Job Access in Disadvantaged Neighborhoods in Cleveland, 1980–2000: Implications for Spatial Mismatch and Association With Crime Patterns

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Abstract

Various social ills in disadvantaged neighborhoods may be attributed to lack of job access. This study uses two distinctive measures to examine the issue: the job proximity index measures the physical distances between residence and job, and the job accessibility index measures residents' ability to reach jobs that also may be affected by availability of transportation means and job competition intensity. This research in Cleveland, Ohio, indicates that disadvantaged neighborhoods actually enjoyed better job proximity or at least that residents were located no farther away from jobs than others. These neighborhoods suffered from poorer job accessibility, however, because of their relatively lower levels of automobile ownership and the more intensive job competition in these high-density residential areas. Job accessibility alone was negatively associated with crime rates in Cleveland throughout the study period (1980–2000). When socioeconomic covariates were controlled for, the relationship remained significant in 1980, became weaker in 1990, and was not statistically significant in 2000.

Introduction

Many researchers recognize that lack of employment opportunities in disadvantaged neighborhoods (that is, mostly inner-city poor neighborhoods with high concentrations of minority residents) has profound impacts, ranging from social disorders to criminal behavior; but researchers disagree on the causes of this employment shortfall. Whether the problem is a *proximity factor* (that is, spatial mismatch between residence and employment location) or a *nonproximity factor* (for example, lack of transportation means, socioeconomic disadvantage, discrimination in housing and job markets) leads to different policy remedies. This research evaluates job access in Cleveland, Ohio, over a 20-year time span (1980–2000) and examines its implications for the spatial mismatch hypothesis and association with crime patterns.

Specifically, the research addresses the following two sets of questions:

1. Are disadvantaged neighborhoods located farther away from the jobs? Do they suffer from poorer job access? Have the patterns changed over time?

2. Is job access associated with crime patterns? Is the relationship different between economic crimes and violent crimes? Does the relationship remain significant after controlling for other socioeconomic covariates? Has it changed over time?

Kain (1968) proposes the original *spatial mismatch* hypothesis that predominantly Black central-city neighborhoods are increasingly isolated from job locations because of persistent employment suburbanization and residential segregation. Wilson (1987) also attributes various social ills, including high levels of crime in some inner-city neighborhoods, to the residents' lack of job access. Although Wilson seeks to explain the particularly high levels of social dislocation in many urban Black communities, his approach is not race specific (Krivo and Peterson, 1996). In fact, Sampson and Wilson (1995: 41) note that the sources of crime are "remarkably invariant across race and rooted instead in the structural differences among communities." For this reason, this project examines the spatial mismatch hypothesis by assessing whether job access in disadvantaged neighborhoods in general, instead of minority neighborhoods per se, is less favorable than in other neighborhoods.

Two important concepts need to be differentiated on the issue of job access. *Job proximity* refers to average distance from a job to a residential location and captures the spatial separation between residence and job. *Job accessibility* measures a person's ability to overcome the spatial and nonspatial barriers to employment and may be affected by transportation means, road networks, congestion, and competition intensity for jobs among resident workers. Job proximity is a spatial issue, and job accessibility involves nonspatial factors. Some recent studies suggest that disadvantaged neighborhoods are actually physically closer to jobs (for example, Shen, 1998; Boardman and Field, 2002; Wang, 2003), but residents still experience more commuting time because of their higher dependency on public transit; this situation reflects the so-called "automobile mismatch" (Taylor and Ong, 1995). The job accessibility measure used in this research takes advantage of recent advances in accessibility measures (for example, Luo and Wang, 2003; Wang and Luo, 2005) and accounts for both the spatial and nonspatial barriers mentioned above.

Most theories of crime assert, or at least imply, an inverse relationship between legal and illegal employment. *Strain* theories (for example, Agnew, 1985) contend that crime results from the inability to achieve desired goals, such as monetary success, through conventional means, such as legitimate employment. *Control* theories (for example, Hirschi, 1969) emphasize the "stake in conformity," which suggests that individuals unemployed or with less desirable employment have less to lose by engaging in crime. *Rational-choice* theories (for example, Cornish and Clarke, 1986) and *economic* theories (for example, Becker, 1968) suggest that people make rational choices to engage in a legal or illegal activity by assessing the cost, benefit, and risk associated with it. Labor market variables should affect individuals' decisions to engage or not engage in crimes, particularly property crimes. Research along this line has focused on the relationship between unemployment and crime rates (for example, Chiricos, 1987). Most previous research, however, uses large areas such as the whole nation, an entire state, or an entire metropolitan area to identify job markets and often relies on time series data. Data for such large units are a crude tool for identifying the link between unemployment and crime (Levitt, 2001), and more variation may be *within* such units than *between* them. Recent work has made significant advancements by analyzing the relationship between *local job market* and crime. For example, drawing on the dual labor market theory, Wadsworth (2000) shows that parents' jobs in the primary or secondary sector influence children's bonds to conformity and levels of delinquency; Bellair and Roscigno (2000) find strong effects of low-wage, service-sector concentration and unemployment on adolescent delinquency.

One danger of linking the rates of unemployment and crime is the implication that crimes were committed by the unemployed alone. Despite high crime rates among the unemployed, only one-third of arrestees were unemployed at the time of their arrest (U.S. Department of Justice, 1997), as were one-third of prison inmates (Beck et al., 1993). Not all earnings from a job are retained, and wages less the commuting costs (both nominal costs and value of time spent on the road) yield the net benefits from a job. In addition to having an adverse effect on employment prospects, poor job access has high monetary and psychological costs for workers already in the labor force and increases their willingness to risk losing their jobs through involvement in deviant or criminal behavior. In Sullivan (1989), a youth interviewee explicitly indicated his frustration with commuting and how it affected his decision to quit his job. Similarly, Anderson (1999: 110–111) notes that the relocation of many Philadelphia jobs to nearby cities necessitates long travel times via public transportation, making the underground economy (for example, drug trade) "a way of life in numerous inner-city communities." To overcome the barrier of physical distance, residents must gain access to jobs either through relocation or by using whatever transportation modes are available to them. For many minority, low-income, and less advantaged residents, relocating to gain better access to job markets is not a feasible alternative. Local family and friendship ties, residential segregation in the housing market, gender and racial discrimination in the job market, imperfect information available to job seekers, and other factors tend to minimize employment-based relocation. Research suggests that income and housing costs place considerable economic constraints on residential mobility (Cadwallader, 1996). Most moves take place between areas of similar socioeconomic characteristics, and socioeconomic status is positively related to mobility rate (Cadwallader, 1981).

This study measures crime at the census tract level, not at the individual level, so we cannot confidently assert that any areal relationships we find are reflective of individual relationships between labor market variables and crime, commonly known as the "ecological fallacy" (Robinson, 1950;

King, 1997). Specifically, finding a relationship between job access and crime rates at the census tract level does not necessarily imply that the individuals who have the worst access to jobs are the ones committing the crimes. Although this implication may be the case, it is also possible that poor job access may be one feature of communities with weak levels of social control and that this lack of social control facilitates the commission of crimes (Gibbons, 1992), regardless of whether individual offenders are employed or not. Either way, we hypothesize a negative relationship between job access and crime. An earlier study (Wang and Minor, 2002) reveals a negative relationship between job access and crime rates in Cleveland in 1990, but that study is limited to simple bivariate regressions and calls for more rigorous work controlling for covariates. Extending the work to 2000 is also important as it offers an opportunity to examine the possible impacts of the Personal Responsibility and Work Opportunity Reconciliation Act (often called the "Welfare Reform Act") of 1996. Although the regression models in this study are to explain intraurban variation of crime rates by job access, it is also possible that crime rates may also affect job access (for example, crime deters employers from locating in certain areas). Possible simultaneity between job access and crime will be explored in future research.

Contributions of this research are summarized as follows:

1. Two distinctive measures, job proximity and job accessibility, are used to identify whether lack of job access is caused by spatial (physical distances from jobs) or nonspatial (for example, availability of transportation means and job competition intensity) factors.

2. The spatial mismatch hypothesis is tested by assessing whether poorer job access is experienced by disadvantaged neighborhoods in general, based on a composite factor accounting for multiple demographic and socioeconomic variables not simply minority populations per se.

