and Denton 1996), the SMH may now apply more generally to less-skilled workers, regardless of race.

In this paper, I use the household and employer surveys of the Multi-City Study of Urban Inequality (MCSUI) data set to investigate the labor market effects of spatial factors, in ways that differ from those of previous analyses. For each respondent, I develop geographic measures of job accessibility using the spatial distribution of the sample of recently filled non-college jobs and net hires from the Employer Survey (which approximates the sample of jobs available to current/recent job searchers). The measures also account for the spatial distribution of the competing workforce for these non-college jobs. Additionally, the MCSUI Household Survey contains extensive information about how and where individuals searched for jobs. This job search analysis is only one of a few studies that analyzes the search durations of both individuals searching while employed and those searching while unemployed.

A primary goal of this research is to improve our understanding of job search behavior and search outcome differences between racial groups, and to investigate the role of the spatial structure of urban areas (specifically, residential segregation and the decentralization of employment) in contributing to these differences. What is of especial importance in this analysis and has important policy implications for less-skilled workers is identifying possible barriers that apply to some racial/income groups and not others, that ultimately contribute to racial disparities in search outcomes and underemployment.

The main results of the paper are as follows. I find that job accessibility for less-educated workers is greatest in predominantly white suburbs more than 10 miles from the centroid of black residential concentration, and that these "job-rich" areas are not served by public transportation. I also find that job search behavior and job search outcomes are affected by the interaction of the degree of residential location constraints facing the job seeker and his/her proximity to employment opportunities. There are significant race differences in the effects of job accessibility. Simulation results show that black's greater sensitivity to local labor market demand conditions contribute significantly to the black-white gap in search durations. In addition, racial differences in the distribution of job accessibility account for nearly one-fourth of the black-white gap in the hazard of successfully completing a job search, and the cumulative effect of racial differences in all the included spatial search-related variables accounts for roughly half of the overall black-white gap.

This paper will proceed as follows. I will begin with a discussion of relevant theoretical issues. Then, I will highlight features of this study that represent important departures from and improvements upon previous studies. In the fourth section, I describe the methodology, data, and variables utilized. Then, I report descriptive and regression results and conclude with a discussion of policy implications.

II. Theoretical Considerations

Spatial mismatch causes (otherwise) identical individuals to achieve different labor market outcomes because of their residential location. The SMH literature has evolved largely without an explicit theoretical model to explain how spatial structure affects labor market activity. Placing the present analysis in the context of a search theoretic framework helps to provide insight into why space matters. Coulson et al. (2001) develop a general equilibrium search model that highlighted the conditions necessary to generate cross-location differences in unemployment and vacancy rates in search equilibrium.

The necessary/sufficient conditions for spatial mismatch to emerge in equilibrium are:

(i) residential location decisions must be constrained,
(ii) firms must face higher costs (set-up/production costs) in areas where residents are constrained,
(iii) search or commuting costs must be non-trivial.

We expect optimal supply-side responses to geographic labor demand shifts to operate through either migration or adjustments of job search/commuting patterns. Thus, in the presence of either free mobility of residences or low commuting and spatial job search costs, market forces will tend to equalize labor market opportunities across neighborhoods and eliminate spatial mismatch. Even with constraints on residential mobility and non-trivial commute/search costs faced by workers, mobility of firms will cause equalization of opportunity because of market pressure on firms to move to equalize access to labor and wages. This underscores the necessity of condition (ii)—firms must face a tradeoff between accessibility to labor and efficiency of production in order for spatial mismatch to exist in equilibrium. There is indeed substantial empirical evidence documenting a number of factors contributing to lower set-up/production costs in the suburbs, including lower land prices, greater accessibility to transportation routes and relevant product markets, less concerns about crime, and lower taxes (e.g., see Erickson and Wasylenko (1980), Wasylenko (1984)).

The necessity and sufficiency of conditions (i)-(iii) to generate spatial mismatch, have implications for race differences in the labor market effects of spatial-related factors. There are at least three reasons why we may expect to find spatial mismatch among blacks and not among whites. First, while suburban land use policies such as exclusionary zoning reduce the residential mobility of both black and white low-income households, blacks face more residential location constraints due to discrimination in housing and mortgage markets (Yinger 1986, 1995). Second, as will be shown in this paper, blacks rely more heavily upon public transit because of lower car ownership rates (relative to whites), increasing their spatial search/commute costs (due to slower form of transportation) and also limiting their potential search radius in areas not served by public transportation. Third, blacks have inferior social networks and information to connect them to available jobs (Ihlanfeldt 1997).

Since whites are relatively unconstrained in their housing choices, have higher car ownership rates, and better information about job opportunities, job accessibility at the beginning of a job search should be less binding, and they should be less sensitive to local labor market demand conditions. In particular, whites, exhibiting forward-looking behavior, may be more likely to search in distant areas, with plans to move after securing employment in a distant locale. Whites will search in a locale and if they really need to be close to get the job, they will move closer; on the other hand, if they prefer the amenities of living far away from the job (e.g., lower per unit housing costs), and their search/commuting technology enables them to still have access to the job, they will live far from the job. Thus, a locational equilibrium is established that sorts whites (residential locations) according to their comparative advantages in commuting long distance. Assuming the migration cost is low enough so that all whites search in the suburbs, whites that continue to reside in the central city are precisely those individuals with the highest commuting ability, and they reverse commute from the CBD to the SBD. On the other hand, because blacks/Hispanics face greater constraints with respect to residential location, transportation, and job information, we would expect blacks/Hispanics to be more sensitive to local labor market demand conditions.

As implied by search theoretical models, we expect an increase in local employment growth to increase local job accessibility, and thus the quality of worker-job matching. The direct effect is to increase worker matching rates, making it easier for searchers to locate job vacancies. This will decrease search costs and expected search duration, and increase rates of search among the non-employed. Secondly, an increase in area employment growth will have an indirect effect on job accessibility in that by increasing opportunities for inter-firm labor mobility, rates of search among the employed will increase. This will cause area turnover rates to rise, resulting in greater accessibility to turnover-induced vacancies.

Access to a data set that can test the empirical validity of various implications of spatial search theoretic models is a major asset of this work. While there is ample empirical evidence documenting the existence of residential mobility constraints facing black workers, and supporting evidence of lower firm set-up/production costs in the suburbs, much less is known about the spatial nature and magnitude of search costs.

III. Empirical Challenges

Testing the SMH involves: (1) confronting the problem of the endogeneity of residential location, and (2) characterizing the spatial distribution of employment opportunities by creating a measure of access. Residential location is endogenous because of the simultaneity between an individual's labor market outcome and residential location decision. Which occurs first—does suburban residence, by conferring better proximity to job opportunities, lead to securing a good job? Or does a good job enable one to obtain suburban residence? If individuals who do well in the labor market voluntarily choose to make longer commutes in exchange for a lower cost per unit of housing (i.e., the income elasticity of housing demand is greater than the income elasticity of commute costs), then this will lead us toward finding no effects of job accessibility. Blacks/Hispanics, however, are less subject to this type of endogeneity bias because they face discrimination in the suburban housing market, and are thus geographically immobile (relative to whites).

In contrast to previous spatial mismatch studies, I have data on job searchers' residential locations at the time the search began, as well as any residential location changes during or after the job search was underway. As a result, I can address a specific kind of endogeneity ex-post—namely, that people might move to the jobs (e.g., Zax & Kain 1996).

Estimated effects of job accessibility may also suffer from omitted variable bias. My use of individual level micro data, as opposed to aggregate neighborhood level data, to examine spatial mismatch offers significant advantages in addressing this source of bias. Analyses of neighborhood employment rates, a common dependent variable (Ellwood 1986; Raphael 1998), do not control for personal and family characteristics that may also differ systematically by race and contribute to racial employment differentials. Thus, the estimated effects of job accessibility will be biased to the extent that neighborhood accessibility is a proxy for unobserved personal characteristics of residents. Previous analyses of individual-level data have not had access to neighborhood descriptors due to confidentiality restrictions. Thus, their exclusion means that measured effects of job accessibility could be biased by negative neighborhood effects arising from the concentration of poverty (Wilson 1987). In my job search model, I include both job accessibility and neighborhood variables, along with an extensive set of controls, to minimize omitted variable bias.

I also separate the effects of spatial structure on the labor force participation decision from their effects on search outcomes. The optimal search policy when employment opportunities are unattractive and information costs are high may be to not search at all. By restricting my sample to individuals who had recently conducted a job search, I focus on the effects of spatial structure on the job search behavior and job search outcomes of labor force participants.

IV. Data Description and Key Variables

The unique attributes of both the household and employer surveys of the Multi-City Study of Urban Inequality (MCSUI) data set make available the opportunity to investigate the effect of spatial factors on labor market outcomes. The MCSUI Employer and Household Surveys were administered between 1992-1994 in four cities: Atlanta, Boston, Los Angeles, and Detroit.

MCSUI Household Survey. The MCSUI Household Survey consists of a stratified random sample of adults living in households in each of the four cities, where households were stratified by income/poverty level and race/ethnicity. A total of 8,916 interviews were conducted. Blacks and residents of low-income neighborhoods were oversampled.[1] The Household Survey allows for a unique analysis of job search behavior and search outcomes because it contains detailed measures of where (in what geographic area) individuals searched for a job within each of the three metropolitan areas, as well as extensive information about the search methods used on the individual's most recent job search and the length of the job search spell (including, when search began, when it ended, and whether the search culminated in obtaining a new job, or whether the search spell was still on-going at the time of the interview). This information was collected from both individuals who were employed and unemployed, allowing a distinction to be drawn between individuals who obtained transitional employment while continuing to search, and those who successfully complete a job search.[2]

I restrict the sample to MCSUI respondents living in Atlanta, Boston, or Los Angeles, who began their most recent job search within the past twelve months (as of the survey interview date). I drop respondents who reported being in school, permanently disabled, retired, homemakers, sick or on maternity leave, as well as respondents who reported being only temporarily laid off. Additionally, I keep only observations for which I have information about the respondents' residential location throughout the duration of their search. Information contained in the data about the residential locations of respondents are geocoded to census tract locations for the duration of their job search. My final sample consists of 1,205 observations.[3]

MCSUI Employer Survey. I use the MCSUI Employer Survey (administered by Harry Holzer during the same period as the Household Survey) to map out the spatial distribution of recently-filled jobs not requiring a college degree, as well as the spatial distribution of net new hires over the past year, in the three MSAs, to construct measures of access to employment opportunities. The survey gathered information from 800 employers per metro area and provides detailed information about the recruitment process and search methods used to fill the most recent job not requiring a college degree.[4] Using appropriate sample weights, the sample of recently-filled non-college jobs constitutes a representative sample of turnover-induced job availability in local labor markets over a period of several months, while use of employer reports of net new hires over the past twelve months account for sources of job availability due to net employment growth.[5,6] The firms are geocoded to census tract locations and I use the sample of recently filled non-college jobs and the sample of net new hires to map out the spatial distribution of available jobs facing current/recent job searchers in Atlanta, Boston, and Los Angeles. I then use 1990 Census data to map out the spatial distribution of the competing workforce—the number of non-college educated individuals in each census tract—that my sample of current/recent job searchers will likely face in the labor market.[7]

V. Modeling Local Labor Market Job Accessibility

In this paper, I use the observed commuting behavior of employed workers as the basis to represent the local labor market. Using actual commuting patterns, I estimate a gravity model to isolate the effect of distance on intra-metropolitan less-skilled labor search/commuting behavior.[8] The estimated distance decay function captures the composite effects of distance in reducing the probability of searching for, finding, and accepting distant job offers. The estimate of the distance decay function is then used to discount distant employment opportunities and to discount distant competing workers, to form measures of accessibility. Below I detail the methods used to construct my accessibility measures, and in Appendix A I detail the methods used to estimate the distance decay function.

Employment opportunities are generated from two sources: non-layoff turnover-induced vacancies (quits, discharges, and retirement), and vacancies created by employment growth. Thus, I construct two measures of job accessibility to account for both sources of job availability. Turnover produces as many job seekers as job openings. I use the spatial distribution of the sample of recently filled non-college jobs from the MCSUI Employer Survey and account for the spatial distribution of the competing workforce for these non-college jobs, to construct my measure of accessibility to employment opportunities generated by turnover. Specifically, I define this measure of job accessibility as:

$$\text{Access}_i = \left[\frac{\left[\sum_{j=1}^{J} \left(\frac{E_j (e^{\lambda d_{ij}})}{E} \right) \right]}{\left[\sum_{k=1}^{K} \left(\frac{NC_k (e^{\lambda d_{ik}})}{NC} \right) \right]} \right]$$

where i, j, k indexes tracts/neighborhoods; $\text{Access}_i \equiv$ access to employment opportunities measure for an individual who lives in neighborhood i; $E_j \equiv$ number of recently-filled non-college jobs in neighborhood j; $E \equiv$ total number of recently-filled non-college jobs, $E = \sum_{j=1}^{J} E_j$; $\lambda \equiv$ distance decay parameter; $d_{ij} \equiv$ distance[9] in miles between neighborhood i and j; $NC_k \equiv$ number of non-college educated individuals that live in neighborhood k; $NC \equiv$ total number of non-college educated individuals, $NC = \sum_{k=1}^{K} NC_k$.

