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Where Youth Live: Economic Effects of Urban Space on Employment Prospects

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Summary. This paper synthesises a series of empirical analyses investigating the role of urban space in affecting minority employment outcomes. It broadens the focus beyond transport and the 'friction of space' and expands the data available for spatial research. The empirical analyses share a common framework linking 'access' to youth labour market performance. The first set of results is based on aggregate data relating access to employment outcomes for black youth at the metropolitan level. Access is broadly defined to include traditional measures of geographical distance, as well as measures of social isolation or social access. Metropolitan areas in which the black poor are more spatially isolated are also found to have higher black youth unemployment rates. The second body of evidence relies on the same type of metropolitan measures, combined with individual data on youth living with at least one parent. When individual and family characteristics are controlled for, and white and Hispanic youth are also considered, metropolitan measures of social access exert distinguishable effects upon youth employment—youth living in urban areas in which they have less residential contact with whites or the non-poor are less likely to be employed. The final piece of analysis links the individual records of such youth to tract-level measures of access, both social (neighbourhood composition variables) and geographical (job-access measures). This is accomplished through the creation of a unique data set at the Bureau of the Census. Again, after controlling for individual and family characteristics, the residential conditions of youth affect their employment. *Ceteris paribus*, youth living in census tracts with fewer employed adults, with fewer whites, and which are further from jobs are less likely to be employed. Results suggest that the overall effects of space on employment outcomes are substantial, explaining 10–40 per cent of the observed racial differences in employment in four urban areas examined. Of this 'spatial' effect, the bulk arises from social/informational measures; job access appears to play a much smaller role. However, when measured more precisely, at the census-tract level, job access does have a significant effect on youth employment. This effect is less important than other spatial influences. Spatial influences are less important in explaining outcomes than are differences in human capital.

1. Introduction

The linkage between urban space and minority employment has been a subject of intense study and controversy for the past three decades. During this period, there have been massive relocations of jobs within and between metropolitan areas, substantial in-

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creases in spatial concentrations of demographic groups (especially the urban poor and minority households) and major changes in transport systems.

Despite the importance of the topic and its obvious policy implications, there is yet no consensus on the effects of spatial residential patterns on employment outcomes for minority households (see Jencks and Mayers, 1990; and Kain, 1992, for reviews). The uncertain conclusions of empirical studies and the associated statistical evidence arise from ambiguity about the nature of 'spatial influences' themselves as well as from limitations in data availability and statistical technique.

This paper summarises a series of empirical analyses addressing the linkage between urban space and minority youth employment. The empirical analyses are based on a common framework linking 'access' to labour market success. The perspective is broader than the traditional economic concept of transport costs and the 'friction of space'. The empirical analyses we summarise are based upon increasingly more precise measures of the relevant concepts, which are obtained when aggregate measures of outcomes are replaced by individual outcomes and when single measures of spatial access at the metropolitan level are replaced by multiple measures of spatial interaction at the neighbourhood level. The first body of evidence presented is based on aggregate information relating access to employment outcomes at the metropolitan level. The second set of results is based upon micro data on individuals and their employment outcomes linked to metropolitan-level information on access. The third body of evidence is based upon micro data on individuals combined with neighbourhood-level information on several dimensions of access. The results suggest that the effects of 'access' on 'outcomes' are substantial, but with improved measurements, they are also seen to be more complex.

Finally, the results provide credible evidence that the linkage has a causal mechanism, not merely one of association. The latter finding gives more importance to the policy conclusions of the work.

2. Space and Employment Access

The original work purporting to demonstrate the linkage between residential location and employment outcomes was based purely upon the costs of commuting between residences and work sites. In essence, the theoretical argument was that more expensive circuitous commutes would increase the reservation wages of spatially isolated workers, causing them to forego employment. As a result, the employment probabilities of minority workers who were forced by discrimination in the housing market to live in spatially isolated neighbourhoods would be lower than the probabilities of otherwise identical workers not similarly constrained (Kain, 1968).

Much of the original empirical work was characterised by this precise but narrow interpretation of the accessibility of residences to workplaces. Early studies measured access by airline distance (Kain, 1968; Offner and Saks, 1971; Leonard, 1987); others relied upon commute time (Ihlanfeldt and Sjoquist, 1990; Ihlanfeldt, 1993). Still others used employment centrality (Harrison, 1972). All of these measures focus strictly on the geographical distance between the individual and job location.

However, several different 'frictions of space' are involved in the job-matching process, and traversing physical distance is only one of them. Learning of job opportunities through residence-based social networks—indeed, even recognising that work is a valuable activity by observing neighbourhood 'role models'—are emphasised by non-economists as concomitants of the concentration of minorities and poverty in central-city areas (Wilson, 1987). This broader perspective focuses on the social isolation or social access of disadvantaged populations. It emphasises, for example, the possibility that youth lack the residence-based networks so helpful for obtaining

employment (Ihlanfeldt, 1997). Although clearly grounded in spatial relationships, this concept of social access is distinct from transport access, and measures of social access may not be correlated highly with measures of physical distance or transport costs.

3. Metropolitan Measures of Access and Employment Outcomes

The social isolation of disadvantaged households suggests an alternative approach to measuring access, one which focuses on the social context of minorities and the poor. Consider, for example, an index of the residential segregation of households. The exposure index, one of several measures of segregation commonly used by demographers and sociologists (see, for example, White, 1986; and Miller and Quigley, 1990), is a direct measure of the residential contact between and among groups. Specifically, the exposure to a given demographic group is the probability that a randomly selected person residing in the same neighbourhood (say, census tract) is a member of the given group. The index measures directly the extent to which members of any group are isolated from or exposed to contact with members of other groups.[1] We use two versions of this index, calculated by Massey and Eggers (1989) at the metropolitan level for black individuals. First, the general exposure-to-poverty index measures the probability that a black poor person comes into contact with poor people (and is thereby exposed to networks containing poor individuals). Secondly, the within-race index focuses more narrowly on contact between black poor and other blacks.

Our premise is that black youth unemployment is greater when access to jobs is lower, with access defined as spatial isolation measured at the level of the metropolitan area. We test this using aggregate data for large MSAs, incorporating both traditional measures of physical access, and the exposure index as a measure of social or informational access. We regress black youth unemployment rates on each of these measures, and several other MSA characteristics which are expected to affect black youth unemployment (white youth unemployment, percentage of employment in manufacturing, percentage of the population which is black). Models 1 and 2 in Table 1 present results for logarithmic regressions for all black youth, using the general exposure index and the within-race index, respectively.

