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TEENAGE EMPLOYMENT AND THE SPATIAL ISOLATION OF MINORITY AND POVERTY HOUSEHOLDS

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Abstract

Teenage Employment and the Spatial Isolation
of Minority and Poverty Households

Using micro data from the US Census, this paper tests the importance of the spatial isolation of minority and poverty households for youth employment in 47 of the largest US metropolitan areas. We first estimate a logit model relating youth employment probabilities to individual and family characteristics, race, and metropolitan location. We then investigate the determinants of the systematic differences in employment probabilities by race and metropolitan area. We find that a substantial fraction of differences in youth employment can be attributed to the isolation of minorities and poor households. Minority youth residing in cities in which minorities are more segregated or in which minorities have less contact with non poor households have lower employment probabilities than otherwise identical youth living in similar but less segregated metropolitan areas. Simulations suggest that the magnitude of these spatial effects is not small and may explain a substantial fraction of the existing differences in youth employment rates for white, black, and hispanic youth.

I. Introduction

Many have argued that the concentration of poor and minority households in central portions of metropolitan areas exacerbates a host of urban problems -- ranging from the low quality of public services, such as education, to the high level of antisocial activity, such as violent crime. The hard evidence on the existence of concentration effects upon social outcomes is somewhat ambiguous (see Jencks and Mayers, 1990, for a review), but the emergence of an urban "underclass" has generated new debate about the implications of the spatial isolation of poor and minority households upon their own well being and that of others.

Regardless of the overall effects of concentrated poverty on social outcomes, there is reason to anticipate specific impacts on the operation of urban labor markets. The well-known "spatial mismatch theory" suggests that minority workers concentrated in central cities will experience lower employment rates than will similar workers who are not spatially isolated from emerging job concentrations at suburban sites. Again, empirical evidence on the magnitude of the mismatch in jobs is not definitive (see Kain, 1992, and Holzer, 1991, for recent reviews), but there can be little doubt that job movement to the suburbs reduces employment opportunities for those left behind. Several recent studies have documented the relationship between the lower employment levels of black and hispanic workers and measures of travel times to jobs (Ihlanfeldt and Sjoquist, 1990; Ihlanfeldt, 1993).

Regardless of the importance of the "mismatch" hypothesis, the *social* isolation arising from concentrations of poverty households may itself present a barrier to employment (Wilson, 1987; O'Regan and Quigley, 1991). Direct observation on job search strategies indicates that a large fraction of job seekers obtain information on specific jobs from friends and relatives (Holzer, 1987). The importance of these informal networks in affecting access to employment suggests that some networks are far more valuable than others in obtaining employment, i.e., networks which include a larger fraction of employed members, or members with "better" jobs. Formal models of job search suggest that those in networks with low employment rates may be further disadvantaged in the labor market (Montgomery, 1991, O'Regan, 1993).

This paper provides an empirical test of the importance of these phenomena. The empirical analysis is conducted in two steps. First, we estimate a logit model relating youth employment probabilities to individual and family characteristics, race and metropolitan region. We then investigate the determinants of the systematic differences in employment probabilities by race and metropolitan area (MSA). Specifically, we relate these differences to aggregate economic conditions in each MSA and to the spatial isolation of minority and poor households in each metropolitan area.

We find that a substantial fraction of the variation in employment probabilities for otherwise identical youth can be attributed to the spatial isolation of poor and minority households. Cities in which minorities are more segregated from whites, or in which the poor are more segregated from the non poor, are cities in which minority youth have lower employment rates than do identical youth in similar but less segregated cities.

We use these results to estimate the employment effects that could reasonably be attributed to an integrated pattern of residence by race and poverty status, thereby reducing two barriers to the labor market access of minority workers. These employment effects are quite large.

II Measurement

Our empirical work is based on 1980 Census data for at-home youth (youth living with at least one parent) aged 16 to 19 whose attributes are recorded in the Public Use Micro Sample (PUMS) and who resided in one of the 47 largest metropolitan statistical areas. The sample includes non hispanic whites (whites), non hispanic blacks (blacks), and hispanics.

We focus on youth because their residential locations, chosen by their parent(s), are clearly exogenous to their employment decisions. Unlike adult workers, we can presume that their residence sites are given, and that these youth seek employment whose accessibility is measured from their residential locations. The PUMS sample of at-home youth includes household level as well as individual data; this permits us to control for a variety of family characteristics. The sample includes observations on 55,393 youth.