3. The relationship between job access and crime rates is examined over time, and spatial regression is used to control for spatial autocorrelation.

Data Sources and Study Area

Cleveland, Ohio, was chosen as the study area because multiple-indicator and multiple-year data, particularly crime data at the small geographic unit (that is, census tracts), are available. Because the study focuses on the nonagricultural job market, the central contiguous urbanized area in the metropolitan areas of Cleveland and Lorain defines the boundary for the job market. The crime data, however, are available only for the city of Cleveland.

The data needed for defining job access are obtained from the 1980 Urban Transportation Planning Package (UTPP) and the 1990 and 2000 Census Transportation Planning Package (CTPP). The 1980 UTPP data were generously provided by Jean-Michel Guldmann at the City and Regional Planning Section of the Ohio State University (originally obtained from the Northeast Ohio Areawide Coordinating Agency [NOACA]). Both the 1990 and 2000 CTPP data were downloaded from the Bureau of Transportation Statistics website (www.bts.gov). Hereafter, all three data sets are referred to simply as the "CTPP data." The CTPP data were compiled by NOACA, Cleveland's metropolitan planning organization. Both the 1980 and 1990 data are available at the traffic analysis zone (TAZ) level, and the 2000 data are available at the census tract level. TAZ is a geographic unit even smaller than a census tract. Because the boundaries of TAZs do not completely match those of census tracts, we use the simplest and most widely used *areal weighting interpolator* (Goodchild and Lam, 1980) to apportion the attribute value from TAZs to census tracts according to the areal proportion. The choice of areal interpolation is not critical for this research because both of our job access measures (proximity and accessibility) are based on surrounding attributes and tend to be similar among nearby tracts. Because crime data and other socioeconomic covariates all are at the census tract level, measures for job access in both 1980 and 1990 are also converted to the census tract level. The job accessibility in 2000 is measured directly at the census tract level. Exhibit 1 summarizes these data sources.

Exhibit 1

Data Sources Used for Defining Job Access

Data Sets	Contents	Geographic Unit
1980 UTPP Part 1	Residential data	TAZ
1980 UTPP Part 3	Workplace data	TAZ
1980 UTPP Part 4	Commuting data	TAZ
1990 CTPP Urban Element Part 1	Residential data	TAZ
1990 CTPP Urban Element Part 2	Workplace data	TAZ
1990 CTPP Urban Element Part 3	Commuting data	TAZ
2000 CTPP Urban Element Part 1	Residential data	Census tracts
2000 CTPP Urban Element Part 2	Workplace data	Census tracts
2000 CTPP Urban Element Part 3	Commuting data	Census tracts

CTPP = Census Transportation Planning Package. TAZ = traffic analysis zone. UTPP = Urban Transportation Planning Package.

The 1990 or 2000 CTPP Part 1 (or 1980 UTPP Part 1) is similar to traditional census data by area of residence with demographic and socioeconomic variables. The 1990 or 2000 CTPP Part 2 (or 1980 UTPP Part 3) provides data by area of work (unique among all census products) and has the number of jobs and breakdowns of wage groups. The 1990 or 2000 CTPP Part 3 (or 1980 UTPP Part 4) provides very detailed journey-to-work information, such as the number of commuters from one TAZ (or census tract) to another TAZ (or census tract) by a specific mode (for example, drive alone, carpool, ride public bus) and the average commuting time between them. Information about resident workers (the "demand side" of the job market) is obtained from Part 1 (CTPP for 1990 and 2000 and UTPP for 1980), information about jobs (the "supply side" of the job market) from Part 2 in 1990 and 2000 CTPP (Part 3 in 1980 UTPP), and the linkage between them (commuting trips) from Part 3 in 1990 and 2000 CTPP (Part 4 in 1980 UTPP). Most TAZ boundaries remain the same from 1980 to 1990, except for a few TAZs created in 1990 in newly urbanized areas. Therefore, the job access analysis in 1980 and 1990 is based on one spatial layer of TAZs. The analysis in 2000 is directly based on the spatial layer of census tracts.

The data needed for defining socioeconomic covariates are from the decennial census. The 1980 census data are extracted from the *CensusCD 1980* by GeoLytics, Inc. The 1990 data are based on the 1990 census STF1 and STF3 files. The 2000 data are based on the 2000 census SF1 and SF3 files.

The 1980–89 crime data are available at the census tract level from the National Archive of Criminal Justice Data associated with a study conducted by Harrell and Gouvis (1995, 1994). The data set was originally prepared by the Center on Urban Poverty and Community Development at the Case Western Reserve University. Harrell and Gouvis deleted 11 tracts that had fewer than 100 residents each (considered nonresidential or institutional) and that also lacked corresponding socioeconomic variables from census data, leaving 193 observations. Crime variables include rates for auto thefts, burglaries, homicides, rapes, robberies, drug sales or possession, and delinquency filings in juvenile court for each year during the 1980–89 period. Rates for larceny and arson are missing for some years and are not covered in this study. Drug-related crimes are usually separated from either economic or violent crimes and are not covered in this study. Rates for aggravated assaults are available for 1989 but not for 1980. All rates are numbers of crime per 1,000 residents. Except for the measure of delinquency (not covered by this study), all other measures came from the Federal Bureau of Investigation's (FBI's) Uniform Crime Reports (UCR). This study uses the 1989 crime rates to match the job access and other socioeconomic variables in 1990 (hereafter simply referred to as 1990 data). Because the 1990 census data (including both the CTPP and standard census data) actually record 1989 year-end data, this approach seems a reasonable assumption.

Crime data for 2000 are downloaded from the Northeast Ohio Community and Neighborhood Data for Organizing (NEO CANDO) (previously Cleveland Area Network for Data and Organizing or CAN DO) website at http://neocando.case.edu. The crime rates in 2000 within the city of Cleveland are also recorded at the census-tract level but are grouped into slightly different categories. The property (economic) crimes include burglary, larceny theft, auto theft, and arson; the violent crimes include homicide, rape, robbery, aggravated assault, nonaggravated assault, and domestic violence assault. For comparisons over time, this study covers homicide, rape, aggravated assault, robbery, burglary, and auto theft in 2000.

Three issues on crime data deserve some discussion. First, one may argue that the FBI UCR data considerably underreport the actual number of incidents; however, they probably provide a more reliable indicator of crime trends than victimization survey data do (Gove et al., 1985; Steffensmeier and Harer, 1999). The second issue concerns using census tracts as the unit of analysis (for example, lack of uniform area or population sizes; see Brantingham and Brantingham [1984]). We use census tracts merely because of availability of data. Finally, by using the census tract in which the crime occurred as a proxy for the location of the offender's residence, we are in effect making the incorrect assumption that all crime trips were intrazonal. Based on the well-established finding of distance decay in crime trips (for example, Van Koppen and De Keijser, 1997; Rengert, Piquero, and Jones, 1999), the stronger the distance decay function is, the better our proxy measure of the offender's residence is.

The spatial or Geographic Information System (GIS) data of the study area came from two sources. Because the 1980–89 crime data are based on the 1980 census tracts, we used the 1980 census tract boundaries from the *CensusCD 1980* by GeoLytics, Inc. Other GIS data came from the data CDs from the Environmental Systems Research Institute (ESRI), Inc., including (1) the TAZ layer, (2) the layers for urbanized areas (1990 and 2000), (3) the layers for census tracts (1990 and 2000), and (4) the layers for road network (1990 and 2000). We checked the 1980 road network in Cleveland (Rand McNally, 1982) and found little difference from the 1990 road network based on the Census Bureau's TIGER file.

Measuring Job Proximity and Job Accessibility

In addition to the major job concentration in downtown Cleveland, jobs are scattered regionwide and are concentrated throughout several suburban job centers, such as the Lorain downtown and the southeast office and service center. One cannot use the classic Mills-Muth monocentric model (Mills, 1972; Muth, 1969) that all employment is concentrated in the central business district to characterize the urban structure and the individual's access to the job market. Adequate measures of job access need to account for all jobs across the whole study area.