Employment concentration is expected to have a negative coefficient, while travel time and poverty exposure are expected to have positive coefficients. After controlling for local economic conditions and population composition, the measures of exposure have the expected signs and are statistically significant. Black youth unemployment rates are lower in MSAs where the black poor are less isolated from the non-poor population. Other measures of access are insignificant.

Other implications of this notion of access can be examined with these data by distinguishing the central city from the suburbs. A larger concentration of employment in central cities increases physical access for youth residing in central cities, but not for youth living in the suburbs. Long commute times reflect more decentralised employment, which decreases access for youth residing in the central city but not for youth residing in the suburbs. And while the measures of exposure are metropolitan-wide, in fact high levels of poverty exposure are indicative of isolated central-city blacks who are much more socially isolated than non-central-city blacks.

Regressions which consider the unemployment of central-city black youth separately from the unemployment of suburban youth are reported in columns 3–6. The coefficients for the exposure index are consistent with this broader concept of access. Both measures of exposure significantly increase the unemployment rates for black youth who live in central cities, but do not exert a significant impact on the employment prospects for black youth who live in the suburbs.

These findings are limited by the level of aggregation of the analysis. Unemployment

Table 1. Regression of unemployment rate for black youth for 47 large MSAs: all variables in logarithms (*t*-ratios in parentheses)

	All black youth		Central-city black youth		Suburban black youth	
Coefficient	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Access						
Employment concentration	−0.05	−0.07	−0.09	−0.11	−0.16	−0.18
(CC jobs/MSA jobs)	(1.05)	(1.30)	(1.39)	(1.65)	(1.94)	(2.06)
Exposure index for black	0.25	—	0.23	—	−0.03	—
poverty	(2.81)	—	(2.06)	—	(0.17)	—
Exposure index for poverty	—	0.37	—	0.38	—	0.11
within race	—	(2.71)	—	(2.28)	—	(0.50)
Average one-way commute	0.25	0.26	0.32	0.35	0.20	0.23
time (minutes)	(1.42)	(1.50)	(1.49)	(1.61)	(0.71)	(0.32)
Other						
MSA percentage black	0.08	0.10	0.04	0.07	0.20	0.19
	(2.61)	(4.18)	(1.19)	(2.21)	(4.20)	(4.67)
MSA percentage manufacturing	0.10	0.10	0.10	0.09	−0.02	−0.02
	(1.92)	(1.87)	(1.50)	(1.45)	(0.19)	(0.28)
Unemployment rate for	0.95	0.94	0.97	0.96	1.13	1.12
white youth	(10.94)	(8.90)	(8.95)	(8.90)	(8.03)	(7.93)
Constant	−0.05	−0.09	−0.24	−0.25	−0.94	−0.83
R^2	0.82	0.82	0.74	0.75	0.72	0.72

Source: See O'Regan and Quigley, 1991, for definitions of variables and sources of data.

rates for black youth are higher in MSAs with spatially isolated black populations. This could, of course, arise because other population characteristics are responsible for both outcomes or because spatial isolation is itself a product of poor employment outcomes.

4. Metropolitan Measures of Access and Individual Measures of Employment Outcomes

To control for population characteristics at the individual level, we created a micro-data set containing a sample of youth, their families and their employment outcomes. These data were extracted from the 1990 Census Public Use Micro Sample for large MSAs.[2] We focus on the employment of youth residing with parents. Thus, household residential location is not determined by employment outcomes of youth. To consider employment outcomes for white, black and Hispanic youth, we use the exposure index at the metropolitan level for each of these groups: for each MSA we have measures of white, black and Hispanic exposure to two groups, whites and non-poor.

The effect of exposure on youth employment is estimated in two stages. In the first stage, we relate youth employment probabilities, p_i, to a vector of individual and family characteristics, X. The model also includes race and ethnicity-specific effects which vary by MSA:

$$\log\,[p_i/(1\text{-}p_i)] = \alpha X_i + \sum_j \beta_{1j}\, w_i\, M_j + \sum_j \beta_{2j}\, b_i\, M_j + \sum_j \beta_{3j}\, h_i\, M_j \qquad (1)$$

M_j is a set of MSA dummy variables, with a value of one if individual i resides in metropolitan area j and zero otherwise. This vector is interacted with a series of race/ethnicity dummy variables: w_i for whites, b_i for blacks, and h_i for Hispanics. The set of parameters β_{rm} (for r = 1, 2, 3 races and m = 1, 2, … 73 MSAs) represents the shift in the logit of employment probability depending on the race of the individual and the metropolitan area in which that individual resides.

The key finding from estimating equation (1) is that, after controlling for individual characteristics, the employment probabilities of 'otherwise identical' white, black and Hispanic youth vary significantly across metropolitan areas. (Appendix 1 lists the individual and household characteristics, X, which are included in the estimation.)

The set of coefficients, β_{rm}, reflecting metropolitan differences, is highly significant in affecting individual outcomes. In the second stage, we analyse the determinants of these metropolitan differences:

$$\beta_{rm} = \gamma Z_m + \delta E_{rm} \qquad (2)$$

Z_m is a vector of MSA characteristics expected to influence local labour market outcomes, and E_{rm} is the race/ethnicity-specific exposure index, and β_{rm} is the set of coefficients estimated in equation (1). The results are presented in Table 2.

To control for local labour market conditions, again we include measures of local employment conditions, the adult white unemployment rate and the percentage of employment in business services. These factors are highly significant in each model estimated—particularly the variable measuring adult unemployment, which summarises aggregate economic conditions in the metropolitan area.[3] We also include race-specific intercepts to capture systematic differences across groups. Finally, we include the exposure indices. Model 1 reports the results using the appropriate access index based on each race/ethnicity group, but where the influence of access is constrained to be common across groups. Model 2 reports coefficients on the exposure index that are race-specific. For all groups, exposure to whites significantly increases youth employment probabilities. Similarly exposure to poverty significantly decreases youth employment probabilities.

