



# Neighborhood disadvantage and obesity across childhood and adolescence: Evidence from the NLSY children and young adults cohort (1986–2010)



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## ABSTRACT

Previous research suggests that youth who grow up in socioeconomically disadvantaged neighborhoods face higher odds of becoming obese. Neighborhood effects scholars, meanwhile, have suggested that contextual influences may increase in strength as children age. This is the first study to examine whether developmental epochs moderate the effect of neighborhood disadvantage on obesity over time. I use thirteen waves of new restricted and geo-coded data on children ages 2–18 from the National Longitudinal Survey of Youth, Children and Young Adults. Bivariate and pooled logistic regression results suggest that neighborhood disadvantage has a stronger impact on adolescents' likelihood of becoming obese. Fixed effects models reveal that after adjusting for observed and unobserved confounders, adolescents continue to face higher odds of becoming obese due to the conditions associated with living in disadvantaged neighborhoods. Moreover, as research on adults suggests, girls experience larger impacts of neighborhood disadvantage than boys.

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## 1. Introduction

Obesity rates in the United States have more than doubled among young children and have quadrupled among adolescents in the past 30 years (National Center for Health Statistics, 2012; Ogden et al., 2014). These troubling trends have motivated public officials to develop national campaigns to intervene in this health crisis beginning at an early age (see Michelle Obama's "Let's Move" campaign: <http://www.letsmove.gov/>). Theoretically, individual-level (e.g., family socioeconomic status [SES] and genes) and contextual-level resources (e.g., food deserts and peer social capital in the neighborhood) may combine to impact obesity at all ages. However, neighborhood-level resources may become increasingly salient as children get older and interact more with neighborhood actors and institutions, perhaps contributing heavily to the observed spike in obesity among adolescents.

This is the first paper to study the impact of neighborhood context on obesity across childhood and adolescence using longitudinal data at the national level. Although researchers have firmly established a link between individual-level SES and adult obesity, very little work has been able to establish a link with neighborhood SES and childhood obesity at any age. As a consequence, although scholars have observed childhood, and especially adolescent, obesity increasing during the past few decades, there is little research that has assessed the independent role of neighborhood disadvantage in either childhood or adolescent obesity. Moreover, by studying the link between neighborhood context and obesity at different stages of development, this paper represents a key departure from most of the "neighborhood effects" literature that assumes that neighborhoods are static entities whose characteristics and effects do not vary as children age (Sampson et al., 2002).

The implications of childhood and adolescent obesity for the life-course are difficult to overstate. Not only does obesity impact self-perceptions (Crosnoe et al., 2008), stigma (Mustillo et al., 2012), peer comparisons (Mueller et al., 2010), and schooling (Crosnoe, 2007; Crosnoe and Muller, 2004; Datar and Sturm, 2006; Datar et al., 2004; Sabia, 2007; Cawley and Spiess, 2008; Kaestner and Grossman, 2009), but it can also impact physical and psychological health later in life (Granberg et al., 2009; Carr and Friedman, 2005; Dave and Rashad, 2009; Ferraro and Kelley-Moore, 2003), can incur a penalty in the labor market (Cawley, 2004; Pagan and Davila, 1997; Glass et al., 2010), and can affect health-related expenditures in adulthood (Monheit et al., 2009). Gaining increased clarity on whether structural conditions, such as growing up in a disadvantaged neighborhood, impacts childhood obesity is crucial to circumvent the exacerbation of inequality that will affect the life-chances of millions in coming decades.

Sociologists have long argued that neighborhoods are salient structural spheres of influence for children's development because the norms and values of residents can influence youth behavior by conditioning the *psychosocial contexts* in which they grow up (Jencks and Mayer, 1990; Crane, 1991). Cultural norms, exposure to chronic stressors, and the physical environment may permeate obesity in a disadvantaged neighborhood by creating an “obesogenic” environment (Harrington and Elliott, 2009; Ross, 2000) that can have an especially negative impact on youth because of the important physical and psychological development stage they are in. In addition, researchers have further argued that social capital (e.g., social connectedness), food insecurity, and physical inactivity are likely mechanisms through which neighborhoods may impact obesity (Kawachi and Berkman, 2003; Drewnowski and Specter, 2004). Yet, while scholars have paid considerable attention to adult obesity, to date there is little research in the sociological literature that unites the “neighborhood effects” literature and skyrocketing trends in childhood and adolescent obesity. Despite heightened concerns about food deserts, excess weight gain, and sedentary lifestyles for youth and decades of research of neighborhood effects on adult health, researchers still know surprisingly little about whether neighborhood SES context actually affects obesity among children, and if it does, if the association varies by age.

What scholars do know on this topic comes from a collection of disjointed local samples or national samples that have only examined very short time periods (e.g., one to only a few years). Most previous studies have also been limited in their ability to control for unobserved factors that may affect estimates of neighborhood effects on childhood obesity. Most importantly, previous scholars have fallen short of providing a developmental conceptualization of how neighborhoods may impact childhood obesity as children age. Perhaps unsurprisingly, the literature on neighborhood effects and childhood obesity is filled with mixed results. One thing, however, is clear: to my knowledge, scholars have yet to analyze the changing impact of neighborhood SES on obesity throughout childhood and adolescence.

This paper will fill these gaps in the literature and provide an analysis of the impact of growing up in a disadvantaged neighborhood on childhood obesity. In this way, I will provide evidence for a link between neighborhood disadvantage and obesity that varies as children age. I will also introduce a new data set into this literature: the restricted National Longitudinal Survey of Youth, Child and Young adult cohort (NLSY:CYA).<sup>1</sup> These data are only accessible via a federal clearance procedure and on-site analysis at the Bureau of Labor Statistics in Washington, DC. This is the ideal data set to study obesity in developmental context because it provides thirteen waves of national data that tie neighborhood conditions, family background, and children's obesity together for youth who were between the ages of 2 and 18 at any point between 1986 and 2010. This will also be the first paper to examine neighborhood effects on obesity over time for the cohort of children and adolescents whom have grown up during the period in which childhood obesity rates have exploded. This study therefore has the potential to improve our understanding of the link between neighborhood disadvantage and obesity among youth and perhaps even guide us toward more useful policy to reduce obesity among children and adolescents.

## 2. Background

Sociologists have established that children in the U.S. grow up within a highly stratified socioeconomic residential landscape (Wilson, 1987; Massey and Denton, 1993). Making the theoretical link between neighborhood ecologies and individual outcomes is a first-order task before estimating the quantitative impact of neighborhood disadvantage (Jencks and Mayer, 1990). One way that neighborhoods can impact youth outcomes is through the adoption of behaviors between peers and friends. Youth who grow up in disadvantaged neighborhoods where crime, gangs, and lacking social services are normative may pass unhealthy behaviors to one another through familial or peer networks. Another way is through normative boundaries and expectations that adults can enforce through the monitoring of youth behaviors. In disadvantaged neighborhoods, unhealthy influences in the form of negative social capital may flow between residents through the approval of unhealthy behaviors that may then lead to negative outcomes (Portes, 1998; Bourgois, 1995). Relatedly, collective efficacy (i.e., the ability of residents of a neighborhood to influence the behavior of children and other residents toward a set of desired goals such as safety and public order) could also transmit the influence of neighborhood context to children (Sampson and Raudenbush, 1999). If the transmission of influence from the neighborhood to the individual works through social contact, then it may make sense to consider how that contact may increase as children age and how neighborhood effects may vary across the early life-course.

<sup>1</sup> I completed all analyses of these restricted NLSY:CYA data on-site at the Bureau of Labor Statistics in Washington, D.C.

From a developmental perspective, middle childhood and early adolescence may increase the magnitude of neighborhood effects compared to earlier epochs of development because children increase their contact with neighborhood social and economic ecologies and institutions over time (Brooks-Gunn et al., 1997; Bronfenbrenner, 1979). Ecological embeddedness naturally increases with age because older youth become increasingly autonomous from their families as they begin to expand their ecological network ties (Aber, Gephart, Brooks-Gunn and Connell, 1997). Similarly, children's perceptions of self and context may impact their cognitive and emotional development vis a vis their perceptions of their home, peer, and school environments which are salient psychological functions in middle childhood and early adolescence (Aber, Gephart, Brooks-Gunn and Connell, 1997). Indeed, the various activity spaces used in daily life, which for youth could expand to include schools, sites for extra-curricular activities, and places where they spend time with friends, can contribute to obesity in unique ways (Zenk et al., 2011). Unfortunately, this analysis relies on data that excludes information on these non-residential contexts. Nevertheless, residential neighborhoods, where scholars have concentrated research on the influence of environmental features (Feng et al., 2010; Leal and Chaix, 2011), may affect obesity and this effect may become increasingly pronounced as children age due to their enhanced interaction with neighborhood peers and institutions.

### 2.1. Neighborhoods and weight

Scholars have argued that neighborhood SES can affect weight gain and the likelihood of developing chronic diseases like diabetes and cardiovascular disease in adulthood (Ludwig et al., 2013; Mobley et al., 2006). Researchers argue that the mechanisms by which neighborhoods affect individuals include the resources that are available in the physical environment (Diez-Roux and Mair, 2010) as well as the levels of social support in one's surrounding environment (Kawachi and Berkman, 2003; Kawachi et al., 2008). Both of these resources may become increasingly salient as children age.