Measuring Job Proximity

To examine whether disadvantaged neighborhoods are located farther away from jobs than are other neighborhoods, the first task of this research is to measure job proximity based on a *gravity model*. In the classic Newton's gravity model, the gravity force between two objects is proportional to each mass but inversely related to the distance squared between them. Here, the influence of jobs at j on resident location i is positively related to the number of jobs there (J_j) but inversely related to the distance or travel time between them (d_{ij}). The distance decay effect is captured by a general exponent term (commonly referred to as "distance friction coefficient") β, instead of 2 in Newton's model. See Wang (2006) for more discussion on various gravity models. Based on the gravity notion, the probability or the portion of resident workers at a tract i taking jobs at a tract j is determined by the influence of jobs at j among the influences of all jobs at various locations:

$$P_{ij} = \frac{J_j / d_{ij}^{\beta}}{\sum_{k=1}^{n} J_k / d_{ik}^{\beta}}, \tag{1}$$

where P_{ij} is the probability (portion) of workers at i taking jobs at j, J is the number of jobs in a tract, β is the distance friction, and n is the total number of job locations. Here, "tract" is a general term to refer to TAZ in 1980 and 1990 or census tract in 2000. Because we are interested in the physical distance between residence and job, d_{ij} can be simply measured by the straight-line aerial distance between tracts i and j. Based on the journey-to-work data, the distance friction coefficient β is estimated by a simple gravity model such as $T_{ij} = aW_iJ_jd_{ij}^{-\beta}$, where T_{ij} is the number of commuters between origin i with W_i workers and destination j with J_j jobs. In this study area, the β value varied from $\beta = 0.78$ in 1980, to $\beta = 0.74$ in 1990, and to $\beta = 0.23$ in 2000, confirming the historical trend of a declining β value over time as observed in other studies (Fotheringham and O'Kelly, 1989). A study by Fotheringham (1980) reported that the β value ranged from 0.1 to 2.2 across the continental United States.

Job proximity for tract i (D_i) is defined as the average of distances between this tract (as origin) and all job sites (as destinations) weighted by the probability P_{ij}:

$$D_i = \sum_{j=1}^{n} P_{ij} d_{ij}. \tag{2}$$

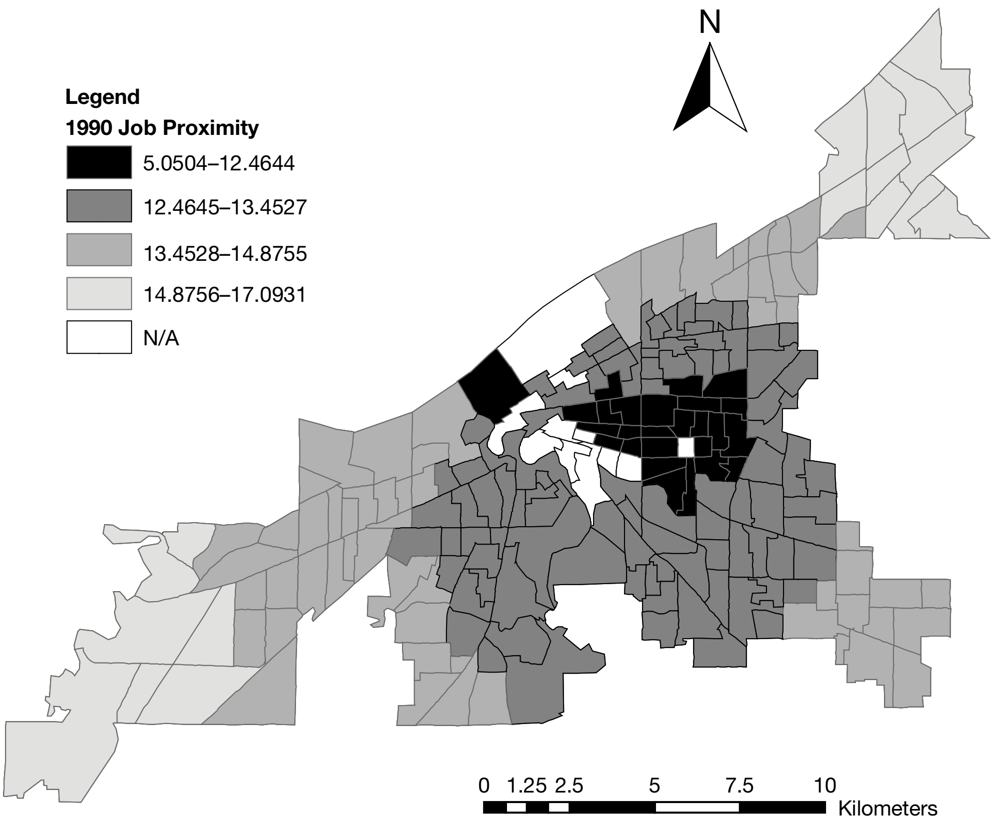
In essence, equation (2) measures how far a residential location is from all jobs. It is a measure superior to the simple average distance from jobs because it values a nearby job more than a remote one.

It may also be interpreted as "predicted commuting distance," given the job distribution patterns (see Wang, 2003). This job proximity index represents, perhaps, the commonly perceived location advantage in the job market without accounting for transportation means or nonspatial factors. The higher the values of job proximity, the farther residents live from the jobs.

As an example, exhibit 2 shows the variation of job proximity in the city of Cleveland in 1990. It exhibits a concentric pattern with the best proximity near the downtown area and increases in the D_i value outwards.

Exhibit 2

Job Proximity in Cleveland in 1990



N/A = not available (no/few residents).

Estimating Travel Times

One important task of implementing the job accessibility measure is to estimate travel times between tracts. The journey-to-work data part in CTPP provides the actual travel times between tracts. Measuring job accessibility, however, requires the input of travel times between all possible origin-destination tracts. Note that accessibility is based on an individual's potential, not necessarily realized, links to jobs. The following discussion addresses how travel times by personal vehicles are estimated.

The first step is to use GIS network modeling techniques to simulate the shortest freeflow travel times through a network composed of all roads (down to neighborhood roads), where speed limits serve as travel impedance values. The simulated travel times (d_0) are preliminary and are between the centroids of tracts.

The next step uses a regression to improve the GIS-based estimated time d_0 by accounting for congestions at both the residential (origin) and workplace (destination) tracts. The dependent variable is the actual travel time d by auto drivers. The explanatory variables include d_0, density of resident workers at the origin tract (DEN_{wk}), and density of jobs at the destination tract (DEN_{jb}) per km^2. For example, the regression in 2000 yields the following model:

$$d = 8.3076 + 0.8011\, d_0 + 0.00169\, DEN_{wk} + 0.000167\, DEN_{jb}$$

where all three explanatory variables are statistically significant at 0.001 and have expected signs. This simple approach considers possible congestions only at the two ends of a trip. Considering traffic congestions during the whole trip would require more detail of road network coding (for example, lane capacity, traffic signal system, residential demographics, and business types). Advanced traffic simulation software considers how the traffic speed interacts with the volume on each segment of the road network and individual travelers optimize the travel time on a trip. That approach is not feasible for this research.

The constant term in the above regression model (that is, 8.30 in the 2000 model) may reflect the intrazonal travel time (including the time a commuter spends on starting the car at the beginning of the trip, finding a parking space at the end of the trip, and walking to the office). The coefficients of density variables may appear small; however, a tract with a residential density of 2,000 workers/km^2 adds 3.4 minutes to the trip, and a tract with a job density of 20,000 jobs/km^2 adds 3.3 minutes to the trip. Such additions are too significant to be neglected.

The final step is to use the regression model to improve the estimated travel time by private vehicles, denoted by d_r.

The regression for public transit following a similar procedure has less fitting power because the model is based on the general road network instead of the actual bus routes (data not available to us). The congestion effects are not significant for public transit. In fact, high-density residential or job areas usually have better access to public transportation and, consequently, offset the congestion effects. For this study, we use a simple regression to estimate travel times by public transit. The dependent variable is reported travel times by public transit d_p, and the only explanatory variable is the above estimated travel time d_r. The following is the regression result for 2000:

$$d_p = 28.0416 + 1.1745 d_r$$

where the constant term includes the time a commuter spends walking from his/her home to a bus stop and from a bus stop to his/her workplace and, thus, is considerably higher.

