THE RELATIONSHIP BETWEEN PERCEPTIONS OF NEIGHBORHOOD CHARACTERISTICS AND OBESITY AMONG CHILDREN.[1]

Bisakha Sen, Ph.D
Department of Healthcare Organization & Policy
University of Alabama at Birmingham
bsen@uab.edu

Stephen Mennemeyer, Ph.D
Department of Healthcare Organization & Policy
University of Alabama at Birmingham
smenneme@uab.edu

Lisa C. Gary, Ph.D
Department of Healthcare Organization & Policy
University of Alabama at Birmingham
lgary@uab.edu

Abstract

It has long been posited by scientists that we need to have a better understanding in the role that larger contextual factors – like neighborhood quality and the built environment – may have on the nation's obesity crisis. This paper explores whether maternal perceptions of neighborhood quality affect children's bodyweight outcomes, and moreover, whether racial and ethnic differences in such perceptions may explain any of the hitherto unexplained gap in bodyweight and obesity prevalence among Whites and minorities. The project uses data from the NLSY79 and the CoNLSY datasets. Results indicate that overall neighborhood quality is not significantly related to children's bodyweight. However, one particular characteristic, namely whether or not the mother believes there is enough police protection in the neighborhood, is related. Lack of police protection has robust and significant effects on the BMI-percentile of the children, though it has less robust effects on the risk of becoming obese per se. Finally, there are differences in perceptions about adequate police protection in their neighborhood between Whites and minorities which remain after controlling for other socio-economic characteristics like maternal education, family income and family structure. However, these differences may only play a minor role in explaining part of the gap in bodyweight between White and minority children.

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"Overweight and obesity are among the most important of these new health challenges. Our modern environment has allowed these conditions to increase at alarming rates and become highly pressing health problems for our Nation. At the same time, by confronting these conditions, we have tremendous opportunities to prevent the unnecessary disease and disability that they portend for our future."

Secretary of Health and Human Services, Tommy G. Thompson, in 'The Surgeon General's call to action to prevent and decrease overweight and obesity.' (2002)[2].

INTRODUCTION.

It is a well established fact that the prevalence of obesity among adults and children has increased markedly in the U.S. over the last three decades, and is considered to be a health problem of epidemic proportions. Given the scale of this problem, it is imperative to decipher the factors that influence the likelihood of obesity. The 'Let's Move' campaign by First Lady Michelle Obama has prioritized the goal of reduction of childhood obesity, thus further emphasizing the need for understanding factors that influence childhood obesity from a policy-making perspective. A report from the National Center for Environmental Health (Cummins & Jackson, 2004) recognizes that community and neighborhood can potentially play important roles in child health – including obesity. However, the report also emphasizes that there has been relatively limited research that actually documents the nature of the relationship between community, neighborhood, and various aspects of child health, and concludes that "This new research field is wide open." Particularly, we were able to identify just one study that explored the relationship between neighborhood quality and obesity in children, using data from 10 cities (Lumeng et al, 2006).

In this study, we extend extant research by exploring the relationship between children's body-mass index (BMI) as well as probability of obesity with different aspects of the neighborhood as reported by the mother using linked data from the National Longitudinal Survey of Youth 1979 (NLSY79) and the Children of NLSY79 (CoNLSY). We also analyze the extent to which hitherto 'unexplained' differences in the prevalence of obesity between non-Hispanic White children and minority children may be explained by the differences in neighborhood quality. We use several years of data where the mothers in the NLSY79 are asked about how they rate their neighborhood as a place to raise children, and also asked about several specific characteristics about their neighborhood, such as whether run-down buildings, lack of jobs, lack

[2] http://www.surgeongeneral.gov/topics/obesity/calltoaction/toc.htm

of police, inadequate transport, indifferent neighbors and so forth are a problem. Our results find that overall maternal rating of the neighborhood as a place to raise children is a significant predictor of the child's BMI or obesity-risk in some models, but that these results are not robust, nor are they statistically significant in models that control for unobserved heterogeneity via 'fixed effects'. However, one key neighborhood characteristic as perceived by the mother – namely, whether she believes that there is sufficient police protection in the neighborhood, – plays a significant role in predicting child BMI and remains robust across a range of model specifications.

BACKGROUND.

Neighborhood Characteristics, Physical Activity, Obesity.

There is an emerging consensus in the scientific community that environmental factors play a role in the obesity epidemic, and that environmental solutions will be needed to address the problem. Thus, there is growing interest in understanding what is an "obesogenic environment" (Glass et al, 2006), with a focus both on characteristics of the built environment – such as transportation or availability of physical activity facilities, as well as socio-economic deprivation at the community level. This literature has been encouraged, in part, by work indicating that moving to a better neighborhood impacts educational outcomes for minority children, though the results are different boys versus girls (Leventhal et al., 2005). Several studies have explored the relationship between neighborhood characteristics and physical activity, though the results have not always been consistent. For example, a report the Centers for Disease Control and Prevention (1999) using data from the Behavioral Risk factor Surveillance System found that higher levels of perceived neighborhood safety correlated with higher levels of physical activity for adults. In contrast, Romero et al (2001) found that children's own perceptions of neighborhood safety were actually inversely related to self-reported physical activity and BMI. Another study, by Brownson et al (2001), found no statistical correlation between neighborhood crime rates and adult physical activity. A review of 19 quantitative studies by Humpel et al (2002) found that neighborhood safety had positive associations with physical activity in some studies, and no statistical association in others, though no negative association was found in any study. In a relatively recent study, Gordon-Larsen et al (2006) found that inequality in access to physical-activity facilities were a major predictor of obesity-risk as well as physical activity, and that low socio-economic status neighborhoods as well as high-minority population neighborhoods were less likely to have good access to physical-activity facilities. Glass et al (2006) used data on elderly adults in the Baltimore area, and found that residents of neighborhoods that ranked high in psychosocial hazards had higher BMI, less physical activity, and less healthy diets than their peers in neighborhoods ranking lower in psychosocial hazards, even after controlling for race-ethnicity, education, household wealth and substance use. However, one problem that few of these studies have been able to address is the potential endogeneity between neighborhood characteristics and either physical activity or obesity. Namely, that the neighborhood that people reside in is at least partly due to their own choice, and persons with unmeasured personal or cultural propensities for greater physical activity and energy-balanced lifestyles might be more likely to live in neighborhoods that facilitate that physical activity and lifestyle.

We are aware of only two studies that directly test the relationship between neighborhood perceptions and obesity. The first of these is by Burdette et al (2006), and use data from the Fragile Families and Child Well-being study. Perceptions of the mothers in that survey about the neighborhood are measured using two separate indexes – a 'neighborhood safety/social disorder' scale based on eight items, like how often the women saw loitering people, drunks/drug dealers, gang activities, and disorderly/misbehaving people in the neighborhood, and a 'collective efficacy' scale based on whether the mothers felt that their neighbors could be trusted, and whether the neighbors would intervene in situations like a fight breaking out in near vicinity or children loitering around. The study finds that mothers living in neighborhoods that they perceived to be relatively unsafe were more likely to be obese than counterparts living in neighborhoods they perceived to be safe, after controlling for indicators of socio-economic status (SES) like income, education, race/ethnicity and marital status. The second study by Lumeng et al (2006), use a sample of 768 children from 10 cities in the U.S., who were part of the National Institute of Child Health and Human Development Study of Early Child Care & Youth Development. They obtain neighborhood quality perceptions using a 16-item measure of neighborhood characteristics, that was completed by the mother and at least one other adult guardian in the household (father, stepfather, grandparent) when the child was in the first grade. The items are then divided into two scales – the 'neighborhood safety subscale' and the 'neighborhood social involvement subscale'. They find that, among 7 year old children, those residing in neighborhoods were the perceived neighborhood safety index was in the lowest quartile had a higher risk of being obese than counterparts in other neighborhoods, and this relationship held after controlling for parental marital status, education, race\ethnicity, and child's participation in after-school activities. This study is based on a relatively small sample of children that is 85 percent White, thus its results may not be generalizable.

Finally, extant studies have found a correlation between the time spent watching television and obesity among children (Dietz & Gortmaker, 1985; Robinson et al, 1993; Robinson, 1997). If there is a correlation between neighborhood quality and the time spent by children in sedentary, indoor activities like watching television, then this could be a potential pathway through which perceived neighborhood quality affects children's' bodyweight. However, we are not aware of any study that explores the relationships between parental neighborhood perceptions and the amount of time children spend watching television.

Race-Ethnicity, Socio-Economic Status (SES) & Obesity among Children

It is well established that obesity disproportionately affects certain minority youth populations. Results from the 1999-2002 National Health and Nutrition Examination Survey (NHANES) found that African American and Mexican American adolescents ages 12-19 were more likely to be overweight (21 percent and 23 percent respectively) than non-Hispanic White adolescents (14 percent). Among children 6-11 years old, 22 percent of Mexican American children and 20 percent of African American children were overweight, compared to 14 percent of non-Hispanic White children (NCHS, 2008). Furthermore, the rate of increase in obesity prevalence among children has been more pronounced among minority children than White children. For example, between 1986 and 1998, obesity prevalence among African Americans and Hispanics increased 120 percent, as compared to a 50 percent increase among non-Hispanic Whites (Strauss and Pollack, 2001).