Racial and poverty concentrations in each MSA are measured by several indices reflecting average level of "exposure" between members of two groups. Each exposure index is calculated from census tract data[1] :

$$(1) \quad E_{ij} = \sum_t (n_{it}/N_i)(n_{jt}/N_t) \quad .$$

E_{ij} is the exposure of the i th group to members of group j. n_{it} and n_{jt} are the number of group i and group j people in tract t, N_i is the total number of group i people in the MSA, and N_t is the total number of people in tract t. Group i's exposure to group j is simply the tract level exposure to group j (the proportion of the tract which belongs to group j) weighted by the fraction of the total population of group i in each tract, and summed over all tracts. The index number, which ranges from 0 to 1, measures the probability, for the average member of group i, that a randomly picked resident of his or her census tract is a member of group j.

[1] The exposure index is one of several measures widely used to measure spatial patterns of the segregation of dividedness of populations. See White (1986) for a comparison of various measures.

Social isolation of minority households decreases their contact with both non minority (white) and non poor households. We rely upon the work by Douglas Massey and Nancy Denton (1987) to measure exposure to whites. For each MSA, we use three measures of exposure to non-minority populations: the exposure of whites to whites; the exposure of blacks to whites; and the exposure of hispanics to whites. We presume that exposure to whites, who have higher employment rates (and perhaps greater influence in workplace decisions) is a measure of access to job contacts and, hence, to jobs.[2]

The second index measures exposure to poor individuals. Using data provided by Douglas Massey, we calculated indices of exposure to poverty for whites, blacks, and hispanics, for each MSA.[3] Poor individuals are presumed to provide less valuable information about jobs.

III. Empirical Models

The first stage of the analysis is based on a logit model relating youth employment probabilities to a vector of individual and family characteristics:

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[2] For this sample of metropolitan areas, the average value of the index measuring exposure to whites is: 0.870 for whites, 0.385 for blacks, and 0.668 for hispanics.

[3] For this sample of metropolitan areas, the average value of the index measuring exposure to poverty is: 0.063 for whites, 0.194 for blacks, and 0.114 for hispanics.

$$(2) \quad \log [\, P_i/(1-P_i)\,] = \alpha X_i \quad ,$$

Where P_i is the probability of employment for youth i, X_i is a vector of human capital and household characteristics, and α is a vector of parameters. A second model expands equation (2) to include race and ethnicity-specific effects which vary by MSA:

$$(3) \quad \log [P_i/(1-P_i)] = \alpha X_i + \sum_j \beta_{1i}\, w_i\, M_j + \sum_j \beta_{2i}\, b_i\, M_j + \sum_j \beta_{3i}\, h_i\, M_j \quad ,$$

M_j is a set of MSA dummy variables, having 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 is a dummy variable with a value of one for whites and zero otherwise, b_i is a dummy variable with a value of one for blacks and zero otherwise, and h_i is a dummy variable with a value of one for hispanics and zero otherwise.

The set of parameters $\beta_{r,m}$ (for r = 1, 2, 3 races and m = 1, 2, ..., 47 metropolitan areas) represents the shift in the logit of employment probability depending upon the race of the individual and the metropolitan area in which that individual resides.

In the second stage we analyze the determinants of these metropolitan wide differences:

$$(4) \quad \beta_{rm} = \gamma\, Z_m + \delta\, E_{rm} \quad .$$

Z_m is a vector of MSA characteristics expected to influence local labor market outcomes, and E_{rm} is the exposure index described in equation (1). We estimate several different forms of equation (4).

IV Results

Table 1 presents a summary of the logit models described in equations (2) and (3). Youth employment probabilities vary with the race, sex, age, and the years of education of the individual. Older, more educated youth, males, and whites, have significantly higher employment probabilities. These differences are large in magnitude and are statistically significant. Youth who are in school are significantly less likely to be employed, as are central city residents. Youth living in households with larger incomes from other sources are more likely to be employed. Those living in households with an employed parent are also more likely to be employed themselves.

The only result which may be surprising is that youth in female-headed households appear more likely to be employed (although the coefficient is only marginally significant). Note that this result holds only after controlling for both race and the presence of a working parent[4] .

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[4] When the dummy variable indicating a working parent is omitted, the coefficient on female-headship is negative and significant. We include both variables in the results reported in the text, but have replicated the analysis omitting this variable (with essentially the same results throughout).