Table 2. Inter-metropolitan differences in youth employment probabilities for 73 large MSAs (*t*-ratios in parentheses)

	Exposure to whites		Exposure to poor	
Coefficient	Model 1	Model 2	Model 1	Model 2
Unemployment rate (percentage)	−0.128 (7.79)	−0.129 (7.98)	−0.103 (5.62)	−0.092 (4.96)
Business services employment (percentage)	0.012 (0.62)	0.014 (0.70)	−0.075 (3.69)	−0.076 (3.82)
Intercept for:				
Whites	−8.490 (46.38)	−8.523 (35.71)	−7.095 (48.99)	−7.006 (46.35)
Blacks	−8.947 (57.94)	−9.014 (55.26)	−7.655 (47.82)	−7.866 (45.45)
Hispanics	−8.543 (50.02)	−8.463 (46.60)	−7.213 (45.94)	−7.127 (42.00)
Exposure to whites	1.105 (10.15)			
Exposure to poor			−2.956 (8.34)	
Exposure to whites/poor by:				
Whites		1.140 (5.72)		−4.526 (5.28)
Blacks	1.279 (6.73)		−2.181 (4.93)	
Hispanics	0.949 (5.69)		−3.783 (6.66)	
R^2	0.820	0.821	0.799	0.808

Source: See O'Regan and Quigley, 1996a, for definitions of variables, sources of data and computational details.

5. Neighbourhood Measures of Access and Micro Measures of Employment Outcomes

A comparison of the results in Tables 1 and 2 suggests that the link between spatial isolation and employment outcomes does not arise because measurable household and individual characteristics are omitted. On the contrary, it seems clear that the spatial configuration which isolates minority households within metropolitan areas 'matters' in explaining employment outcomes for minority youth. However, measurement of spatial and social isolation at the metropolitan level is rather blunt indeed. Much of the theory underlying these spatial effects is presumed to operate at the level of the block, neighourhood, or census tract.

To conduct the analysis at the level of the neighbourhood, where social interaction takes place, where social isolation is felt and where transport access is well defined, we created a unique data set at the Bureau of the Census. This data set contains all records of non-Hispanic white, black and Hispanic youth (aged 16–20) residing with at least one parent in the four largest metropolitan areas in the state of New Jersey (Newark, Bergen-Passaic, Middlesex and Monmouth). The data set consists of all records on youth and their families from the 1990 Census—more than 28 000 observations. The most important aspect of the data set is that each record

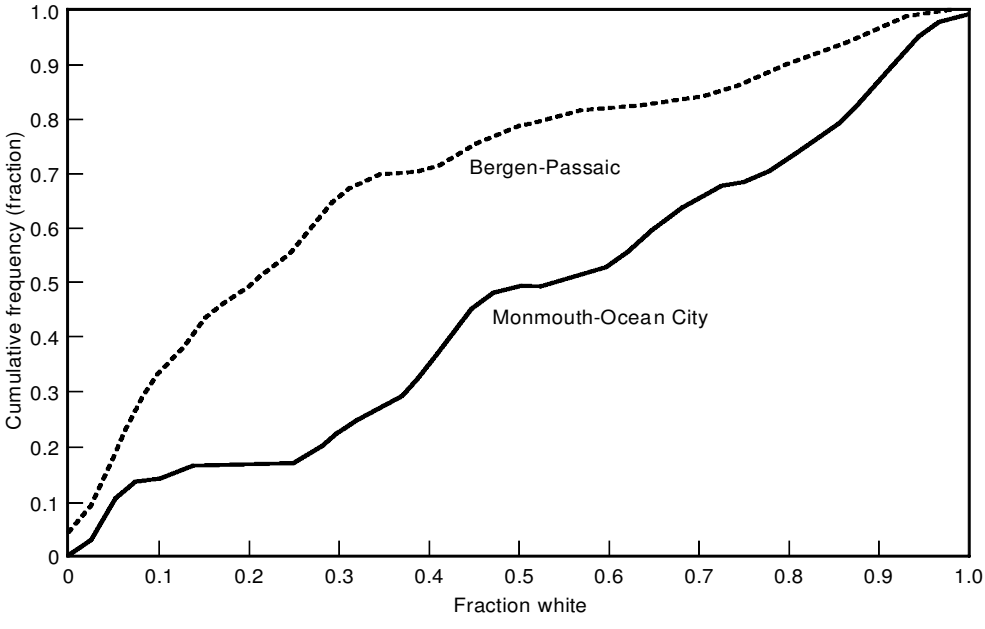

Figure 1. Black exposure to whites for Bergen–Passaic and Monmouth–Ocean City MSAs.

is coded by census tract, which establishes a link between data on individual youth and their neighbourhoods (census tracts).

These data are sufficient to provide a direct test of the importance of neighbourhood and concentration effects upon youth employment outcomes. The social isolation resulting from the concentration of minorities and the poor in central-city areas manifests itself in neighbourhoods (i.e. census tracts) through disproportionate representation of the poor, the unemployed, the welfare-dependent, etc. If concentration matters, measures of neighbourhood composition represent this.

Clearly, while contributing to metropolitan aggregates, census-tract measures of geographical isolation vary substantially within metropolitan areas. For example, Figure 1 illustrates the intra-metropolitan variation in spatial isolation of minority households. For two metropolitan areas in New Jersey, Bergen–Passaic and Monmouth (both MSAs are data points in the inter-metropolitan analyses reported in Table 2), the figure reports the cumulative frequency distribution of the exposure index computed at the level of the census tract. The figure also reports, for each metropolitan area, the exposure index computed at the metropolitan level. (This is the measure used in the analysis reported in Tables 1 and 2.) For Bergen–Passaic whole, for example, the value of the metropolitan exposure index is about 0.3. That is, the average black lives in a census tract with a population which is 30 per cent white. However, about one third of the black population lives in census tracts which are less than 5 per cent white, while 10 per cent of the black population lives in census tracts which are more than 85 per cent white. Clearly, the social isolation of the 'typical' black in the MSA conveys only limited information. There is a great deal of variation in the exposure to whites of black households within these two metropolitan areas. This is also the case for the other two MSAs, Newark and Middlesex. Similarly, there is a great deal of variation in the exposure to whites of the Hispanic population in all four MSAs.