I use the spatial distribution of net hires to construct my measure of accessibility to job opportunities generated by employment growth, defined as:

$$\text{Access}_i = \left[\sum_{j=1}^{J} \left(NETHIRES_j (e^{\lambda d_{ij}}) \right) \right] .$$[10]

These two job accessibility measures jointly capture a worker's proximity to job openings relative to the competing workers for these jobs, discounting distant job openings and distant competing workers by the distance decay parameter λ (obtained from the first-stage gravity model estimation). The estimated distance decay parameter for less-skilled workers was -.101 in Atlanta, -.149 in Boston, and -.093 in the Los Angles MSA. Thus, using our estimated distance decay parameter for less-skilled workers in Atlanta, jobs (competing workers) located at distances of 0, 5, 10, 15, and 20 miles would have weights of 1, .60, .36, .22, and .13, respectively. Using these measures of job accessibility for the census tracts throughout each of the MSAs, allows us to determine as well the search areas (defined in the MCSUI Household Survey) within each MSA that are relatively rich in employment opportunities for less-educated individuals (using the average computed access measures for the census tracts that make up the various search areas).

VI. Descriptive Results

I begin by documenting and addressing to what extent spatial mismatch exists in the Atlanta, Boston, and Los Angeles MSAs. Is access to employment opportunities for non-college graduates greater in the suburbs than in the central city? Due to the non-uniform geographic pattern of suburban job growth, is there significant variation in access within the suburbs?

Residential Segregation. The minority population of Atlanta contains mostly blacks and relatively few Hispanics and Asians, while the minority populations are more mixed between the three groups in Los Angeles and Boston. Blacks are concentrated within a core area of the central city—almost all neighborhoods are either less than 10% black, or more than 70% black in each of the MSAs. Blacks are significantly more segregated than Hispanics and Asians. For example, in Los Angeles and Boston the black-white dissimilarity index[11] was 73 and 70, respectively. In contrast, the Hispanic-white index was 61 and 55 and the Asian-white index was 46 and 44 in Los Angeles and Boston, indicating much less segregation (Iceland & Weinberg 1999). These racial/ethnic differences in the degree of residential segregation have implications for job search, since we expect the labor market outcomes and job search behavior of racial/ethnic groups that face greater residential location constraints to be more sensitive to local job accessibility.

Spatial Distribution of Job Accessibility. The maps entitled "Spatial Distribution of Job Accessibility" show the variation in job accessibility within and between both the central city and suburbs of the three MSAs. Although there is variation in the degree of job decentralization across them (Stoll et al. 2000), I find from both accessibility measures (i.e., from both sources of job availability: the measure capturing turnover-induced employment opportunities and the measure capturing employment opportunities generated by job growth) the consistent pattern that job accessibility is greatest in white suburban areas. Suburbs also exhibit a significant amount of variability in job accessibility. This is most pronounced in Atlanta, which is one of the few MSAs that have large fractions of blacks living in suburban areas (indeed, 60.6%). The variation in job accessibility within suburban areas has a distinct spatial pattern that follows the pattern of residential segregation in Atlanta.

As illustrated in the "Spatial Distribution of Job Accessibility" maps for Atlanta, the suburbs in Atlanta containing large percentages of blacks are located in the south side of the metropolitan area and have relatively poor access to employment opportunities. Conversely, Atlanta's predominantly white suburbs on the north side are shown to have the best access to employment opportunities. However, only a small portion of the north side of Atlanta is served by public transportation, which makes it difficult for blacks, whether they live in the central city or the southern suburbs, to reach available jobs because they rely more heavily upon public transit (Ihlanfeldt 1997). The spatial structure and patterns in Atlanta highlight the importance of examining the intrametropolitan variation in access (within and between both the central city and the suburbs), and the weakness of relying on the crude central city/suburban dichotomy.

To further illustrate the relationship between the geographic labor demand shift and racial residential patterns, I compute the number of net new hires over the past year (employment growth/loss) within different commuting distances for whites and blacks.[12] Specifically, the number of net hires within a distance *k* from neighborhood *m* is

$$\text{NETHIRES}_{mk} = \sum_{p=1}^{N} NETHIRES_p \ , \text{ if } d_{mp} < k,$$

where NETHIRES_p is the number of net hires in neighborhood *p*, *N* is the number of neighborhoods, and d_{mp} is the distance from neighborhood *m* to neighborhood *p*. Similarly, the number of net hires within a distance *k* for the average worker of race *R* is computed by summing across neighborhoods, weighting by the fraction of the racial group's population that resides in each neighborhood:

$$\text{NETHIRES}_{Rk} = \left(\frac{1}{\sum_{m=1}^{N} pop_{Rm}} \right) \sum_{m=1}^{N} \sum_{p=1}^{N} pop_{Rm} * (NETHIRES_p) , \quad \text{if } d_{mp} < k,$$

where pop_{Rm} is the population of group *R* in neighborhood *m*. These results are shown in Figures 1a-1c. The vertical line at 10 miles marks the average one-way commute distance for non-college graduates. Figures 1a-1c reveal that the degree of employment growth (loss) over the past year (1993) within different commuting distances of the average black worker were significantly less (more) than that experienced for the average white worker, in the three MSAs. For example, in Atlanta (Figure 1a), about 5,000 jobs were lost within a 10-mile radius of the average black worker, while about 5,000 jobs were gained within that radius for the average white worker. Similar patterns are found in Boston and Los Angeles.[13] Furthermore, the distribution of accessibility to employment growth experienced by black workers is more tightly distributed around the lower mean (at various commuting distances), due to racial segregation.

I use the job accessibility measures to determine which search areas are rich in employment opportunities for non-college graduates. Search areas are rich in non-college jobs if the number of jobs relative to the supply of non-college educated individuals is high (using the average computed access measures for the census tracts that make up the various search areas). The northern suburbs of Atlanta (Marietta/Smyrna, Roswell/Alpharetta, Norcross), the Metro West area of Boston, and the West San Fernando Valley area of Los Angeles, were the search areas classified as job rich. These job-rich search areas are consistent with other sources and previous studies (see for example Stoll et al. (2000), and Ihlanfeldt (1997) for Atlanta). All of these job-rich search areas are located in predominantly white suburbs more than 10 miles from the centroid of black residential concentration, and these areas are not served by public transportation. I find that 75% of the individuals that self-reported not searching in these job-rich areas, did not do so because of reasons related to travel distance, lack of transportation, and traffic problems.

These patterns are consistent with spatial mismatch—spatial asymmetries in non-college job availability and the residential concentration of minorities. I next discuss the empirical model I use to investigate the effects of access to employment opportunities and dimensions of job search behavior on search duration.

VII. Empirical/Econometric Model

Using a sample of individuals who had recently conducted a job search[14], search duration (i.e., the length of the search spell) is analyzed by estimating the conditional probability of a search spell ending in a particular week via obtaining a new job. The benefit of this hazards framework is that this technique easily accommodates censoring problems.

The type of censoring that occurs in the data is due to the retrospective nature of the information about when job search began and ended. Namely, random censoring occurs with a fixed end point of observation (i.e., the date of the interview), but a random entry point (since individuals' job search began at different times). Even among spells that are not right-censored, not all search spells end in employment—some individuals stop searching without accepting a new job offer. I am able to determine whether individuals have successfully completed their job search (i.e., the individual found a job and is no longer searching) through job search survey questions about when last searched, duration of search, whether individuals received a job offer while searching, and current job tenure.[15] Individuals that are observed continuing their search after obtaining a job are assumed to have taken a temporary/transitional job.

My job search analysis is one of the few that includes both individuals searching while employed (on-the-job search) and those searching while unemployed. I distinguish between individuals who obtain transitional employment while continuing to search, and those who successfully complete a job search. A dimension of a job offer not usually considered in the search literature is the anticipated length of job tenure. A searcher choosing between two acceptable offers that are similar in all aspects except expected job tenure, will select that wage/tenure combination having the greater present discounted value. However, as searches drag on and resources diminish, one adjustment to not finding a job is to lower one's expectations regarding the relative permanence of the next job (Stephenson 1976). Thus, as unemployment duration increases, given imperfect capital markets, the searcher (at some point) may take whatever he/she can get, even if it means jobs of very short duration (i.e., temporary jobs or jobs characterized by high turnover), jobs offering relatively low pay, and/or little opportunity to advance. In accepting such a job, the unemployed job searcher maintains a minimal income and/or reduces the rate of skill decay (actual or perceived due to the negative stigma attached to long unemployment durations) until a better job can be found, and continues searching while employed. Consequently, analyzing job search spells, rather than unemployment spells, is an important distinction. I find that a sizeable fraction of less-educated searchers took transition jobs while continuing to search, to alleviate part of the financial burden that accompanies unemployment.

I model the probability of a search spell ending via finding a new job in each subsequent week for individuals who began their job search sometime within the last year of the interview date. The hazard function $\lambda_i(t_{0i}, t)$, is the probability than an individual's search spell ends via finding a new job at week $t_{0i} + t$ given that the individual begins searching at calendar week t_{0i} and has been searching for each of the prior $t - 1$ weeks. The hazard is specified in a logit form, where the explanatory variables include a constant, the direct duration effect on the hazard (i.e., the influence of spell duration holding all other variables constant), and a vector of characteristics (X):

$\lambda(T; X) = 1/(1 - \exp[\beta X + \alpha_1 T + \alpha_2 T^2]\ )$.[16]

I model the dependence of the hazard rate on time in the spell by the duration of the current spell and its square.[17] Among the search-related explanatory variables that make up the vector X include the number of hours spent searching per week, the number of hours searched squared, the relative reservation wage, the number of employed persons in the individual's social network (proxy for the quality of the individual's social network), the reservation commute time (in minutes), dummy variables indicating whether individual searched with credential-based references, whether searched with network-based references, whether individual had access to a car while searching, whether individual lives in (low) medium or high poverty-rate neighborhood/tract, whether individual searched in a job-rich search area (interacted with non-college graduate dummy), and the job accessibility measures.[18]

To minimize concerns about endogenous migration, I fix job accessibility as of the beginning of the spell (i.e., I use job accessibility measures based on the respondent's residence when the search began). [19] This addresses a specific kind of endogeneity ex-post—namely, that people might move to jobs. I interact the job accessibility measure with race (and education) to test for differential effects of job access by race (education).

VIII. Empirical Results

Summary Statistics. In Tables 1a-1aa, I present the summary statistics for minority/white non-college graduates separately by job accessibility, to explore the relationship between search intensity and local job accessibility. The prevalence of job search activity for minority (blacks, Hispanics, Asians) non-college graduates are lower among individuals with poor accessibility to employment growth—40.3% of those with high accessibility to net employment growth had searched for work within the past year, relative to only 30.5% of those with low accessibility to net employment growth. As well, current employment is more often the result of the success of a recent job search among individuals with high accessibility to job growth (7.4% vs. 4.2%), and more often the result of accepting transitional employment while continuing to search (7.9% vs. 2.5%), relative to the comparable proportions among individuals with low accessibility. Among the currently employed, higher fractions of minority non-college graduates with high accessibility to net employment growth had recently begun a job search while on the current job, and higher fractions had searched within the past year more generally, relative to minority non-college graduates with low accessibility. These results appear to reflect the greater stability of existing job matches in low employment growth areas, thus reducing turnover-induced job availability. "Discouraged" workers are more prevalent among minority non-college graduates with poor accessibility, as I find they have higher fractions reporting ending job searches without accepting a new job offer amongst both the employed and non-employed populations, relative to minority non-college graduates with high accessibility. In contrast, in Table1aa, we do not see these same patterns by accessibility to net employment growth among white non-college graduates. The search activity of white non-college graduates appears to be less sensitive to accessibility to net employment growth. Whether these correlations simply reflect worker heterogeneity across residential locations is unclear without a more complete multivariate analysis.

For the remainder of the analysis, I restrict my sample to individuals who had begun a job search within the past year, and I focus my regression analysis on the effects of spatial structure on the job search behavior and job search outcomes of labor force participants. In Table 2, I present the means of the variables of the duration (hazard) model separately by race/ethnicity. As shown in Table 2, 21% of the sample had successfully completed their job search by obtaining new jobs (as of the survey interview date). As of the survey interview date, 7.9% were working in transitional jobs while continuing the job search; 17.7% had begun searching while on the job and were still searching; 22.9% had begun searching while on the job and had stopped searching without obtaining new jobs; 25.6% were not employed and were still searching; 4.8% were not employed and had stopped searching.

