EARLY PREDICTORS OF OBESITY AND HEALTH BEHAVIORS: A RETROSPECTIVE ANALYSIS OF COLLEGE STUDENTS

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ABSTRACT

Extensive previous research has shown that low socioeconomic status in childhood is predictive of adult obesity. Thus, children growing up in situations with fewer economic resources have a higher risk of adult obesity. The Cumulative Stress Model suggest that the confluence various stressors associated with childhood poverty, results in chronic stress, which, in turn, leads to adult obesity as a result of consumption of high fat and high sugar foods that serves as a coping mechanism. The current study investigated the whether chronic stress during childhood was a better predictor of adult obesity than other proposed models. These included the Food Choice Constraints Model, the Neighborhood Affluence Model, and the Feast and Famine Cycle Model, as well as a model based on health disparities at birth. This study used of a novel retrospective survey to examine the influence of various childhood circumstances on adult body mass index (BMI) among a group of college students including as subgroup oversampled for childhood poverty. Results failed to confirm the predicted relationship between childhood poverty and increased adult BMI or other measures typically associated with BMI, including dietary fat intake, fruit and vegetable intake, and physical activity. The best childhood predictors of adult BMI were low birth weight and father's overweight. SNAP participation was positively associated with increased fruit and vegetable intake, which provides tentative support for the Feast and Famine Cycle Model. This model predicts overeating of all types of foods as food becomes more plentiful. Future research is needed to elucidate those specific aspects of childhood poverty that predict adult obesity. Such data may suggest the most effective approaches to avoiding the life-long negative health consequences of child poverty, including obesity

INTRODUCTION

There are few current public health concerns more pervasive than the obesity epidemic. The Centers for Disease Control and Prevention classify 35.7% of the adult population of the United States as obese (2012). Additionally, 34.4% of the population is classified as overweight. The greatest concern is its reliable association with several of the leading causes of preventable deaths in the United States, including heart disease, stroke, and certain types of cancer. As a result, obesity also drives up healthcare costs. In 2008, the healthcare costs associated with this problem were estimated at 147 billion dollars (CDC, 2012). Despite public concern, the causes of the recent rise in obesity rates remain uncertain.

Somewhat paradoxically, research has consistently shown obesity to affect, disproportionately, those living at lower socioeconomic status (SES) levels (CDC, 2012). Furthermore, research has shown lower childhood SES to predict higher levels of adult obesity (Parsons, Power, Logan, & Summerbell, 1999). This finding has puzzled researchers because logic would suggest that those living with fewer resources should be undernourished rather than overnurished. Indeed, lower SES itself is not hypothesized to cause obesity. Instead, research has suggested that certain qualities of life associated with lower SES, such as poor education, lack of available resources, and/or certain individual behaviors, may mediate poverty's effects on weight status. A number of theories have been proposed to account for what I will call this "poverty-obesity relationship," which will be reviewed below. Importantly, few of these theories have directly tested the poverty-obesity relationship as it relates to childhood poverty and adult

obesity; however, I will discuss proposed pathways further below. Though this study focuses on obesity specifically, the studies discussed below differ as to the examination of obesity alone, or overweight and obesity together, which will be noted. Though they are distinguishable, literature often treats these conditions as one, with overweight simply providing a less conservative cutoff.

Three of these areas of research, which I will refer to as food availability theories, focus on either food availability and/or the ability of low SES persons to make healthy food choices. Initially, research among impoverished people showed food insecurity to be a likely mediator of the poverty-obesity relationship among adults (Olson, Bove, & Miller, 2006). The Food Choice Constraint Model (FCCM) was the first to attempt to explain how food insecurity might mediate the poverty-obesity relationship. This model proposed that limited resources forces food insecure individuals to purchase inexpensive foods that are more likely to be high in energy density, the consumption of which has been shown to have a significant effect on increased calorie consumption (Martin, 2005). In competition with this model is the Feast and Famine Cycle Model (FFCM), which is based on the once per month dispensation of benefits from the Supplemental Nutrition Assistance Program (SNAP), which, itself, has also been positively associated with obesity. The FFCM model has posited that the constant cycle of periods of binging when resources are plentiful followed by periods of restriction as those resources diminish creates a binging cycle (Dinour, Bergen, & Yeh, 2007). Another area of research, suggesting a third explanation for the obesity-poverty relationship, is examining neighborhood affluence, which I will refer to as the Neighborhood Affluence Model

(NAM). Indeed, low-income neighborhoods have been shown to be environments less conducive to healthy eating and physical activity than higher-income neighborhoods. In particular, low-income neighborhoods have fewer supermarkets, less public transportation, and increased crime, all of which may limit availability or increase the costs of obtaining healthy foods (Black & Macinko, 2008). The intricacies and evidence supporting these three food availability models will be discussed further below.

One final theory approaches the poverty-obesity relationship from a very different perspective. According to this Cumulative Stress Model (CSM), a confluence of multiple stressors, which are positively correlated with poverty, places the developing child under chronic stress that affects nearly every part of the child's life and later psychological development (Evans, 2003). Experimental evidence has shown stress to significantly increase total food intake and consumption of foods high in sugars and fats in particular (Dallman, Pecoraro, & la Fleur, 2005). In support of the CSM, research has shown that greater overall life stress, both in childhood, and over the lifespan, is associated with increased weight in adulthood (Chen & Qian, 2012; Wells, Evans, Beavis, & Ong, 2010).

The current study attempts to assess the contributions of various childhood factors that these areas of research have suggested as potential mediators of the relationship between childhood poverty and adult obesity. Certainly, these factors alone will not account for the entire obesity epidemic but taken together they may help us understand how impoverished children can be affected disproportionately (Parsons et al., 1999). This paper will first review the proposed linkages suggested by each model noted above and the evidence supporting each. As will be explained below, CSM currently shows the

most promise as a framework for understanding the effects of childhood poverty on adult obesity. To our knowledge, no single previous study has attempted to assess all of these models in an effort to measure their relative abilities to predict adult obesity. Although longitudinal studies are optimal for examining such developmental factors, such studies are rarely feasible within limited cost and time constraints. Thus, the current study will also test a retrospective method of examining these childhood influences of adult obesity and health behaviors. More specifically, this study will investigate college students, a group largely neglected in this research area. College students are particularly suitable for retrospective assessment of childhood factors since they typically have only recently moved out of their childhood environment, which includes the relevant familial and situational factors examined here. Though very promising, this design may be limited due to potential inaccuracies in self-report measures. Furthermore, this relationship may not be observable in such a young sample. Despite these potential limitations, this study will ascertain if this strategy of assessment is feasible in answering these questions.

Evidence for the Poverty-Obesity Relationship

The childhood poverty-adult obesity relationship first became apparent in epidemiological studies that spanned multiple countries and included very large participant samples, over many years of observation. As noted above, within the developed world, these studies consistently showed that low SES during childhood was associated with adult obesity, regardless of SES in adulthood (Parsons et al., 1999; Poulton, Caspi, Milne, Thomson, Taylor, Sears, & Moffitt, 2002; Senese, Almeida, Fath,

Smith, and Loucks, 2009). This section will review the current evidence for the poverty-obesity relationship from childhood to adulthood.