In addition, we compute a measure of transport and access to metropolitan work sites for each census tract.[4] Transport access is measured by an index of employment

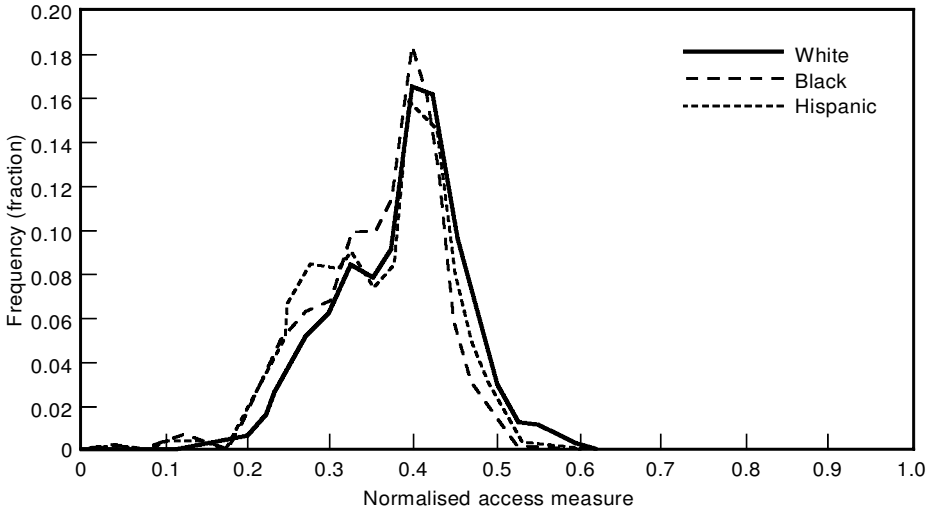

Figure 2. Distribution of the normalised access measure for Bergen–Passaic tracts.

'potential' derived from the assumption that work-trip destinations are generated by a Poisson process (see Appendix 2). Figures 2 and 3 present frequency distributions of the transport access experienced in two of these metropolitan areas by race. The differences in access are much less pronounced, on average, by race, but there are substantial differences in the access to jobs available to individuals of the same race and to those of different races.

The individual data are used to relate youth employment probabilities, p_i, to individual and family characteristics (analogous to the models presented in Table 2) where we now control directly for tract characteristics:

$$\log [p_i/(1-p_i)] = \alpha X_i + \beta A_i + \gamma N_i, \qquad (3)$$

where, X_i is a vector of relevant individual and family characteristics; A_i is a measure of employment access; and N_i is a vector of neighbourhood characteristics. Individual and family characteristics are similar to those used previously and are listed in Appendix 1.

Preliminary analysis with a larger set of neighbourhood variables established that one measure of racial composition (percentage white) and four measures of tract poverty or employment levels (percentage: poor; on public assistance; unemployed; and adults working) are consistently important in affecting employment outcomes. Since the appropriate functional form for these variables is not known *a priori*, we estimated a series of models to test for non-linearities. There is some evidence that the relationship is complicated, but no simple non-linear representation is superior to the inclusion of continuous measures of neighbourhood attributes. We report results using continuous measures.

The model is estimated for youth in all four metropolitan areas, with specific intercepts for each. MSA-specific coefficients are also estimated for all tract variables. Table 3 reports a variety of models which include the job-access measure and various neighbourhood variables. The table includes results for the estimation of employment probabilities, and summaries of the results for the estimation of the probability of idleness (i.e. not working and not in school).

Model 1 (employment) reports estimates of youth employment probabilities as a function of neighbourhood access measures, individual and household characteristics. (Again, the measures used in the regression are reported in Appendix 1.) Access has a significantly positive effect on youth employment in three of the four MSAs; Monmouth is the exception.

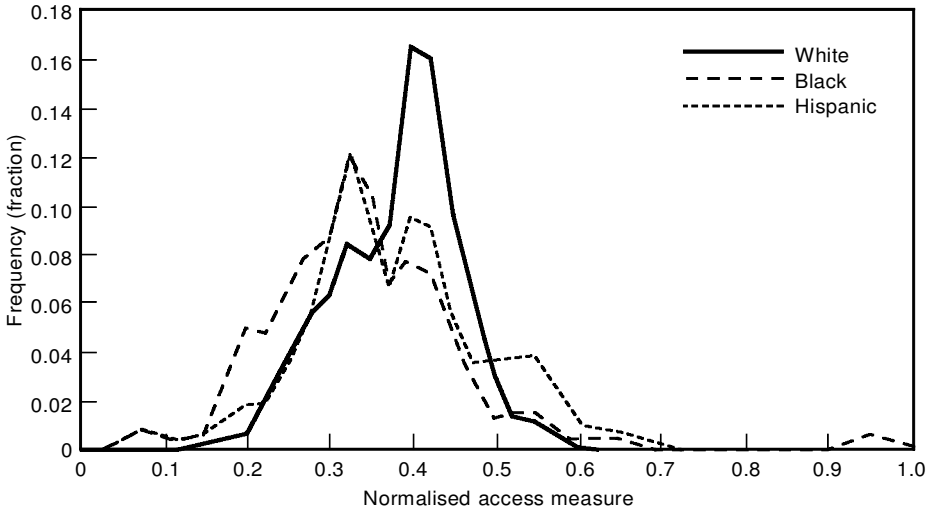

Figure 3. Distribution of the normalised access measure for Monmouth–Ocean City tracts.

Models 2–6 (employment) include job access, but introduce other neighbourhood characteristics (percentage: white; on public assistance; and adults not at work). The inclusion of these neighbourhood variables has somewhat different effects across urban areas. For Newark, transport access is no longer significant in any of the models. For Monmouth, once any neighbourhood variables are included, the measure of job access is highly significant. For Bergen–Passaic, the coefficient on job access and its significance are unaffected by neighbourhood variables, while their inclusion causes mixed results for Middlesex: in some cases, job access remains significant, but in instances where the percentage of adults not at work is included in the model, job access becomes insignificant.

While neighbourhood variables clearly affect youth employment probabilities, the effects are different across MSAs. However, the variable measuring the percentage of adults not at work—perhaps the best measure of social access—is consistently significant in each model for each MSA.[5]

Table 3 also reports similar results using youth idleness as the dependent variable. Not surprisingly, factors which affect school status play a larger role in predicting idleness. For example, job access decreases in significance, while neighbourhood racial and poverty characteristics have a consistently significant effect. These characteristics may more directly affect school status, while the presence of working adults is more relevant for employment status.

6. Exogeneity in a Model of Neighbourhood Influences

Framing the model in terms of individuals and their neighbourhoods raises the question of whether neighbourhoods are exogenous to employment outcomes. (see Corcoran *et al.*, 1992; Evans *et al.*, 1992; and Plotnick and Hoffman, 1995). It is worth noting that the measure of job access employed in the statistical models is not computed from the observed commuting patterns of teenagers. Nor is it computed with reference to the location of jobs which might be 'suitable' for teenagers (Ihlanfeldt and Sjoquist, 1990). Rather, it is calculated from observations on the work-trip patterns of all resident workers—adults and teenagers—within the entire urban area.