There exist significant racial differences in search outcomes (see destination frequencies, Table 2). I will focus on the black-white differences in my discussion, but significant differences exist between Hispanics and whites as well. Specifically, while 27.9% of whites had successfully completed job searches, only 13.5% of blacks and 9.8% of Hispanics had done so. Additionally, among individuals who had not successfully completed job searches, blacks and Hispanics were twice as likely as whites to take a transitional job while continuing to search. This pattern suggests a greater willingness of blacks and Hispanics to accept a job and continue searching, given the lower offer rates for unemployed blacks and Hispanics relative to unemployed whites.

In Table 2, looking at the search method patterns, we see that job seekers engage in multiple-method search strategies. Nearly everyone used their social networks to obtain information about jobs, and/or conducted an open market search (which include the use of newspaper ads, answering help-wanted signs, sending a resume or calling an employer). However, there are important racial differences in the quality of the social networks used to obtain information about potential jobs—namely, blacks and Hispanics have fewer employed persons in their social networks than their white counterparts. Blacks appear to rely more heavily upon state and temporary employment agencies, which we expect to offer less effective referrals than other more credential-based formal labor market intermediaries (labor union/school placement officer/private employment service). Moreover, the use of government and temporary employment agencies are in many cases search methods of last resort, and employers often perceive government agencies as listing primarily entry-level jobs and referring job seekers with very little screening of applicants. Blacks and Hispanics are less likely to have searched for work with credential-based references (i.e., references from former/current employers, co-workers, teachers). We do not see significant differences in average search intensity by race/ethnicity. Whites have higher relative reservation wages than both blacks and Hispanics.

In Table 2, we see significant racial differences among the key spatial search variables of interest in the search model. Namely, on average, blacks and Hispanics are less likely to have had access to a car while searching, blacks report longer reservation commutes (i.e., longest commute time willing to commute to work), and black and Hispanic non-college graduates are far less likely to have searched for work in job-rich areas than white non-college graduates. As expected, we see a much higher fraction of blacks and Hispanics living in neighborhoods of medium to high poverty concentrations relative to whites.

Interestingly, the mean of the job accessibility measure capturing turnover-induced job availability for white non-college graduates is not statistically different from that for black non-college graduates (using standard errors of unweighted means).[20] This is the result of historical land use patterns, which have left the central city with large stocks of jobs. However, as was highlighted in the previous section and demonstrated also in Table 1, whites have far superior access to employment opportunities generated by job growth, than do blacks and Hispanics. Moreover, mean job accessibility among whites, blacks, and Hispanics, masks considerable racial differences in the variation around the mean. Namely, the variance in both job accessibility measures among white non-college graduates is much greater than that for black and Hispanic non-college graduates, due to the fact that whites are more spatially dispersed across the respective metropolitan areas than are blacks and Hispanics, because of racial residential segregation (even among non-college graduates). In sum, black and Hispanic non-college graduates have less job accessibility, on average, than do white non-college graduates (stemming from differential access to employment growth areas), and the distributions of accessibility experienced within the black and Hispanic less-educated populations are more tightly distributed around their lower means.

Primary Hypothesis to be Tested. One of the central hypotheses of this study is that the job search behavior (e.g., the reservation wage, reservation commute, and search intensity) and the job search outcomes of more residentially constrained racial/ethnic groups are more sensitive to local job accessibility. How job search behavior and job search outcomes (among individuals facing residential location constraints) are affected by local job accessibility is dependent on the fluidity of the labor market (i.e., the degree of search frictions across space and extent of spatial job search/commute costs, which is approximated by the distance decay parameter estimated in Appendix A). For example, given residential location constraints, the elasticity of reservation commute time with respect to a change in local job accessibility will increase as commute costs and search frictions across space decline, while the elasticity of the reservation wage with respect to a change in local job accessibility will decrease as commute costs and search frictions across space decline. In other words, given residential location constraints, workers will respond to a decrease in local job accessibility (due to an exogenous geographic labor demand shift) by increasing their reservation commute times without significantly changing their reservation wages, when search frictions are sufficiently low (resulting in no spatial mismatch). In contrast, when workers are faced with high commute costs/search frictions across space, they will increase their reservation commute times by a smaller amount (and perhaps not at all), and will instead decrease their reservation wages, in response to a decrease in local job accessibility (resulting in spatial mismatch). On the other hand, we expect to find significantly smaller effects (if any at all) of job accessibility on the reservation commute time and reservation wages (and on search behavior and search outcomes more generally) of whites, because their residential location decisions are relatively unconstrained. I test these hypotheses in the regression analyses below.

Regression Results. I begin by exploring the relationship between job search behavior (specifically, the reservation commute time, reservation wage, and search intensity) and job accessibility, to provide an initial look at this hypothesis. In the first three columns of Table 3, I present regression results using the reservation commute time, the reservation wage, and the level of search intensity (number of hours spent searching per week), respectively, as dependent variables, on measures of job accessibility and other characteristics. I do not give the estimated coefficients presented in Table 3 any structural or "causal" interpretation because negative duration dependence among these search choices, coupled with the correlation between search duration and job accessibility, may bias the estimated effects of job accessibility. Instead, I use this framework to summarize some of the relations between these aspects of job search behavior and job accessibility. The results highlight how the search methods chosen by job seekers are shaped by the interaction of two important features of urban spatial structure: (1) extent of involuntary residential segregation, and (2) the job searcher's proximity to employment opportunities.

As shown in the first column of Table 3, I find racial differences in the effects of job accessibility on reservation commute time.[21] While the magnitudes of the effects are not particularly large, the patterns are nonetheless interesting. In particular, black non-college graduates with poor accessibility to employment growth report longer reservation commute times than comparable blacks with high accessibility to employment growth, while white non-college graduates' reservation commute times are less sensitive to accessibility to employment growth.[22] This suggestive evidence of blacks' greater willingness to adjust their commute patterns in response to a geographic labor demand shift is consistent with the predictions of theory, given the greater residential mobility constraints/costs facing blacks. As well, blacks report longer reservation commute times on average for any given level of job accessibility. I also find that individuals that did not have access to a car report longer reservation commute times, likely due to their having to rely on slower forms of transportation. As expected, college graduates and workers with job training report longer reservation commute times, reflecting more geographically expansive commute patterns among highly educated workers (which parallels the smaller distance decay parameters estimated for higher-income workers—see Appendix A). Women, and workers with child care concerns, and workers who are married all have shorter reservation commute times (other things being equal), reflecting more localized commute patterns among these workers.

I restrict my sample to non-college graduates to examine the relationship between reservation wages and job accessibility. These regression results are reported in the second column of Table 3. I find racial differences in the effects of job accessibility on reservation wages as well. Again while the magnitudes of the effects are not particularly large, the patterns are nonetheless interesting. In particular, black and Hispanic non-college graduates with poor accessibility to employment growth have lower reservation wages than comparable blacks and Hispanics with high accessibility to employment growth, while white non-college graduates' reservation wages are insensitive to accessibility to employment growth. These results are consistent with the subsequent emergence of spatial mismatch (i.e., otherwise identical individuals achieve different labor market outcomes because of their residential location) among blacks and not among whites, as predicted and discussed in the theoretical section. Blacks and Hispanics have lower reservation wages for any given level of job accessibility. I also find that individuals that did not have access to a car have lower reservation wages. This effect could be picking up fixed unobserved worker quality as previous employment success may have enabled individuals to buy a car. The estimated effects of the set of standard human capital variables included in the model are all significant and in the expected directions. Of course, unobserved skills correlated with residential location, may upward bias the estimated effects of job accessibility on reservation wages in this simple model; but the existence of racial differences in the correlations of job accessibility and reservation wages is clear from this analysis.

I report the results for search intensity in the third column of Table 3. I find that individuals with better access to employment growth search more intensely (i.e., they spend more hours per week searching). This may reflect greater expected returns to search for individuals residing in areas with better local labor market demand conditions, or may be because these individuals face lower costs of search due to being able to locate alternative vacancies easier. The magnitude of the effect of job accessibility did not differ significantly by race (not shown). I do not find significant effects of race on search intensity. I find that college graduates spend less hours per week searching, likely due to higher rates of on-the-job search among highly educated workers. Women and individuals with working spouses search less intensely. In the fourth column of Table 3, I also present suggestive evidence of the relationship between the quality of an individual's social networks in connecting them to potential job opportunities (proxied by the number of employed persons in an individual's social network) and the concentration of neighborhood poverty. The results suggest that individuals that live in medium and high poverty neighborhoods have poorer quality social networks, consistent with the social isolation hypothesis (Wilson 1987, 1996). Whether these results capture a truly causal relation and thus one of the negative externalities of concentrated poverty, is unclear from this simple model, but I note the significant correlations. As well, blacks still have poorer quality social networks after controlling for these other factors.

Hazard Model Results. Table 4 contains the reduced-form hazard estimates of the effects of the extensive set of explanatory variables in my job search model on the conditional probability of a search spell ending via obtaining a new job in a given week. The average percentage changes in the hazard due to simulated changes in the explanatory variables are displayed.[23] The effects of the spatial search-related variables reveal the importance of spatial aspects of the labor market in shaping the structure of opportunity.

The most insightful result of the analysis is the differential effect of access by race (and education). Importantly, I find that the patterns of racial differences in the effects of job accessibility mirror the patterns of racial differences in the extent of residential location constraints (documented in the residential segregation literature), as predicted by theory.[24] Specifically, I find that increasing accessibility to turnover-induced job availability from its mean value to one standard deviation above its mean, increases the hazard (of ending the search via finding a new job) by 77.6% for black non-college graduates and by 75.3% for Hispanic non-college graduates, while increasing the hazard by only 5.2% and 11%, for white and Asian non-college graduates, respectively (with statistically insignificant effects for whites and Asians). I find that increasing accessibility to job opportunities generated by employment growth from its mean value to one standard deviation above its mean, increases the hazard by 43.6% for black non-college graduates, while increasing the hazard by 11.5% for Hispanic non-college graduates (this effect is not statistically significant for Hispanics), and having small and insignificant effects for white and Asian non-college graduates. In sum, the length of job search duration is extremely sensitive to changes in access to employment opportunities for less-educated blacks and Hispanics, while the length of job search duration for similarly educated whites and Asians is insensitive to proximity to employment opportunities.

The effect of job accessibility to turnover-induced (non-college) job availability among college graduates is small and statistically insignificant. This effect was expected since the job accessibility measure is constructed based upon the spatial distribution of non-college jobs relative to competing non-college graduates (not the jobs and workers college graduates are as likely to be competed for/with). As well, the search patterns of more-educated workers are more expansive, and the residential location choices of high-income individuals are not restricted, and thus, more educated individuals are not as sensitive to local labor market demand conditions. I do, however, find positive effects of accessibility to employment growth on the hazard of finding a new job for college graduates.

As shown in Table 4, the effects of the other spatial and search-related variables are all significant and in the expected direction. In particular, access to a car while searching is estimated to increase the weekly hazard of successfully completing a job search by 48.3%. This estimate may be upward biased to the extent that having a car is picking up fixed unobserved worker quality, as previous employment success might have determined their ability to buy a car. However, my extensive set of controls lead me to believe that this effect is real (not totally spurious). Longer reservation commutes (i.e., the maximum number of minutes an individual is willing to commute to work) are found to be associated with longer expected search durations. For example, an increase from 20 to 40 minutes in a job searcher's reservation commute time is estimated to decrease the weekly hazard of a search spell ending via finding a new job by 13.5%. This result may be explained by the fact that a willingness to search over a greater search radius, while increasing the field of potential job opportunities, may also require more search time, particularly if searchers experience search efficiency losses as knowledge about job opportunities declines with distance.

The probability that a job searcher will find employment in a given search area is the product of three other probabilities: the probability that a worker will search there, the probability that the worker will receive an offer having searched, and the probability that the worker will accept the offer having received it. As shown in Table 3, for non-college graduates, searching for work in job-rich search areas increases the weekly hazard of ending a search spell via finding a new job by 34.9%.

Better quality social networks (as proxied by the number of employed persons in the individual's social network) significantly increase the hazard of a search spell ending in a given week via finding a new job. Interestingly, the effects of whether lived in a medium or high poverty neighborhood, (where low poverty neighborhood is the reference category), which was designed to capture the effects of the neighborhoods themselves (negative externalities—social isolation), are insignificant in the presence of the other spatial and search related variables. This was particularly the case after controlling for the quality of social networks, suggesting that the negative externality of living in medium and high poverty neighborhoods is captured in part by my proxy for the quality of social networks.