In an extensive systematic review, Parsons and colleagues (1999) examined a wide variety of childhood influences on adult obesity, including parental fatness, social factors (e.g. SES), birth weight, rate of maturation, physical activity, dietary factors, and behavioral or psychological factors. With the exception of physical activity, dietary factors, and behavioral or psychological factors, all of these factors showed strong and consistent evidence in predicting obesity over numerous large studies. However, the authors were hesitant to draw many conclusions in any of these areas because few of these studies controlled for the other factors in this review. For example, higher birth weight was consistently shown to predict adult obesity, but few of these studies controlled for parental fatness, which is related to both increased birth weight and offspring adult obesity.

Twelve of the studies in the Parsons et al. review of childhood SES and obesity were longitudinal in nature, spanning 10 to 55 years of the participants' lives. The authors reported that the majority of these longitudinal studies measured SES via parental education, occupation, and/or income. Importantly, of the 12 longitudinal studies examined, all but two showed a significant negative relationship between childhood SES and adult obesity for both males and females. The authors reported similar results for cross sectional studies, although less consistently for males. Of the 21 cross sectional studies reviewed, 18 showed this negative relationship. Parsons and colleagues also indicated that few studies considered parental weight in their analysis. This is a likely

confound as women and possibly men who are living at lower SES have higher rates of obesity, which might be expected to affect offspring eating and body weight. Despite this caveat, the authors concluded that the relationship between lower SES during childhood and adult obesity was robust and that future studies should examine it in more detail. The authors proposed that this relationship might be due to circumstances related to poverty that may affect energy balance such as material circumstance, poor eating behaviors, or a lack of knowledge about healthy eating. The authors further point out that future studies should control for health factors at birth (Parsons et al., 1999). Controlling for these factors is one of the goals of the current study, as explained in more detail below.

Subsequently, Poulton and colleagues (2002) conducted a longitudinal study of 1019 members of the Dunedin Multidisciplinary Health and Development Study from birth to age 26. This study sought to investigate previously shown correlations between childhood poverty and health disparities. The investigators examined children at birth and every two years until age 18 as well as ages 21 and 26. The researchers assessed SES, measured via parents', and later the participants', adult occupation. A variety of health outcomes, including physical health, dental health, mental health, and substance abuse were also examined. BMI and waist to hip ratio were measured as two aspects of physical health. Because SES was measured at different time points, the authors were able to examine both the duration and trajectory of SES (i.e.,, direction of social mobility) over time. Critically, this study also controlled for prenatal and infant health status as well as adult SES. In this way, health disparities associated with poverty at birth or a relationship between childhood poverty and adult poverty could not explain any

association between childhood poverty and adult health (including obesity). The regression analysis showed a significant inverse relationship between childhood poverty and likelihood of adult disparities in physical health, dental health, mental health, and substance abuse. Of particular relevance to the current study, this relationship was shown for both adult BMI and waist to hip ratio (Poulton et al., 2002).

In a further analysis, focusing on the influence of social mobility, Poulton and colleagues (2002) separated participants at the high and low extremes of SES into four groups, representing persistently low SES, persistently high SES, upward social mobility, and downward social mobility. This analysis revealed a lower waist to hip ratio for the upward mobility group than the persistently low group. However, health disparities were consistently greater for participants who spent their childhood in lower SES families, regardless of adult SES. Specifically, the analysis showed this effect for both waist to hip ratio and BMI. This study supports the so-called social origins hypothesis, suggesting that in spite of upward mobility and health at birth, low SES during childhood reliably predicts increased BMI in adulthood (Poulton et al., 2002).

Recent research has continued to show that children growing up in lower SES conditions have higher BMI during adulthood, although with mixed results. Senese, Almeida, Fath, Smith, and Loucks (2009) followed up on Parsons and colleagues' work with an updated systematic review of 30 studies covering the period from 1998 to 2008, which examined childhood SES and adult obesity. The poverty-obesity relationship was shown in 14 of the 20 studies that analyzed females and four of the 15 that analyzed males. These numbers were reduced, as other covariates were included in the analyses,

such as parental BMI. Overall the authors concluded that this association persists among females but not males in the recent literature. The authors suggest that certain unhealthy behaviors, such as less physical activity and higher fat intake, which are associated with lower SES may be modeled by parents for young girls which leads to the development of poorer health behaviors in adulthood (Senese et al., 2009). These, as well as other potential mechanisms related to food intake for the poverty-obesity relationship, will be discussed below.

Food Availability Models for the Poverty-Obesity Relationship

Food Insecurity.

Food insecurity has been suggested as a potential mediator of the relationship between lower SES in childhood and obesity in adulthood. (Larson & Story, 2011, Townsend, Peerson, Love, Achterberg, & Murphy, 2001). The definition of food security and the evidence supporting its involvement in the poverty-obesity relationship are discussed here. The United States Department of Agriculture (USDA) has defined food insecurity as an economic and social condition in which the family has limited or unreliable access to food considered adequate for a healthy and active lifestyle (USDA, 2012b). Numerous studies have shown the relationship between food insecurity and obesity, in both adults and children (Townsend et al., 2001; Jilcott, Wall-Bassett, Burke, & Moore, 2011; and Larson & Story, 2011).

For example, Townsend and colleagues (2001) examined the influence of current food insecurity on adult overweight through analysis of data from the 1994–1996

Continuing Survey of Food Intakes by Individuals (CSFII). This analysis included 4,537 women and 5,004 men, all above the age of 20. The researchers chose these participants from the 1994, 1995, and 1996 CSFII based on age and availability of height, weight, and income data. As expected, the authors found a significant negative correlation between income and food security, such that participants at the lowest level of income were also the least food secure. Logistic regression revealed that food insecurity and African American race were the strongest predictors of being overweight. Other significant, although weaker, predictors of overweight included age, Hispanic ethnicity, less education, increased television viewing, and participation in the Food Stamps Program. Townsend and colleagues also found the relationship between food insecurity and overweight in women remained significant after controlling for household income. The analysis showed a significant relationship between food insecurity and overweight status for women but not for men (Townsend et al., 2001). However, other research has shown this relationship among men, although less consistently than among women (Larson & Story, 2011).

Research has revealed a great deal of evidence for food insecurity being a mediator of the poverty-obesity relationship. However, the specific mechanisms involved in the link between food insecurity and obesity among adults remains unclear. Furthermore, food insecurity does not yet provide an adequate explanation for the positive relationship between childhood poverty and adult obesity because it lacks a distinct mechanism that explains its positive association with obesity. The sections

below have outlined three models that attempt to explain the relationship between poverty/food insecurity and obesity and the evidence for each.

Food Choice Constraint Model (FCCM).