A comprehensive review of literature by Stobal and Stunkard (1989) finds that, among adults, there is a consistent negative relationship between higher socioeconomic status (SES) (as measured by income, education, or occupation status) and being obese, but the relationship appears weaker and less consistent in children. While many studies included in the above review find that SES is negatively associated with children's obesity risk, other research suggests that this relationship varies by ethnicity. Specifically, the negative relationship between better SES and prevalence of obesity seems more apparent among White children and adolescents, but much less apparent among Black or Mexican-American (and presumably other Latino) adolescents (Troiano and Fegal, 1998). In other words, Black and Latino children from families with higher SES are no less likely to be overweight or obese than those in families with lower socioeconomic status. It has been speculated that the difference in the relationship between SES and obesity may be driven by cultural differences in eating habits as well as attitudes towards body weight (Strauss & Knight, 1999). We speculate that one other factor may play a role – specifically, neighborhood quality. Extant research finds that White families are more likely than Black and Latino families to move into better and 'non-poor' neighborhoods, even after accounting for income (South & Crowder, 1997; Hango, 2002), and that Black families are less likely than non-Black families to convert dissatisfaction with neighborhood to an actual move (South & Deane, 1993). If better neighborhood quality is negatively related to the risk of childhood obesity, then the racial and ethnic differences in neighborhood quality among families of comparable SES might explain some of the racial and ethnic differences in children's obesity among families of comparable SES.

DATA & METHODS.

Theoretical Framework & Empirical Models

Essentially the approach we take here is to assume that there exists a simple "production function" of a child's BMI percentile (or, alternatively a binary indicator of whether the child is obese or not) as a function of caloric intake and energetic versus sedentary activities, and these in turn are determined by the mother's perception of the neighborhood, as well as other familial, demographic and socio-economic characteristics that might have a bearing on the child's exercise and eating patterns.

We posit a very simple model that is broadly within the framework of Grossman's model of health, where parents attempt to optimize 'healthy weight' for the child, where the arguments in the production function for healthy weight include the child's caloric intake, and caloric expenditure through exercise and activity. Thus, the child's BMI can be written as a 'production function' of these inputs:

$$BMI = F(C_{(+)}, E_{(-)}, S_{(+)}; R) \qquad \text{(i)}$$

Where C represents caloric intake, E represents time spent in energetic activity, and S represents time spent in sedentary activities. Arguably the two groups of activities are mutually exclusive and exhaustive, however we choose to explicitly include both in the production function. R represents other 'residual' unobserved factors, including genetics. The signs in parenthesis indicate whether each of these components is expected to increase or decrease BMI. Fully specifying and expanding the model -- which would yield demand functions for caloric intake and types of activities as functions of the market prices of the inputs, shadow prices of time, and income – is beyond the scope of this paper. However, we can posit that neighborhood quality is a factor in the demand functions of each of the components of the production function, since it arguably plays a role in determining the 'price' of each of the components.

Specifically, $C = C(N, X)$; $E = E(N, X)$; $S = S(N, X)$. (ii)

Where 'N' is a measure of neighborhood characteristics that for simplicity is termed 'neighborhood quality', and 'X' represents other demographic and socio-economic characteristics that play a role in determining market or shadow prices, as well as income and preferences.

Poor-quality and dangerous neighborhoods are likely to make outdoor activities – be it playing outdoors or walking to schools and recreational facilities – hazardous and hence more 'costly'. Thus, children may be made to spend more time indoors by parents, and thus spend more time in sedentary occupations. Poor-quality and dangerous neighborhoods could also make it more difficult for parents to acquire healthy foods like fresh produce, which in turn could contribute to an unhealthy diet by the children. On the other hand, it could be argued that, if older children in particular had more license to be outdoors and to walk to various places, then they may also be able to go to stores or fast-food establishments and buy calorically dense foods without their parents' supervision. Furthermore, it could be argued that other built environment characteristics – for example, the lack of sidewalks – could make the issue of outdoor activities moot even if the neighborhood was otherwise perceived as 'high-quality' and 'safe'. Thus, it is difficult to predict *a priori* what effects neighborhood quality will have on each of the arguments in the production function for healthy-weight, and thus, ultimately, how neighborhood quality will affect a child's weight. Hence, this question must be empirically determined.

To explore this empirically, we start by Substituting (ii) into (i) and creating a reduced-form BMI production function as

$$BMI = F(N, X, R) \qquad \text{(iii).}$$

Based on equation (iii), we posit a simple linear specification model such that the BMI of the i^{th} child in the t^{th} period is expressed as

$$BMI_{it} = \alpha N_{it} + X_{it}\beta + R_{it} + \varepsilon_{it} \qquad \text{(iv)}$$

Empirical studies on children's weight often use dichotomous models to investigate what covariates influence the odds of children being obese or overweight. However, a recent study by Field et al (2005) reports that, simply being in the upper half of the age and gender specific BMI distribution is a good predictor of becoming obese as an adult as well as developing health problems like hypertension in early adulthood. This suggests that, in addition to investigating what factors correlate with the risk of obesity/overweight in children, researchers should also be concerned about what factors simply predict a higher BMI in children. Hence, we estimate models with continuous measures of BMI (specifically, the BMI percentile score as well as the BMI-z score), in addition to linear probability models when the dependent variable is a binary indicator of whether the child is obese or not. To account for the fact that there are repeated observations for each child, as well as multiple children of the same mother in the data, standard errors are clustered at the maternal level.

We face the standard dilemma here that R_{it}, which represents unobserved determinants of the child's obesity, may also be correlated to the variable used to measure neighborhood quality. Neighborhood characteristics are not purely exogenous. For example, it may be speculated that families who have unobserved preferences for sedentary pastimes may disproportionately select into neighborhoods which are not conducive to outside activities. If the mother has a genetic predisposition towards obesity which she passes on to her children, then that predisposition towards obesity could also impose wage-penalties upon her (Cawley, 2004), and in turn decide the nature of the neighborhood that she can afford to live in. Thus, failing to account for these unobservables are likely to result in biased estimates of the effects of neighborhood quality on child bodyweight. Finally, in a situation where the neighborhood quality is measured based on the mother's perceptions of the neighborhood with no other external validation, there is the added issue that R_{it} may include unmeasured maternal characteristics that correlate both with such perceptions and her children's health outcomes. For example, a mother who is suffering from depression or other mental health problems may perceive the neighborhood as being an unsafe and hostile place, and at the same time she may also be less capable of properly monitoring the caloric intake and physical activities of her children to ensure their healthy weight.

We initially approach this problem by explicitly controlling for past maternal BMI in the model. The argument here is that past maternal BMI may serve both as a proxy for the genetic endowments in the family as well as the mother's unobserved preferences for caloric intake and physical activity, but it will not in itself be affected by current neighborhood quality (though one might argue that some mothers will continue to be in neighborhoods that are identical or very similar to the ones they grew up in themselves). Thereafter, we also use the fairly standard methods of 'fixed effects' models, where we first estimate the models after including mother-level fixed effects, and thereafter we estimate them including child-level fixed effects. We have a slight preference for the former. Given that our measures of neighborhood quality are based entirely on the mother's reports, arguably the primary concern is the existence of maternal unobserved characteristics that correlate both with her perceptions about the neighborhood as well as her children's bodyweight outcomes. We also attempt a 'propensity score regression method' where we calculate the probability of the mother living in a neighborhood of a certain quality based on an extensive list of her characteristics, and include that probability as a specific control variable in the regression equation (give cites). We recognize the inherent shortcomings of all of these methods. For example, the fixed effects methods fail to account for unobservables that may be time-variant over the period of study, tend to accentuate the effects of measurement error, and can lead to the loss of statistical power. Propensity score regressions account for mother-level observables, but will not eliminate the bias in results that arise from variables that remain unobservable and unmeasured. Nonetheless, we believe that these are the best tools that we have to minimize the effects of bias-inducing unobservables in this study, even if we cannot altogether eliminate that bias.[3]

One of the specific contributions of this paper is to explore whether differences in maternal perceptions of neighborhood quality can explain any of the hitherto unexplained

[3] We debated using instrumental-variable techniques, but were not aware of any viable instruments that would correlate to maternal perceptions of the neighborhood, but not have any direct bearing on the BMI of her children.

differences in BMI and obesity-risk between minority and non-minority children. To do this, we start by estimating the following empirical model:

$$N_{it} = M_i\mu + X_{it}\lambda + u_{it} \qquad \text{(v)}$$

Where M_i are binary indicators of the race-ethnicity of the mother – one binary indicator to denote whether she is Black, and one binary indicator to denote whether she is of Hispanic origin. X_{it} is now defined (with slight abuse of notation) as a vector of indicators of socio-economic and demographic status other than race-ethnicity. The purpose is to statistically test whether the above minority populations are likely to have worse perceptions of their neighborhood compared to their White peers after controlling for the other socio-economic and demographic characteristics.

We follow this up with a Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973), which is a technique that was originally used in labor market analysis to compare mean differences between two groups in the dependent variable of a regression model – typically wages. Here we use the technique to examine mean differences in the BMI percentile score of groups of children. We compare Non-Hispanic Whites (hereafter, "Whites") to African-Americans (hereafter "Blacks") and, later, Whites to Hispanics using the approach discussed in Jann (2008).