I find differential effects of having references by type of reference. Specifically, I find that searching for work with credential-based references (i.e., having references from former/current employers, co-workers, or teachers) increases the weekly hazard of a search spell ending via finding a new job by 23.2%, relative to searching for work without credential-based references (though this effect is not statistically significant). On the other hand, having only network-based references (i.e., having references from friends or relatives) negatively affects the hazard. This result is expected due to employers' preference for job searchers with credential-based references, as they may provide more accurate information about a potential job candidate's skills and productivity.

Next, examining the effects of search variables contained in standard search models, we see that increasing the number of hours spent searching per week from 8 hours (mean search intensity) to 9 hours increases the weekly hazard of ending the search spell via finding a new job by about 3.2%. The coefficient on the search hours squared term, included to capture diminishing returns to search, is negative (in the expected direction), though not statistically significant. The ratio of self-reported reservation wages to the market wage (where the market wage or the mean of the wage offer distribution facing the job searcher is proxied by the wage on the respondent's most recent job) is statistically significant and has the expected negative effect on the hazard.[25]

Among the human capital variables, we see that graduating from college relative to dropping out of high school increases the weekly hazard of successfully completing a job search by 52.5%, due in part to the interaction of the spatial search variables and education. While the signs of the other human capital variables are all positive, none of them are statistically significant. This may be due to the inclusion of the relative reservation wage variable, which includes in its denominator the wage earned on the most recent job (to proxy for the mean of the wage offer distribution facing the job searcher). As well, since employers expend more resources and search over a greater geographic area to fill their higher-skilled job vacancies (due in part to greater concerns about the quality of the job match because of employers' plans to invest more in on-the-job training for their higher-skilled workers (Barron et al. 1997)), it is not clear as a matter of theory that high-skilled workers are expected to have shorter search durations.

I turn next to examine the effects of the demographic variables in the model. Being a younger worker increases the likelihood of ending a search spell in a given week via finding a new job. Job stability is likely to be a more important aspect of a job offer for older workers, and thus, greater concerns about the job match component of a job offer prolongs the duration of their job searches. Being a woman reduces the weekly hazard of finding a new job and ending search by 20%, and having child-care concerns reduces the weekly hazard by 25.5% (although the coefficient is not statistically significant). Having some type of work-limiting health condition decreases the probability of successfully completing a search spell in a given week by 18.5% (although the coefficient again is not statistically significant). The signs on the duration coefficients suggest that the probability of finding a new job (and ending search) decreases with the duration of the spell. Of course, it is not possible here to distinguish true duration dependence from unobserved heterogeneity.

Despite controlling for an extensive set of spatial and search-related variables, significant racial differences remain. Namely, being black or Hispanic significantly lower the hazards of successfully completing a job search via finding a new job in a given week.[26] In the following section, I perform a decomposition analysis to determine how much of the overall black-white gap can be accounted for by racial differences in the measured spatial and search-related variables, human capital variables, and demographic variables, in the model. I also conduct simulations to assess the effect of the differential effect of access by race in explaining the greater search durations among blacks, relative to whites.

To assess the economic importance of the variables in the model, as well as their relative importance, I begin by performing simulations of the effects of changes in each of the selected variables on the probability of successfully completing the job search within 1 month, 3 months, 6 months, and 9 months, and one year, respectively. These results are presented in Table 5. The first column of the respective tables shows the change in the variable used for the simulation.[27] As shown in Table 5, the differential effects of job accessibility by race contribute significantly to the black-white gap in search durations. A one standard deviation increase in both job accessibility measures from their respective mean values increases the probability of successfully completing the job search spell within six months by .267 (62.5%) for black non-college graduates, while not significantly affecting the probability for whites. Thus, these simulated results imply that a spatial redistribution of jobs that gives blacks high accessibility to employment opportunities will considerably narrow the black-white gap in average search duration, no matter what the effect the spatial redistribution has on whites' present job accessibility. As previously discussed, this result is likely because whites face far fewer residential location constraints and thus are more residentially mobile.

How do the effects of changes in job accessibility compare with changes in other explanatory variables? As shown in Table 5, we see large effects among the other spatial search related variables. Access to a car while searching increases the probability of successfully finding a job and ending search within six months by .111 (20.6%). Searching in a job-rich area increases the probability of successfully finding a job and ending search within six months by .082 (14.3%) for non-college graduates. In contrast, simulating an increase in reservation commute time from 20 minutes to 40 minutes decreases the probability of successfully finding a job and ending search within six months by .07 (10.3%). Simulating an increase in social network quality from poor to good social networks (proxied by simulating change from not having any individuals in immediate social network with a steady job to having all the individuals in immediate social network with steady jobs) increases the probability of successfully finding a job and ending search within six months by .08 (13.6%). Having credential-based references increases the probability of successfully completing a job search within six months by .058 (9.9%). Being black decreases probability of successfully completing a job search within six months by .289 (38.9%), due in part to the race-specific effects of job accessibility. Among the selected human capital and demographic variables, we see somewhat smaller effects. Simulating an increase in education from less than 12 years (high school dropout) to 16 years or more (college graduate) increases the probability of successfully finding a job and ending search within six months by .07 (12.2%). Having child care concerns decreases the probability of successfully completing the job search within six months by .082 (12.8%).

Decomposition Analysis: Accounting for Racial Differences in Search Outcomes. The large black-white gap in the hazard of successfully completing a job search (.039 vs. .070—ignoring duration dependence, these transition rates imply average search durations of 25.6 weeks for blacks and 14.3 weeks for whites) can be decomposed into two parts: (1) the gap due to racial differences in the distributions of individual characteristics, and (2) the gap due to racial differences in the returns of job accessibility (likely stemming from racial differences in residential location constraints) and unexplained racial differences (which may reflect labor market discrimination and/or the inability to include unmeasurable variables). I employ a variation of the Blinder-Oaxaca decomposition method developed by Fairlie (1999) to estimate the proportion of the black-white gap in the hazard of successfully completing a job search that can be explained by differences in spatial and search related characteristics, human capital characteristics, and demographic characteristics.

For a linear regression, the standard Blinder-Oaxaca decomposition of the black-white gap in the average value of the dependent variable, Y, can be expressed as

$$\bar{Y}^W - \bar{Y}^B = [(\bar{X}^W - \bar{X}^B)\beta^B] + [\bar{X}^W(\beta^W - \beta^B)],$$

where $\bar{X}^j$ is a row vector of average values of the independent variables and β^j is a vector of coefficient estimates for race j. However, because of the nonlinearity of the equation that predicts the probability of successfully completing a job search, the equivalent decomposition for the discrete hazard model estimated in this paper is expressed as

$$\bar{Y}^W - \bar{Y}^B = \left[\sum_{i=1}^{N^W}\frac{F(X_i^W\beta^B)}{N^W} - \sum_{i=1}^{N^B}\frac{F(X_i^B\beta^B)}{N^B}\right] + \left[\sum_{i=1}^{N^W}\frac{F(X_i^W\beta^W)}{N^W} - \sum_{i=1}^{N^W}\frac{F(X_i^W\beta^B)}{N^W}\right],$$

where $\bar{Y}$ is the average probability of successfully completing a job search in a given week, F is the logistic function, β^j are the coefficient estimates reported in Table 4b for race j, and N^j is the sample size for race j. This alternative expression for the decomposition is used because $\bar{Y}$ does not necessarily equal $F(\bar{X}\beta)$. The first term in brackets represents the part of the racial gap that is due to racial differences in distributions of X, and the second term represents the part due to racial differences in the returns of job accessibility and unexplained racial differences. However, as discussed in more detail by Fairlie (1999), an additional calculation is needed to identify the contribution of racial differences in specific variables to the gap. Specifically, in the decomposition estimates presented in Table 5, I define the independent contribution to the racial gap of the variable of interest (X_1) as

$$\frac{1}{N^B}\sum_{i=1}^{N^B} F(X_{1i}^W\beta_1^B + X_{2i}^B\beta_2^B) - F(X_{1i}^B\beta_1^B + X_{2i}^B\beta_2^B),$$

where X_2 and β_2 are all other variables (and their associated coefficients) in the model except the variable of interest. I use this expression to compute simulated estimates of the reduction in the black-white transition rate gap that would result from giving blacks the same distribution of X_1 as possessed by whites, while holding the distribution of the other variables constant. I replicate this procedure substituting a different variable of interest for X_1 to estimate the contribution of each variable to the gap.[28]

Table 6 reports estimates from this procedure for decomposing the black-white gap in the hazard successfully completing a job search. These results provide estimates of the reduction in the black-white transition rate gap resulting from giving blacks the same distribution of all included variables as whites, as well as the relative contributions of specific subsets of variables to the gap. The contribution estimate indicates that racial differences in all included variables account for roughly two-thirds of the gap. Examination of racial differences in specific subsets of variables reveals that racial differences in job accessibility play an important role in explaining the transition rate gap. The contribution estimate indicates that racial differences in job accessibility account for 23.1%. The results indicate that if blacks were given the car ownership rates of whites, the transition rate gap would be reduced by 8%. The other spatial and search related variables contribute to the gap as well. Racial differences in the proportion searching in job-rich search areas accounts for 5.1% of the gap; racial differences in social network quality account for 5.6% of the gap; racial differences in reservation commute time account for 2.8%; and racial differences in the distribution of search intensity account for 9.5% (although it is important to note, these differences may have arisen endogenously). In sum, the contribution estimates indicate that the cumulative effects of racial differences in the spatial and search related variables account for roughly half of the black-white gap. In contrast, despite the large differences between blacks and whites in levels of education and work experience, differences in human capital characteristics explain a much smaller part of the gap—10%. This result is mainly due to the weaker relationship between education and job search duration. Similarly, racial differences in demographic variables account for only 5.1% of the gap.

IX. Summary/Conclusion/Policy Implications

This paper provides strong evidence supporting the spatial mismatch hypothesis, which states, broadly, that if discrimination in housing markets limits the residential locations of a specific racial group of workers, it should discourage them from searching for or accepting jobs at workplaces far from their residences. This restricts the racial group's employment opportunities and makes them more sensitive to local labor market demand conditions. The inconsistency of the results of previous studies that have attempted to test the spatial mismatch hypothesis, and the resulting controversy concerning the relevance of space in explaining racial differences in labor market outcomes, is a byproduct of the use of imprecise/inappropriate measures of job accessibility. The detailed geographic measures of job accessibility developed in this paper are an important contribution to the analysis of spatial issues examined in this study. I show that the geographic areas within each MSA that were relatively rich in employment opportunities for non-college graduates were not only located in predominantly white suburbs more than 10 miles from the centroid of black residential concentration, but were also areas that are not served by public transportation (exacerbating spatial mismatch).

There are significant race differences in the effects of job accessibility. The role of residential segregation in constraining black's and Hispanic's residential location choices appears to be the source of the differential effect of access by race. Simulation results show that black's greater sensitivity to local labor market demand conditions contribute significantly to the black-white gap in search durations. In addition, racial differences in the distribution of job accessibility account for nearly one-fourth of the black-white gap in the hazard of successfully completing a job search, and the cumulative effect of racial differences in all the included spatial search-related variables accounts for roughly half of the overall black-white gap.

The results of this study suggest that greater enforcement of fair housing laws, as well as policies to alter the distribution of jobs in metropolitan areas in favor of the central city, such as empowerment zones, combined with full employment policies that tighten labor markets will significantly improve blacks' and Hispanics' job search outcomes. The findings of this study on the role of job accessibility and dimensions of job search has important policy implications for the success of welfare reform, as PRWORA's work requirements and participation mandates have led most states and localities to implement programs focusing on job search assistance. The analysis also provides some micro foundations to the aggregate trends of demand shifts and population adjustments documented by Bound and Holzer (2000), who report that differential responses to local demand shifts across groups, as well as the geographic distribution of the shifts themselves, help to account for the regional pattern of inequality that developed in the 1980s. This research has sought to analyze the mechanisms through which a worker's location within the economy affects his return to human capital, and to identify the processes that hinder a smooth adjustment to changing labor market conditions. Further analysis is needed along these lines.

