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by

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Introduction

One of the most salient characteristics of poor urban neighborhoods is poor labor-market outcomes. Since its conceptualization in the late 1960s, the spatial mismatch hypothesis (SMH) has been cited to explain the employment problems encountered by residents of disadvantaged urban communities (Kain 1968, 1992; Kasarda 1980). Scholars have noted an increasing geographic separation between job opportunities and low-income minorities, many of whom have remained trapped in inner-city ghettos and barrios while jobs have decentralized into the suburbs. Physical distance, then, has been recognized as an employment barrier.[i] Spatial mismatch has also been tied to the development of underclass neighborhoods – those where at least two-fifths of the residents fall below the poverty line. These communities have experienced an exodus of the middle-class, which in turn has weakened community institutions and social networks, created a paucity of positive role models, and devastated neighborhood economies. Empirical studies have found that spatial mismatch adversely impacts labor-market outcomes for African Americans in older cities,[ii] but the hypothesis may not be relevant for all disadvantaged urban neighborhoods.

A fundamental limitation of the SMH is a myopic focus on minority neighborhoods, which ignores a much larger urban process. Increasing geographic separation between residential and employment sites is not a unique experience to inner-city residents. Suburbanization has not only shifted jobs away from the urban core, but it also has increased the commute into the urban core and generated long suburb-to-suburb commutes. Indeed, the most recent census data confirm that this trend continued through the 1990s. In other words, spatial mismatch, defined simply as physical separation, is not confined to just the inner-city of a modern metropolis. Neighborhoods with a high level of spatial mismatch, as well as those with a low level of spatial mismatch can be found throughout the metropolitan area. Many suburban neighborhoods are devoid of jobs and therefore extremely mismatched, yet finding employment is not a problem for neighborhood residents.

Although spatial mismatch is a ubiquitous phenomenon, its impact on employment is not uniform. Residents of disadvantaged neighborhoods are distinguished by a relative lack of transportation resources to overcome distance (Taylor and Ong 1995; Ong 1996; Ong 2002). The urban structure is increasingly predicated on the ubiquity of automobile, but inner-city residents are disproportionately less likely to own a car. This translates into dependency on a public transit system that creates employment barriers by increasing the burden of job search and work commutes. In other words, residents of disadvantaged neighborhoods are mismatched relative to the transportation needed to live in a modern metropolis. Within the context of widespread spatial mismatch, transportation mismatch is the intervening factor that generates negative employment outcomes. However, formulation of the problem in this way is complicated by the issue of causality. That is, does the absence of a car hurt labor-market outcomes or do poor employment outcomes lower car ownership? Understanding the role of access to automobiles requires addressing this simultaneity problem.

This paper examines the impact of spatial mismatch, car ownership, and employment outcomes in the Los Angeles primary metropolitan statistical area (PMSA). The analysis uses census tract data, focusing on the employment-to-population ratio and the unemployment rate. The endogeneity problem is addressed by using two-stage least-square estimates. The rest of the paper is divided into three parts. Part I provides a statistical overview of Los Angeles, Part II presents the empirical results, and Part III discusses the implications for poor neighborhoods. The analysis shows that spatial mismatch is not particularly pronounced in economically disadvantaged neighborhoods, that job access matters but not in a consistent fashion, and that the lack of car ownership is associated with lower employment ratios and increases in the unemployment rate.

Part I – Overview of Los Angeles

The Los Angeles metropolis the second largest metropolitan area in the United States and is coterminous with the County of Los Angeles, home to about 10 million persons and over 3 million households. A little over a third of the population (3.7 million persons in 2000) reside in the City of Los Angeles, which is the second largest city in the nation. The Los Angeles metropolitan area is polycentric, with a distinct central business district (CBD) and a number of sizable, secondary job centers. (See Map 1, Job Density.) The highest job density is within the CBD, with a density of a million jobs per square mile. The other major employment concentration forms the Wilshire Corridor, a band of economic activity stretching from the CBD to the Pacific Ocean. There are also major employment centers located in the San Fernando Valley northwest of the CBD, in an industrial zone southeast of the CBD, and in several clusters scattered throughout the region.

[INSERT MAP 1 HERE]

The labor-force is distributed in a pattern similar to the distribution of jobs, but the density is lower and more evenly distributed. (See Map 2, Working-Age Population Density). The density of the labor force is highest in and around the CBD, and generally declines with distance. The are minor concentrations located in the core of secondary cities, such as in Long Beach at the southern edge of the county. Much of the population is linked to job centers by an extensive network of highways. Within the county, there are 570 miles of freeways.

[INSERT MAP 2 HERE]

The poor in Los Angeles are unevenly distributed. Map 3 shows tracts shaded according to the percent of a tract's population living below the federal poverty line. In 1999, the poverty line for a family of four was approximately $17,029.[iii] For our purpose, tracts are used to approximate neighborhoods.[iv] The category with the highest level of poverty correspond to the classification used to define underclass neighborhoods (Wilson 1987). In Los Angeles, these very poor areas account for about 7 percent of the tracts and 5 percent of all households. The Census Bureau uses poverty rates over 20 percent to designate 'poverty areas,' and we adopt that criterion to define 'Poor' neighborhoods—tracts with poverty rates between 20 and 39 percent. Finally, we distinguish between levels in the non-poverty neighborhoods with the most affluent falling into the 0-9 percent poverty category, the remainder falling into the 10-19 percent category.

[INSERT MAP 3 HERE]

The distribution of neighborhoods by poverty level forms a distinctive geographic pattern. Poor and very poor neighborhoods are concentrated near the CBD, but there are other economically disadvantaged neighborhoods throughout the region. The high-poverty area south of the CBD is known as South Central Los Angeles, the site of the 1992 civil unrest. Historically, this was a predominantly African American area, but more recently, the number of Hispanics has increased dramatically. There are other pockets of poverty, including the sizable area in Long Beach, which is disproportionately populated by Hispanics and Southeast Asians. The more affluent neighborhoods are concentrated along the coastal areas and in the Santa Monica Mountains.

Map 4 shows the percentage of households without cars. There is a strong correlation between carlessness and with the high poverty areas in the central city area.

However, the more suburban poor neighborhoods (e.g. those in the San Gabriel Valley) do not indicate such high rates of carlessness. In part this may be explained by a greater need for cars in areas where the transit network is sparse, and the density of destinations is low. Another factor may be a lower cost of car insurance in outlying areas that puts the overall cost of ownership within reach of more households. A similar pattern can be seen in the data on modal choice for commute to work. Non-car commutes – work commutes relying on a means of transportation other than private automobiles, principally commutes using public transit – are over four times higher in very poor neighborhoods than in affluent neighborhoods and, similar to carless households, non-car commutes are much more likely in the central city areas.

