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JOB DISPLACEMENT AND THE DURATION OF JOBLESSNESS: THE ROLE OF SPATIAL MISMATCH

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Abstract—This paper presents a new approach to the measurement of the effects of spatial mismatch that takes advantage of matched employer-employee administrative data integrated with a person-specific job accessibility measure, as well as demographic and neighborhood characteristics. We focus on a group of job searchers for plausibly exogenous reasons: lower-income workers with strong labor force attachment separated during a mass layoff. Our results support the spatial mismatch hypothesis. We find that better job accessibility significantly decreases the duration of joblessness among lower-income displaced workers, especially for blacks, women, and older workers.

I. Introduction

THE spatial mismatch hypothesis (SMH) encompasses a wide range of research questions, all focused on whether a worker with locally inferior access to jobs is likely to have worse labor market outcomes. The hypothesis originated with Kain (1964, 1968), who argued that persistent unemployment in central city black communities might be due to a suburbanization of jobs, coupled with the inability (due to factors such as housing discrimination) of those residents to relocate closer to jobs. A voluminous literature has ensued evaluating disparities in job access and extending the original focus on urban blacks to include youth and low-earning workers in general, using both empirical and theoretical approaches (e.g., Ellwood, 1986; Ihlanfeldt & Sjoquist, 1990; Ihlanfeldt, 1993; O'Regan & Quigley, 1996; Rogers, 1997; Raphael 1998b; Zax and Kain 1998; Brueckner & Zenou, 2003).[1] The overriding goal is to explain how a scarcity of local jobs, restrictions on residential mobility, and difficulties in job finding or commuting may affect employment, earnings, or commuting distance. While many empirical studies have found evidence of a spatial mismatch, the existence of a causal effect on employment outcomes has remained uncertain due to methodological and data limitations. In particular, Glaeser (1996) and others have emphasized that cross-sectional empirical specifications designed to test the SMH omit unobserved person characteristics that may be correlated with neighborhood location as well as employment outcomes. This phenomenon may bias estimates of the effect of job accessibility that rely on neighborhood-specific effects.

We overcome the limitations of the existing literature using matched employer-employee data. Our approach exploits differences in search durations for lower-income workers with strong labor force attachment who are subject to a mass layoff.[2] This approach yields a group of workers searching for jobs for plausibly exogenous reasons. Focusing on this group, our rich data infrastructure permits constructing a person-specific job accessibility measure and controlling for demographic and neighborhood characteristics. The basic hypothesis is that if spatial mismatch is present, then greater job accessibility should shorten unemployment duration.[3]

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[1] Reviews include Kain (1992), Ihlanfeldt and Sjoquist (1998), Houston (2005), Kain (2004), and Gobillon, Selod, and Zenou (2007).

[2] A substantial literature in labor economics studies the impact of job displacement. Using matched employer-employee data for the state of Pennsylvania, Jacobson, Lalonde, and Sullivan (1993) showed that workers separating from an employer that is sharply contracting experience a substantial and persistent loss in earnings. A closely related literature has shown that separations from a sharply contracting business are more likely to be associated with a layoff (an involuntary separation) as opposed to a quit (see Davis, Haltiwanger, & Faberman, 2012, for a summary of this literature).

[3] Others have explored the impact of job accessibility on search duration. For example, Rogers (1997), Dawkins, Shen, and Sanchez (2005), Johnson (2006), and Gobillon, Magnac, and Selod (2011), look at search duration in this context and find that greater job accessibility reduces search duration. However, we are the first to study this for a group searching for plausibly exogenous reasons: workers searching after a mass layoff.

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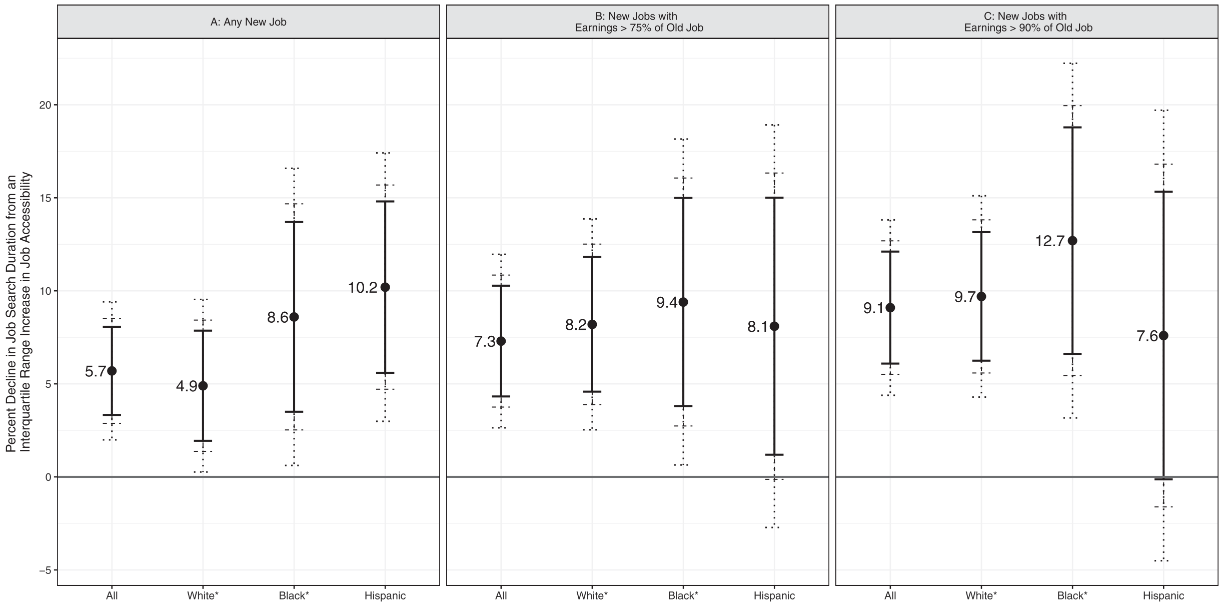
FIGURE 1.—DECLINE IN EXPECTED DURATION OF JOBLESSNESS FROM AN INCREASE IN JOB ACCESSIBILITY



The figure presents the estimated percent decline in expected duration between job displacement and finding any new job (left panel), jobs that replace at least 75% of prior job earnings (middle panel), and jobs that replace at least 90% of prior job earnings (right panel) as a result of a group-specific interquartile range increase in job accessibility for all workers and by specific demographic groups defined by race and ethnicity according to the estimation results in tables 3 and 4. The solid, dashed, and dotted lines represent the 90th, 95th, and 99th percent confidence interval around the point estimates, respectively. The sample design, creation of job accessibility measures, and empirical analysis are explained in detail in subsequent sections of the paper. * = Non-Hispanic.

Our approach makes use of the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau, which tracks worker outcomes over time. This employer-employee matched data set provides quarterly earnings for nearly all wage and salary jobs. Unique identifiers facilitate matching the jobs data to records on persons and employers, including information on where workers live, where establishments are located, and their demographic characteristics and industry. The data allow us to identify mass layoffs for individual workers, the subsequent spells of nonemployment, and the transition to new jobs. In addition, the LEHD data infrastructure enables us to control for a worker's predisplacement earnings, industry, job tenure, and travel time, as well as demographic and neighborhood characteristics.[4]

Our measurement of job accessibility addresses a number of important issues raised about its proper measurement in testing the SMH (Ihlanfeldt & Sjoquist, 1998; Perle, Bauder, & Beckett, 2002; Houston, 2005).[5] For each lower-income worker, we create an accessibility index that considers detailed residential location at the time of layoff, the likelihood of commuting by auto or transit,[6] and the detailed spatial locations of lower-income jobs and potentially competing job seekers (see Raphael, 1998a). Our index is a commuting-time-weighted measure of the spatial distribution of the local job market for each worker. To achieve this, we begin with all relevant auto and transit commute times from a home to the universe of potential worksites in the same metropolitan area. We then tabulate the number of lower-income jobs in each workplace census tract and weight them using an impedance function based on a worker's predicted travel time. To account for competition for potential jobs, we use the same data sources to summarize how many other lower-income workers could be seeking the same jobs. These calculations are made possible by using the spatial distribution of jobs from LEHD, origin-destination travel time information from metropolitan planning organizations, and neighborhood (census tract) characteristics from aggregate Census Bureau data. The study spans the years 2000 to 2005 for nine large metropolitan areas in all eight states bordering the Great Lakes, a region encompassing the cities studied in the initial research on spatial mismatch (Chicago and Detroit). We follow about 250,000 displaced workers in our analysis.

Our results support the spatial mismatch hypothesis. We find that better job accessibility significantly decreases the duration of joblessness among lower-paid displaced workers. To present the magnitude of our estimates, we consider the implied effect of increasing a worker's job accessibility from the 25th to the 75th percentile of job accessibility. Figure 1 presents the impact of job accessibility for three labor market outcomes: finding any job and finding a job that replaces at least 75% or 90% of the worker's earnings prior to displacement. For the sample of all workers, this interquartile increase in job accessibility is associated with

[4] We also estimate a layoff fixed-effects model that implicitly compares the relative job accessibility of former coworkers (though we believe this model understates the effect of job accessibility).

[5] Other literature reviews of accessibility measures are Handy and Niemeier (1997), Bhat et al. (2000), El-Geneidy and Levinson (2006), and Bunel and Torar (2013).

[6] Raphael and Stoll (2001) find that having access to a car is particularly important for understanding job accessibility by blacks and Latinos. Several other studies, including Baum (2009), Ong and Miller (2005), Johnson (2006), and Korsu and Wenglenski (2010), also find that vehicle ownership improves job accessibility.

a 4.4% reduction in joblessness duration for finding any job, and a 5.6% and 7.0% reduction for finding jobs meeting the 75% and 90% earnings thresholds, respectively.