Appendix A: Estimating the Distance Decay Function

Gravity models (often referred to as spatial interaction models) have been used extensively in the urban transportation literature to model commuting patterns (Isard 1960; Sen & Smith 1995; Fotheringham 1989). Using CTPP data (designed for transportation planners) on journey-to-work flows between neighborhoods in the Atlanta, Boston, and Los Angeles MSAs, I model the extent of commuting between every possible neighborhood (origin (*i*)-destination (*j*)) pair as a function of: the number of workers that live in neighborhood *i* (L_i); the number of jobs located in neighborhood *j* (E_j); the accessibility of job location *j* to all alternative job locations available (A_j); the occupational/skill compatibility between workers that live in neighborhood *i* and neighborhood *j*-jobs (occ_{ij}); and the distance in miles between neighborhoods *i* and *j* (d_{ij}) and cost of overcoming this distance (captured by the distance decay function, F_{ij}). I estimate the aggregate commute flow of labor from an origin to a destination neighborhood by the gravity equation

$$T_{ij} = KL_i^{\alpha} E_j^{\beta} A_j^{\delta} \exp(\phi occ_{ij})\, F_{ij} \quad , \qquad (1)$$

where $T_{ij} \equiv$ number of workers that live in neighborhood *i* and work in neighborhood *j*;
F_{ij} (distance decay function) = $\exp[\gamma_1 (d_{ij}) + \gamma_2 (d_{ij} * plinc_i)]$;
$plinc_i \equiv$ % of workers that live in neighborhood *i* that earn less than $25,000/year;
and $K, \alpha, \beta, \delta, \phi, \gamma_1, \gamma_2$ are parameters to be estimated.
Equivalently, if we use lower-case letters to denote the logarithms of variables denoted by corresponding capital letters (e.g., $\ln A_i = a_i$), we can write the gravity model (1) as

$$t_{ij} = k + \alpha\, l_i + \beta\, e_j + \delta\, a_j + \phi\, \text{occ}_{ij} + [\gamma_1 (d_{ij}) + \gamma_2 (d_{ij} * plinc_i)]. \qquad (1')$$

As the dependent variable in equation (1) is the count of workers that commute between given neighborhoods, estimation requires the use of an econometric model that takes the dependent variable as being generated from a discrete probability process (Greene 1993; Raphael 1998). I estimate equation (1) with a negative-binomial count model. A negative-binomial regression equation can be written:

$$Y_i = \exp\left(\sum_{i=1} \beta_i X_i\right) + \varepsilon_i ,$$

where Y_i follows a negative-binomial distribution whose expected value is equal to $\exp\left(\sum_{i=1} \beta_i X_i\right)$; equivalently, the natural logarithm of Y_i is equal to the linear predictor. Thus, in the gravity model case, the negative-binomial regression equation becomes:

$$T_{ij} = \exp[k + \alpha\, l_i + \beta\, e_j + \delta\, a_j + \phi\, \text{occ}_{ij} + [\gamma_1 (d_{ij}) + \gamma_2 (d_{ij} * plinc_i)]] + \varepsilon_i . \quad (1'')$$

The origin labor supply (L_i) and the destination labor demand (E_j) capture the possible scale of interaction between the two neighborhoods. By entering labor supply and demand multiplicatively in the gravity equation, the potential scale of interaction increases in the total possible combinations of worker-job matches, with $\alpha, \beta > 0$ (Raphael 1998).

It is also important to control for the configuration of competing job location destinations—i.e., the destination neighborhood's proximity to all other job location destinations. A_j reflects the competition between location *j* and all alternative job locations for commuting flows (workers). As the accessibility of a job location to all alternative job locations increases, we expect the commuting volume to that job location to decrease, other things being equal (Fotheringham 1989)—thus, $\delta < 0$. I use the following measure for the proximity of a destination to all others:

$$A_j = \sum_{k=1}^{K} \left(\frac{E_k}{d_{jk}}\right) .$$

Obviously if a residential neighborhood has all blue-collar employees, there would not be many people from that neighborhood holding jobs in a predominantly white-collar area. Ideally, one would construct a separate model for each occupational/skill category, but the necessary data are not available. Therefore, I take the approach used previously by Sööt & Sen (1991) to construct an occupational/skill compatibility index. Let

$p_i^{(1)}, \ldots, p_i^{(7)}$ be the proportion of employees in each of seven employment categories living in i, and let $q_j^{(1)},\ldots, q_j^{(7)}$ be the proportion of jobs in each category employed in j. Following Sööt & Sen (1991), I define the occupational compatibility index as

$$occ_{ij} = \left[\sum_{m=1}^{M} \sqrt{p_i^{(m)}}\sqrt{q_j^{(m)}}\right] .$$

By the Cauchy-Schwartz inequality (Rao 1973),

$$\left[\sum_{m=1}^{M} \sqrt{p_i^{(m)}}\sqrt{q_j^{(m)}}\right] \leq \left[\sum_{m=1}^{M} p_i^{(m)}\right]^{1/2} \left[\sum_{m=1}^{M} q_j^{(m)}\right]^{1/2} = 1,$$

with the equality holding if and only if $p_i^{(m)} = q_j^{(m)}$ for all m. Thus, $(occ_{ij}) = 1$ when the match is "perfect" (i.e., $p_i^{(m)} = q_j^{(m)}$ for all m (employment categories)), and equal to zero when the match is essentially nonexistent (i.e., $p_i^{(m)} q_j^{(m)} = 0$ for all m (employment categories)), and increases with improving matches. The occupational/skill compatibility index entered as in equation (1) implies the aggregate flow of labor between given neighborhoods increases proportionately with the degree of occupational compatibility between workers and jobs in the given neighborhoods ($\phi>0$). The seven occupational categories used were (a) professional, executive, administrative, and managerial, (b) technicians and related support, (c) sales, (d) administrative support (including clerical), (e) service, (f) precision products, craft, and repair, and (g) operators, fabricators, and laborers.

Of primary interest is the estimation of the distance decay parameters (γ_1, γ_2) of the distance decay function (F_{ij}). The specific functional form of the decay function in equation (1) is a more general form of the function often used in transportation planning models (Sen & Smith 1995), and implies that the aggregate flow of labor declines proportionately with distance ($\gamma_1 < 0$). Ideally, we would like to model the commuting patterns of low-wage or less-educated workers separately, since commuting patterns differ by earnings/skill, but disaggregated commuting flow data by earnings or education levels are not available. Consequently, when modeling the relationship between observed commuting patterns and distance, it is important to control for the average earnings of neighborhood workers since the commuting patterns of low-wage workers tend to be more localized than those of high-wage earners (for reasons discussed elsewhere). Spatial search theoretic models predict the attenuating effect of distance on low-wage workers' search and commute patterns to be greater than that for high-wage workers (Simpson 1992). Thus, I interact the percent of workers that live in neighborhood i that earn less than $25,000 per year with the measure of distance between neighborhood i and j. This interaction variable ($d_{ij}*plinc_i$) effectively assigns a larger distance decay parameter (in absolute value) when the origin neighborhood is composed of a larger percentage of workers that have low earnings—that is, $\gamma_2 < 0$. Given the high level of earnings homogeneity within neighborhoods, due to residential segregation by income, I argue $\gamma = \gamma_1 + \gamma_2$ provides a good estimate of the distance decay parameter for less-skilled workers. Thus, the estimated distance decay function for low-wage workers is $\hat{F}_{ij} = \exp\left(\hat{\gamma} d_{ij}\right)$, and captures the composite effects of distance in reducing their probability of searching/finding/accepting distant job offers.

Gravity Model Estimation Results. Using the negative-binomial count model for the gravity equation yielded an estimated distance decay parameter for less-skilled workers of -.101 in Atlanta, -.149 in Boston, and -.093 in the Los Angeles MSA. As expected, the estimated distance decay parameters for higher-income workers are smaller in magnitude (in absolute value), reflecting more spatially expansive search/commute patterns (relative to lower-income workers). The estimated distance decay parameter for higher-income workers is -.073 in Atlanta, -.063 in Boston, and -.046 in Los Angeles. As previously discussed, the estimated distance decay function is used to weight nearby jobs (competing workers) more than distant jobs (competing workers). Thus, using our estimated distance decay parameter for less-skilled workers in Atlanta, jobs (competing workers) located at distances of 0, 5, 10, 15, and 20 miles would have weights of 1, .60, .36, .22, and .13, respectively. The effects of the other explanatory variables of the gravity equation were all significant and in the expected directions. These first-stage estimation results are shown in Appendix Tables A. I chose not to estimate race-specific distance decay parameters because I did not want to confound the effects of race and space inherently in the construction of my job accessibility measures.

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[1] I use sample weights in the descriptive tables to adjust for this over-sampling. The MCSUI Household data closely parallel U.S. 1990 Census distributions of age, sex, education, and occupation, within each major racial/ethnic group.

[2] Data sets such as the National Longitudinal Survey (NLS), the Panel Study of Income Dynamics (PSID), the Current Population Survey (CPS), and the Survey of Income and Program Participation (SIPP), do not allow an individual to be working and searching for work simultaneously, because the employed are not asked any questions about job searching.

[3] From the 8,916 respondents in the total sample, 1,543 (17.3%) observations were dropped due to non-comparable job search questions among Detroit respondents; an additional 5,628 (63.1%) observations were dropped after restricting the sample to individuals who had searched within the past year; an additional 309 (3.5%) observations were dropped due to either being sick/maternity, retired, permanently disabled, a homemaker, a student, or only temporarily laid-off; an additional 69 (0.8%) observations were dropped due to either missing search duration or residential location information; and an additional 162 (1.8%) observations were eliminated after dropping left-censored search spells (i.e., job search spells that *began* more than a year before the survey interview date).

[4] Information was also obtained on the hiring requirements, job tasks, and firms were asked about their proximity to public transit, amongst many other things (for a more detailed description of the MCSUI employer survey, see Holzer (1996)). The sample was restricted to employers who had hired in the past three years, and the survey was administered to the individual responsible for entry-level hiring.

[5] The sampling frame was stratified ex-ante by establishment size categories so as to reproduce the distribution of employment across these categories in the workforce. I use two different sets of sample-weighting schemes of the firms ex-post. The first weighting scheme generates representative *employee-weighted* samples of firms for each metropolitan area (i.e., firms are represented in proportion to the number of workers they employ). This employee-weighted scheme is appropriate for the sample of recently filled non-college jobs because it heavily represents employers that do a lot of hiring because of their large number of employees; firms that have many recent hires because of high turnover rates receive no extra weight (Holzer 1996). However, because the sample of recently filled non-college jobs is weighted by the existing stock of jobs, the employee-weighted sample is unable to account for sources of job availability due to net new employment growth (i.e., firms that do a lot of hiring due to net employment growth do not receive any extra weight) (Holzer 1996). Thus, the sample of recently filled non-college jobs constitutes a fairly representative sample of turnover-induced job availability in local labor markets over a period of several months. The sample-weighting scheme that must be employed to generate a random sample of net new hires is to first undo the implicit size weighting ex-post and use appropriate sample weights to produce random samples of firms (without regard to stock) for each metropolitan area. My re-weighting of firms across establishment size categories (0-19 employees; 20-99 employees; ≥ 100 employees) is based on 1993 County Business Pattern data, for each MSA, of the fraction of firms in each establishment size category.

[6] Employer reports of net new hires over the past year are not disaggregated by skill level/education requirements of the job.

[7] Given the trends in residential segregation by race and income, this spatial representation of competing less-skilled labor (using 1990 Census data) will closely parallel that which existed at the time when my sample of current/recent job searchers were looking for work.

[8] A similar approach was used previously by O'Regan & Quigley (1998), Raphael (1998), and Mouw (2000).

[9] The distance between neighborhood *i* and *j* is calculated:

$$Distance_{ij} = \frac{\left(\sqrt{\left(HH_{xi} - E_{xj}\right)^2 + \left(HH_{yi} - E_{yj}\right)^2}\right)}{0.0145}$$

where HH_{xi} is the latitude coordinate for the centroid of the household tract; HH_{yi} is the longitude coordinate for the centroid of household tract; E_{xj} is the latitude coordinate for the centroid of the employer tract; E_{yj} is the longitude coordinate for the centroid of the employer tract. To convert from coordinate distance to miles, the tract-to-tract distances were divided by 0.0145.

[10] I also used an alternative measure of accessibility to job opportunities generated by employment growth by normalizing the above measure by the size of the local labor market's competing workforce—specifically,

$$\left[\frac{\left[\sum_{j=1}^{J} \left(NETHIRES_j (e^{\lambda d_{ij}}) \right) \right]}{\left[\sum_{k=1}^{K} \left(NC_k (e^{\lambda d_{ik}}) \right) \right]} \right]$$

. This alternative measure did not qualitatively change any of the underlying findings reported in this paper.

[11] The dissimilarity index is the most commonly used measure of housing segregation and represents the percentage of minority members that would have to change neighborhoods to achieve an even distribution.

[12] Similar patterns are observed for Hispanic-white differences in average accessibility to job growth in Los Angeles and Boston, though these differences are smaller in magnitude relative to black-white differences (results available from author upon request).

[13] The differences in magnitude (in absolute value) in the overall levels of annual employment growth between the MSAs is in part driven by the size of the respective MSAs (total employment (1993) 1,456,178 in Atlanta; 2,282,136 in Boston; 3,495,246 in Los Angles from County Business Pattern data). As well, Los Angeles may have been suffering through a post 1980s slump, as well as from likely negative labor market effects of the racial disturbances of April 1992 and the Northridge earthquake in 1994 (Holzer 1996). In contrast, Atlanta was enjoying a pre-1996 Olympics boom during this period. Recall the surveys were administered to firms in the period between 1992 and 1994, during which time the national economy was recovering from recession.