[INSERT MAP 4 HERE]

One of the most salient characteristics of poor neighborhoods in Los Angeles is poor labor-market outcomes. We use two indicators. The first is the employment-to-population ratio, based on 2000 census data, which we calculate as the ratio of working adults to the population sixteen years old and older. Given the age range, the ratio should not approach 100 percent because the population includes retired elderly and youths in schools. What is relevant is the variation in the ratio. The employment ratio drops as the poverty rate increases. While over two-thirds of males in very-low poverty neighborhoods are employed, only half are in very-high poverty neighborhoods (These are unweighted averages for tracts, but results are similar with weights.). The difference is even larger among women. The other indicator is the unemployment rate, which is the number of persons actively seeking employment divided by the total labor force (i.e., working adults plus job-seeking adults). Again, there are sizeable discrepancies across poverty categories. The unemployment rates in the very poor neighborhoods are three to four times higher than the rates in the neighborhoods with very low poverty rates.

[INSERT TABLE 1 HERE]

The data on unemployment and employment ratio show a clear relationship with the neighborhood poverty levels. However, when we look at job access, we do not see a pattern consistent with the spatial mismatch hypothesis. To quantify spatial mismatch, we use two different, but related measures. The first is the number of neighborhood jobs divided by the population between the ages of 21 and 64.[v] The ratio can be taken as a measure of employment opportunities (or job richness) within the immediate neighborhood. Higher values of this ratio tend to cluster toward the extremes, with most neighborhoods either extremely job rich, or extremely job poor. The three-mile job-access index in Table 1 provides an alternative measure that incorporates employment opportunities within a reasonable commute distance. The job-access index is based on the sum of jobs within three miles of a neighborhood inversely weighted by distance from the neighborhood center (See Appendix A for details.) .

Neither of our job-access measures are consistent with the spatial mismatch hypothesis. The jobs-to-population ratio is extremely high in the very-poor neighborhoods. By this measure, there does not appear to be a spatial mismatch (nor does it appear that "underclass" neighborhoods have a weak employment base). One of the limitations of the ratio is that it does not take into account nearby employment opportunities. This is important because previous research shows that even in the most job-rich neighborhoods, the vast majority of workers are employed outside their neighborhoods (Blumenberg and Ong 1998). The statistics on the 3-mile index are also contrary to the SMH. In other words, the job-access index does not indicate a spatial mismatch for very-poor neighborhoods but does indicate that the affluent are relatively geographically isolated from jobs. On the other hand, the pattern for transportation access is consistent with the transportation mismatch hypothesis. This can be seen in the statistics for the percentage of households without automobiles present. The percentage is eight to nine times higher in very-poor neighborhoods than in neighborhoods at the other extreme.

Table 2 provides the correlations between the job-access and transportation-access measures and employment outcomes. The spatial mismatch hypothesis predicts that the employment ratio should be positively related to job access – that is, the more nearby job opportunities, the higher the employment ratio. The impact on the unemployment rate is more ambiguous. Areas with fewer nearby employment opportunities would increase the number of those willing to work but jobless, thus pushing up the unemployment rate. However, the lack of nearby jobs would also discourage many of these individuals from actively looking for work, thus pushing down the official counts of the unemployed (which is defined as those without work but actively participating in job search).

Our first job access measure, the relative numbers of neighborhood jobs, is weakly, although statistically significantly, correlated with the employment ratios. However, the correlation is negative for females. Neighborhood jobs are not significantly correlated with the unemployment rate. Again, this index does not take into account jobs within a reasonable distance. The 3-mile job access index is more strongly correlated with the employment variables, but the signs are unexpected, particularly for the employment ratios. This may be due to confounding variables that are collinear with the index, an issue addressed later in this paper. The statistically significant correlation between household car ownership and employment ratio suggests that the lack of a car adversely impacts employment, and the correlation with non-car commutes suggests that public transit is less effective than cars in linking workers to jobs.

[INSERT TABLE 2 HERE]

Part II: Modeling Labor-Market Outcomes

Bivariate correlation cannot be taken as conclusive evidence of the validity of the either hypothesis because other factors also affect labor-market outcomes. The demographic and human-capital characteristics of the labor market also influence employment and unemployment levels (O'Regan and Quigley 1996). Because many of these factors are correlated with job access and transportation access, the bivariate correlations are biased estimates of their relationship with labor-market outcomes. Multivariate methods are required to separate the contributions of the causal factors. The employment ratio (*ER*) for the i^{th} neighborhood is a function of the characteristics of the population (*X*), job access (*J*), and transportation access (*T*):

$$ER_i = f(X_i, J_i, T_i) \qquad \text{Eq. 1}$$

The unemployment rate (*UR*) is also a function of these characteristics.

$$UR_i = g(X_i, J_i, T_i) \qquad \text{Eq. 2}$$

The above functions can be estimated using ordinary least squares (OLS) regressions under most conditions. Given the fact that large majority of workers are employed outside their immediate neighborhoods, the 3-mile index is an appropriate job-access variable. Also, because the use of public transit is strongly determined by automobile ownership and the two transportation-access variables are extremely collinear, we employ the percent of households without a car as the best measure of transportation-access.

OLS is likely to produce biased estimates if it doesn't fulfill the unidirectional causality assumption. Because having a car aids in the ability to find work and having a job makes it easier to own a car (Ong 1996; Raphael and Rice 2002; Raphael and Stoll 2000; Ong 2002), this creates a statistical problem known as simultaneity, which means that OLS is inappropriate because it does not account for the reverse causality. The relationship between car availability and employment status can be shown conceptually in the following equations. The employment ratio (and the unemployment rate) for the i^{th} neighborhood is a function of the characteristics of the population (*X*), job access (*J*), and the percent of households without a car (*A*):

$$ER_i = f(X_i, J_i, A_i) \quad \text{Eq. 3}$$

At the same time, the carless rate is a function of income (*Y*), and thus employment (*ER*), as well as additional characteristics (*D*) that influence the demand for automobiles.

$$A_i = g[Y_i(ER_i), D_i] \quad \text{Eq. 4}$$

One way to overcome this problem is to solve this system of simultaneous equations. An alternative is to replace observed the carless rate (*A*) in equation 3 with a predicted rate ($\hat{A}$) constructed from an instrumental variable or instrumental variables that are highly correlated with the lack of car ownership but not correlated with the stochastic component of equation 4. The predicted carless rate can be conceived as a function of three exogenous factors:

$$\hat{A}_i = h(C_i, N_i, T_i) \quad \text{Eq. 5}$$

C_i denotes the cost of auto ownership, N_i captures the number of activities that can be conducted within the neighborhood, and T_i measures the availability of alternative transportation.[vi] The specific functional form of equation 5 is determined by regressing C_i, N_i, and T_i on A_i to produce the estimated car-ownership rates. Appendix B provides a description of this first-stage regression.

