# JOB RELOCATION AND THE RACIAL GAP IN UNEMPLOYMENT IN DETROIT AND CHICAGO, 1980 TO 1990

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*The spatial mismatch hypothesis argues that residential segregation and job decentralization combine to adversely affect the employment opportunities of minorities. While employment is increasingly located outside of central cities, residential segregation prevents minorities from moving closer to suburban jobs. Although this hypothesis has intuitive appeal, there is little consensus regarding its empirical validity. This study (1) constructs detailed geographic measures of changes in employment opportunities, (2) estimates a fixed-effects model of changes in the unemployment rate over time, and (3) accounts for spatial correlation in the error term. Neighborhood-level employment data from 1980 and 1990 are used to measure changes in the distance to jobs from census tracts in the Detroit and Chicago metropolitan areas. In both cities, the decentralization of employment and the loss of manufacturing jobs resulted in substantial changes in the spatial distribution of employment. The empirical results indicate that a decline in the spatial proximity to employment is associated with an increase in the unemployment rate for blacks.*

ARE the employment prospects of inner-city minorities limited because of the suburbanization of employment? The spatial redistribution of employment in large urban areas over the past several decades is well documented (Kasarda 1995). At the same time, the level of racial residential segregation in these large cities has been relatively constant (Massey and Denton 1993). Kain (1968) argues that the redistribution of employment combined with residential segregation produces a "spatial mismatch" that reduces the employment outcomes for blacks. Because of segregation, blacks are forced to live farther from regions of suburban job growth than whites, who face no such constraints on residential mobility. If the costs of finding and commuting to more distant jobs in the suburbs are significant, then the ensuing mismatch will decrease the wages and/or the employment levels of urban blacks. This model is intuitively appealing because it provides a clear mechanism linking residential segregation to economic outcomes. The spatial mismatch hypothesis forms the structural basis for Wilson's (1987, 1996) widely debated thesis that the loss of jobs in the inner city has resulted in high levels of endemic poverty among urban blacks. However, 30 years of empirical research has yielded little consensus about the magnitude of the effect of employment relocation on the racial gap in unemployment and earnings (Holzer 1991; Jencks and Mayer 1990).

Part of the problem in testing the spatial mismatch hypothesis is that residential location is not truly exogenous because it is

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likely to be related to unobserved factors that also affect unemployment and earnings (Jencks and Mayer 1990). Most early tests of the relationship between distance to jobs and employment utilized cross-sectional data on neighborhoods (Hutchinson 1974; Kain 1968). However, the direction of causality can run in both directions: Living in a good neighborhood may help you get a good job, but having a good job will also help you live in a good neighborhood. Therefore, in research that uses cross-sectional data, it is difficult to argue that the true effect of employment decentralization has been properly identified.

In contrast to previous cross-sectional studies, I use longitudinal neighborhood-level data to test the relationship between changes over time in job proximity and unemployment rates. The primary difficulty of such an approach is the geographic noncomparability of successive population censuses. The strategy taken here is to transpose the 1980 census tracts into 1990 census tracts, weighting 1980 tracts that are divided across multiple 1990 tracts by the degree of geographic overlap in each. In addition, data on the geographic location of jobs in 1980 and 1990 from the Census Transportation Planning Package (CTPP) for Detroit and state payroll records for Chicago allow for a precise calculation of employment redistribution during the 1980s.

## REVIEW OF THE LITERATURE

Kain (1968) was the first to test the hypothesis that employment decentralization limits minority employment in segregated cities. In what has become known as the spatial mismatch hypothesis, he argued that the employment outcomes of blacks will be limited if (1) employment is decentralizing; (2) residential segregation prevents black workers from moving to regions of job growth; and (3) the effect of distance on job search and/or commuting costs is significant. Using data from the 1950s, Kain divided Detroit and Chicago into 98 workplace areas and found that the fraction of blacks employed in each of those areas decreased as the distance from the center of the ghetto increased. From these results, he estimates that residential segregation resulted in a mismatch that significantly decreased black employment in Detroit and Chicago.

A large empirical literature on spatial mismatch has followed Kain's work (for reviews, see Holzer 1991; Jencks and Mayer 1990). Kain's conclusions have been criticized. Offner and Saks (1971), for instance, used Kain's data and found that an alternative specification substantially changes the results. Hutchinson (1974) estimated the cross-sectional employment probabilities of whites and blacks using detailed data on the geographic location of employment and found a weak relationship between unemployment and job accessibility, measured by the travel time to different jobs using public transit.

Because of the problem of causality when linking neighborhood location to employment outcomes, recent research has focused on the employment of out-of-school teenagers (Ellwood 1986; Ihlanfeldt and Sjoquist 1990; Raphael 1998). If these teenagers still live at home with their parents, then their residential location could be considered exogenous. A problem with this, of course, is that the school dropout rate may be related to unobserved local characteristics, such as the quality of schools and neighborhood socioeconomic status, that also affect employment levels. Ellwood (1986) found small effects of job proximity measures on youth employment rates in Chicago. He concluded that the spatial mismatch hypothesis does not adequately explain the high levels of joblessness among black teenagers and that "race not space" is the decisive factor. Leonard (1987), however, argued that Ellwood's results may be misleading because he used a relatively small sample of workers to calculate the geographic distribution of employment. Ihlanfeldt and Sjoquist (1990, 1991) and Raphael (1998) also measured effects of job proximity on teenage employment and argued that proximity explains roughly 30 percent of the white/black gap in unemployment. However, Ihlanfeldt and Sjoquist measured job accessibility by average travel times, which, depending on the urban area, may not accurately reflect racial differences in job proximity. Raphael, on the other hand, found that the collective significance of his measures of spatial job accessibility are not significant in regressions using the unemployment rate for black youths, suggesting that his estimates are unreliable.

A different approach to the problem of endogenous residential choice involves using longitudinal data. Dworak-Fisher (1997) constructed a panel using data on suburban and central city counties for 55 metropolitan areas from 1970 to 1990 and found small but significant effects of intrametropolitan employment shifts on changes in the earnings of urban blacks. Nonetheless, the use of county-level data relies on arbitrary divisions of the metropolitan area that may reduce variation in the measures of employment outcomes and geographic changes in the location of jobs. Zax (1991) and Zax and Kain (1996) studied several years of employment records from a single firm that relocated to the suburbs. By analyzing racial differences in quit rates after the move, they concluded that black workers are less able to adjust to a change in job location than white workers are. In addition, Fernandez (1994) calculated changes in commuting times for a firm planning to relocate to the suburbs in Milwaukee and found that the increased commuting costs disproportionately affect minority workers. However, the study of a single firm cannot assess the magnitude of metropolitan job decentralization as a whole or the subsequent employment outcomes of those workers who quit the firm (Fernandez 1994).

Overall, there is much controversy over the validity of the spatial mismatch hypothesis. In their review of the literature on spatial mismatch, Jencks and Mayer (1990) argued that the results are ambiguous and that there is little effect on black employment outcomes in intrametropolitan studies that use detailed measures of job proximity. I argue here that employing a fixed-effects model that incorporates the detail of neighborhood-level data provides a more accurate estimate of the effect of job proximity on changes in minority unemployment rates.

## THEORETICAL MODEL

### *The Problem of Selective Migration*

To assess the spatial mismatch hypothesis, the relationship between the proximity to jobs and the black unemployment rate in different neighborhoods should be tested. However, the basic problem with using neighborhood location as an independent variable is that it is likely to be endogenous to other individual factors that affect unemployment. The selective migration to wealthy neighborhoods of workers with high-paying jobs means that there may appear to be a strong relationship between neighborhood location and employment outcomes, even if this relationship is entirely due to the neighborhood's demographic composition. In American cities, wealthy neighborhoods tend to be distant from the city center (Simpson 1992), which means that only workers with sufficiently high incomes can move to the suburbs.[1] Consequently, as employment in established cities decentralizes, wealthy suburban neighborhoods are likely to be closer to regions of job growth than are poor neighborhoods. In the cross-section, the causal order is difficult to establish: Do suburban workers fare better because of their proximity to regions of job growth, or do they live in the suburbs because they have better jobs to begin with?

The difficulties arising from the selectivity of suburban migration can be depicted as follows. For the sake of simplicity, assume that the unemployment status of worker $i$ can be represented by the following linear relationship:

$$u_{it} = \beta_1 P_{jt} + \beta_2 X_{it} + \beta_3 Q_{it} + H_j + \varepsilon_{it}, \qquad (1)$$

where $i = 1, \ldots, I$ indexes the universe of workers in the city, $j$ indexes the neighborhood that worker $i$ lives in at time $t$, $u_{it}$ is a dichotomous variable indicating whether worker $i$ is unemployed at time $t$, $P_{jt}$ is the proximity of neighborhood $j$ to employment, $H_j$ represents fixed unobserved neighborhood-specific characteristics, $\varepsilon_{it}$ is an error term, and $X_{it}$ and $Q_{it}$ are individual characteristics measuring observed and unobserved factors, respectively. $X_{it}$ measures observable variables, such as years of education, race, and gender, while $Q_{it}$ represents difficult-to-measure attributes, such as ability and motivation. Everything else being equal,

[1] For example, the median value of owner-occupied homes in the suburbs is about 25 percent higher than those in the central city (Jencks and Mayer 1990).

increasing the proximity to employment, $P_{jt}$, decreases unemployment (i.e., $\beta_1 < 0$). However, individuals sort themselves across neighborhoods on the basis of their preferences for particular neighborhood characteristics and the quality of housing they can afford given their employment status and income level. Therefore, residential location is probably endogenous to the same individual characteristics ($X_{it}$ and $Q_{it}$) that affect unemployment. This selective migration will bias estimates of the effect of job proximity on unemployment if there are unobserved characteristics, $Q_{it}$, that affect both residential location and the probability of being unemployed. In cross-sectional studies of spatial mismatch, a negative relationship between living in the suburbs and unemployment rates may merely reflect higher levels of unobserved ability among suburban workers rather than the effect of proximity to regions of suburban job growth (Jencks and Mayer 1990).