[14] The sample contains individuals who had begun a job search within the last 12 months of the survey interview date. Individuals who began their job search more than a year before the interview date are not included in the analysis (i.e., spells already in progress as of a year prior to the survey interview date (left-censored spells) are dropped).

[15] Specifically, individuals are classified as having successfully completed their job search if the following 5 conditions hold: (1) must have searched within the last year and must have contacted an employer within the last month of search; (2) must have received a job offer while searching; (3) must have obtained a current job within the last year; (4) cannot be involuntarily working part-time due to demand-side constraints, and (5) must have stopped searching after obtaining current job.

[16] For spells that are completed during the sampling period the density function equals the probability of a search spell ending via finding a new job in week t times the conditional probability of the individual's search spell not ending in each of the prior t - 1 weeks. This is specified as $f_i\,(t_{0i},\, t) = \lambda_i\,(t_{0i},\, t) \prod_{r=1}^{t-1} \left[1 - \lambda_i (t_{0i}, r) \right]$. For incomplete spells, the survivor function equals the probability that the individual's search spell did not end via finding a new job in each of the prior t_i weeks. The survivor function is specified as $[1 - F_i\,(t_{0i},\, t)] = \prod_{r=1}^{t_i} \left[1 - \lambda_i (t_{0i}, r) \right]$. Complete spells ($i \in C$) are combined with incomplete spells ($i \in IC$) to form the likelihood function which equals $L = \prod_{i \in C} f_i (t_{0i}, t) \prod_{i \in IC} \left[1 - F_i (t_{0i}, t) \right]$. The likelihood function is maximized with respect to the explanatory variables to obtain coefficient estimates.

[17] I experimented with a variety of other specifications to model duration dependence within this discrete time framework, including the log of current duration and its square. I also experimented with a number of continuous time models using different distributional assumptions for the duration data. The results across these different specifications were not fundamentally different and did not change the basic results reported below.

[18] The job search literature suggests that some of the choice variables of a searcher vary over the course of the search spell. In this paper, however, I must assume fixed choices for the variables in the job search model because the information collected—in particular, the reservation wage and the number of hours spent searching per week—refer to the level of these variables that prevailed in the last (most recent) month of the search spell rather than at the beginning of the search spell. The resulting bias of not allowing time-variation or intensity variation in search strategies over the course of the spell could upward bias estimated effects of search intensity and could bias toward zero the estimated effect of reservation wages, if the stationarity assumption does not hold. Such biases may be reinforced by the presence of unobserved skills, which should be correlated with reservation wages, search intensity, and the probability of job search success in a given week. Thus, I estimate models with and without the search method variables. The inclusion of duration

variables and the extensive set of controls in the full model minimize concerns that the estimated effects of job accessibility are being driven by unobserved heterogeneity.

[19] Only about 5% of the sample changed residential locations while the job search was still on-going; not enough time had elapsed to assess what percent changed residential locations after a successful job search.

[20] Computed standard errors on weighted means are generally not correct, since population rather than sample sizes is used during the computation. But standard errors for unweighted means give a fairly good indication of the relevant standard errors.

[21] I standardize both job accessibility measures to have mean 0, standard deviation 1 (using the respective mean job accessibility (and standard deviation) across all neighborhoods of the MSAs) in the regression, so that a one-unit change in the standardized job access measure can be interpreted as a one standard deviation change. The mean accessibility measure capturing turnover-induced job availability across all neighborhoods of the MSAs was 1.0708 with standard deviation = .2085. The mean accessibility measure capturing net employment growth across all neighborhoods of the MSAs was -8,067 with standard deviation = 25,022. The negative mean for net employment growth accessibility is due to significant job loss that occurred in the Los Angeles MSA between 1992-1994, the same period in which the survey was conducted.

[22] Similar results to those shown in Table 3 were found using the job accessibility measure capturing turnover-induced job availability.

[23] Due to the nonlinearity of the model, average effects of discrete changes in explanatory variables are calculated throughout this paper by evaluating the effect of varying the explanatory variable of interest in a given way for each individual (holding all other variables constant and evaluated at the beginning of the spell), and then computing the sample-weighted mean of these effects (e.g., the percentage change in the hazard, or the change in the probability that a search ends spell within six months). Sample weights are not used to estimate the coefficients of the hazard model to avoid introducing additional heteroscedasticity, and because factors affecting the weights are controlled for in the model. I do, however, use the sample weights to weight the observations when computing the average (marginal) effects and computing the decomposition estimates, so that these results are representative of a sample of recent job searchers in these MSAs.

[24] The estimated effects of accessibility are robust to the inclusion/exclusion of the arguably exogenous search method variables (relative reservation wage, search intensity, reservation commute, whether searched in job-rich areas, whether used formal or informal search methods, and whether received AFDC or unemployment insurance).

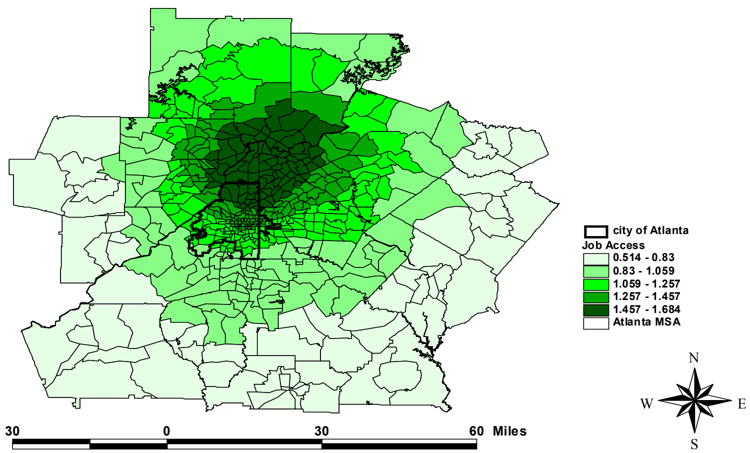
[25] Additional dummy variables have been included in these equations to account for missing values in the search hours and relative reservation wage variables. In cases of missing values, these latter variables take on the value of zero and the dummy variables take on the value of one.

[26] I experimented with various other specifications that included a variety of interaction terms with race and some of the spatial and search related variables. For example, I interacted car with job access since having access to a car while searching would be expected to matter a lot more for individuals with limited job accessibility. However, this interaction and others were not significant. I also estimated separate regressions by race. However, F-tests between the pooled and separate versions of the model failed to reject pooling (in favor of separate analyses by race). I also experimented with various interaction terms of the two job accessibility measures, to attempt to capture the indirect effect of an increase in accessibility to employment growth on overall accessibility to job opportunities through its effect in (also) increasing area turnover rates (e.g., $access_1 * access_2 > 0$). The inclusion of these interaction terms, however, did not significantly improve the fit of the model.

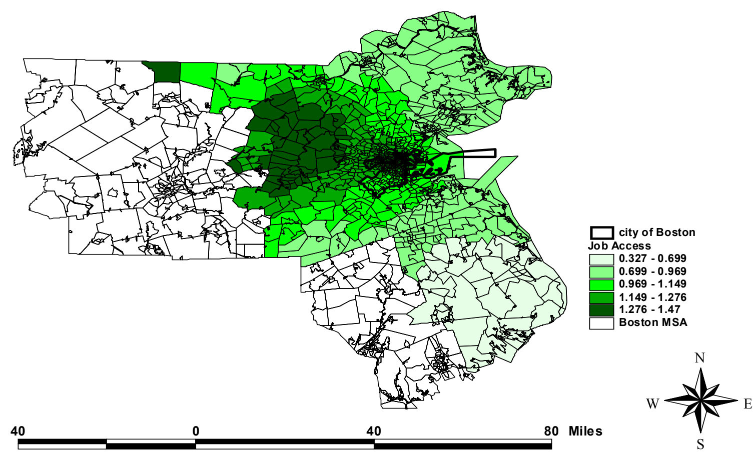
[27] The simulations use the coefficient estimates shown in Table 4, ignoring duration dependence (i.e., assume there is no true duration dependence and the measured effect of duration reflects unobserved heterogeneity).

[28] These calculations, however, are not possible without first matching the white distribution of X_1 and the black distribution of X_2. I follow the procedure used by Fairlie (1999) to match these distributions. Specifically, using the coefficient estimates reported in Table 4, I calculate predicted probabilities for all observations in the white sample and all observations in a random subsample of blacks with sample size equal to N_W, since the black sample is slightly larger than the white sample (N_B=409 > N_W = 313, resulting from the over-sampling of blacks). I draw a large number of random black subsamples (100 random subsamples of blacks of size 313) and present the mean value of estimates from these samples. I rank each member of the two samples by the value of this predicted probability and match them by their respective ranks. This procedure assigns low transition probability blacks the same characteristics as low transition probability whites.

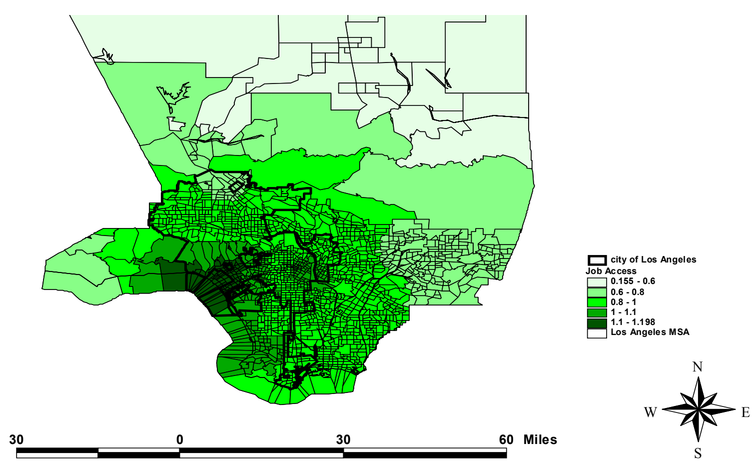
Atlanta MSA
Access to Turnover-Induced Non-college Job Availability



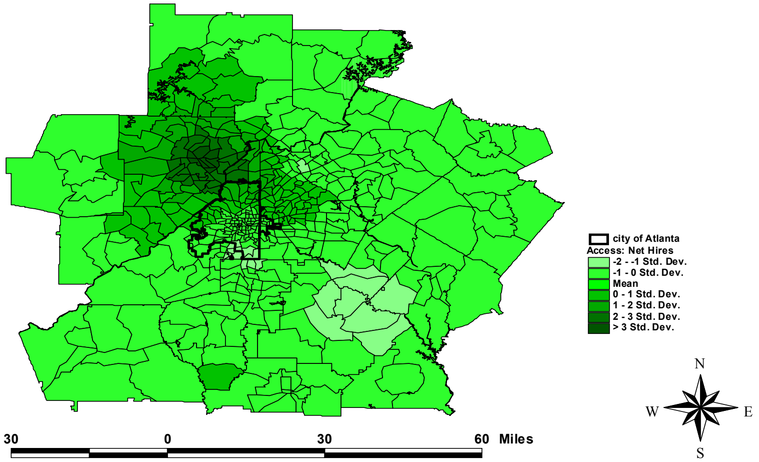
Boston MSA
Access to Turnover-Induced Non-college Job Availability



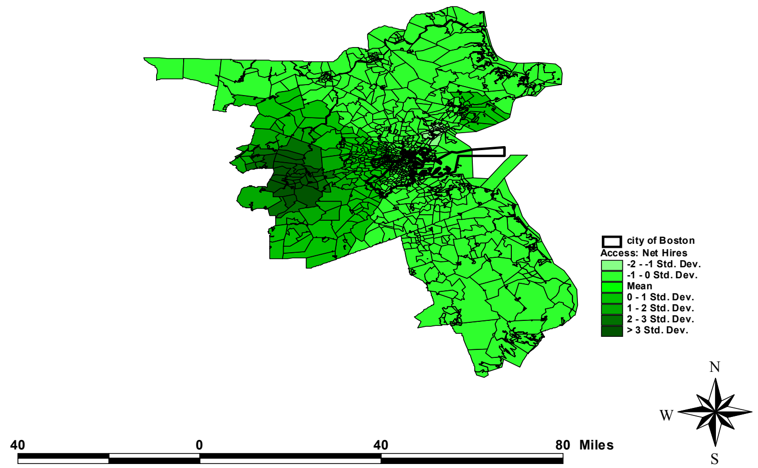
Los Angeles MSA
Access to Turnover-Induced Non-college Job Availability



