# Who Benefits from Concentrated Affluence? A Synthesis of Neighborhood Effects Considering Race, Gender, and Education Outcomes

Odis Johnson, Jr.
*University of Maryland*

*Using Hierarchical Linear Modeling, the author synthesizes the findings of forty sample estimates to ascertain the significance and magnitude of neighborhood affluence effects on education outcomes according to race and gender. The findings show that the presence of high socio-economic status (SES) neighbors is positively related to education outcomes, even when controlling for variation in study quality. However, examining these effects according to race and gender reveals the existence of "benefit gaps." The race analysis indicates that whites benefit more from living with high SES neighbors than blacks, while the gender analysis shows females benefit more than males. The race and gender interaction effects estimation indicates that white males derive the greatest educational benefit from having high SES neighbors, while black males experience negative educational outcomes related to neighborhood affluence. The conclusion presents implications for urban and education policies whose aims are to create economically heterogeneous settings as a remedy for persistent inequalities in educational opportunity and achievement.*

Economic segregation has grown tremendously in recent decades (Benabou 1996), prompting one social scientist to call the twenty-first century the "age of extremes" (Massey 1996). As the rise in concentrated disadvantage became a subject of interest to policymakers, commentators and researchers (Wilson 1987; Jargowsky 1997; Traub 2000), others began to take note of a corresponding increase in concentrated affluence (Massey 1996; St. John 2002). The studies of concentrated affluence that followed revealed some of the largest neighborhood effects in social science, and did so with greater consistency than studies that estimated the effects of concentrated poverty (Johnson 2003). In addition, some researchers began to define neighborhood disadvantage as the absence of residents with capital rather than as the presence of low-income families. Crane's analysis (1991), for instance, revealed that as the percentage of residents with middle class professions in a neighborhood declined, rates of teenage pregnancy and dropping out of school rose at a greater rate. These findings prompted some demographers to argue the effects of concentrated capital are among the more important neighborhood predictors of social outcomes (Massey 2001; Johnson 2003). Capital's unequal distribution across places makes it a pressing social concern for those interested in limiting disparities in the cognitive and developmental outcomes of children.

The consequences of capital's uneven distribution across neighborhoods have been particularly acute for African Americans. Not only are African Americans less likely to live in, and thus benefit from, higher income neighborhoods (Jargowsky 1997), some researchers have found that African Americans living among the middle class benefit less than their white residential counterparts (Ginther, Haveman, and Wolfe 2000; Johnson 2003). These findings remain speculative because they appear rather inconsistently within these studies, a fact that is likely influenced by significant study quality variations. No doubt, these features of the research limit our ability to draw conclusions and, ultimately, make informed policy decisions concerning the social costs and benefits of the inequitable distribution of capital for subpopulations. A quantitative synthesis of the research in this area would expand our understanding and help propel efforts to address these inequities, yet until now a synthesis of neighborhood effects studies has not been the subject of publicly available research. This study, therefore, employs quantitative methods in research synthesis to ascertain the impact of neighborhood capital measures on the learning outcomes of children. At the center of the study are four related questions:

1. Are there differences, according to race, in the size of the benefit children derive from residing in areas of concentrated capital?
2. If there are differences or "benefit gaps" according to race, how large are they?
3. Are there gender differences within the racial categories?
4. To what extent does study quality moderate the relationship between neighborhood affluence and educational outcomes and, subsequently, the size of the benefit gap?

The exploration of these questions begins here with a review of the relevant theory and research in the areas of neighborhood capital, race, and gender, followed by a detailing of the process of identifying studies included in the research synthesis, an explanation of how the information in these studies is treated in meta-analysis to allow for its synthesis, and a discussion of using Hierarchical Linear Modeling (HLM) to generate an overall effect size, estimate its variance, and explain effect size variation by considering sample characteristics, in this case race, gender, and study quality (Raudenbush and Bryk 2002). The article concludes with a discussion of the findings and their policy implications.

## The Role of Endogenous Capital in Neighborhoods

According to neighborhood effects research, the concentration of capital produces "effects" of various types within neighborhoods that are net of individual characteristics (Jencks and Mayer 1990). As these effects enable social mobility they come to represent a form of endogenous capital within neighborhoods and institutions. Unlike traditional conceptualizations that assume one's socioeconomic status is an exogenous individual level attribute, endogenous capital recognizes the economic returns to individual capital depend on the social class of the associations or larger membership in which it is situated. Therefore, the benefits accruing to middle class families residing in affluent neighborhoods, for example, may be greater than those accruing to families of comparable income living among the less advantaged, not only because the synergistic outcome in collective capitalization processes is dependent on the individual capital of its group members, but also due to the inequitable conferral of social awards. Those who collectively have more, create more, and often are given more. Thus, this capital possesses properties that are specific to places and is ostensibly used to create structures that support processes of capitalization, among them political activity, the cultivation of complementary community norms, and individual dispositions toward success. Sociologists Wilson (1987) and Jencks and Mayer (1990) referred to these effects as "concentration effects" and detailed their influence within peer relations, role modeling, and institutional processes. Extending the concept of concentration effects, Quercia and Galster (2000) defined the "threshold effect" as a point when the representation of a particular characteristic reaches some "critical mass over a predefined area," making it increasingly more effective in shaping the behavior of others (147).

In just the past decade we have seen the formulation of endogenous capital theories that are useful in illustrating the role concentrated social class plays in creating social outcome variability. Economists Lundberg and Startz (2000), for example, termed capital's spatial situation "community social capital" and defined it as "the average stock of human capital" that one generation transmits to the next (273). Differences in social outcomes across communities and neighborhoods persist as previous generations bequeath their inequities in human capital to the next through an unequal investment in local educational systems. Putnam (2000) referred to community social capital as the prevailing "norms of reciprocity and trustworthiness" arising from relationships among individuals (19). Putnam (2000) also implied that community social capital may at times indicate the social capital of neighborhoods rather than, or in addition to, those of communities. Differences in these norms, according to Putnam, lead to differences in the benefits they generate. Johnson (2008) articulated related forms of endogenous capital called "proximity" and "proximal" capital, the former referring to the capital of the context while the latter is an individual possession resulting from the conversion of proximity capital into social mobility. This conceptualization of capital recognizes the externalities arising from social interaction as noted in Putnam's and Lundberg and Startz' work, but it also acknowledges that social interaction is not required for youth to adopt examples of behavior that local adults and peers provide. Adopting these behaviors becomes more likely as their prevalence within the proximity increases. Therefore, there are active and passive agents of child socialization, the former directly impacting the next generation through social interaction (or social capital), and the latter through mere presence. Durlauf (2001) would identify the latter effects as "feedbacks" from group characteristics to its individual behaviors. Through these processes, endogenous capital pervades neighborhoods and their institutions, including schools.