The Oaxaca-Blinder decomposition can be summarized with the expression

$$R= \{E(X_w) – E(X_b)\}' B_w + \{ E(X_b)' (B_w - B_b)\} \qquad \text{(vi)}$$

This can be abbreviated as

$$R = Q + U \qquad \text{(vii)}$$

Where:

$$Q = \{E(X_w) – E(X_b)\}' B_w \qquad \text{(viii)}$$

$$U = \{ E(X_b)' (B_w - B_b)\} \qquad \text{(ix)}$$

Assume that we estimated a linear model for the BMI percentile score for Whites (subscript w) and then again for Blacks (subscript b). Here, Q represents the difference in the mean values of right hand side regressors $E(X_w) – E(X_b)$ (i.e. the "endowments") multiplied by the regression coefficients B_w of the White group, against whom it is assumed that there is no discrimination (or alternatively, for whom it can be assumed that the coefficient estimates represent the 'correct' response of the dependent variable to a change in the independent variable) . Thus for our analysis, Q is the part of the differential in the BMI percentile score that is explained by group differences in the levels of the regressors (the “quantity effect”). U is the unexplained part of the differential. In the labor market literature, U is often interpreted to be the part due to “discrimination” as well as the effect of any unobserved differences between the two groups. In our analysis, we interpret U as the effect of unobserved differences between the two groups.

Data

The primary sources of data for this project are the National Longitudinal Survey of Youth 1979 cohort (NLSY79) and the Children of the NLSY79 (CoNLSY). We use survey year data from 1992 to 2000, which are the only years when questions were asked about neighborhood quality.

The NLSY79 is a multi-purpose panel survey that originally included a sample of 12,686 individuals who were within the age-range of 14 to 21 years of age on December 31, 1978. This original sample consists of three subsamples: a cross-sectional sample of 6111 individuals representative of the non-institutionalized civilian U.S. population within the prescribed age-range; a supplemental sample designed to oversample Hispanics, Blacks, and economically disadvantaged White U.S. population within the prescribed age-range; and a sample of 1280 respondents designed to represent U.S. military personnel within the prescribed age range.

Annual interviews were conducted beginning in 1979, with a shift to a biennial interview mode after 1994. The NLSY79 provides extensive information on all its respondents, including labor force activities, demographic characteristics, marital status, income, education, spousal characteristics, health status, and other socio-economic characteristics. In year 2000, 4,113 of the original 6,283 female respondents remained in the sample. Of the missing 2,170, 441 were members of a military over-sample dropped in 1984, 890 were from an over-sample of economically disadvantaged White people dropped in 1990, and 105 were deceased. The remainder is lost due to attrition

The CoNLSY sample is comprised of all children born to NLSY79 female respondents who live with their mother fulltime or at least part time, who have been independently followed and interviewed in various ways biennially, starting in 1986. Children who cease to live with their mothers altogether following a divorce are no longer included. The records from NLSY79 and CoNLSY can be easily linked via the mother’s sample identification number. As of 2000, a total of 11,205 children had been identified as having been born to the original 6,283 NLSY79 female respondents, mostly during the years that they have been interviewed (of course, an unknown number of additional children may have been born to respondents after they attritioned or were dropped from the sample). Given the design of the CoNLSY survey, not all the children are assessed in each survey year. Children 'enter' the dataset after they are born, and once they reach the age of 15, they are dropped from this survey.[4] Given this design, there are more very young children entering the CoNLSY dataset in the early years, when the mothers in the NLSY79 are in their peak childbearing years; whereas in the later years there are fewer children in the dataset overall (since more have exceeded the age of 15), and fewer very young children are entering the dataset since fewer NLSY79 female respondents are giving birth.

Neighborhood Perceptions: In 1992, the NLSY79 started to include a series of questions addressed to the mothers in the dataset about their perceptions about their neighborhood. They were asked how they rated their neighborhoods overall as a place to raise children, with potential answers being 'excellent', 'very good', 'good', 'fair' and 'poor'. Thereafter the respondents are specifically asked about selected neighborhood features, including neighbors lacking respect for law and order, crime and violence, abandoned and run down buildings, lack of police protection, lack of public transportation, parents who do not supervise children, neighbors who are indifferent about other neighbors, and people unable to find jobs. For each of these issues, respondents state whether they consider it 'a big problem', 'somewhat of a problem' or 'not a problem' in their neighborhoods. These questions were discontinued after the 2000 survey.

We use this information to create binary variables for overall neighborhood quality – namely, whether the mother qualifies the neighborhood as being an excellent or very good place to bring up children, and whether she qualifies it as only a fair or a poor place to bring up children. Thereafter we create a series of binary indicators for the specific characteristics to indicate whether the mother considers each of those characteristics to be at least somewhat of a problem in the neighborhood.

Height & Weight Information: The CoNLSY survey covers numerous developmental and health aspects of the children. For all children below the age of 14, the child's height and weight at the time of interview are recorded. In the majority (approximately 65%) of cases, interviewers measure height by tape measure and weight using a scale. In the remaining cases

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[4] Once the children are over the age of 15, they leave the CoNLSY and enter another survey called the 'NLSY79 Young Adults.'

height and weight are reported by the child's mother. We include all child-observations, regardless of whether the height and weight were mother-reported or interviewer-measured. However, we do include an explicit binary indicator to identify those cases where height and weight were interviewer-measured.

While the above height and weight information can be used to create a conventional BMI score using the standard formula of (weight in lbs x 703)/ (height in inches)^2 , it should be noted that, unlike adults, absolute BMI scores carry less meaning for growing-age children in terms of health-markers. Therefore, we follow the convention in the literature and alternately use BMI-z scores and BMI-percentile scores, which show how the child's BMI compares with his or her age and gender specific BMI distribution.[5] Equation (iv) is estimated using both BMI-z and BMI-percentile scores. We also follow the convention of denoting a child to be obese if his or her BMI is at or above the 95th percentile of the age and gender specific BMI distribution of the reference period.

Other Variables: We draw upon the rich array of information on socio-economic and demographic characteristics that are available in the NLSY79 and CoNLSY for all respondents to control for other familial characteristics. Since current maternal BMI may also be a function of contemporaneous neighborhood quality (since poor neighborhood quality may also limit adult physical activity), we use maternal BMI based on height and weight information from the first time it was asked in the NLSY79 – in the 1981 survey. Finally, we include information from the NLSY79 Geocode data to identify the counties where each mother lives in each survey year, and use this information to merge in county characteristics likely to be associated with neighborhood perceptions. Specifically, we used FBI Uniform crime statistics aggregated at the county level. Variables included murders, forcible rapes, robberies, aggravated assaults, burglaries, larcenies, motor vehicle thefts, and arsons each defined per hundred thousand of population in the county. These data are available annually. We used the collection from the University of Virginia. (U.S. Federal Bureau of Investigation, 2004). Other descriptors of the county include the percentages of the county population that was Black and Hispanic, the percent of households with a female head, and income per capita were obtained from Area Resource File using data from the U. S.

[5] The BMI-z and BMI-percentile scores were created using SAS programs provided by the CDC at http://www.cdc.gov/nccdphp/dnpa/growthcharts/resources/sas.htm. We acknowledge our debt to Laura Argys, who played a key role in using the programs and generating the BMI-z and BMI-percentile values. These scores were initially created for use in an ongoing project by Argys & Sen (2008).

Census for 1900 and 2000 (and for 1995 for per capita income) and interpolated from intervening years. (U.S. Bureau of Health Professions, 2007). County annual unemployment rates were obtained from the Bureau of Labor Statistics. (U.S. Bureau of Labor Statistics, 1992 - 2000).

RESULTS & DISCUSSION

Maternal Perceptions of Neighborhood Characteristics and Child Bodyweight.

Table 1 presents descriptive statistics for the full sample, by race-ethnicity, and by neighborhood quality rating. The mean BMI-percentile in the pooled full sample is 56.9, and the obesity rate is about 17 percent. About 56 percent of the mothers in the pooled full sample report that their neighborhood is a 'very good' or 'excellent' place for children (hereafter referred to as 'very good'), while 23 percent rate it as 'fair' or 'poor' (hereafter referred to as 'not good'). The remaining mothers rate it as 'good'. Among the specific characteristics, the one that is perceived as at least somewhat of a problem by the largest fraction of responding mothers is 'unsupervised children' (45.6 percent), followed by lack of respect for law and order (36.7 percent), jobless people (35.2 percent), indifferent neighbors (33.2 percent), crime & violence (30.4 percent), lack of transport (30.1percent), lack of police protection (25.4 percent) and run-down buildings (19.9 percent). Not surprisingly, the Black and Hispanic sub-samples rate their neighborhoods more poorly and report more problems than does the White sub-sample. This is probably due at least in part to the fact that the Black and Hispanic sub-samples also have lower family income, lower levels of educational attainment, and higher proportions of them live in central-cities compared to the White sub-sample. It can also be seen that the sub-sample living in 'not good' neighborhoods have higher mean BMI-percentile for their children as well as higher rates of obesity. Not surprisingly, higher proportions of this sub-sample are minorities, more likely to live in the inner city, be single-parent households, have lower family income, have mothers who are not working and with lower educational attainment, and have mothers who had higher BMI themselves in 1981, compared to their counterparts living in better neighborhoods. Living in 'not good' neighborhoods also correlates with reporting higher rates of specific neighborhood problems. With the exception of 'lack of transportation'-- where the proportions across the two groups are somewhat comparable -- those living in 'not good' neighborhoods are substantially more likely to answer in the affirmative about the existence of specific problems in the neighborhood. The Cronbach's alpha for the eight specific dimensions of neighborhood quality is 0.84, indicating high internal consistency. Therefore, these eight items reliably represent the construct of perceived neighborhood quality.