Measuring Job Accessibility

The job proximity index measures the average distance from jobs at a residential location but does not account for transportation means or competition among resident workers. A better measure is the job accessibility index.

Consider a simple but primitive measure of job accessibility such as

$$A_i = \sum_{j=1}^{n} J_j \, d_{ij}^{-\beta}, \tag{3}$$

where A_i is the job accessibility at location i, J_j is the number of jobs in location j, d_{ij} is now the travel time between them, β is the friction coefficient, and n is the total number of job locations.

One limitation of equation (3) is that it considers only the supply side of jobs and not the demand side—the competition for available jobs among workers. By incorporating the demand side, the job accessibility measure can be redefined (Shen, 1998) as

$$A_i = \sum_{j=1}^{n} \frac{J_j \, d_{ij}^{-\beta}}{V_j}, \text{ where } V_j = \sum_{k=1}^{m} W_k \, d_{kj}^{-\beta} \tag{4}$$

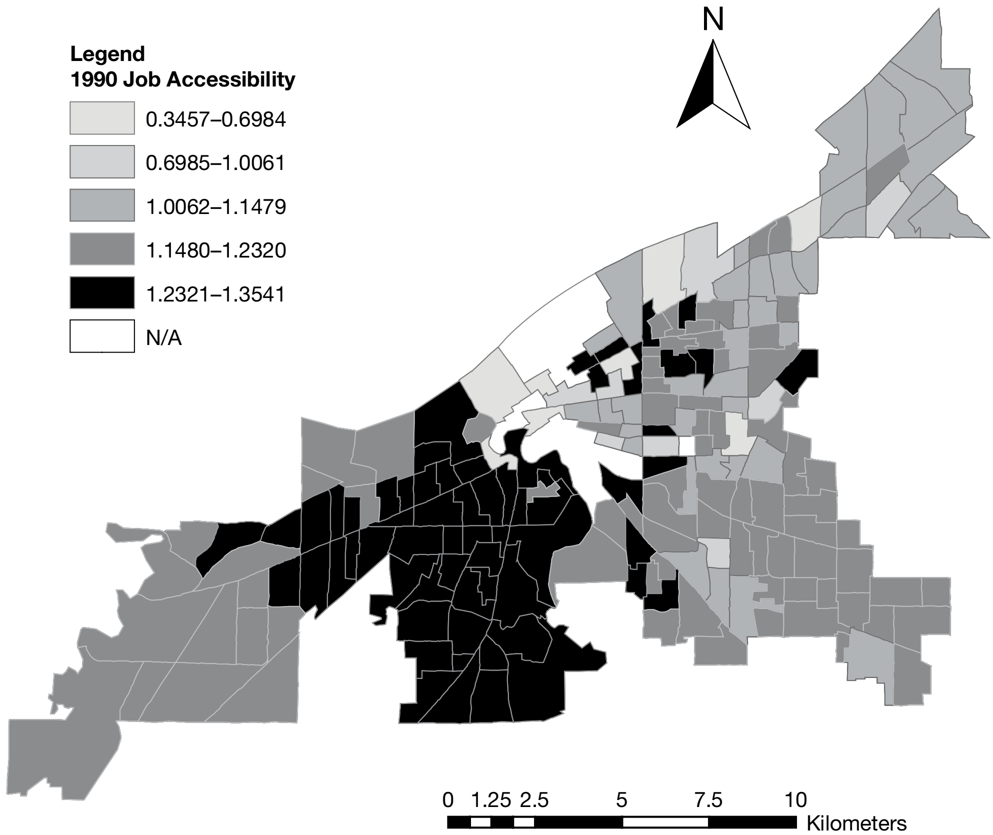
This new index rescales the accessibility to a job location j (j = 1, 2, …, n) by the location's job competition intensity (V_j), and V_j is measured by this job location's proximity to all workers (W_k, k = 1, 2, …, m). The number of job locations n does not have to be identical to the number of resident worker locations m.

Equation (4) is the generic form of job accessibility. Vehicle availability limits a person's choices of transportation modes, and public transit is much slower than travel by personal vehicle. Resident workers by various travel modes (for example, drive alone vs. ride public transit) have different values of job accessibility. It is assumed that workers without vehicles have to rely on public transit. Based on the 1980 UTPP data in Cleveland, it takes 95.3 percent more time for a person to travel by bus than to drive alone in his/her personal vehicle. Based on the 1990 and 2000 CTPP data, it took 110.4 percent more time by bus in 1990 and 117.7 percent more time in 2000. The final job accessibility is the weighted average of workers by personal vehicle and by bus based on the UTPP or CTPP data (Wang and Minor, 2002). The higher the values of job accessibility, the better access a person has to the overall job market.

For example, exhibit 3 shows the overall job accessibility pattern in the city of Cleveland in 1990. Because of limited space in this article, except in the section Results and Discussion, only the 1990 analysis (including measuring job proximity and job accessibility and consolidating socioeconomic covariates) is presented as exemplary work. Many inner-city tracts, although near the major job concentration of downtown Cleveland, suffer the worst job accessibility. The poor job accessibility of these inner-city areas is attributed to (1) poor vehicle availability (and thus relying on much slower public transportation), (2) traffic congestion in high-density residential areas, and (3) stiff competition for jobs with nearby resident workers. In comparison to exhibit 2, tracts on the southwest side enjoy better job accessibility for high vehicle availability and easy access to the highway network.

Exhibit 3

Job Accessibility in Cleveland in I990



N/A = not available (no/few residents).

Consolidating Socioeconomic Variables

Analysis of socioeconomic variables serves three purposes. First, the literature on accessibility indicates that accessibility is affected by both spatial and nonspatial factors. The *spatial (proximity) factor* is determined by the distribution of supplies and demands (jobs and resident workers in the case of job access) and the transportation network that connects them; the *nonspatial (nonproximity) factors* include socioeconomic and demographic characteristics of residents (Joseph and Phillips, 1984). To a large extent, the job accessibility index in equation (4) captures the spatial factor, although it is also affected by vehicle availability (a nonspatial factor). The analysis of socioeconomic variables helps us understand the nonproximity factors that also affect an individual's accessibility to jobs. Second, socioeconomic variables are consolidated for developing a more comprehensive index to identify disadvantaged neighborhoods. Finally, socioeconomic variables serve as covariates in regression analysis of possible association between job access and crime patterns.

The selection of socioeconomic covariates is based on a literature survey. For instance, Land, McCall, and Cohen (1990) and Morenoff, Sampson, and Raudenbush (2001) identify various community structural characteristics that possibly affect neighborhood crime levels. Specifically, this research considers nine covariates within the following three aspects:

1. Concentrated disadvantage: *Black residents, families below the poverty line, female-headed households with children under 18, unemployment,* and *mean family income*. Previous studies have shown that it is difficult to separate the influence of the percentage of Black from the other components of the disadvantage scale (Sampson and Wilson, 1995; Krivo and Peterson, 1996).

2. Residential instability: *residents who moved in the last 5 years* and *renter-occupied homes*.

3. Educational attainment and density: *residents without high-school diploma* and *households with an average of more than one person per room*.

All variables, except mean family income, are measured in percentages. Socioeconomic variables are often correlated, and factor analysis (FA) is used to consolidate them and uncover underlying dimensions. Additional benefits of FA include (1) consolidated factors that are independent from each other and thus make it easy to interpret regression results and (2) explained variances associated with factors that clearly indicate the relative importance of individual factors. Principal components analysis (PCA) is often used as an initial step of FA to help determine how many factors to include in the analysis. Eigenvalues generated from PCA provide a basis for judging which components (factors) are important and which are not and, thus, deciding how many components to retain. By reviewing the PCA results in 1980, 1990, and 2000, it is decided that four components (factors) are retained. This decision is based on the *scree graph* in each year. A scree graph plots eigenvalues against component number (Hamilton, 1992). In this study, each scree graph levels off after component 4, indicating that components 5 through 9 account for relatively little additional variance. The four factors account for 85.8 percent of total variance of the original nine variables in 1980, 81.8 percent in 1990, and 84.8 percent in 2000. In each year, the first component is by far the dominant factor (accounting for more than 50 percent of the variance captured by the four factors).