Table 1

Logit Models of Employment Probabilities
for at-Home Youth
(55,339 observations)

	I	II
Sex (1=female)	-0.100 (5.34)	-0.102 (5.37)
Central City (1=yes)	-0.147 (6.88)	-0.100 (4.33)
Age (years)	0.276 (22.30)	0.274 (21.76)
Education (years)	0.248 (25.77)	0.267 (27.03)
In School (1=yes)	-0.609 (24.62)	-0.615 (24.50)
Female Headed Household (1=yes)	0.054 (1.97)	0.050 (1.79)
Education of Head (years)	-0.006 (1.98)	-0.010 (3.10)
Other Household Income (thousands)	2.060 (3.03)	1.320 (1.89)
Parent Working (1=yes)	0.585 (16.81)	0.537 (15.17)
White (1=yes)	-7.434 (40.40)	*
Black (1=yes)	-8.507 (45.45)	*
Hispanic (1=yes)	-7.847 (42.26)	*
Chi-squared	9618.5	10639.3
degrees of freedom	12	145

Note: Model II includes 136 dummy variables: race of the individual interacted with dummy varibles for metropolitan areas. t-ratios are in parentheses.

The second column summarizes results when we expand the model to include race/ethnic specific MSA dummies, which corresponds to equation (3). This model includes the same variables measuring individual and household characteristics. The signs, magnitude and significance of the coefficients of these variables are similar to those in column I. However, instead of estimating one coefficient for each of the three racial groups, we estimate coefficients for race which vary for each of the 47 MSAs.[5] The set of coefficients is highly significant (x^2 = 2042 with 133 degrees of freedom), and their magnitudes vary considerably across races and metropolitan areas.[6] The key finding here is that, after controlling for individual characteristics, the employment probabilities of "otherwise identical" white, black, and hispanic at-home youth vary substantially by MSA.

We now investigate the sources of these systematic differences in employment probabilities. The coefficients estimated from equation (3) and reported in Table A1 are the dependent variables, and we estimate models of the form of (4). Since the dependent variables in this analysis are regression

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[5] There were too few hispanics in the PUMS sample from Columbus, Dayton, Indianapolis, Nashville, or Pittsburgh to estimate coefficients for these MSAs. Thus, instead of estimating 141 coefficients (3 coefficients for 47 MSAs), we only estimate 136 coefficients.

[6] The individual coefficients and t statistics are reported in Appendix A1.

coefficients (observed with sampling error), the models are estimated by generalized least squares.[7]

Table 2 presents several regressions relating the differences in employment probabilities for otherwise identical youth to aggregate economic conditions by metropolitan area, and to the level of racial segregation by race. We expect that differences in employment probabilities for youth across metropolitan areas depend upon the aggregate economic conditions in these MSAs. We use the unemployment rate for white adults in each metropolitan area as a measure of general economic conditions. Youth employment probabilities are significantly lower in MSAs with higher unemployment rates. This variable has a highly significant and large coefficient in every version of these regressions we have explored.

Other aspects of the local economy differentially affect youth employment. We included a variety of measures of industry mix and found the fraction of MSA employment in the business service sector to be the best summary measure.[8] We tested several other categories of variables in these regressions, all which proved to be insignificant.[9]

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[7] The GLS procedure incorporates information about the estimated variance and covariances of the dependent variable (see Hanushek, 1974).

[8] In other regressions, we included other measures of industrial structure -- the fraction of employment in manufacturing, retail and wholesale trade, etc. None of the other results are affected by these more extensive measures of industrial structure.

[9] First, we included several MSA-level variables describing the human capital characteristics of the population (median age,

Table 2
Racial Segregation and Youth Employment:
Exposure of Individuals by Race, to White Individuals
(136 Observations)

	Model I	Model II	Model III
Unemployment Rate (percent)	-0.113 (6.21)	-0.111 (6.21)	-0.111 (6.35)
Business Services Employment (fraction)	0.007 (0.41)	-0.013 (0.72)	-0.017 (0.93)
Intercept	-8.434 (35.91)		
Intercept:			
Whites		-7.845 (27.70)	-7.569 (10.24)
Blacks		-8.171 (33.66)	-8.258 (33.83)
Hispanics		-7.818 (29.94)	-7.608 (25.20)
Exposure to Whites	1.712 (14.27)	1.222 (7.37)	
Exposure to Whites:			
Whites			0.939 (1.23)
Blacks			1.564 (7.68)
Hispanics			0.928 (3.44)
R^2	0.553	0.564	0.582

Note: R^2 is from ordinary least squares regression. t ratios are in parentheses.