## Role of Race and Gender

Conceptualizations of endogenous capital are complicated by race in both racially segregated and integrated environments. In the former, middle class African Americans are more likely than whites of a comparable socioeconomic status to have lower income individuals as relatives, neighbors, peers in schools, and members of their churches (Pattillo-McCoy 1999). Economic diversity has been an enduring feature of middle class African American neighborhoods, which, as DuBois (1897) lamented over a century ago, lack social class differentiation. Nonetheless, the economic diversity within the networks of the black middle class may help lower income individuals experience social mobility while simultaneously draining the resources of the black middle class and lessening its accumulation of capital.

The processes reviewed thus far cast the effects of concentrated advantage on status groups in the positive. However, there are competitive social processes, a number of which Jencks and Mayer (1990) and Gephardt (1997) model, which limit the conversion of proximity capital into social mobility within racially integrated middle class neighborhoods. The cultural conflict model, for example, examines the tensions that arise when individuals or groups with different social affiliations, beliefs, and histories interact. These cultural incongruities may yield contests within public spaces or public schools. The ethnic/racial membership model recognizes that deprivation feelings can develop among populations that understand the influence race holds in the distribution of opportunities and social privileges. This awareness may lead youth of color to develop an identity consistent with their observations, resulting in perceptions of limited opportunity and diminished aspirations (Ogbu 1987). These social processes suggest the benefits of living among the middle class hinge on the race of both the individual and his or her middle class neighbors.

In addition to the moderating influence of race with regard to endogenous capital, there are differences within racial groups according to gender. Differences in endogenous capital's importance to the educational development of males and females may stem from gender differences in rearing practices and how those practices in turn manage the exposure of males and females to environmental influences (Furstenburg et al. 1999). Male youth tend to spend more time in their neighborhood away from the immediate supervision of families than females and, subsequently, may have more interaction with individuals possessing human and cultural capital and beneficial networks. Restraining females from engaging their surroundings may limit the acquisition of experiential skills that could prove helpful to them away from home and in school. To the extent that these parenting behaviors differ according to gender among and within racial groups, we may observe differences in neighborhood capital's effects on education outcomes. In addition, neighbors, schools, peers and other local institutions may respond differently to females and males. The findings of the Moving to Opportunity (MTO) housing relocation experiment imply that "better" environments may advantage one sex while disadvantaging the other. Black male MTO participants in particular did less well in school than their female counterparts after moving to more prosperous areas (Sanbonmatsu et al. 2006).

## Inconsistency in Findings and Variation in Study Quality

Despite the abundance of theoretical work in this area of scholarship, a review of empirical research produces inconclusive evidence as to the influence of neighborhoods. Though high socio-economic status (SES) effects have been cited as one of the more consistent predictors of education outcomes (Levanthal and Brooks-Gunn 2000; Duncan and Raudenbush 1999), no one has systematically assessed the consistency of these findings. A cursory review reveals the findings vary considerably across studies and even among studies that use similar data. Duncan (1994), for example, estimated the effects the percentage of high SES neighbors had on years of completed schooling for black males, black females, white females and white males using data from the Panel Study of Income Dynamics (PSID). He found the percentage of high SES neighbors is positively related to years of completed schooling for all groups except black males. Drawing a sample from the same data source, Duncan, Connell and Klebanov (1997) also estimated the influence of high SES on years of completed school for all four groups. This analysis produced a positive effect for all four groups, including black males.

Likewise, the works of Crane (1991) and Clark (1992) offer conflicting findings. Crane (1991) used the 1970 Public Use Microdata Sample (PUMS) data to generate a sample of 22,000 young people from several of the largest statistical metropolitan sampling areas (SMSAs). He estimated the probability of dropping out according to the percentage of high status residents. He observed large increases in dropout rates as the percentage of high status residents dropped below 5% for all ethnic/racial and gender subgroups. Clark (1992), using a larger 1980 PUMS sample of males from the largest SMSAs, was unable to replicate Crane's results (1991). Clark (1992) observed no large increases in dropping out as the percentage of high status residents fell to extremely low levels for any ethnic/racial and gender subgroup. While some studies report significant high SES effects (Halpern-Felsher et al. 1997; Chase-Lansdale 1997; Ainsworth 2002) others do not (Ensminger 1996; Foster and McLanahan 1996; Lopez-Turley 2002). Yet another study (Ginther, Haveman, and Wolfe 2000) shows a negative relationship between the percentage of high SES neighbors and the likelihood of graduating from high school for African Americans, suggesting neighborhood affluence is not always beneficial.

Ginther, Haveman, and Wolfe's analysis (2000) also gives reason to question neighborhoods' ability to make substantial contributions to the educational development of youth. The authors examined how the robustness of neighborhood effects varies in magnitude according to model specifications. They found that as more family and individual level controls are added, the effect-size magnitude reduces dramatically until only one neighborhood factor retains significance. They argued those factors typically unobserved in neighborhood research could account for much of the variation we would otherwise attribute to neighborhood characteristics.

## Identifying and Selecting Studies

For this analysis, I identified and selected studies through three processes: (1) a search of bibliographies, references and citations to locate comparable quantitative studies; (2) informal networking and contacts with scholars in the field, which produced a number of studies that were in press, disseminated at academic conferences, or available as reports from research organizations; and (3) a search of databases such as *Wilson*, *EconLit*, *ERIC* and *PsycLIT* using the keywords neighborhood, community, urban, concentration, spatial, education, achievement, learning, test scores, attainment, and dropping out in various combinations. The database searches produced several hundred studies but few relevant ones that had not already identified. The literature search revealed seventy-five studies that contained effect size estimates of neighborhood influences on education outcomes.

A successful research synthesis depends on a number of "conditions" primarily associated with the quality of studies. These conditions constitute a set of criteria with which to assess the studies' acceptability. For example, a synthesis of low socioeconomic effects on test score performance requires employing both variables within a significant number of studies. This study's focus on affluence led to identifying studies that included high SES as a neighborhood level predictor. Eliminating studies that did not contain high SES variables from consideration reduced the number of studies to sixteen.

The second condition for selection concerned the reporting of vital statistical information. Not all studies reported the necessary information, presenting a problem of missing data. Eliminating these studies would have weakened the external validity of the meta-analysis results; I could not with certainty generalize the findings back to a body of research if many of the studies were not in the analysis. I requested missing information from recent studies or found information in other studies that used identical data.

Meta-analysis also requires an assumption of independence among the estimates pooled from the available studies. Presenting more than one estimate from the same sample source, whether calculated within the same study or across several studies, violates this assumption and may produce serial auto correlation among the estimates. For example, six studies used Infant Health and Development Program (IHDP) data to estimate the effects of various neighborhood qualities on education outcomes. Because this study examined race and gender, I chose the IHDP study that disaggregated data according to race and gender (i.e., Chase-Lansdale et al. 1997). I assumed estimates produced from the analysis of sub-samples (disaggregated data according to race, age, gender etc.) were independent and acceptable. For studies that produced several estimates from models with different combinations of covariates, I selected the estimates of "full models" as opposed to models with fewer covariates. In cases where it remained unclear which coefficient from the study to include, I averaged multiple coefficients to produce a single effect size estimate. As a result, I took all of the effect sizes in the synthesis from studies that included individual and family-level controls.[1] Safeguarding the assumption of independence required reducing the number of studies to ten, with a total of fifteen data sources and forty sample estimates.