Perhaps a more serious source of concern is the choice of neighbourhood by household. By selecting youth living with at least one parent, we can presume that the residential

Table 3. Neighbourhood differences in employment outcomes in four New Jersey MSAs (28 191 observations) (*t*-ratios in parentheses)

	Model					
Coefficient	1	2	3	4	5	6
A. Employment						
Access						
Bergen–Passaic	0.066	0.068	0.069	0.070	0.069	0.071
	(3.45)	(3.49)	(3.52)	(3.63)	(3.51)	(3.65)
Middlesex	0.026	0.028	0.023	0.017	0.028	0.021
	(2.17)	(2.34)	(1.99)	(1.39)	(2.38)	(1.74)
Monmouth	0.006	0.007	0.006	0.007	0.008	0.008
	(1.86)	(2.25)	(1.96)	(2.07)	(2.38)	(2.35)
Newark	0.004	0.002	0.001	0.001	0.001	0.001
	(3.37)	(1.88)	(0.45)	(0.99)	(0.51)	(0.71)
Percentage white						
Bergen–Passaic			0.156		0.229	0.027
			(1.17)		(1.06)	(0.19)
Middlesex			0.819		0.893	0.731
			(3.86)		(2.96)	(3.38)
Monmouth			−0.210		−0.691	−0.268
			(0.94)		(2.30)	(1.19)
Newark			0.592		0.203	0.225
			(6.43)		(1.63)	(2.26)
Percentage public assistance						
Bergen–Passaic			−0.269		0.443	
			(0.42)		(0.42)	
Middlesex			−2.798		0.521	
			(2.48)		(0.32)	
Monmouth			−0.760		−2.785	
			(0.87)		(2.38)	
Newark			−0.753		−2.248	
			(7.62)		(4.58)	
Percentage adults not at work						
'Bergen–Passaic				−2.049		−2.140
				(3.58)		(3.60)
Middlesex				−1.536		−1.261
				(3.25)		(2.62)
Monmouth				−1.059		−1.115
				(2.99)		(3.14)
Newark				−3.579		−3.285
				(11.03)		(9.24)
Chi-squared	3 848	3 904	3 913	4 002	3 931	4 021
-2logL	35 233	35 177	35 168	35 079	35 150	35 060

B. Idleness						
Access						
Bergen–Passaic	−0.026	−0.011	−0.004	−0.026	−0.005	−0.010
	(3.58)	(0.27)	(0.10)	(0.66)	(0.11)	(0.25)
Middlesex	−0.003	−0.001	0.003	0.010	0.004	0.011
	(0.11)	(0.04)	(0.12)	(0.35)	(0.16)	(0.39)
Monmouth	0.001	0.002	0.002	0.000	0.001	0.001
	(0.14)	(0.25)	(0.26)	(0.03)	(0.21)	(0.21)
Newark	−0.007	−0.003	0.000	−0.002	0.000	−0.001
	(3.16)	(1.37)	(0.13)	(0.78)	(0.08)	(0.23)
Percentage white						
Bergen–Passaic		−0.690			−0.543	−0.676
		(3.25)			(1.61)	(2.98)
Middlesex		−0.855			−0.255	−0.651
		(2.42)			(0.41)	(1.77)
Monmouth		−0.811			−0.198	−0.752
		(2.31)			(0.38)	(2.14)
Newark		−0.986			−0.614	−0.808
		(6.23)			(3.13)	(4.71)
Percentage public assistance						
Bergen–Passaic			2.179		0.882	
			(2.34)		(0.58)	
Middlesex			4.114		4.033	
			(2.22)		(1.24)	
Monmouth			3.192		3.297	
			(2.37)		(1.65)	
Newark			3.077		2.007	
			(6.35)		(3.28)	
Percentage adults not at work						
Bergen–Passaic				0.955		0.329
				(0.96)		(0.30)
Middlesex				2.265		2.108
				(2.25)		(2.00)
Monmouth				0.909		0.908
				(1.36)		(1.33)
Newark				2.400		1.590
				(4.88)		(2.94)
Chi-squared	27 913	27 955	27 960	27 944	27 970	27 969
-2logL	11 167	11 126	11 121	11 137	11 110	11 111

Notes: Logit models include household-level variables reported in Appendix 1. Each model also includes separate intercepts for the different metropolitan areas.

Source: See O'Regan and Quigley, 1996b, for definitions of variables and sources of data.

choice is made by the parent. To the extent that factors affecting parents' employment prospects underlie this choice, and these are correlated with youths' prospects, we control for parents' employment status in the statistical model. However, to the extent that household choices about residential location are influenced by parents' perceptions about the effect of neighbourhood characteristics on youth employment and idleness, simultaneity remains an issue. And to the extent that omitted from our model are family or individual variables correlated with neighbourhood variables, the results may be misleading.

We adopt two approaches to analyse the exogeneity of neighbourhood; the first is informal, and the second relies upon a formal statistical test. The main source of potential endogeneity is households' choice of neighbourhood based on their concern about the effect of neighbourhood influences on youth employment and idleness. To the extent that this occurs, youth who have lived in a neighbourhood longer should be more strongly influenced by neighbourhood characteristics than are newer residents. To test for this difference in the relative size of the impacts, we stratified the sample into those youth who had moved in the last five years (movers) and those who had not (non-movers). In the stratified models of youth employment probabilities, coefficients on neighbourhood variables remained the same or declined for movers; they remained the same or increased for non-movers. In the stratified models of youth idleness, however, the coefficients on neighbourhood variables are higher for non-movers. Thus, at least for the analysis of youth employment, the statistical results are more consistent with contemporaneous spatial influences, rather than merely sorting over space.

The second test of endogeneity leads to similar conclusions. The most general models of employment and idleness include three of the four measures of neighbourhood characteristics. To test formally for endogeneity, we create instruments for each of these variables and include both sets of variables in the statistical model. This permits a test of the joint significance of the instruments. The hypothesis that the neighbourhood variables are jointly exogenous can be tested using likelihood ratios. (This is the standard Hausman test.)

As instruments, we use census-tract measures correlated with each of the four neighbourhood indicators but not themselves determinants of employment outcomes. Each of our measures uses information on household and neighbourhood characteristics to determine probabilistic measures of residence.[6] Table 4 reports the results of the Hausman test for the employment probabilities of Newark youth, for different age-groups. The tests are constructed separately for in-school and out-of-school youth and for all youth, for various age-groupings. The test is specified so that the null hypothesis is exogeneity. Significant chi-squared test statistics indicate the rejection of exogeneity, giving evidence of endogeneity.