Economic and social resources that are shared among residents in a neighborhood can shape the environment in which healthy (or unhealthy) behaviors and attitudes can become normative and can impact residents' weight outcomes (Jencks and Mayer, 1990; Kawachi and Berkman, 2003; Sampson, 2003; Crane, 1991). Structurally, living in a socioeconomically disadvantaged neighborhood may promote weight gain not only through a paucity of healthy food outlets (i.e., food deserts) and safe places to exercise but also because the consumption of high-calorie and low nutrition meals and unhealthy behaviors may become normative, creating a *psychosocial context* in which negative norms and values get passed down to children and can lead to unhealthy weight outcomes.

However, previous studies have for various reasons, including the lack of adequate data, provided opportunities upon which to improve our understanding of the role that neighborhoods play in obesity among youth. For instance, many previous studies lack repeated measurements of neighborhood conditions, obesity, or both across childhood and adolescence. This has limited our understanding and has mostly led to snapshots of the relationship between neighborhoods and obesity for youth. Second, many previous studies lack national samples which has left researchers with scattered evidence that may be tied to idiosyncrasies of specific cities or regions of the country. The current paper builds on the evidence that researchers have brought to bear on the relationship between neighborhoods and obesity among adults as well as the limited scholarship on youth and contributes evidence that enhances our understanding of the role that neighborhood disadvantage plays in obesity across childhood and adolescence.

### 2.2. Disadvantaged neighborhoods and children's weight

Although neighborhood effects research on adult obesity and weight outcomes have become commonplace (Black et al., 2010; Ruel et al., 2010; Harrington and Elliott, 2009; Robert and Reither, 2004; Ludwig et al., 2011), much less attention has been placed on neighborhood effects on obesity among children and adolescents. Previous research suggests that neighborhoods may in fact be associated with childhood obesity, but the strength of that association across children's developmental stages is unknown.

For example, Grow and colleagues (2010) found that a ten percent decrease in neighborhood (i.e., census tract) median income increased obesity among children ages 6–18 in King County, Washington using multi-level regression models that controlled for child's sex, age, and medical insurance at the individual level, but without controlling for family background variables such as parental education, income, poverty, or household structure. Further, Grow and colleagues found that a higher percent of neighborhood home ownership was paradoxically associated with an increased risk of obesity. In another study that controlled for parents' years of education, occupation, income, and financial assets in savings, separate indicators of neighborhood (i.e., block group) SES such as the percent of families with a high school education or more, the percent of families that were employed, median family income, and median value of owner-occupied houses were each associated with decreases in body mass index (BMI) among high school students in St. Louis (Chen and Paterson, 2006). However, this study lacked controls for age and sex of adolescents in its regression models, which present a critical limitation to the findings because boys and girls experience growth spurts that affect weight at different rates during adolescence. Indeed, experimental findings from the Moving to Opportunity (MTO) project suggest that neighborhoods impart differential effects on health outcomes for girls and boys (Kling et al., 2007; Ludwig et al., 2013).

Moving away from individual indicators of neighborhood SES, some scholars have turned to composite measures that are said to provide a more complete and multidimensional measure of neighborhood SES conditions than individual measures. For example, using a composite indicator of neighborhood (i.e., census tract) economic hardship (EH) composed of

2005–2009 5-year measures from the American Community Survey of crowded housing, neighborhood poverty, mean unemployment, mean levels of education, and mean income, [Shih and colleagues \(2012\)](#) found that EH was associated with a higher prevalence of childhood obesity among 5th, 7th, and 9th grade public school students in Los Angeles County in 2008–2009. This study only included children's sex, grade, and race variables in the regression model. Unfortunately, by excluding covariates that impact both obesity and the probability of living in an EH neighborhood such as family history of obesity or family socioeconomic status, estimates of the independent impact of EH may be biased. Excluding such theoretically relevant covariates that predict obesity and selection into neighborhoods may produce biased estimates of neighborhood effects by increasing covariate imbalance in the regression models. Nevertheless, the studies by [Grow and colleagues \(2010\)](#), [Chen and Paterson \(2006\)](#), and [Shih and colleagues \(2012\)](#) provide useful suggestive evidence for the association between neighborhood disadvantage and childhood obesity. However, these studies are subject to threats from unobserved heterogeneity and they fall short of examining how children's interaction with their neighborhoods, and the possible effects of the resources within neighborhoods, may change as they age.

Moreover, other studies have used neighborhood safety as a proxy for neighborhood socioeconomic disadvantage and have drawn similar conclusions. For example, [Lumeng and colleagues \(2006\)](#) found that neighborhoods in ten urban and rural U.S. sites that were perceived as the least safe (versus the safest) by parents were associated with an increased risk of obesity among a cross-section of 7 year old children. This study controlled for child's age, sex, race, child's participation in structured after school activities, levels of stimulation and support for the child at home, maternal education, maternal marital status, and maternal depression in its regression model. In doing so, it advanced knowledge in this area by extending the geographic scope to more than a single location. In another study that used nationally representative data from the 2007 National Survey of Children's Health, [Singh and colleagues \(2010\)](#) also found that unsafe (versus safe) neighborhoods (that were defined by respondents) increased the odds of obesity among 10–17 year olds. This study included covariates such as age, sex, race and ethnicity, household composition, metropolitan residence, household poverty status, parental education, television viewing time, computer use, and physical activity in its regression model. This study went even further by employing a national sample and by including key variables, but only used a cross-section of data, thereby limiting its ability to address whether neighborhood effects varied across the early life-course.

In contrast to positive findings about the relationship between neighborhood disadvantage and childhood obesity, [Burdette and Whitaker \(2005, 2004\)](#) found no significant association between living in the most (versus the least) safe neighborhood and childhood obesity using baseline Fragile Families and WIC data. These findings are ostensibly surprising, but National Health and Nutrition Examination Survey (NHANES) trend data has shown a steady *closing* of the childhood obesity gap between high and low SES children in recent decades ([Wang and Zhang, 2006](#); [Wang et al., 2008](#)). Moreover, [Scharoun-Lee \(2011\) and colleagues](#) also found that the material advantages of a middle-class upbringing were associated with obesity nearly as much as a working-poor upbringing. [Bader and colleagues \(2013\)](#) even found that an increase in the number of fast food restaurants in one's neighborhood, often a sign of contextual disadvantage, actually decreases the risk of childhood obesity. Furthermore, other studies have also failed to find statistically significant associations between neighborhood disadvantage and childhood obesity. For example, [Nelson and colleagues \(2006\)](#) used a cross-section of nationally representative data from The National Longitudinal Study of Adolescent to Adult Health (Add Health) and failed to find a significant association between neighborhood disadvantage and childhood obesity. Neighborhood safety was also not significantly associated with BMI among 11- to 16-year-olds in a study conducted in Chicago ([Molnar et al., 2004](#)). These studies introduce doubt into the widespread concern regarding the effects of growing up in a severely socioeconomically distressed neighborhood on childhood obesity.

Of course, these studies differ in their geographic scope, their inclusion of sociodemographic control variables, the number of data points they use, the age range of children, the definition of neighborhoods (e.g., tracts, block groups, or self-defined), the way they choose to measure neighborhood SES (i.e., separate indicators versus composite scales), and the way they choose to model neighborhood effects (i.e., linear versus non-linear approaches). What they have in common is the inability to assess whether children are more sensitive to neighborhood contexts as they get older. In contrast, I use data from a national sample and 24 years of repeated data on key components of family background and household structure to assess whether neighborhood effects on obesity vary as children age.

### 2.3. Theoretical mechanisms

Theoretically, there is little in the previous literature on neighborhood effects on youth weight outcomes that discusses what could drive the association, if one actually exists, between neighborhood disadvantage on childhood obesity and what could possibly increase the association as children age. Here, I draw upon previous work in the wider neighborhood effects and developmental literatures to offer four possible explanations: food insecurity, physical activity, interaction with peers, and epigenetics.

First, food insecurity is often brought up in discussions of weight status in the U.S. as a predictor of obesity ([Institute of Medicine and National Research Council, 2009](#)). At the neighborhood-level, scholars have conceptualized food insecurity as the lack of nutritious food options in disadvantaged neighborhoods, representing a reduction in available healthy food resources for youth (see the literature on "food deserts" [Beaulac et al., 2009](#); [Boone-Heinonen et al., 2011](#)). Moreover, scholars have found that low-income parents may travel up to 1.58 miles to access healthy food ([Hillier et al., 2011](#)), at once supporting the notion that disadvantaged neighborhoods lack healthy food options and

suggesting considerable heterogeneity in where adults go grocery shopping. Yet, scholars have also found that adding a grocery store to a “food desert” may have little impact on adults’ dietary behavior or obesity (Cummins et al., 2014), suggesting that changing adults’ food purchasing and consumption patterns in disadvantaged neighborhoods requires more holistic approaches than simply adding a grocery store. Despite the fact that parents often shop outside of the residential neighborhood, youth may be more susceptible to food options within the residential neighborhood because they may be unlikely to travel far away for groceries and instead rely on more local food options. Residential neighborhood food choices may matter more for older children because they may be more likely to spend time outside in the neighborhood where their behaviors are unsupervised as opposed to younger children who may remain closer to home under their parents’ watchful eye.