### *FIXED-EFFECTS MODELS*

***INDIVIDUAL-LEVEL APPROACH.*** One way to avoid the problem of selective migration would be to follow individual workers who move to different neighborhoods. For example, data from the Panel Study of Income Dynamics (PSID) provide information on the neighborhood location and employment status of individual workers over several years. If one assumes that the worker's unobserved characteristics do not change over time (i.e., $Q_{it} = Q_i$), then a "fixed-effects" model of changes in unemployment over time can be estimated in which the bias resulting from the unobserved effect of $Q_i$ is "differenced" out of the model:

$$\begin{aligned} u_{it+1} - u_{it} &= \Delta u_i \\ &= \beta_1 \Delta P_j + \beta_2 \Delta X_i \\ &\quad + \Delta H_j + \Delta \varepsilon_j . \end{aligned} \qquad (2)$$

Although using longitudinal data on individual workers is appealing, several limitations remain. First, the assumption that the worker's unobserved characteristics do not change over time may be implausible (i.e., $Q_{it} \neq Q_i$). Even though the same individuals are followed over time, changes in $Q_{it}$ may result in the selective migration of workers among neighborhoods. As a result, even a fixed-effects model based on individual data is not immune to the problem of selective migration. Second, longitudinal data sets like the PSID do not contain enough cases per city to test the relationship between job proximity and unemployment on a city-by-city basis, and the researcher is forced to rely upon intercity variation in job proximity, which may increase error due to unmeasured city-specific characteristics. Finally, because data sets like the PSID have data on workers from many different cities, the construction of spatial measures of job proximity from census-tract data requires a time-intensive process of acquiring and manipulating job data for each city. In practice, job-location data for data sets like the PSID are available only at the county-level from sources like the State and Metropolitan Area Data Books (U.S. Bureau of the Census 1991). The crude geographic detail of county-level data obscures intrametropolitan variation in job proximity for different neighborhoods within the same county, as well as comparisons across cities, because of the arbitrary division of metropolitan areas into counties.

***NEIGHBORHOOD-LEVEL APPROACH.*** I use an alternative fixed-effects strategy based on longitudinal neighborhood data from Detroit and Chicago that include detailed information on the spatial location of jobs. By focusing on individual metropolitan areas it is possible to construct detailed spatial measures of the intrametropolitan change in job proximity over time. As a result, the analysis of the relationship between job proximity and unemployment can be performed separately for each city, relying on variation in job proximity within the city to identify the effect on unemployment rates. However, the disadvantage of using neighborhoods as the unit of analysis is that the demographic composition of neighborhoods may change due to migration. For example, if the linear model of unemployment in equation 1 is aggregated to the neighborhood level, the unemployment rate in each neighborhood would depend on neighborhood-specific characteristics ($P_{jt}$ and $H_j$), the neighborhood average of individual characteristics ($X_{it}$, $Q_{it}$), and the error term ($\varepsilon_{it}$). However, if a fixed-effects model similar to equation 2 is estimated using neighborhood-level data, migration will change the average level of unobserved individual characteristics ($Q_{it}$) over time, regardless of whether they are assumed to be fixed at the individual level.

I argue that longitudinal neighborhood data can be used to estimate fixed-effects models of unemployment, not by assuming that $Q_{it}$ is fixed but by assuming that neighborhood selectivity—the degree to which neighborhoods tend to attract successful workers—is constant over time. While individual workers may migrate in and out of neighborhoods over time according to their varying degree of success in the labor market (i.e. because of changes in their endowments $X_{it}$ and $Q_{it}$), the actual selectivity of different neighborhoods may not change much. In other words, individuals' residential-location decisions may be based on relatively stable characteristics of neighborhoods such as group or class preferences to live in particular areas, the neighborhood's reputation and status level, fear of crime, the quality of local schools and services, transportation networks, and other geographic characteristics. Empirical studies of housing markets, for example, emphasize the importance of neighborhood externalities, such as the occupation, income, and racial composition of neighborhood residents, on the market prices of individual houses and (Coulson and Bond 1990; Rothenberg et al. 1991).

If neighborhood selectivity is constant over time, then neighborhood-level data can be used to estimate a fixed-effects model of changes in unemployment over time. First, suppose the average level of the unobserved individual-level factors affecting unemployment in neighborhood $j$ at time $t$, $\overline{Q}_{jt}$, can be depicted as the sum of two components—one that is fixed and one that varies over time:

$$\overline{Q}_{jt} = \frac{\sum^{i \in j} Q_{it}}{g_j} = \alpha_j + \eta_{jt}, \tag{3}$$

where $g_j$ is the number of workers in neighborhood $j$, $\alpha_j$ is the neighborhood-specific component that does not vary over time, and $\eta_{jt}$ is the component that changes over time. As a result, the unemployment rate in neighborhood $j$ at time $t$ is given by taking the average of equation 1 at the neighborhood level:

$$\begin{aligned} \overline{u}_{jt} &= \frac{\sum^{i \in j} u_{it}}{g_j} \\ &= \beta_1 P_{jt} + \beta_2 \overline{X}_{jt} \\ &\quad + \beta_3(\alpha_j + \eta_{jt}) + H_j + \overline{\varepsilon}_{jt}, \end{aligned} \tag{4}$$

where $\beta_1$, $\beta_2$, and $\beta_3 < 0$, $\overline{X}_{jt}$ is the neighborhood average of the observed $X_{it}$ values, and $\overline{\varepsilon}_{jt}$ is the average of the individual-specific error terms. If neighborhood selectivity is fixed over time, then $\eta_{jt}$ equals 0, and subtracting the unemployment rate in neighborhood $j$ for year $t$ from year $t + 1$ results in both $\alpha_j$ (the fixed effect of worker selectivity) and $H_j$ (the fixed effect of neighborhood-specific factors) dropping out of the model:

$$\begin{aligned} \Delta U_j &= \overline{u}_{jt+1} - \overline{u}_{jt} \\ &= \beta_1 \Delta P_j + \beta_2 \Delta \overline{X}_j + \Delta \overline{\varepsilon}_j. \end{aligned} \tag{5}$$

Equation 5 depicts the change in the neighborhood unemployment rate as the result of changes in proximity, changes in $\overline{X}_{jt}$, and an error term. Of course, the plausibility of this approach depends on whether the selectivity of neighborhoods is a result of relatively fixed characteristics, $\alpha_j$ from equation 3, as opposed to time-varying factors. While the relative stability of neighborhood selectivity over the 10-year interval between censuses may make equation 5 an attractive means of testing the mismatch hypothesis, the consequences of changes in selectivity ($\Delta\eta_{jt}$) and how to mitigate them must be considered. To begin with, the notion of a general process of neighborhood succession whereby populations with decreasing socioeconomic status occupy a neighborhood is well established in sociology (Cressey 1938; Guest 1974; Hoover and Vernon 1959; Schwirian 1983). Likewise, urban economists observe that most new residential housing is relatively high-quality construction that is initially occupied by high-income households, but that as it becomes obsolete over time it is eventually occupied by lower-income households (Grigsby et al. 1987; Quigley 1978).[2] Therefore, despite the possibility

[2] There is, however, some disagreement over whether this downward trend is the result of the physical deterioration of housing structures over

that gentrification may at some time reverse the decline in neighborhood socioeconomic status, it seems plausible to assume that neighborhood selectivity declines over time in established neighborhoods.

If the trend in established neighborhoods is toward declining neighborhood selectivity over time, then as cities decentralize and expand outward, established neighborhoods may become less selective in unobserved ways ($\Delta\eta_{jt} < 0$) at the same time that they find themselves located farther from regions of suburban job growth ($\Delta P_{jt} < 0$). Because low levels of selectivity are associated with high unemployment rates (i.e., $\beta_3 < 0$), this may result in a *downward* bias on estimates of the relationship between changes in job proximity and unemployment rates. Consequently, one should be careful about changes in the neighborhood demographic composition over time.

I include several variables to control for changes in demographic composition and neighborhood selectivity: changes in education levels, gender composition, car ownership, and housing values. A change in the education level of a neighborhood's residents indicates fluctuations in observed skill levels. An increase in education should result in a decrease in the unemployment rate. Similarly, a change in the proportion of the neighborhood's labor force that is female may affect the aggregate unemployment rate if there are gender differences in labor-force attachment. Car-ownership rates may indicate the ability to commute to distant jobs. I would expect, for instance, that a decrease over time in car ownership by black workers would be associated with an increase in the unemployment rate for blacks. By including this variable directly in the regression models, I control for the possibility that employment decentralization is important only because of racial differences in rates of automobile ownership rather than the geographic distribution of employment per se.

I also use changes in neighborhood housing values as a proxy for changes in neighborhood selectivity not picked up by changes in education, gender composition, and car ownership. Increasing housing prices indicates a process of gentrification in which high-income workers move in, bid up housing values, and improve housing quality. Similarly, neighborhoods vacated by high-income groups moving to new housing may experience a decline in housing values because of decreased demand. Finally, once low-income groups move in, they may invest less on maintenance, which will result in a downward trend in prices (Quigley 1978). If a decline in housing prices reflects a decline in the class composition of the neighborhood, this should be associated with an increase in neighborhood unemployment rates.

Care should be taken when relying on changes in housing values to reflect unobserved individual characteristics. First, housing markets are sensitive to local and national macroeconomic conditions like interest rates and may fluctuate cyclically and others (Rothenberg et al. 1991). For this reason, I use relative rather than absolute changes in housing values. A decline in the value of a neighborhood's housing stock relative to changes in the metropolitan area as a whole should indicate a change in that neighborhood's selectivity rank over time. Second, even if there is no in- or out-migration, a change in neighborhood income levels will affect housing prices by changing the level of maintenance and/or upgrading of houses in the neighborhood. Therefore, even without population changes, a decrease in income because of an increase in the unemployment rate will result in a decrease in housing values if workers respond by investing less in housing. Thus, part of the causal effect of job proximity on unemployment may be spuriously attributed to changes in housing values, which would bias the coefficient on job proximity toward zero. Consequently, caution should be exercised in interpreting models that include changes in housing values.