This model is based on evidence showing that in the United States food environment, an inverse relationship exists between energy dense foods and their costs (Martin, 2005). Drewnowski and Specter (2004) noted this relationship by examining food prices in grocery stores in Seattle in the winter of 2003, where they found a significant negative relationship between energy density and energy cost. For example, they found that potato chips were approximately 20 cents per megajoule (MJ), whereas fresh carrots cost 95 cents/MJ. The authors attributed much of this relationship to different prices based on shelf life; nonperishable foods tend to be far less costly than perishable alternatives. Additionally, a large proportion of nonperishable foods contain added sugars and fats, which increase energy density (Drewnowski & Specter, 2004).

Although the inverse relationship between energy density and price does not explain increased caloric intake, the model further posits that the energy density of food can influence overall caloric intake, since humans tend to eat the same volume of food regardless of energy density (Bell & Rolls, 2001). In further support of FCCM, research has shown that total energy intake and weight status are positively related to dietary energy density (Ledikwe, Blanck, Khan, Serdula, Seymour, Tohill, & Rolls, 2006). Therefore, according to this theory, those who are economically driven to purchase food at a low cost (i.e.,, food insecure) are more likely to purchase cheaper, more energy dense, food items. Further, because volumetric intake remains stable regardless of

calorie content, eating these foods leads to a substantial increase in calorie consumption per day (Drewnowski & Specter, 2004). Assuming no excess expenditure of energy to offset the excess caloric intake, this model provides a framework for understanding how lower SES, and food insecurity specifically, might lead to obesity (Martin, 2005).

Neighborhood Affluence Model (NAM).

Potentially complementary to the FCCM, some researchers have theorized that the so-called "built environment" associated with poverty may account for the poverty-obesity association. The NAM has posited that low-income neighborhoods are more likely to be food deserts, which is a general term applied to places that have few supermarkets and little public transportation to facilitate the procurement of healthful foods. Furthermore, this theory suggests that low-income neighborhoods also have fewer open spaces and/or athletic facilities as well as increased crime. Thus, low-income neighborhoods diminish residents' ability to obtain healthful foods (i.e.,, foods recommended by the USDA) and to engage in recommended amounts of physical activity. According to this theory, these combined factors lead to increased rates of obesity (Evans, 2004; Black and Macinko, 2008).

In a large systematic review, Black and Macinko (2008) examined recent evidence supporting the NAM. The authors first reviewed studies that examined overarching, general correlations between neighborhood resources and weight status. Of the 16 studies reviewed, 14 showed a significant negative association between neighborhood SES and resident BMI. Three of these studies found this association only for adult women. The authors also reported studies that showed specific qualities of low

SES neighborhoods that may account for this relationship. In particular, low SES neighborhoods have been shown to have fewer large supermarkets and greater distances required for residents to travel to get to supermarkets; thus qualifying these areas as food deserts. Supermarkets tend to sell more fresh fruits and vegetables and lower fat items in general (i.e.,, less energy dense foods), as well as sell them at lower prices than gas stations or corner stores. The authors report that nine of the studies reviewed showed a positive relationship between neighborhood SES and number of stores selling healthy foods. These low income areas were also shown to have an increased number of fast food restaurants, which tend to sell foods very high in fat and sugar. Furthermore, the authors cited studies that showed significant positive associations between neighborhood affluence and food intake quality, with lower affluence being related to lower intake of healthy food and increased intake of fast foods. The authors did not review any studies that showed a relationship between food availability in the neighborhood and childhood obesity.

The authors additionally reviewed studies showing the negative impact of low SES neighborhoods on physical activity. Specifically, low SES areas have fewer open spaces and recreational organizations, such as the YMCA. Furthermore, there are significant negative associations between resident body weight and factors such as distance to commercial areas, available sidewalks, and pleasing neighborhood aesthetics. Finally, the research in this review shows a strong positive relationship between access to recreational facilities and physical activity in all age groups. Overall, the authors

conclude that the physical environment associated with poverty is likely a strong contributor to overweight and obesity (Black & Macinko, 2008).

With the exception of one study reviewed below, little research has examined the effect of neighborhood affluence during childhood on later adult obesity and the NAM does not directly address this issue. Nevertheless, it seems probable that children growing up in low SES neighborhoods may develop behaviors, such as increased fat intake, low fruit and vegetable consumption, and little physical activity, that persist into adulthood, leading to obesity and other health disparities.

Feast and Famine Cycle Model (FFCM).

An alternate model of the relationship between food insecurity and obesity is related to the Supplemental Nutrition Assistance Program (SNAP, formerly known as Food Stamps). This program provides financial assistance in the form of item-restricted access cards provided to low income individuals for the purchase of food. Although policy-makers intend this program to relieve food insecurity in the United States, many participants still experience it (Dinour et al., 2007) and a number of studies have shown a positive relationship between the receipt of SNAP benefits and increased likelihood of being obese, even when controlling for SES and food insecurity (Townsend, 2001; Jilcott, et al., 2011; Vartanian & Houser, 2012). Dinour and colleagues have proposed a model to explain this relationship, which centers on a "Feast and Famine Cycle." This refers to the fact that SNAP participants receive limited benefits at one specific time each month. According to this proposal, families experience about three weeks of relatively plentiful food, followed by a week or so of restricted food resources as SNAP benefits

dwindle. The exact timing for the stages of this cycle, of course, varies depending on the economic state of the home. When families receive benefits again and the monthly period of restricted food resources ends, overeating or binge eating begins. Although a relationship between food insecurity and childhood obesity has been seen less consistently than for adults, Dinour and colleagues (2007) suggest that the cyclic nature of benefit delivery to families on the SNAP program may also promote childhood obesity. Furthermore, children growing up with SNAP benefits may learn a binging and restriction cycle of eating that lasts into adulthood. Viewing ones' parents exhibiting this behavior every month may serve as a model for a child's own behavior. Past research has shown parental modeling to be a strong predictor of a child's behavior. Indeed, this behavior of binging or overeating when resources are plentiful may persist into adulthood (Pearson, Timperio, Salmon, Crawford, Biddle, 2009).

In spite of the prevalence of food insecurity-related research among adult and child participants independently, there has been little research investigating the effects of childhood food insecurity on the development of adult obesity. However, in one recent study of childhood obesity, Vartanian and Houser (2012) investigated the association of childhood SNAP participation and childhood neighborhood affluence with adult overweight and obesity through an analysis of the 1968-2005 Panel Study of Income Dynamics (PSID). The investigation included a wide variety of variables thought to influence obesity such as age, race, smoking, and parental educational attainment. However, the main research question concerned the role of SNAP participation and neighborhood affluence, at different ages during childhood, on later adult weight status.

The main analysis was conducted using sibling fixed effects models with 3,306 siblings, which drew conclusions from patterns of differences between siblings. Indeed, the household environment is constantly changing, especially in the case of income and receipt of assistance, producing differing experiences among siblings at different ages, while still maintaining similarities in more constant factors, such as genetic variability and parental educational attainment. This type of analysis permits comparison between siblings, which allows for some control of the numerous confounding variables. In particular, one criticism of the FFCM is that the positive relationship between SNAP usage and body weight remains unclear because SNAP users are a self-selected group and, therefore, may often differ in some way compared to low income nonreceipients (Townsend et al., 2001; Vartanian & Houser, 2012).