Table 2 presents three sets of results from regressing measures of the child's bodyweight (BMI-percentile, BMI-z score, and a binary indicator of obesity) upon the overall neighborhood rating and other characteristics. The initial specification includes demographic and geographic characteristics, but no other indicators of socio-economic status. The second specification includes measures of socio-economic status – maternal education, presence of a father in the household, total family income and maternal employment status. The third and final specification additionally includes maternal BMI as measured in 1981. Perceived neighborhood quality is captured by two binary indicators of 'very good' and 'not good', with the basis for comparison being whether the neighborhood is 'good'. It can be seen that being in a not-good neighborhood is associated with a higher BMI-percentile in the first two model specifications, and with a higher BMI-z score in the first model specification. However, once the full range of familial socio-economic characteristics as well as maternal BMI from 1981 are controlled for, no further statistical associations remain between any of the outcome variables and the overall neighborhood quality measures. Models using maternal fixed effects and child fixed effects also failed to find any statistical relationship between the outcome variables and the neighborhood quality measures. Those results are available upon request.

We repeated the estimations after substituting each of the eight specific neighborhood characteristics (that is, the binary indicator for whether a specific issue was at least 'somewhat' of a problem) in place of the general rankings. For brevity, only the results pertaining to the neighborhood characteristics are presented (Table 3). Most of the specific characteristics do not have any significant relationship to the BMI outcomes or obesity risk -- with the exception of the problems of indifferent neighbors and inadequate police protection. The children of mother's who report that indifferent neighbors are a problem on average belong to a 1.84 higher BMI-percentile and are at a 2 percent higher risk of obesity compared to children whose mothers do not report it as a problem. The children of mother's who report that inadequate police protection is a problem on average belong to a 3.65 higher BMI-percentile and are at a 3 percent higher risk of obesity compared to children whose mothers do not report it as a problem.

Thereafter, we used only these two characteristics to estimate further models, including those that controlled for the mother's BMI from 1981, and those that included maternal and child fixed effects. We found that there no longer remained any significant relationship between the problem of indifferent neighbors and the outcomes. However, inadequate police protection continued to have a significantly negative effect both on the BMI-percentile and BMI-z-scores in almost all the model specifications, though not always on the risk of obesity per se (Table 4). We also ran models that included the full set of specific neighborhood characteristics in addition to other characteristics, and there too inadequate police protection continued to be statistically significant in almost all models, thus alleviating the concern that the estimated effects of inadequate police protection when included only by itself was simply picking up the effects of other neighborhood characteristics omitted from the model.

Upon re-running the analyses separately for (non-Hispanic) Whites, Blacks and Hispanics, we found that inadequate police protection typically had larger and more significant effects on BMI-percentile of Black and Hispanic children compared to Whites, but that for all the sub-samples, the effects on the risk of obesity per se tended to be statistically imprecise. These results are also in Table 4.

As mentioned earlier, we used one further approach to test the robustness of the results pertaining to inadequate police protection – a propensity scores approach. This method, described by D'agostino (1998), and used in previous studies like Sen and Swaminathan (2007), essentially involves estimating first stage binary regressions for the 'treatment' in question using as control all available and relevant observable characteristics; obtaining the predicted probabilities of being subject to the treatment; and finally, including that predicted probability (i.e. the 'propensity for the treatment') as an added control in the final outcomes regression which also includes the binary indicator of treatment. While propensity scores, by definition, only control for observable factors, if one is able to use a wide range of observables that directly measure or adequately proxy for the potential confounders to construct this scores, then arguably the omitted variable bias in the coefficient estimate of the binary treatment is substantially reduced. The advantages of including the propensity score in the final regression rather than attempting a more conventional propensity score 'matching' method proposed by Rosenbaum & Ruben (1984) is that it prevents the loss of sample size since we do not have to omit observations from the control group which do not closely match members from the treated group, and also helps avoid the problems regarding which particular matching technique is the appropriate one.

We estimate initial probit equations on perceptions of inadequate police protection using the following maternal characteristics: whether she grew up in an intact parental family herself, whether either parent was an immigrant and a foreign language was spoken at home, her religious attendance as reported in the first survey year, whether her mother was employed outside the home, proxy variables for the importance of education in the home environment in form of whether newspapers came to the house and whether the family had a library card when she was 14, whether she reported binge drinking in a past survey (the question is asked in the 1985 survey), whether anyone in her family had a problem with alcohol, her family's poverty status in 1978, and whether in the 1982 survey she reported facing discrimination when looking for a job based on sex, race, or nationality, whether she faced discrimination based on age (i.e. considered too young), and finally, her self-esteem score based on the 10-item Rosenberg Self-Esteem Scale based on the individual's self-evaluation Higher scores on this scale are indicative of greater self-esteem.[6] The NLSY79 administered these questions and created the scale in the 1980 and 1987 interviews. We use the information from 1987. Of our selected variables, being in poverty in 1978 and binge drinking significantly increases the probability of reporting inadequate police protection, whereas maternal employment, newspapers and a library card in the house when she was 14, and higher self-esteem significantly reduces the probability of reporting inadequate police protection. Living in an intact parental family herself reduces the probability of reporting inadequate police protection with weak statistical significance, while religious attendance, parental immigrant status or alcohol problems among other family members do not have any significant effect. Full results are available upon request. As explained above, we then create the predicted probabilities (i.e. the 'propensity scores') of reporting inadequate police protection from the probit model, and then use that as an added control in our equations for the child's bodyweight. We find that the relationship between inadequate police protection and child's BMI-percentile as well as likelihood of being obese remain comparable to earlier findings

[6] The scale is short, widely used, and has accumulated evidence of validity and reliability. It contains 10 statements of self-approval and disapproval with which respondents are asked to strongly agree, agree, disagree, or strongly disagree. Of these, on five items disagreeing is indicative of higher self-esteem, while on the remaining five disagreeing is indicative of lower self-esteem, and thus must be reversed when the items are added.

using maternal fixed effects – namely, inadequate police protection significantly increases both BMI-percentile and risk of obesity for the full sample, but for sub-samples by race-ethnicity, the effects on risk of obesity tend to be statistically imprecise, and the effects on BMI-percentile appear to be larger and more significant for Blacks and Hispanics compared to Whites.[7]

It would be useful to be able to explore the causal pathways between perceived inadequate police protection and children's bodyweight. Unfortunately, the CoNLSY datasets provide very limited information on either energetic versus sedentary activities or diet quality. The only 'pathway' we were able to consider from this data is the sedentary activity of television watching, an activity that has been found to be associated with increased risk of obesity in previous studies (Dietz & Gortmaker, 1985; Robinson et al, 1993; Robinson, 1997). We estimate the relationship between maternal perceptions of inadequate police protection and reported average hours of television watching per day by the children during weekdays and during weekends, in models with and without controls for the other neighborhood characteristics, mother-level fixed effects, child-level fixed effects, and the previously calculated propensity scores. The results are reported in Table 5. Maternal reports of inadequate police protection are associated with increases in the children's television watching by 0.36 to 0.47 hours during weekdays and 0.26 to 0.42 hours on weekends in the models without fixed effects. When maternal fixed effects are included, estimated impact on television watching on weekdays is about 0.32 hours, and continues to be statistically significant. When child fixed effects are included, the estimated effect falls to about 0.20 hours and becomes statistically insignificant. In models with maternal or child fixed effects, the relationship between inadequate police protection and TV-watching during weekends is statistically insignificant, and the sign on the effect is counterintuitive. Furthermore, we are concerned regarding the validity of the results because of possible measurement error in the television watching variable in the CoNLSY dataset. A number of respondents reported watching television for more than 20 hours a day on weekdays and weekends, and some reported watching television for more than 24 hours a day. Hence, there is likely to be measurement error in the hours of television watching variable, and

[7] It has been argued that propensity score regressions yield results similar to those yielded by including all mother level characteristics in the final model individually, with the only advantage being that fewer degrees of freedom are lost when including a single propensity score rather than an array of individual variables. (Bhattacharya and Vogt, 2007) Indeed, when we repeated the regression models for child BMI-percentile and obesity-risk after explicitly including all maternal characteristics instead of the predicted propensity score, our results stayed very similar.

whether this affects the estimates of interest depends on the nature of the measurement error. If the measurement error is uncorrelated to the actual value of hours of television ('classical measurement error'), then it will not bias the model estimates, though it may increase the standard errors. However, if the measurement error is uncorrelated with the reported value but correlated with the true value of the outcome variable, then model estimates will be biased towards zero (Hyslop & Imbens, 2001). The most complex scenario is when the measurement error in the outcome variable is potentially correlated with the inadequate police protection (for example, respondents who report the more outlying values of television hours may do so because they have relatively low cognitive abilities, and this in turn may be correlated to how they perceive their neighborhood), whereby the bias in the estimate could be large and its direction non-decipherable without more information. (Hyslop & Imbens, 2001). Thus, we treat these results with some skepticism. s Ultimately, the issue of pathways through which neighborhood quality perceptions influence bodyweight must be addressed using other datasets that provide more thorough and better measures of energetic/sedentary activities and diet quality.[8]