### *Racism and Firm Relocation*

In addition to the effect of proximity on labor supply, a fixed-effects model may also have advantages when considering the effects of labor demand and employer discrimination as well. Do suburban firms

time or an increase in the demand for housing combined with the difficulty of upgrading existing dwellings (Grigsby et al. 1987; Muth 1969).

avoid hiring blacks? The cross-sectional relationship between location and minority employment may be obscured by the possibility that discriminatory firms choose to relocate to the suburbs. Stoll (1996) argues that if firms that discriminate against blacks move to the suburbs to avoid minority applicants, then the relationship between employment decentralization and unemployment is spurious. In this case, improving the job accessibility of inner-city minorities will not reduce their unemployment rate. However, the model I propose here provides a better measure of the role of distance. If a discriminatory firm relocates to the suburbs, then the net effect on black unemployment over time is likely to be negligible, because the firm had an aversion to hiring minorities in the first place. Therefore, if changes in job proximity have a significant effect on *changes* in the black unemployment rate, the effect can be attributed to employment decentralization rather than to employer racism per se. If this were not the case (i.e., if the only way a discriminatory firm could avoid hiring blacks was by moving to the suburbs), then improving minority access to suburban jobs would restore the jobs that were lost by the firm's move.[3] The benefit of the longitudinal approach is that it differences out the constant effect of discriminatory preferences and thereby narrows the parameters whereby racial discrimination by firms may be confounded with their spatial location.

This is not intended to downplay the role of discrimination in the racial gap in unemployment. Empirical research using audit studies, for instance, indicates the degree to which direct employer discrimination affects hiring probabilities among equally qualified candidates (Struyk and Fix 1993). The significance of the spatial mismatch hypothesis is that it provides a causal link between discrimination in housing markets and labor market outcomes. In this sense, the models presented here attempt to assess the contribution of residential segregation to the racial gap in unemployment.

[3] In the "Discussion" section (p. 747) I consider a possible exception to this argument based on the possibility that relocating firms become more discriminatory after they move to the suburbs.

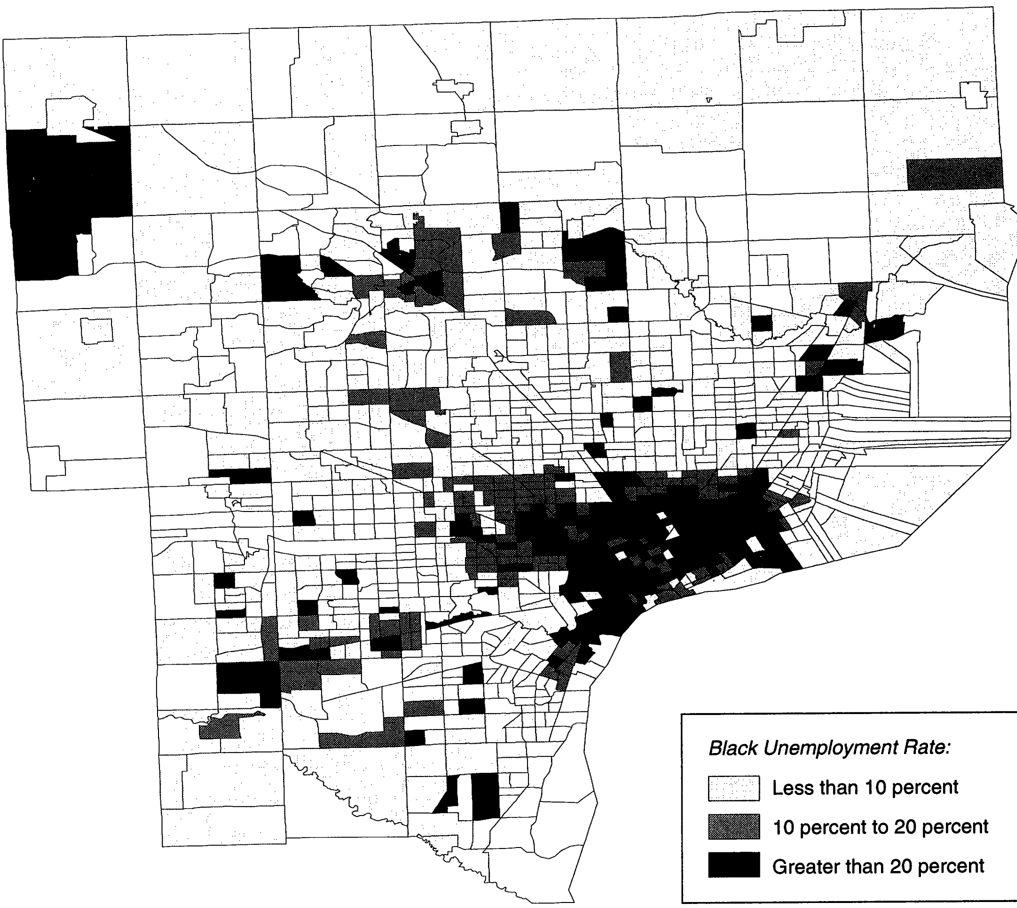
## DATA AND METHODS

Chicago and Detroit are large metropolitan areas that exemplify the conditions for the existence of a spatial mismatch. Both cities have experienced significant employment decentralization, particularly in manufacturing industries (Kain 1968; Kasarda 1995), combined with persistently high levels of residential segregation (Massey and Denton 1993). In both cities, the black unemployment rate is more than three times the white unemployment rate. In 1990, the black unemployment rate in Detroit was 21 percent compared with 6.1 percent for whites; in Chicago it was 17.2 percent for blacks and 4.1 percent for whites (1990 5-Percent Public Use Micro Sample).

To test whether changes in neighborhood unemployment rates are systematically associated with changes in proximity to jobs, I use neighborhood-level data on unemployment rates and job location. Data on unemployment in Detroit and Chicago neighborhoods come from the 1980 and 1990 population censuses. Because tract boundaries are not comparable across different censuses, a geographic correspondence file linking 1980 tracts with 1990 tracts was created using the MABLE/Geocorr program at the University of Missouri. The 1980 tract data are transposed into 1990 tracts based on the degree of spatial overlap among the tracts.[4]

The distribution of black unemployment in Detroit in 1990 shows a clear geographic pattern (Map 1). Within a core area of the central city, the unemployment rate is uniformly above 20 percent. Next, the location of jobs is added to the picture. Data on jobs for Detroit come from the Census Transportation Planning Package (CTPP). The CTPP is prepared by the Bureau of Transportation Statistics from census data taken from the long form of the decennial census. It provides a count of total jobs by industry and

[4] Of the 1980 census tracts, 602 of 1,603 in Detroit, and 532 of 1,829 tracts in Chicago were merged onto multiple 1990 tracts. The other tracts remained the same between 1980 and 1990. Because of the large degree of spatial association among the variables of interest it is unlikely that this process introduced any systematic bias into the data.




**Map 1. Black Unemployment Rate, by Census Tract: Detroit, 1990**

occupation within census tracts for all major urban areas. Data on jobs for Chicago were provided by the Northeastern Illinois Planning Commission (NIPC). The NIPC data set provides the number of jobs in aggregated industry categories for every quarter section (160-acre sections) of the six-county Chicago metropolitan area (McHenry, Lake, Kane, Cook, DuPage, and Will counties). These data are collected directly from state payroll records, supplemented by a survey estimating public-sector employment. Because the NIPC data come largely from employer records, they are probably a more accurate source of employment location than the CTPP, which is based on the census survey of households.

Given the population count and the number of jobs in each neighborhood, it is possible to calculate the number of jobs within different commuting distances for whites and blacks. Specifically, the number of jobs within a distance $k$ from neighborhood $m$ is

$$E_{mk} = \sum_{p=1}^{N} E_p, \qquad \text{if } d_{mp} < k, \qquad (6)$$

where $E_p$ is the number of jobs in neighborhood $p$, $N$ is the number of neighborhoods, and $d_{mp}$ is the distance from neighborhood $m$ to neighborhood $p$. Likewise, the number of jobs within a distance $k$ for the typical worker of race $R$ is calculated by summing across neighborhoods, weighting by the fraction of the racial group's population that resides in each neighborhood:

$$E_{Rk} = \frac{1}{\sum_{m=1}^{N} pop_{Rm}} \sum_{m=1}^{N}\sum_{p=1}^{N} pop_{Rm} \times (E_p),$$

$$\text{if } d_{mp} < \text{k}, \qquad (7)$$

**Table 1. Number of Jobs (in 1,000s) by Commuting Distance in 1990, by Race**

| | Commuting Distance (in Miles) | | | |
|---|---|---|---|---|
| City and Race | 5 | 10 | 15 | 20 |
| *Detroit* | | | | |
| All jobs: | | | | |
| Blacks | 134 | 503 | 920 | 1,270 |
| Whites | 83 | 303 | 612 | 944 |
| B/W ratio | 1.61 | 1.66 | 1.50 | 1.35 |
| Manufacturing jobs: | | | | |
| Blacks | 30 | 123 | 228 | 315 |
| Whites | 22 | 78 | 152 | 231 |
| B/W ratio | 1.36 | 1.57 | 1.89 | 1.36 |
| Labor force: | | | | |
| Blacks | 152 | 488 | 904 | 1,296 |
| Whites | 92 | 328 | 646 | 990 |
| B/W ratio | 1.65 | 1.48 | 1.40 | 1.31 |
| *Chicago* | | | | |
| All jobs: | | | | |
| Blacks | 192 | 849 | 1561 | 2,088 |
| Whites | 131 | 497 | 1019 | 1,570 |
| B/W ratio | 1.46 | 1.71 | 1.53 | 1.33 |
| Manufacturing jobs: | | | | |
| Blacks | 34 | 134 | 238 | 326 |
| Whites | 25 | 91 | 180 | 271 |
| B/W ratio | 1.36 | 1.47 | 1.32 | 1.20 |
| Labor force: | | | | |
| Blacks | 249 | 766 | 1,331 | 1,840 |
| Whites | 144 | 434 | 808 | 1,243 |
| B/W ratio | 1.72 | 1.76 | 1.64 | 1.48 |

where $pop_{Rm}$ is the population of group $R$ in neighborhood $m$.