In no case, in the analysis of out-of-school youth, can exogeneity be rejected. Similarly, when all youth are included in the sample, exogeneity is never rejected. However, when the sample is limited to in-school youth, there are some instances when exogeneity can be rejected. Again, this suggests that endogeneity might be an important issue when considering neighbourhood impacts on school outcomes.

7. Metropolitan Differences

The results of these endogeneity tests support the existence of a causal link between spatial factors and youth employment outcomes. Furthermore, when measured at the neighbourhood level, both social access (as measured by demographic characteristics) and transport access (as measured by the employment potential index) are generally statistically significant. The effect of these factors upon youth employment differs across metropolitan areas, however. To put these differences in context, Table 5 summarises descriptive data on the four metropolitan areas. These data provide some insight into

Table 4. Tests of exogeneity of neighbourhood influences upon employment outcomes for Newark teenagers (chi-squared statistics)

Age-group	In-school youth	Out-of-school youth	All youth
Neighbourhood influences (percentage white, access, percentage on public assistance)			
Ages 16–20	8.045	3.669	7.513
Ages 16–19	8.596	2.347	6.027
Ages 17–20	9.397	4.014	7.343
Ages 17–19	10.146	3.908	5.395
Neighbourhood influences (percentage white, access, percentage adults not at work)			
Ages 16–20	4.536	3.895	5.114
Ages 16–19	4.303	2.364	3.294
Ages 17–20	5.846	4.529	5.169
Ages 17–19	5.616	4.439	2.772

Note: The critical values of χ^2 with 3df are 7.810 and 11.300 respectively at the 0.05 and 0.01 levels of confidence.

potential explanations for inter-metropolitan variation.

Of the four metropolitan areas, Newark is the largest and the poorest. It has the largest minority and black population, the highest unemployment rate, the greatest concentration of central-city employment and the highest public transit use rate. Bergen–Passaic is the next-largest urban area. Its sizeable minority population is much more Hispanic, and its poverty and unemployment rates are more similar to Middlesex and Monmouth than to Newark. Middlesex is a relatively well-to-do community, with the lowest unemployment and poverty rates, and a median family income for blacks that is almost 40 per cent higher than in Newark. Monmouth is a community which also has less income differentiation across race than the large urban areas, but with a less wealthy white population. The median income for white families in Monmouth is only slightly higher than the median income for black families in Middlesex. (See the map in Appendix 3 for more geographical information.)

It is possible that these differences in the demographic profiles of these urban areas condition the empirical results. Individuals may, indeed, be affected differently by social and spatial access depending on their race or socioeconomic status.[7] Consider Middlesex, a metropolitan area in which job access is not consistently significant for youth employment. Given the higher socioeconomic profile of the community, perhaps spatial access is less of a constraint on youth employment. In fact, unlike each of the other MSAs, in Middlesex black youth reside in census tracts with slightly higher measures of job access than do white youth. Investigating such inter-group differences in larger metropolitan areas (with very large minority communities) would reveal whether the metropolitan differences reported in Table 3 arise from inter-metropolitan differences in the mix of demographic groups or from intra-metropolitan spatial factors.

These four metropolitan areas differ not only in their populations, but in the spatial distribution of these populations. Not surprisingly, neighbourhood composition variables are highly correlated with each other in each MSA. This high correlation probably contributes to the observed inter-metropolitan differences in neighbourhood effects—with such high levels of correlation, it is difficult to isolate the effects of a specific characteristic.

The correlations might also explain the apparent insignificance of job access in Newark. The correlations for a selection

Table 5. Descriptive information on four New Jersey metropolitan areas

Variable	Bergan–Passaic	Middlesex	Monmouth	Newark
A. General characteristics				
Population	1 220 490	965 834	968 304	1 780 291
Number of census tracts	252	253	227	445
Median family income (dollars)				
White	56 260	56 639	47 241	57 797
Black	35 395	45 828	34 388	32 864
Hispanic	32 575	38 778	38 376	30 812
Mean travel time to work (minutes)	24.1	25.6	26.5	25.7
White	24.7	26.2	27.5	26.0
Black	23.4	26.7	22.6	27.4
Hispanic	22.4	23.3	26.1	24.1
Access (index)				
White	0.366	0.346	0.409	0.218
Black	0.337	0.360	0.331	0.175
Hispanic	0.341	0.330	0.375	0.187
B. Percentages				
Population				
White	78.5	85.6	90.2	66.0
Black	8.6	7.2	6.1	23.8
Hispanic	11.9	7.3	3.7	10.2
Unemployment rate	5.5	4.5	5.7	6.9
White	4.4	3.7	5.0	4.0
Black	11.3	8.2	11.0	12.6
Hispanic	9.3	9.8	8.8	10.3
Poverty rate	6.2	4.3	5.5	9.0
Work in MSA	68.8	67.3	72.5	73.6
Work in central city	6.6	7.1	—	17.2
White	3.4	5.3	—	8.8
Black	17.0	14.6	—	28.8
Hispanic	16.6	19.4	—	32.6
Commute by public transit	9.4	6.4	5.1	11.1
White	7.7	5.4	5.0	6.0
Black	16.1	11.9	7.4	22.5
Hispanic	12.5	7.5	8.0	12.6

Table 6. Correlations of various demographic variables with access measure

Variable	Bergan–Passaic	Middlesex	Monmouth	Newark
Work in central city	−0.089	0.044	n.a.	−0.307
Percentage using public transit	−0.379	0.071	−0.283	−0.367
Average commute time	−0.290	−0.001	0.021	−0.205
Percentage white	0.224	−0.065	0.246	0.368
Percentage poor	−0.305	−0.066	−0.149	−0.514
Percentage on public assistance	−0.243	−0.066	−0.129	−0.477
Percentage unemployed	−0.165	−0.136	−0.161	−0.500
Percentage adults not at work	−0.217	−0.240	−0.030	−0.414

of tract-level characteristics and job access are presented in Table 6. Neighbourhood characteristics are more strongly correlated with job access in metropolitan areas with poorer populations. There is no correlation between tract characteristics and access in Middlesex, low correlations in Monmouth, slightly higher in Bergen–Passaic, and the highest in Newark. Regardless of the underlying forces which have led to this greater socioeconomic segregation from jobs, these forces affect the precision of the statistical model. When other neighbourhood characteristics are ignored, job access has a significant effect on youth employment in Newark. However, once neighbourhood characteristics are included, job access is insignificant. The former result could be dismissed as spurious correlation, the latter result as a multicollinearity problem.