Using the estimate constructed from exogenous variables, we modify equations 1 and 2 in the following manner:

$$ER_i = f(X_i, J_i, \hat{A}_i) \qquad \text{Eq. 6}$$

$$UR_i = g(X_i, J_i, \hat{A}_i) \qquad \text{Eq. 7}$$

We employ weighted[vii] two-stage least squares regressions to estimate the independent impact of the rate of carless households on employment and unemployment.

Our two outcome measures, and most of our independent variables, are constructed from census data. As previously discussed, the employment ratio (*ER*) is the number of employed persons aged 16 and older divided by the total population aged 16 and older. The unemployment rate (*UR*) is based on the labor force for the same age group and is the population of job seekers divided by the total labor force. Each model is estimated separately by sex.

The vector of population characteristics (*X*) is composed of human-capital and other factors. It includes the proportion of the adult population (25 and older) with less than a high school education and the proportion with at least a bachelor's degree. To account for life-cycle behavior (school attendance of youths and retirement of the elderly), we include the proportion between the ages of 16 and 21 and the proportion 65 and older. To account for racial differences in employment opportunities, we include the proportions of

Asians/Pacific Islanders, African Americans, and Latinos.[viii] Because Los Angeles has a significant number of immigrants with limited language ability, we include the proportion of persons who were either unable to speak English or do not speak English well according to the 2000 census. In the models for females, the percent of families headed by females is included to account for recent changes in welfare policy mandating employment among welfare recipients. $\hat{A}_i$ is the predicted percent of households without a car and is estimated in the first stage with the specification (equation 5) discussed above and in Appendix B. For each variable, we report the mean and standard deviation. The independent variables used in the models are summarized in Table 3.

[INSERT TABLE 3 HERE]

Regression Results

The results of the weighted least squares regressions are listed in Table 4. Model one estimates the male employment ratio and model three estimates the female employment ratio. Model two estimates the male unemployment rate and model four estimates the female unemployment rate. In all models, the included education variables are sex specific, e.g., high-school noncompletion rate is for women when the model is estimating outcomes for the female population. In models three and four, an additional variable representing the percentage of households with a female head of household was included.

[INSERT TABLE 4 HERE]

In general the estimated coefficients agree with *a priori* expectations. (See Appendix C for OLS results using observed car availability.) High school education is significant in all models and has the expected effects. There is a strong negative correlation between employment ratio and noncompletion of a high-school education, and as expected, the unemployment rate works in the opposite direction, with unemployment rising in areas with a high noncompletion rate. This effect is nearly twice as strong in the model predicting female unemployment. Higher education seems to have a weaker influence on employment, particularly in the models predicting female employment ratios and unemployment. While having a bachelor's degree has a significant, though small, impact on increasing the male employment ratio, and reducing the male unemployment rate, the coefficients for this term are small and not statistically significant for the female models.

There is a strong negative association between high percentages of 16 to 21 year olds and the employment ratio, and conversely a positive association with unemployment and percentages of young persons. Since this population has relatively little work experience, this follows our expectations. The situation is slightly different for the population over 65. For neither men nor women is percentage over 65 significant. This is probably due to a relatively large percentage of this group having left the labor market, a conclusion that is supported by the strong negative association of this variable with employment ratio for both sexes.

Race/ethnicity variables (African American, Asian/Pacific Islander (API), and Latino) have mixed effects on the models. African American is significant in every model except the model of female unemployment. This term has a negative correlation in both employment ratio models and a positive correlation in the unemployment models. Percent API is significant in only model one and model four. This variable has a negative association in all four models. Percent Latino is highly significant in the unemployment models, but less significant in employment ratio models. The associations run opposite to the associations with percent African American, i.e., percent Latino is positively associated with employment ratio and negatively associated with unemployment.

English proficiency as measured by percentage of the population with limited English proficiency is significant in all models except for the female unemployment model. Limited English is actually associated with higher employment ratios and lower unemployment among men. Among women the relationship is reversed, with the employment ratio negatively associated with limited English skills. This relationship may be due to cultural emphasis among many recent immigrants discouraging work among women and expecting men to provide financial support for the family. If this is the case, then it is not surprising that English proficiency is not significant in the model of female unemployment since this model relates only to women who are in the labor force.

The percentage of female headed households was included in the models of female unemployment and employment ratio to control for changes that have taken place since the welfare reforms of the mid 1990s. Welfare cases are predominantly female headed households, and under the old welfare policy, single mothers were substantially less likely to be in the labor market. If this policy shift has made a difference, we should see more single mothers forced into the labor market, and these households will not appear significantly different from other households. The model results are consistent with such a process. The coefficient on this variable in the employment ratio model is not significant. However, in the model of unemployment it is highly significant and positively correlated with unemployment rates.

Two dummy variables for location were included in the model – one flags all tracts south of the Angeles National Forest, and the other flags tracts in census designated urban areas. These two variables are highly correlated, but conceptually, these two indicators are different. The dummy variable for the area south of the national forest captures a marked difference between north Los Angeles County, which is largely rural and extremely low-density, and the southern portion of the county that is functionally integrated in the urban area. The urban dummy variable selects the tracts that, due to density criteria, are classed 'urban' by the census. These variables are not significant in the model of male unemployment, furthermore, their coefficients are very small. The urban variable is significant in the male employment ratio model, and has a weak positive relationship. In the female models, the coefficients are significant, but again the relationships are weak. Nevertheless, the signs on the coefficients are in line with our expectations.

The influence of the job-access variable is not strong, nor is it consistent across the models. Although the term is highly significant for both the men's unemployment and the women's employment ratio, the magnitudes of the coefficients are quite small. In all models there is a positive relationship between the dependent variable and this term. Since these models considers all people regardless of income level, it is not particularly surprising that spatial job access is a weak predictor of employment levels, since access to cars among the great majority of workers eliminates distance effects.

The instrumental variable for car ownership is significant for all models. The effect of increasing percentages of carless houses is strongest for the male employment ratio model, where, all else being held constant, a 10 percent increase in the carless rate results in a 3 percent drop in the employment ratio. As expected, the models for unemployment show the opposite tendency. Both of the female models show weaker effects than the male models, perhaps because car access is generally lower among women than men, and therefore being in a carless household does not alter car access as much for women as it does for men.