Finally, as a prelude to exploring whether differences in police protection can explain any part of the variation in children's bodyweight across race-ethnicity, we first verify that there exist differences in levels of (perceived) police protection between White mothers, Black mothers and Hispanic mothers that cannot be explained by differences socio-economic factors such as income, education, presence of a husband in the household and so forth. Table 6 reports results from linear probability models based on equation (v), where the lack of police protection, as well as a general rating of the neighborhood as not good, are regressed on race-ethnicity as well as all the socio-economic and geographic controls in the other models. Results show that, compared to White mothers, Black mothers have a 13 percent higher probability and Hispanic mothers have an 8.2 percent higher probability of reporting that lack of police protection is a problem in their neighborhood. Moreover, compared to White mothers, Black mothers have about a 16.3 percent

[8] We debated about the possibility of regressing BMI on television-watching in a 2SLS framework with inadequate police protection serving as an instrument for television watching. We eventually decided against this. An objective, external measure of neighborhood safety would have probably served as a good instrument. But we have concerns about whether mother-reported perceptions of police protection could in some cases be correlated with certain maternal emotional and mental health issues which could also affect her maternal skills and thus her child's bodyweight. Under circumstances, we do not believe that maternal perceptions of inadequate police protection would satisfy the characteristics of a good instrument.

higher probability and Hispanic mothers have about an 8.3 percent higher probability of reporting that the overall quality of the neighborhood was not good. Hence, there exist differences across race-ethnicity in neighborhood quality that are not explained away by differences in socio-economic status across race-ethnicity. This provides justification for doing Oaxaca-Blinder decomposition.

Oaxaca-Blinder Decomposition.

Table 7 shows the Oaxaca-Blinder decomposition based on OLS models with robust standard errors, and Table 8 shows the Oaxaca-Blinder decomposition based on models with mother-level fixed effects. For brevity, we mostly confine our detailed discussion to the results presented in Table 7. The left hand side of the table (columns 2 to 4) has the (non-Hispanic) White v. Blacks comparison; the right hand (columns 5 to 7) is the (non-Hispanic) White v. Hispanic comparison. In case of Whites versus Blacks, for example, the mean predicted BMI percentile scores are respectively 55.06 and 60.46 with a statistically significant difference (at 1%) of -5.40 BMI percentile points. This difference can be broken down in columns 3 and 4 respectively into the total explained part that is due to differences in the levels of the regression variables – i.e. Q in equation (vii) -- which is -2.73 (z= 2.75), and the total unexplained part , U in equation (vii), which is -2.67 (z=1.91). The rest of the entries in columns 3 and 4, show the decomposition at the level of the individual variables.

A comparison of the above models with Oaxaca-Blinder decomposition models that exclude perceived police protection finds that, in absence of controlling for police protection, of the -5.40 BMI percentile points gap between Whites and Blacks, -2.50 (z=2.57) is explained, and -2.90 (z=2.09) is unexplained. Of the -1.90 BMI percentile points gap between Whites and Hispanics -1.66 (z= -1.86) is explained and -0.244 (z=0.17) is unexplained in absence of controlling for police protection (full results from these models are available upon request). Thus, accounting for the differences in the levels of perceived police protection explains part of the otherwise unexplained gap in BMI between the groups in our sample. Table 7 shows that the differences in perceived police protection between Blacks and Whites account for somewhat more than 12 percent (-0.348 of -2.729) of the 'explained' gap between the two groups, and Whites versus Hispanics the differences in the level of police protection account for almost 15 percent (-0.2681 of -1.771) of the 'explained' gap between the two groups. However, the corresponding z-statistics, which are derived based on the assumption that both the coefficient estimates and the sample means of the X variables are subject to sampling variation (Jann, 2008), indicate that the results are statistically imprecise. Thus, we cannot say whether differences in perceived police protection can help explain the BMI-gap between White and Black or Hispanic children in the general population.

The differences in the mother's BMI contributes significantly to the explained gap between both Whites and Blacks and Whites and Hispanics. Some other variables that are significant but have no practical implications are a variable that summaries the effects of the various year dummies and a binary indicator of whether the child's height and weight were measured by the survey interviewer (rather than being based on the mother's report.).

The differences in the levels of police protection are not statistically significant in the Oaxaca-Blinder decompositions based on fixed effects models either. However, one factor that is significant in these fixed effects models and worth commenting on is the presence of the father in the household. A father's presence in the household has an important effect on the weight of a Black child but no discernible effect for White children. For a Black child, a father's presence has a statistically significant effect that on average reduces a child's weight by almost 7 percentile points. For a White child, a father's presence has a small (1/10 of a BMI percentile point) and statistically insignificant effect on the child's weight. (Detailed regression results for these effects are not reported here but are available from the authors.) White children in the NLSY sample have more fathers present than Black children (77% v. 35%). The Oaxaca decomposition says that, for two otherwise identical White and Black children, if a Black father had acted like (i.e. had the same regression coefficient as) a White father, then the child would be heavier by about 2.3 BMI percentile points. Further, if as many Black children had fathers present as White children and if the fathers acted like White fathers, this would have no statistically significant effect on the average weight of Black children. Thus, when they are present, Black fathers have an important and favorable influence on their children's weight.

In the White v. Hispanic comparison, the presence of a father does not appear to play a statistically significant role in explaining differences between the two groups.

Our main regression analysis found that mothers who are concerned about a lack of police in their neighborhoods tend to have heavier children. We also found that minority mothers reported greater lack of police protection than their White counterparts even after accounting for other family characteristics. Nonetheless, the Oaxaca-Blinder decompositions show that this difference in perceived police protection is not able to explain away the difference in the average bodyweight of minority children compared to White children. Hence we conclude that there are other unobserved factors that largely account for these group differences.

Correlates of Perceived Neighborhood Quality.

One issue in this paper is that the neighborhood quality variables are based purely on the mother's reports, and there is no external validation. Thus, this raises the question about what factors may play a role in affecting the mother's perceptions. This is a particularly important issue, especially if the larger policy implication here is that one method to address the childhood obesity epidemic might be to improve neighborhoods that they reside in.

While we have no objective measures of neighborhood characteristics, we can identify the counties that the respondents reside in using the NLSY79 Geocode data.[9] One hypothesis is that women who live in counties that have high crime and where the population has low socio-economic status will, ceteris paribus, express more concern about poor neighborhood quality and inadequate police protection (we make this hypothesis with the caveat that there may be immense within-county variation in quality of neighborhoods). To examine this issue, use the county identifier to link each responding mother to crime statistics and other variables we have attempted to link the mothers' perceptions to official crime data and other variables describing the county in which the mother lived at the time of the NLSY surveys.

We estimate linear probability regressions for whether or not the mother reports inadequate police protection after including all county-level characteristics as well as mother-level characteristics that are potentially time-variant, both without (model 1) and with (model 2) mother-level fixed effects, for the full sample and separately by race-ethnicity. Results are in Table 9.

We find that the crime variables have mixed effects on the probability of mothers reporting inadequate police protection. In fact, none of the variables yield estimated effects that are consistent in terms of direction and significance across the two sets of models. For example, rape and aggravated assault increase the probability for the full sample in model 1, but are not

[9] Unfortunately, the Geocodes are not able to do the linkage for finer resolution such as a census track which might be linked to data from individual police departments.

consistent across the sub-samples. In model 2, rape has a counterintuitive negative sign for almost all the groups. We speculate that one reason for the counterintuitive negative signs is that certain types of violent crime could lead to the deployment of more police in the county, so that police presence may actually become more visible in the immediate aftermath of an increase in crime. The county characteristics that seem to consistently affect the probability of reported inadequate police protection in model 1 are the percent of female headed households and the per capita income in the county, with the former increasing and the latter decreasing the probability of reported inadequate police protection. Higher unemployment rates increase the probability of reported inadequate police protection for Whites and Blacks, but surprisingly, seem to decrease it for Hispanics. In model 2 the directions of the effects remain the same, but they become statistically imprecise, possibly because of the lack of variation in these county-level variables over the period of the study.

With regard to the personal maternal characteristics that affect maternal reports of inadequate police protection, the ones that remain significant in model 2, even after accounting for unobserved mother-level time-invariant heterogeneity, are the variables indicating the mother's education level. Residing in central city is significant for all groups except Hispanics, while total family income is only significant for non-Hispanic Whites. We repeated the analyses using maternal fixed effects and the mother-level characteristics but omitted the county level characteristics, and found very similar results.

A final question may be whether changes in perceptions about police protection are driven by changes in the quality of the existing neighborhood or by an actual relocation to a different neighborhood. About 35 percent of the sample of mothers change their reports about adequacy of police protection at least once over the period of study. Unfortunately, once again, the Geocode data does not permit us to identify how many of these women actually changed neighborhoods, but only if their county of residence changed between one survey and the next. About 28 percent of our sample changes their counties of residence at least once within the period of study. However, of those who reported a change in adequacy of police protection, only 27 percent also reported a change in county of residence, and of those who did change their county of residence, 66.7 percent reported no change in adequacy of police protection. We emphasize again that we are not able to capture changes in residential locations that occur within a county in this dataset, but the above findings do suggest that most of the reported variation in police protection cannot be explained by relocations to new neighborhoods in different counties.