8. Conclusion

As noted above, the high correlations among the census-tract variables measuring exposure and job access make it difficult to ascribe employment differences among youth to the influences of particular variables. Despite this, we can draw some rough quantitative conclusions.

Table 7 presents estimates of the employment rate differentials in the four metropolitan areas based on the results reported in Table 3 (specifically, Model 2). The estimated difference in employment rates between black and white youth implied by the model is 14.9 percentage points in the Bergen–Passaic MSA (i.e. the rate is estimated to be 43.4 per cent for white youth and 28.5 per cent for black youth). Of this difference, about 12.6 points (or almost 85 per cent of the differential) is due to the large differences in the household and human capital characteristics, on average, between black and white youth. About 1.4 percentage points (or 9.4 per cent) is due to differences in exposure and the residual, 0.9 points (or 6.0 per cent), arises from differences in job access.

In Newark, the black–white youth employment differential is predicted to be more than 19 percentage points, but only 57 per cent of this is due to variations in household and human capital attributes. Of the remainder, 7.6 percentage points (or 39.4 per cent) is due to differences in exposure.

The estimated differences in employment rates for white and Hispanic youth are much smaller. However, a smaller fraction of the difference in youth employment is attributable to household and human capital differences by ethnicity. In the Bergen–Passaic MSA, less than 70 per cent of the difference in estimated employment rates is attributable to household and human capital differences. One-sixth of the difference is due to variations in social access or exposure, and the remaining difference–about 1 percentage point in youth employment—is attributable to differences in access to employment.

The results confirm the fact that the largest source of disparities in employment rates between white and minority youth is the discrepancy between the average human capital and household characteristics between white and minority youth. The results also suggest that a substantial fraction of the differences in employment outcomes by race is attributable to intra-metropolitan spatial factors. Of these, social access or exposure seems more important than job access as measured by proximity to employment.

Table 7. Decomposition of employment rate differentials by race

	Bergen–Passaic	Middlesex	Monmouth	Newark
Predicted white–black differential				
Due to individual characteristics (percentage points)	+ 12.6	+ 12.5	+ 12.7	+ 11.0
Due to exposure (percentage points)	+ 1.4	+ 4.2	− 1.8	+ 7.6
Due to job access (percentage points)	+ 0.9	− 0.3	+ 0.8	+ 0.7
Net differential (percentage points)	+ 14.9	+ 16.4	+ 11.7	+ 19.3
Due to individual characteristics (percentage)	84.6	76.2	108.5	57.0
Due to exposure (percentage)	9.4	25.6	− 15.4	39.4
Due to job access (percentage)	6.0	− 1.8	6.8	3.6
Total (percentage)	100.0	100.0	100.0	100.0
Predicted white–Hispanic differential				
Due to individual characteristics (percentage points)	+ 4.6	+ 5.0	+ 7.0	+ 4.7
Due to exposure (percentage points)	+ 1.1	+ 5.2	− 0.7	+ 5.6
Due to job access (percentage points)	+ 0.9	+ 0.3	+ 0.4	+ 0.6
Net differential (percentage points)	+ 6.6	+ 10.5	+ 6.7	+ 10.9
Due to individual characteristics (percentage)	69.7	47.6	104.5	43.1
Due to exposure (percentage)	16.7	49.5	− 10.4	51.4
Due to job access (percentage)	13.6	2.9	6.0	5.5
Total (percentage)	100.0	100.0	100.0	100.0

Notes

1. More precisely, this interaction index across demographic groups is the exposure index, while within a demographic group it is termed the isolation index. As these terms are simply complements, we use the term exposure for both forms of interaction.
2. The sample contains individual and family information for all non-Hispanic white (white), non-Hispanic black (black) and Hispanic youth aged 16–19 living with at least one parent and in one of the 73 largest MSAs in 1990.
3. We tested several other categories of MSA characteristics, including the average commute time and other transport-related measures of access at the MSA level. None of these variables were significant.
4. This is computed from another source of data, the Census Transportation Planning Package (CTPP). The CTPP provides direct information about commuting patterns and proximity to jobs at the census-tract level for each of these MSAs. The raw data provided by the CTPP, matrices of zone-to-zone commuting patterns and peak commute times, are sufficient to create a variety of well-defined, tract-level measures of employment access. We employ the Poisson measure of access described in Appendix 2.
5. However, as noted in Table 6, the high correlation between neighbourhood characteristics means that the relative importance of neighbourhood characteristics cannot be determined with precision.
6. We use information on the occupation of the head of household as well as industry affiliation to measure the likelihood of residence in a given tract, given that tract's occupation and industry composition. Similarly, we use a measure of the availability of appropriately sized housing units, conditioning on household size, and the tenure composition in the tract conditioned on household tenure status.
7. For example, there is some indication in sociological literature on neighbourhood effects that youth with higher socioeconomic status—more resources at home—may be at less risk from negative neighbourhood influences (see Jencks and Mayers, 1990; and Duncan, 1994).

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Appendix 1

Table A.1. Individual-level variables included in youth employment models

Equation (1) Table 2	Equation (3) Table 3
Sex (1 = female)	Sex (1 = female)
Age (years)	Age (years)
In school (1 = yes)	In school (1 = yes)
—	Education (years)
—	HS graduate (1 = yes)
Female-headed household (1 = yes)	Female-headed household (1 = yes)
Education of head (years)	Education of head (years)
Parent working (1 = yes)	Parent working (1 = yes)
Other household income (thousands)	Other household income (thousands)
White (1 = yes)	White (1 = yes)
Black (1 = yes)	Black (1 = yes)
Hispanic (1 = yes)	Hispanic (1 = yes)
—	Family size (persons)
—	Children ever born (1 = yes)

Appendix 2: The Measurement of Job Access

In the analysis reported in Table 3, we employ a measure of the accessibility of each census tract to employment locations. This measure is derived from the potential access measures widely used by transport planners (see Smith, 1984). These measures are derived from observations on the work-trip patterns of commuters and the transport linkages in an urban area.