Importantly, previous studies almost always focus on access to healthy food and obesity among adults (Larson et al., 2009), limiting our knowledge about how they affect children. Children may experience increased weight in these contexts because of the following processes: 1) youth in the most disadvantaged neighborhoods fail to find healthy food options (e.g., because of the lack of supermarkets); 2) youth look to one another and to other adults in the neighborhood to define their dietary habits and norms; and 3) youth in disadvantaged neighborhoods resort to eating inexpensive and energy dense junk food from bodegas and fast-food outlets that increase their risk of becoming obese (Drewnowski and Specter, 2004). Based on the food desert literature, I would expect children in disadvantaged neighborhoods to be more likely to be obese than children in better-off neighborhoods given the paucity of healthy food options at their disposal.

Second, the inability to access any food options in the most disadvantaged neighborhoods may also be compounded by a decrease in physical activity, leading to increases in weight. One possible explanation for why children in disadvantaged neighborhood may exercise less relates to class differences in the supervision and structuring of children’s free time that lead disadvantaged children be much less involved in structured physical activities (Lareau, 2003). The “achievement of natural growth” that prevails in working- and lower-class families may reduce the amount of time that children from these families spend exercising relative to middle- and upper class children. Because class also stratifies the residential landscape, then perhaps sedentary lifestyles become normative in these neighborhoods and combine with unhealthy food options to increase the prevalence of obesity among adolescents in disadvantaged neighborhoods.

Third, interactions with neighborhood peers and other institutional actors may increase as children get older and spend increasing amounts of time outside of the home. Children spend more time with their friends and may adopt unhealthy behaviors that are conditioned by the available food resources in the neighborhood. In disadvantaged neighborhoods, increased exposure to unhealthy environments vis a vis the physical and social resources available to them as they get older and spend increasing amounts of time out of the home and out with friends may influence adolescents to adopt unhealthy dietary and behavioral habits that could increase their likelihood of becoming obese.

Fourth, epigenetics suggests that genes may in fact be able to impact obesity despite the fact that genes are fixed within youth. This is because although genes are invariant over time, their expression may indeed be influenced by the environment to which children and adolescents are exposed. That is, while genes do not change over time, how they get expressed can change depending on environmental conditions. For instance, if mothers faced neighborhood adversity that affected the nutritional status of the fetus, then it is likely that these in utero environments could developmentally program children for obesity. This would accord with the fetal origins hypothesis (Barker et al., 2006) and would provide yet another mechanism for neighborhood effects on obesity.

What is clear is that previous studies suggest a much more complex picture of the role played by neighborhood disadvantage in childhood obesity compared to adult obesity, one in which the influence of neighborhood context increases as children age. Disadvantaged neighborhoods may increase obesity directly through the lack of healthy food options and a lack of resources that support physical activity and indirectly through the influence of friends and other significant actors on prevailing norms in the neighborhood. As children age, their interaction with all of these neighborhood processes may increase, leading to a stronger impact of these contextual resources on obesity.

#### 2.4. Sex

Although the first order goal of this paper is to establish whether neighborhood disadvantage exerts an influence on children’s odds of obesity and if there is a moderating effect for age, I would be remiss if I neglected to assess whether or not neighborhoods have unequal impact on youth by sex. Specifically, previous findings suggest that neighborhoods may have disparate impacts for boys and girls (Ludwig et al., 2013; Kessler et al., 2014) and several studies of adult samples have found that neighborhood socioeconomic disadvantage is associated with obesity for females but not for males (Robert and Reither, 2004; Black and Macinko, 2008). For example, Smith et al. (2011) found that neighborhood walkability was inversely related to BMI, overweight, and obesity risk, but only among females. Coping strategies for the stress associated with living in a disadvantaged neighborhood such as eating and sedentary behavior may underlie stronger neighborhood effects for females than males. Still, we know almost nothing about whether sex moderates the relationship between neighborhood disadvantage and obesity among youth. Therefore, it is important to examine whether neighborhood disadvantage has a differential effect on obesity for boys and girls using national longitudinal data, which represents another contribution of this paper. This leads to my research questions.

## 2.5. Research questions

- (1) Does neighborhood disadvantage increase the odds of being obese for youth of all ages?
- (2) Does neighborhood disadvantage more adversely impact adolescents' odds of being obese compared to young school-aged children?
- (3) Does sex moderate the association of neighborhood disadvantage on obesity for youth?

Based on previous studies, I expect neighborhood disadvantage to increase all children's odds of being obese and that older children will be more sensitive than younger children to neighborhood disadvantage. Furthermore, I expect girls to be more sensitive to neighborhood disadvantage than boys. However, I must emphasize that these hypotheses may rely on mechanisms such as food insecurity, physical activity, and peer effects that the NLSY data is unable to measure directly.

## 3. Data

I use thirteen waves (1986–2010) of restricted data on a cohort of mothers and their children from the NLSY 1979 (NLSY79) and NLSY Child and Young Adult (NLSY:CYA) data sets, respectively. The NLSY79 is an ongoing nationally representative multi-stage clustered sample of 12,686 young men and women who were 14–22 years old when they were first surveyed in 1979.<sup>2</sup> The survey includes information on educational attainment, labor force behavior, income, health conditions, marital and fertility histories, and Census tract locations in each wave. The Bureau of Labor Statistics (BLS) granted me access to the restricted tract-level NLSY79 data under the condition that I complete all analyses on encrypted machines at BLS headquarters in Washington, D.C. I dropped male respondents from the NLSY79 because only female respondents who have ever had children are linked to the NLSY:CYA cohort.

The NLSY:CYA is composed of children born to the female respondents from the NLSY79 and has essentially gone untouched by neighborhood effects researchers (for a rare exception see [Chase-Lansdale and Gordon, 1996](#)). The BLS started collecting information biennially for all of the children that were born (or would be born) to female respondents of the NLSY79 cohort beginning in 1986 ([Center for Human Resource Research, 2009](#)). By 2010, a total of 11,504 children have been born to NLSY79 mothers, the oldest being 38 years old. The 2010 wave was the thirteenth wave of the ongoing survey and contained information for 6997 children and young adults. An average of 6823 children have been interviewed at each wave between 1986 and 2010 with a median response rate of 90 percent across the panel.

I use data on children and adolescents who were between the ages of 2 and 18 in any wave of the NLSY:CYA between 1986 and 2010 (i.e., children who were already born or were subsequently ever born to NLSY79 females beginning in 1986). The BLS classifies those under the age of 14 as children and those who are 15 and older as young adults. The average number of waves a child or young adult was observed in the NLSY:CYA data is 7.5 (15 years) with a minimum of 2 waves (4 years) and a maximum of 9 waves (18 years). Interviewed mothers in 2010 fell between the ages of 45 and 53, underscoring the fact that most NLSY79 women are approaching the end of their childbearing years. Also in 2010, 87 percent of the child sample is over the age of 15 and about 58 percent are age 21 and over. The youngest members of the sample of children reside in middle class households and were born to women at older ages. Although the earliest waves included large proportions of children who had been born to adolescent mothers, 89% of the children and young adults interviewed in 2010 had been born to women age 20 and over, diluting any bias associated with teenage childbearing in the NLSY79 cohort over time. In fact, all children interviewed in 2010 were born to women over the age of 30 and only about 13% of interviewed young adults were born to adolescent mothers ([Center for Human Resource Research, 2009](#)). I analyzed data that was imputed to correct for missingness ([Allison, 2002](#); [von Hippel, 2007](#)).

Although neighborhoods are difficult to conceptualize, measure, and analyze ([Lee and Campbell, 1997](#)) and despite literature that suggests that non-residential activity spaces may impact obesity-related behaviors ([Zenk et al., 2011](#)), I followed previous neighborhood effects researchers by operationalizing neighborhoods using residential Census tracts ([Sharkey and Elwert, 2011](#); [Feng et al., 2010](#); [Leal and Chaix, 2011](#)). Moreover, the NLSY lacks data for the full roster of activity spaces that youth use in daily life, forcing me to focus on residential contexts. Despite convention, there has been considerable debate regarding what defines one's neighborhood. Indeed, scholars going back to the venerable Chicago School have agreed that neighborhoods can be defined as “ecological units nested within successively larger communities” ([Sampson et al., 2002](#)

<sup>2</sup> The NLSY sampling strategy created three independent probability samples that are designed to represent the entire population of youth aged 14 to 21 as of December 31, 1978, residing in the United States on January 1, 1979. First, a cross-sectional sample (6111) designed to represent the noninstitutionalized civilian segment of young people living in the United States in 1979 and born January 1, 1957, through December 31, 1964. Second, a set of supplemental samples (5295) designed to oversample civilian Hispanic or Latino, black, and economically disadvantaged, nonblack/non-Hispanic youths born in the same time period. Third, a military sample (1280) designed to represent the population born January 1, 1957, through December 31, 1961, serving in the military as of September 30, 1978. The inclusion of the military sample allows comparative civilian-military analyses. Beginning in 1986, additional information was collected about children born to female NLSY79 respondents. The sampling procedures used to select the civilian and military subsamples differed and are discussed in the *Interviewer's Manual* for the 1978 household screening ([NORC 1978](#)). Sampling issues related to the Children of the NLSY79 are discussed in the *NLSY79 Child & Young Adult Data Users Guide*. The results presented in this paper are unweighted nonrepresentative estimates for a national sample of children living in the U.S. between 1986 and 2010. For further information, see <https://www.nlsinfo.org/content/cohorts/nlsy79/intro-to-the-sample/sample-design-screening-process>.