Statistically significant and economically important effects of job accessibility are pervasive across demographic groups. Although the differences across groups are not statistically significant, the point estimates illustrated in figure 1 imply that black non-Hispanics are two-thirds more sensitive to job accessibility compared to white non-Hispanic job seekers. In this study, we present numerous additional findings that suggest that demographic groups differ in terms of how constrained they are by local job opportunities, including the finding that job accessibility is especially important for women and for older workers.

Understanding and quantifying the role of spatial mismatch is relevant for a wide range of policy prescriptions for using job accessibility as a way to improve employment outcomes. Examples of policies that depend on identifying the role of spatial mismatch include moving jobs closer to neighborhoods with high unemployment, as is intended by enterprise zones (Neumark & Kolko, 2010); enhancing transportation links between high-unemployment neighborhoods and locations with an abundance of jobs, as is done with transit expansions (Holzer, Quigley, & Raphael, 2003); and relocating residents from high- to low-poverty neighborhoods, as might occur with a targeted housing voucher program (Katz, Kling, & Liebman, 2001).[7] It is beyond the scope of this paper to evaluate specific policies; rather, our objective is to provide estimates of the roles of spatial mismatch that are relevant for this debate.

The remainder of this paper is organized as follows. Section II presents our empirical model and job accessibility measure. Section III describes the data and sample construction. Section IV presents our primary estimation results along with the economic significance of our findings, and section V provides our conclusions.

II. Modeling and Measuring Job Accessibility

A. Empirical Specification

Key to our identification strategy is that we explicitly restrict the population of job searchers to those who likely become job searchers for reasons other than locally available job opportunities. We follow the displacement literature by focusing on workers with strong labor force attachment (at least four quarters of tenure with the firm) who experience a displacement. Focusing on workers with strong labor force attachment subject to a mass layoff thus yields a group of at-risk searchers who are plausibly searching for exogenous reasons.

To test for the presence of spatial mismatch effects in the sample of displaced job searchers, we employ the following empirical specification that relates joblessness duration to an index of job accessibility and other control variables:

$$\ln(D^*_{ijt}) = \alpha A_{ijt} + \beta' x_{ijt} + \varepsilon_{ijt}. \tag{1}$$

Specifically, the parameter of interest α measures the impact of our measure of person- and location-specific job accessibility A_{ijt} (described below) on the natural logarithm of the duration of joblessness for worker i, residing in census tract j, who was laid off in year t. To safeguard against omitted variable bias, the specification includes a rich set of control variables for worker, previous job, and neighborhood characteristics in the vector x_{ijt}. For example, x_{ijt} includes measures capturing previous job earnings and tenure prior to displacement. The full set of control variables is provided in online appendix E.

In appendix A, we show that our empirical specification and measure of job accessibility can be motivated from a simple job search theoretic framework with spatial frictions in the form of commuting costs. The model intuitively predicts that the expected duration of joblessness is decreasing in the job offer arrival rate and the likelihood of obtaining a job offer with associated commuting costs below a reservation commuting cost level, which in turn is increasing in wages and decreasing in unemployment benefits and the option value of continued search.

A feature of our data is censoring of the dependent variable. In particular, the actual duration of joblessness (measured in quarters) is observed only if the displaced worker has found a job within two years (including the quarter of job separation). A significant fraction—over 20%—of the displaced workers in our sample have no reported earnings within these first two years after separation. Thus, observed duration of joblessness, D, is related to latent duration of joblessness, D^*, according to

$$D_{ijt} = \begin{cases} D^*_{ijt} & \text{if } D^*_{ijt} D_H \\ D_H & \text{if } D^*_{ijt} \geq D_H \end{cases}, \tag{2}$$

where D_H corresponds to the maximum observed duration of joblessness in the data of eight quarters.[8] Equations (1) and (2), along with a normally distributed residual, define the tobit regression model that we employ in the empirical analysis.

B. Measuring Job Accessibility

According to the theoretical framework in appendix A that motivates our empirical specification, job accessibility is proportional to the effective labor market tightness in each location, which in turn depends on the spatial distribution of

[7] See Ilanfeldt and Sjoquist (1998) for further discussion of the policy relevance of the spatial mismatch hypothesis.

[8] Because we use quarterly earnings data to measure duration, we assume that a job is obtained midway through a quarter, such that finding a new job in the same quarter as displacement corresponds to a measured duration of joblessness of 0.5 quarters and not having found a job within two years corresponds to a censoring threshold of 8.5 quarters. In practice, we also account for the concentration of same-quarter new jobs, with duration of 0, by imposing a lower censoring limit at 0.5 quarters.

labor market tightness in all other locations.[9] Our empirical analog, the job accessibility measure A_{ijt} in equation (1), is constructed as a symmetric difference measure of "job opportunities" and "competing searchers."[10] Specifically,

$$A_{ijt} = \frac{(JO_{ijt} - CS_{ijt})}{1/2 \cdot (JO_{ijt} + CS_{ijt})}, \tag{3}$$

where JO_{ijt} sums employment at nearby workplaces (within 60 minutes of travel time) discounted by an impedance function based on person-specific travel time to those destinations; and where CS_{ijt} sums workers in residences surrounding the workplaces discounted for travel time to those same destinations and then further discounted by the importance of each destination to worker i, as described by JO_{ijt}. Properties of this job accessibility measure include that it is bounded by -2 and 2 and less sensitive to extreme values.[11] Another advantage of this measure is that it is scale invariant; that is, differences in labor market tightness can be measured on the same scale for both larger and smaller metropolitan areas.

With our impedance function, we seek to represent several features of the costs associated with seeking, obtaining, or working at a potential job. While these costs may be multidimensional, including information limitations, discrimination based on location, and amenities of workplace locations, we represent only costs relating to predicted morning commute travel time. We estimate sequential models for vehicle ownership and mode choice. We then use the parameter estimates to make out-of-sample predictions of vehicle ownership and mode choice probabilities for each possible commuting destination for each person in the displaced worker sample. In brief, we find that higher-earning workers are more likely to travel by automobile, especially for routes where it is faster than transit. For each displaced worker, we apply these predicted travel times and the stock of jobs in nearby workplaces in the year of displacement to the impedance function described above and calculate job opportunities. We use tuning parameters from the literature and evaluate the robustness of our results to the parameter values. We calculate competing searchers using the same impedance function but assume that all competing searchers commute only by automobile.

A detailed discussion of the construction of the job accessibility measure, including the specifics and results of the transit mode model is provided in appendix B.

III. Data and the Measurement of Job Accessibility

The technical advances in this study are made possible by the LEHD Infrastructure Files, which provide virtually universal coverage of jobs covered by unemployment insurance (UI). The LEHD program at the Census Bureau constructs the files from integrated state and federal administrative data and survey data and releases public use data products (see Abowd et al., 2009). We use LEHD to extract a sample of displaced workers and also to measure the spatial distribution of jobs by workplace and residence.

Each job assembled from state-provided wage records links the unique identifiers for a worker and employer and lists the quarterly earnings for that job. There is no information on the reason for job transitions, but hiring and separation can be inferred from the beginning or end of an earnings history. State-provided employer files list the location, industry, and size of establishments.[12] Worker identifiers can be linked to residential locations from federal administrative data as well as survey responses, including those from the 2000 Census.

This study uses morning peak-period travel time to provide a better approximation than straight-line or road distance of the cost of traveling to a job opportunity from a place of residence. Metropolitan planning organizations (MPOs) estimate both automobile and public transit travel times between all points in an urban area in order to assess transportation needs and have provided their estimates to us for research purposes. Their modeling incorporates traffic congestion, so the data approximate rush hour conditions where commutes may be slower.[13]

[9] Specifically, according to equation A6, job accessibility in location j is proportional to $\sum_{k=1}^{K}(v_k/u_k)e^{-\theta d_{jk}}$, where v_k/u_k is the number of possible positions over the number of possible searchers for location k; d_{jk} is the commuting time between locations j and k, and θ is a decay parameter.

[10] Our job accessibility measure is defined in terms of employment levels, as opposed to actual vacancies and job searchers, which we do not observe. Even so, we expect it to be representative of local job market thickness. Examining the Quarterly Workforce Indicators (QWI), produced by the Census Bureau and based on LEHD data, we find that the quantity of new hires has a correlation of 0.986 with the stock of beginning-of-quarter jobs at the county/quarter level of aggregation. (It is also reasonable to think about using net job creation to measure job opportunities. However, net job creation has a correlation of only 0.535 with new hires.) Shen (2000) finds that the great majority of job openings occur in locations with an abundance of jobs.

[11] Davis, Haltiwanger, and Schuh (1996) use the symmetric growth rate measure to study job creation and destruction, where firm births and deaths play an important role in overall changes. Our ratio is bounded in the closed interval of -2 (when there are no job opportunities) to 2 (when there are no competing searchers). For ratios of job opportunities to competing searchers close to 1, the symmetric measure is very close to the log of the ratio. The two measures can be related through a first-order Taylor series approximation of the natural logarithm of the ratio of job opportunities over competing job searchers, that is, $\ln\left(\frac{JO}{CS}\right)\big|_{\left(\frac{JO}{CS}\right)=1} \approx \frac{(JO-CS)}{0.5(JO+CS)}$.

[12] For multiunit employers, the inputs to LEHD usually do not specify the assignment of establishments to workers. The LEHD program has developed an imputation model that attempts to replicate the observed distributions of establishment sizes within employers and of commuting distances more generally (Abowd et al., 2009). For describing displaced workers' employers, we use the first of ten draws from the model. For describing the spatial distribution of jobs, we use a weighted aggregation of all ten draws. Specific establishment assignments are not a significant concern for this analysis, which focuses primarily on the observed residential location of workers.