The accessibility measures are based upon the data available through the Census Transportation Planning Package (CTPP) for large metropolitan areas. The CTPP data are obtained from the Transportation Supplement of the 1990 Census. Each metropolitan area is divided into Traffic Analysis Zones (TAZs). Zone-to-zone peak commute flows (T_{ij}) as well as peak travel times (d_{ij}) are reported. From the elements of the matrix, the number of workers resident in each TAZ (R_i) can be estimated ($R_i = \sum_j T_{ij}$). Similarly, the number of individuals working in each zone (W_j) can be estimated ($W_j = \sum_j T_{ij}$).

The most widely used empirical model of the accessibility of particular residential locations is based upon the gravity concept:

$$T_{ij} = \alpha R_i^{\beta} W_j^{\gamma} / d_{ij}^{\delta}, \tag{2.1}$$

where, Greek letters denote parameters. Isard (1960) provides a number of physical and social scientific justifications for the formulation. Flows between i and j are positively related to the 'masses' of residences and workplaces and inversely related to the 'distances' (travel times) between i and j.

Estimates of the parameters yield a measure of employment potential— i.e. the accessibility of each residence zone to the workplaces which are distributed throughout the region (Isard, 1960, p. 510),

$$A_i = \sum_j \hat{T}_{ij} / R_i^{\hat{\beta}}, \tag{2.2}$$

where, $\hat{T}$ is computed from the parameters estimated by statistical means.

We use a more sophisticated measure of access which recognises that the transport flows to each destination are count variables; the Poisson distribution is a reasonable description for counts of events which occur randomly.

Assuming the count follows a Poisson distribution, the probability of obtaining a commuting flow T_{ij} is

$$\text{pr}(T_{ij}) = e^{-\lambda ij} \lambda_{ij}^{T_{ij}} / T_{ij}! \tag{2.3}$$

where, λ_{ij} is the Poisson parameter. Assuming further that

$$\exp[\lambda_{ij}] = \alpha R_i^{\beta} W_i^{\gamma} / d_{ij}^{\delta}, \tag{2.4}$$

yields an estimable form of the count model (since $E(T_{ij}) = \lambda_{ij}$). See Smith (1984) for a discussion. Estimates of the parameters similarly yield a measure of the accessibility of each residence zone to workplaces in the region

$$A_i = \sum_j \hat{\lambda}_{ij} / R_i^{\hat{\beta}} \tag{2.5}$$

The coefficients of the parameters in equation (2.4) are estimated using the CTPP data, separately for each metropolitan area. In each metropolitan area, the employment potential or job access of each census tract is computed from equation (2.5). (For each of the four metropolitan areas TAZs are co-terminous with census tracts.)

Appendix 3

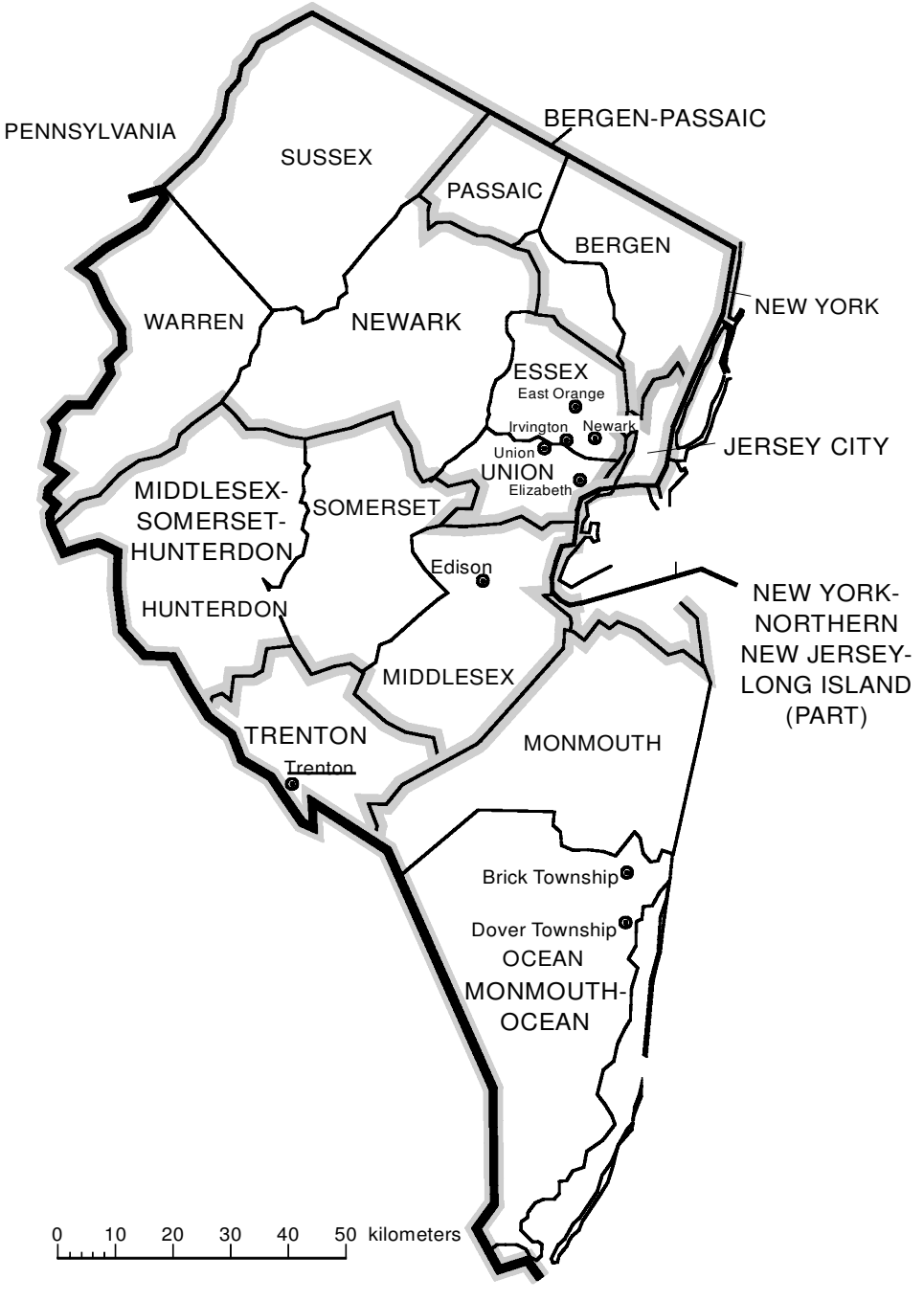

Figure 4. The location of the study areas.