**Table 1**  
Mean percentages for neighborhood disadvantage components by neighborhood quintile.

Neighborhood quintile	Neighborhood disadvantage component						
	BA+	Managers and Professionals	Median housing value	Median income	Poverty	Unemployment	Not in labor force
1 (least disadvantaged)	37.78	38.76	277194.90	80142.33	5.30	4.01	26.04
2	22.53	25.80	172923.50	56626.20	9.63	5.64	29.70
3	16.45	19.87	137500.20	47224.17	13.49	7.09	33.53
4	11.95	15.32	109868.10	38479.79	18.75	9.15	37.83
5 (most disadvantaged)	6.83	11.04	75643.45	26888.03	32.92	15.19	45.3

Source: U.S. Bureau of Labor Statistics, NLSY 1979

p. 445), suggesting a hierarchy of “natural areas” that may differ on the impact they have on residents. This means that neighborhood effects may vary depending on the geographic level of aggregation that scholars employ in their research and on the outcomes under study. For instance, Hipp (2007) found that while tract level racial and ethnic composition has stronger effects on perceptions of crime and disorder, economic resources has more localized effects at the block level. These findings highlight the various pathways through which neighborhood effects may operate and speak to the myriad ways that neighborhoods can impart influence, despite the traditional Census-based criteria most scholars rely on. Unfortunately, the NLSY does not provide geographic identifiers smaller than the tract.

Recognizing these differences in effects by levels of aggregation (and outcomes), I used tract-level neighborhood data from the Geolytics Neighborhood Change database (<http://www.geolytics.com>) to measure neighborhood disadvantage and I linked these data with NLSY data using the restricted NLSY79 geocode associated with mothers' residence location. I primarily focused on tracts to align my study with previous obesity studies. Geolytics provides data on tract socioeconomic characteristics for 1980, 1990, 2000 using the Census long form, normalized to 2000 tract boundaries. However, in 2010, the Census Bureau replaced the historic long form with a much less comprehensive Summary File 1 (SF1) that lacked many of the key socioeconomic tract variables such as income, housing value, employment, and educational attainment. To make up for this deficiency in the Census 2010 SF1, Geolytics provides the 5-year 2005–2009 American Communities Survey (ACS) data that contains these tract level socioeconomic indicators, normalized to 2000 tract boundaries. The 2010 ACS is no longer normalized to 2000 so it is incompatible with the NLSY79 geocode data (which is only normalized to 2000 and before). Following previous literature (Sampson et al., 2008; Sharkey and Elwert, 2011), I linearly-interpolated neighborhood characteristics to fill-in neighborhood data for every NLSY wave between 1986 and 2010 using four waves of Census data (1980, 1990, 2000, and 2009). The standard in the literature is to essentially draw a line between Census waves to capture neighborhood conditions in inter-Census years. I extended the interpolated trajectory between 2000 and 2009 one year to capture 2010 neighborhood conditions.

### 3.1. Neighborhood disadvantage

I followed previous research and operationalized my main explanatory variable, neighborhood disadvantage, by creating a scale so as to more accurately capture a multidimensional underlying contextual disadvantage (Harding, 2009; Shih et al., 2012). This scale is the mean of the following seven standardized variables that I measured four times (Censuses: 1980, 1990, 2000, and 2009) and linearly interpolated to create a 24 year history: percent of residents at or below 100% of the poverty threshold as defined by the U.S. Census Bureau, the percent of residents who are unemployed, the percent of residents out of the labor force, the percent who have at least a Bachelor's degree (reverse coded), the percent of managers and professionals in the neighborhood (reverse coded), median income (reverse coded), and the median housing value (reverse coded).<sup>3</sup> I then created neighborhood quintiles where the least disadvantaged neighborhood type (i.e., the reference category) is coded as 1 and the most disadvantaged neighborhood type is coded as 5. I did so because, as some research suggests, neighborhood effects may follow a non-linear trajectory (Wang and Zhang, 2006). The inter-item correlation was 0.51 and the Chronbach's  $\alpha$  was 0.88 for the neighborhood disadvantage scale, suggesting that the seven variables reliably form a single scale that measures the same underlying neighborhood disadvantage concept.

Table 1 summarizes mean levels of the seven components of the neighborhood disadvantage scale across the neighborhood quintiles. Means for the seven components of the neighborhood disadvantage scale demonstrate that indicators of education, occupational status, median housing value, and income decrease while indicators of poverty, unemployment, and lack of labor force participation increase between the first to the fifth quintiles.

### 3.2. Outcome

I constructed the outcome of this analysis, obesity, by using NLSY:CYA data on children's age, sex, height, and weight for every survey wave between the ages 2–18. Data on height and weight were provided by mothers or were directly measured

<sup>3</sup> I adjusted for the price index for neighborhood median income and housing value.

by the interviewer, depending on the age of the child. Unfortunately, the NLSY does not provide any other data on physique that I could use to define obesity (e.g., waist to hip ratio). I created a binary obese variable for children if they fell at or above the 95th body mass index percentile in each survey wave for their given sex and age in accordance with the Center for Disease Control and National Center for Health Statistics growth charts for boys and girls (Kuczmarski et al., 2002; Ogden et al., 2002). The 95th percentile cutoff excludes fringe cases and those that would be considered non-obese using metrics other than BMI while also conforming to International Obesity Taskforce and Centers for Disease Control recommendations.

### 3.3. Individual-level covariates

While race-ethnicity, income, and education are the primary predictors of selection into neighborhoods (Sampson and Sharkey, 2008) and can impact one's likelihood of being obese (Caprio et al., 2008; Pudrovska et al., 2014), I include a diverse array of time-varying and time-invariant theoretically relevant social and demographic controls variables in all models. Table 2 provides a full summary of means and standard deviations (split into between- and within-person standard deviations) for all of the variables in this analysis. Time-varying controls include mother's poverty status, the number of weeks that the mother has been unemployed, the number of children in the home, income (logged 2010 dollars), single parenthood, mother's education, age of youth (quartiles), and whether or not the mother was obese. Single parenthood is an especially salient variable given that scholars have recently revealed it to be a significant predictor of child obesity (Schmeer, 2012). I also include time-invariant controls in all models such as race and ethnicity, foreign-born status of the mother, and sex of the child because, while they drop out of the FE model, including them can reduce bias stemming from the possibility that these time-invariant variables may have different effects as children mature (Allison, 2009).

## 4. Methods

I began by running a conventional pooled logistic model that uses between-child variation across the entire study period to establish a basic pattern of association between neighborhood disadvantage and obesity while controlling for observed background characteristics. I followed up by using fixed effects models to minimize the possibility that the estimated contextual effects are artifacts of systematic selection bias that predicts neighborhood residence and obesity. The fixed effect model capitalizes on variation in neighborhood conditions during thirteen waves of the NLSY survey that result from two processes: children moving between neighborhoods and neighborhoods changing around children over time. For example, 57 percent of the sample never moved and therefore exclusively experienced variation in neighborhood conditions exogenously through changes to their environment around them over time. In contrast to other methods (e.g., multi-level models, propensity score matching, etc.), the FE models allow me to minimize bias by controlling for *unobserved* time-invariant characteristics of children and families which have been a critical limitation in previous studies of neighborhood effects on individual outcomes (Diez-Roux, 2004, 2008; Oakes, 2004; Shadish et al., 2002).

**Table 2**  
Descriptive statistics for 2–18 year old children of NLSY mothers.

	Mean	Standard deviation	
		Between	Within
<b>Mother &amp; household characteristics</b>			
Mother is obese	0.430	0.388	0.309
In poverty	0.305	0.323	0.331
Weeks unemployed	3.509	6.552	13.165
Number of children in household	2.308	1.031	0.795
Income (logged 2010 dollars)	10.629	0.681	0.822
Single parent	0.403	0.377	0.318
Parental education: less than high school degree	0.160	0.328	0.181
Parental education: high school degree	0.435	0.425	0.258
Parental education: some college	0.24	0.36	0.23
Parental education: Bachelor's or higher	0.164	0.320	0.187
Foreign born (0 = born in USA; 1 = not born in USA)	0.076	0.265	0.000
<b>Child characteristics</b>			
White	0.490	0.500	0.000
Black	0.310	0.470	0.000
Latino	0.190	0.400	0.000
Age	10.305	1.671	4.488
Female	0.490	0.500	0.000
<b>Neighborhood characteristics</b>			
Neighborhood disadvantage scale (1 = least disadvantaged; 5 = most disadvantaged)	3.036	1.157	0.840
<b>Outcome</b>			
Obese	0.430	0.360	0.341

Notes: Between standard deviations pertain to differences between separate children while within standard deviations pertain to differences between the same child in separate years.

Source: NLSY 1979–2010; NLSY CYA 1986–2010.



Within-group regression, such as FE models, has been touted as a useful way to isolate contextual effects (Gangl, 2010), but has rarely been used in empirical studies of neighborhood effects (see Vartanian and Houser, 2012; Aaronson, 1998). Factors that are both time-varying, such as income and employment, and those that are time-invariant (and often unobserved), such as genes or mother's underlying neighborhood preference, may simultaneously affect the selection of neighborhoods and can impact individuals' weight status. Recent research from the Training Interventions and Genetics of Exercise Response (TIGER) Study (Sailors et al., 2010) reveals that specific genes are strongly associated with both obesity and the probability of sticking with an exercise program. However, the study also finds that genes only account for about 50% of the variation in weight, leaving diet and environmental factors (and interactions among these factors) to explain much of the remaining variation.