[13] To evaluate the quality of these data, we compared the MPO data with morning travel times reported in the 2000 Census long form, made available as public tabulations in the Census Transportation Planning Products (see online appendix table C1). We find that for the set of commuting routes available in the CTPP data, automobile travel times are very similar between the two sources. Transit travel times provided by MPOs are somewhat longer than for comparable commutes reported in the CTPP. A crucial advantage of the MPO data over the CTPP is that the MPOs provide a complete matrix of commuting times rather than just those that are actually traveled by the one-in-six sample of households responding to the long form. For calculating accessibility to potential jobs, we need to know all commuting times even if those trips are unlikely. See online appendix C for more detail on the travel time data.

Finally, we incorporate several neighborhood characteristics available from tabulated data from the 2000 Census (Summary File 3). In particular, we use (sample-based) census tract measures of poverty, homeownership, population density, building vintage, and use of public transit. We include these variables in estimation models to control for neighborhood characteristics other than relative job accessibility that may also be related to employment outcomes.

We construct a sample of lower-income job seekers who resided in nine large metropolitan areas in states adjacent to the Great Lakes with the following principal cities (listed from west to east): Minneapolis–St. Paul, Milwaukee, Chicago, Indianapolis, Detroit, Columbus, Cleveland, Pittsburgh, and Buffalo.[14] All nine metropolitan areas have over 1 million inhabitants. Their housing stocks are of a similar vintage, and they generally have discernible central business districts along with substantial suburbanization over the past sixty years. Although the amount of public transit varies, it usually consists of bus and/or light rail; some have heavy rail. Since early studies and much later work on spatial mismatch focused on cities in this region, using a similar set of cities will facilitate comparisons to earlier findings.

We define mass layoffs as cases where an employer of size 25 or greater loses over 30% percent of its workers over one year (consistent with Jacobson et al., 1993). We identify workers separating during such a four-quarter span with at least a year of job tenure who also do not return for at least two years. We require that the workers were 20 to 64 years old at the time of job loss (based on age from the 2000 Census) and that they had total earnings (from all jobs) of \$15,000 to \$40,000 in the year prior to displacement. These restrictions focus the analysis on a high-attachment sample that likely has full-time earnings but who are also likely to search locally for work.[15] We link these displaced workers by residence location in the year before displacement to a census tract, for which we will seek to measure job accessibility and to which we link the 2000 Census summary information. The resulting sample consists of approximately 247,000 potential job seekers displaced from 2000 to 2005 and residing in a county composing our set of Great Lakes MPO areas.

For each displaced worker, we use LEHD, person and neighborhood characteristics, and MPO travel times to construct person-specific job accessibility measures, as defined by equation (3). We produce an extract of LEHD jobs for a reference date of April 1 each year, retain only the highest-earning job of each worker, and produce census-tract-level tabulations of job opportunities and competing searchers proxied for by the workplace and residence margins of job counts. We further limit the extract to low- or medium-earning private sector jobs, with annualized earnings of less than \$40,000, a level commensurate with the earnings lost by workers in our mass displacement sample (the earnings restriction excludes about one-third of jobs). To provide a sense of scale for our proxy measures, job seekers have, on average, the equivalent of 112,000 job opportunities and 99,000 competing searcher equivalents within 60 minutes of travel time before weighting by the impedance function, with a median job accessibility value of approximately 0.021 from equation (3).

We use LEHD to produce our dependent variable, the count of quarters until a new job is obtained, and use the assembled microdata to produce additional explanatory variables. For demographics, we define a job searcher's race/ethnicity, sex, age, and marital status (in the time of displacement). For job history, we identify the predisplacement industry, year and quarter of displacement, estimated driving time to the previous job, job tenure, count of jobs, and earnings (both personal and household). Additional details on the sample construction are provided in online appendix D.

Table 1 provides the distribution of several job search outcomes for the estimation sample. Among displaced workers, 32% find a new job in the same quarter, and almost 80% do so within the subsequent two years.[16] The next two measures require that a single, new job account for at least a particular share of predisplacement earnings.[17] Column 2 requires new job earnings to be 75% of predisplacement earnings, while column 3 requires 90%. Accessions to these higher-earning jobs are less frequent, and only 22% and 19% of workers, respectively, obtain such jobs in the first quarter. Duration spells for these measures are also more often censored, with only 65% and 60% obtaining such jobs within two years.

The second and third measures aim to capture accessions to a job that may be acceptable in the longer run. We choose the 75% threshold to be approximately in line with the typical experience of a displaced worker.[18] We choose the 90% threshold to identify searchers finding a new job that is approximately comparable to their predisplacement job.

[14] All of the metropolitan areas we consider are in a Consolidated Metropolitan Statistical Area (CMSA) that is either entirely or mostly contained within one state (the exceptions are five of fourteen counties in Chicago-Naperville-Joliet IL-IN-WI and two of thirteen in Minneapolis-St. Paul–Bloomington MN-WI). We use only counties with MPO travel time data, all of which are in the same state as the principal cities listed.

[15] According to Molloy, Smith, and Wozniak (2011), workers with a college education have almost double the interstate migration rate as those with high school or less education. High-earning workers also migrate marginally more. Higher-earning workers in general also face fewer liquidity constraints, and thus have relatively higher reservation wages along with a better ability to wait for a highly desired specialized job.

[16] The job search durations reported here are broadly in line with other analyses of displaced workers. For example, Fallick, Haltiwanger, and McEntarfer (2012) used LEHD data and found that 37% of distressed separators in 2001 found a job in the same quarter and over 80% within one year.

[17] Because we do not know when in a quarter a worker is hired, we allow this earnings threshold to be passed in either the quarter of hire, or the next quarter.

[18] Von Wachter, Song, and Manchester (2009) found an average earnings loss of 20% in the first year compared to not-displaced coworkers.

Table 1.—Job Search Outcomes by Quarter after Job Separation

Quarters of Job Search	Any New Job(s)	Single New Job, Earnings > 75% Previous Job	Single New Job, Earnings > 90% Previous Job	Single New Job, Earnings > 75% Previous Job: Job Accessibility < −0.5	Single New Job, Earnings > 75% Previous Job: Job Accessibility > 0.5
Same quarter	31.7%	22.3%	18.9%	21.6%	23.7%
1–2 quarters	30.2	24.7	22.6	24.2	24.9
3–4 quarters	10.5	9.5	9.0	9.7	9.5
5–8 quarters	6.9	8.5	9.1	8.7	8.2
9+ quarters	20.8	35.0	40.5	35.8	33.7

Sample of about 247,000 displaced workers. Job search outcomes constructed from LEHD quarterly earnings records indicate the count of quarters after the displacement quarter until the job seeker obtained a new job (if within two years). Quarterly earnings thresholds in columns 2 through 5 can be obtained in either the quarter of hire or in the subsequent quarter. See equation (3) for the definition of the job accessibility, which has a lower bound of −2 and an upper bound of 2. Approximately 50,000 job seekers (20%) have job accessibility less than −0.5 (see equation [3]), while 44,000 (18%) have job accessibility greater than 0.5.

Table 2.—Sample Composition and Distribution of Job Accessibility

Sample	Sample Percent	Median	25th Percentile	75th Percentile	Interquartile Range
All	100.0	0.021	−0.390	0.379	0.769
White non-Hispanic	67.8	−0.020	−0.398	0.366	0.764
Black non-Hispanic	18.6	0.183	−0.336	0.391	0.727
Hispanic	9.4	−0.093	−0.469	0.338	0.807
Other race non-Hispanic	4.3	0.263	−0.145	0.568	0.713
Central city	35.9	0.259	−0.192	0.511	0.703
White non-Hispanic within central city	(43.7)	0.372	0.107	0.586	0.479
Black non-Hispanic within central city	(36.9)	0.235	−0.337	0.419	0.756
Remainder of central county	28.0	0.085	−0.207	0.428	0.635
White non-Hispanic within remainder of central county	(76.7)	0.084	−0.199	0.405	0.604
Black non-Hispanic within remainder of central county	(11.6)	−0.042	−0.311	0.348	0.659
Outside central county	36.0	−0.265	−0.652	0.095	0.747
White non-Hispanic within outside central county	(85.0)	−0.313	−0.702	0.023	0.725
Black non-Hispanic within outside central county	(5.8)	−0.044	−0.354	0.320	0.674
Male	46.9	0.016	−0.391	0.383	0.774
Female	53.1	0.025	−0.390	0.376	0.766
Age 20 to 34	42.0	0.046	−0.365	0.396	0.761
Age 35 to 54	46.2	0.005	−0.404	0.366	0.770
Age 55 to 64	11.9	−0.006	−0.408	0.363	0.771
Married, primary earner	13.0	−0.031	−0.416	0.355	0.771
Married, secondary earner	11.8	−0.036	−0.425	0.351	0.776
Marital status uncertain	75.2	0.040	−0.378	0.387	0.765
Previous earnings $15,000 to $29,999	62.3	0.017	−0.396	0.368	0.764
Previous earnings $30,000 to $40,000	37.7	0.026	−0.380	0.396	0.776
Industry: Goods producing and distribution	39.5	−0.039	−0.440	0.354	0.794
Industry: Local services	28.3	0.052	−0.355	0.391	0.746
Industry: Professional services	18.3	0.086	−0.330	0.422	0.752
Industry: Education and public services	3.8	−0.005	−0.424	0.371	0.795
Industry: Health care services	10.1	0.048	−0.373	0.367	0.740

Number of observations: 247,000. Percentages in parentheses are for shares of the relevant percentage.

As a preview of results to come, we present simple Kaplan-Meier estimates of duration for high and low job accessibility ratios in the last two columns of table 1. For illustration, we focus on the durations for new jobs with at least 75% of predisplacement earnings. Caution needs to be used in interpreting these results since they reflect no controls. Still, it is apparent that workers with greater job accessibility are more likely to find jobs in the first quarter and fewer are still searching after eight quarters.