Part III: Implications for Poor Neighborhoods

The model results from Table 5 can be applied independently to different neighborhood types to perform a simulation that estimates the decomposed contribution of the variables included in our models. The simulation represents gaps between neighborhood types and the contribution of each term in widening or closing that gap. For each variable included in the model we produce the predicted contribution for each variable using the unweighted means for the two extreme neighborhood types, the most affluent and very poor neighborhoods. The mean values of these neighborhood groups are reported in Table 3. The decomposition is based on the following formulas:

$$\Delta ER_{i-j} = \hat{b}\overline{Z}_i - \hat{b}\overline{Z}_j \qquad \text{Eq. 8}$$

$$\Delta UR_{i-j} = \hat{g}\overline{Z}_i - \hat{g}\overline{Z}_j \qquad \text{Eq. 9}$$

Where, $\overline{Z}$ represents the vector of mean values of independent variables in very poor neighborhoods (*i*) and affluent neighborhoods (*j*). $\hat{b}$ and $\hat{g}$ are the vectors of estimated coefficients for employment ratio and unemployment rate respectively. We have performed several versions of this simulation using the observed auto access as well as with instrumental-variable approximations.

[INSERT TABLE 5 HERE]

Model 1 is the OLS model that includes the observed percentage of households without a car as an independent variable. (See Appendix C for estimates); this approach generates a high estimate of the effects of transportation access. Model 2 is the two-stage results reported in the previous section. Model 3 is an alternative 2SLS estimate where the exogenous variables for the first stage are limited to insurance rate and population density; this specification produces a low range estimate of the impact of transportation access. The three models provide a high to low range of the estimated impacts.

Table 6 reports the results of the simulations. The total percentages reported represent the predicted differences using the mean values from each neighborhood type for each variable. For example, 7 percent reported for Model 1 under male unemployment, is the predicted difference in employment rates for males living in very poor neighborhoods compared with those living in affluent neighborhoods as described in equations 8 and 9.[ix]

[INSERT TABLE 6 HERE]

We are primarily interested in the contribution of our car availability instrumental variable, which has a substantial contribution in every model. Nevertheless, it is clear that traditional labor market variables (education in particular) are the most important variables in explaining the neighborhood differences in both employment and unemployment rates. Differences in high-school education across very poor and affluent neighborhoods are associated with the biggest contribution to the differences in employment outcomes between these neighborhood types. Other terms are also relatively important. Age differences in neighborhood composition, on the whole, cancel out, however, differences in the neighborhood values for percent 16 to 21 and percent over 65 contribute to widening and closing respectively the employment ratio gaps. In the unemployment models, the 'over 65' term is not significant, and therefore we see the contribution of compositional age differences mostly widening the gaps in unemployment rates.

The race variables together are relatively minor contributors to the differences between neighborhood types, however, the individual terms in this grouping may partially cancel each other. For instance, the individual contributions of the Latino and African American variables in the male employment ratio models are approximately the same magnitude, but opposite signs, and thus cancel one another. The Latino term has a substantial impact on neighborhood differences in employment ratio and unemployment rate. The increased prominence of Latinos in poor neighborhoods is actually associated with greater employment among working age population, and lower unemployment among those in the labor force. On the other hand, African American presence in poor neighborhoods is associated with lower labor force participation, and higher unemployment. The implication of this is that race taken together is not a substantial indicator of neighborhood employment dynamics. Nonetheless, the magnitude of these terms individually indicates that race is important for understanding employment outcomes in different types of neighborhoods.

Spatial mismatch, as measured by our three-mile job access measure increases female employment ratios by between one and one and a half percentage points.

However, this variable has no impact on male employment rates, and is not significant in two of the three models. This term has a relatively minor impact on unemployment rates, but the relationship is contrary to that posited by the SMH – that is, increasing job access is associated with increased unemployment. This may be due to the types of jobs held by those in very poor neighborhoods, that is, jobs in industries with high unemployment rates.

In every case, transportation mismatch, as measured by Percent No Car, has a significant contribution. Male employment ratios are reduced by as much as four and a half percent by differences in auto access between neighborhood types. Among women, this effect is somewhat smaller, but still substantial. Transportation mismatch has the anticipated, opposite effect on unemployment. In the first model, both male and female unemployment are over two and a half percent higher in very poor neighborhoods than in affluent neighborhoods because of differences in auto access. The models using instrumental variables generally produce lower estimates, such that the lack of car ownership increases unemployment by a percentage point. This result, combined with the results for spatial mismatch, tends to confirm our contention that transportation mismatch is more important for understanding neighborhood outcomes than is non-contextual spatial isolation.

Concluding Remarks

This paper addressed several major shortcomings of the spatial mismatch literature. The first is the implicit assumption made by many researchers about the abilities of low-income workers to overcome spatial separation between home and work. For a spatial mismatch to occur, potential workers must be unable to overcome the friction of distance. Most researchers measure only the number of jobs within a reasonable distance and disregard differences in the levels of transportation access. Unfortunately, this is a serious conceptual and empirical omission.

Having a car makes most trips easier to accomplish. Assuming that poor people rely primarily on transit ignores considerable data documenting the almost universal availability of cars, regardless of income. The decision for most low-income workers is not whether to buy a car, but when to buy a car. Nevertheless, car ownership is not universal and those without cars may be at a disadvantage in searching for jobs. This study support the contention that, while spatial separation is not a groundless concern, car access outweighs any disadvantage of simple spatial separation. The results indicate that access to a vehicle independently contributes to improved labor market outcomes.

The findings have ramifications for public policy related to transportation programs for the poor and for poor neighborhoods. Simply adding transit routes or additional service on existing routes may not be enough to overcome transportation barriers to employment. Transit availability is already high in many of the poorest neighborhoods in Los Angeles; furthermore, many of the poor have good spatial access to employment. The problem is that use of transit is cumbersome compared to ease of travel by car. Policies that prioritize overcoming spatial separation miss the point that accessibility is also contingent on the ease of travel. Given current development patterns, the most straightforward way of addressing this transportation mismatch is to ease access to cars among the poor.

The analysis has some limitations that should be addressed in future research. Micro-level (individual-level) data would provide greater insights into how transportation access and spatial mismatch affects workers, and overcome the problem of multiple collinearity inherent in aggregate data. Additional factors on the cost and demand for car ownership should be included as instrumental variables in the 2SLS model. Finally, it is critical to replicate that analysis for metropolitan areas other than Los Angeles because differences in urban form can affect the relationships.