Table 1 shows the number of jobs within different commuting distances, by race, in 1990. It is evident that blacks are closer to more jobs than are whites at all distances in 1990 in Detroit and Chicago, even to manufacturing jobs. Overall, there are on average 60 to 70 percent more jobs within a 10-mile radius of blacks compared with whites. Cohn and Fossett (1996) obtained similar findings in a study of Boston and Houston, indicating that blacks are actually closer to the stock of jobs than whites by virtue of living closer to the center of the city. Cohn and Fosset argued that this indicates that there is no spatial mismatch. However, their conclusion may have been premature. The number of workers competing for these jobs is also greater near black neighborhoods. Table 1 shows that the size of the total labor force within a 10-mile radius of the average black worker is 48 percent *larger* than that of the average white worker in Detroit, and 76 percent larger in Chicago.[5] Moreover, while it is theoretically plausible to redistribute jobs so that inner-city blacks find employment within a reasonable commuting distance, the fact is that a large racial gap in unemployment exists even with a large stock of jobs near blacks. The redistribution of a significant number of these jobs to the suburbs during the 1980s can hardly be expected to improve the situation. The findings in Table 1 contradict the basic premise of the spatial mismatch hypothesis only if attention is restricted to cross-sectional analysis and the effects of competing labor are ignored. To assess the magnitude and effect of this employment redistribution requires data from two time points.

Figures 1 and 2 illustrate the redistribution of jobs between 1980 and 1990 by race. These figures are calculated by applying equation 7 to the 1980 and 1990 job counts, using the 1990 black and white neighborhood population totals as weights. The figures show the number of jobs that were lost or gained within different distances from the average white worker's and black worker's homes. For commuting distances between 1 and 20 miles, the typical black worker experienced a much greater degree of job loss than did the typical white worker. Figure 1 indicates that the average black worker in Detroit lost about 100,000 jobs within a 10-mile radius, while the typical white worker experienced little job loss. In Chicago, the loss of jobs for blacks was negligible, but blacks did significantly worse than whites in job proximity (Figure 2). Both Chicago and

[5] The size of the labor force (employed + unemployed workers) within a 20-mile radius is smaller than the number of available jobs because employment is still clustered at the city center while the population is dispersed around it. In addition, because the Chicago data include only Illinois counties, workers from northern Indiana who commute into Chicago are not included in the population totals.

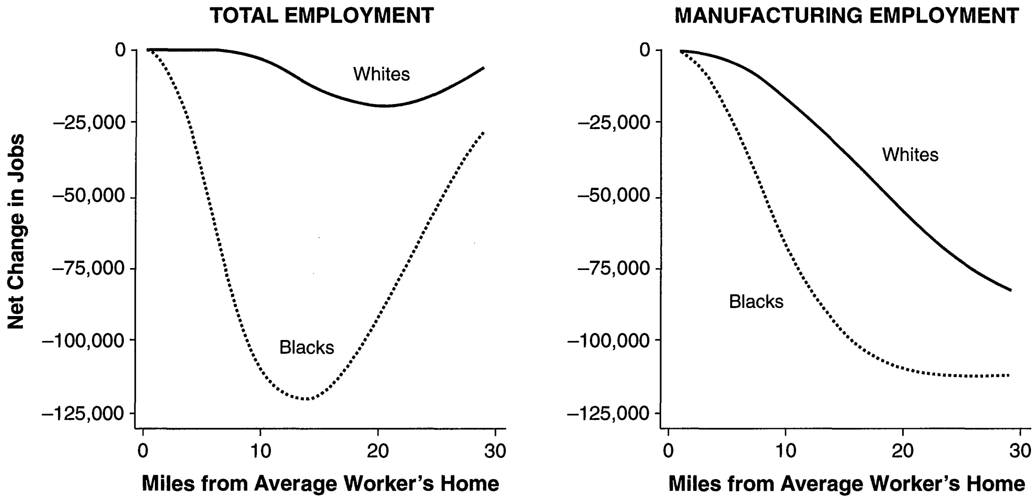



**Figure 1. Net Change in Jobs by Distance from the Average Worker's Home, by Race: Detroit, 1980 to 1990**

Detroit saw their manufacturing base erode during the 1980s, and these figures show that the loss disproportionately affected black workers. Apparently it was the firms nearest to blacks that closed or relocated. This result is similar to that obtained by Kain (1968) for shifts in manufacturing employment in Chicago between 1950 and 1960.

These geographic changes in employment are summarized for Detroit in Map 2, which depicts the percent change in total employment within a 5-mile radius, by neighborhood, for Detroit from 1980 to 1990. This shows that the core black residential areas lost jobs while rapid employment growth occurred in the suburban fringe. A similar pattern was evident for Chicago (not shown). Given that most of the job growth between 1980 and 1990 occurred in the suburbs, the next question is whether blacks were able to relocate in order to take advantage of regions of job growth. Map 3 depicts the restraints on black residential mobility in Detroit: Rapid black population growth was

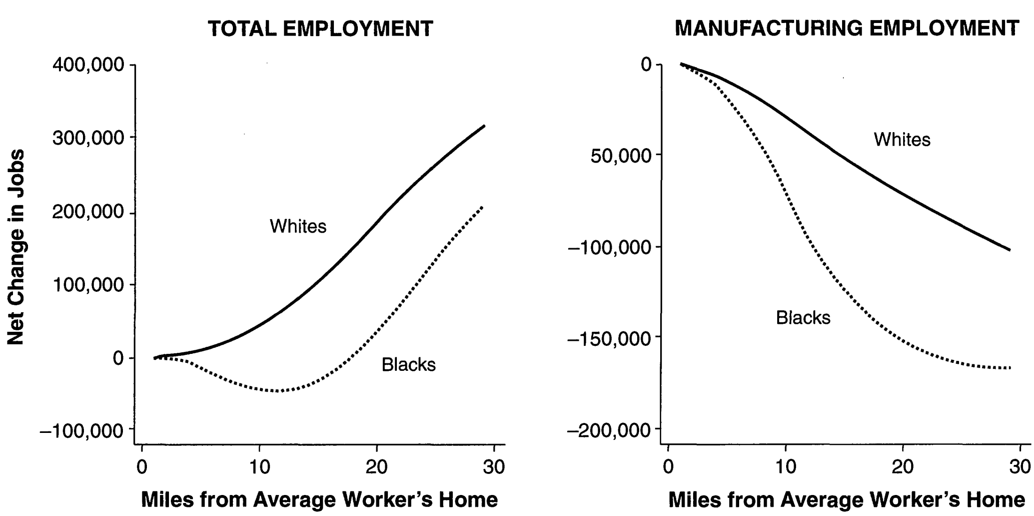
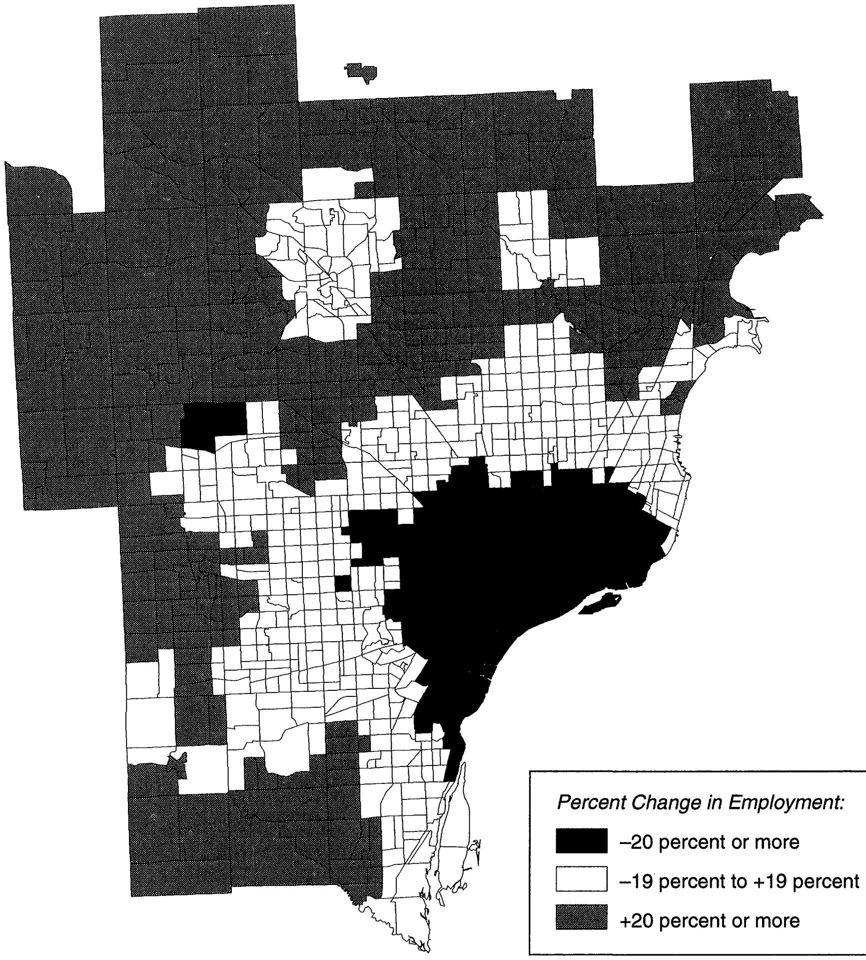