Despite their seemingly low number, the selected studies represented a combined sample size of 139,937 youth. Furthermore, the estimate $n$ ($n$ = 40) was sufficient considering well-regarded research syntheses have been conducted with a similar number of studies and samples (Cooper et al. 1996; Raudenbush and Bryk 2002) and far fewer estimates (Raudenbush 1984; Raudenbush 1988; Kalaian and Raudenbush 1996). Some may wonder why I generated so many samples and estimates from just ten studies. First, many studies used more than one data set. Halpern-Felsher et al. (1997), for example, produced estimates from six data sets, five of which I found did not violate the

[1] I conducted a separate analysis to assess effects' variation according to age; in all synthesis models, effects did not vary significantly. Research in child and adolescent development suggests neighborhoods bring their effect to bear over time with young children less exposed to extra-familial influences than older youth (Brooks-Gunn, Duncan and Aber 1997). The lack of difference in neighborhood factors' influence according to age may be explained by the cross-sectional nature of the studies in the meta-analysis and their inability to ascertain and account for how long study respondents were exposed to the corresponding environmental characteristic. Residential mobility remains a significant confounder of neighborhood influences in developmental research.

assumption of independence among the estimates and included in this synthesis. Also, the majority of the studies contained disaggregated data. This allowed a single study to produce as many as four independent estimates, one each for black males, black females, white females, and white males. These conditions maximized the *n* within the analysis while supporting the assumption of independence among the estimates. Table 1 lists the studies, data sources, original study coefficient, and other descriptive data.

**TABLE 1.** List of studies, data sources, sample characteristics, and study estimates.

| First Author | Year | Data Source | *N* | Percent Black | Percent Male | *d* |
|---|---|---|---|---|---|---|
| Halpern | 1997 | New York | 101 | 0 | 100 | -.41 |
| | | middle childhood | 414 | 100 | 100 | .15 |
| | | | 94 | 0 | 0 | -.25 |
| | | | 431 | 100 | 0 | .03 |
| | | New York | 638 | 0 | 100 | -.29 |
| | | early adolescence | 102 | 100 | 100 | .08 |
| | | | 5 | 0 | 0 | -.05 |
| | | | 607 | 100 | 0 | -.17 |
| | | | 113 | | | |
| | | | 6 | | | |
| | | Atlanta | 237 | 100 | 100 | -.38 |
| | | | 109 | 100 | 0 | 8.51 |
| | | New York/ | 134 | 0 | 100 | -.30 |
| | | Baltimore/ | 129 | 100 | 100 | .02 |
| | | District of Columbia | 175 | 0 | 0 | .11 |
| | | | 231 | 100 | 0 | -.02 |
| | | New York | 275 | 0 | 100 | -.32 |
| | | middle adolescence | 653 | 100 | 100 | .02 |
| | | | 204 | 0 | 0 | .02 |
| | | | 665 | 100 | 0 | -.21 |
| Pebley | 2003 | L.A. FANS | 182 | 9 | 51 | 2.14 |
| | | | 6 | 9 | 51 | 3.09 |
| | | | 229 | | | |
| | | | 3 | | | |
| Chase | 1997 | IHDP | 269 | 0 | 50 | 2.65 |
| | | Ages 3-6 | 412 | 100 | 48 | 1.29 |
| | | NLSY | 495 | 0 | 55 | .38 |
| | | | 284 | 100 | 55 | -.98 |
| | | | 372 | 0 | 55 | 2.31 |
| | | | 272 | 100 | 55 | -.20 |

**TABLE 1.** List of studies, data sources, sample characteristics, and study estimates (*continued*).

| First Author | Year | Data Source | *N* | Percent Black | Percent Male | *d* |
|---|---|---|---|---|---|---|
| Crane | 1991 | PUMS 1970 | 173 | 100 | 100 | .91 |
| | | | 7 | 100 | 0 | .73 |
| | | | 176 | 0 | 52 | .54 |
| | | | 1 | 0 | 52 | .57 |
| | | | 775 | | | |
| | | | 08 | | | |
| | | | 468 | | | |
| | | | 4 | | | |
| Lopez-Turley | 2002 | PSID-CDS | 868 | 43 | 49 | -.01 |
| Ainsworth | 2002 | NELS | 131 | 14 | 50 | 1.13 |
| Ensminger | 1996 | Chicago | 230 | 100 | 100 | .03 |
| | | | 265 | 100 | 0 | .03 |
| Clark | 1992 | PUMS 1980 | 22534 | 16 | 100 | -.02 |
| Duncan | 1994 | PSID | 783 | 0 | 100 | .04 |
| | | | 884 | 100 | 100 | -.01 |
| | | | 818 | 0 | 0 | .03 |
| | | | 954 | 100 | 0 | .04 |
| Fischer | 2004 | Philadelphia | 234 | 61 | 48 | -8.67 |

## Method and Analytical Procedure

### *The Variables*

Frequently the variables involved in meta-analysis are composites because of the varying variable definitions used in the primary studies. *High SES*, for instance, is defined in the primary studies as the percentage of individuals making above $30,000, the percentage of white-collar workers, the percentage professional and managerial workers, and the absolute income of the top quintile. *Education Outcomes*, the outcome of interest, is also a composite indicator which includes standardized test scores, attainment, and school GPA. Using a composite indicator as an outcome presents both some benefits and limitations. The differing variable definitions across studies limits the practical interpretability of the findings; the effect magnitudes presented in the synthesis cannot be used to determine how grades or test score points correspond to standard deviation unit increases or decreases. These benefits, however, are not central to this study's research questions. A composite increases the external validity and generalizability of the findings by allowing the inclusion of all of the relevant studies. Moreover, the consideration of education composites is common in social science (Connell and Halpern-Felsher 1997; Halpern-Felsher et al. 1997; Lopez-Turley 2002) and in meta-analysis (Cooper et al. 1996).

Ginther et al. (2000) suggested that neighborhood effect sizes vary according to model specifications, an attribute central to understanding study quality. Others have warned that the inclusion of theoretically irrelevant covariates in statistical models can artificially suppress estimates of a neighborhood's influence (Sampson, Morenoff and Gannon-Rowley 2002). Therefore, an investigation of model specifications should not only consider variation in study quality as it occurs in the representation of covariates, but also in the theoretical relevance of covariates. Such an approach in a synthesis of neighborhood effects is preferable but not simple; while studies may reference theory, researchers' reliance on census measures severely limits the degree to which model specifications reflect ecological or neighborhood social organization theory. As the field progresses, the inclusion of theoretically relevant covariates will no doubt permit such evaluations of variation in study quality.