Fixed effect models are useful because they control for anything that may be unobserved and time-invariant for both children and their families by using individuals as their own controls over time (Allison, 2009; Greene, 2008; Wooldridge, 2002; Halaby, 2004; Oakes, 2004; Gangl, 2010; Johnston and DiNardo, 1997). The weakness of the FE approach is that it cannot account for any time-varying unobserved characteristics. FE models use only within person variation to identify effects, and are therefore less precise even though they are more efficient estimators than conventional regression models. Nevertheless, FE models approximate an “apples to apples” comparison because variation is confined to within individuals while unobserved time-invariant characteristics are held constant.

I use the mean deviation FE approach for all of the analyses (Allison, 2009; StataCorp LP, 2012). The mean deviation approach avoids the cumbersome challenge of computing FE models with dummy variables by expressing each variable as a deviation from its person-specific mean (Hill et al., 2011). First, I calculate, for each person and for each time-varying variable (both outcome and predictor variables), the means of those variables over time. The second step is to subtract the person-specific means from the observed values of each of the  $y$  and  $x$  variables. In the final step I regress the mean-deviations of obesity,  $y^*$ , on the mean-deviations of the main predictor,  $x^*$  (i.e., neighborhood disadvantage), and those variables that represent time, net of controls. I corrected for the clustering of observations within children over time and all of the FE results contain robust bootstrapped standard errors (StataCorp LP, 2012).

Some scholars argue that environmental effects could be developmental and cumulative (Sampson, 2012). If this is true in the case of childhood obesity, then the FE models can only pick up short-term (i.e., two years) cumulative effects of exposure to a disadvantaged neighborhood. That is, because the waves are two years apart, a given change in neighborhood conditions, whether through moving or experiencing change around children, could have happened as far back in time as two years prior to the measurement of obesity. However, there remains debate on this issue. For instance, recent findings from the MTO suggest that youth outcomes are likely more affected by more contemporaneous neighborhood conditions than any accumulated exposure to neighborhood contexts (Ludwig et al., 2013).

Finally, because the FE models rely on variation in neighborhood contexts, Fig. 1 shows how children's neighborhood contexts change as a result of changes (i.e., either physically moving or staying as neighborhoods change around youth over

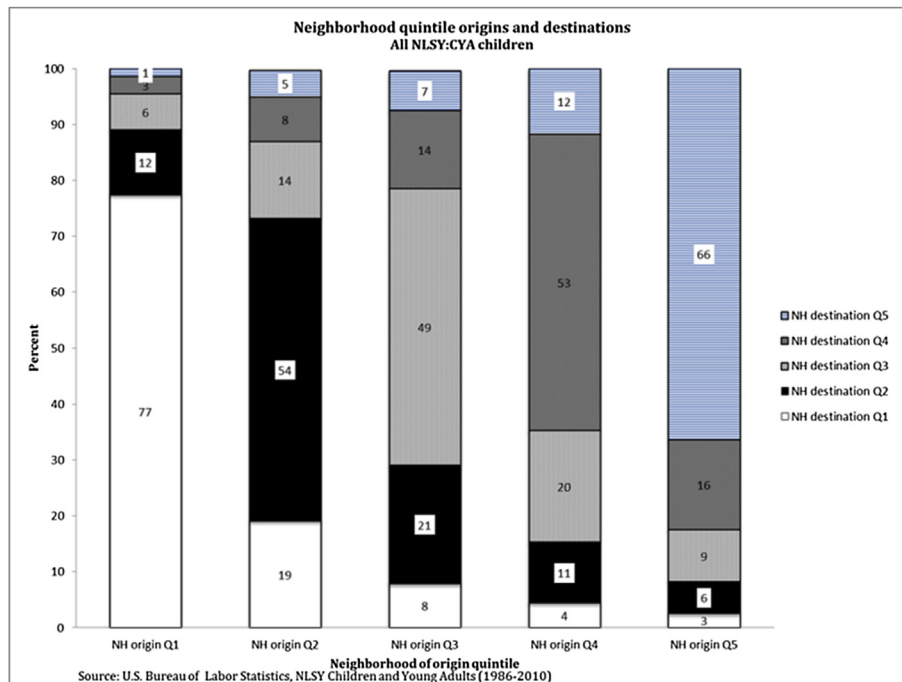


Fig. 1. Rigidity in transitions between neighborhood quintiles (1 = least disadvantaged; 5 = most disadvantaged).

time) between neighborhood quintiles. Quite simply and effectively, this graph shows that mobility between neighborhood types is uncommon between any two NLSY waves. For example, 77 percent of children who originate in the first neighborhood quintile end up in the first neighborhood quintile. Similarly, 66 percent of children who originate in the fifth neighborhood quintile end up in the fifth neighborhood quintile. These findings, and those for children who originate in the second, third, and fourth quintiles, suggest that a rigid mobility structure pervades in the U.S. where individuals often experience very little change in neighborhood type, supporting previous intra- and inter-generational neighborhood mobility findings from the Project on Human Development in Chicago Neighborhoods (PHDCN) and Panel Study of Income Dynamics (PSID) (Sampson and Sharkey, 2008; Sharkey, 2013, 2008). However, there remains sufficient variation in neighborhood type to conduct FE analyses.

## 5. Results

### 5.1. Descriptive results

Table 2 shows descriptive results for the full sample of NLSY children and youth ages 2–18 whom the NLSY interviewed between 1986 and 2010, representing 11,499 children and young adults. The table shows means in addition to overall, between-person and within-person standard deviations for all variables used in this analysis. The between-person standard deviation (SD) pertains to differences between separate children while the within-person SD pertains to differences for the same child over time. I can therefore summarize variation in individual- and neighborhood-level variables both between individuals and within individuals across time.

Additionally, the table presents descriptive statistics on obesity. The descriptive statistics demonstrate that 43 percent of the sample of children and adolescents experienced being obese at some point between 1986 and 2010. Obesity among NLSY children is much higher than the national average has ever been and suggests that the NLSY children may be especially prone to obesogenic conditions. For example, in 2011–2012 17 percent of children ages 2 to 19 were obese in the U.S. representing the largest prevalence of obesity ever recorded (Ogden et al., 2014). Also, among NLSY79 respondents, 40 percent of mothers were single and 30 percent of children and their families were in poverty at some point during the study. For comparison, in 2011 36 percent of mothers in the U.S. were not married (Shattuck and Kreider, 2013) and in 2010 22 percent of children were in poverty (DeNavas-Walt, Proctor and Smith, 2011), suggesting that the NLSY sample of mothers may be more disadvantaged than the national average. However, these trends in many respects parallel those of the experimental MTO project upon which much of the neighborhood effects literature has relied for estimates of associations between neighborhood context and children's outcomes (Ludwig et al., 2013).

Fig. 2 shows changes in the bivariate association between neighborhood disadvantage (quintiles) and obesity over time. First, this figure shows that the least disadvantaged neighborhoods (category 1), represented by hollow diamonds, historically demonstrated the lowest mean prevalence of obesity among NLSY youth ages 2–18. I would expect this given the levels of education, dietary habits, and physical activity behaviors in the most advantaged neighborhoods. This intuitive finding, however, is accompanied by a somewhat counterintuitive finding: there seems to be very little difference between the prevalence of obesity in the most disadvantaged (category 5; represented by Xs) neighborhoods and the least disadvantaged (category 1; diamonds) neighborhoods across time. This pattern is evident across the 24 years of the study and is in contrast with what I would expect from neighborhood effects studies among adults. However, the pattern may align with recent findings that suggest a convergence in obesity prevalence for low and high SES households (Wang and Zhang, 2006; Burdette

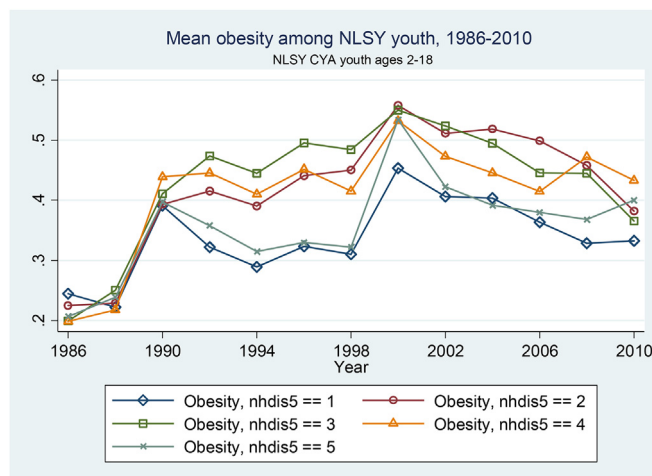


Fig. 2. Mean obesity among NLSY youth by neighborhood quintiles (1 = least disadvantaged; 5 = most disadvantaged), 1986–2010.

and Whitaker, 2005). Neighborhoods that lie within the middle range of socioeconomic disadvantage, quintiles 2–4, have a much higher level of obesity prevalence compared to the neighborhoods at the extremes of the disadvantage distribution, suggesting that neighborhoods in the middle of the disadvantage distribution may have stronger impacts on childhood obesity. For example, in the past decade, neighborhoods in the second neighborhood disadvantage quintile represented by the hollow circle have had the highest prevalence of obesity compared to all other neighborhoods while the those in the fourth quartile represented by the full circle have demonstrated a lower prevalence of obesity approaching that of the extremes of the neighborhood disadvantage distribution.