Table 2 provides information on the composition of the sample and the distribution of the job accessibility variable. The relatively large share of black workers reflects both the large numbers of blacks in the metropolitan areas in the Great Lakes region and their greater likelihood of having lower incomes. The sample is spatially distributed almost evenly across zones defined as (a) the central (principal) city of each metropolitan area, (b) the remainder of that county, and (c) the surrounding counties. Blacks constitute over a third of the central city population but less than 6% of the peripheral zone. We group workers by displacing employer industry into five broad categories.[19] Almost 40% of displacements are from goods-producing industries.

There is considerable spatial variation in our measure of accessibility, both across and within subpopulations of the sample. We provide the median, the 25th and 75th percen-

[19] Industries aggregated as follows: goods-producing and distribution (North American Industrial Classification System sectors 11,21,22,23,31–33,42,48–49), local services (44–45,56,71,72,81), professional services (51,52,53,54,55), education and public (61,92), and health care (62).

Table 3.—Spatial Mismatch Effect under Alternate Model Specifications

	(1) Tobit	(2) Ordinary Least Squares	(3) Employer/Year Fixed Effects
A. Any new job			
Job accessibility parameter estimate	−0.057***	−0.029***	−0.012*
	(0.0144)	(0.0070)	(0.0067)
R^2	0.032	0.093	0.381
B. Single new job with earnings > 75% previous job			
Job accessibility parameter estimate	−0.073***	−0.033***	−0.015**
	(0.0181)	(0.0079)	(0.0066)
R^2	0.027	0.074	0.379
C. Single new job with earnings > 90% previous job			
Job accessibility parameter estimate	−0.091***	−0.038***	−0.019***
	(0.0183)	(0.0076)	(0.0064)
R^2	0.026	0.068	0.377
Controls	Yes	Yes	Yes
Observations	247,000	247,000	247,000
Number of employer/year fixed effects	None	None	42,000

The first specification is an upper and lower censored tobit, while the second and third are linear models without censoring. All specifications include controls for job and demographic characteristics, and the quarter of job loss. Columns 1 and 2 include controls for previous employer's industry and metropolitan area by year indicators, while column 3 replaces these with employer by year fixed effects. Complete estimation results for the main tobit regressions are presented in online appendix E. Robust standard errors (reported in parentheses) are clustered by residence PUMA in columns 1 and 2 and by residence PUMA and by employer/year in column 3. The McFadden's pseudo R^2 measure is reported for the tobit model and is not directly comparable to the R^2 reported for the least square specifications. R^2 for the employer/year fixed-effects model includes both within and between variation. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

tiles, and the interquartile range. The medians for workers living in the central city, the central county (but not the central city), and outside the central county are 0.259, 0.085, and −0.265 respectively. This distribution is in keeping with the spatial structure of large, older Great Lakes metropolitan areas. In most cases, there is a great deal of employment in the central business district and adjoining areas even though substantial suburbanization of jobs has occurred. Our job accessibility measure, of course, also includes competing searchers. The number of competing searchers for central city lower-income jobs exceeds the comparable number in suburban locations. However, as reflected in our job accessibility index, job opportunities relative to competing searchers are higher in central areas and lower in suburban areas.[20]

Given the overall spatial pattern of job accessibility, it is not surprising that our accessibility index varies across demographic groups due to differing residential location patterns. While blacks have higher median job accessibility than white non-Hispanics and Hispanics, this largely reflects their concentrated residence in neighborhoods that are typically closer to a high-employment central city; 71% of the blacks in our sample reside in central cities, compared to 36% of the full sample. Put differently, while blacks constitute 19% of the full sample, they make up 37% of the sample residing in the central city of each metropolitan area.[21] Even so, central city whites actually have higher job accessibility (0.372) than blacks (0.235), which partially reflects whites' higher likelihood of commuting by auto. Our use of predicted mode choice lowers the job accessibility measure for blacks, who are much more likely to be users of public transportation due to their lower rates of vehicle ownership.

IV. Results for Unemployment Duration and Spatial Mismatch

In this section, we empirically test for the impact of job accessibility on the duration of joblessness among displaced workers. Column 1 of table 3 presents the main upper- and lower-censored tobit estimation result relating job search success (as measured by the log of quarters of search duration) to the job accessibility ratio and control variables, as specified in equation (1). As in table 2, we define success as finding any job (panel A), finding a job that provides more than 75% of earnings at the previous job (panel B), or finding a job that provides more than 90% of earnings at the previous job (panel C). We calculate job accessibility as in equation (3), using predicted travel times to weight the contribution of jobs and competing searchers. A negative coefficient signifies that greater job accessibility reduces the duration of joblessness. The specifications presented in table 3 include controls for previous job and demographic characteristics, previous employer's industry, each metropolitan area by year, and the quarter of job loss. Complete parameter estimates for the tobit regression, along with a brief discussion of effects of control variables, are provided in online appendix E.

We cluster standard errors by a place of residence geography defined as a Public Use Microdata Area (PUMA). The Census Bureau designs PUMAs, composed of census tracts, to include a population of at least 100,000 and uses them to release Public Use Microdata Samples. We have

[20] One concern might be that our sample of displaced workers is not representative. In results not presented here, we also calculate the median job accessibility across all census tracts, using the 2000 Census population and 2000 Census labor force for weights and find little difference in the distribution.

[21] The finding of higher job accessibility for blacks varies across studies, which vary widely in measures employed and metropolitan areas considered. Hellerstein, Neumark, and McInerney (2008), for example, find higher overall job accessibility for blacks but lower accessibility to lower-education jobs.

about 6,500 tracts in the study area that make up our 168 PUMA clusters.[22]

For each dependent variable specification, we find that greater job accessibility reduces job search duration, with greater effects for jobs with incomes approaching the earnings of the lost job. A one unit increase in job accessibility, approximately equal to an increase from the 20th to the 80th percentile in the job accessibility distribution across workers, is associated with a 5.7% reduction in search duration for finding any job, and a 7.3% and 9.1% reduction for accessions to a new job with 75% and 90% of prior job earnings, respectively. A move across the narrower interquartile differences in table 2 (i.e., from the 25th to the 75th percentile) reduces search duration by 4.4%, 5.6%, and 7.0%, respectively. The greater effect for the higher earnings thresholds in panels B and C is consistent with improved measurement of a job the worker would maintain in the long run, while the "any new job" outcome in panel A could include temporary jobs.[23] Because only new jobs within the same state are included, long-distance relocations resulting in a new job are considered a failure to find a local job.[24]

Although we have an extensive set of person-specific and previous job-specific controls, one concern is that the unobserved characteristics of a job seeker, such as ability, may be related to job search outcomes and place of residence. As a robustness check to control for sorting to employers with respect to unobserved characteristics, we estimate a specification with fixed effects for the previous employer and the year in which the layoff occurred. The linear noncensored specifications shown in column 3 of table 3 include about 42,000 fixed effects for workers sharing an employer/year separation; other control variables remain the same, but industry and metropolitan area effects are omitted. Whereas in the specifications in column 1 we clustered by residence PUMA, in column 3 we use two-way clusters, by employer/year and PUMA. We again find a significant negative effect of job accessibility in column 3 for each job search outcome, though with a lower-magnitude coefficient than for OLS and also with lower standard errors. To compare the magnitude of this effect with the result in column 1, we also estimate a noncensored model using OLS, with no employer effects (column 2). Based on what has been observed to be a powerful empirical regularity (Green, 1980), we can rescale the OLS result by dividing the estimated coefficient by the share that is not censored in the tobit regression (47.5%, 42.8%, and 40.6% for panels A, B, and C, respectively). For each outcome, the rescaled OLS coefficient is similar in magnitude to the censored tobit estimate in column 1 (-0.059, -0.077, and -0.094 for panels A, B, and C, respectively). The rescaled fixed effects estimates are approximately half the magnitude of the primary result (-0.025, -0.034, and -0.047 for panels A, B, and C, respectively).

One drawback of the fixed effects model stems from the fact that many workers reside relatively near their work, which means that the degree of variation in job accessibility among coworkers will be substantially less than among the full population. We conclude that the robustness of the main result to employer by year fixed effects underscores our spatial mismatch finding, but we focus on the tobit model without employer effects for other extensions and interpretation.

The magnitude of our estimated effect of job accessibility can be put into perspective by comparing it against the effect of other neighborhood characteristics. For example, the 25th and 75th percentiles of the neighborhood poverty rate for our sample are 0.037 and 0.142 (with a mean of 0.106 and a median of 0.070). As shown in online appendix E, table E1, we find a positive effect on job search duration for neighborhood poverty (coefficients of 0.13, 0.43, and 0.59). Moving from a high- to a low-poverty neighborhood, a decrease of 0.105 in the poverty rate, would be expected to reduce job search time by 1.4%, 4.5%, and 6.2%, respectively, for the three job search outcomes; this is a smaller reduction than the effect of an interquartile improvement in job access (4.4%, 5.6%, and 7.0%). While demographic and job history factors still play the principal role in determining job search outcomes (blacks take 24% longer to find a comparable job), the similarity in magnitudes of these census tract effects suggests that job accessibility is an important metric for characterizing a neighborhood. Job accessibility captures a different dimension of a neighborhood than is represented by tabulations of resident data, with a correlation of only 0.1 with poverty rate (conditional on metropolitan area) and similarly low relationships with other neighborhood variables.