I elected to consider the stringency of the model specifications within the primary studies by constructing a moderating variable, *study quality*. If the findings of Ginther et al. (2000) are correct, the inclusion of seemingly less relevant covariates within the primary study models may have suppressed the estimates included in this synthesis. Thus, it is unknown to what extent the results of the study quality analysis reflect the suppressed effects generated at the primary study level (due to the inclusion of presumably less relevant covariates) or differences among studies in the inclusion of adequate controls. However, these complications do not seriously jeopardize the merit of considering model specifications as a measure of study quality; a finding of "no difference" among studies that vary in model stringency would not support the influence of artificial suppression, while finding larger effect sizes for studies with more controls would go further to challenge the threat of suppression. Nonetheless, this article includes the analysis with and without the study quality variable.

In constructing the *study quality* variable I first reviewed the model specifications of the primary studies. The review revealed 186 different variables across the primary studies. I organized these variables according to their unit of analysis (individual, family structure and process, school, and neighborhood structure, etc.). I then organized the variables within each unit of analysis according to common social science constructs. For example, within the unit "family demographics," I grouped and coded the variables *single parenting*, *fraction of time in mother-only family*, *stepparent household*, *father present*, and *ever coreside grandmother* as indicators of "adult presence." Other constructs within the family demographics heading are family origin, family size, parental education, parental health and parent's age. The organization of the primary study variables yielded fifty-two constructs.

The next step in assessing study quality involved coding the estimates according to the specifications of the models from which they emerged. I tallied a study quality score for each estimate by allocating a point for each of the fifty-two constructs in the primary study models. I repeated this process and resolved any discrepancies between the two point totals in a third review of the primary studies. The study quality scores ranged from 6 to 25, with a mean of 9.797. I used this mean to construct a dichotomous variable, *study quality*. In coding *study quality*, I entered a value of 0 for those estimates that had a study quality score below the mean and a value of 1 for those that exceeded it.

Study characteristics also varied according to the racial composition of the sample. I classified each sample as either black or white if its racial composition was at least 85% homogenous. I selected a relatively high threshold for the racial classification of study samples because the likelihood of detecting differences among them corresponded to their degree of homogeneity. Despite selecting 85% as a lower threshold for making classifications, Table 1 shows that over 80% of the samples within this study were 100% racially homogeneous. Thus, I included two dummy variables, *Black* and *White*, each coded 1 for yes, 0 for no.

I followed the same procedure in creating variables for the gender analysis, identifying the sample estimates as *female* (1 = yes, 0 = no) and *male* (1 = yes, 0 = no). Although I applied the same 85% threshold in classifying the samples, the process yielded entirely homogenous female and male sub-samples. In the final analysis, I identified the estimates according to racial and gender composition as *black female* (1 = yes, 0 = no), *black male* (1 = yes, 0 = no), *white female* (1 = yes, 0 = no) and *white male* (1 = yes, 0 = no).

*Statistical Conversions: Computations of Half-Standardized Coefficients, d.*

Most of the studies reported the effect size estimate as a regression coefficient, sometimes in both the metric coefficient (unstandardized) $\beta^m$, and standardized coefficient $\beta^*=\beta^m s_x/s_y$ (where the sample estimate of $\beta^m$ is denoted as $B^m$, the estimate of $\beta^*$ as $B^*$ and the estimate of $\delta$ as *d*). Due to the consideration of a socioeconomic status predictor, I converted the original study estimates and estimate averages listed in Table 1 to half-standardized estimates ($\delta=\beta^m/s_y$). For questions about SES, it is better to report half-standardized estimates than to report $\beta^*$, primarily because with $\beta^*$ communities with a restricted SES range will generate a smaller effect size than communities with a larger SES range, even if the actual effect sizes are the same. In this analysis, $\delta = \Delta y$ for each percentage point increase in *X*. Because none of the studies reported half-standardized values, I used the statistical information from each to calculate half-standardized coefficients.

I computed the half-standardized estimates uniformly across all estimates except where the amount of statistical information available within a particular study was limited. Some studies in this sample did not report standard errors. Fortunately, these estimates were all statistically significant, suggesting an upper bound of the standard error value. I then assigned these estimates a standard error approximately half ($\beta$/1.96) of the estimate value. I assigned values infrequently (in less than 15% of the estimates); this was preferable to the bias that would arise from eliminating the estimates. Nonetheless, the effect of assigning standard error values for significant coefficients in meta-analysis is generally negative, yielding a more conservative overall effect size estimate. I computed the half-standardized coefficient as $d=B^*/\sigma_x$ based on the reasoning that $B^*/\sigma_x = (B^m\sigma_x/\sigma_y)/\sigma_x = B^m/\sigma_y = d$. The statistical conversions completed the data set. Table 2 shows the means and standard deviations of the outcome, predictor, and moderating variables.

**TABLE 2.** Means, definitions, and standard deviations of study characteristics.

| Variables | Definition | *N* | Mean | Std. Deviation |
|---|---|---|---|---|
| High SES effect size | Effect of High SES (percentage professional or managerial, percentage of families with incomes > $30,000, percentage of white collar, and absolute income of top quintile) on education outcomes (school GPA, years of schooling, and test scores) | 40 | .0648 | .13130 |
| Study quality | Number of constructs represented in model specifications. Above the mean = 1, below the mean = 0 | 40 | .4250 | .5006 |
| Sample size | Number of primary study sample participants | 40 | 3498.4225 | 12655.0364 |
| Black | Sample is at least 85% black | 40 | .4750 | .5057 |
| Black male | Sample is at least 85% black and male | 40 | .2000 | .4051 |
| Black female | Sample is at least 85% black and female | 40 | .2000 | .4051 |
| White | Sample is at least 85% white | 40 | .3250 | .4743 |
| White male | Sample is at least 85% white and male | 40 | .1500 | .3616 |
| White female | Sample is at least 85% white and female | 40 | .1250 | .3349 |

*Hierarchical Linear Modeling*

As Raudenbush and Bryk (2002) point out, it is "natural to apply hierarchical linear models to meta-analytic data because such data are hierarchically structured" (206). In other words, effect sizes are nested within studies. HLM attends to hypothesis testing by (1) generating an overall effect size; (2) estimating the variance of the effect size parameters (as distinct from the variance of the effect size estimates); and (3) explaining variation in the effect size parameters by considering subject and study characteristics in linear models. In this study, I considered a specific study that estimates the effect of a neighborhood level variable on educational indicators, denoted as $\delta$. The aim was to compare these estimates in a meta-analysis of the *j* studies in a test of the null hypothesis, $H_0$: $\gamma_s = 0$, $f$, which implies that the effect $\gamma$s of study characteristic $W_s$ on a particular effect size is zero. I applied this procedure to a univariate and multivariate meta-analysis, where the estimates were assumed to be independent, and in an analysis of robustness, where I trimmed 5% of the estimates at each end of the distribution of effect sizes to assess the potential influence of outliers.