What is more, there is a clustering of obesity prevalence across neighborhoods in the first few waves of the NLSY:CYA when the sample of children was at its youngest and a separation occurring after 1990 when the median age of the sample was growing. For instance, in 1986 only 1 of the 4971 interviewed children and young adults was age 15 or older and in 1992, when neighborhood disparities in mean obesity prevalence first appear, 379 (6%) of 6809 respondents were over 15. This provides suggestive evidence that neighborhood effects may not appear until children are of the age to interact with their environment in more meaningful ways. Indeed, scholars have highlighted that the likely reason why the association between neighborhood socioeconomic deprivation and weight is stronger in older age groups is because adolescents likely have increasing interaction with their environments as they age (Schwartz et al., 2011). However, it is important to study children at this young age because scholars have previously found disparities in obesity prevalence beginning at this early stage of development (Ogden et al., 2014).

Fig. 3 more clearly demonstrates the disparities in the bivariate associations between neighborhood disadvantage and obesity by age. Here, I followed previous developmental literature and stratified the sample of youth into two categories: young school-aged children ages 2–10 and adolescents ages 11–18.<sup>4</sup> The graph demonstrates that adolescents' risk of obesity was larger than that of young children as function of neighborhood disadvantage. This pattern of stronger impacts of neighborhood disadvantage on the likelihood of being obese is evident in each neighborhood quintile among adolescents ages 11–18. These gross differences in neighborhood effects suggest that age may indeed moderate the effect of neighborhood disadvantage on obesity among youth and that adolescents may be at higher risk of obesity due to living in disadvantaged neighborhoods compared to younger children. Still, these results cannot uncover the mechanisms that may drive these associations nor can they rule out alternative explanations as to why youth experience gains in obesity risk due to living in disadvantaged neighborhoods. Although the data limit my ability to tease out underlying mechanisms, I turn to a multivariate analysis to examine if adjusting for observed and unobserved variables undermines these gross associations between neighborhood disadvantage and obesity among youth and to examine whether age continues to act as a moderator after including sociodemographic controls.

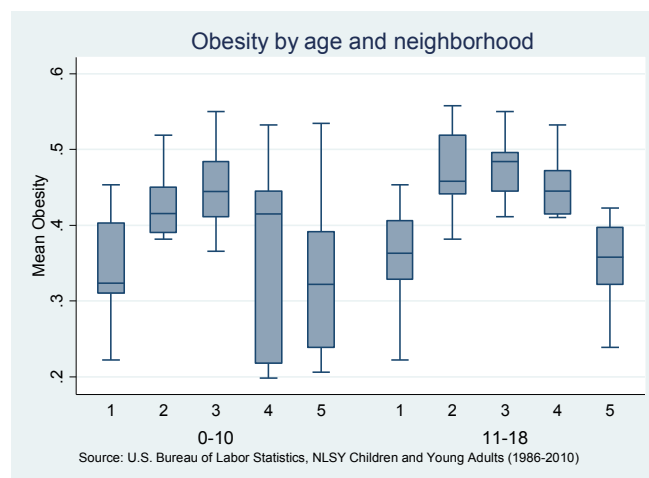


Fig. 3. Bivariate associations between neighborhood disadvantage quintiles (1 = least disadvantaged; 5 = most disadvantaged) and obesity by age of youth.

<sup>4</sup> There is a variety of theoretical "epochs" or "stages" of childhood in the developmental literature (Aber, Gephart, Brooks-Gunn and Connell, 1997). Classic examples include Freud's notion of psychosocial stages and Piaget's theory of cognitive structural stages of development. The main point is that children relate to themselves and to their environments differently at different ages. Importantly, developmentalists state that clear-cut difference may not exist between stages of development based solely on age. Therefore, scholars instead focus on transitions to divide childhood into distinct epochs (e.g., school, cognition, biology, or social events). I generally follow Brooks-Gunn and colleagues' (1997) method of differentiating between adolescents (approximately ages 11 to 16) and early school-age children (those approximately 10 and younger) in this study to examine neighborhood effects' across children's early life-course. I extend the adolescent period two years to include 18 year olds to capture all youth in the data.

## 5.2. Multivariate results

Table 3 shows results for a logistic regression model and for a child FE model estimating the effect of neighborhood disadvantage on obesity after controlling for observed individual-level background characteristics. I have separated the coefficients by category of the neighborhood disadvantage scale to demonstrate any uneven patterns that could indicate non-linear neighborhood effects and the results are in the metric of odds ratios. Therefore, the estimates display whether there are any significant differences between categories of neighborhood disadvantage (relative to the least disadvantaged neighborhoods).

In model 1, the pooled logistic results indicate that neighborhoods between the 20th and 79th percentiles yielded strong and statistically significant associations with childhood obesity. The odds of being obese wane for youth who experience neighborhood change down the quintiles from the least socioeconomically disadvantaged neighborhoods to the most socioeconomically disadvantaged neighborhoods. Specifically, neighborhoods in the second quintile exert a 54 percent greater odds ( $e^{0.43} = 1.542$ ), neighborhoods in the third quintile exert a 59 percent greater odds ( $e^{0.46} = 1.591$ ), and neighborhoods in the fourth quintile exert a 32 percent greater odds ( $e^{0.28} = 1.321$ ) of being obese compared to the least disadvantaged neighborhood type. Neighborhoods above the 80<sup>th</sup> percentile of disadvantage were no different than neighborhoods in the lowest quintile in terms of odds for childhood obesity. That is, there is no difference in the odds of being obese as a function of living in the most disadvantaged neighborhoods, category 5, relative to living in the least disadvantaged neighborhood for youth of all ages.

In Model 2 I added child fixed effects. Here, the association between neighborhood disadvantage and obesity decreases in size, indicating that the pooled regression results were moderately spurious to unobserved time-invariant confounders. This model also represents a key advancement over previous studies of neighborhood effects on obesity among youth because it addresses unobserved heterogeneity in addition to longitudinally controlling for important observed sociodemographic characteristics of the family and children.

Neighborhoods in the second quintile exert a 40 percent greater odds ( $e^{0.33} = 1.40$ ), neighborhoods in the third quintile exert a 37 percent greater odds ( $e^{0.31} = 1.37$ ), and neighborhoods in the fourth quintile exert a 21 percent greater odds ( $e^{0.19} = 1.209$ ) of being obese compared to the least disadvantaged neighborhoods when adjusting for unobserved time-invariant confounders. Meanwhile, mirroring the results from the pooled logistic regression model, there is no discernable difference in the risk of obesity between the most and the least disadvantaged neighborhoods. These FE results suggest that neighborhood disadvantage increases children's odds of being obese. However, these results cannot tell us whether neighborhoods impart different impacts on obesity across the early life-course or if girls are more sensitive to neighborhoods than boys. To answer these questions, I turn to interaction models in the following section.

## 5.3. Age interactions

The first set of interaction models address whether age moderates the association between neighborhood disadvantage and obesity among youth. Table 4 displays both main effects and interaction effects for age\*neighborhood disadvantage on obesity where the reference category for age is children ages 2–10 and the reference category for neighborhood disadvantage is the first quintile (i.e., the least disadvantaged quintile).

The pooled logistic regression model demonstrates that adolescents between the ages of 11–18 are indeed more likely to become obese as a function of living in disadvantaged neighborhoods compared to children ages 2–10. Moreover, the impact of neighborhood disadvantage not only grows as a function of age, but also becomes stronger as neighborhood disadvantage becomes increasingly acute. This is evidenced by the fact that the odds ratio increases from 1.26 among adolescents living in the second neighborhood disadvantage quintile to 1.43 for adolescents living in the fourth neighborhood quintile.

**Table 3**

The impact of neighborhood disadvantage on obesity among youth ages 2–18 (NLSY: CYA, 1986–2010).

	(1) Pooled logistic regression	(2) Child-fixed effects
	Odds Ratio	Odds Ratio
Neighborhood disadvantage scale (1 = least disadvantaged; 5 = most disadvantaged)		
Quintile 2 vs 1	1.54*** (0.04)	1.40*** (0.07)
Quintile 3 vs 1	1.59*** (0.04)	1.37*** (0.07)
Quintile 4 vs 1	1.32*** (0.03)	1.21*** (0.07)
Quintile 5 vs 1	1.03 (0.03)	0.98 (0.06)
Constant	0.97 (0.09)	—
Person-years	76,421	52,337

Notes: All models control for mother obese, family in poverty, mother's weeks unemployed, number of children in household, logged income, single parent, mother's education, mother's foreign born status, race/ethnicity, child's age, and child's sex. Standard errors in parentheses. Child-fixed effects models include robust bootstrapped standard errors that are corrected for clustering.

\*p < .05; \*\*p < .01; \*\*\*p < .001.

**Table 4**

Interaction model between age and neighborhood disadvantage on obesity among youth (NLSY: CYA, 1986–2010).