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Appendix A

The three-mile job-access index in Table 1 provides an alternative measure that incorporates employment opportunities within a reasonable commute distance. The job-access index (J_i) is calculated in the following manner. Jobs in and around a given census tract (*i*) are summed and weighted according to the distance away from the ith tract *i*. This sum is then normalized by the number of prime-working-age adults, P_j (adults aged 21-64). The final index (Equation 1) is the log of the ratio to correct for skewness in the raw ratio:

$$J_i = \ln\left(\frac{\sum_j \left[E_j \cdot f(d_{ij})\right]}{P_i}\right) \qquad \text{Eq. 1}$$

Where the distance weight *f(d)* is described by:

$$f(d) = \begin{Bmatrix} 1 & for\ d \le 1 \\ \frac{1}{d^2} & for\ 1 < d \le 3 \\ 0 & for\ d > 3 \end{Bmatrix} \qquad \text{Eq. 2}$$

Appendix B

One of the most important factors affecting the cost of ownership is the cost of automobile insurance premiums. For an identical person, the cost of basic automobile insurance in Los Angeles can vary by nearly two to one, depending on location (Ong 2002). The cost varies systematically according to the racial and income characteristics of the neighborhood. Along with insurance cost, we expect that automobile ownership should vary with the need for an automobile. Densely populated neighborhoods are more likely to have more amenities, community activities, and services, and denser social networks; consequently, the demand for automobiles is lower (Hess and Ong 2003). The demand for automobiles is also lower when public transit is readily available as a substitute to meet intra-urban travel demand. For example, one study has shown that higher levels of transit service increase employment among those without a car (Ong and Houston 2002).

We estimate the instrumental variables using the following data for the independent variables. Population density (ratio of total population to census tract area in square miles) is used as a proxy for neighborhood activities. Availability of public transit is measured by the total transit capacity passing through a given census tract during the morning peak. The calculation of this term was based on the following method:

$$\text{Transit Availability} = (\text{Buses per hour})\cdot(3\text{ hours})\cdot(43\text{ seats per bus})\cdot(\text{load factor}).$$

These data are for June 2000 and were obtained from the Los Angeles Metropolitan Transportation Authority (MTA).

The key cost-of-ownership variable is insurance cost, which is based on an average cost constructed from quotes for a hypothetical person. The quotes came from the following website: http://www.realquote.com. Multiple quotes from different insurers were requested for each zip code. To capture the "pure" geographic variation of insurance rates, we held the characteristic of the "applicant" constant by using the same demographic profile for every zip code: a 25-year old employed single mother, who has been driving for seven years, had taken a driver training course, and has one moving violation, but no accidents and is a non-smoker. She owns a 1990 Ford Escort LX, 2-door hatchback with no anti-theft devices, no anti-lock brakes and no airbags, which is parked on the street. She carries only the minimum insurance required ($15/30,000 bodily liability, $5,000 property liability) with no deductibles. The insurance premium for each zip code is the average of quotes from at least a half dozen companies. The zipcode-level data were used to estimate tract-level data using the following procedure: Census tracts were assigned to the zip code in which the tract centroid (the point describing the center of a bounding box constructed around tract boundaries) was located. All tracts assigned to a given zip code were given the same value for the average insurance cost. In a few cases, no insurance data were available for a zip code. In these cases, values were interpolated based on the values of all adjacent zip codes.

The dependent variable is the percent of households without a car, and the estimated parameters are:

$$\hat{A}_i = (-0.043 + 0.073*\text{insurance index} + 0.597*\text{population density} + 0.724*\text{Transit})$$

The adjusted R^2 is 0.59, and all of the coefficients are significant at the $p<0.0001$ level. The estimated equation is used to construct the instrumental variable for predicted percent of households without a car.

Appendix C:

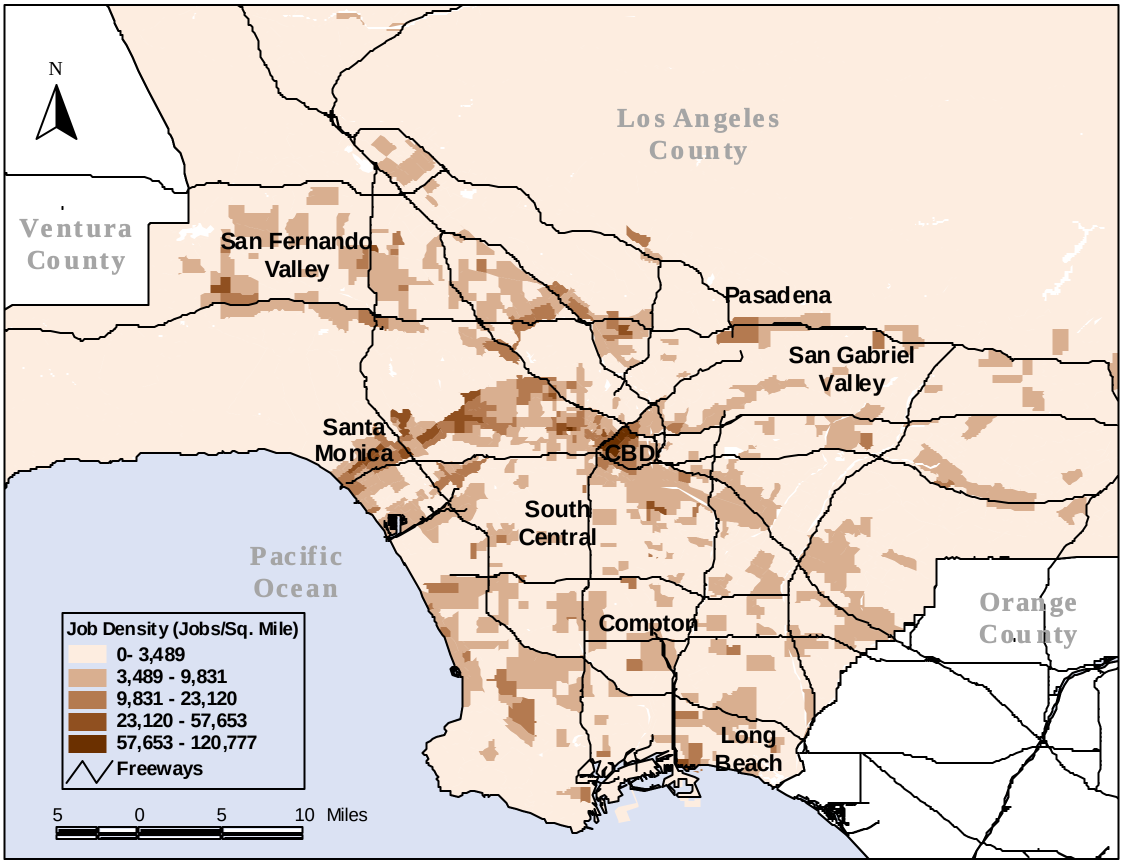
OLS Estimated Model Coefficients

	Male		Female	
	Employment Ratio	**Unemployment Rate**	**Employment Ratio**	**Unemployment Rate**
Intercept	0.812	0.029	0.672	0.027
High School	-0.334 ****	0.068 ****	-0.398 ****	0.167 ****
Bachelor's Degree	0.085 ****	-0.041 ****	0.022	0.026
Percent Age 16-21	-0.458 ****	0.295 ****	-0.310 ****	0.139 ****
Percent Age 65+	-0.481 ****	0.007	-0.658 ****	0.001
Asian/Pacific Islander	-0.174 ****	0.002	-0.034 **	-0.037 ***
African American	-0.138 ****	0.058 ****	-0.067 ****	0.014
Latino	0.037 *	-0.035 ***	0.030 *	-0.021
English Proficiency	0.261 ****	-0.081 ***	-0.013	-0.061 *
Female Headed Households			0.100 ****	0.107 ****
South L.A. County	-0.012	0.002	0.018 **	-0.020 **
Urbanized L.A. County	0.035 ****	0.007	0.032 ****	-0.011
Spatial Job Accessibility	-0.003	0.002	0.005 **	0.001
Households w/ No Car (Observed)	-0.182 ****	0.127 ****	-0.143 ****	0.134 ****
Adjusted R^2	0.625	0.415	0.724	0.487

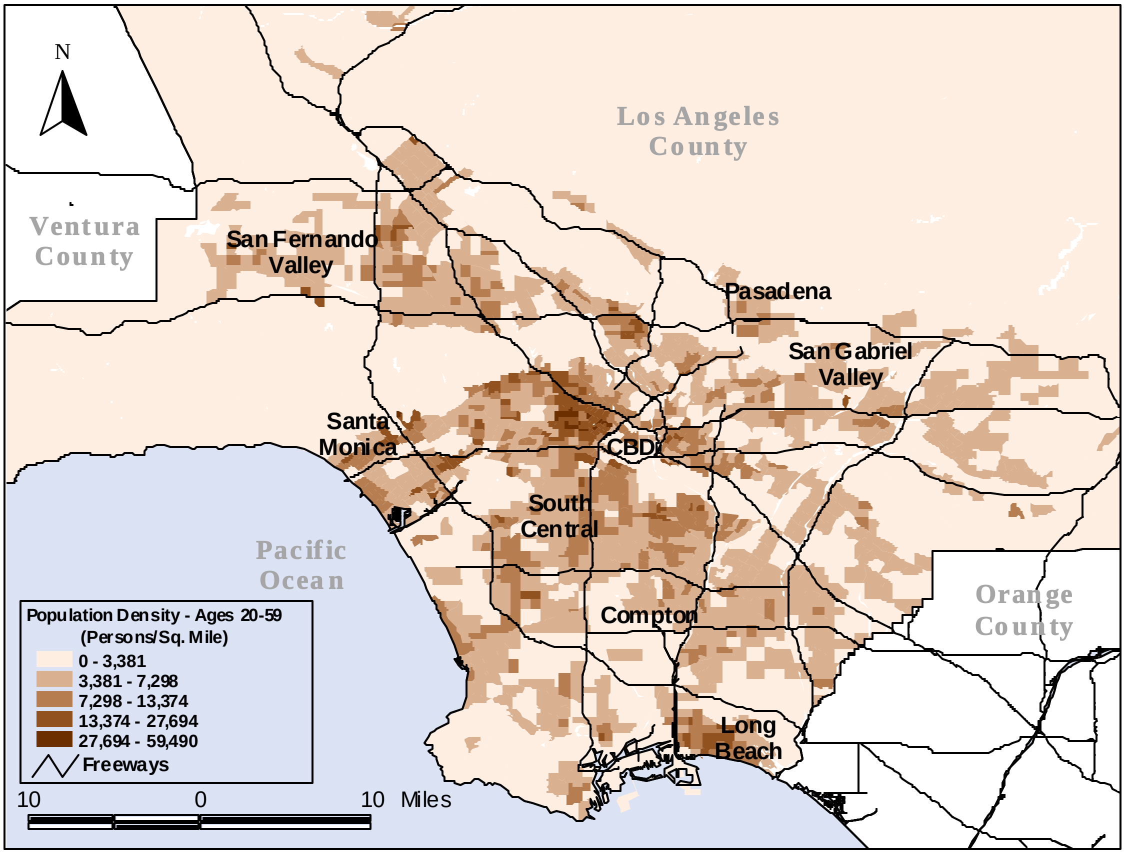
Notes on OLS estimates:

1. OLS coefficients for demographic variables are generally consistent with the results for the 2SLS models.
2. Some of the differences in the locational variables (South L.A., Urbanized L.A.) are possibly due to correlations with the variable measuring households without cars.
3. The job access variables are less statistically significant in the OLS models than in the 2SLS models.
4. In accordance with expectations, three out of four of the transportation access coefficients from the OLS models are larger than the 2SLS estimates.