We have conducted a number of additional robustness checks on the main results in table 3. As discussed in online appendix F, our primary results of reduced search duration associated with increased job accessibility are robust to reasonable variations in the specification of the impedance function, including the use of different normalizations and decay parameters. Other types of robustness checks include the estimation of effects in an ordered logistic regression model instead of our tobit specifications. The results yield quantitative and qualitative patterns of expected accessibility

[22] Our job accessibility measures vary at the person level through the influence of worker characteristics on transportation mode choice. However, there is substantial and systematic variation in commuting times from tract to tract so there is a clear correlation across people in the same census tract. Furthermore, one concern might be that census tracts are still too narrow for defining the set of job seekers who may be influenced by spatially correlated job accessibility shocks. To address this concern, we cluster by PUMA throughout. Tobit standard errors with PUMA clusters are slightly higher than those based on census tract clusters, but the significance levels of the main results do not change across clustering methods.

[23] The results for higher-earning jobs may also better reflect the tradeoff of offer value and commuting distance for a job seeker. Imposing the threshold is equivalent to reducing the offer arrival rate, which is expected to increase search duration.

[24] We think this limitation would affect mainly high-skilled, high-income individuals whom we exclude from this analysis. As is discussed earlier, the MPOs used to define residence counties are only in the state of the principal city.

Table 4.—Effects of Job Accessibility, by Subsample

Search Outcome	Job Accessibility Effect for Tobit Estimation, by Subsample				
	A. Race/Ethnicity				
	White Non-Hispanic	Black Non-Hispanic	Hispanic	Other Race Non-Hispanic	
Any new job	−0.049***	−0.086***	−0.102***	0.009	
	(0.018)	(0.031)	(0.028)	(0.048)	
Earn > 75% previous	−0.082***	−0.094***	−0.081*	0.040	
	(0.022)	(0.034)	(0.042)	(0.055)	
Earn > 90% previous	−0.097***	−0.127***	−0.076	−0.026	
	(0.021)	(0.037)	(0.047)	(0.056)	
	B. Sex and Age				
	Male	Female	Age 20 to 35	Age 35 to 54	Age 55 to 64
Any new job	−0.056***	−0.058***	−0.036*	−0.055***	−0.130***
	(0.018)	(0.017)	(0.018)	(0.018)	(0.034)
Earn > 75% previous	−0.055**	−0.091***	−0.049**	−0.069***	−0.198***
	(0.022)	(0.023)	(0.021)	(0.021)	(0.048)
Earn > 90% previous	−0.071***	−0.111***	−0.078***	−0.078***	−0.225***
	(0.022)	(0.023)	(0.021)	(0.022)	(0.048)
	C. Household and Earnings				
	Married, Primary Earner	Married, Secondary Earner	Not Married	Previous Earnings $<$ \$30,000	Previous Earnings $\geq$ \$30,000
Any new job	−0.048*	−0.045	−0.062***	−0.040***	−0.077***
	(0.027)	(0.030)	(0.015)	(0.015)	(0.019)
Earn > 75% previous job	−0.072**	−0.080**	−0.076***	−0.046**	−0.112***
	(0.034)	(0.033)	(0.018)	(0.018)	(0.025)
Earn > 90% previous job	−0.081**	−0.091***	−0.096***	−0.063***	−0.130***
	(0.034)	(0.033)	(0.019)	(0.018)	(0.026)
	D. Industry				
	Goods Producing	Local Services	Professional Services	Education and Public	Health Care
Any new job	−0.090***	−0.014	−0.000	−0.125*	−0.104**
	(0.019)	(0.023)	(0.035)	(0.071)	(0.052)
Earn > 75% previous	−0.106***	−0.034	−0.045	−0.127	−0.102*
	(0.023)	(0.026)	(0.041)	(0.090)	(0.058)
Earn > 90% previous	−0.129***	−0.050**	−0.060	−0.182**	−0.096*
	(0.024)	(0.024)	(0.041)	(0.089)	(0.054)

Standard errors clustered by residence PUMA in parentheses. Each estimate is the variable of interest in a separately estimated specification. Specifications include all control variables used in table 3, column 1 except for indicators used in each panel to define race/ethnicity, sex, age, household status, earnings, or industry. See table 2 for sample share in each estimation model. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

effects quite similar to those in table 3. To evaluate the importance of focusing on mass layoff events, we also estimate the search model for a comparable sample of over 350,000 nondisplaced separators (not presented here). For these nondisplaced searchers, we find no statistically significant relationship between job accessibility and search duration. This finding highlights the importance of focusing on those who are searching for plausibly exogenous reasons.

Table 4 presents results for various subsamples, with the job accessibility estimate from an independent regression in each cell. As with the main results, estimates for the effect on finding any job tend to be less significant and more attenuated, while estimates for earnings greater than 90% of previous job estimates are strongest. These subsample results highlight some groups that are especially sensitive to spatial mismatch but also suggest that job accessibility is broadly relevant for all job seekers.

Panel A of table 4 shows results disaggregated by race and ethnicity. This provides a reference point of particular interest for the spatial mismatch literature, which has often focused on outcomes for lower-earning inner-city blacks. We first note that non-Hispanic whites, non-Hispanic blacks, and Hispanics are all sensitive to job accessibility. However, we find that for obtaining comparable jobs, blacks are especially sensitive evaluated at the point estimates. For finding any job, a job at 75% of previous earnings, or a job at 90% of previous earnings, blacks are more sensitive to job accessibility than whites. Table 4 shows that the relative white-black coefficients for these three cases are −0.049 versus −0.086, −0.082 versus −0.094, and −0.097 versus −0.127, signifying that blacks are approximately 76%, 15%, and 31% more responsive to accessibility than whites for the three earnings levels examined (although the differences are not statistically different from each other). We also note that Hispanic job seekers are most responsive for finding any job based on the point estimates.

Turning to results by sex and age (panel B of table 4), men and women have little difference in outcomes for

Table 5.—Effects of Same-Type Job Accessibility, by Race/Ethnicity and Industry Subsample

Search Outcome	Same-Type, Job Accessibility Effect for Tobit Estimation, by Subsample				
	A. Race/Ethnicity				
	White Non-Hispanic	Black Non-Hispanic	Hispanic	Other Race Non-Hispanic	
Any new job	−0.051***	−0.066***	−0.113***	0.015	
	(0.018)	(0.025)	(0.026)	(0.047)	
Earn > 75% previous job	−0.085***	−0.080***	−0.084**	0.042	
	(0.023)	(0.029)	(0.038)	(0.053)	
Earn > 90% previous job	−0.102***	−0.106***	−0.071*	−0.016	
	(0.021)	(0.031)	(0.043)	(0.054)	
	B. Industry				
	Goods Producing	Local Services	Professional Services	Education and Public	Health Care
Any new job	−0.102***	−0.011	0.004	−0.076	−0.087
	(0.019)	(0.023)	(0.029)	(0.066)	(0.054)
Earn > 75% previous	−0.113***	−0.026	−0.042	−0.080	−0.088
	(0.023)	(0.026)	(0.034)	(0.091)	(0.057)
Earn > 90% previous	−0.129***	−0.043*	−0.062*	−0.104	−0.083
	(0.024)	(0.024)	(0.035)	(0.092)	(0.054)

Standard errors clustered by residence PUMA in parentheses. Each estimate is the variable of interest in a separately estimated specification. Specifications include all control variables used in table 3 column 1, except for indicators used in each panel to define race/ethnicity or industry. For each subsample, the job accessibility variable, defined in equation (3), limits job opportunities and competing searchers to those in the same subsample as the job searcher. See table 2 for the sample share in each estimation model. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

finding any job. However, women are especially sensitive to job accessibility for finding a comparable job, with an effect that is 71% greater than that for men. Workers aged 55 to 64 are substantially more sensitive to job accessibility for all earnings outcomes, with the effect on obtaining a comparable job being almost three times greater than for those aged 35 to 54. This finding is consistent with the hypothesis that younger workers are more willing to commute or perhaps to relocate locally in order to obtain a new job (younger workers are more likely to be renters than older workers, with a concomitant lower transaction cost of moving). A 25th to 75th percentile change in job accessibility for a female or older job seeker would be expected to reduce search times for a job earning 75% of their previous job by 6.9% and 15.1%, respectively.

Panel C shows differences by household type and earnings level. Among married households, secondary earners (the lesser earner in a household) have estimates similar to primary earners. Using the point estimates, workers with greater predisplacement earnings (those earning \$30,000–\$39,999) are actually more sensitive to job accessibility than lower-earning workers (\$15,000–\$29,999).[25]

In panel D, we find that most displaced industry groups are sensitive to job accessibility, especially when search outcomes are defined as a comparable job. Those displaced from typical blue-collar industries, labeled here as "goods producing" (including construction, manufacturing, utilities, and distribution), are especially sensitive to spatial mismatch. Workers displaced from public sector and education jobs are also highly sensitive. Health care workers have a similar accessibility effect across all outcome types, suggesting that such workers are primarily finding new jobs with similar earnings to their previous jobs. The lower-magnitude effect for local services workers may simply reflect a greater accumulation of job search experience by workers in a high-turnover industry. Alternately, given that the job opportunities in local services are more spatially distributed, job accessibility may be less of a constraint. Similar considerations may apply to lower-earning workers in professional services, which also has smaller effects.

In table 5, we provide estimates for the effect of job accessibility in the same race/ethnicity or industry as the job searcher as a means to further refine the set of job opportunities and competing searchers who might be most relevant. If race/ethnicity is a proxy for job types, discrimination in hiring, or labor market networks (see Hellerstein et al., 2008), then race/ethnicity-based accessibility measures may be more relevant than the overall measures. Similarly, skills specific to industries might make industry-based measures more relevant. While our analysis on these dimensions is only exploratory, the results in table 5 show that the same-type results for race-ethnicity and industry are largely similar to the overall job accessibility effects. In short, we do not find evidence that the impact of spatial mismatch is greater if we refine the accessibility measures to same-type measures on these dimensions. If anything, we find somewhat weaker results for blacks when using same-type measures. Same-type results for those laid off from goods-producing industries are again strong, though results from education, public, and health care workers are no

[25] According to the model, the estimated greater sensitivity to job accessibility can be interpreted in terms of a higher job offer arrival rate from all locations among higher-income workers as compared to low-income workers, consistent with the greater human capital requirements for some jobs.

longer significant.[26] Part of the reason for the overall similar findings is the high correlation between accessibility for all jobs and same race/ethnicity jobs: 0.99 for whites and 0.95 for blacks (conditional on metropolitan area). Likewise, we find similarly high correlations between access to all jobs and same-sector jobs.