**Figure 2. Net Change in Jobs by Distance from the Average Worker's Home, by Race: Chicago, 1980 to 1990**




**Map 2. Percent Change in the Total Number of Jobs in a Five-Mile Radius: Detroit, 1980 to 1990**

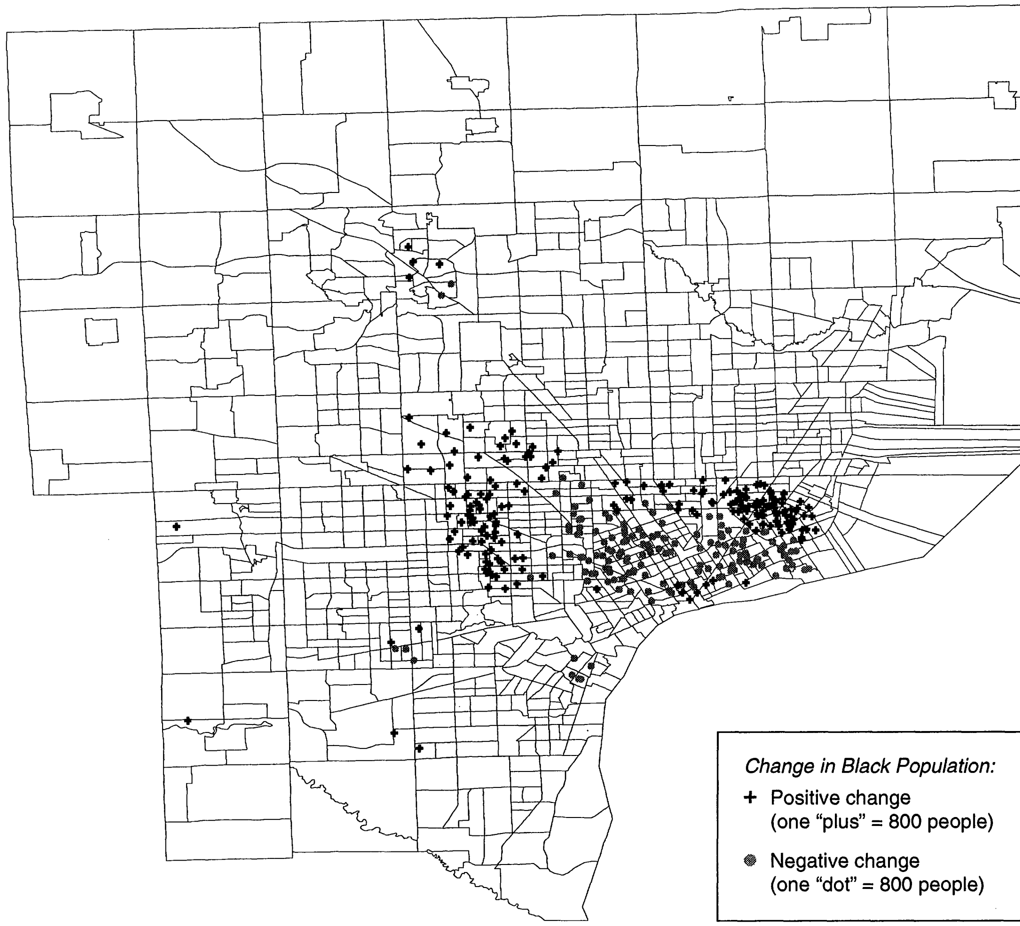
primarily limited to areas near the center of the city. Although there is a slight increase in the black population in some other areas, in general black workers did not relocate to the suburbs. A comparison of Maps 2 and 3 shows that the primary areas of black residential growth in Detroit are relatively distant from the major areas of job growth. In contrast, large migrations of the white population from the central city to the suburbs took place in Detroit and Chicago (maps available from the author by request).

### *Calculating the Change in Job Accessibility*

To model the effects of job accessibility on employment outcomes requires a single parameter measure of job redistribution. Previous studies have relied on an arbitrary commuting radius to determine the size of the local labor market (i.e. Ellwood 1986). If the boundaries of the local labor market are too large or too small, then the effect of job proximity on employment will not be estimated correctly. Raphael (1998) estimates a distance-decay parameter for job accessibility that takes actual commuting patterns into account. Following a large literature in urban transportation (Fotheringham 1989; Ord 1975), Raphael estimates a "gravity equation" in the form of a negative binomial count model:

$$T_{mp} = kL_m^{\alpha} E_p^{\beta} \exp(\gamma d_{mp}), \tag{8}$$

where $T_{mp}$ is the number of workers who commute from neighborhood $m$ to neighborhood $p$, $L_m$ is the number of workers in




**Map 3. Changes in the Black Population by Census Tract: Detroit Metropolitan Area, 1980 to 1990**

neighborhood $m$, $E_p$ is the count of jobs in neighborhood $p$, $d_{mp}$ is the distance between the two neighborhoods, and $k$, $\alpha$, $\beta$, and $\gamma$ are parameters to be estimated. The parameter $\gamma$ describes the weights for jobs at different distances. The advantage of this model is that it provides an accurate single parameter measure of *actual* commuting patterns. Following Raphael (1998), I estimate this gravity function from the CTPP data on traffic flows between neighborhoods in Detroit and Chicago in 1990.[6] This estimate of the decay parameter is then used to construct a measure of changes in the spatial distribution of employment for every neighborhood in Detroit and Chicago.[7] Specifically, I define the spatial change in job proximity for each neighborhood as

$$\Delta Jobs_m = \ln \sum_{p=1}^{N} E_{p1990} \exp(\hat{\gamma} d_{mp}) - \ln \sum_{p=1}^{N} E_{p1980} \exp(\hat{\gamma} d_{mp}), \quad (9)$$

[6] There are 1,414 zones for Detroit in 1990 and 1,781 zones for Chicago. This results in a 1,414 × 1,414 matrix of commuting flows in Detroit, and a 1,781 × 1,781 matrix for Chicago. Because of computer memory limitations, the negative binomial model was estimated 10 times with separate 10-percent samples.

[7] The estimate for $\hat{\gamma}$ is –.089 (S.E. 9.23 × $10^{-4}$) for Detroit and –.087 (S.E. 8.12 × $10^{-4}$) for Chicago. Using the estimate of $\hat{\gamma}$ for Detroit, jobs located at distances of 0, 5, 10, and 20 miles would have weights of 1, .64, .41, and .17 respectively.

where $E_{py}$ is the number of jobs in tract $p$ in year $y$. Equation 9 simply counts the natural log of the number of jobs around a neighborhood in 1990 minus the natural log of the number of jobs around the same neighborhood in 1980, weighting nearby jobs more than distant jobs according to the parameter $\gamma$. This equation was used to calculate the change in employment levels for all jobs as well as for jobs in four different industry categories. It turned out that all of the measures of employment change (total jobs, manufacturing jobs, retail, transport/communications/wholesale trade, and services) are correlated above .95, except for total jobs and manufacturing in Chicago, which are correlated at .88.[8] This indicates that the spatial patterns of job decentralization are similar—despite differences in the average levels of change. Because of this multicollinearity, it is impossible to isolate the effect of changes in industry composition on changes in the unemployment rate by using all the employment variables together in the same model. To do so with statistical confidence would require a data set of cities that exhibited sufficient variation in decentralization across industries (Kmenta 1986). Thus I restrict my attention to estimating the effect of changes in job access for all jobs and manufacturing jobs by introducing the variables separately into regression equations. Although the estimated coefficients are similar because of the high degree of collinearity, there are significant differences in the predicted effects on unemployment because the average changes differ, which may lead to different substantive conclusions.

The estimate of employment levels using this decay parameter may overstate job proximity for blacks, who are less likely to own automobiles, because the probability of commuting to a job without a car should drop more rapidly as distance increases. In Detroit in 1990, for example, only 4.2 percent of white households did not own a car, compared with 26.3 percent of black households. If car ownership is treated as exogenous, then the actual distance-decay function should be steeper for blacks, weighting distant jobs less for blacks than for whites. However, it is difficult to determine whether car ownership is exogenous to labor market outcomes, as it may be the result of poor job access rather than the cause. I adopt the methodologically conservative approach of estimating identical job-accessibility functions for blacks and whites. In the sensitivity analysis below, I relax this assumption and consider models in which access to jobs depends upon the proportion of white or black households in each neighborhood that have access to cars. Also, in addition to allowing the distance-decay function to change depending upon car-ownership rates, I also estimate simpler models in which the change in the black or white rate of car ownership in the neighborhood is entered directly into the regression equation as an independent variable.

It is also important to consider changes in labor supply. Because the population may be receding from the center of cities at the same time that employment is decentralizing, spatial changes in employment alone will not necessarily reflect changes in job availability. If the population decreased more rapidly than employment, the number of jobs per worker would actually be increasing. Therefore, to measure spatial mismatch accurately, I calculate the change in the size of the competing labor force by applying equation 9 to the number of employed and unemployed workers in 1980 and 1990:

$$\Delta\ \mathit{Competing\ Workers}_m = \ln \sum_{p=1}^{N} LF_{p1990} \exp(\hat{\gamma} d_{mp}) - \ln \sum_{p=1}^{N} LF_{p1980} \exp(\hat{\gamma} d_{mp}), \quad (10)$$

where $LF_{pt}$ indicates the size of the labor force in neighborhood $p$ at time $t$.

Finally, I define the change in overall job accessibility as the change in the "density" of jobs per worker by calculating the change in the ratio of the number of jobs to the number of competing workers:[9]

[8] Summary statistics and the correlation matrix for all of the different industry categories are available from the author on request.

[9] Keep in mind that:

$$\ln(a/c) - \ln(b/d) = (\ln a - \ln b) - (\ln c - \ln d).$$

$$\Delta Job\ Access = \Delta Jobs_m - \Delta Competing\ Workers_m. \quad (11)$$

In addition to this measure of job accessibility, a proxy for the change in labor market conditions of traditional blue-collar workers is defined, using equation 11, as the change in the ratio of manufacturing jobs to the number of workers with a high school degree or less.

Table 2 displays the summary statistics for the variables used in the analysis.[10] The analysis is restricted to census tracts that have white (black) unemployment counts for both 1980 and 1990.[11] The variable "change in job proximity" (Δ *Jobs*) shows the overall change in proximity to work as calculated from equation 9. This variable describes the change in the number of "nearby" jobs between 1980 and 1990, weighting nearby jobs more than distant jobs according to the weights that are derived from actual commuting behavior. The weighting scheme holds commuting patterns constant by weighting both the 1990 and 1980 data with weights obtained from 1990 commuting patterns. In this sense it is a relative rather than absolute measure of change in job proximity. In Detroit during the 1980s there was a decrease in the proximity of jobs of about 9 percent for black workers, and almost no change for white workers.[12] In contrast, blacks in Chicago experienced an increase in job proximity of 3.1 percent, although this was much less than the increase for whites. In both Detroit and Chicago, the variable "change in manufacturing job proximity" indicates large losses of proximity to manufacturing employment for both blacks and whites.