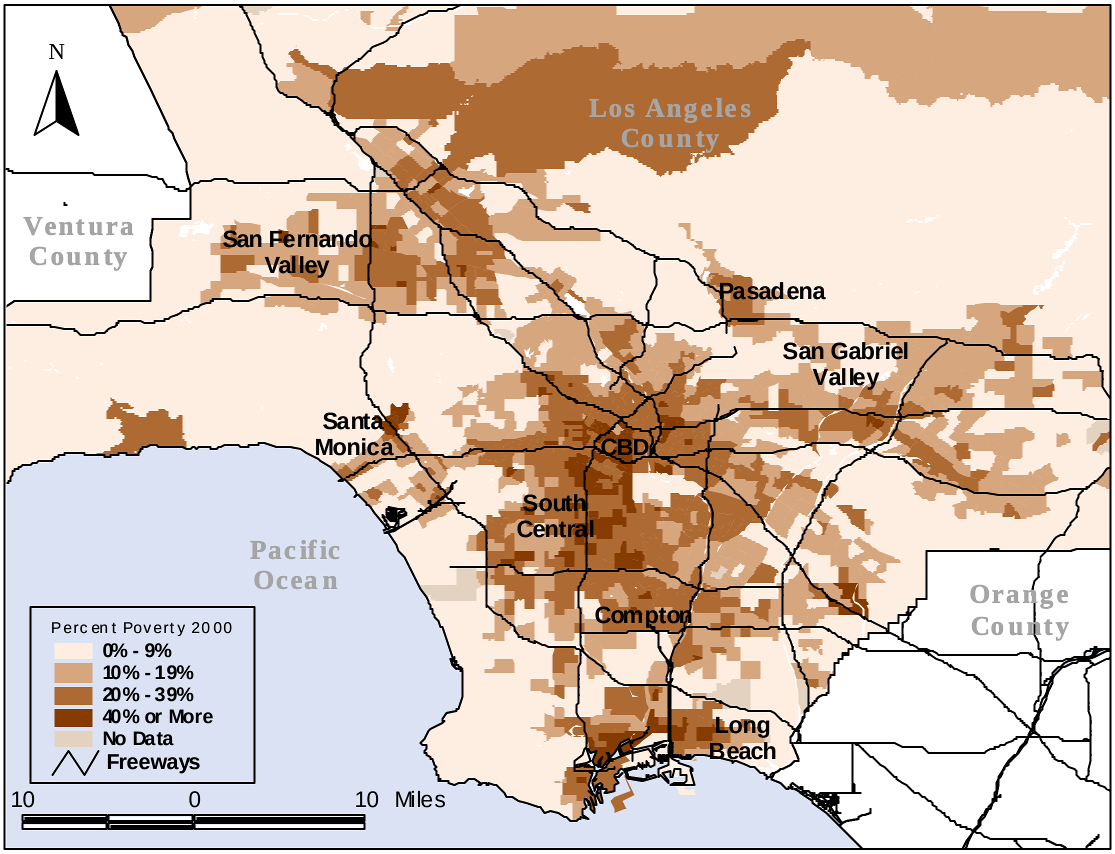
Map 1: Job Density



Map 2: Working-Age Population Density



Map 3: Neighborhood Poverty Rates



Map 4: Percentage of Households Without Cars

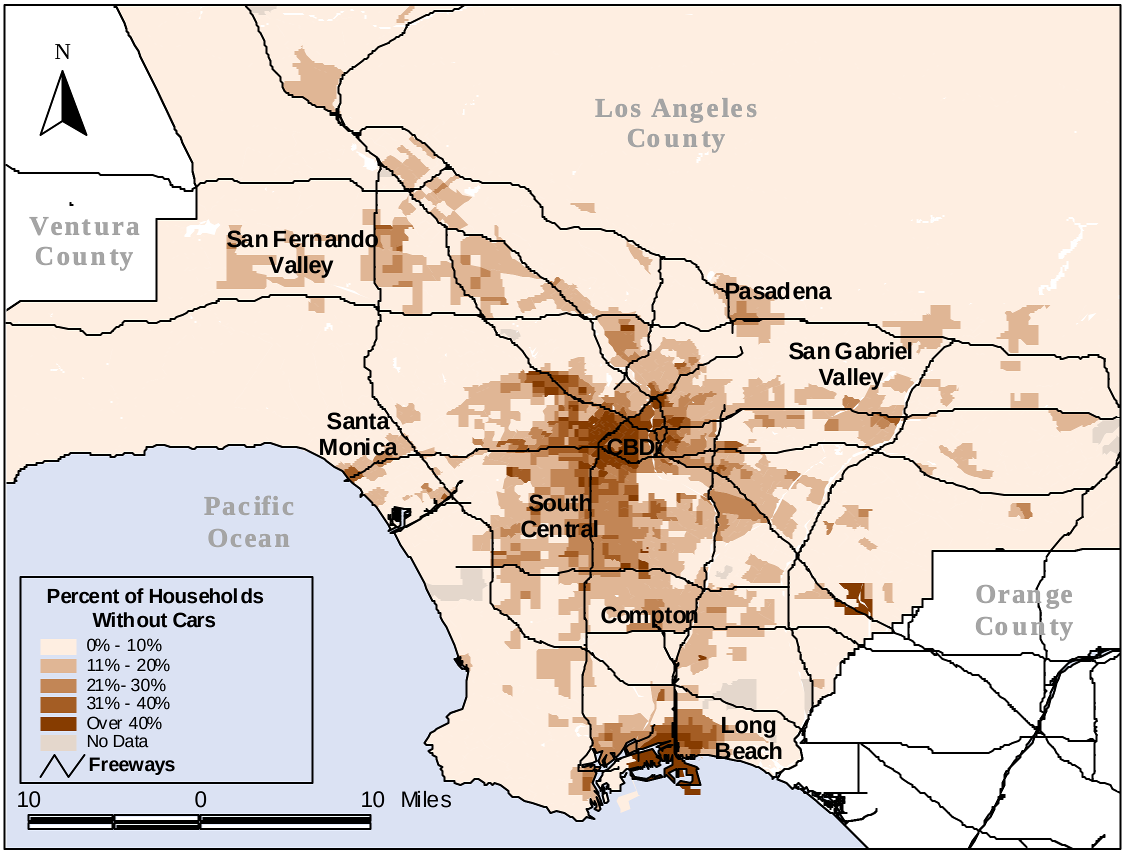


Table 1: Tract characteristics by neighborhood type

	Neighborhood Poverty Rate			
	0-9%	**10-19%**	**20-39%**	**40+%**
Neighborhood Size				
Tracts	676	570	656	139
Households	1,059k	978k	909k	152k
Employment Ratio				
Male	69.7%	63.5%	57.0%	49.9%
Female	55.3%	50.7%	41.9%	33.1%
Unemployment Rate				
Male	4.9%	7.6%	10.6%	15.6%
Female	4.9%	8.0%	13.3%	20.0%
Job Access				
Neighborhood Jobs Per Person	9.14	0.87	0.78	38.25
3-Mile Job-Access Index	1.02	1.28	1.68	2.45
Transportation				
Households w/o Cars	4%	10%	21%	38%
Non-car Commute	9%	12%	21%	39%

Table 2: Correlation between variables.

	Employment Ratio		**Unemployment Rate**	
	Male	Female	Male	Female
Job Access				
Neighborhood Jobs	0.12	-0.10	-0.05	-0.01
3-mile Index	-0.24	-0.25	0.20	0.24
Transportation				
Households w/o Cars	-0.50	-0.61	0.45	0.57
Non-car Commute	-0.37	-0.46	0.37	0.45

Table 3. Descriptions and Means of Variables.

Variable Description	Mean	Standard Deviation
Percent of female population with less than a high school degree	0.329	0.226
Percent of male population with less than a high school degree	0.321	0.231
Percent of female population with at least a bachelor's degree	0.215	0.170
Percent of male population with at least a bachelor's degree	0.250	0.208
Percent of population between ages 16 and 21	0.116	0.064
Percent of population over age 65	0.130	0.062
Percent of population reporting race as Asian or Pacific Islander	0.128	0.146
Percent of population reporting race as African American	0.094	0.156
Percent of population reporting race as Latino	0.434	0.296
Percent of population with limited English proficiency	0.159	0.127
Percent of households headed by women	0.209	0.097
Indication of location in Southern Los Angeles County	0.938	0.242
Indication of location in urbanized Los Angeles County	0.961	0.193
Job Access Measure	1.403	1.080
Instrumental Variable -- percent of population with no household car	0.129	0.090

Table 4. 2SLS Estimated Model Coefficients.