V. Conclusion

The spatial mismatch hypothesis encompasses a wide range of research questions, all focused on whether a worker with locally inferior access to jobs is likely to have worse labor market outcomes. Kain (1964, 1968) suggested that persistent unemployment in urban black communities might be due to a movement of jobs away from those areas, while suburban housing discrimination prevented those individuals from relocating closer to suburban jobs. Subsequent research has evaluated the existence and extent of spatial mismatch in many contexts. A primary concern has been how to state the problem and appropriately test the SMH.

Numerous contributions have advanced this literature, including, for example, explicit recognition of the value of automobile availability for search and commuting, use of commuting times instead of distance, and consideration of competing searchers. But no other study has combined and built on these advances using appropriate data and satisfactorily dealing with identification. Furthermore, the literature has been primarily cross-sectional, and despite efforts to account for various threats to identification such as the endogeneity of residential location, the existing literature has come under considerable criticism.

Relative to this literature, the analysis in this paper is the first in the spatial mismatch literature to focus on workers displaced from a mass layoff, a critical aspect of our identification strategy. The basis of our approach is that if spatial mismatch is present, the duration of search for a new job after a displacement should decline with accessibility to appropriate jobs. We take advantage of longitudinal, matched employer-employee administrative data integrated with worker characteristics and neighborhood data from the 2000 Census, and with comprehensive transportation network data for nine large Great Lakes metropolitan areas.

Our results support the spatial mismatch hypothesis. We find that better job accessibility significantly decreases the duration of joblessness among lower-paid displaced workers. In the center of the job accessibility distribution, an increase from the 25th to the 75th percentile of job accessibility is associated with a 4.2% reduction in search duration for finding any job and a 5.6% and 7.0% reduction for accessions to a new job with 75% and 90% of prior job earnings, respectively. While job accessibility is only one of many factors affecting job search outcomes, it appears to play an especially important role for blacks, who have long been a focus of this research area. We find that black non-Hispanics are 71%, 15%, and 35% more sensitive to job accessibility than white non-Hispanic job seekers, respectively. We also find that job accessibility is especially, respectively important for women and older workers.

There are many areas for further inquiry. We note that caution needs to be used in drawing inferences from our results for differences in unemployment rates across groups driven by spatial mismatch. We have identified the impact of spatial mismatch on job search duration, but we are missing the other key pieces for drawing inferences about unemployment rates, specifically the impact of spatial mismatch on labor force participation and job separation rates. Cross-sectional and time series differences in the latter are substantial by race and ethnicity, as well as other characteristics. For example, the overall decline in labor force participation rates is especially dramatic for blacks and less educated workers in the post-2000 period (see, e.g., Davis & Haltiwanger, 2014). Exploring the role of spatial mismatch on these other key labor market outcomes would be of great interest.

We close by noting that our results differ from the inferences often drawn from the Moving to Opportunity (MTO) demonstration project (Sanbonmatsu et al., 2012). Those results have been interpreted as yielding little support for the spatial mismatch hypothesis. We think there are a number of reasons our results are more directly relevant for the spatial mismatch hypothesis. First, our analysis examines individuals with plausibly exogenous variation in residential location with likely much greater variation in job accessibility than MTO participants. Second, we are studying individuals with strong labor force attachment. Third, MTO focuses on neighborhood poverty rate, while we examine accessibility to jobs in and around a neighborhood. In short, we develop a person-specific measure of job accessibility that exhibits a wide range for job searchers who have plausibly exogenous variation in residential location. We find that job accessibility matters for the duration of joblessness.

[26] One reason for attenuation in the public and education sector may be that we exclude state and local government jobs from our job accessibility measure because such jobs are often measured with less geographic precision (e.g., local school jobs are sometimes reported in one central administrative location rather than distributed to worksites).

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APPENDIX A

Job Search Model

In this appendix we demonstrate how our empirical specification can be derived from a simple job search theoretic framework.

A. Theoretical Motivation

Following closely the theoretical exposition in Rogerson, Shimer, and Wright (2005), consider an individual searching for a job in continuous time. This individual seeks to maximize the expected value of

$\left[\int_{t=0}^{\infty} y_t e^{-r}\right]$, where r (0,1) is the discount factor and y_t is the income at time t. Income is $y = w - c$ if employed with wages w and commuting costs c, and $y = b$ if unemployed. To introduce a spatial dimension, we depart slightly from the standard job search model that assumes that job offers are heterogeneous with respect to wages. Instead, we assume heterogeneity in terms of the location of the prospective employer and that the value of a given job offer depends on the associated commuting costs.

An unemployed individual receives i.i.d. job offers with a Poisson arrival rate of a from a known distribution $F(c)$. If the offer is rejected, he remains unemployed. If accepted, he remains employed forever.[27] Hence, we have the Bellman equations (Bellman 1957):

$$rV(c) = w - c, \tag{A1}$$

$$rU = b + a\int_{0}^{\infty} \max\{U, V(c)\}dF(c), \tag{A2}$$

where $V(c)$ is the payoff from accepting a job with commuting costs of c and U is the payoff from rejecting a job offer. Since $V(c) = (w - c)/r$ is strictly decreasing in cost, there is a unique value of $c = R$, such that $V(c) = U$, with the property that the worker should reject the job offer if $c > R$ and accept if $c \leq R$. Substituting $U = (w - R)/r$ and $V(c) = (w - c)/r$ in the expression for U, we obtain

$$w - R = b + \frac{a}{r}\int_{0}^{\infty} \max\{w - c, w - R\}dF(c). \tag{A3}$$

Using integration by parts and simplifying gives the following expression for the reservation commuting costs:

$$R = w - b - \frac{a}{r}\int_{0}^{R} F(c)dc. \tag{A4}$$

Equation (A4) demonstrates that the reservation commuting costs (i.e., the level of commuting costs associated with a job offer at which the unemployed worker is indifferent between accepting and rejecting the offer) are increasing in the wage level, decreasing in unemployment benefits, and decreasing in the option value of continued search.

The probability that a worker has not found a job after a spell of length t is e^{-Ht}, where the hazard rate $H = aF(R)$ equals the product of the job offer arrival rate and the probability of accepting a job. The expected duration of unemployment, $E(D)$, is given by

$$E(D) = {}_{0}^{\infty} tHe^{-Ht}dt = \frac{1}{H}. \tag{A5}$$

B. Model Specification

By the law of total probability, the total hazard rate of individual i residing in location j $H_{ij} = \sum_{k=1}^{K} H_{ijk}$ equals the sum across the K destination-specific hazard rates. To proceed, we specify the components of the destination-specific hazard $H_{ijk} = a_k F\left(R_{ijk}\right)$. Following the job matching literature (e.g., Mortenson & Pissarides, 1994), we assume that the job offer arrival rate is a function of the labor market tightness in the location, such that $a_k = f(v_k/u_k)$ where v_k denotes vacancies in k and u_k is the number of competing job searchers for those vacancies. As a simplifying approximation, we assume that the job offer arrival rate is proportional to the labor market tightness at each destination, with $a_k = \gamma\, v_k/u_k$. We parameterize the acceptance probability as $F\left(R_{ijk}\right) = e^{-\theta d_{jk} - x_i\beta}$, where d_{jk} is the commuting time (a cost measure) between the origination and destination tract, θ captures the discounting of offers due to associated commuting costs, x_i is a vector of individual-specific variables affecting the reservation commuting cost (also discussed in the next section), and β is the associated vector of parameters.

This specification captures the potential for spatial mismatch since the destination-specific hazard incorporates location-specific (and person-specific) heterogeneity in the accessibility of jobs. We have discussed the formal model in terms of heterogeneity across locations arising from heterogeneity in commuting times. It may be that there are also spatial frictions in the probability of obtaining a job offer. That is, it may be that both the job offer arrival rate a and the commuting costs depend on the time to commute to the job's location. But we note that this distinction is only important for how to interpret the commuting cost parameter in the empirical model we estimate below; to the extent that both types of frictions are relevant, our specification captures both effects.[28]

Under these assumptions, the total hazard of individual i residing in location j is given by

$$H_{ij} = e^{-1x_i 1\beta}\gamma\left[\sum_{k=1}^{K} (v_k/u_k)e^{-\theta d_{jk}}\right]. \tag{A6}$$

We insert equation (A6) into the expression in equation (A5) for the expected duration of unemployment, take the natural logarithm of both sides, and append a residual ε assumed to be distributed $N(0, \sigma_\varepsilon)$. The resulting regression specification,

$$\ln\left(D_{ij}\right) = x_i\beta - \ln\left[\gamma\sum_{k=1}^{K}(v_k/u_k)e^{-\theta d_{jk}}\right] + \varepsilon_{ij}, \tag{A7}$$

relates duration of joblessness to a measure of job accessibility (normalized job opportunities) within brackets and individual-specific factors that have an impact on the reservation commuting costs. Equation (A7) serves as the foundation for our empirical analysis.[29]

APPENDIX B

Components of the Job Accessibility Measure

A. Job Opportunities, Competing Searchers, and Job Accessibility

To account for the spatial variation in labor market tightness, we measure each job seeker's job accessibility at the time of his or her separation using a proximity-weighted index of nearby job opportunities and competing searchers for those jobs. Worker i, residing in tract j, in year t, may commute by mode m (automobile or transit) to any tract k in metro area M, indexed from 1 to K_M. We define effective job opportunities, JO_{ijtm}, as the sum of jobs in all tracts discounted by an impedance function based on a mode's travel time to each tract. We use a composite job opportunities measure weighted by the probability of a job seeker using automobile or transit to reach each tract, calculated as

$$JO_{ijt\hat{m}} = \sum_{k=1}^{K_M} JO_{ijtk\hat{m}}, \tag{B1}$$

where

$$JO_{ijtk} = \sum_{m} \hat{p}_{ijkm}\frac{Jobs_{kt}^{workplace}}{\exp\left(\theta \cdot \max\left(0, d_{jkm} - \tau\right)\right)}.$$

In equation (B1), $m = \hat{m}$ signifies the use of predicted commute mode, and $JO_{ijtk\hat{m}}$ is the effective job opportunities in each tract. The predicted probability of worker i using either mode, m, to reach tract k is $\hat{p}_{ijkm}$, with $\Sigma_m\hat{p}_{ijkm}$. In a case where only automobile travel is an option, job opportunities would simply reduce to a function of auto travel time, which would be written as $JO_{ijt(\text{auto})}$. We describe the mode choice model in section C. We use total employment in each census tract, $Jobs_{kt}^{workplace}$, to proxy for the distribution of job offers available across locations in year t.