*Meta-Analysis of Effects Assumed Independent*

The analysis of independent effect-size estimates proceeded in two parts. In the first (unconditional) analysis, I estimated the mean and variance of the effects. In the second (conditional) analysis, I estimated a model to predict the effect sizes and the residual variance of the effects. I started with an unconditional (within-studies) model of neighborhood socioeconomic effects at Level-1:

$$d_j = \delta_j + e_j \tag{1}$$

where $d_j$ was the estimated effect size for study *j*, $\delta_j$ was the corresponding parameter with a sampling variance, $V_j$, assumed known. In the unconditional analysis the effect sizes, $\delta_j$, varied around a grand mean, $\gamma_0$, plus a Level-2 error, $u_j$. No predictors were involved at Level-2. The specifications at Level-1 and Level-2 yielded the combined model:

$$d_j = \gamma_0 + u_j + e_j \tag{2}$$

where

$d_j$ was the estimated effect-size for study *j*
$\delta_j$ was the true effect-size parameter
$\gamma_0$ was the estimate of the grand mean
$u_j$ was a Level-2 random effect
$e_j$ was the sampling error associated with $d_j$ as an estimate of $\delta_j$
$\tau$ was the estimated variance of the effect parameter, $\delta_j$
$V_j$ was the variance error with which $d_j$ estimated $\delta_j$,

implying $d_j \sim N(\gamma_0, \Delta_j)$ with $\Delta_j = \tau + V_j$.

To test the possibility that the variability in environmental effects may have been related to the design and analytical characteristics of the studies, I constructed a conditional (between-studies) analysis where Level-1 was left unchanged. At Level-2, I used the information about the moderating covariates, model specifications to predict the effect sizes. The model was:

$$\delta_j = \gamma_0 + \gamma_1(\textit{Study Quality})_j + \ldots + \gamma_s W_{sj} + u_j. \tag{3}$$

The specifications at Level-1 and Level-2 yielded the combined model:

$$\delta_j = \gamma_0 + \gamma_j W_j + \gamma_2 W_j + \ldots + \gamma_s W_{sj} + u_j + e_j \tag{4}$$

where

$\delta_j$ was the estimated effect size
$W_{1j}, \ldots, W_{sj}$ were study characteristics

$\gamma_0,\ldots,\gamma_s$ are coefficients
$u_j$ is a residual for which I assumed $u_j \sim N(0,\tau)$,

implying $d_j \sim N(\gamma_0 + \gamma_1 W_j + \ldots + \gamma_s W_{sj}, \Delta_j)$, where $\Delta_j = \tau + V_j$ is the conditional variance in $d_j$ after controlling for moderating variables.

*Multivariate Mixed Linear Modeling*

Since one of this study's questions concerned the possibility that the outcomes of subpopulations may vary in their sensitivity to neighborhood influences, I first considered a multivariate model to estimate the effect of having high SES neighbors on two racial categories, and then again with those racial categories separated according to gender. The estimation of the multivariate model proceeded in two stages. I estimated a within-study model in the first analysis, where I specified the effect sizes that were present and absent. One may view the estimation of the within-study model as relating the estimated effect sizes from each study to the "true" effect sizes (Kalaian and Raudenbush 1996). The between-studies model specified the distribution of the effect sizes across a universe of studies. In the second analysis, I controlled for the model specifications within the primary studies, an indicator of study quality.

As noted earlier, different studies report results for different subpopulations. While ecological research may include many subpopulations, few of the studies will include all of them. In the multivariate analysis, I started with the assumption that no matter how many effect sizes were actually estimated in a given study, that study had $M = 2$ latent effect sizes, one for each subpopulation.

In the first analysis, I associated with each study ($j$) a complete vector of $M$ effect sizes, $\delta_j = (\delta_{1j}\ldots,\delta_{Mj})^T$. In this, the first multivariate analysis, I considered two subpopulations; hence, $M = 2$ and $\delta_j = (\delta_{1j}, \delta_{2j})^T$, where $\delta_{1j}$ is the effect-size for black samples, and where $\delta_{2j}$ is the effect size for white samples. Although $M$ effect sizes were associated with study $j$, only $P_j$ effect size estimates were reported by study $j$, $P_j \leq M$.

The within-study model can have many interactions according to the number of outcomes a study reports. To illustrate the within-study model with the $P_j$ effect size estimates for black and white samples, if study $j$ reported only an effect size from black samples, then $p = 1$, and the within-study equation was

$$\begin{aligned} d_{1j} &= \delta_{1j*}(1) + \delta_{2j*}(0) + e_{1j} \\ &= \delta_{1j} + e_{1j} \end{aligned} \tag{5}$$

Equation 5 was rearticulated for P parameters $\delta_{2j}$, where study $j$ reported only one effect size. If however, study $j$ reported two effect sizes, then $P_j = M = 2$, the within-study equation for $p = 1$ became

$$\begin{aligned} d_{1j} &= \delta_{2j}W_{11j} + \delta_{2j}W_{12j} + e_{1j} \\ &= \delta_{1j*}(1) + \delta_{2j*}(0) + e_{1j} \\ &= \delta_{1j} + e_{1j} \end{aligned} \tag{6}$$

for black samples, and $p = 2$ became

$$\begin{aligned} d_{2j} &= \delta_{1j} W_{21j} + \delta_{2j} W_{22j} + e_{2j} \\ &= \delta_{1j*}(0) + \delta_{2j*}(1) + e_{2j} \\ &= \delta_{2j} + e_{2j} \end{aligned} \tag{7}$$

for white samples, where

> $\delta_j$ was the estimated effect size
> $W_{1j},\ldots, W_{sj}$ were study characteristics
> $e_j$ was a residual for which I assumed a multivariate normal sampling distribution with variances $V_{ppj} = 0$.

Equations 6 and 7 were rearticulated for $P$ parameters, $\delta_{1j}$ and $\delta_{2j}$, where study $j$ reported two effect sizes. Level-2 in the within-studies analysis involved no predictors. In the between-studies model, the $M$ latent effect sizes for each study became the outcome variables and varied as a function of predictor variables introduced at Level-2, plus the error. Considering percent study quality as the only *W*s, the between-studies equation read:

$$\delta_j = \gamma_0 + \gamma_1 (\textit{Study Quality})_j + u_j,\ u_j \sim N\ (0,\tau) \tag{8}$$

The specifications at Level-1 and Level-2 yielded the combined model:

$$d_j = \gamma_0 + \gamma_j W_j + \gamma_2 W_j + \gamma_j u_j + e_j \tag{9}$$

where

> $d_j$ was the estimated effect-size for study $j$
> $W_j$ was a moderating predictor variable
> $\delta_j$ was the effect size parameter
> $\gamma_0$ was the estimate of the grand mean
> $u_j$ was the unique effect for each study $j$
> $e_j$ was the sampling error associated with $d_j$ as an estimate of $\delta_j$.