	Male		Female	
	Employment Ratio	**Unemployment Rate**	**Employment Ratio**	**Unemployment Rate**
Intercept	0.830 ****	0.044 ****	0.695 ****	0.035 ***
High School	-0.328 ****	0.107 ****	-0.367 ****	0.172 ****
Bachelor's Degree	0.100 ****	-0.045 ****	0.030	0.014
Percent Age 16-21	-0.487 ****	0.259 ****	-0.344 ****	0.166 ****
Percent Age 65+	-0.550 ****	0.009	-0.716 ****	-0.004
Asian/Pacific Islander	-0.150 ****	-0.006	-0.011	-0.054 ****
African American	-0.144 ****	0.062 ****	-0.058 ****	0.007
Latino	0.035 *	-0.053 ****	0.034 **	-0.044 ****
English Proficiency	0.238 ****	-0.068 **	-0.119 ****	0.009
Female Headed Households			0.034	0.137 ****
South L.A. County	-0.007	-0.005	0.015 *	-0.023 ****
Urbanized L.A. County	0.021 *	-0.001	0.025 **	-0.016 *
Spatial Job Accessibility	0.002	0.005 ****	0.009 ****	0.004 *
Households w/ No Car (IV)	-0.257 ****	0.095 ****	-0.096 ****	0.060 **
Adjusted R^2	0.641	0.424	0.731	0.513

**** $p<.0001$ *** $p<.001$ ** $p<.01$ * $p<.05$

Table 5. Means of Variables by Neighborhood Type.

Variable Name	Means	
	Very Poor	Affluent
High School (female)	62%	12%
High School (male)	62%	11%
Bachelor's Degree (female)	7%	36%
Bachelor's Degree (male)	8%	43%
Percent Age 16-21	19%	9%
Percent Age 65+	8%	16%
Asian/Pacific Islander	7%	16%
African American	16%	5%
Latino	68%	19%
English Proficiency	32%	5%
Female Headed Households	32%	13%
South L.A. County	0.99	0.89
Urbanized L.A. County	1.00	0.92
Spatial Job Accessibility	2.45	1.02
Households w/no Car (first IV)	38%	7%
Households w/no Car (2nd IV)	25%	8%

Table 6. Model Decomposition Results.

		Employment Ratio		Unemployment	
	Predicted Differences	Males	Females	Males	Females
Model 1	**Total**	-14%	-17%	7%	11%
	Education	-17%	-18%	6%	7%
	Race	0%	0%	-1%	-1%
	Experience/Lifecycle	7%	1%	-1%	0%
	Three-Mile Index	0% (NS)	2%	0%	0% (NS)
	Percent No Car (Observed)	-5%	-4%	3%	3%
	Others	0% (NS)	2%	0% (NS)	1%
Model 2	**Total**	-17%	-20%	8%	13%
	Education	-20%	-19%	7%	8%
	Race	1%	1%	-2%	-2%
	Experience/Lifecycle	6%	0%	1%	5%
	Three-Mile Index	0% (NS)	1%	1%	1%
	Percent No Car (IV)	-5%	-3%	2%	2%
	Others	0%	1%	0% (NS)	2%
Model 3	**Total**	-17%	-18%	8%	12%
	Education	-19%	-19%	7%	8%
	Race	2%	1%	-2%	-2%
	Experience/Lifecycle	4%	-1%	1%	2%
	Three-Mile Index	0%	1%	1%	1%
	Percent No Car (IV)	-2%	-1%	1%	1%
	Others	0%	1%	0%	2%

Notes:

[i] There are two other place-space factors. The first is weak informational networks. Residential segregation diminishes informal interactions with individuals, organizations, and employers outside minority neighborhoods. Weak external linkages create an additional barrier to economic opportunities. Second, employers are reluctant to hire people from inner-city neighborhoods. Firms often avoid recruiting in these areas, and applicants are at times stigmatized by stereotypes ascribed to their neighborhoods.

[ii] Labor-market studies find that adult joblessness is associated with low job access, but the relationship may due to the locational choice of those with weak labor market attachment (Holzer 1991; Stoll, Holzer, and Ihlanfeld 2000). Studies showing an adverse impact on youth employment are less likely to be biased by this reverse causality. Additional evidence comes evaluations of Chicago's Gautreaux program, which moved inner-city black families into suburbs during the 1970s and 1980s, which produced some positive outcomes (Rubinowitz and Rosenbaum 2000). Early evaluations of HUD's Moving to Opportunities demonstration program indicate that the impact of relocation on employment appears to be minimal, at least for the short run (Shroder 2002).

[iii] The exact figure varies slightly based on the family composition. For further information see www.census.gov/hhes/poverty/threshld/thresh99.html

[iv] We assume that census tracts can be considered neighborhoods. Tracts are geographic units defined by the Census Bureau as "relatively homogenous areas with respect to population characteristics, economic status, and living conditions." Census tracts contain about 4,000 – 5,000 people and while they do not exactly replicate neighborhood

boundaries, they are a reasonable approximation (Coulton, et al. 2001; Small and Newman 2001; Kasarda 1993).

[v] Employment figures come from 2000 American Business Information data. These data tend to underestimate public sector employment. To adjust for this we have added public sector jobs from the 1990 Census Transportation Planning Package allocated to 2000 tracts. The population used to normalize this figure is the prime-working-age population (adults aged 21 to 64).

[vi] There are other factors that influences automobile ownership, but many of these factors are not exogenous to the system of equations.

[vii] Weighted least squares is appropriate to correct for non-constant variance associated with different neighborhood sizes. For employment ratio models we weighted by the square root of the population aged 16 and older, by sex according to whether the model was for men or women. For unemployment models, we weighted by the square root of the total labor force, again by sex according to the model.

[viii] Since the 2000 census introduced more complex categories for race and ethnicity, we constructed these categories using an 'inclusive' count of races. Specifically, African Americans includes people who identified themselves as Black regardless of Hispanic Origin. Also, persons who indicated they were White and Black in the 2000 Census are classified as African American. Latinos include Whites of Hispanic origin and Others of Hispanic origin. Asian/Pacific Islanders include Asians and Native Hawaiians and Other Pacific Islanders, regardless of Hispanic Origin. Also, multi-race individuals who indicated they were Asian and Native Hawaiians or Other Pacific Islander in the 2000

Census are classified as Asian/Pacific Islanders. Non-Hispanic Whites include Whites that did not indicate Hispanic origin.

[ix] In this case, the model predicts an unemployment rate of 14% for very poor neighborhoods and only 6% in affluent neighborhoods.