Finally, after controlling for these other effects, we investigate the importance of exposure to whites. For all three models, holding other factors constant, increased exposure to whites significantly increases youth employment probabilities.

In Model I, the intercept is common across groups, as is the coefficient measuring exposure to whites. In Model II, we permit intercepts to vary for the three groups.[10] Any systematic differences in youth employment probabilities across race/ethnicity should be reflected in these intercepts. The intercepts do vary significantly by race and ethnicity. Controlling for this, exposure to whites still significantly increases youth employment probabilities. In Model III, in addition to varying intercepts, we permit the coefficient of exposure to whites to vary by race.[11] The effect of exposure to

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percent of the population with a high school diploma, etc.). These measures were insignificant; after controlling for individual human capital characteristics, aggregate measures provided no additional information. Second, we attempted to control for transport access in a variety of ways. From the Census, we used the average one-way commuting time and the share of total MSA employment in the central city as two measures of access. We also used an index designed to measure the access provided by local transit systems (see Linneman and Summers, 1993). Finally, using data from the Department of Transportation on public transportation systems, we created a variety of transit indices. None of these measures adequately captures physical proximity between workers and jobs, and none of these measures were significant in our regressions.

[10] Specifically, we estimate $\beta_{rm} = I_1 + I_2 + I_3 + \gamma Z + \delta E_{rm}$, where I_1 is the intercept for whites, I_2 is the intercept for blacks, and I_3 is the intercept for hispanics.

[11] Specifically, we estimate $\beta_{rm} = I_1 + I_2 + I_3 + \gamma Z_m + \delta_1 E_{1m} + \delta_2 E_{2m} + \delta_3 E_{3m}$, where I_1 refers to whites, I_2 refers to blacks, and I_3 refers to hispanics.

whites appears to be different across groups. While the coefficient is significant and positive for both blacks and hispanics, it is no longer significant for whites.

Table 3 presents analogous results using the poverty exposure index to measure social access. The results are quite similar to those reported in Table 2. In each of the models, exposure to poverty has large and negative effects upon the employment probabilities for otherwise identical at-home youth. The last column suggests that the employment probabilities for all youth are effected substantially by proximity to poverty.[12]

The nonlinearity of the logit relationship makes it difficult to interpret the magnitude of these coefficients. The importance of these effects can be assessed more easily by simulation. We use the results reported in Tables 2 and 3 to conduct several simulations of the impact of reduced segregation on the employment probabilities of youth. The results of a representative set of these simulations are presented in Table 4.

Column 1 presents the base case, the observed employment levels. Using the coefficients from Tables 1 and 2, we simulate the effect of racial integration on youth employment probabilities. For each MSA, we calculate the exposure to whites under integration and compute the implied employment probability. Column 2 presents these probabilities, aggregated by race and ethnicity across these large MSAs. Column 3 presents the change.

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[12] While the results for the two indices are similar, the two measures are not equivalent. When both measures are included in the regression, both are significant

Table 3
Poverty Segregation and Youth Employment:
Exposure of Individuals by Race, to poor Individuals
(136 Observations)

	Model I	Model II	Model III
Unemployment Rate (percent)	-0.080 (4.30)	-0.086 (4.67)	-0.084 (4.52)
Business Services Employment (fraction)	-0.039 (2.20)	-0.044 (2.47)	-0.042 (2.35)
Intercept	-6.299 (29.74)		
Intercept:			
Whites		-6.316 (28.41)	-6.170 (18.90)
Blacks		-6.578 (25.61)	-6.567 (23.17)
Hispanics		-6.306 (28.88)	-6.440 (25.44)
Exposure to Poor	-6.615 (14.72)	-5.131 (6.47)	
Exposure to Poor:			
Whites			-7.903 (1.88)
Blacks			-5.328 (5.31)
Hispanics			-4.250 (3.18)
R^2	0.543	0.556	0.558

Note: R^2 is from ordinary least squares regression. t ratios are in parentheses.