After deciding on the number of factors (four), the FA is used to consolidate the nine socioeconomic variables. The FA here used the popular Varimax rotation technique to maximize the loadings of a variable on one factor and minimize the loadings on all others. For example, the rotated factor pattern in 1990 is presented in exhibit 4. The factor patterns in 1980 and 2000 are similar to exhibit 4. Analyses in all 3 years indicate that factors 1 and 2 capture those variables of socioeconomic disadvantages (Black residents, female-headed households with children under 18, residents without high-school diploma, unemployment, mean family income, families below the poverty line); variables such as renter-occupied homes and residents who moved in the last 5 years are primarily loaded onto factor 3; and the density variable (households with an average of more than one person per room) is loaded onto factor 4. Therefore, we may label factor 1 as "primary indicator of concentrated disadvantages," factor 2 as "secondary indicator of concentrated disadvantages," factor 3 as "residential mobility," and factor 4 as "density." Scores of the primary indicator of concentrated disadvantages are mapped in exhibit 5 in the city of Cleveland in 1990. The higher the score, the more disadvantaged a neighborhood is.

Exhibit 4

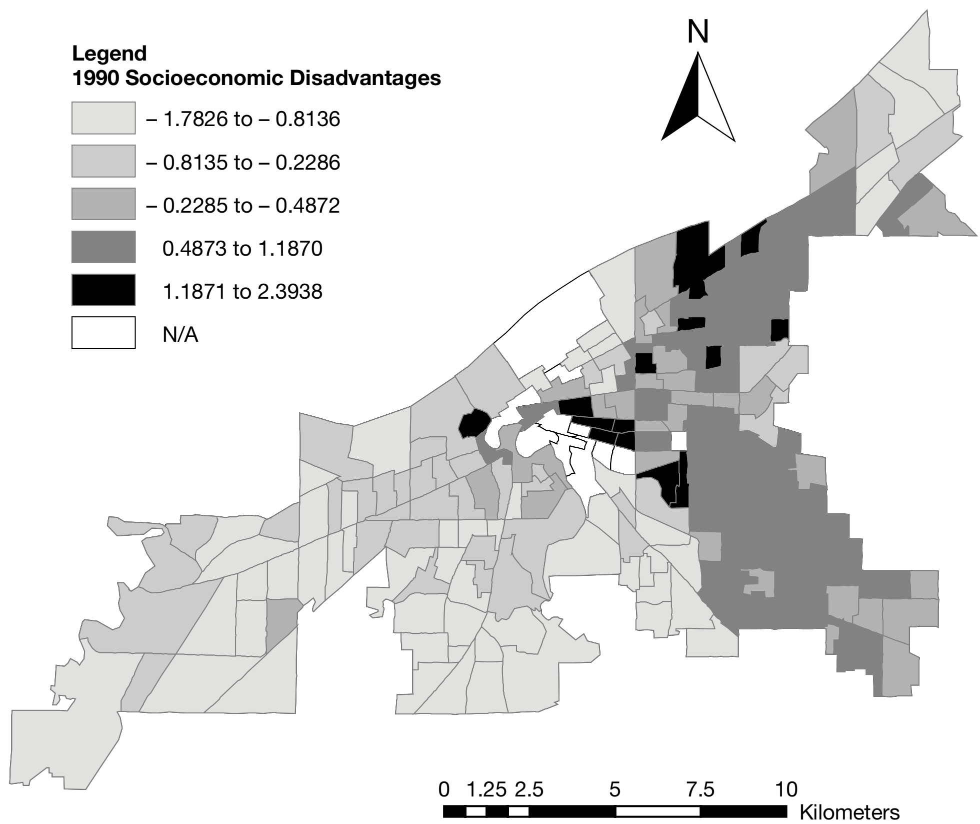
Factor Pattern of Socioeconomic Covariates in 1990

Variable	Factor 1: socioeconomic disadvantage 1	Factor 2: socioeconomic disadvantage 2	Factor 3: neighborhood instability	Factor 4: crowdedness
Blacks	**0.4561**	– 0.1743	– 0.2357	0.1484
Female-headed households	**0.3833**	– 0.2138	0.1378	– 0.2590
Unemployment	**0.3075**	– 0.0305	– 0.0612	0.0507
Residents without high-school diploma	– 0.2329	**0.6589**	– 0.2216	0.1816
Mean family income	0.0570	**– 0.3680**	– 0.0731	0.1645
Families below poverty	0.1390	**0.1955**	0.1102	0.0109
Renter-occupied homes	0.0433	0.1114	**0.3411**	0.1252
Residents moved in last 5 years	– 0.0942	– 0.1435	**0.6285**	– 0.0686
Households with >one person/ room	– 0.0098	0.0659	– 0.0336	**0.8971**

Note: Bold numbers indicate the highest loading of each variable on one of the four factors.

Exhibit 5

Primary Indicator of Concentrated Disadvantages in Cleveland in 1990



N/A = not available (no/few residents).

Results and Discussion

This research considers the following two sets of substantive questions:

1. Are disadvantaged neighborhoods located farther away from the jobs? Do they suffer from poorer job accessibility? Have the patterns changed over time?

2. Is job access associated with crime patterns? Does the relationship remain significant after controlling for other socioeconomic covariates? Is the relationship different between economic crimes and violent crimes? Has it changed over time?

Answers to the first set of questions shed light on the spatial mismatch hypothesis. The second set of questions addresses the effects of job accessibility on crime patterns. Although the measures of job access are based on the contiguous urbanized region as explained previously, all regression analyses in this section are limited to the city of Cleveland, where crime data are available. Only census tracts with valid socioeconomic variables are included. Tracts with no census information for defining the socioeconomic variables (generally tracts with few residents) are excluded. Such exclusion leads to 193 tracts for the analyses in 1980 and 1990 and 212 tracts for the analysis in 2000.

Measures of Job Access Versus Primary Indicator of Concentrated Disadvantages

Simple bivariate regressions are used to examine the relationship between both measures of job access (job proximity and job accessibility) and the primary indicator of concentrated disadvantages (that is, scores of factor 1). Only the most important factor (that is, the primary indicator of concentrated disadvantages) is chosen because it accounts for the majority of the variance from the original set of variables. The regression results are presented in exhibit 6. Because the factor scores from factor analysis are standardized with a mean of zero (0), the constant terms in the bivariate regressions on job proximity (or job accessibility) by the factor scores are also the average values of job proximity (or job accessibility). Exhibit 6 indicates that the average job proximity increased from 12.02 km in 1980, to 13.40 km in 1990, and to 14.21 km in 2000—about an increment of 1 km every decade during 1980–2000. In other words, on average, resident workers in the city moved farther away from their jobs over the study period, consistent with the national trend of decentralization of jobs and residents. The coefficients of factor 1 on job proximity and corresponding *t*-values show that job proximity was negatively associated with the primary indicator of concentrated disadvantages in both 1980 and 1990 (and statistically significant), but the relationship got weaker over time (smaller *t*-value in 1990 than in 1980) and was no longer significant in 2000 (and the sign was even reversed). That is to say, resident workers in neighborhoods with more socioeconomic disadvantages enjoyed better proximity to jobs (closer to the job market in terms of physical distances) in 1980 and 1990, but such an advantage faded over time and no longer existed in 2000.