These effects were assumed multivariate normally distributed, with a mean of 0, variance $\tau_{pp}$, and with covariances of $\tau_{pp'}$ between $u_{pj}$ and $u_{p'j}$. I repeated the multivariate analysis is repeated for the gender groups where $M = 2$ and again for racial subgroups according to gender where $M = 4$ and $\delta_j = (\delta_{1j}, \delta_{2j}, \delta_{3j}, \delta_{4j})^T$, where $\delta_{1j}$ was the effect size for black male samples, $\delta_{2j}$ was the effect-size for black female samples, $\delta_{3j}$ was the effect-size for white male samples, and $\delta_{4j}$ was the effect size for white female samples.

*Estimation*

Unequal sample sizes would have compromised the interpretability of the meta-analysis results. Since each $d_j$, has valuable and unique properties, I constructed weights to ensure the appropriate consideration of effect size estimates (Raudenbush and Bryk 2002). In viewing each $d_j$ as an independent, unbiased estimator of $\delta_j$ with variance $\Delta_j$, the precision of $d_j$ is defined as the reciprocal of its variance:

$$\text{Precision } (d_j) = \Delta_j^{-1} \tag{10}$$

These weights figured in the construction of a dummy variable for $P$ parameters $\delta_{1j}$ and $\delta_{2j}$, for both the racial and gender analysis, and again for the final multivariate analysis where $M = 4$.

**Results**

Tables 3 through 6 present the findings of Model 1 (unconditional) and Model 2 (conditional). The unconditional analysis, which specified estimates of the grand mean effect size $\gamma_0$ and, at Level-2, the variance of the effect size $\tau$, addressed whether having high SES neighbors has an influence on education outcomes. The effect size for affluence, $\hat{\gamma}$ = .0355, is large, implying that for every unit increase in the percentage of affluent neighbors, there is an increase of about .035 standard deviation units in education outcomes. This magnitude translates into an increase in the outcome of close to .90 standard deviations if the number of affluent residents increases by twenty-five percentage points.

Regarding the consistency of this effect size across studies, the estimated variance of the effect parameter was $\hat{\tau}$ = .0038 with a corresponding standard deviation of .0613. These estimates suggest that much variability exists between study samples in the effect size. For example, an effect with one standard deviation above the average would be $\delta_j$ = .0968, while a study with an outcome one standard deviation below the mean would produce a much smaller effect size, $\delta_j$ = -.0258. The variance component $\hat{\tau}$ = .00375 has a corresponding $X^2$ of 2504.61927 and a $p$ = .000 significance level, suggesting the inconsistency in study findings is not inadvertent.

**TABLE 3.** Models of neighborhood high SES effects in education and study quality moderator variable.

| | Model 1 | | | | Model 2 | | | |
|---|---|---|---|---|---|---|---|---|
| Fixed effects | Effect | SE | t | df | Effect | SE | T | df |
| Intercept, $\gamma_0$ | .0355* | .0136 | 2.618 | 39 | .0312* | .0151 | 2.062 | 38 |
| Study quality, $\gamma 1$ | | | | | .0253 | .0302 | 0.836 | 38 |
| Random effects | Variance component | $X^2$ | | p-value | Variance component | $X^2$ | | p-value |
| | .00375 | 2504.61927 | | .000 | .00355 | 3769.46610 | | .000 |

(***) $p < .001$
(**) $p < .01$
(*) $p < .05$

Model 2 in Table 3 includes the moderator variable, study quality, and the estimates of $\gamma_0$, $\gamma_{01}$ and $\tau$. The conditional analysis yielded a positive estimate for study quality, $\gamma_{01}$= .0253, $p$ = .409, indicating that the effect sizes in primary studies that employ more stringent controls are much larger; however, the estimate is insignificant. According to the variance component $\hat{\tau}$ = .00355, slightly less variability exists between the effect sizes in the conditional analysis than in the unconditional analysis $\hat{\tau}$ = .00375. Model 2 explains approximately 53% of the variation.

Table 4 shows the findings of the multivariate analysis of high SES effects among black and white samples. In Model 1, the effect-size for black samples, $\hat{\gamma}_{10}$ = -.0347, $p$ = .273, is not significantly different than the high SES effect, $\hat{\gamma}_{00}$ = .0390. The negative estimate implies that black Americans benefit less, educationally, from concentrated affluence than whites. For instance, if the number of high SES residents within a neighborhood were to increase by twenty-five percentage points, we would witness an increase in the education outcome of black Americans approximately of .11 standard deviation units. This modest effect size is much smaller than the magnitude of the effect size for whites, estimated at .0469 beyond the mean effect-size $\hat{\gamma}_{00}$. This is an uncommonly large effect likely due to the inclusion of urban data sets that, more often than the national data sets, have large differences in the disaggregated effect size estimates favoring white populations. For white Americans, going from a neighborhood with no affluent residents to one where 25% of its residents are affluent would yield a 2.15 standard deviation unit increase in education outcomes. The robustness analysis that concludes the summary of findings gives an idea of how large an influence the presence of extreme values in the full sample may have. The variance component, $\hat{\tau}$ = .00404, and corresponding standard deviation, .06357 are significant, indicating there is much variability among the effect sizes.

**TABLE 4.** Models of neighborhood high SES effects, race, and study quality moderator.

| | Model 1 | | | | Model 2 | | | |
|---|---|---|---|---|---|---|---|---|
| Fixed effects | Effect | SE | t | df | Effect | SE | t | df |
| Intercept, $\gamma_{00}$ | .0390** | .0135 | 2.880 | 37 | .0368* | .0153 | 2.412 | 36 |
| Black, $\gamma 10$ | -.0347 | .0311 | -1.115 | 37 | -.0320 | .0291 | -1.097 | 36 |
| White, $\gamma 20$ | .0467 | .0429 | 1.095 | 37 | .0480 | .0431 | 1.113 | 36 |
| Study quality, $\gamma 30$ | | | | | .0179 | .0290 | .618 | 36 |
| Random | Variance component | $X^2$ | | p-value | Variance component | $X^2$ | | p-value |
| | .00404 | 4099.26807 | | .000 | .00407 | 5059.13426 | | .000 |

(***) $p < .001$
(**) $p < .01$
(*) $p < .05$

Model 2 in Table 4 shows the findings of the race analysis, controlling for study quality. The effect size estimates differ little once study quality is considered. The effect size estimate for black and white Americans remains insignificantly different than $\hat{\gamma}_{00}$ and for blacks, negative ($\hat{\gamma}_{10}$ = -.0320). The smaller magnitude of the Model 2 intercept and the modest growth in the effect size for white Americans ($\hat{\gamma}_{20}$ = .0480) offset to make the racial benefit gap nearly the same size as in Model 1. The study quality variable remains insignificant.