As measures of the changes in the size of the competing labor force, the variables "change in competing labor force" and "change in workers with a high school education or less" show spatial measures of the change in the number of nearby workers, also calculated using equation 10. These measures show that the 9 percent decrease in the number of nearby jobs for African Americans in Detroit is partly offset by a 3 percent decrease in the size of the competing labor force. The change in the number of workers with a high school education or less is a proxy for changes in the size of the blue-collar labor force. In both Detroit and Chicago, a large reduction in the size of the competing blue-collar labor force mitigates the decline in overall proximity to manufacturing jobs for black workers. Finally, two measures of the overall change in the density of jobs per worker are calculated using equation 11. The variable "change in number of jobs per worker" (Δ *Job Access*) is simply "change in job proximity" (Δ *Jobs*) minus "change in size of competing labor force" (Δ *Labor Force*). Likewise, "change in manufacturing jobs per blue-collar workers" is "change in manufacturing job proximity" minus "change in workers with high school education or less."

The other variables included in the analysis in addition to job access are intended to account for changes in demographic composition. The three education variables show the change in the proportion of the tract's black or white population with less than high school education, high school, or 1 to 3 years of college. The reference category is workers with four or more years of college.[13] Also included is the change in the proportion female in the tract's black or

[10] The neighborhoods are weighted by

$$wgt = \left(\frac{1}{LF_{1990}} + \frac{1}{LF_{1980}}\right)^{-1},$$

where $LF_{1990}$ and $LF_{1980}$ are the size of the group's neighborhood labor force in 1990 and 1980, respectively. This weighting scheme follows from the assumption that the variance of the neighborhood unemployment rate in each year is inversely proportional to the size of the neighborhood labor force.

[11] The census tract data on unemployment by race are suppressed in 1980 if the size of the labor force of that race is fewer than 10 workers. This results in the loss of 5.4 percent of the black labor force from the data set in 1980 in Detroit and 6.9 percent in Chicago.

[12] Converting from log change to percent, –9 percent $\cong 100 \times \exp(-.095) - 100$.

[13] The aggregate education measures are not directly comparable between the 1980 and 1990 censuses. The 1980 data are for the population age 19 and older, while the 1990 data are for the population age 25 and older. In addition, the 1980 census asks for years of education, while the 1990 data are based on degrees obtained.

**Table 2. Means (Weighted) and Standard Deviations for Variables Used in the Analysis, by Race, for Detroit and Chicago**

| | Detroit | | Chicago | |
|---|---|---|---|---|
| Variable[a] | Whites | Blacks | Whites | Blacks |
| Change in tract unemployment rate (fraction) | –.029<br>(.033) | .005<br>(.077) | –.005<br>(.027) | .037<br>(.072) |
| Spatial change in job proximity | .003<br>(.086) | –.095<br>(.057) | .163<br>(.120) | .031<br>(.069) |
| Spatial change in manufacturing job proximity | –.226<br>(.086) | –.333<br>(.057) | –.198<br>(.151) | –.361<br>(.084) |
| Spatial change in size of competing labor force | .021<br>(.051) | –.034<br>(.031) | .084<br>(.067) | .016<br>(.038) |
| Spatial change in labor force with a school education or less | –.183<br>(.022) | –.212<br>(.015) | –.156<br>(.040) | –.190<br>(.021) |
| Spatial change in number of jobs per worker | –.018<br>(.036) | –.060<br>(.027) | .079<br>(.064) | .015<br>(.036) |
| Spatial change in number of manufacturing jobs per blue-collar worker | –.043<br>(.067) | –.121<br>(.043) | –.042<br>(.118) | –.171<br>(.066) |
| Change in tract proportion with less than a high school education | –.067<br>(.052) | –.046<br>(.071) | –.078<br>(.062) | –.066<br>(.086) |
| Change in tract proportion with a high school education | –.077<br>(.057) | –.057<br>(.073) | –.068<br>(.056) | –.048<br>(.080) |
| Change in tract proportion with 1 to 3 years of college education | .110<br>(.050) | .095<br>(.063) | .084<br>(.054) | .095<br>(.076) |
| Change in proportion of tract labor force that is female | –.061<br>(.037) | .038<br>(.058) | –.051<br>(.037) | .039<br>(.069) |
| Change in tract proportion of households without a car | .017<br>(.038) | .085<br>(.088) | –.005<br>(.057) | .054<br>(.145) |
| Change in housing values[b] | .528<br>(.309) | .366<br>(.390) | .850<br>(.390) | .883<br>(.480) |
| Number of tracts | 918 | 463 | 1,442 | 827 |

*Note*: All tract-level variables are calculated separately by race. Numbers in parentheses are standard deviations.

[a] Changes are between the years 1980 and 1990.

[b] Equals the natural log of the ratio of average housing values in 1990 and 1980.

white labor force. The change in the proportion of the tract's households (by race) that do not own an automobile is included to test whether increases in neighborhood unemployment rates are a result of the lack of cars needed to get to suburban jobs. Finally, changes in relative housing values are calculated as the log of the ratio of the value of the average house in the neighborhood in 1990 and 1980 divided by the average change in the metropolitan area as a whole. This variable may indicate fluctuations in neighborhood selectivity over time.

### *Spatial Autocorrelation*

One final complication relates to the analysis of geographic data. Geographic data are similar to time-series data in that adjacent cases may have correlated error terms. The boundaries of neighborhoods and many other geographic units are arbitrary, and unobserved factors that affect one neighborhood will likely affect its neighbors also. Models of spatial autocorrelation attempt to treat this possibility much as would be done for time-series data by allowing the error term to be

**Table 3. Spatial GLS Coefficients for Regressions of the Change in the Black Unemployment Rate on Selected Independent Variables: Detroit and Chicago, 1980 to 1990**

| | Detroit | | | | Chicago | | | |
|---|---|---|---|---|---|---|---|---|
| Independent Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Spatial change in number of jobs per worker | −.660** (.161) | −.593** (.162) | −.549** (.162) | −.436** (.160) | −.311** (.085) | −.306** (.082) | −.293** (.080) | −.274** (.080) |
| Change in tract proportion with less than a high school education | — | .117 (.071) | .080 (.071) | .085 (.070) | — | .185** (.044) | .172** (.044) | .174** (.043) |
| Change in tract proportion with a high school education | — | .152* (.063) | .116 (.068) | .103 (.068) | — | .219** (.045) | .206** (.044) | .209** (.044) |
| Change in tract proportion with 1 to 3 years college education | — | −.054 (.072) | −.077 (.071) | −.087 (.071) | — | .138** (.046) | .141** (.045) | .143** (.045) |
| Change in proportion of tract labor force that is female | — | −.148** (.057) | −.139* (.056) | −.150** (.055) | — | −.005 (.035) | −.012 (.034) | −.012 (.034) |
| Change in tract proportion of households without a car | — | — | .159** (.038) | .154** (.038) | — | — | .080** (.016) | .082** (.016) |
| Change in housing values | — | — | — | −.028** (.009) | — | — | — | .008 (.005) |
| Constant | −.035** (.011) | −.006 (.013) | −.019 (.013) | −.020 (.012) | .041** (.003) | .050** (.005) | .044** (.005) | .045** (.005) |
| $\rho$ | .275** (.060) | .296** (.059) | .312** .058 | .283** (.059) | .261** (.045) | .236** (.046) | .222** (.047) | .219** (.047) |
| $R^2$ | .053 | .092 | .124 | .143 | .025 | .054 | .078 | .078 |
| Number of tracts | 463 | 463 | 463 | 463 | 827 | 827 | 827 | 827 |

$^*p < .05$ $\quad ^{**}p < .01$ (two-tailed tests)

correlated across adjacent neighborhoods. The key difference between conventional ordinary-least-squares (OLS) models and the generalized-least-squares (GLS) spatial error models estimated in this paper is that the GLS models also include an estimate of the degree of autocorrelation between error terms ($\rho$). Technical details of the spatial-error model are given in Appendix A. All of the models presented here exhibit positive spatial autocorrelation ($\rho > 0$), which would otherwise inflate OLS significance tests. Estimates of r range from about .2 to .4.

## RESULTS

Tables 3 and 4 show results from generalized-least-squares (GLS) spatial error models that estimate the effect of employment decentralization on unemployment rates for blacks and whites. Model 1 includes only the job access variable and the constant term. The access variable—change in number of jobs per worker—is significant for blacks in both Chicago and Detroit (Table 3). Model 2 adds controls for changes in education levels and the gender composition of the labor force. In both Detroit and Chicago, the effect of change in jobs per worker is still large and statistically significant for blacks. The coefficient indicates that a 10-percent decline in job access (i.e., a 10-percent loss in the number of jobs per worker) would increase the black unemployment rate by about 5.6 percentage points in Detroit and 2.9 percentage points in Chicago.[14]

[14] A 10-percent increase in jobs per worker would result in a 100 × ln(1.1) = 9.5 percent increase in the variable "change in jobs per worker."