Table 4

Estimated Change in Youth Employment Rates
from Spatial Integration

		Integration by Race *			Integration of Poverty Population**		
	Actual Employment Rate	Projected Employment Rate	Change in Employment Rate	Percent Change	Projected Employment Rate	Change in Employment Rate	Percent Change
Whites	47.77%	45.01%	-2.76 pts.	5.78%	44.36%	-3.41 pts.	-7.70%
Blacks	23.08	36.40	13.32	57.46	36.83	13.75	59.58
Hispanics	36.74	42.66	5.92	16.11	41.58	4.84	13.17
Average	42.37	43.27	0.90	2.12	42.77	0.40	0.94

Notes:
* Based on coefficients reported in Table 2, column 2.
** Based on coefficients reported in Table 3, column 2.

Our simulation takes a limited resource ("social access"), currently distributed so as to benefit white youth, and redistributes it equally among all youth. This integration would increase the exposure of minority youth to whites, but would decrease the exposure of white youth to other whites. This reallocation of minority populations leads to a 13.3 percentage point increase in black youth employment, a 5.9 percentage point increase in hispanic youth employment, and a 2.8 percentage point decline in white youth employment. While this simulation reveals a large reallocation of employment, given the relative sizes of the populations and coefficients, the aggregate employment rate changes by less than one percentage point, and increases.

The second simulation focuses on the segregation of poverty. The actual level of exposure to poverty is replaced by that which would be experienced if poverty were evenly dispersed across census tracts within each MSA.[13] Again, this reallocation of the poverty population decreases minority exposure to poverty, and increases white exposure to poverty. Minority youth employment rates would increase -- by 4.8 percentage points for hispanics, and by 13.8 percentage points for blacks. White employment rates would decrease by 3.4 percentage points, and the aggregate employment rate for youth would remain about the same.[14]

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[13] For each MSA, complete integration of the poor would result in exposure rates equal to the MSA poverty rate.

[14] We have conducted these simulations for Models I and III, Tables 2 and 3, with results similar to those presented in Table 4.

V Implications and Conclusions

The results of this analysis provide strong empirical support for the existence of concentration effects. The employment prospects of otherwise identical at-home youth depend, not only on the general economic conditions in the metropolitan areas in which they reside, but also on the patterns of isolation and segregation by race and by poverty status. Exposure to whites increases the employment probabilities for youth, while residential exposure to the poor reduces employment probabilities.

Given the high correlation between social and spatial access, our empirical work cannot confirm that either is a more important mechanism connecting youth to jobs. However, some aspects of our results suggest that social access is important.

For example, we estimated similar regressions in which two alternative exposure measures were used: exposure to blacks, and exposure to hispanics. Exposure to blacks had the opposite effect of exposure to whites -- it significantly decreased youth employment probabilities, for all youth. Exposure to hispanics, however, had an insignificant effect on white and black youth employment, but significantly increased hispanic youth employment. While it is difficult to explain this pattern strictly on the basis of spatial access, it is consistent with an explanation in terms of social networks -- in which linguistically based networks among hispanics provide more effective job contacts than networks among blacks.

We also note that while the mismatch hypothesis relates principally to minority households, whose residential choices are constrained by racial discrimination in the housing market, the social network hypothesis applies to white workers as well. Our findings are consistent with a spatial explanation that applies to all youth; all youth are negatively affected in their labor market prospects by increased contact with poor individuals.

Regardless of the specific mechanism which relates youth employment outcomes to the spatial configuration of labor markets, these results document an important connection. In addition to human capital and general economic conditions, youth employment probabilities also depend on spatial isolation, and these latter factors work to the disadvantage of minority youth.

The simulations suggest that the effect of isolation is quite large. For the simulations presented, approximately 21 to 25 percent of the existing employment gap between white and hispanic youth is attributable to the spatial isolation of hispanics. Approximately 30 to 35 percent of the employment gap between white and black youth arises from the spatial isolation of blacks. While complete spatial integration may be an implausible extreme, in cities with particularly isolated minority and poor populations, changes in spatial isolation of these populations would dramatically improve their employment prospects.