Table 5 shows the findings of the multivariate analysis of high SES effects according to gender. Model 1 contains no moderators while Model 2 controls for study quality. The analysis results show $\hat{\gamma}_{00}$ to be significant (.0354, $p$ = .009) and that the effect sizes for females ($\hat{\gamma}_{10}$ = -.0184, p = .54) and males ($\hat{\gamma}_{20}$ = -.0313, p = .39) are insignificantly different from $\hat{\gamma}_{00}$. Females apparently experience greater educational benefits than males from living in areas with affluent neighbors. This benefit gap increases slightly from .0129 standard deviation units in Model 1 to .0143 in Model 2 but nonetheless pales in comparison to the benefit gap according to race noted in Table 4. The between-study components indicate that there continues to be sizable variation among the effect sizes, which changes very little in Model 2 ($\hat{\tau}$ = .00396, SD = .06297).

The corresponding significance level ($p$ = .000) suggests the inconsistency in study estimates is not a chance occurrence.

**TABLE 5.** Models of neighborhood high SES effects, gender, and study quality moderator.

| | Model 1 | | | | Model 2 | | | |
|---|---|---|---|---|---|---|---|---|
| Fixed effects | Effect | SE | t | df | Effect | SE | t | df |
| Intercept, $\gamma_{00}$ | .0354** | .0128 | 2.761 | 37 | .0323* | .0152 | 2.129 | 36 |
| Female, $\gamma 10$ | -.0184 | .0299 | -0.616 | 37 | -.0140 | .0300 | -0.466 | 36 |
| Male, $\gamma 20$ | .0313 | .0356 | -0.879 | 37 | -.0283 | .0329 | 0.859 | 36 |
| Study quality, $\gamma 30$ | | | | | .0209 | -.0313 | .0668 | 36 |
| Random | Variance component | $X^2$ | | p-value | Variance component | $X^2$ | | p-value |
| | .00407 | 2323.48054 | | .000 | .00396 | 3164.51803 | | .000 |

(***) $p < .001$
(**) $p < .01$
(*) $p < .05$

Table 6 contains the findings of the multivariate analysis of affluence effects according to race and gender. Model 1 includes the effect sizes and parameters (black male, black female, white male, and white female) and Model 2 the study quality moderating variable. The results indicate that the relatively lower effect size for males in the gender analysis (Table 5) is due to the less beneficial association between affluence and education outcomes for black males. Of the four sub-sample populations, only the estimate for black males is significantly different than the intercept ($\hat{\gamma}_{00} = -.0803$, $p$ = .015) and suggests that the relationship between having high SES neighbors and education outcomes is negative. This relationship remains unchanged in Model 2. In contrast, the effect size estimates for white males are the most positive of any subpopulation in both models. Hence, the benefit gap between white and black males is the largest: $\delta_j$ = -.0426 for black males and .0806 for white males. Assuming a linear relationship, as the percentage of affluent neighbors increases, so does the size of the education gap between black and white males.

**TABLE 6.** Models of neighborhood high SES effects, race and gender, and study quality moderator.

| | Model 1 | | | | Model 2 | | | |
|---|---|---|---|---|---|---|---|---|
| Fixed effects | Effect | SE | t | df | Effect | SE | t | df |
| Intercept | .0374** | .0132 | 2.827 | 35 | .0367* | .0146 | 2.505 | 34 |
| Black male, γ10 | -.0813** | .0317 | -2.562 | 35 | -.0793* | .0321 | -2.472 | 34 |
| Black female, γ20 | -.0132 | .0326 | -0.405 | 35 | -.0105 | .0341 | -0.309 | 34 |
| White male, γ30 | .0418 | .0611 | 0.685 | 35 | 0.439 | .0630 | 0.697 | 34 |
| White female, γ40 | -.0306 | 0.333 | -0.920 | 35 | 0.285 | .0348 | -0.819 | 34 |
| Study quality, γ30 | | | | | -.0101 | -.0311 | -0.325 | 34 |
| Random | Variance component | $X^2$ | | p-value | Variance component | $X^2$ | | p-value |
| | .00475 | 13680.48667 | | .000 | .00494 | 15111.54366 | | .000 |

(***) $p < .001$
(**) $p < .05$
(*) $p < .10$

The white females estimate ($\gamma_{40}$ = -.0306, $p$ = .364) in Model 1 suggests a weaker relationship between affluence and education for this group; each percentage increase in higher SES neighbors equals a mere .0068 standard deviation unit increase in the education outcome. This suggests that females' greater benefit over males is due to the stronger relationship between affluence and the education outcomes of black females. For every percentage point increase in higher SES neighbors, we can expect a .0242 standard deviation unit increase in the outcome for black females, an estimate over three and one-half times the size of the benefit for white females. No noteworthy differences in the benefit gap for white and black females emerge after controlling for study quality. The between-study variance point estimate, $\hat{\tau}$, in Model 2 is .00494, with a corresponding standard deviation of the square root of .00494, of .07029 ($p$ = .000). This indicates that significant variation between studies' effect sizes remains and is unlikely accidental.

To ascertain whether unusually large effect-sizes influenced the analysis results, I constructed a 90% sample which eliminated the bottom and top 5% of the distribution of effect sizes. I then repeated the analysis with the same model specifications from

Tables 3 through 6. Table 7 summarizes the findings of the robust analysis and full analyses, presenting.

**TABLE 7.** Robust analysis of high SES effects on education with study quality variable.

| Effect Size | Full Sample Analysis | | 90% Sample Analysis | | Difference |
|---|---|---|---|---|---|
| Group | Estimate | Significance | Estimates | Significance | Estimate |
| Intercept | .0368 | .021 | .0337 | .022 | -.0031 |
| Black | -.0320 | .281 | -.0292 | .319 | .0028 |
| White | .0480 | .273 | .0419 | .338 | -.0061 |
| Intercept | .0323 | .040 | .0330 | .026 | .0007 |
| Female | -.0283 | .396 | -.0109 | .717 | .0174 |
| Male | -.0140 | .644 | -.0331 | .314 | -.0191 |
| Intercept | .0367 | .017 | .0347 | .016 | -.0020 |
| Black Male | -.0793 | .019 | -.0729 | .024 | .0064 |
| Black Female | -.0105 | .759 | -.0095 | .780 | .0010 |
| White Male | .0439 | .490 | .0236 | .697 | -.0203 |
| White Female | -.0285 | .419 | -.0186 | .604 | .0099 |

As Table 7 shows, the estimates produced in the full and robust analyses of race are similar: There are only small declines in the magnitude of the intercept and the white effect size and a smaller increase in the estimated relationship for blacks. Comparing the full and robust estimates to the gender analysis shows the intercept virtually unchanged, but a definite increase in the size of the benefit gap favoring females. The increase is due not only to a stronger relationship between higher SES residents females' education outcomes, but also to a considerable drop in males' average educational benefit. Regarding race and gender interactions, the robust analysis reveals only modest increases for black males, black females, and white females, suggesting that the relative benefits of each group in the full analysis are not influenced by unusually large estimates. The effect size for white males, however, declines a great deal in the robust analysis from .0439 in the full sample to .0236 in the 90% sample. Even with this decline, white males continue to enjoy a boost from neighborhood SES twice that of black females, and significantly more than white females and black males.