Job accessibility better measures an individual's potential to access jobs by accounting for the actual road network, possible congestion in high-density areas, availability of personal vehicles, and the intensity of competition for jobs. From exhibit 6, the job accessibility was clearly negatively related to the primary indicator of concentrated disadvantages. In other words, resident workers in more

Exhibit 6

Regressions on Job Proximity and Accessibility by Primary Indicator of Concentrated Disadvantages, 1980–2000

	Job Proximity			Job Accessibility		
	1980 (*n*=193)	1990 (*n*=193)	2000 (*n*=212)	1980 (*n*=193)	1990 (*n*=193)	2000 (*n*=212)
Constant	12.0169 (169.79)***	13.4019 (160.73)***	14.2144 (42.41)***	1.0790 (99.34)***	1.1629 (96.67)***	1.0779 (734.00)***
Factor 1	– 0.7117 (– 9.82)***	– 0.2344 (– 2.55)*	0.3335 (0.64)	– 0.0319 (– 2.86)**	– 0.0395 (– 2.97)**	– 0.0145 (– 9.87)***
R^2	0.335	0.033	0.002	0.041	0.044	0.317

*Notes: P*P* p *< .05; P**P* p *< .01; P***P* p *< .001;* t*-values in parentheses.*

socioeconomically disadvantaged areas suffered from poorer job access. The relationship was statistically significant in 1980 and 1990 and became highly correlated in 2000 (with a correlation coefficient of 0.563). Better job proximity in disadvantaged neighborhoods was not able to be converted into better job accessibility in 1980 and 1990. When no advantage in job proximity for residents of these neighborhoods was observed in 2000, their disadvantages in job accessibility became more evident.

Association Between Job Accessibility and Crime Rates

To address the question of whether the variation in crime rates and the variation in job accessibility are related to each other, the analysis begins with simple ordinary least squares (OLS) bivariate regressions between crime rates and job accessibility at the census tract level. In analyzing crime rates, a common practice is to measure the dependent variable by the logarithmic transformation of rates to better resemble a normal distribution (see Land, McCall, and Cohen, 1990). One (1) is added to the rates to avoid taking a logarithm of 0. The choice of adding 1 (instead of 0.2, 0.5, or others) is arbitrary and may bias the coefficient estimates. Different additive constants, however, have minimal consequence for significance testing as standard errors grow proportionally with the coefficients and thus leave the t values unchanged (Osgood, 2000). In addition, adding 1 ensures that $log(r+1) = 0$ for $r = 0$.

Exhibit 7 presents the regression results using both the total crime rate and its logarithmic transformation in each year as the dependent variable. Regressions on specific crimes yield similar results. In all cases, job accessibility is negatively correlated with crime rates. The relationship is statistically significant but has become weaker over time.

To control for socioeconomic covariates, the four factor scores are added as explanatory variables in the OLS regressions on various crime rates. Because of limited space, only the analysis results in 1980 are presented. Exhibit 8 shows the OLS regressions on crime rates; exhibit 9 shows the OLS regressions on logarithms of crime rates. As with exhibit 7, the results on crime rates and their logarithmic transformations are generally consistent with each other. In the following discussion, only regressions using logarithms of crime rates will be presented.

One likely problem of intraurban data is the positive spatial autocorrelation (or spatial dependence) among observations, which occurs when attributes of nearby areas are more similar than those of distant ones. The presence of spatial dependence, in which the dependent variable is correlated with the dependent variable of nearby observations, results in inconsistent and inefficient estimators by OLS. This problem can be corrected by spatial regression models that are implemented by the maximum likelihood estimation techniques (Smirnov and Anselin, 2001). One commonly used spatial regression model is a *spatial lag model*. The model includes the mean of the dependent variable in neighboring areas (that is, *spatial lag*) as an extra explanatory variable (for example, Anselin, 1988). The model can be written as

$$y = p\, y_{-1} + b\, x + e,$$

where y is the rate of a particular crime (or all crimes), y_{-1} is its spatial lag, x is employment access, and e is the random error. Spatial statistical software GeoDa, a free package developed by Luc Anselin and his colleagues (www.geoda.uiuc.edu), is used to estimate the above spatial lag model.

Exhibit 10 shows the spatial regression results on the 1980 crime rates based on GeoDa. In all spatial regressions on crime (except for rape), the coefficients and significance levels of spatially lagged crime rates indicate strong positive spatial autocorrelation. This observation indicates that census tracts with high crime rates tend to be bordered by other census tracts with high crime rates. The presence of spatial autocorrelation confirms the necessity of using spatial regressions over OLS regressions. The results from spatial regressions, however, are generally consistent with those from the OLS regressions in exhibit 9 in terms of signs of coefficients and statistical significance levels for explanatory variables.

For the 1990 and 2000 crime rates, the spatial regression results are summarized in exhibits 11 and 12, respectively.

Exhibit 7

Regressions on Total Crime Rates by Job Accessibility, 1980–2000

	Crime Rates			Logarithms of Crime Rates		
	1980 (*n*=193)	**1990 (*n*=193)**	**2000 (*n*=212)**	**1980 (*n*=193)**	**1990 (*n*=193)**	**2000 (*n*=212)**
Constant	850.92	352.20	595.50	6.7130	6.0217	8.5612
	(9.29)***	(11.36)***	(2.62)**	(20.59)***	(20.51)***	(9.60)***
Job accessibility	– 687.48	– 230.35	– 473.51	– 2.2507	– 1.5477	– 6.1443
	(– 8.19)***	(– 8.74)***	(– 2.24)*	(– 7.53)***	(– 6.20)***	(– 4.11)***
R^2	0.260	0.286	0.023	0.229	0.168	0.074

*Notes: * p < .05; ** p < .01; *** p < .001; t-values in parentheses.*

Exhibit 8

OLS Regressions on Crime Rates in 1980

	Homicide	Rape	Robbery	Burglary	Auto Theft	All Crimes
Constant	2.3594 (4.70)***	10.0168 (6.62)***	177.67 (8.63)***	257.22 (7.02)***	488.36 (8.44)***	945.59 (8.69)***
Job accessibility	– 1.5940 (– 3.47)***	– 7.6653 (– 5.53)***	– 146.16 (– 7.75)***	– 198.08 (– 5.90)***	– 14.18 (– 7.82)***	– 774.76 (– 7.78)***
Factor 1	0.2962 (4.89)***	0.6025 (3.3)**	10.57 (4.26)***	7.34 (1.66)	7.00 (1.00)	27.07 (2.07)*
Factor 2	0.0286 (0.43)	– 0.2272 (– 1.12)	– 0.12 (– 0.04)	– 2.37 (– 0.48)	– 3.23 (– 0.42)	– 6.64 (– 0.46)
Factor 3	0.0968 (1.66)	– 0.0655 (– 0.37)	– 5.44 (– 2.27)**	– 13.09 (– 3.07)**	– 27.93 (– 4.15)***	– 46.54 (– 3.68)***
Factor 4	0.1346 (2.14)*	0.8179 (4.32)***	4.34 (1.68)	16.14 (3.52)***	15.43 (2.13)*	37.30 (2.74)**
R^2	0.243	0.291	0.374	0.254	0.317	0.337

OLS = ordinary least squares.

*Notes: P*P p < .05; P**P p < .01; P***P p < .001; t-values in parentheses; n = 193.*

Exhibit 9

OLS Regressions on Logarithms of Crime Rates in 1980

	Homicide	Rape	Robbery	Burglary	Auto Theft	All Crimes
Constant	0.9339 (3.97)***	2.1462 (7.05)***	4.2941 (10.92)***	4.7875 (15.86)***	5.8080 (13.95)***	6.2548 (18.77)***
Job accessibility	– 0.5049 (– 2.34)*	– 1.2699 (– 4.55)***	– 1.7158 (– 4.76)***	– 1.1738 (– 4.25)***	– 2.4989 (– 6.55)***	– 1.8311 (– 6.00)***
Factor 1	0.1531 (5.40)***	0.2292 (6.25)***	0.5861 (12.36)***	0.2393 (6.58)***	0.2619 (5.22)***	0.3284 (8.18)***
Factor 2	0.0311 (0.99)	0.0023 (0.06)	– 0.0949 (– 1.80)	– 0.0467 (– 1.15)	– 0.0446 (– 0.80)	– 0.0524 (– 1.17)
Factor 3	0.0838 (3.06)**	0.1342 (3.79)***	0.0896 (1.96)	– 0.0127 (– 0.36)	– 0.1308 (– 2.70)**	– 0.0312 (– 0.81)
Factor 4	0.0795 (2.70)**	0.1521 (3.99)**	0.2056 (4.17)***	0.1780 (4.71)***	0.1453 (2.79)**	0.1755 (4.21)***
R^2	0.265	0.394	0.589	0.374	0.374	0.472

OLS = ordinary least squares.