[27] Although the empirical implications would be largely unchanged, the model can easily be extended to incorporate job separations (see Rogerson et al., 2005).

[28] Since we have no data on job offers, only whether a job is accepted or not, we have no ability to separately identify spatial frictions in the form of job offers and commuting costs.

[29] We are assuming separability between individual characteristics and the role of location-specific factors. While we do not investigate all possible interactions, we do estimate the model separately for subgroups, which provides some perspective on interactions. See tables 4 and 5 in the main text and accompanying discussion.

We use April 1 as a reference date to count LEHD primary jobs as our measure of total employment. This extract of jobs is constructed using the same methodology as the data preparation for the LEHD Origin-Destination Employment Statistics (LODES), a public use data product, and consists of jobs held in both the first and second quarters of each year.[30] We further limit the set of jobs to include only an individual's highest-earning job at that time, or primary job, and also limit the jobs to those with annualized earnings of less than $40,000 a year in current dollars. The extract includes both the workplace and residence census tract of each job. We use the workplace margin to compute a count of jobs by workplace, $Jobs_{kt}^{workplace}$, and the residence margin to compute a count of workers by home location, $Jobs_{lt}^{residence}$, discussed below.

We use an impedance function in the denominator of equation (B1) to discount employment more as travel time, *d*, from *i*'s home increases. For this analysis, we use a discounting formula that imposes no discount for the first 10 minutes of travel, denoted τ. Thus, for these short commutes, where $d_{jkm} \leq \tau$, the denominator of equation (B1) equals 1, and there is no discount. For commutes beyond the travel time threshold τ, we use an exponential function of the product of a factor θ and the surplus travel time for jobs up to 60 minutes away.[31] For the principal analysis, we follow several recent implementations and set $\theta = 0.1$.[32] To illustrate this functional form, consider 100 jobs located in tract $j = k$ (0 distance), 100 in a tract where $d_{jkm} = 10$ minutes, and another 100 where $d_{jkm} = 20$ minutes (and only one travel mode). While the first two tracts would each contribute 100 effective jobs to $JO_{ijt\hat{m}}$, the third would contribute only the equivalent of 36.7 effective jobs, reflecting the increased cost of commuting to that location. In online appendix E, we report sensitivity analysis showing that our main findings are robust to variations in the key parameters (e.g., the threshold τ).[33]

We chose this functional form for several reasons.[34] First, compared to other weighting schemes, such as an often-used divisor of d_{jkm} or d_{jkm}^2, the exponential discounting approach described above is more gradual. Second, using the threshold τ reduces sensitivity to the precision of travel time estimates for very short commutes, which may be more dependent on modeling assumptions of vehicle or transit access time or within-census tract location. Third, there are precedents in both the empirical and theoretical literature for not discounting jobs in one's immediate vicinity. In the empirical literature, no discounting is often a simplifying assumption and accompanied by complete discounting for jobs beyond that area. For example, considering the ratio of jobs to residents in the same neighborhood (Ellwood, 1986) or in the same and adjacent postal codes (Hellerstein et al., 2008), or considering only those jobs within 45 minutes travel time (Gobillon et al., 2011). In a theoretical analysis of urban spatial job search, Zenou (2009) assumes that search effort does not dissipate at all until after a certain distance from a business district.[35]

While the presence of nearby job opportunities may improve job search, the presence of nearby competing searchers for those same jobs may hinder a searcher.[36] Indeed the search theory literature that underlies equation (A7) highlights that indicators of labor market tightness that take into account both job opportunities and competing searchers are needed in this context. To help capture the tightness of a local labor market, we also calculate a measure of competing searchers, defined as

$$CS_{ijt\hat{m}} = \sum_{k=1}^{K_M} CS_{ijtk\hat{m}} \tag{B2}$$

where

$$CS_{ijtk\hat{m}} = \frac{JO_{ijtk\hat{m}}}{JO_{ijt\hat{m}}} \sum_{l=1}^{L_M} \frac{Jobs_{it}^{residence}}{\exp\left(\theta \cdot \max\left(0, d_{lk(\text{auto})} - \tau\right)\right)}.$$

In parallel with equation (B1), equation (B2) uses the count of LEHD workers by place of residence to proxy for the distribution of potential job seekers. $Jobs_{lt}^{residence}$ gives the count of workers residing in tract *l* who can arrive at jobs in census tract *k* in d_{lkm} minutes. Having little information on the characteristics of competing searchers, we assume they all commute by automobile.[37] For these workers, we use the same discounting formula as in equation (B1). To approximate the expected number of competing searchers per job offer, we weight-effective competing searchers for each tract by the share of a searcher's effective job opportunities located in that tract, giving $CS_{ijtk\hat{m}}$. Thus, competing searchers will have a larger weight if they are close to a large mass of jobs or job opportunities that are nearby a searcher. Because of the weighting, the count of effective competing searchers is of comparable magnitude to the count of effective job opportunities.[38]

B. Mode Choice Prediction

A unique feature of our approach is that we construct person-specific job accessibility measures taking into account not only the heterogeneity across locations but also person-specific differences in mode choice, $\hat{p}_{ijkm}$. A detailed description of the estimation of the predicted mode choice probabilities is below, but we provide a brief description here. After sequentially estimating models for vehicle ownership and mode choice, we then use the parameter estimates to make out-of-sample predictions of vehicle ownership and mode choice probabilities for each possible commute destination for each person in the displaced worker sample. The weighted average of the probability of using public transit on each route is calculated as

$$\begin{aligned}\hat{p}_{ijk}(\text{transit}) &= \widehat{vehicle}_{ij} \cdot \widehat{transit}_{ijk}|[\text{vehicle}] \\ &\quad + \left(1 - \widehat{vehicle}_{ij}\right) \cdot \widehat{transit}_{ijk}|[\text{no vehicle}],\end{aligned} \tag{B3}$$

where $\widehat{vehicle}_{ij}$ is the expected probability of having a vehicle and $\widehat{transit}_{ijk}$ is the expected probability of using transit, conditional on having a vehicle or not. This probability of transit use feeds into the predicted job opportunities calculation in equation (B1).

Because automobile travel is faster on most routes (many of which are not served by transit), that is, $d_{jk(\text{auto})} < d_{jk(\text{transit})}$, it is usually true that a car driver can reach more jobs in the same time (though at greater financial cost), making $JO_{ijtk(\text{auto})} > JO_{ijtk(\text{transit})}$. Thus, a worker with a higher probability of vehicle ownership and automobile use will tend to have more effective job opportunities in a given destination and greater job accessibility overall.[39]

[30] LODES processing refers to this intermediate file as the WHATB.

[31] Earlier versions of this paper used 40 minutes; results were quite similar.

[32] El-Geneidy and Levinson (2006) compute this same parameter for the Minneapolis–St. Paul area as 0.1, and Shen (2000) computes this as "approximately 0.1" for the Boston area. Yang and Ferreira (2005) assume this parameter to be 0.1 for their model of Boston.

[33] In unreported results, we found that results are also robust to reasonable changes to the decay parameter θ.

[34] See Houston (2005) and Perle et al. (2002) for discussions of distance decay measures.

[35] The travel time literature also finds that commuters' value of time is low in the initial stage of a trip but is sensitive across intermediate distances (Johansson, Klaesson, & Olsson 2003).

[36] Raphael (1998a) explores the roles of information disadvantages and competing searchers. He controls for the intervening opportunities and intervening labor supply for origin-destination pairs. This factor decreases the negative effect of distance on the labor flow between zones by almost 90%. Johnson (2006) uses competing searchers to scale a job accessibility measure.

[37] In the census tracts where our sample resides, only 7.4% of workers use public transit.

[38] In a boundless metropolitan area with a uniform density of jobs and workers, or a town where all tracts are within the discounting threshold, τ, from one another, searchers in any location will have an equal number of job opportunities and competing searchers. For both conceptual and measurement reasons, the relative opportunities measure we use has great appeal.

[39] Raphael and Stoll (2001) approach spatial mismatch by asking if increasing minority automobile ownership rates can narrow interracial employment gaps. Making a comparison across metropolitan areas, they find that the difference in employment rates between car owners and non–car owners that is greater among blacks than among whites. Johnson (2006, p. 361) finds that "access to a car while searching is estimated to increase the weekly hazard of successfully completing a job search by 49.8%."