**Discussion**

This analysis revealed considerable and highly significant effects of neighborhood levels of high SES on learning outcomes that remained while controlling for variation in model specifications. Nonetheless the amount of variation in the effect sizes left unexplained was considerable, which alludes to the impact of other aspects of study quality beyond the conceptual interests of this analysis. Caution should be used however in interpreting the results of this analysis given the methodological limitations of the primary studies

(Jencks and Mayer 1990; Manski 1993; Durlauf 2001). Endogenous effects are very difficult to isolate in correlational studies due to the non-random allocation of individuals in neighborhoods. As efforts to protect causal inferences in correlational studies continue, future empirical reviews can account for the influence analytical approaches may have on the research synthesis of neighborhood effects research. Until that time, the assumption of endogenous effects here can only rely on the significant findings in the Gautreaux and MTO studies that have employed some degree of randomization and, subsequently, support a causal link between neighborhood features and education rather than a mere association.

While unbiased estimates can only be beneficial in research syntheses, the strength of this analysis is that its focus on the relative influence of a neighborhood's capital is somewhat resilient to the potential problem. There is no reason to believe the impact of selection bias among the study estimates will vary according to the primary study samples' demographic characteristics and, consequently, lessen the accuracy of this analysis' findings of benefit gaps according to race and gender. In terms of race, the analysis also revealed that a greater neighborhood educational benefit accrues to white over black Americans. This suggests inequality in educational performance derives not only from the unequal distribution of capital across neighborhoods according to race, but also within socioeconomic categories—in this case, high SES—and the inability of affluent residents to benefit youth—especially black males—equally. Let us consider the relevance of this finding in two contexts, *within* racially integrated settings and *between* homogenous settings.

In racially homogenous settings, community affluence may not insulate black Americans, and black males in particular, from disadvantageous social conditions to the extent it does white Americans. Mary Pattillo-McCoy (1999) convincingly argued that black Americans residing in racially homogeneous middle class areas, regardless of their individual family economic status, are more likely than whites to have friends, extended family, and neighbors who are less advantaged. The greater presence of less advantaged individuals within the social networks of middle class blacks reduces their ability to benefit from, and be a benefit to, other middle class neighbors. Given the considerable residential (and perhaps social) segregation of economically prosperous black Americans, these synthesis findings may reflect the relatively lower economic benefit produced by their social networks.

Racial benefit gaps may also develop within racially heterogeneous environments due to the dispositions of affluent neighbors. As Jencks and Mayer (1990) and Wells and Crain (1997) observed, affluent families tend to advocate for more stratification within diverse schools (the addition of gifted, honors, magnet, and accelerated placement programs), which often leads to greater variation in learning outcomes favoring some groups while disadvantaging others. These dynamics partly explain the "affluent college town" phenomenon under which black Americans are not performing as well as their higher SES white neighbors. Researchers have provided exogenous explanations for these persistent achievement gaps that highlight family practices or black youth's dispositions (Ogbu 2003) without exploring the obvious relationship between concentrated affluence and stratified schooling experiences. For example, Brantlinger's study (2003) of affluent white families in a college town revealed several informants that explicitly argued for exclusive schools; they rejected plans for mixed ability grouping and redrawing obviously "gerrymandered" school catchment areas that produce homogeneous schools within economically heterogeneous environments. These families were quite politically influential in achieving a school arrangement that preserved their proximal capital.

The gender analysis produced a smaller benefit gap between males and females than the one between blacks and whites. However, the gender gap, though smaller, is significant, and the large differences within gender according to race imply that race is a more salient factor in explaining the benefits of neighborhood capital. In other words, race becomes an increasingly important factor in affluent settings for males; such environments elevate the educational outcomes of white males while failing to do the same for black males. It is likely these differences extend from disparities in white and black males' typical environments. As stated earlier, the black middle class is likely to live in more economically diverse areas, contiguous to sections of concentrated poverty, and attend relatively lower performing schools (Jargowsky 1997; Pattillo-McCoy 1999; Sampson, Morenoff, and Earls 1999). Given these conditions and the likelihood that males interact more with their environments than females, it is understandable why these gaps are larger for males according to race than for females. Nonetheless, moderate benefit gaps exist for white females relative to white males and black females.

These findings feature several limitations, of course, many of them common in meta-analysis. Some important studies that could have influenced the findings were not included for various reasons. Studies focused on education outcomes that were not indicators of learning (e.g., discipline, engagement, course-taking), for instance, were not considered. Second, despite rigorous efforts, I may have overlooked some studies or they may have only become available during the latter stages of this work. Last, publication bias may have also influenced the findings of this study. It is possible that some studies were not published because their findings were similar to other studies already published or seemed inconsistent with the current direction of neighborhood research.

Nonetheless, as the first meta-analysis in neighborhood studies, this work makes noteworthy contributions. Meta-analysis in urban and neighborhood studies stands to explain why findings may vary according to theory and methods. This analysis has confirmed the importance of neighborhood affluence and how its effects vary according to race and gender. Research synthesis has long been used to lessen ambiguity surrounding pressing social issues with the intent to inform policy, most notably in the school desegregation movement of the 1970s. This analysis clarifies certain aspects of important economic, educational, racial, and gender questions that can also inform the adoption of social policies. The findings suggest that achieving economically heterogeneous neighborhoods may not end educational inequality—a reality consistent with the MTO findings that black males who relocate to the suburbs do less well than both black females and black males who remain in high poverty urban areas (Sanbonmatsu et al., 2006; Hilsenrath and Gerena-Morales 2006). To remedy these outcomes, policy efforts and social science should address the stratification of schools within more prosperous areas and the social status of black Americans whose relative individual deprivation tends to mute the beneficial effects of residing in economically heterogeneous neighborhoods.

**Odis Johnson, Jr.**, PhD, is currently an assistant professor in African American studies and a faculty associate at the Maryland Population Research Center at the University of

Maryland. He was previously an assistant professor in the School of Education at the University of California, Davis. His research focuses on urban/community sociology, the sociology of education, and social policy and has been supported by fellowships from the National Academies Ford Foundation Fellowship Program and the Spencer Foundation. He offers courses in program evaluation, quantitative methods, policy analysis and urban/community studies. He is a member of the editorial board of the journal, *The Urban Review*. He can be contacted at ojohnson@umd.edu.

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