*Notes: P*P p < .05; P**P p < .01; P***P p < .001; t-values in parentheses; n = 193.*

Exhibit 10

Spatial Regressions on Logarithms of Crime Rates in 1980

	Homicide	Rape	Robbery	Burglary	Auto Theft	All Crimes
Spatial lag	0.2094 (2.27)*	– 0.0720 (– 0.75)	0.3224 (4.25)***	0.3599 (4.47)***	0.4700 (6.53)***	0.4092 (5.52)***
Constant	0.7246 (3.32)***	2.1290 (7.08)***	3.3616 (8.19)***	3.3896 (8.22)***	3.7823 (8.34)***	4.2501 (9.15)***
Job accessibility	– 0.3917 (– 2.00)*	– 1.2136 (– 4.62)***	– 1.5842 (– 4.98)***	– 1.0529 (– 4.30)***	– 1.9743 (– 6.00)***	– 1.5947 (– 5.93)***
Factor 1	0.1248 (4.16)***	0.2510 (6.01)***	0.4110 (6.87)***	0.1555 (3.99)***	0.1497 (3.00)**	0.1999 (4.52)***
Factor 2	0.0287 (0.95)	0.0050 (0.12)	– 0.0756 (– 1.54)	– 0.0349 (– 0.93)	– 0.0316 (– 0.63)	– 0.0367 (– 0.89)
Factor 3	0.0719 (2.63)**	0.1452 (3.89)***	0.0501 (1.16)	– 0.0126 (– 0.39)	– 0.1062 (– 2.42)*	– 0.0342 (– 0.96)
Factor 4	0.0687 (2.40)*	0.1569 (4.07)***	0.1643 (3.51)***	0.1524 (4.26)***	0.1086 (2.29)*	0.1414 (3.62)***
Sq. Corr.	0.286	0.385	0.633	0.447	0.513	0.559

*Notes: P*P p < .05; P**P p < .01; P***P p < .001; z-values in parentheses; n = 193.*

Exhibit 11

Spatial Regressions on Logarithms of Crime Rates in 1990

	Homicide	Rape	Aggravated Assault	Robbery	Burglary	Auto Theft	All Crimes
Spatial lag	– 0.1070 (– 1.07)	0.2800 (3.58)***	0.3317 (5.12)***	0.3476 (4.46)***	0.3744 (4.73)***	0.4868 (6.83)***	0.2939 (4.21)***
Constant	0.7835 (4.13)***	1.2080 (4.46)***	1.3600 (5.29)***	1.9811 (4.87)***	2.2245 (6.73)***	2.4911 (6.53)***	3.6620 (9.59)***
Job accessibility	– 0.4341 (– 2.69)**	– 0.4786 (– 2.16)*	– 0.1131 (– 0.57)	– 0.5481 (– 1.75)	– 0.2419 (– 1.29)	– 0.8429 (– 3.33)***	– 0.5760 (– 2.96)**
Factor 1	0.1422 (5.19)***	0.2581 (6.36)***	0.3661 (9.18)***	0.2845 (5.18)***	0.0459 (1.54)	0.0142 (0.36)	0.2336 (6.61)***
Factor 2	0.0865 (3.70)***	0.1860 (5.43)***	0.2780 (8.38)***	0.2108 (4.38)***	0.1534 (5.23)***	0.1095 (2.92)**	0.2386 (7.49)***
Factor 3	– 0.0088 (– 0.38)	0.0751 (2.34)*	0.0932 (3.23)**	0.1475 (3.19)**	0.0787 (2.79)**	0.1303 (3.38)***	0.1346 (4.54)***
Factor 4	0.0020 (0.08)	0.0987 (2.85)**	0.1016 (3.26)**	0.1092 (2.23)*	0.0915 (3.14)***	0.1141 (2.92)**	0.1488 (4.86)***
Sq. Corr.	0.240	0.542	0.728	0.514	0.446	0.505	0.674

*Notes: P*P p < .05; P**P p < .01; P***P p < .001; z-values in parentheses; n = 193.*

Exhibit 12

Spatial Regressions on Logarithms of Crime Rates in 2000

	Homicide	Rape	Aggravated Assault	Robbery	Burglary	Auto Theft	All Crimes
Spatial lag	– 0.0110	0.1096	0.3339	0.3370	0.3036	0.4435	0.4556
	(– 0.11)	(1.17)	(4.54)***	(4.31)***	(3.74)***	(6.30)***	(6.75)***
Constant	14.8854	0.8039	– 1.8101	1.1781	0.7071	0.0681	0.0702
	(2.10)*	(0.12)	(– 0.55)	(0.38)	(0.38)	(0.04)	(0.04)
Job accessibility	– 12.8840	2.6824	5.3635	2.7860	4.0795	3.6878	4.3991
	(– 1.96)*	(0.42)	(1.74)	(0.96)	(2.34)*	(2.12)*	(2.83)**
Factor 1	0.0894	0.6486	0.4429	0.2673	0.0824	0.1253	0.1321
	(0.59)	(4.25)***	(5.62)***	(3.80)***	(2.07)*	(3.09)**	(3.64)***
Factor 2	0.1337	0.0130	0.1985	0.1975	0.0970	0.1737	0.1975
	(1.05)	(0.11)	(3.19)**	(3.37)***	(2.80)**	(4.74)***	(5.79)***
Factor 3	– 0.2068	0.2108	0.4356	0.3120	0.2345	0.2105	0.1978
	(– 1.60)	(1.67)	(6.58)***	(5.21)***	(6.43)***	(5.80)***	(5.94)***
Factor 4	0.1950	0.3017	0.1149	0.0047	0.0118	– 0.0340	0.0097
	(1.67)	(2.67)**	(2.07)*	(0.09)	(0.38)	(– 1.11)	(0.35)
Sq. Corr.	0.071	0.187	0.506	0.397	0.336	0.472	0.541

Notes: P*P p < .05; P**P p < .01; P***P p < .001; *z-values in parentheses;* n = 212.

Based on exhibits 8 through 10, we consider the effects of two methodological decisions:

1. *Does it matter whether we use crime rates or logarithms of crime rates as the dependent variable?*

   Not really. The regression results are, in general, consistent with each other in terms of statistical significance levels of explanatory variables. Nevertheless, the models using the logarithms of crime rates tend to yield better R^2. From a statistical analysis point, it is perhaps more appropriate to use the logarithmic transformation of crime rates if the crime counts (for example, homicide and rape) in small areas (such as census tracts) are low and the rates are often skewed toward the left. Otherwise, it is convenient to simply use the crime rates.

2. *Does it matter whether we use OLS regressions or spatial regressions?*

   Yes. The presence of spatial dependence necessitates the usage of spatial regressions. In our case, the OLS and spatial regressions are generally consistent with each other. The application of spatial regressions usually needs the knowledge of GIS and calls for usage of special software of spatial statistics. One may use OLS regressions for preliminary analysis when access to spatial regression analysis is not available.

The analysis now focuses on exhibits 10 through 12, all based on spatial regressions on logarithms of crime rates. The following discussion summarizes the findings to address the substantive questions raised earlier.

1. *Is there a relationship between job access and crime rates in Cleveland?*

   Yes, with more at the beginning of the study period, but getting weaker over time. In 1980, coefficients for job accessibility in all crime models were negative, as expected, and were statistically significant. In 1990, the coefficients remained negative but were significant in only four models (homicide, rape, auto theft, and all crime). In 2000, the coefficient was negative and significant in only the model for homicide; in others, the coefficients became positive and even significant in the models for burglary, auto theft, and all crime. Although the simple bivariate regressions between job accessibility and crime rates in exhibit 7 show that areas with poorer job access indeed were correlated with higher crime rates, the relationship got weaker over time and became not significant or even reversed (in some cases) when socioeconomic covariates were controlled for.