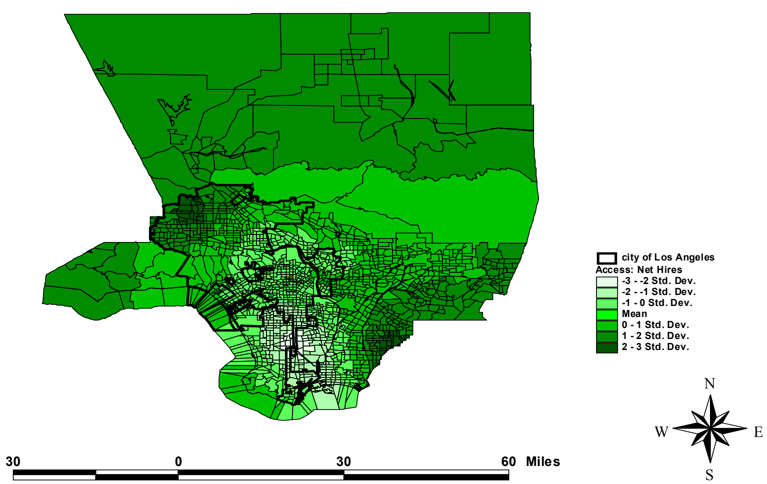
Atlanta MSA
Accessibility to Net Employment Growth

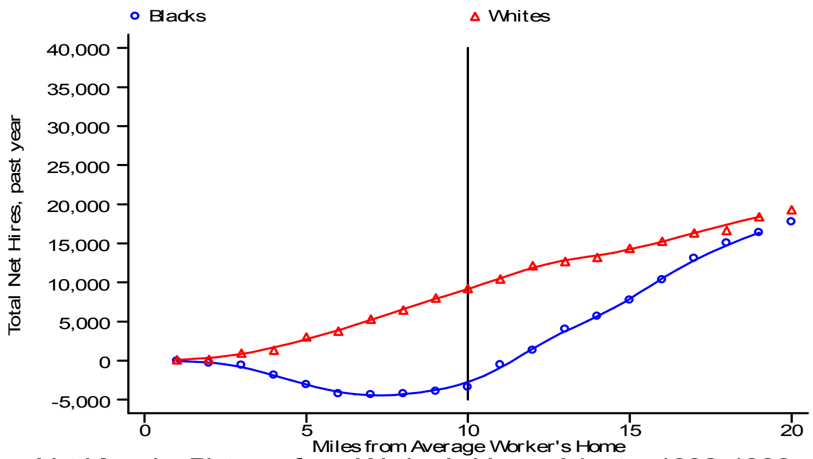


Boston MSA
Accessibility to Net Employment Growth

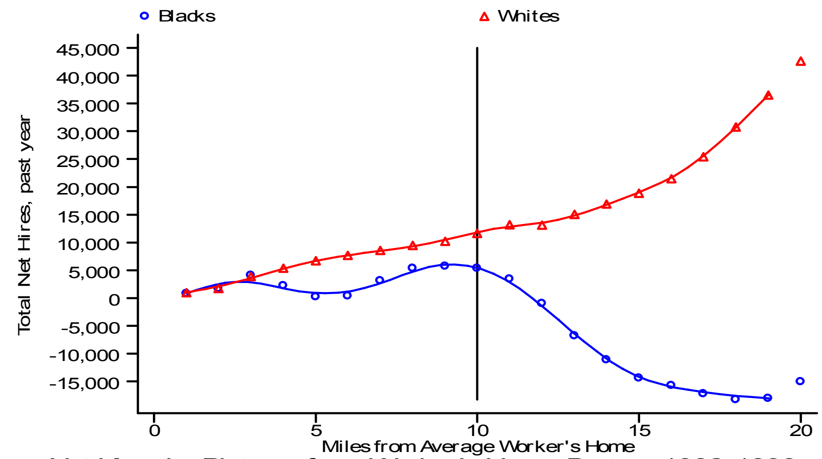


Los Angeles MSA
Accessibilty to Net Employment Growth

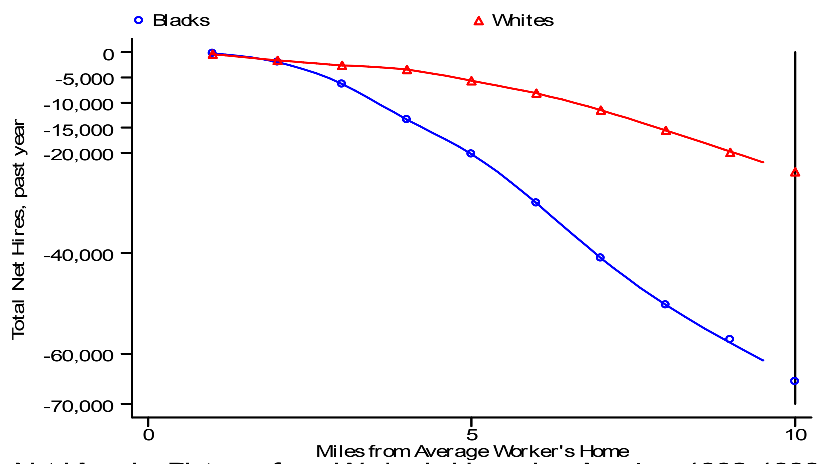




Net Hires by Distance from Worker's Home: Atlanta, 1992-1993



Net Hires by Distance from Worker's Home: Boston, 1992-1993



Net Hires by Distance from Worker's Home: Los Angeles, 1992-1993

Table 1a: Employment and the Prevalence of Job Search Activity Among Minority Non-college Graduates by Accessibility to Employment Growth [1,2]

	Low Access to Job Growth	High Access to Job Growth
Searched within past year	.3048	.4031
Currently employed	.7801	.8144
Current employment result of:		
Success of most recent job search (within past yr)	.0424	.0742
Accepted transitional job offer, still searching	.0247	.0785
Began search while on current job, still searching	.0500	.1226
Began search while on current job, stop search w/o accept offer	.0989	.0435
Have not recently searched (within past yr)	.7840	.6812
Current nonemployment result of:		
Not Searching (OLF-have not searched within past yr)	.3801	.2274
Still searching	.4690	.7127
Searched within past year, but stopped search w/o accept offer	.1422	.0447

Footnotes: [1]Here I define low accessibility to net employment growth as accessibility that is less than or equal to -10,000; I define high accessibility to net employment growth as accessibility that is greater than or equal to +5,000. The (sample-weighted) proportion of minority non-college graduates with low accessibility was about 60% (N=2341), and the proportion with high accessibility was only 16% (N=569). In contrast, the (sample-weighted) proportion of white non-college graduates with low accessibility was about 30% (N=428), and the proportion with high accessibility was also about 30% (N=427). I experimented with alternative thresholds for low/high job accessibility, none of which qualitatively changed the patterns shown in these tables.

[2]Sample includes all MCSUI household survey respondents in the Atlanta, Boston, and Los Angeles MSAs, except whites, college graduates, and those who reported being sick/maternity, retired, permanently disabled, homemakers, or students

Table 1aa: Employment and the Prevalence of Job Search Activity Among White Non-college Graduates by Accessibility to Employment Growth

	Low Access to Job Growth	High Access to Job Growth
Searched within past year	.3176	.2501
Currently employed	.8553	.8961
Current employment result of:		
Success of most recent job search (within past yr)	.0988	.0645
Accepted transitional job offer, still searching	.0192	.0567
Began search while on current job, still searching	.0411	.0207
Began search while on current job, stop search w/o accept offer	.0728	.0400
Have not recently searched (within past yr)	.7681	.8180
Current nonemployment result of:		
Not Searching (OLF-have not searched within past yr)	.1760	.1624
Still searching	.6493	.7589
Searched within past year, but stopped search w/o accept offer	.1747	.0760

Footnotes: [1]Here I define low accessibility to net employment growth as accessibility that is less than or equal to -10,000; I define high accessibility to net employment growth as accessibility that is greater than or equal to +5,000. The (sample-weighted) proportion of white non-college graduates with low accessibility was about 30% (N=428), and the proportion with high accessibility was also about 30% (N=427). In contrast, the (sample-weighted) proportion of minority non-college graduates with low accessibility was about 60% (N=2341), and the proportion with high accessibility was only 16% (N=569). I experimented with alternative thresholds for low/high job accessibility, none of which qualitatively changed the patterns shown in these tables.

[2]Sample includes all MCSUI household survey respondents in the Atlanta, Boston, and Los Angeles MSAs, except college grads, blacks, Hispanics, Asians, and those who reported being sick/maternity, retired, permanently disabled, homemakers, or students.

Table 2: Job Search Sample Means[1] (Standard Errors) by Race/Ethnicity

	All [Full Sample]		White		Black		Hispanic	
Search Duration (weeks)[2]	10.8	(.8439)	11.7	(1.3613)	11.2	(1.6367)	9.9	(1.2511)
Destination Frequencies								
Successfully completed job search	.2099		.2787		.1350		.0982	
Accepted transitional job offer, still searching	.0788		.0528		.1077		.1201	
Began search while on-the-job, still searching	.1770		.1509		.1990		.1788	
Began sch while on-the-job, stop sch w/o accept offer	.2290		.2305		.2303		.2335	
Not employed, still searching	.2563		.2537		.2639		.2915	
Not employed, stopped search w/o accepting offer	.0478		.0314		.0640		.0780	
Search Method Variables								
# of search methods used	2.4	(.0522)	2.4	(.0827)	2.6	(.0882)	2.2	(.0821)
Open mkt search	.9278		.9530		.9593		.8595	
Social netwk search	.8191		.8014		.8636		.8204	
# employed in social netwk (max:3)	1.6	(.0728)	1.9	(.1032)	1.6	(.1289)	1.2	(.1126)
Use state/temp emp agency	.3047		.2987		.4875		.2642	
Union/school/priv emp svc	.3274		.3818		.3043		.2207	
Credential-based refs	.7875		.8865		.7776		.6048	
Netwk-based refs	.5732		.6398		.6325		.4361	
# of hrs spent sching per week	8.7	(.7444)	8.7	(1.2491)	8.6	(.9296)	9.2	(.9610)
Relative rsv wage	1.03	(.0298)	1.077	(.0500)	1.049	(.0580)	.968	(.0276)
Spatial Search Variables								
Access to car when schd	.8304		.9087		.7489		.7151	
Rsv commute time (minutes)	45.1	(1.3243)	43.8	(1.9367)	50.5	(2.1157)	44.2	(1.9366)
Among non-college grads:								
Access to turnover-induced job availability	1.057	(.0160)	1.0465	(.0329)	1.1170	(.0260)	1.0382	(.0098)
Access to employment growth	-8,237	(2,117)	412	(2,875)	-13,839	(2,560)	-19,807	(1,933)
Schd in job-rich area	.3290		.4481		.2758		.1927	
Live in <10% poverty tract	.6429		.8879		.4381		.2898	
Live in 10-30% poverty tract	.2826		.1081		.4356		.5195	
Live in >30% poverty tract	.0745		.0040		.1263		.1908	
Metropolitan Area								
Atlanta	.1478		.1857		.3099		.0125	
Boston	.2674		.3918		.1463		.0424	
Los Angeles	.5909		.4457		.5171		.9093	
Demographic Variables								
Age (yrs)	34.5	(.6764)	36.3	(1.1488)	31.3	(.7710)	32.8	(.8761)
Female	.5325		.4891		.5835		.4117	
Married	.1333		.5857		.3855		.5350	
Child care concerns	.2832		.1430		.1810		.1685	
Rec'vd unemp insurance	.2095		.2319		.1557		.2297	
Rec'vd AFDC	.0837		.0389		.2435		.1067	
Wk-limiting health cond'n	.1126		.1144		.1285		.1151	
Human Capital Variables								
Dropout	.1734		.0619		.0804		.4545	
HS Grad/GED	.2356		.2457		.2779		.2199	
Some College	.2842		.2734		.4385		.2273	
College grad	.3037		.4150		.2009		.0960	
Full-time wk experience (yrs)	11.7	(.6458)	12.8	(1.0754)	9.3	(.8169)	11.3	(.8930)
Part-time wk experience (yrs)	1.8	(.2613)	1.8	(.4041)	1.0	(.1455)	2.5	(.5001)
Job training	.2600		.3216		.2479		.1800	
Number of Observations	1205		313		409		368	