TABLE B1.—CONSTRUCTION OF TRANSIT MODE CHOICE SAMPLE

Sample Restriction	Household Sample	Percent Dropped
Respondent commuting to job in selected metropolitan areas in 2000	693,000	NA
Linked to residence in same metropolitan area	682,000	1.6%
Residence tract has > 5% workers commuting by transit	572,000	16.1%
Residence tract has MPO provided transit travel times for >10% routes	527,000	7.9%
Worker linked to full year of LEHD earnings	498,000	5.5%
Annual earnings of $15,000 to $40,000	109,000	78.1%

Sources: Authors' tabulations from the Census 2000 long-form microdata matched with residence locations in the Composite Person Record, travel time matrices from Metropolitan Planning Organizations, Census 2000 Summary File 3, and LEHD Infrastructure Files. All tables in appendix B use these same sources.
Sample counts are rounded to the nearest thousand.

C. Individualized Travel Time Prediction

This section describes the development of the personalized prediction of transit use on each potential commute route. The goal is to generate an expectation of whether a particular job seeker would use automobile or transit to commute to a job in any tract. Because LEHD jobs data and the MPO travel time data have no information on an individual's commute choices, we impute commute modes based on responses to the 2000 Census long form, internally the Sample Edited Detail File (SEDF). We estimate models of vehicle count and mode choice for respondents and use the parameter estimates to predict whether individuals in the job seeker data set are likely to commute by public transit. We use this predicted probability of auto or transit use to weight accessibility to jobs in a tract, with the accessibility of each mode depending on travel time for that mode.

We combine the 2000 Census long-form responses with the same input data sets used to create the sample of displaced workers. We first extract a sample of approximately 693,000 employed respondents from the SEDF, who commute to a job in one of the nine metropolitan areas in our sample.[40] As with the displaced worker sample, we match these records to neighborhood, commute time, and earnings data, with sample restrictions documented in table B1.[41] Because we are focusing on mode choice, we limit the sample to residents of tracts with a feasible transit option by requiring that at least 5% of residents report commuting by transit and that at least 10% percent of routes to workplaces from that tract have an MPO transit travel time.[42] These restrictions reduce the sample by a cumulative 84.3%, resulting in a sample of approximately 109,000 workers who might plausibly use either mode.

We use the combined data sets to construct the mode choice variables, as well as variables that are identical to those available for the displaced worker sample. Table B2 presents the cross-tabulation of the vehicle count categories and transit use for the linked sample described in table B1, which we derive from responses on the long form.[43] We define transit as any mode besides car/truck/van, taxicab, or motorcycle (with those working at home excluded). Thus, walking and bicycle riding are included in transit use. Even for this transit-feasible subset, the dominance of automobile use is evident; 90.9% have at least one vehicle and 81.8% travel by car. Note that even among workers with no vehicle of their own, over a third commute by car (presumably many of these workers participate in carpools).

TABLE B2.—VEHICLE POSSESSION AND MODE USE OF TRANSIT CHOICE SAMPLE

Household Count of Automobiles	Vehicle Count Percentages	Commute Mode Row Percentages	
		Automobile	Transit
0	9.1%	34.8%	65.2%
1	33.0	78.9	21.1
2	39.7	90.2	9.8
3+	18.2	92.3	7.7
All households	100.0	81.8	18.2

Authors' tabulations from Census 2000 long-form using sample of 109,000 households defined in table B1.

Our approach has two stages of estimation. First, for all workers, we estimate the number of vehicles in a worker's household with an ordered logistic model, for the categorical values in table B2. Using these estimates, we predict vehicle count within sample and create a variable for the probability that a worker has at least one car. These same estimates are then used to predict vehicles both within the SEDF-based sample and for the out-of-sample displaced workers. Second, for the SEDF-based sample, we run two binary logistic regressions with transit use as the dependent variable. The first logit weights each worker by his or her predicted probability of having a car, and the second one weights by the complement. Our explanatory variables include a measure of transit inefficiency to a worker's current workplace, measured as MPO transit time divided by auto time. We use the LEHD earnings data for a worker and household members to measure the count of persons, earners, annual worker and household earnings, and earnings per worker. We construct demographic variables from the 2000 SEDF and include measures of neighborhood characteristics.

Table B3 presents estimates from the both stages and shows how some factors affecting transit use depend on the likelihood of having a vehicle. Column 1 presents the first stage, where we find, unsurprisingly, that households with more earners, persons, and higher earnings have more cars. A worker with an inefficient transit commute is especially likely to be in a household with cars. Blacks, those in dense neighborhoods, and those with high public transit use are less likely to have cars.

Columns 2 and 3 present the second stage, where we find that workers with inefficient transit routes are less likely to use transit, as are those with higher earnings. Coefficients have different magnitudes and signs across the two logits due to the differences in probability of having a car. The interaction of transit inefficiency and annual worker earnings shows that as transit becomes less practical, higher-earning workers are especially likely to switch to auto commuting. This finding is consistent with higher earners' having a higher value of travel time and being more willing to pay for auto travel, which typically saves time but costs more. We find that women, non-Hispanic whites, older workers, and those in high public transit neighborhoods are more likely to use transit. Young workers are less likely to use transit if their household has a car. Denser neighborhoods reduce transit use when a household is more likely to have a car.

[40] We limit the sample to responses with a unique Census Bureau identifier for matching to administrative records. We define employment status based on an Employment Status Recode of 1 (employed, at work) and a Class of Worker of 1 to 4 (private sector and state and local government employees). We also limit to those aged 20 to 64 in 2000, those commuting to a job in an MPO county (we exclude those working from home), and those with household information (a small share of records do not match to the household file). We exclude Michigan and Ohio from this estimation because LEHD lacks sufficient pre-2000 earnings histories for them.

[41] We match to the Composite Person Record file of administrative residence data for the year 2000 and require residence in one of the MPO counties. We then match the respondent to MPO travel time data by place of work and place of residence census tract, and to the Summary File 3 neighborhood data by residence census tract. We limit to those having LEHD earnings in each quarter from 1999:2 to 2000:2 and require that earnings from 1999:2 to 2000:1 be between $15,000 and $40,000.

[42] MPOs report estimated auto travel times between almost all tract pairs but sometimes omit transit. Some MPOs have explained that they do not provide transit times when that mode is not available.

[43] From the long-form question, "How many automobiles, vans, and trucks of one-ton capacity or less are kept at home for use by members of your household?" we construct an automobile count of up to three or more vehicles for a household. From the long-form question "How did this person usually get to work LAST WEEK?" we construct a commute mode variable indicating whether a worker used transit.

TABLE B3.—ESTIMATION OF VEHICLE COUNT AND TRANSIT MODE CHOICE

Dependent Variable:	Number of Vehicles (0, 1, 2, or 3+)	Transit Use (with vehicle)	Transit Use (no vehicle)
Weights:	None	Probability Has a Vehicle (from column 1)	Probability Has No Vehicle (from column 1)
Model:	Ordered Logit	Binary Logit	Binary Logit
Variable	(1)	(2)	(3)
Household earners (maximum 10)	0.237***		
	(0.009)		
Persons in household (maximum 10)	0.011***		
	(0.004)		
Household annual log earnings (LEHD)	0.666***		
	(0.014)		
Ratio of transit to auto travel time	0.130***	−1.478***	−1.071***
	(0.013)	(0.020)	(0.017)
Worker annual log earnings (LEHD)		−0.774***	−0.934***
		(0.042)	(0.038)
Worker annual log earnings × Ratio of transit to auto travel time		−1.119***	−0.948***
		(0.067)	(0.055)
Log earnings per worker (LEHD)		−0.179	−0.114**
		(0.026)	(0.027)
Female	−0.116***	0.189**	0.142**
	(0.012)	(0.019)	(0.016)
Black non-Hispanic	−0.322***	−0.052	−0.093
	(0.017)	(0.025)	(0.019)
Hispanic	0.224***	−0.405***	−0.485***
	(0.020)	(0.030)	(0.027)
Other race non-Hispanic	0.184***	−0.038***	−0.150**
	(0.027)	(0.041)	(0.038)
Age 20 to 24	0.489***	−0.005**	0.021
	(0.022)	(0.032)	(0.031)
Age 35 to 44	−0.106**	0.012***	0.097***
	(0.015)	(0.024)	(0.019)
Age 45 to 54	0.015***	0.059	0.209***
	(0.016)	(0.025)	(0.021)
Age 55 to 64	−0.165***	0.080***	0.142***
	(0.020)	(0.032)	(0.025)
Census tract: Population per square mile (000s)	−23.675***	−17.274***	3.319
	(2.149)	(2.933)	(1.678)
Census tract: Public transit use rate	−2.576***	3.593***	3.129***
	(0.083)	(0.116)	(0.077)
Census tract: Poverty rate	0.431***	−0.740***	−1.113***
	(0.083)	(0.120)	(0.080)
Census tract: Homeownership rate	1.467***	−0.955***	−1.128***
	(0.039)	(0.060)	(0.050)
Census tract: Median home age (in 2000)	−0.005***	0.007***	0.001***
	(0.000)	(0.001)	(0.001)

Standard errors in parentheses. Number of observations: 109,000. Estimates from model 1 are used to predict probabilities of having a vehicle. These expectations are used as weights in model 2, while the complement (not having a car) weights model 3. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

For the displaced worker sample, we use the estimates from table B3 to calculate expected transit use for each possible route using equation (B3). Because the displaced worker sample has identically constructed variables, it is possible to make this out-of-sample prediction. First, we calculate the expected probability of the job seeker's household having a vehicle, using the estimates from column 1. Then, for the same worker, we calculate the probability of transit use conditional on having a vehicle or not with the estimates in columns 2 and 3. Using the same rules as described above for transit feasibility, we apply these probabilities to workers residing in the 41% percent of census tracts with feasible transit options. We assume all other workers possess a car and drive to potential job opportunities. Likewise, we assume that competing searchers travel by automobile.

The results presented here are informative about the factors affecting transit use. However, auto availability and use is widespread. Ultimately, the minimal use of transit limits the efficacy of this approach in adding personalized variation to travel time measures.