   Two factors may have played some roles in explaining this observation. First, the correlation between job accessibility and crime rates indeed became weaker as evidenced in the declining R^2 values over time in the bivariate regression models shown in exhibit 7 (for example, $R^2 = 0.260$ in 1980, 0.286 in 1990, and 0.023 in 2000 in the crime rate models; $R^2 = 0.229$ in 1980, 0.168 in 1990, and 0.074 in 2000 in the logarithmic models). Second, the correlation between job accessibility and primary indicator of concentrated disadvantages became stronger over time ($R^2 = 0.041$ in 1980, 0.044 in 1990, and 0.317 in 2000), and, therefore, more explanation power of crime rates was captured by the socioeconomic covariates in multivariate regressions. This observation highlights the dominant effect of socioeconomic disadvantages on crime patterns, and increasingly so over time. By 2000, poorer job accessibility became so closely associated with disadvantaged neighborhoods that it may be regarded as just another indicator of socioeconomic disadvantages. Early analysis on the job proximity pattern (for example, increasing spatial separation between job and residence and disappearing job proximity for disadvantaged neighborhoods) may explain part of the puzzle; however, this finding also calls for more indepth analysis on the possible changed roles of job access over time. What has contributed to the change? Was it the change of land use pattern, automobile ownership, transportation network, or others? Did the 1996 Welfare Reform Act play any role?

2. *Are socioeconomic disadvantages associated with higher crime rates?*

   Yes. The primary indicator of concentrated disadvantages (factor 1) was positively associated with crime rates with the highest statistical significance in most cases. The secondary indicator of socioeconomic disadvantages (factor 2) was not significant in 1980 models but was significant in most of the 1990 and 2000 models. The other factors were of less importance because they accounted for less variance of the original set of socioeconomic variables.

3. *Do the relationships differ by type of crime?*

   Yes. Previous research has shown a pattern of stronger relationships between unemployment and property crimes than between unemployment and violent crimes (Chiricos, 1987). Following the classification by the FBI in the UCRs, auto theft and burglary are property offenses or economic crimes, and homicide, rape, aggravated assault, and robbery are violent crimes. The coefficients and corresponding z-values for job accessibility were generally larger in models of economic crimes than those in models of violent crimes in 1980 and 1990. This observation seems to support the theory that job access is more relevant in explaining economic crimes than violent crimes. Regression results in job accessibility in 2000 were puzzling and were discussed earlier: the coefficient was either negative (in the case of homicide) or not significant (rape, aggravated assault, robbery) in models of violent crimes but was positive in models of economic crimes. On the contrary, the coefficients and corresponding z-values for factor 1 (primary indicator of concentrated disadvantages) were generally smaller in models of economic crimes than those in models of violent crimes throughout the study period 1980–2000. Those results seem to suggest that socioeconomic disadvantages affect violent crimes more than economic crimes. In all 3 years, models for homicide have the lowest R^2. The models for rape have lower R^2 in both 1980 and 2000 but relatively higher R^2 (0.50) in 1990. In both 1990 and 2000 (data not available in 1980), the models for aggravated assault have the highest R^2.

4. Have the relationships changed over time?

Overall, more stability than change in relationship seems to exist between socioeconomic covariates and crime rates over time. The role of job access, however, has become less important in affecting crime rates over time.

Summary and Public Policy Implications

This section briefly summarizes major findings and discusses possible policy implications.

Principal Findings

Neighborhoods with more socioeconomic disadvantages tended to enjoy better job proximity (that is, closer to jobs in terms of physical distance) in 1980 and 1990 but gradually lost the advantage over time and no longer had it in 2000. Better job proximity was not converted into better job accessibility, however, because many resident workers in those neighborhoods had limited transportation mobility with relatively lower levels of automobile ownership and the competition for jobs was intense among high-density residential areas. In fact, resident workers in disadvantaged neighborhoods suffered from poorer job access throughout the study period 1980–2000, and the negative correlation between job accessibility and the primary indicator of concentrated disadvantages was strong in 2000.

The job accessibility alone was negatively associated with crime rates in Cleveland throughout the study period (1980–2000). When socioeconomic covariates were controlled for, the relationship remained significant in 1980, became weaker in 1990, and was not important in 2000. This trend, on the one side, indicates a less important role played by job accessibility in affecting crime patterns over time. At the same time, stronger correlation between job accessibility and primary indicator of concentrated disadvantages over time implies that more explaining power of crime rates has been captured by the socioeconomic covariates, highlighting the dominant effect of socioeconomic disadvantages on crime patterns. Poor job access leads to difficulties in job search or job retention and, consequently, to poverty and socioeconomic disadvantages. On the other side, socioeconomic disadvantages reduce a person's mobility by limiting both residential choices and vehicle availability and, thus, impair job accessibility. Although we cannot determine which direction of the causal effects is more important than the other, the research suggests that poor job access represents another indicator of socioeconomic disadvantages and, collectively, explains intraurban variations of crime rates.

Theoretical Implications

The findings seem compatible with contemporary versions of social disorganization theory (for example, Bursik and Grasmick, 1993; Wilson, 1996, 1987) or the social stress theory (Brown, 1980; Rose and McClain, 1990). Socioeconomic disadvantages or social stressors, whether they are poverty, unemployment, or lack of access to jobs, form "an unfavorable perception of the social environment and its dynamics," and thus are explicitly linked to social problems, including crime (Brown, 1980). Data used for this study, however, are ecological in nature and do not justify a conclusion that individuals living in disadvantaged neighborhoods with poor job access are the individuals who commit crimes (Robinson, 1950). Rather, it may simply be that communities with poor job access are communities with larger numbers of people who are discouraged, disengaged, desperate, or otherwise lacking the social bonds that restrain criminality (Allan and Steffensmeier, 1989).

Policy Implications

This research demonstrates that being closer to jobs in physical distances does not necessarily transfer into an advantage in job access. Access is a transportation issue as well as a mobility issue. Both may be handicapped by socioeconomic disadvantages. "The best welfare-reform plan was jobs. The best housing plan was jobs. The best educational plan was jobs" (Raines, 2003: 81). To solve the complex web among socioeconomic disadvantages, job access, and crimes, the best hope is perhaps to focus on job access. Jobs are important, but jobs make a difference *only when the jobs are accessible*. As indicated by this research, the benefit of better job access goes beyond alleviating poverty; it also helps curtail crimes. Two policy remedies have been attempted to reduce the spatial mismatch: (1) relocating low-income and minority residents to suburbia where some claimed to have more entry-level or low-wage jobs (particularly in retail services) than in central cities, and (2) creating new jobs in disadvantaged communities. The first approach has led to very limited success because the public transportation service in suburbia is often inadequate and thus handicaps the job access of these relocated residents, most of whom are transit dependent. The second approach includes the Enterprise Zone (EZ) Program, which provides special incentives to encourage business investment and promote the creation of new jobs in economically distressed areas. For EZ companies, incentives include extension of operating loss carry-forward, tax credits, preference points in bidding for state contracts, and others. Although the factors representing concentrations of socioeconomic disadvantages are already included in the current EZ Program, it is also important to consider depletion of jobs and lack of job access in the designations. For a sustainable EZ Program, policymakers may also consider programs that specifically address the transportation needs of prospective employees in the areas, as discussed in the following paragraph.

If job proximity for disadvantaged inner-city neighborhoods is not a major issue, public policy should be focused on overcoming other barriers. Recent studies in developing transportation alternatives for welfare recipients moving to work shed light on improving job accessibility for lower income residents. Some researchers suggest programs of *encouraging automobile ownership* (Wachs and Taylor, 1998) through subsidies for purchasing autos and insurances; however, the high cost (more than $6,000 per client in one typical program) makes such programs infeasible on a large scale (Sawicki and Moody, 2000). More researchers favor solutions from *public transportation improvements* (Bania, Leete, and Coulton, 2001). Existing fixed-route transit systems suffer from many drawbacks, such as the inability to provide access to human services (child care and health care), confined service areas, and inflexible schedules. Proposed programs include extending the reach of public transit by using small buses to carry people outside the public transit service area and providing transportation via small buses from local neighborhood collection centers to employment clusters (Sawicki and Moody, 2000). Studies in Portland, Oregon, and Atlanta, Georgia, showed that better access to public transit significantly improves average rates of labor participation (Sanchez, 1999). Others (Roder and Scrivner, 2005) found that provision of transportation services for inner-city job seekers to access suburban jobs had little effect in improving the employment and earnings. In the latter case, lengthy commutes by participants in the Bridges to Work demonstration projects (more than half had one-way commutes of more than 45 minutes) may explain partially the less-than-promising outcome.

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