CONCLUSION

Our paper addresses the relatively unexplored question of the effects of contextual factors – such as neighborhood quality – on children's bodyweight and obesity-risk. The main advantages of this study include the nationally representative nature of the data, as well as the longitudinal nature of the data, which allows us to control for time-invariant confounding factors at the maternal level. In summary, our paper finds that overall maternal perceptions of neighborhood quality is not a particularly strong determinant of children's bodyweight outcomes. However, one specific neighborhood characteristic – the perceived lack of police protection, is a significant determinant of such bodyweight outcomes. Moreover, there are significant differences in perceived lack of police protection between White and minority women, though it is arguable whether this can explain part of the hitherto unexplained gap in bodyweight between non-Hispanic White and minority children in the population.

It is not entirely clear why police protection in particular plays a significant role in effecting children's bodyweight, when other neighborhood characteristics – such as crime and violence, or lack of respect for law and order, do not. One might speculate that, at the margin, visible police presence might reduce certain activities that would make parents fearful of letting their children outdoors -- such as drug-peddling, loitering, or physical violence and bullying on the playground.

The paper has several shortcomings. The most important of these is our inability to completely control for time-variant unobservable factors that might both influence the mother's perceptions of police protection as well as the child's weight. Furthermore, the key variables of interest – overall neighborhood quality and specific neighborhood characteristics -- are based purely on mother reports, with no external validation. Also, we are not able to account for any characteristics of the child's school, including the quality of physical education programs or of school lunches in those schools, since the CoNLSY does not include that information. Insofar as children from low-quality neighborhoods are also more likely to go to schools were meal plans are of a lower quality and physical education programs are sub-standard, this could exacerbate the detrimental effects of poor neighborhood quality on bodyweight. Finally, we are not able to adequately explore what causal pathways might lead from perceptions of inadequate police protection to increased child bodyweight.

Since this is one of the first papers that explore the relationship between neighborhood perceptions and children's bodyweight outcomes using a national-level dataset, and since the previously mentioned limitations preclude us from determining a definitive causal link between actual neighborhood quality and children's BMI, it seems premature to make policy recommendations before these results are validated via further research. One suggested direction for future research is to explore the extent to which perceptions of neighborhood characteristics such as adequate police protection are correlated to objective measures of neighborhood characteristics. If perceptions of police protection are driven by the actual number of police personnel available to the neighborhood, then arguably providing resources to increase police-protection in low-income and minority neighborhoods, or provide housing subsidies that allows a low-income individual to move into a higher socioeconomic neighborhood with better police protection, [10] However, if the perceptions of inadequate police protection are influenced by more complex issues such as whether neighborhood residents believe that, even though the police are present, they are indifferent or even hostile towards the residents, then addressing this problem becomes considerably more challenging. The NLSY data are inadequate to explore these issues, and hence these questions must be further investigated using more appropriate datasets.

[10] We could not explore this issue with the NLSY because, while it does report on the receipt of housing subsidies, it does not distinguish between living in a public housing facility in a low income neighborhood or living in free standing rental space in a better neighborhood.

Table 1. Descriptive Statistics

Variable	Description	Full Sample (N=12256) Mean	White (N=6434) Mean	Black (N=3431) Mean	Hispanic (N=2391) Mean	Poor Neighborhood [A] (N=2805)	Good Neighborhood [B] (N=9451)
bmipct	Child BMI Percentile	56.904 (34.508)	55.021 (34.002)	60.457 (34.608)	56.871 (35.318)	59.191 (34.043)	56.22 (34.543)
bmiz	Child BMI-z score	0.134 (1.881)	0.056 (1.783)	0.287 (1.950)	0.125 (2.022)	0.205 (2.081)	0.112 (1.810)
vow	Binary indicator child is obese	0.171	0.144	0.214	0.180	0.190	0.164
ngh_rate_n~d	Neighborhood rates ‘fair’/ ‘poor’	0.230	0.123	0.386	0.292	--	--
ngh_rate_v~d	Neighborhood rates ‘excellent’ /‘very good’	0.563	0.702	0.381	0.452	--	--
ngh_nolaw	No respect for law & order a problem	0.367	0.283	0.504	0.394	0.778	0.244
ngh_crime	Crime and violence a problem	0.304	0.191	0.473	0.365	0.670	0.190
ngh_bldg	Run-down buildings a problem	0.199	0.139	0.307	0.206	0.454	0.123
no_police	Lack of police protection a problem	0.252	0.165	0.365	0.323	0.522	0.171
no_trans	Lack of transport a problem	0.301	0.262	0.373	0.299	0.330	0.291
no_super	Unsupervised children a problem	0.456	0.394	0.571	0.459	0.778	0.360
no_care	Uncaring neighbors a problem	0.332	0.263	0.426	0.383	0.623	0.244
no_jobs	Too many jobless people a problem	0.354	0.213	0.556	0.443	0.679	0.258
male	Child is male	0.505	0.506	0.489	0.526	0.528	0.498
Black	Mother is African-American	0.281	--	--	--	0.472	0.224
Hisp	Mother is Hispanic	0.195	--	--	--	0.247	0.179
childage	Child’s age	7.197 (2.531)	7.017 (2.535)	7.469 (2.518)	7.291 (2.503)	7.400 (2.481)	7.135 (2.542)
scaletape	BMI from scale & tape measures by interviewer	0.697	0.679	0.730	0.700	0.700	0.696
mom_age	Mother’s age	26.585 (3.881)	27.169 (3.752)	25.766 (3.935)	26.196 (3.881)	25.711 (3.821)	26.840 (3.860)
no_smsa	Does not live in MSA	0.173	0.207	0.158	0.103	0.141	0.182
cen_city	Lives in central city	0.164	0.079	0.294	0.207	0.285	0.128
momnowork	Mother not employed outside home	0.215	0.199	0.220	0.250	0.287	0.193
dadpresent	Father in household	0.628	0.772	0.347	0.647	0.396	0.699
tnfaminc_r~l	Annual family income (real)	60883.07 (104320.20)	73692.61 (118856.40)	40655.15 (72355.05)	55639.23 (96230.12)	37762.99 (49040.12)	67772.79 (114903.40)
momed12_15	Mother has some college	0.700	0.680	0.737	0.701	0.721	0.692
momed16_20	Mother has at least 4 yrs of college	0.189	0.264	0.116	0.096	0.061	0.226
mombmi81	Mother’s BMI, 1981	21.887 (3.509)	21.388 (3.270)	22.604 (3.857)	22.196 (3.387)	22.470 (3.875)	21.715 (3.373)

Notes: [A]: Those who rate neighborhood as fair or poor. [B]: Those who rate neighborhood as ‘good’ or higher.

Table 2. Regression Results for Child BMI, Obesity-Risk & Overall Neighborhood Ratings.

	Model 1			Model 2			Model 3		
	BMI-percentile	BMI-z score	Obese	BMI-percentile	BMI-z score	Obese	BMI-percentile	BMI-z score	Obese
	β (t-stat)	β (t-stat)	β (t-stat)	β (t-stat)	β (t-stat)	β (t-stat)	β (t-stat)	β (t-stat)	β (t-stat)
ngh_rate_n~d	2.421** (2.24)	0.024** (2.25)	0.059 (0.98)	2.350** (2.13)	0.017 (1.56)	0.072 (1.21)	1.710 (1.57)	0.043 (0.73)	0.011 (0.99)
ngh_rate_g~d	0.999 (1.03)	0.017* (1.70)	0.029 (0.56)	0.792 (0.81)	0.011 (1.08)	0.027 (0.53)	0.309 (0.32)	0.005 (0.11)	0.006 (0.61)
male	0.306 (0.37)	0.028*** (3.28)	0.058 (1.41)	0.413 (0.51)	0.029*** (3.34)	0.064 (1.55)	0.567 (0.70)	0.071* (1.73)	0.030*** (3.59)
Black	4.461*** (3.64)	0.070*** (5.52)	0.200*** (3.20)	4.052*** (3.18)	0.064*** (4.79)	0.196*** (3.02)	2.613** (2.08)	0.130** (2.03)	0.050*** (3.78)
Hisp	2.261 (1.63)	0.046*** (3.55)	0.101 (1.42)	2.064 (1.47)	0.039*** (2.96)	0.103 (1.45)	1.173 (0.86)	0.062 (0.90)	0.030** (2.29)
childage	1.379*** (5.76)	-0.007*** (-2.83)	0.068*** (5.46)	1.314*** (5.46)	-0.007*** (-2.97)	0.066*** (5.22)	1.058*** (4.44)	0.054*** (4.24)	-0.010*** (-4.14)
scaletape	-7.114*** (-9.36)	-0.085*** (-9.97)	-0.369*** (-8.93)	-7.135*** (-9.41)	-0.085*** (-10.06)	-0.368*** (-8.96)	-7.04 *** (-9.34)	-0.364*** (-8.87)	-0.084*** (-10.04)
mom_age	0.155 (0.71)	0.000 (-0.07)	0.005 (0.43)	0.193 (0.87)	0.001 (0.44)	0.005 (0.47)	-0.001 (0.00)	-0.004 (-0.32)	-0.001 (-0.47)
no_smsa	0.361 (0.28)	0.006 (0.50)	0.049 (0.71)	0.220 (0.17)	0.002 (0.16)	0.047 (0.69)	-0.431 (-0.35)	0.017 (0.26)	-0.005 (-0.38)
cen_city	1.423 (1.18)	0.011 (0.80)	0.055 (0.88)	1.359 (1.13)	0.010 (0.76)	0.056 (0.89)	0.874 (0.74)	0.034 (0.55)	0.005 (0.42)
momnowork				-4.605*** (-4.40)	-0.028*** (-2.85)	-0.231*** (-4.01)	-4.386*** (-4.22)	-0.221*** (-3.83)	-0.026*** (-2.68)
dadpresent				-0.872 (-0.83)	-0.002 (-0.20)	-0.009 (-0.17)	-0.900 (-0.86)	-0.011 (-0.20)	-0.003 (-0.24)
tnfaminc_r~l				0.000 (-0.73)	0.000*** (-2.81)	0.000 (-1.05)	0.000 (-0.38)	0.000 (-0.69)	0.000 (-2.47)
momed12_15				-0.702 (-0.47)	-0.011 (-0.67)	0.018 (0.21)	-0.086 (-0.06)	0.046 (0.52)	-0.005 (-0.33)
momed16_20				-1.797 (-0.96)	-0.051*** (-2.59)	-0.006 (-0.06)	-0.623 (-0.34)	0.047 (0.46)	-0.039** (-2.06)
mombmi81							1.470*** (10.05)	0.067*** (8.72)	0.015*** (9.97)
R^2	0.07	0.06	0.04	0.08	0.06	0.05	0.10	0.07	0.06
F	60.23	44.77	23.87	47.64	34.49	20.83	54.67	35.76	26.29