The authors theorized that the other main variable of interest, neighborhood affluence, would influence obesity through a number of related factors, including access to grocery stores. As noted earlier, previous research has shown that low-income neighborhoods tend to have fewer supermarkets than their higher income counterparts do. Related research also shows a link between access to supermarkets and the quality of food intake (Evans, 2004). Additionally, the higher incidence of crime and/or fewer recreational areas in low-income areas are also theorized to contribute to increased obesity rates (Black & Macinko, 2008). Conversely, Vartanian and Houser (2012) also theorized that living at a lower level of SES *relative* to the rest of the neighborhood might increase psychological stress, since the *relative disadvantage* of one's life would be

constantly salient. Moreover, affluent neighborhoods, despite more available resources, may offer fewer services designed for low income residents (Vartanian & Houser, 2012).

In line with the FFCM, Vartanian and Houser's analysis revealed that SNAP participation during childhood was an independent predictor of increased BMI in adulthood, and these results were still significant when adult receipt of SNAP was added to the model. Additionally, and in line with this theory, it was not only participation or nonparticipation that predicted higher adult BMI, but also the duration of SNAP participation, with the highest body weights being related to the longest duration of participation. However, the strongest predictor was the interaction between SNAP benefit receipt and neighborhood affluence, with SNAP participants in more affluent neighborhoods showing greater increases in adult BMI than individuals receiving benefits in less affluent neighborhoods. Additionally, neighborhood affluence alone did not significantly predict adult BMI. Age was also an important factor, as receipt of SNAP benefits prior to age five did not significantly influence increased adult BMI. In contrast with many of the studies reviewed above, these findings were significant among both males and females, with stronger associations among males. However, the authors did not attempt to explain this gender difference (Vartanian & Houser, 2012).

Overall, this interaction is quite surprising, given that the NAM would predict that greater neighborhood disadvantage should predict higher adult BMI. However, these results make it clear that this may not be the case. The authors also showed that *relative* disadvantage, which is family disadvantage compared to the rest of the neighborhood, did not explain these results. Relative deprivation was defined as the percent of families in

an income bracket above the participant compared to the percent in the same or a lower income bracket. Furthermore, data on crime that was included in the models did not account for the interaction. However, the crime data was county level, not neighborhood level, which makes it more difficult to draw conclusions. The stress of living in a high crime area may account for some the results shown here, although this would not explain the SNAP results. Although relative disadvantage did not account for the results, the study did not include a direct measure of stress. SNAP families in more affluent neighborhoods may experience greater stress due to social stigma (Vartanian & Houser, 2012). Further potential influences of stress at the personal and neighborhood level will be discussed below. The authors suggest that, although more advantaged neighborhoods tend to have access to more nutritious foods at a lower cost, this may not change the behavior of consumers making use of SNAP benefits. Indeed, it may be that the purchase of lower quality foods is still required or preferred by SNAP benefit recipients. (Vartanian & Houser, 2012).

This explanation, however, is contradicted by recent research by Martin and colleagues (2012) on the effect of grocery stock on consumer behavior. Their analysis of 372 individuals shopping in 19 food stores in Hartford, CT, showed that SNAP participation and food insecurity were negatively correlated with the frequency of shopping in large supermarkets. Additionally, the results showed that a higher stock of fruits and vegetables, which was manipulated experimentally, was associated with increased purchase of these items overall. Critically, SNAP participants were significantly more likely to purchase fruit when it was available compared to non-SNAP

participants (Martin, Havens, Boyle, Matthews, Schilling, Harel, & Ferris, 2012). Thus, it seems unlikely that the SNAP effects reported by Vartanian and Houser (2012) are due to consumer behavior.

Vartanian and Houser's (2012) study, although comprehensive, did not examine overall life stress of SNAP benefit recipients. Research shows that food insecurity and the stress associated with it are not reduced among participation in the SNAP program (Jilcott, Wall-Bassett, Burke, & Moore, 2011). It may be the case that the need for SNAP benefits, which is as sign of food insecurity and therefore a source of stress, is compounded by the stress of living in an affluent neighborhood, which may make the negative social stigma, related to receiving assistance, more salient. High affluence neighborhoods may also be more stressful because few resources are available for low-income families, such as free clinics and inexpensive public transportation (Vartanian & Houser, 2012). More investigation of the relationship between neighborhood affluence, SNAP participation, and stress is still needed. Indeed, life stress may be a unifying variable linking all or most of the factors previously discussed.

Evidence Linking Poverty, Obesity, and Stress

The CSM suggests that stress is the main mediator of the poverty–obesity relationship. Indeed, much research has shown an increase in consumption of food in organisms under stress (Dallman, Pecoraro, & la Fleur, 2005, Greeno & Wing, 1994). Dallman and colleagues (2005) theorized that this increased consumption is due to a biological response to a stressor, which activates glucocorticoids in the body that

stimulate food intake. Additionally, this increased intake in response to a stressor tends to be preferential for foods higher in fats and sugars, sometimes termed "comfort foods." Indeed, this intake of comfort foods has been shown to reduce the effects of the stress response in the brain (Dallman et al., 2005). Chen and Qian (2012) theorized that over a long period, such as in cases of chronic life stress, this higher intake would result in increased body weight. Indeed, chronic life stress has been shown to be associated with greater intake of fats and sugars (Chen & Qian, 2012).

Related to the current study, three previous studies have looked in depth at the influence of stress during childhood on body weight in late adolescence and early adulthood. Williamson, Thompson, Anda, Dietz, and Felitti (2002) examined the association of retrospectively reported childhood abuse on participants' body weight. This study examined data from the Adverse Childhood Experiences (ACE) study which collects current health and retrospective childhood experiences from members of the Kaiser Permanente Health Maintenance Organizations in San Diego California. This study examined data from 13,177 participants, who were selected based on the availability of relevant data and not having been pregnant at the time of data collection. Covariates included in the model were age, ethnicity, childhood household dysfunction (i.e., frequent fights, alcohol consumption, and/or maternal abuse), smoking, alcohol consumption, physical activity, education, employment, and number of births among women. After adjustment for these covariates, linear regression showed a significant positive relationship between childhood abuse and adult BMI (Williamson et al., 2002).

In a more recent study, Chen and Qian (2012) examined data from the Canadian Community Health Survey in order to investigate the relationship between life stress and body size. Participants (N=112,716) who were over the age of eighteen were included in the analysis. Participants were asked to report their heights and weights as well as their perceived lifetime stress. For perceived lifetime stress, participants were asked to consider their lifetime stress and quantify how stressed they were most days on a five point likert scale. Logistic regression revealed that perceived lifetime stress predicted an increased risk in obesity for women but not for men. The regression model included potential confounding variables, including sex, age, income, education, race, immigrant status, marital status, alcohol intake, and exercise (Chan & Qian, 2012). These results are most compelling for the influence of stress over the lifespan on body size. However, the question of what kind of stressors have the greatest effect on body weight and whether or not such stressors can account for the relationship between childhood poverty and adult obesity, remains unanswered.