[1]All means here are sample-weighted

[2]Search duration avgs consist of both complete and incomplete spells

Table 3: Spatial Factors Influencing Search-Related Variables

	Dependent Variables:							
	Rsv Commute Time (min.)		ln(Rsv HourlyWage) (Non-college Grads)		# of Hrs Spent Searching (per wk)		# of Employed Persons in Social Ntwk (range 0-3) Ordered Probit	
Explanatory Variables:	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Spatial Variables								
Employment growth Accessibility (standardized)	-1.1265	(1.7887)	-.0251	(.0301)	1.0245**	(.4734)		
Employment growth Accessibility*Black	-.8384	(1.9106)	.0503*	(.0330)				
Employment growth Accessibility*Hispanic	-.4719	(2.1708)	.0650*	(.0369)				
Employment growth Accessibility*Asian	3.0475	(2.4894)	.0720	(.0577)				
Employment growth Accessibility*College-grad	.8101	(1.8528)						
Live in 10-30% poverty tract							-.3186***	(.0833)
Live in >30% poverty tract							-.4640***	(.0899)
Total Effect of Employment Growth Access - White Non-college Grads	-1.1265							
Total Effect of Employment Growth Access - Black Non-college Grads	-1.9649*							
Total Effect of Employment Growth Access - Hispanic Non-college Grads	-1.5984							
Total Effect of Employment Growth Access - Asian Non-college Grads	1.9210							
Access to car when searched	-4.9208***	(1.6595)	.1437***	(.0266)	-.1610	(.7650)		
Human Capital Variables								
HS Grad/GED	-1.4702	(2.1664)	.1004***	(.0324)	.0024	(.9945)	.0741	(.0962)
Some College	-.3169	(2.1820)	.2653***	(.0329)	-.3581	(1.0028)	.4504***	(.0960)
College grad	3.3145*	(2.5085)			-1.5234*	(1.1426)	.4521***	(.1123)
Full-Time Work Experience	.0030	(.0753)	.0080***	(.0012)	.0010	(.0343)	-.0045*	(.0033)
Part-Time Work Experience	-.0815	(.1870)	.0060**	(.0031)	.0217	(.0861)	-.0181**	(.0084)
Job Training	3.2796**	(1.6206)	.0691***	(.0270)	.5760	(.7377)	.1152*	(.0714)
Demographic Variables								
Black	6.1795***	(2.0295)	-.1108***	(.0358)	.4281	(.9130)	-.1878**	(.0905)
Hispanic	.7285	(2.2829)	-.1884***	(.0388)	.5354	(1.0369)	.2371***	(.1012)
Asian	-2.4357	(2.9236)	-.0659	(.0607)	-.3472	(1.3447)	-.6614***	(.1259)
Female	-5.4447***	(1.5374)	-.0514**	(.0261)	-2.1828***	(.7052)	-.1067*	(.0668)
Married	-4.7335***	(2.4313)	.1278***	(.0387)	1.2323	(1.1006)	-.1352*	(.1098)
Married*working Spouse	.4615	(2.5414)	-.0223	(.0413)	-1.7152*	(1.1618)	.0265	(.1147)
Household size	.4830	(.4709)	-.0115*	(.0074)	.1701	(.2142)	-.0241	(.0209)
Childcare Concerns	-2.6270*	(2.0329)	.0301	(.0321)	-.8460	(.9423)		
Metropolitan Area Dummies								
Atlanta (ref. cat: Los Angeles)	1.2307	(2.6981)	-.1516***	(.0455)	-.7196	(1.1865)		
Boston	-.3444	(2.3442)	.0002	(.0388)	-2.4567***	(1.0644)		
Constant	51.0559***	(3.3599)	1.7546***	(.0559)	10.4522***	(1.5295)		
R^2	.0609		.2604		.0267			
Number of Observations	1,179		935		1,127		1,200	

*p<.10 (one-tailed test), **p<.05, ***p<.01

Table 4: Hazard Model Estimates -- Full Model Specification

	Change in Variable	Coef Estimates	% Change in Hazard
Spatial Search Variables			
Total Effect of Turnover-induced Job Access for White Non-college Grads		.0639	5.2%
Total Effect of Turnover-induced Job Access for Black Non-college Grads	Mean to	.6016**	77.6%
Total Effect of Turnover-induced Job Access for Hispanic Non-college Grads	(1 std dev above	.5956**	75.3%
Total Effect of Turnover-induced Job Access for Asian Non-college Grads	mean)	.1180	11.0%
Total Effect of Turnover-induced Job Access for College Grads		-.4229**	-32.5%
Total Effect of Employment Growth Access for White Non-college Grads		-.0814	-7.7%
Total Effect of Employment Growth Access for Black Non-college Grads	Mean to	.4575**	43.6%
Total Effect of Employment Growth Access for Hispanic Non-college Grads	(1 std dev above	.1920	11.5%
Total Effect of Employment Growth Access for Asian Non-college Grads	mean)	.0092	-7.6%
Total Effect of Turnover-induced Job Access for College Grads		.3681*	31.3%
Access to car when searched	0 to 1	.4159**	48.3%
Rsv commute time (minutes)	20 to 40	-.0077**	-13.5%
Effect of searching in job-rich areas for non-college grads	0 to 1	.3178*	34.9%
# of steadily employed persons in social network	0 to 3	.1024*	33.2%
Live in 10-30% poverty tract (ref. cat:<10%)	0 to 1	-.0983	-8.2%
Live in >30% poverty tract	0 to 1	-.1160	-10.1%
Search Method Variables			
Credential-based references	0 to 1	.2256	23.2%
Network-based references	0 to 1	-.2823*	-23.7%
Search hours (per week)	8 to 9	.0365**	3.2%
Search hours squared	64 to 81	-.0001	
Relative reservation wage	1 to 1.10	-.3597**	-3.3%
Human Capital Variables			
HS Grad/GED (ref. cat: HS Dropout)	0 to 1	.3620	39.3%
Some College	0 to 1	.2857	28.8%
College grad	0 to 1	.4343	52.5%
Work experience (yrs)	5 to 6	-.0029	0.0%
Job training	0 to 1	.0382	4.5%
Demographic Variables			
Age < 25 (ref. cat: 25-34)	0 to 1	.4323**	51.0%
Age > 35	0 to 1	-.4586*	-36.2%
Black (ref. cat: White)	0 to 1	-1.1432***	-41.9%
Hispanic	0 to 1	-.7241***	-34.9%
Asian	0 to 1	-.1861	-14.0%
Female	0 to 1	-.2454*	-20.0%
Married	0 to 1	.1371	14.9%
Married*working spouse	0 to 1	.0912	6.6%
Household Size	3 to 4	.0809*	7.7%
Child care concerns	0 to 1	-.3025	-25.5%
Wk-limiting health cond'n	0 to 1	-.2175	-18.5%
Metropolitan Area Dummies			
Atlanta (ref. cat: Los Angeles)	0 to 1	.0468	4.9%
Boston	0 to 1	-.6209**	-44.2%
Rec'vd unemp insurance	0 to 1	-.7598***	-53.3%
Rec'vd AFDC	0 to 1	.1063	11.8%
Duration (weeks)		-.1877***	
Duration squared		.0033***	
Constant		-2.8164***	
Log-likelihood		-762.3656	
Number of Subjects		1,205	

*p<.10 (one-tailed test), **p<.05, ***p<.01

Table 5: Duration of Search Spells of Blacks and Whites Using Hazard Estimates: Evaluated at Different Levels of Selected Explanatory Variables

	Proportion of Search Spells Successfully Completed in:				
Simulated Values	< = 1 Month	< = 3 Months	< = 6 Months	< = 9 Months	< = 12 Months
Job Access Measures = Mean - SD:					
Black non-college graduate	.038	.107	.210	.289	.357
White non-college graduate	.253	.519	.728	.819	.871
Job Access Measures = Mean:					
Black non-college graduate	.094	.244	.427	.541	.623
White non-college graduate	.247	.510	.721	.813	.866
Job Access Measures = Mean + SD:					
Black non-college graduate	.216	.476	.694	.791	.846
White non-college graduate	.242	.502	.713	.807	.861
No Car	.144	.338	.538	.649	.773
Access to Car while searched	.200	.438	.649	.751	.813
No search in job-rich area for non-college grad	.165	.372	.572	.678	.747
Search in job-rich area for non-college grad	.211	.448	.654	.753	.814
Reservation Commute Time = 20 minutes	.221	.470	.680	.778	.836
Reservation Commute Time = 40 minutes	.196	.430	.610	.743	.806
# of steadily employed persons in social netwk = 0	.166	.380	.588	.696	.765
# of steadily employed persons in social netwk = 3 (max)	.211	.456	.668	.767	.827
No Credential-based references	.167	.379	.584	.691	.760
Credential-based references	.198	.433	.642	.744	.806
Black	.130	.285	.453	.554	.627
White	.249	.524	.742	.835	.886
HS Dropout	.167	.374	.575	.682	.752
College Graduate	.209	.444	.645	.741	.801
No Child Care Concerns	.198	.433	.642	.744	.806
Child Care Concerns	.155	.358	.560	.669	.740

Due to the nonlinearity of the model, average effects of discrete changes in explanatory variables are calculated throughout this paper by evaluating the effect of varying the explanatory variable(s) of interest in a given way for each individual (holding all other variables constant and evaluated at the beginning of the spell), and then computing the sample-weighted mean of these effects (e.g., the change in the probability that a search ends spell within six months). These simulations use the coefficient estimates from Table 4 (which allows for race-specific effects of job accessibility), ignoring duration dependence (i.e., assume there is no true duration dependence and the measured effect of duration reflects unobserved heterogeneity). Sample weights are not used to estimate the coefficients of the hazard model to avoid introducing additional heteroscedasticity, and because factors affecting the weights are controlled for in the model. I do, however, use the sample weights to weight the observations when computing the average (marginal) effects, so that these results are representative of a sample of recent job searchers in these MSAs.

Table 6: Decomposition of Black-White Differences in Hazard of Successfully Completing Job Search

	Black	White
Predicted weekly hazard (gap=.032) (evaluated at beginning of search spell)	0.039	0.070
Contribution to the gap from racial differences in the following variables:		
1. Job Accessibility	0.0073	
	23.1%	
2. Car ownership	0.0025	
	8.0%	
3. Search in job-rich areas	0.0016	
	5.1%	
4. Social network quality	0.0018	
	5.6%	
5. Reservation commute time	0.0009	
	2.8%	
6. Search intensity	0.0030	
	9.5%	
7. Human Capital Variables	0.0032	
	10.0%	
8. Demographic Variables	0.0016	
	5.1%	
Total explained (All Variables)	0.0219	
	69.3%	

Note: Sample weights are not used to estimate the coefficients of the hazard model to avoid introducing additional heteroscedasticity, and because factors affecting the weights are controlled for in the model. I do, however, use sample weights when computing the decomposition estimates, so that these results are representative of a sample of recent job searchers in these MSAs. These decompositions use the coefficient estimates from Table 4 (which includes race dummies and allows for race-specific effects of job accessibility). Thus, the decompositions use pooled coefficients for all variables except job accessibility, for which I use the estimated effects of job access on blacks.

Appendix A: Gravity Model Estimates from Negative Binomial Regressions

Atlanta, Boston, and Los Angeles MSA Commute Patterns

Dependent Variable: **# of Workers that Live in Neighborhood *i* and Work in Neighborhood *j***	**Atlanta Coef Estimate**	**Boston Coef Estimate**	**Los Angeles Coef Estimate**
$\ln(L_i)$	.8930***	.7488***	-.1766***
$\ln(E_j)$	.8420***	.7502***	.0607***
$\ln(A_j)$	-.1817***	-.2999***	
Occ_{ij}	52.7205***	87.5901***	337.0598***
$Distance_{ij}$ (miles)	-.0728***	-.0626***	-.0459***
$Distance_{ij}$ *$plinc25_i$	-.0283***	-.0868***	-.0470***
Total Distance Decay Parameter for Lower-Income Workers	-.1011***	-.1493***	-.0929***
Constant	-9.2160***	-6.3433***	.8728***
ln(alpha)	2.8124***	2.7498***	3.3280***
Log-Likelihood	-571389.93	-605522.6	
N	794,988	744,769	267,029

***p<.01

L_i = the number of workers that live in neighborhood *i* ;

E_j = the number of jobs located in neighborhood *j*

A_j = the accessibility of job location *j* to all alternative job locations available

Occ_{ij} = the occupational/skill compatibility between workers that live in neighborhood *i* and neighborhood *j* -jobs

d_{ij} = the distance in miles between neighborhoods *i* and *j* .
$plinc25_i$ = % of workers that live in neighborhood i that earn less than $25,000/year.
I tried alternative threshold levels for low earnings—e.g., % of workers that live in neighborhood with earnings less than $20,000 ($30,000)—but none significantly altered the estimate of the distance decay parameter.

There are 892 zones in Atlanta. This results in a 892x892 matrix of commuting flows for Atlanta.

There are 863 zones in Boston. This results in a 863x863 matrix for Boston.

There are 1,653 in Los Angeles. This results in a 1653x1653 matrix for Los Angeles. Because of computer memory limitations, the negative binomial model was estimated 10 times with a separate 10% sample for the Los Angeles gravity estimates.