Notes: All models also include region fixed effects and year fixed effects. Standard errors clustered upon mothers. *: p<0.10, **: p<0.05, ***: p<0.01.

Table 3. Child BMI, Obesity Risk, and Specific Neighborhood Characteristics.

		BMI-percentile	Obese
		β (t-stat)	β (t-stat)
ngh_nolaw	No respect for law & order a problem	0.94 (1.11)	-0.004 (-0.50)
ngh_crime	Crime and violence a problem	1.13 (1.27)	0.007 (0.82)
no_super	Unsupervised children a problem	0.27 (0.33)	-0.001 (-0.33)
ngh_bldg	Run-down buildings a problem	0.44 (0.43)	-0.005 (-0.49)
no_jobs	Too many jobless people a problem	1.09 (1.19)	0.01 (0.99)
no_trans	Lack of transport a problem	0.39 (0.52)	-0.003 (0.39)
no_care	Uncaring neighbors a problem	1.84** (2.23)	0.02** (2.31)
no_police	Inadequate police protection a problem	3.65*** (3.98)	0.03*** (2.82)

Notes: All models also control for the variables included in model 2, Table 2, as well as region and year fixed effects. Standard errors clustered upon mothers.
*: $p<0.10$, **: $p<0.05$, ***: $p<0.01$.

Table 4. Different Models for Child BMI, Obesity Risk, and Lack of Police Protection, Full Sample and by Race-Ethnicity.

	BMI-percentile	Risk of Obesity
Full Sample	β (t-stat)	β (t-stat)
Models excluding mother's BMI	3.65*** (3.98)	0.03*** (2.82)
Models including mother's BMI	3.10*** (3.46)	0.02** (2.27)
Models with maternal fixed effects	2.44*** (2.64)	0.016 (1.45)
Models with child fixed effects	1.93** (2.04)	0.01 (1.08)
Models including maternal propensity scores	3.22*** (3.47)	0.02** (2.40)
Full Sample, Includes Other Neighborhood Characteristics		
Models excluding mother's BMI	3.77*** (3.76)	0.03*** (2.70)
Models including mother's BMI	3.44*** (3.47)	0.03*** (2.44)
Models with maternal fixed effects	2.37** (2.41)	0.01 (1.33)
Models with child fixed effects	1.93** (2.04)	0.01 (1.14)
Models including maternal propensity scores	3.49*** (3.42)	0.02** (2.45)
Non-Hispanic Whites		
Models excluding mother's BMI	2.45* (1.64)	0.02* (1.94)
Models including mother's BMI	1.72 (1.18)	0.02 (1.46)
Models with maternal fixed effects	1.26 (0.89)	0.02 (1.11)
Models with child fixed effects	0.51 (0.37)	0.01 (0.60)
Models including maternal propensity scores	1.81 (1.18)	0.02 (1.57)
Blacks		
Models excluding mother's BMI	3.09** (2.14)	0.02 (1.34)
Models including mother's BMI	2.65* (1.91)	0.01 (0.79)
Models with maternal fixed effects	2.97* (1.86)	0.02 (0.94)
Models with child fixed effects	2.94** (1.96)	0.02 (0.91)
Models including maternal propensity scores	3.01** (2.06)	0.02 (1.18)
Hispanics		
Models excluding mother's BMI	5.32*** (2.84)	0.03 (1.52)

Models including mother's BMI	4.67** (2.51)	0.03 (1.29)
Models with maternal fixed effects	3.68* (1.85)	0.01 (0.46)
Models with child fixed effects	2.64 (1.36)	0.01 (0.44)
Models including maternal propensity scores	4.55** (2.41)	0.02 (0.83)

Notes: The second set of models control for the full array of specific neighborhood characteristics in addition to inadequate police protection. All models also control for the variables included in model 2, Table 2, as well as region and year fixed effects. Standard errors clustered upon mothers.
*: p<0.10, **: p<0.05, ***: p<0.01.

Table 5. Television Watching on Weekdays and Weekends, and Lack of Police Protection

	Hours of TV watched during Weekdays	Hours of TV watched during Weekends
Full Sample	β (t-stat)	β (t-stat)
Models excluding mother's BMI	0.470*** (3.15)	0.420*** (3.48)
Models including mother's BMI	0.452*** (3.04)	0.407*** (3.30)
Models with maternal fixed effects	0.316** (2.29)	-0.016 (-0.15)
Models with child fixed effects	0.201 (1.32)	-0.033 (-0.28)
Models including maternal propensity scores	0.437*** (2.81)	0.385*** (3.08)
Full Sample, Includes Other Neighborhood Characteristics	β (t-stat)	β (t-stat)
Models excluding mother's BMI	0.373** (2.25)	0.275** (2.09)
Models including mother's BMI	0.363** (2.29)	0.268** (2.02)
Models with maternal fixed effects	0.324** (2.21)	-0.133 (-1.15)
Models with child fixed effects	0.193 (1.20)	-0.182 (-1.46)
Models including maternal propensity scores	0.372** (2.27)	0.261* (1.94)

Notes: The second set of models control for the full array of specific neighborhood characteristics in addition to inadequate police protection. All models also control for the other variables included in Table 4, as well as region and year fixed effects. Standard errors clustered upon mothers.
*: $p<0.10$, **: $p<0.05$, ***: $p<0.01$.

Table 6: Reported Lack of Police Protection, Poor Neighborhood Quality & Respondent Characteristics.

	Lack of Police Protection A Problem	Overall Neighborhood Rating ‘Fair’ or ‘Poor’
	β (t-stat)	β (t-stat)
Black	0.129 *** (7.07)	0.163 *** (9.03)
Hisp	0.083 *** (3.77)	0.082*** (4.09)
childage	0.003 (1.03)	-0.004 (-1.22)
mom_age	-0.001 (-0.32)	-0.003 (-1.10)
no_smsa	0.047 ** (2.49)	-0.029 * (-1.85)
cen_city	0.119 *** (6.52)	0.116*** (6.20)
momnowork	0.044 ** (2.51)	0.056 *** (3.58)
dadpresent	-0.035 (-2.33)	-0.125 *** (-8.61)
tnfaminc_r~l	0.000 *** (-2.91)	0.000 *** (-5.63)
momed12_15	-0.108 *** (-4.11)	-0.115 *** (-4.59)
momed16_20	-0.180 *** (-6.18)	-0.191 *** (-7.07)
R^2	0.09	0.150
F	21.03	42.93

Notes: All models also control for region and year fixed effects. Standard errors clustered upon mothers.
*: p<0.10, **: p<0.05, ***: p<0.01.

Table 7: Oaxaca-Blinder Decomposition of BMI-Percentile Difference.

	White v Black β (t-stat)			**White v Hispanic** β (t-stat)		
	Differential	Explained	Unexplained	Differential	Explained	Unexplained
Prediction_1	**55.059***** **(80.442)**			**55.059***** **(80.439)**		
Prediction_2	**60.462***** **(69.952)**			**56.966***** **(52.198)**		
Difference	**-5.402***** **(-4.900)**			**-1.907** **(-1.480)**		
no_police2		-0.348 (-1.173)	-0.339 (-0.458)		-0.268 (-1.165)	-0.944 (-1.244)
mombmi81		-1.809*** (-4.720)	2.927 (0.405)		-1.192*** (-3.555)	-3.488 (-0.402)
male		0.009 (0.474)	0.406 (0.433)		-0.012 (-0.486)	-0.655 (-0.599)
childage		-0.295* (-1.946)	-5.336 (-1.334)		-0.180* (-1.811)	-6.996 (-1.542)
scaletape		0.411*** (3.807)	-0.921 (-0.675)		0.172 (1.628)	0.621 (0.449)
mom_age		0.187 (0.422)	8.511 (0.676)		0.130 (0.421)	-0.056 (-0.004)
no_smsa		0.001 (0.012)	0.088 (0.184)		0.002 (0.012)	0.387 (0.974)
cen_city		0.094 (0.214)	0.148 (0.186)		0.058 (0.214)	-0.477 (-0.700)
momnowork		0.126 (1.185)	-0.311 (-0.616)		0.274* (1.879)	-0.901 (-1.298)
dadpresent		-0.450 (-0.688)	0.228 (0.266)		-0.130 (-0.683)	-1.247 (-0.739)
tnfaminc_real		-0.078 (-0.501)	-0.066 (-0.177)		-0.041 (-0.498)	-0.089 (-0.225)
momedu		-0.462 (-1.416)	-3.414 (-1.113)		-0.597 (-1.296)	-2.369 (-0.791)
region		-1.050** (-2.390)	4.571* (1.799)		-0.992 (-1.614)	6.045* (1.801)
years		0.934*** (4.174)	-4.374** (-2.255)		1.003*** (4.163)	-1.632 (-0.722)
Total		**-2.729***** **(-2.756)**	**-2.673*** **(-1.910)**		**-1.771*** **(-1.955)**	**-0.136** **(-0.093)**

*: p<0.10, **: p<0.05, ***: p<0.01.
The Oaxaca-Blinder decompositions use the ‘Oaxaca’ command in STATA 10, which also calculates variance estimates for the components of the Oaxaca-Blinder decomposition.