Wells, Evans, Beavis, and Ong (2010) conducted a longitudinal analysis of children at ages 9, 13, and 17 years in order to examine the influence of poverty and cumulative risk exposure on later childhood overweight and obesity. Cumulative risk exposure (CRE) is a measurement of the additive effect of particular life stressors that often covary and together have been shown to reliably predict disease risk later in life. CRE researchers propose that lifetime stress is comprised of six risk factors, including three physical risks, which are crowding, noise, and substandard housing, and three social risks, which are family turmoil, child separation from parents, and exposure to violence.

Wells and colleagues (2010) analyzed data collected over 9 years on 329 children and adolescents. Linear growth curve analyses were used to examine the effect of poverty and CRE on participant BMI over the three time points. The models in the analysis first examine the effect of time over the trajectory of the target variable, which was BMI percentile (i.e., children above the 85 percentile of BMI for their age were considered overweight). Next, other variables, including poverty and CRE, were added into the model to explain differences in these trajectories among individuals in the sample. The analysis showed poverty had a significant effect on BMI trajectory. Additionally, poverty was shown to significantly predicted changes in CRE. Finally, the analysis showed CRE to have a significant independent effect on BMI trajectory. Critically, when controlling for CRE, poverty no longer predicted variance in BMI trajectory, providing evidence for CRE as the principle mediator of the poverty-obesity relationship. Thus, the authors suggested that stress resulting from the simultaneous or sequential effects of these various risk factors may access a biological process leading to energy conservation (see above) or that the stressful environment may impact opportunities for physical activity and healthy eating, as well as related parenting practices of adult family members (Wells et al., 2010). Although these results are very compelling, the analysis did not specifically include the potential influences of neighborhood affluence, food insecurity, or SNAP participation, which may also covary with the factors of CRE. Additionally, few of the studies reviewed above controlled for health disparities at birth, which are disproportionately common at lower income levels (Parsons et al., 1999).

Evidence for Health Disparities at Birth as Predictors of Adult Obesity

One possible additional influence on the association between poverty and obesity are health disparities among low SES persons during pregnancy and birth. Indeed, it has been theorized that disturbance during a critical period of pregnancy may have lasting effects that increase the likelihood of certain diseases during adulthood (Jansson & Powell, 2007). For example, Dahri, Snoeck, Reusens-Billen, Ramcle, and Hoet (1991) placed gestating rats on a low protein diet and examined the pancreatic function in the offspring. The results showed that the offspring had significantly diminished pancreatic function. Critically, whether they continued receiving a low protein diet after birth or received a normal, full protein from birth onward, neither group made up for the protein deficit during gestation and both groups showed impairment in insulin secretion throughout adulthood (Dahri, Snoeck, Reusens-Billen, Ramcle, and Hoet, 1991). In this way, the fetus was theorized to biologically adapt, permanently, to the uterine environment during development, which does not match the environment in which the infant is born and leads to health disparities throughout the lifespan (Jansson & Powell, 2007).

As a further example, human infants born to mothers with gestational diabetes consistently have a higher birth weight and a higher risk for obesity later in life. This is thought to be because maternal glucose, but not insulin, crosses the placenta to the infant. Therefore, the fetal pancreas must produce enough insulin to handle a very large amount of glucose. Insulin is also a growth hormone and the increased production of it likely

accounts for the increased birth weight. The later risk for obesity is theorized to be due to an increased amount of fat storage in utero, leading to a higher number of fat cells in the infant, which do not diminish after birth. Thus, the increased energy received during gestation due to gestational diabetes is theorized to program the infant to grow more fat cells and to more readily store energy for the rest of its life (Oken & Gillman, 2003).

In a related recent human study, Morandi and colleagues (2012) examined the influence of several infant health variables on the risk of childhood obesity using the Northern Finland Birth Cohort in 1986, which included 4,032 infants. The researchers also collected data on what they described as traditional predictors of childhood overweight, including gender, pre-pregnancy parental BMI, parental professional category, single parenthood, gestational weight gain, pre-pregnancy maternal smoking, gestational smoking, household crowding, and birth weight. Specific genetic predictors were also included in the model. These factors were incorporated into a model based on the Finland birth cohort and then validated in two other cohorts. One validation sample was a retrospective analysis of 1,503 students in Veneto, Italy and the other was a prospective analysis of 1,032 children in Massachusetts. Model development was completed using stepwise logistic regression. Parental BMI, birth weight, maternal gestational weight gain, number of household members, maternal professional category and smoking habits were all independent significant predictors of childhood obesity risk. Critically, this was also the case with genetic factors included in the model (Morandi et al., 2012). Investigating the predictive validity of these infant health variables is not a main goal of the current study. However a number of these variables are included in our

analysis in an attempt to account as much as possible for their predictive relationship to obesity later in life. These include paternal and maternal overweight or obesity, birth weight, and mother smoking before and after pregnancy (Morandi et al., 2012, Parsons et al., 1999, Oken & Gillman, 2003).

Current Investigation

The current study seeks to bring together the literature reviewed here and introduce a new retrospective method of assessing childhood influences on adult obesity. To date, no study has attempted to bring together predictions from the Food Choice Constraints Model, the Neighborhood Affluence Model, the Feast and Famine Cycle Model (i.e.,, SNAP receipt), and the Cumulative Stress Model, to assess their relative influences on adult obesity. Additionally, we will include some measures of health disparities at birth shown to be related to both poverty and obesity. The purpose of this study is to retrospectively examine health disparities at birth and childhood experiences, including childhood food insecurity, childhood neighborhood quality, childhood SNAP participation, and childhood cumulative stress on adult BMI in the context of the four models reviewed above in order to determine which influences, and thus potentially which model(s), best predict adult BMI. This study will also investigate the predictive value of these variables on current health behaviors related to BMI including levels of physical activity, proportion of fat in the diet and intake of fruits and vegetables.

Previous research has also been restricted by the reliance on large cohort studies, which may not include the specific variables related to all of these models within a given

sample. Additionally, much of this research is longitudinal. While this type of research is invaluable, it is also costly and time consuming. The current study aims to determine which childhood variables and which model of childhood influences best predicts adult BMI. Related to these methodological issues, this study also introduces a retrospective method of assessment of these variables.

Largely adapted from the ACE study and the American Housing Survey, the retrospective survey developed for the current study was designed to gather information related to stressful life events, food insecurity, SNAP benefits participation, as well as other variables including race, gender, and current eating and physical activity practices. Additionally, this survey asked questions about the participants' infancy, including birth weight, parent body size, and maternal smoking before and after pregnancy.