	(1) Pooled logistic regression	(2) Child-fixed effects
	Odds Ratio	Odds Ratio
<b>Main effects</b>		
Age 11–18	0.98 (0.03)	1.22*** (0.07)
Neighborhood disadvantage scale (1 = least disadvantaged; 5 = most disadvantaged)		
Quintile 2 vs 1	1.17*** (0.04)	1.16* (0.09)
Quintile 3 vs 1	1.21*** (0.04)	1.08 (0.08)
Quintile 4 vs 1	0.99 (0.04)	0.96 (0.50)
Quintile 5 vs 1	0.85*** (0.03)	0.81** (0.06)
<b>Interaction effects</b>		
Age 11–18*Quintile 2 vs 1	1.26*** (0.06)	1.29*** (0.09)
Age 11–18*Quintile 3 vs 1	1.32*** (0.06)	1.53*** (0.12)
Age 11–18*Quintile 4 vs 1	1.43*** (0.07)	1.58*** (0.11)
Age 11–18*Quintile 5 vs 1	1.19*** (0.06)	1.45*** (0.11)
Constant	0.97 (0.10)	–
Person-years	76,421	52,337

Notes: All models control for mother obese, family in poverty, mother's weeks unemployed, number of children in household, logged income, single parent, mother's education, mother's foreign born status, race/ethnicity, child's age, and child's sex.

Standard errors in parentheses. Child-fixed effects models include robust bootstrapped standard errors that are corrected for clustering.

\*p < .05; \*\*p < .01; \*\*\*p < .001.

The second model in this table adds the child-fixed effects to control for unobserved time-invariant sources of bias but the results tell the same overall story: Adolescents are more likely to become obese as a function of growing up amidst neighborhood disadvantage compared to young children. However, this time the results are robust to the possible undermining effect of time-invariant unobserved confounders. Moreover, the interaction effects in the fixed effects model demonstrates that the magnitudes of the associations amplify for adolescents living in each neighborhood quintile compared to the results from the pooled logistic regression model. That is, the fixed effects model reveals that the pooled logistic regression model included an unobserved suppressor bias that the fixed effects has accounted for. Finally, the child fixed effects model demonstrates that the main effects, that is the associations between neighborhood disadvantage and obesity for young children, are spurious save for the associations for children growing up in the second and fifth neighborhood disadvantage quintiles.

Still, these results may be affected by the developmental cutoffs that I borrowed from the literature. That is to say, alternative age cutoffs may impact the results. As a robustness check to test whether age had an overall linear impact on the association between neighborhood disadvantage and obesity, I used the continuous age variable and re-ran the models. Table 5 shows the results from the models in which I interacted the continuous age variable with neighborhood disadvantage quintiles. In short, these models re-confirm the results from Table 4: Neighborhood disadvantage increases the odds of being obese and age moderates the association between neighborhood disadvantage and obesity among youth across the early life-course. In particular, the FE model shows that as age increases, the impact of neighborhood disadvantage on obesity becomes stronger for youth, net of observed and unobserved (time-invariant) covariates.

#### 5.4. Sex interactions

The neighborhood effects literature among adults suggests that females may be more sensitive to neighborhood disadvantage than males. To explore this possibility with the NLSY:CYA sample of girls and boys, I ran models where I interacted neighborhood disadvantage with sex to test whether there were any significant differences between boys and girls in the risk of obesity due to living in disadvantaged neighborhoods. Table 6 summarizes the results from the pooled two way full factorial logistic regression model and from the within-child two way full factorial fixed effects model where the base categories are males and neighborhoods with the lowest levels of socioeconomic disadvantage (i.e., quintile 1).

The results from the pooled model show that neighborhood disadvantage increases the risk of obesity as all children, boys and girls, experience neighborhood change from the least disadvantaged to more disadvantaged neighborhoods, with the one exception of boys who change from the least to the most disadvantaged neighborhoods (OR: 0.85; SE: 0.03). However, girls experience a greater risk of obesity due to these changes in neighborhood context than boys. While girls in the highest SES neighborhoods are less likely than boys in these neighborhoods to be obese (OR: 0.84; SE: 0.03), girls who experience change from these affluent neighborhoods are at an even greater risk of being obese than boys who do so. As expected from prior research, neighborhood disadvantage has an even greater impact on girls than it does on boys.

In the FE model, I find a similar pattern for boys as I did in the pooled model with the exception of change to the most disadvantaged neighborhoods that no longer impacts boys' odds of being obese. Unlike in the pooled model where girls had even greater risk than boys of being obese due to change to more disadvantaged neighborhoods, for the most part girls and boys have equal risk of obesity as a result of change with the exception of change from the least to the most disadvantaged neighborhoods. Girls continue to experience a greater risk of obesity than boys due to change from the least to the most

**Table 5**

Interaction model between continuous age and neighborhood disadvantage on obesity among youth (NLSY: CYA, 1986–2010).

	(1) Pooled logistic regression	(2) Child-fixed effects
	Odds Ratio	Odds Ratio
<b>Main effects</b>		
Age	0.99* (0.00)	1.02*** (0.01)
Neighborhood disadvantage scale (1 = least disadvantaged; 5 = most disadvantaged)		
Quintile 2 vs 1	0.98 (0.06)	1.01 (0.09)
Quintile 3 vs 1	0.97 (0.06)	0.78** (0.08)
Quintile 4 vs 1	0.77*** (0.05)	0.73** (0.08)
Quintile 5 vs 1	0.76*** (0.05)	0.66*** (0.07)
<b>Interaction effects</b>		
Age*Quintile 2 vs 1	1.02*** (0.01)	1.03*** (0.01)
Age*Quintile 3 vs 1	1.04*** (0.01)	1.06*** (0.01)
Age*Quintile 4 vs 1	1.04*** (0.01)	1.05*** (0.01)
Age*Quintile 5 vs 1	1.02*** (0.01)	1.04*** (0.01)
Constant	1.05 (0.11)	–
Person-years	76,421	52,337

Notes: All models control for mother obese, family in poverty, mother's weeks unemployed, number of children in household, logged income, single parent, mother's education, mother's foreign born status, race/ethnicity, child's age, and child's sex. Standard errors in parentheses. Child-fixed effects models include robust bootstrapped standard errors that are corrected for clustering.

\*p < .05; \*\*p < .01; \*\*\*p < .001.

**Table 6**

Interaction model between sex and neighborhood disadvantage on obesity among youth (NLSY:CYA, 1986–2010).

	(1) Pooled logistic regression	(2) Child-fixed effects
	Odds Ratio	Odds Ratio
<b>Main effects</b>		
Female	0.84*** (0.03)	–
Neighborhood disadvantage scale (1 = least disadvantaged; 5 = most disadvantaged)		
Quintile 2 vs 1	1.27*** (0.04)	1.38*** (0.09)
Quintile 3 vs 1	1.34*** (0.05)	1.42*** (0.09)
Quintile 4 vs 1	1.11** (0.04)	1.21* (0.07)
Quintile 5 vs 1	0.85*** (0.03)	0.91 (0.07)
<b>Interaction effects</b>		
Female*Quintile 2 vs 1	1.10* (0.05)	1.03 (0.10)
Female*Quintile 3 vs 1	1.10* (0.05)	1.02 (0.09)
Female*Quintile 4 vs 1	1.16** (0.06)	1.11 (0.11)
Female*Quintile 5 vs 1	1.25*** (0.06)	1.33** (0.14)
Constant	0.89 (0.09)	–
Person-years	76,421	52,337

Notes: All models control for mother obese, family in poverty, mother's weeks unemployed, number of children in household, logged income, single parent, mother's education, mother's foreign born status, race/ethnicity, child's age, and child's sex.

Standard errors in parentheses. Child-fixed effects models include robust bootstrapped standard errors that are corrected for clustering. \*p < .05; \*\*p < .01; \*\*\*p < .001.

disadvantaged neighborhoods. The earlier result from the pooled model that found that neighborhood disadvantage has an even greater impact on girls than it does on boys is robust to unobserved confounders in the FE model, but only when we compare change from the least to the most disadvantaged neighborhoods.

### 5.5. Components of neighborhood disadvantage

Estimating the separate effects of the neighborhood characteristics is important because policy intervention may become clearer if one or two characteristics are exceedingly strong predictors of obesity. To this end, [Appendix A](#) summarizes fixed effects estimates of neighborhood effects for each of the seven neighborhood characteristics separately. [Appendix A](#) shows results for the interaction between the age dummy (2–10 vs. 11–18) and a continuous version of each of the seven neighborhood characteristics. These fixed effects estimates suggest that increases in the percentage of residents who are not in the labor force and decreases in the percentage of managers and professionals have the strongest positive impact on obesity. The remaining five neighborhood characteristics do not seem to strongly predict obesity among NLSY youth.

## 6. Discussion

Overall, the multivariate analyses support the bivariate analysis that I presented in graph form in [Fig. 3](#) – that is, neighborhood disadvantage has a stronger impact on adolescents than young school-aged children. Age appears to moderate

the impact that neighborhood disadvantage has on obesity among youth. My findings also suggest that sex moderates the relationship between neighborhood disadvantage and obesity whereby girls are at a much stronger risk of becoming obese due to living in a disadvantaged neighborhood than boys.

I can surmise from these analyses that neighborhood disadvantage increases the odds of obesity but that the effects are acute for adolescents ages 11–18 who grow up in socioeconomically disadvantaged contexts and for girls who grow up in the most socioeconomically disadvantaged neighborhoods. Both of these results contribute new insights to the literature of neighborhoods and obesity among youth. The age interaction results demonstrate that developmental epochs of the early life-course can moderate the impact of neighborhoods, possibly through enhanced peer and institutional interaction as children get older and extend their sphere of influence to include actors outside of the home. The sex interaction results demonstrate that similar to adults, girls are also at an increased risk of becoming obese due to living in disadvantaged neighborhoods, possibly due to enhanced stress levels and calorie intake.