Table 8: Oaxaca-Blinder Decomposition of BMI-Percentile Difference with Fixed Effects.

	White v Black β (t-stat)			White v Hispanic β (t-stat)		
	Differential	Explained	Unexplained	Differential	Explained	Unexplained
Prediction_1	**55.059*** (155.273)**			**55.059*** (155.273)**		
Prediction_2	**60.462*** (112.723)**			**56.966*** (90.582)**		
Difference	**-5.402*** (-8.402)**			**-1.907*** (-2.641)**		
no_police2		-0.256 (-0.887)	-0.626 (-0.796)		-0.197 (-0.886)	-0.773 (-0.985)
male		0.022 (1.052)	0.722 (0.849)		-0.027 (-1.094)	-1.580 (-1.558)
childage		0.040 (0.086)	3.403 (0.236)		0.025 (0.086)	-10.358 (-0.656)
scaletape		0.324*** (4.321)	0.196 (0.154)		0.136** (2.035)	0.560 (0.425)
mom_age		-0.968 (-0.665)	32.948 (0.663)		-0.673 (-0.664)	-18.572 (-0.331)
no_smsa		-0.033 (-0.373)	-0.639 (-0.989)		-0.073 (-0.374)	-0.182 (-0.390)
cen_city		0.230 (0.537)	0.993 (1.122)		0.142 (0.537)	-0.911 (-1.244)
momnowork		0.062 (1.434)	-0.100 (-0.163)		0.135 (1.611)	0.311 (0.387)
dadpresent		-0.043 (-0.055)	2.369** (1.994)		-0.012 (-0.055)	-1.053 (-0.466)
tnfaminc_real		0.116 (0.790)	-0.161 (-0.372)		0.061 (0.786)	0.291 (0.499)
momedu		-0.820 (-0.692)	0.233 (0.025)		-0.800 (-0.521)	6.560 (0.750)
region		0.241 (0.205)	2.836 (0.374)		2.931* (1.690)	-19.614* (-1.832)
years		1.300*** (2.584)	-7.084 (-1.116)		1.382*** (2.598)	1.009 (0.143)
Total		**0.215 (0.107)**	**-5.618*** (-2.688)**		**3.029 (1.268)**	**-4.936** (-1.991)**

*: p<0.10, **: p<0.05, ***: p<0.01.

The Oaxaca-Blinder decompositions use the ‘Oaxaca’ command in STATA 10, which also calculates variance estimates for the components of the Oaxaca-Blinder decomposition.

Table 9. Lack of Police Protection and County & Respondent Characteristics. By Race-Ethnicity.

	Models Without Fixed Effects β (t-stat)				Models With Fixed Effects β (t-stat)			
	All	**Whites**	**Blacks**	**Hispanic**	**All**	**Whites**	**Blacks**	**Hispanic**
murder100k	-0.000	-0.000	-0.003**	-0.002	0.003	0.002	0.004	-0.002
	(-0.289)	(-0.154)	(-2.570)	(-0.722)	(1.451)	(0.744)	(1.336)	(-0.353)
rape100k	0.000*	0.000	0.001	0.000	-0.000	-0.001*	0.003**	-0.004***
	(1.921)	(0.769)	(1.401)	(0.220)	(-0.374)	(-1.730)	(2.191)	(-2.614)
rob100k	0.000	0.000	0.000*	0.000	0.000	0.000	-0.000	0.000
	(1.338)	(0.184)	(1.800)	(0.709)	(1.040)	(0.964)	(-0.084)	(0.944)
aggas100k	0.000*	-0.000	0.000***	0.000	0.000	0.000	0.000	-0.000
	(1.702)	(-0.169)	(3.328)	(0.815)	(0.635)	(0.616)	(0.598)	(-0.019)
burg100k	-0.000	0.000*	-0.000	0.000	-0.000	0.000	-0.000*	0.000
	(-0.417)	(1.669)	(-0.986)	(0.030)	(-1.244)	(0.173)	(-1.722)	(0.941)
larc100k	-0.000***	-0.000	-0.000***	-0.000	0.000	-0.000	0.000	0.000
	(-3.061)	(-1.108)	(-3.031)	(-0.718)	(0.528)	(-0.768)	(1.186)	(1.459)
mvtheft100k	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000
	(0.468)	(-0.800)	(0.690)	(0.611)	(0.123)	(0.325)	(0.756)	(-1.299)
arson100k	0.000	0.000	0.000	0.000	0.001***	0.001	0.001	0.000
	(1.362)	(1.055)	(0.631)	(1.208)	(2.967)	(1.574)	(0.703)	(1.133)
unemplyrate	-0.001	0.004*	0.009*	-0.007**	-0.007	-0.004	-0.003	0.004
	(-0.760)	(1.801)	(1.799)	(-2.330)	(-1.194)	(-0.568)	(-0.168)	(0.352)
pctBlack	0.000	-0.001	-0.001	-0.001	-0.020*	-0.016	-0.035	0.039
	(0.465)	(-1.033)	(-1.043)	(-0.435)	(-1.795)	(-1.033)	(-1.624)	(0.812)
pcthisp	0.001***	0.001**	-0.005***	0.001	-0.005	0.008	-0.019	0.005
	(3.048)	(2.117)	(-4.683)	(0.923)	(-0.730)	(0.884)	(-1.415)	(0.234)
pctfemhead	0.008***	0.004*	0.009***	0.008**	0.025	-0.002	0.061	0.031
	(4.817)	(1.844)	(2.896)	(1.995)	(1.312)	(-0.093)	(1.599)	(0.612)
pcincome	-0.000***	-0.000***	0.000	-0.000***	-0.000	0.000	-0.000	-0.000
	(-4.751)	(-4.311)	(0.801)	(-3.412)	(-0.461)	(1.170)	(-0.406)	(-1.142)
mom_age	-0.002*	0.001	-0.005*	-0.005	-0.002	0.001	-0.005	-0.001
	(-1.949)	(0.751)	(-1.866)	(-1.531)	(-1.429)	(0.238)	(-1.617)	(-0.211)
no_smsa	0.044***	0.027*	0.063**	-0.021	0.001	-0.014	0.001	-0.060
	(3.600)	(1.910)	(2.235)	(-0.556)	(0.027)	(-0.405)	(0.017)	(-0.632)
cen_city	0.081***	0.036**	0.109***	0.020	0.121***	0.067**	0.151***	0.007
	(6.713)	(1.960)	(4.910)	(0.752)	(5.679)	(2.215)	(3.758)	(0.150)
momnowork	0.037***	0.033***	-0.003	0.075***	0.035*	0.033	-0.010	0.092*
	(3.882)	(2.848)	(-0.162)	(3.222)	(1.920)	(1.416)	(-0.288)	(1.941)
dadpresent	-0.051***	-0.043***	-0.048***	0.026	-0.039**	-0.024	-0.035	0.025
	(-6.034)	(-3.745)	(-2.705)	(1.211)	(-2.520)	(-1.078)	(-1.174)	(0.652)
tnfaminc_real	-0.000***	-0.000***	-0.000*	-0.000*	-0.000***	-0.000**	-0.000	-0.000
	(-3.922)	(-2.606)	(-1.751)	(-1.652)	(-2.730)	(-2.311)	(-1.270)	(-0.665)
momed12_15	-0.121***	-0.128***	-0.171***	-0.015	-0.101***	-0.118***	-0.110**	-0.018
	(-9.530)	(-6.304)	(-7.092)	(-0.598)	(-3.699)	(-2.717)	(-2.272)	(-0.359)
momed16_20	-0.196***	-0.193***	-0.248***	-0.067*	-0.165***	-0.154***	-0.189***	-0.027
	(-12.623)	(-8.707)	(-7.216)	(-1.645)	(-5.276)	(-3.367)	(-2.945)	(-0.332)
R^2	0.087	0.043	0.102	0.031	0.172	0.215	0.180	0.118
F	47.252	12.507	16.503	3.903	6.388	2.671	2.897	1.309

Notes: All models also control for region and year fixed effects. Standard errors clustered upon mothers.
*: p<0.10, **: p<0.05, ***: p<0.01.

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