Surprisingly, childhood influences on adult obesity have not yet been examined in college-age adults. This is a somewhat unique group of adults, since many have recently left their childhood environment. Thus, we will be examining childhood influences at an early time point in adulthood when the effects of the childhood environment are manifest. The age and intelligence of this adult group is also potentially advantageous for a retrospective survey, as all participants will be recalling fairly recent events covering a similar time period in their lives.

For each dependent variable, three analyses will be conducted. First, correlations between each dependent variable and each independent variable will be analyzed. Following this, large multiple regression analyses will be conducted for each dependent variable, which will include all independent variables in one model. Finally, hierarchical

regression analyses will be conducted for each dependent variable, which will include birth and/or demographic items in the first step of each model. Each model will subsequently include each composite independent variable alone and one in which all are included. Exploratory analyses will also be conducted with the goal of creating the most parsimonious model, which will allow for better judgment of what to investigate in future research.

Each model discussed above would predict a different pattern of results across the dependent variables. FCCM posits that the poverty-obesity relationship is due to increased consumption of energy dense foods, which are less costly, and decreased consumption of fruits and vegetables, which are more costly. The extension of this model in order to explain the relationship between childhood poverty and adult obesity proposes that the experience of childhood food insecurity would lead to increased consumption of energy dense foods and decreased consumption of fruits and vegetables in childhood and that this behavior would persist in adulthood. Therefore, FCCM would predict, in this study, that Childhood Food Insecurity would significantly predict adult BMI above that of birth and demographic factors as well as the other independent variables. Additionally, FCCM would predict that Childhood Food Insecurity would also significantly predict a higher percentage of fat in the diet as well as decreased intake of fruits and vegetables.

NAM posits that the poverty-obesity relationship is due to the limited resources available in low-income neighborhoods, including limited access to adequate grocery stores and safe recreational areas. In the case of childhood poverty being related to adult

obesity, this model would predict that behaviors learned in childhood (i.e., the consumption of low quality foods and little physical activity) would persist into adulthood, leading to adult obesity. In this study, NAM would be supported if Poor Neighborhood quality was predictive of increased adult obesity, a higher percentage of fat in the diet, decreased intake of fruits and vegetables, and decreased physical activity.

FFCM proposes that the mechanism behind the poverty-obesity relationship is the SNAP program, which provides assistance once per month and may lead to a binging cycle due to fluctuating resources throughout the month. Children growing up with the SNAP program are thought to adapt this binging, which persists into adulthood and leads to adult obesity. In this study, evidence for FFCM would be observed if increased childhood SNAP receipt was related to increased BMI. Though binging behavior will not be directly measured in this study, this model would predict increased binging behavior among those that received SNAP benefits. For the purpose of this study, FFCM does not predict differences in intake of different types of foods and would therefore predict the same pattern of results for percentage of fat in the diet and fruit and vegetable intake.

CSM posits that the poverty-obesity relationship, among both children and adults is due to the chronic life stress associated with poverty and situations that often co-occur with poverty, such as substandard housing and abuse. CSM further proposes that situations of chronic stress lead to a consistent intake of high-fat, high-sugar "comfort foods," greater consumption of which has been related to both increased stress and increased BMI. In terms of this study, CSM would predict Cumulative stress to be predictive of both increased BMI and higher percentage of fat intake. Indeed, in this

study, CSM is hypothesized to be the best model for the prediction of adult BMI and energy intake, which is reflected in the hypotheses below.

First, it is predicted that a positive association will be observed between BMI and the percentage of energy from fat. Furthermore, a negative association is predicted between BMI and physical activity. The initial multiple regression, which will include all of the independent variables, is hypothesized to significantly predict variance in BMI, with Cumulative Stress predicting the most variance in the model. Within the hierarchical regression models, it is hypothesized that fetal health data, when available, will be a significant predictor of adult BMI. Independent of this association, childhood food insecurity is also expected to significantly predict adult BMI. However, this association is hypothesized to become nonsignificant when SNAP usage and neighborhood quality are added to the model, which both are also expected to significantly predict variance in BMI. Furthermore, the interaction of SNAP usage and Neighborhood quality is hypothesized to predict variance in BMI above and beyond the previously noted variables, such that increased SNAP usage should be most predictive of increased BMI for those that grew up in lower quality neighborhoods. This is in opposition to Vartanian and Houser's study (2012) because the neighborhood measure here is more closely related to NAM. Indeed, Vartanian and Houser only examined neighborhood affluence, whereas this study examines crime, quality, and availability of resources. Therefore, we expect the results to reflect this difference.

Finally, cumulative life stress is expected to be the strongest predictor of adult BMI, diminishing the previously significant predictors. Indeed, CSM is thought to be a

unifying theory because the relationships observed between BMI and childhood food insecurity, increased time receiving SNAP, poor neighborhood quality, and the interaction of the latter two variables, could be explained by the stressful nature of living within these disadvantaged conditions.

Percentage of energy intake from fat and intake of fruits and vegetables will be analyzed in separate, but similar models. In both cases the initial, large multiple regression analysis will include all of the independent variables listed above with the exception of birth items, due to the lack of theoretical basis for their inclusion. It is hypothesized that the initial multiple regression will significantly predict percentage of fat intake, with cumulative stress predicting the largest amount of variance in the model. Furthermore, childhood food insecurity, increased time receiving SNAP benefits, poor neighborhood quality, and the interaction of SNAP and neighborhood quality are expected to predict an increased percentage of energy from fat when they are the only variables in the model with demographic data. However, when entered together, cumulative life stress is hypothesized to predict the largest amount of variance in the model. Conversely, the interaction of SNAP and neighborhood quality is hypothesized to be the most predictive of decreased intake of fruits and vegetable in the initial multiple regression. It is further hypothesized that hierarchical regression will show food insecurity, increased snap usage, poor neighborhood quality, and the interaction of the latter two variables to significantly predict decreased fruit and vegetable intake beyond that of demographic data. Cumulative stress is not predicted to show any relationship with fruit and vegetable intake when added to the final hierarchical regression model.

Indeed, in the final model, the interaction of SNAP and neighborhood quality is hypothesized to be the most predictive of fruit and vegetable intake, with those who grew up in the most disadvantaged neighborhoods showing the strongest negative association with SNAP participation.

Fewer analyses will be conducted in the case of physical activity because only NAM makes any predictions regarding this variable. As with the other dependent variables, initial Pearson Product-Moment Correlation Coefficients will be analyzed with all of the independent variables. Physical activity is hypothesized to show a negative association with poor neighborhood quality. These correlation coefficients will also be used in an exploratory capacity in order to assess if any other independent variables should be included in the hierarchical regression model in order to assess its predictiveness above the demographic variables. It is hypothesized that poor neighborhood quality will significantly predict lower amounts of weekly physical activity above and beyond the demographic variables.

METHOD

Participants

The sample consisted of 97 undergraduate students, from the Psychology 100 subject pool at Montana State University - Bozeman. Students were given course credit for their involvement and had the option of an alternate assignment for course credit if the declined participation in this study. Both males and females were included in the sample. Of the participants, 47 met a prescreening criteria for childhood poverty (see below). Human subjects approval was obtained from the MSU – Bozeman Institutional Review Board prior to the beginning of the study.