These findings answer the first research question in the affirmative; disadvantaged neighborhoods do increase the odds of being obese. The results also answer the second research question in the affirmative; age appears to moderate the impact of neighborhood disadvantage on obesity. Finally, my results also support earlier research on adult women and finds that neighborhood disadvantage has a stronger impact on girls than boys. The three hypotheses that are rooted in previous literature are supported here, net of observed and unobserved sources of bias.

In regards to the component-specific analyses, it may be that structural economic deprivation associated with detachment from the labor force and decreases in managers and professionals reduces the availability of healthy food options in the neighborhood, thus increasing obesity. Indeed, the basically null finding for household income (and all of the other components) suggests that the paucity of high earning households alone is not enough to increase obesity. Rather, something that is associated with not having managers and professionals in the neighborhood and detachment from the labor force increases obesity. Still, pinpointing exactly which elements of those households and lifestyles that impact obesity risk is beyond the scope of this paper, unfortunately.

## 7. Conclusion

Rising obesity rates among children, and especially adolescents, in the U.S. threaten to widen already egregious inequality in education, health, and labor market outcomes in adulthood. Recent studies of neighborhood effects on obesity among youth have been limited to city-specific and cross-sectional analyses that lack rich sociodemographic variables across the early life-course and are susceptible to unobserved heterogeneity. The current analysis uses previously unanalyzed national NLSY panel data that covers the decades when childhood and adolescent obesity has skyrocketed. Moreover, this study has contributed a more nuanced understanding of the impact that neighborhood disadvantage has on obesity among youth by examining developmental and sex interactions with neighborhood disadvantage. While previous research has mostly focused on adult obesity, this study provides the first longitudinal examination of the impact of neighborhood disadvantage on obesity among youth at a national level.

I find a statistically significant association between neighborhood disadvantage and obesity, net of observed and unobserved sources of bias. However, in line with previous work on neighborhood effects that has called for increased attention for dynamic developmental aspects of contextual effects (Sampson et al., 2002; Tienda, 1991), it is adolescents, not young school-aged children, who are the most sensitive to neighborhood disadvantage. I find statistically significant differences between young school-aged children between the ages of 2–10 and adolescents between the ages of 11–18 that suggest that adolescents face higher odds of being obese as a function of growing up in disadvantaged neighborhoods. Further, as studies on adults have suggested, I find that girls who grow up in the most disadvantaged neighborhoods are also more likely than boys who do so to be obese. In effect, this study joins together a developmental perspective on neighborhoods and obesity among youth using unique longitudinal data and a more rigorous methodology to fundamentally alter our understanding of the influence of neighborhood disadvantage and obesity among youth.

In terms of mechanisms, there are a few possible explanations as to why adolescents in disadvantaged neighborhoods are more likely to be obese than children in these contexts: food insecurity, physical activity, and interaction with peers. The first possibility comes from the food insecurity literature. Some scholars have found that food insecurity has a positive impact on weight gain among adults (Townsend et al., 2001). Children who grow up in neighborhood contexts where healthy food is scarce may resort to consuming high-calorie and low-nutrition foods that can increase their weight and their chances of being obese. The food deserts that exist in many disadvantaged contexts may drive the associations that I have presented here.

Another theoretical explanation comes from the literature on physical activity among children. Physical activity is often thought of as having a protective influence on weight gain. However, the lack of structured activity schedules among low-income and working-class children may contribute to decreased outdoor play and higher levels of obesity among youth in the most disadvantaged neighborhoods. Where structured physical activity is not a routinized part of socioeconomically disadvantaged children's lives (Lareau, 2003), sedentary activity may become normative and obesity may become more prevalent as a result.

As previous neighborhood scholars have suggested (Turley, 2003), older children may be more susceptible to neighborhood effects due to their increased access to the influence of neighborhood peers and institutional actors. From a developmental perspective, middle childhood and early adolescence may increase the magnitude of neighborhood effects compared to earlier epochs of development because children increase their contact with neighborhood social and economic ecologies

and institutions over time (Brooks-Gunn et al., 1997; Bronfenbrenner, 1979). Ecological embeddedness naturally increases with age because youth become increasingly autonomous from their families and because older youth are beginning to expand their ecological network ties (Aber, Gephart, Brooks-Gunn and Connell, 1997). Therefore, the influence of peers and other social actors may provide the conduit through which the impact of food deserts and norms around physical activity pervade among youth to increase obesity in disadvantaged neighborhoods.

I cannot directly account for what makes girls more susceptible to the negative impact of growing up in a severely disadvantaged neighborhood directly. However, previous research has suggested that adult women may use food as a coping mechanism to the stress associated with living in disadvantaged neighborhoods. Another possibility is that girls in the most disadvantaged neighborhoods may be shielded from outdoor play due to dangerous conditions that often accompany low SES contexts. Future research should examine whether girls, in particular, tend to be more sedentary or are more likely to have an energy intake/outtake imbalance due to stress associated with growing up in the most disadvantaged neighborhoods.

The findings I have presented suggest that policy makers may do well to consider implementing programs that target adolescents to combat obesity. Similarly, this and other research suggests that food security and access to resources that enhance physical activity in the most disadvantaged neighborhoods may also be in need of increased attention from policy makers in order to ensure that children in severely disadvantaged contexts are receiving sufficient nutrition. Considering my findings about age and sex together suggests that future policy efforts should attempt to intervene not only among older children in general but also among female adolescents in particular.

In spite of my efforts, this analysis contains several limitations that qualify the conclusions herein. First, fixed effects models are an improvement on previous models because of their ability to account for unobserved sources of bias. However, FE models are not immune to possible unobserved bias because they cannot control for unobserved time-varying confounders. Therefore, these findings are susceptible to the particular assumptions of within-group estimation that, much like the vast majority of research that uses observational data, constricts causal inference. Second, FE models are limited because they may shroud any cumulative effects beyond two years since neighborhood changes here are assumed to have occurred at most two years prior to the measurement of obesity among youth. Third, although linear interpolation is used in practically every study of neighborhood effects, it would be ideal to have empirical data on neighborhood conditions at much closer intervals than every ten years. Fourth, focusing solely on residential neighborhoods may obfuscate the influence of other activity spaces on obesity among youth (Inagami et al., 2006; Inagami et al., 2007; Troped et al., 2010; Rodriguez et al., 2005; Morenoff, 2003; Kestens et al., 2010; Zenk et al., 2011). Finally, although I have attempted to move beyond the disadvantage scale to try to identify specific levers (e.g., unemployment, poverty, or income) that policy makers can focus on for change and have discovered that the lack of managers and professionals and a detached labor force increase obesity risk, there is still much to be learned about why these specific characteristics impart the largest significant effects that is beyond the scope of this paper. Still, I believe that this analysis provides scholars and policy makers who are interested in the contextual processes that affect obesity among youth with a more nuanced perspective that will enhance our understanding of the link between structural inequality and children's health outcomes.

A possibly fruitful avenue for future research is to further examine how the physical and social-economic characteristics of neighborhoods interact to affect children's weight. More research is also needed to uncover how social ties (Sampson et al., 1997; Sampson and Raudenbush, 1999) among residents may affect children's weight through the willingness of neighbors to intervene and direct the behavior of youth toward healthy lifestyles and diets. Much more research is also needed to uncover the contours of inter-personal relationships between neighbors and how they can affect children's weight in a rapidly changing urban environment (Desmond, 2012; Tach, 2009; Kawachi and Berkman, 2003). The study of neighborhood context and childhood obesity is just beginning to expand and promises to shed light on a most urgent public health concern that affects the life-chances of millions of children from all socioeconomic backgrounds.

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## Appendix A. Interaction models between age and neighborhood characteristics on obesity among youth (NLSY: CYA, 1986–2010)

	Child-fixed effects Odds Ratio						
	BA+	Managers & Professionals	Median housing value	Median household income	Poverty	Unemployment	Not in labor force
<b>Main effects</b>							
Age 11–18	1.96*** (0.98)	2.62*** (0.015)	2.20*** (0.099)	2.34*** (0.16)	1.61*** (0.06)	1.73*** (0.07)	0.70** (0.07)
Neighborhood characteristic	0.995** (0.002)	0.97*** (0.002)	0.999** (0.00)	0.99*** (0.00)	1.00 (0.002)	1.00 (0.004)	1.005* (0.002)
<b>Interaction</b>							
Age 11–18*Neighborhood characteristic	1.009*** (0.002)	1.03*** (0.002)	1.00*** (0.00)	1.00*** (0.00)	1.002 (0.002)	0.995 (0.005)	1.03*** (0.003)
Person-years	52337.00	52337.00	52337.00	52337.00	52337.00	52337.00	52337.00

Notes: All models control for mother obese, family in poverty, mother's weeks unemployed, number of children in household, logged income, single parent, mother's education, mother's foreign born status, race/ethnicity, child's age, and child's sex.

Standard errors in parentheses. Child-fixed effects models include robust bootstrapped standard errors that are corrected for clustering.

\*p < .05; \*\*p < .01; \*\*\*p < .001

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