**Table 4. Spatial GLS Coefficients for Regressions of the Change in the White Unemployment Rate on Selected Independent Variables, Detroit and Chicago, 1980 to 1990**

| | Detroit | | | Chicago | | |
|---|---|---|---|---|---|---|
| Independent Variable | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| Spatial change in number of jobs per worker | –.070<br>(.046) | –.058<br>(.043) | –.050<br>(.042) | –.049**<br>(.015) | –.056**<br>(.016) | –.061*<br>(.016) |
| Change in tract proportion with less than a high school education | — | .044<br>(.028) | .025<br>(.028) | — | .093**<br>(.015) | .087**<br>(.015) |
| Change in tract proportion with a high school education | — | –.020<br>(.026) | –.029<br>(.026) | — | .072**<br>(.014) | .068**<br>(.015) |
| Change in tract proportion with 1 to 3 years college education | — | –.117**<br>(.029) | –.124**<br>(.029) | — | –.025<br>(.016) | –.029<br>(.016) |
| Change in proportion of tract labor force that is female | — | –.015<br>(.029) | –.012<br>(.029) | — | .001<br>(.020) | .001<br>(.020) |
| Change in tract proportion of households without a car | — | — | .096**<br>(.027) | — | — | .021<br>(.014) |
| Constant | –.030**<br>(.002) | –.017**<br>(.004) | –.019**<br>(.004) | –.002<br>(.002) | .013**<br>(.002) | .013**<br>(.002) |
| $\rho$ | .426**<br>(.042) | .349**<br>(.045) | .343**<br>(.045) | .322**<br>(.038) | .282**<br>(.039) | .283**<br>(.039) |
| $R^2$ | .040 | .091 | .110 | .012 | .081 | .082 |
| Number of tracts | 918 | 918 | 918 | 1,442 | 1,442 | 1,442 |

$^{*}p < .05$ $^{**}p < .01$ (two-tailed tests)

Model 3 adds a control for the change in the proportion of black or white households that do not own a car. The lack of car ownership may also be the result rather than the cause of unemployment, because individuals who lose their jobs may be unable to pay for a car. Therefore, I am cautious about interpreting this variable. Nonetheless, if job decentralization affects only those workers who don't have access to automobiles, then including the change in the proportion of households without a car should greatly reduce the coefficient of change in jobs per worker. Model 3 shows that this is not the case: Although the lack of car ownership is significantly associated with high neighborhood unemployment rates, including the variable results in only a small reduction in the job access coefficient. This suggests that car ownership itself cannot explain away the association between declining job access and increasing unemployment rates for black workers. Although the data used here paper cannot explain *why* distance to jobs matters, it seems likely that increasing the physical distance to jobs increases the costs of commuting and makes job search more difficult—especially for jobs that hire through help-wanted signs or employee referrals.

Model 4 includes changes in housing values as a control for changes in neighborhood selectivity not adequately measured by education, gender composition, and car-ownership rates. I hypothesize that an increase (decrease) in average neighborhood housing prices, relative to the change in the metropolitan area as a whole, indicates an increase (decrease) in the social class composition of the neighborhood. However, even if there is little in- or out-migration, there are good reasons to believe that household income affects housing values because of income-sensitive investments in structural maintenance and upgrades. Consequently, as with car ownership, I am cautious about interpreting models that include this variable. Nonetheless, in both Detroit and Chicago, the coefficient on change in jobs per worker in Table 3 is still statistically significant in regressions that include housing values, although its magnitude in both cities is somewhat diminished.

**Table 5. Predicted Effect on The Unemployment Rate, 1980–1990**

| City and Race | Spatial Change in Number of Jobs per Worker (from Table 2) (A) | Estimated Coefficient (from Model 3) (B) | Predicted Percentage-Point Change in Unemployment Rate, 1980–1990 (A × B × 100) |
|---|---|---|---|
| *Detroit* | | | |
| Whites | –.018 | –.050 | +.1 |
| Blacks | –.060 | –.549 | +3.3 |
| *Chicago* | | | |
| Whites | .079 | –.061 | –.5 |
| Blacks | .015 | –.293 | –.4 |

Table 4 shows the results for changes in the unemployment rates for white workers. In contrast to the results for black workers in Table 3, the effect of change in jobs per worker on the unemployment rate for white workers is small in Chicago, and not statistically different from zero in Detroit. The coefficient in both cities for all models is negative, which suggests that decreased job access is associated with increased unemployment rates, but the size of the coefficients is much smaller than the coefficients for black workers in Table 3.

Finally, Table 5 indicates the predicted effect on unemployment rates during the 1980s. The predicted effect is obtained by multiplying the estimated coefficient from Tables 3 and 4 by the magnitude of the change in jobs per worker from Table 2.[15] The model predicts that employment decentralization raised the black unemployment rate by 3.3 percentage points in Detroit and reduced the rate for blacks in Chicago by 0.4 percentage points, net of other factors. This is because the spatial availability of all jobs actually improved slightly in Chicago during the 1980s.

## DISCUSSION

Results indicate that employment decentralization is associated with statistically significant increases in the unemployment rate for blacks. In the 1980s in Detroit, employment decentralization resulted in the loss of about 100,000 jobs within a 10-mile radius of the average black worker's home (see Figure 1)—an 18-percent decline. In Table 5, the predicted increase in the black unemployment rate as the result of this large movement of jobs in Detroit during the 1980s is 3.3 percentage points. The estimated effect of decentralization in the 1980s on the black unemployment rate in Detroit is comparable to the national impact of a recession: During the recession of the early 1980s, for example, the national unemployment rate increased about 4.5 percentage points (from a low of 6.3 percent in January 1980 to a high of 10.8 percent in December of 1982). Nonetheless, this decentralization explains only about one-quarter of Detroit's 15-point gap between black and white unemployment rates in 1990.

In Chicago, overall job access actually increased during the 1980s for black workers. As a result, models predict a slight decline in black unemployment rates. While changes in job access in the 1980s are significantly associated with changes in the neighborhood unemployment rate for blacks, this variable is not a sufficient explanation for the overall black/white gap in unemployment rates.

Despite the fact that the results do not explain the entire black/white gap in unemployment, the evidence does support the conclusion that employment decentralization is associated with higher unemployment rates for

[15] For example, the actual change in jobs per worker for blacks during the 1980s in Detroit was –.060, and the estimated coefficient for changes in jobs per worker on unemployment was –0.549, from Model 3 in Table 3. Therefore, the predicted effect of employment decentralization on the black unemployment rate is –.060 (–.549) = +.033.

blacks. For whites, however, all of the models show that there is little indication that job relocation has much of an effect on unemployment rates. It may be that because whites are not constrained in their residential mobility, they are able to adjust to the changing location of jobs in order to equilibrate between geographic demand and supply. For blacks, however, the situation is different. While the direction of black residential growth was toward suburban regions of job growth, it was still located in areas that are distant from these regions (Map 3). Although the pattern of black residential mobility suggests an attempt to adjust to changes in job proximity, restraints imposed by the persistence of residential segregation result in a limited population response and an adverse effect on black unemployment rates. If residential segregation were not so persistent, the black labor force would be able to adjust to the changing geographic distribution of work just as the white labor force does, preventing an oversupply of workers in central city areas that have fewer jobs.

### *SENSITIVITY ANALYSIS*

To verify the robustness of the results presented here, three alternative specifications were tested. All of the models presented here use the control variables from Model 2 of Table 3, and complete results are available from the author on request. First, I estimated models where change in manufacturing jobs per blue-collar worker (defined in Table 2 as the spatial change in proximity to manufacturing jobs minus the spatial change in the number of blue collar workers) is the independent variable of interest. It is possible that blue-collar workers were the workers most likely to be affected by industrial restructuring and employment decentralization. The coefficient of change in manufacturing jobs per blue-collar worker on unemployment was –.359 (S.E. = .099, $p < .01$) in Detroit, and –.106 (S.E. = .045, $p < .01$) in Chicago, resulting in an estimated increase in the black unemployment rate of 4.3 percentage points in Detroit, and 1.8 percentage points in Chicago—slightly larger than the results reported for change in total jobs per worker in Table 5. However, any model that seeks to distinguish the separate effect of changes in different industries must incorporate data from other urban areas in which the pattern of change is not so highly correlated among the industry categories.[16]

Second, I estimated models in which the measurement of job accessibility was allowed to depend directly on the proportion of black or white households in the neighborhood that did not own an automobile.[17] Because the effects of decentralization are likely to be mitigated by car ownership, these models allow for interactive effects between the physical distance to jobs and car ownership in the calculation of the job proximity variable. Because blacks are less likely than whites to own cars, the effect of increased distance to jobs on accessibility will be more pronounced for blacks.[18] Using this measure of job access based on neighborhood rates of car ownership, the predicted effect on unemployment is 2.7 percentage points in Detroit and –0.1 percentage points in Chicago—about the same as the results presented in Table 5.[19] This indicates that

[16] The correlation coefficient between change in total jobs per worker and change in manufacturing jobs per worker is .92 for Detroit and .87 for Chicago (using the black population weights).

[17] The gravity equation that is estimated is

$$T_{ij} = kL_i^{\alpha} E_j^{\beta} \exp(\gamma d_{ij} + \beta d_{ij} X_i),$$

where $X_i$ is the proportion of the racial group's households that do not own a car and $\hat{\gamma}_{(car)} = \gamma + \beta X_i$. When the effect of distance on job accessibility is allowed to vary based on neighborhood rates of car ownership, the distance-decay parameter used in calculating job proximity, $\hat{\gamma}_{(car)}$, is estimated to be (–.085 – .070 × the proportion of white or black households without cars) in Detroit and (–.081 – .053 × proportion without cars) in Chicago.

[18] When both change in job proximity and change in size of competing labor force are calculated with $\hat{\gamma}_{(car)}$, which depends on car ownership, instead of $\hat{\gamma}$, which does not, the change in jobs per worker for blacks is –.114 in Detroit and .016 in Chicago. The estimated effect of this measure of change in jobs per worker on black unemployment is –.221 (S.E. = .049, $p < .01$) in Detroit and –.132 (S.E. = .031, $p < .01$) in Chicago. These models incorporate car ownership directly into the access variable and do not also include the change in car ownership itself as a separate independent variable.

[19] As in Table 5, the predicted effect is ob-

whether car ownership is treated as endogenous or exogenous to job proximity does not make much difference in the overall effect on changes in the unemployment rate—the effect of the spatial redistribution of employment is still significant.

Finally, I estimated models using the change in the black employment-to-population ratio as the dependent variable instead of the unemployment rate. In both Detroit and Chicago, the employment rate is positively associated with the change in number of jobs per worker: the coefficient is .401 (S.E. = .124, $p < .01$) in Detroit, and .127 (S.E. = .070) in Chicago. The positive sign indicates that an increase in job access increases the employment-to-population ratio. However, in Chicago the coefficient is small and only approaches statistical significance ($p = .07$).