Prescreen

The Psychology 100 subject pool (N=399) was prescreened for childhood socioeconomic disadvantage (i.e.,, poverty). Due to the relatively small number of participants in this study, prescreening was used to oversample participants who had grown up at lower levels of SES, and therefore, had likely experienced more life stress. This was accomplished by asking all students in the subject pool whether or not they had received free or reduced lunch from the School Lunch Program. The students who answered "yes" to this question (N=64) were not directly recruited. However, a multitude of participation time slots were made available exclusively to them, in order to increase the likelihood of their choosing this particular study for their course credit requirement. Regardless of their answers to the prescreen question, none of the study

participants were aware that the opportunity to sign up for this study was based on their answers.

Materials

With the exception of BMI, all of the variables in this study were collected using surveys. The first survey, termed the Behavioral Questionnaire (see Appendix A), measured three of the dependent variables in this study, including Physical Activity, Percent Energy Intake from Fat, and Servings of Fruits and Vegetables. The Behavioral Questionnaire was constructed from two surveys that have been used in previous studies of this nature. These surveys and the measurement of BMI, the other dependent variable, are discussed in the first three subsections below.

The independent variables in this study (Age, Gender, Race, Birth Weight, Paternal Overweight, Maternal Overweight, Mother Smoking Prior to Pregnancy, Mother Smoking During Pregnancy, Childhood Food Insecurity, Poor Childhood Neighborhood Quality, Time Receiving SNAP Benefits, and Cumulative Childhood Stress) were assessed with a large retrospective survey, which I will refer to as the History Questionnaire (HQ) (See Appendix B). The HQ was constructed from a variety of previously validated scales measuring each of these variables. The scales from which the HQ was created are discussed in the fourth, fifth, sixth, and seventh subsections below. Critically, the independent variable Cumulative Stress was intended to be an adapted retrospective version of the variable used by Wells and colleagues (2010). In this way, the subsequent sections define surveys that were adapted to measure the six risk factors

that are used in the composite score of Cumulative Stress: child abuse, family turmoil, separation from family, substandard housing, noise, and crowding. These factors were only used to create the composite score of Cumulative stress, which is discussed in the fifth through eighth section below.

Assessment of Current Dietary Intake (National Cancer Institute, 2011). Two dependent variables, Percent Energy from Fat and Servings of Fruits and Vegetables were assessed using the Multifactor Screener (MFS) from the National Cancer Institute (NCI, 2011), which assesses broad diet quality. Specifically, this measure includes 17 items assessing the frequency of intake of fats, fiber, fruits, and vegetables. For each food item, the participant was instructed to select 1 out of 9 frequencies, ranging from "never" to "4 or more times per day" (NCI, 2011). These frequencies were converted into times per day the participant reported consuming each food. In this way the scores were converted based on the midpoint of the time frame of each answer (e.g. "3 – 4 times per week" = 0.5 times per day). Next, this frequency was used in a scoring algorithm developed from the CSFII 94-96. This algorithm provides portion sizes based on gender and age and was used to compute percent of intake from fat and servings of fruits and vegetables that closely represent that of the population. This measure and scoring procedure have been shown to be valid as compared to 24-hour recalls and Food Frequency Questionnaires in both The Eating at America's Table Study (N=462) and the National Institutes of Health-American Association of Retired Persons Diet and Health Study (N=416) (Thompson, Midthune, Subar, Kahle, Schatzkin, & Kipnis, 2004).

Assessment of Current Physical Activity (IPAQ, 2012). Current physical activity, another dependent variable, was assessed using the short self-administered International Physical Activity Questionnaire (IPAQ). The IPAQ is used to obtain frequencies over the previous 7 days of vigorous and moderate physical activity, walking, and leisure time. Participant indicate how many days over the last 7 they engaged in each activity. Next, the participant indicates how many hours and minutes per day they spent doing each activity. To score the IPAQ, the frequencies provided by participants were first converted to minutes per week for each activity. Leisure activities were only calculated for minutes per week. The minutes and intensity of each level of physical activity was then transformed to Metabolic Equivalents of Task (METs) for each intensity and then added together to provide total METs per week. A MET is a standardized continuous measurement of energy cost of physical activities (IPAQ, 2012). The IPAQ has shown good test-retest reliability and has been shown to be valid as compared to computerized motion sensors worn for 7 days prior to answering the questionnaire (Craig, et al., 2003).

BMI Assessment. BMI (kg/m^2) was the main dependent variable in the study and was calculated from height and weight, which were measured by the researchers. Height was measured to the nearest tenth of an inch using a Seca stadiometer. Weight was measured to the nearest tenth of a pound using digital Tanita scales model # BWB-800A. A BMI of less than 18.5 is considered underweight. Healthy BMI is considered to be 18.5 through 24.9. A BMI between 25.0 and 29.9 is considered overweight. A BMI of 30.0 to 34.9 is considered obese class 1. A BMI of 35.0 to 39.9 is classified as obese

class 2. Finally, a BMI over 40 is obese class 3, which is also known as morbid obesity (CDC, 2012).

Childhood Food Insecurity (Bauer et al., 2012). Childhood food insecurity was assessed using an adapted, retrospective version of the United States Department of Agriculture (USDA, 2012) Six-Item Short Form of the Household Food Security Scale. This scale consists of six questions asking participants if and how often food in their family household did not last, if they ever felt hungry, and if there was not sufficient money for enough or nutritionally balanced food. (USDA, 2012). Participants who reported sometimes or often experiencing the above conditions were scored with one point per question, which were then summed for a total food security score. Those who responded affirmatively to only one question were considered "food secure" in childhood. Two to 4 affirmative responses qualified the participant for "low food security." Five or six affirmative responses indicated "very low food security" (Bauer et al., 2012). This measure has been shown to be valid as compared to the original 18-item Household Food Security Scale (Blumberg, Bialostosky, Hamilton, & Briefel, 1999). Adaptations to this scale consisted of placing each item in the past tense and referring to "any twelve month period" in place of "the past twelve months" in the original. This adaptation allowed for the assessment of the entire childhood rather than only one year. In the analysis in this section, Childhood Food Insecurity was treated as a continuous independent variable. Additionally, two questions were added that asked if participants had received benefits from the SNAP/Food Stamps program and, if so, for how long.

The length of time of childhood SNAP participation provided another independent variable, Time Receiving SNAP Benefits.