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Appendix Table A1
Coefficients for Race and Metropolitan Area
in Logit Model
(Table 1, Column II)

Metropolitan Area	White	Black	Hispanic
Albany	-7.913	-7.391	-7.569
	(36.80)	(12.96)	(7.43)
Anaheim	-7.395	-7.904	-7.568
	(36.94)	(13.86)	(30.97)
Atlanta	-7.624	-8.583	-8.252
	(38.21)	(37.01)	(12.71)
Baltimore	-7.481	-8.285	-8.112
	(37.60)	(37.66)	(12.44)
Birmingham	-7.864	-9.085	-7.811
	(35.24)	(31.56)	(5.63)
Boston	-7.290	-8.084	-7.488
	(37.45)	(27.49)	(18.30)
Buffalo	-7.743	-9.387	-7.898
	(38.10)	(25.18)	(10.55)
Chicago	-7.215	-8.833	-7.804
	(37.98)	(43.01)	(35.14)
Cincinati	-7.525	-8.407	-9.421
	(36.96)	(28.12)	(8.16)
Cleveland	-7.328	-8.520	-8.083
	(36.83)	(34.31)	(16.87)
Columbus	-7.457	-8.246	*
	(35.42)	(25.33)	
Dallas	-6.964	-8.189	-7.482
	(35.51)	(35.01)	(29.82)
Dayton	-7.728	-8.808	*
	(36.43)	(23.00)	
Denver	-7.422	-7.477	-7.852
	(36.50)	(20.25)	(28.47)
Detroit	-7.496	-8.668	-7.794
	(39.16)	(39.64)	(21.51)
Ft. Lauderdale	-7.158	-8.698	-7.323
	(33.09)	(25.93)	(5.40)
Greensboro	-7.544	-7.998	-6.491
	(34.37)	(26.96)	(6.22)
Houston	-7.244	-7.946	-7.369
	(36.40)	(35.03)	(31.57)
Indianapolis	-7.524	-8.186	*
	(36.65)	(28.04)	
Kansas City	-7.312	-8.402	-6.823
	(35.82)	(29.56)	(15.61)
Los Angeles	-7.565	-8.567	-8.017
	(39.10)	(40.90)	(40.57)
Louisville	-7.742	-9.023	-8.106
	(36.52)	(24.11)	(6.91)
Miami	-7.691	-8.550	-7.615
	(34.69)	(33.83)	(35.44)
Milwaukee	-7.140	-8.463	-7.096
	(35.48)	(27.73)	(13.75)

Appendix Table A1
Coefficients for Race and Metropolitan Area
in Logit Model
(Table 1, Column II)
(continued)

Metropolitan Area	White	Black	Hispanic
Minneapolis	-6.817	-7.913	-8.325
	(34.54)	(17.65)	(13.54)
Nashville	-7.724	-8.282	*
	(35.40)	(26.94)	
Newark	-7.608	-8.928	-7.875
	(37.93)	(37.78)	(25.99)
New Orleans	-7.904	-8.754	-7.682
	(36.13)	(35.14)	(16.12)
New York	-8.007	-9.081	-8.683
	(41.60)	(44.29)	(42.21)
Oklahoma	-7.173	-8.045	-7.541
	(33.14)	(22.77)	(5.19)
Philadelphia	-7.713	-9.199	-8.133
	(40.24)	(40.71)	(24.15)
Phoenix	-7.337	-8.022	-8.136
	(35.89)	(19.22)	(31.25)
Pittsburgh	-7.851	-8.727	*
	(39.96)	(29.78)	
Portland	-7.498	-8.114	-7.641
	(36.41)	(16.76)	(9.72)
Providence	-7.627	-8.236	-6.588
	(34.72)	(15.11)	(8.68)
Riverside	-7.636	-8.518	-8.270
	(36.76)	(21.84)	(32.64)
Rochester	-7.450	-8.858	-8.647
	(35.44)	(20.39)	(11.72)
Sacramento	-7.728	-8.052	-7.919
	(36.02)	(21.08)	(25.88)
St. Louis	-7.650	-8.584	-6.795
	(39.06)	(35.46)	(8.12)
Salt Lake City	-7.142	-6.656	-7.000
	(34.00)	(4.66)	(15.30)
San Antonio	-7.615	-8.229	-7.894
	(33.13)	(19.87)	(35.27)
San Diego	-7.545	-8.037	-7.983
	(36.81)	(21.42)	(32.86)
San Francisco	-7.491	-8.794	-7.687
	(37.73)	(34.87)	(33.51)
San Jose	-7.263	-7.410	-7.338
	(34.82)	(16.13)	(28.92)
Seattle	-7.349	-8.995	-7.787
	(36.43)	(17.86)	(14.89)
Tampa Bay	-7.331	-8.342	-7.695
	(35.86)	(27.09)	(21.07)
Washighton, D.C.	-7.454	-8.263	-8.054
	(37.85)	(38.94)	(21.75)

Note: *Insufficient observations on hispanic youth to estimate coefficient. t-ratios are in parentheses.