### *Possible Biases*

There are, of course, some important qualifications that should be made regarding the generalizability of these results. To begin with, I have utilized data from only the Detroit and Chicago metropolitan areas, and the analysis only addresses the issue of employment changes between 1980 and 1990. The degree of employment loss and decentralization has been particularly significant in Detroit and Chicago (Kasarda 1995), and statistically significant effects might not be found in other cities. Next, I cannot definitively ascertain the accumulated effect of decentralization during previous decades on the racial gap in unemployment without including data on the magnitude of job loss during the 1960s and 1970s. In other words, part of the unexplained racial gap in unemployment rates in 1990 may be a result of the persistence of a labor market disequilibrium caused by job relocation in earlier decades.

One must also be cautious about the use of aggregate neighborhood data. It is possible that changes in neighborhood demographic composition over time will bias the results, despite the use of variables controlling for observed changes in neighborhood education levels, gender composition, car ownership, and housing values. The tendency for neighborhood socioeconomic status to decline over time in established central-city neighborhoods may result in an overestimation of the effect of changes in job access on unemployment rates. This will happen if the unobserved quality of the neighborhood's work force is declining at the same time that the neighborhood's proximity to employment is decreasing. However, if neighborhood selectivity is relatively stable over time so that the bias due to changes in unobserved quality is small, then longitudinal models should be more accurate than cross-sectional models. Nonetheless, the assumption of stable neighborhood selectivity cannot be tested empirically, and it should be recognized that longitudinal data is not a panacea for all forms of endogeneity bias.

It is also important to point out some potential problems regarding the location decisions of firms. While the fixed-effects model may help difference out the constant effect of racial discrimination by firms that move from the central city to the suburbs, the possibility that moving to the suburbs allows firms to adopt more discriminatory hiring patterns cannot be ruled out. Two considerations mitigate this problem. First, if suburban firms hire fewer black workers because of distance from the central city per se, perhaps because they advertise jobs locally and receive few black applicants, then improving the geographic access of black workers to the suburbs would restore the lost jobs. In this case, the effect on unemployment would be correctly attributed to distance. Second, if relocating firms act more discriminatory in the suburbs than they did in the central city, perhaps because of the lack of enforcement of antidiscrimination laws, then this will bias the coefficient on the change in number of jobs per worker toward zero.[20] As

tained by multiplying the coefficient by the magnitude of the change in job access.

[20] This would occur because the models estimated here rely upon intrametropolitan differences in the change in number of jobs per worker among black neighborhoods to identify the effect of changes on black unemployment rates. For example, if black workers near the boundaries of white suburbs cannot get hired because of the increased propensity of relocating firms to discriminate, then it will seem as if (relative) proximity to these suburban regions of job growth is not very important, driving the coefficient on job

a result, if firms that relocate to the suburbs are more discriminatory, then the finding that the coefficient on the job-access variable is negative and statistically significant is actually a stronger test of the mismatch hypothesis. A different problem is encountered if firms decide to relocate to the suburbs because of increases in some unobserved factor such as crime rates. However, the effect of the firm's move on unemployment rates is still correctly attributed to distance unless this unobserved factor also directly affects the unemployment rate, in which case the problem is identical to that of a decline in unobserved neighborhood selectivity, as discussed above.

Finally, the results here indicate that the effect of proximity to work is not entirely attributable to car ownership. While changes in car ownership do affect unemployment rates, they do not explain away the role of spatial changes in job proximity. This indicates that one should be concerned about the consequences of employment decentralization and residential segregation even if black workers had car ownership rates identical to those of white workers. I would argue that there are at least two reasons why the spatial mismatch is not just an "automobile mismatch." First, there are per-mile commuting costs—in addition to the cost of the worker's time—that may represent a significant percentage of wages in low-paying jobs. For example, if commuting costs equal 20 cents per mile, then the cost of commuting an additional 10 miles one-way to work represents 10 percent of the daily before-tax wages of a $5-per-hour job. Second, job-search costs probably increase significantly with distance. Information about suburban jobs may not be readily available for inner-city black workers, and this may increase the time needed to find work. For example, research using firm-level data shows that the number of black applicants decreases substantially as distance from black population areas increases (Holzer and Ihlanfeldt 1997). Nonetheless, although the data used here indicate that distance to work matters, they cannot pinpoint exactly why it matters.

access toward zero. A similar logic holds if nondiscriminatory central city firms go out of business and are replaced by discriminatory suburban firms. In contrast, the bias would be negative if the cases were independent of each other (such as comparisons among the central cities of different metropolitan areas), or if firms that relocate to the suburbs discriminate less with respect to suburban black workers and more with respect to inner-city black workers than they did before they moved.

## CONCLUSION

The models presented here provide an empirical test of the spatial mismatch hypothesis based on the relationship between changes in a neighborhood's unemployment rate and changes in the spatial proximity to job opportunities. The use of a fixed-effects model is intended to improve upon previous cross-sectional estimates of the intrametropolitan effect of job decentralization that may be confounded by the relationship between existing urban structure and regions of suburban employment growth. Ideally, it allows me to talk directly about unemployment rates for the working population as a whole rather than restrict attention to teenagers (i.e., Ellwood 1986). The use of the "gravity equation" allows me to calculate changes in job proximity based on actual commuting behavior. This permits a definition of job access that is not dependent on arbitrary geographic boundaries and does not weigh distant jobs the same as nearby jobs. Finally, the use of spatial econometric models corrects for the fact that the units of analysis—neighborhoods—are not independent of one another and may exhibit error correlations similar to that in time-series data.

The results presented here indicate that job decentralization, combined with persistent residential segregation, increases the unemployment rate of African Americans. Again, this is not intended to trivialize the effects of racism and other factors that also contribute to the black/white employment gap. Indeed, the results suggest that recent employment decentralization cannot be the only explanation of persistently high unemployment rates as only about 3 to 4 points of the 14-percentage-point gap in unemployment between blacks and whites in Detroit in 1990, for instance, can be attributed to job relocation during the 1980s. Nonetheless, the effect of spatial mismatch is statistically significant even though it does not account for everything. In sum, I conclude that if a city experienced a large degree of job loss, similar to Detroit's loss in the 1980s, there would be a substantial impact on the black unemployment rate, but it is unlikely to be the only explanation of the black/white gap in unemployment. While these results need to be validated with data from other cities, they do suggest empirical support for a clear causal mechanism linking discrimination in housing markets to adverse employment outcomes.

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## APPENDIX A. SPATIAL AUTOCORRELATION

The simplest specification of this problem is the spatial-error model (Anselin 1988). The spatial-error model is similar to other generalized-least-squares (GLS) models except that the error terms are hypothesized to have a distinct spatial structure. It takes the form

$$\mathbf{Y} = \mathbf{X}\beta + \boldsymbol{\varepsilon}, \tag{A-1}$$

$$\boldsymbol{\varepsilon} = \rho\mathbf{W}\boldsymbol{\varepsilon} + \mu, \tag{A-2}$$

where $\mathbf{Y}$ is a vector of $N$ observations of the dependent variable, and $\mathbf{X}$ is an $N \times K$ matrix of dependent variables, $\boldsymbol{\varepsilon}$ is a vector of residuals, $\mathbf{W}$ is an $N \times N$ spatial weights matrix, $\rho$ is the spatial autoregression coefficient, and $\mu$ is an independently and normally distributed error term.

If $\rho = 0$, then there is no spatial autocorrelation in the error term and the model reduces to ordinary least squares (OLS). If $\rho \neq 0$, then the error term in equation A-1 is the weighted sum of all the other error terms as given in equation A-2. If $\rho \neq 0$, then OLS parameter estimates are still consistent, but estimates of the variance are biased. Therefore, the standard significance tests are no longer valid. Furthermore, in the case of positive spatial autocorrelation ($\rho > 0$), OLS underestimates the variance of $\beta$, leading to inflated significance tests. In equation A-2, the matrix $\mathbf{W}$ describes the strength of the spatial interaction between any two neighborhoods. If $w_{ij}$ is large, it means that neighborhoods $i$ and $j$ exhibit a strong spatial interaction; these neighborhoods are expected to have a stronger error correlation. The specification of the matrix $\mathbf{W}$ is difficult because there are often no a priori reasons to justify a particular weighting scheme (Anselin 1988). Here, a binary contiguity matrix was constructed where $w_{ij} = 1$ if neighborhoods $i$ and $j$ are adjacent to each other, and 0 if they are not.[A-1] This is the simplest type of spatial structure.

The spatial-error model described above is a form of generalized least squares in which the error-covariance matrix is specified by the weights matrix and the correlation coefficient. Estimation requires the maximization of the following likelihood function:

$$L = -(N/2)\ln(\pi) - .5\ln|\boldsymbol{\Omega}| - .5(\mathbf{Y} - \mathbf{X}\beta)'\boldsymbol{\Omega}^{-1}(\mathbf{Y} - \mathbf{X}\beta),$$

where $\boldsymbol{\Omega} = (\mathbf{I} - \rho\mathbf{W})'(\mathbf{I} - \rho\mathbf{W})$. Because maximization of $L$ requires taking the determinant and the inverse of an $N \times N$ matrix, it is computationally intensive. Estimation is done in SpaceStat (Anselin 1995).

In addition to the binary contiguity matrix, a weights matrix based on the distance-decay parameter estimated above was also tested with the data. In this case, $w_{ij} = \exp(-\hat{\gamma}d_{ij})$. There is some justification for using the distance-decay weights matrix because it takes into account spatial interaction in commuting behavior. However, I am not certain that it accounts for all forms of association between neighborhoods. In the analysis, I report only those results using the binary contiguity matrix, because it is the most concise explanation of the spatial interaction. The alternative weighting scheme does not alter the significance of the major variables of interest or the substantive conclusions.

[A-1] If $\mathbf{W}$ is row-standardized so that $\sum_{j=1}^{J} w_{ij} = 1$, then $\rho$ exhibits the desirable property of being bounded by 1 and −1 (Anselin 1988). Therefore, I standardize $\mathbf{W}$ by dividing each element by the row sum of weights.

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