Adverse Childhood Experiences (ACE) (Felitti, et al., 1998). Six factors related to cumulative risk exposure and life stress were selected for study from among a number of other retrospective stress scales. Abuse items were taken from the Adverse Childhood Experiences (ACE) questionnaire and were related to psychological, physical, and sexual abuse. The ACE study is a large prospective study (N=13,494) by the CDC examining the effects of retrospectively reported negative childhood experiences on health risk behavior and disease (Felitti et al., 1998). Additionally, the ACE survey has shown good test-retest reliability (Dube, Williamson, Thompson, Felitti, & Anda, 2004). Every item in this section had only yes or no answers. For psychological abuse, the questionnaire included two items assessing whether or not the participant had experienced verbal abuse from an adult and if an adult had frequently incited fear in them. The items pertaining to physical abuse asked if the participant had been often pushed or slapped by an adult or been hit so hard marks were left. Regarding sexual abuse, the questionnaire included two items assessing whether or not an adult 5 years or older than the participant at the time had initiated sexual touching or encouraged the child to initiate it (Felitti et al., 1998). The abuse score was calculated by summing the affirmative answers to each of these questions. The abuse score was used in the calculation of Cumulative Stress.

Items related to family turmoil were also adapted from the ACE questionnaire, including those related to substance abuse, mental illness, criminal behavior, family

disturbance, and violence against a maternal figure. The substance abuse items asked if the childhood household included anyone who used street drugs or was an alcoholic. The mental illness items asked if the household included any persons who attempted suicide or who was mentally ill. There was also one item assessing whether or not the childhood household included anyone who had been to prison, which assessed criminal behavior. An item was also included that asked about parents or guardians having many arguments or fights in order to assess family disturbance (Felitti et al., 1998). Finally, the items related to violence against a maternal figure were adapted to cover violence against either parent based on a communication from the director of the Montana State University – Bozeman Counseling Center of the observation of a high level of stress in the students related to violence against either parent (P. Donahoe, personal communication, January 8, 2013). The affirmative answers to these questions were summed to create one family turmoil score, which was further used in the calculation of Cumulative Stress.

Life Events Checklist (Kilmer, Cowen, Wyman, Work, & Magnus, 1998). Questions for the assessment of child separation from parent were taken from the Life Events Checklist (LEC). This scale was also used for the same assessment by Wells and Colleagues (2010). These items referred to death in the family, divorce, and whether or not the participant took care of other children in the family. Additionally, the questionnaire assessed whether or not protective or preventative services had become involved with the family or if the child had been sent to a foster home or lived with a relative or friend. Kilmer and colleagues conducted a factor analysis on this scale. All of the LEC questions included in this

questionnaire loaded onto the "Family Separation" factor shown by the factor analysis (Kilmer et al., 1998). Once again, the affirmative answers to these items were summed to create a family separation score, which was included in the composite score of Cumulative Stress.

American Housing Survey (US Census Bureau, 2011). The American Housing survey was the assessment used in a longitudinal study of the United States' housing characteristics conducted by the US Census Bureau. Of particular importance for the present study, two of the topics covered in the AHS are housing quality and neighborhood quality. The housing quality items were used to create noise and substandard housing scores, which were parts of the Cumulative Stress independent variable. Neighborhood Quality items were used to create a separate independent variable. The AHS started in 1973 and included 60,000 housing units, which have been followed in subsequent decades along with newer housing units added to the sample in 1985 and 2005. The AHS continues to be administered biannually and the current sample includes 155,108 housing units. In the present study, the assessment of noise, substandard housing, and neighborhood quality made use of items adapted from the American Housing Survey. Adaptations consisted of phrasing all questions in the past tense, in the same format as the ACE questions.

Assessment of noise consisted of asking participants whether or not neighbors or traffic could often be heard from the outside the childhood home and whether or not this noise, as well as if noise inside the house, was bothersome. Substandard housing items referred to the structural integrity of the childhood home. These included items about

cracks in the walls, broken windows, water leaking from inside or outside the home, stairways with broken steps, a sagging roof, sloping walls, or exposed electrical wiring (U.S. Census Bureau, 2011). Substandard housing and noise scores were used as part of the overall composite scores of cumulative stress, which are discussed below.

The items related to neighborhood quality were also from the AHS. These included the presence or absence of recreational/open spaces, public transportation, crime, adequate grocery stores, and the availability of safe tap water, which had yes/no response options. Additionally from the AHS, the participants were asked to give an overall judgment of neighborhood quality on a 10 point scale (U.S. Census Bureau, 2011). The final score of neighborhood quality in this study was a summed score of each yes/no item, which was multiplied by the participant's overall judgment rating out of 10. Positively valenced questions were reverse coded, making higher score indicate a lower quality neighborhood.

Assessment of Crowding (Wells, et al., 2010). The assessment of overcrowding was adapted for this study from the strategy used by Wells and colleagues' initial study of Cumulative Risk Exposure, in which trained researchers counted the number of rooms in the household and calculated a ratio of people per room (Wells et al., 2010). The retrospective survey used in the present study asked participants to report this information. Specifically, participants were asked to report the number of rooms in the household where they had lived the longest and the highest number of people that lived there permanently. From these two numbers, a ratio was calculated for people per room,

which constituted the overcrowding score. This score was the final piece of the Cumulative Stress variable.

Conditions at Birth and Demographic Items. Finally participants were asked five questions related to conditions at birth, including birth weight, overweight or obesity of mother and/or father, and maternal smoking before or during pregnancy. These items were included in the study in order to account for conditions during pregnancy and at birth that have been shown to predict obesity (Morandi et al., 2012, Parsons et al., 1999, Oken & Gillman, 2003). Each of these items asked if each condition was satisfied, to the best of the participant's knowledge (e.g. "To the best of your knowledge was your father overweight or obese when you were born?"). Maternal overweight/obesity, Paternal Overweight/obesity, smoking prior to pregnancy, and smoking during pregnancy were yes or no questions, with yes indicating that the participant had this risk factor. Additionally, this set of items also included a "do not know" response option. The birth items were not combined in any way for the final analysis. In addition, this section included an item that asked the prescreen question again (i.e., whether or not the participant had received benefits from the School Lunch Program), in case the participant signed up for the wrong study. This last section also instructed the participant to indicate age, gender, and race.

Retrospective Survey Packet Structure. The childhood questions described above, including individual sections related to abuse, family turmoil, separation from parents, substandard housing, overcrowding, noise, food insecurity, neighborhood

condition, and health influences at birth were combined into a single History Questionnaire (HQ). Related items were kept together in individual sections; however, the order of each sections within the HQ was rotated, which yielded seven versions of the questionnaire. In all 7 versions demographic and birth items were always placed at the end of the questionnaire. Participants were randomly assigned to HQ versions. Additionally, every page of the HQ, with the exception of the demographics page, included a header that reminded participants that all of the questions in that section referred to the first seventeen years of their life, when they were living with their parents or guardians. The scoring procedure for cumulative stress was the same as Wells and colleagues' study.

The scoring procedures in this study were all designed to reflect an amount of risk for each particular factor. As noted above, scoring for Food Insecurity consisted of a sum of affirmative answers. This was the same for Poor Neighborhood Quality, which positive items recoded. Time Receiving SNAP Benefits was only converted into total months. Cumulative Stress was scored as the sum of the average affirmative answers for abuse, family turmoil, family separation, substandard housing, noise, as well as the ratio of people per room for overcrowding.

Procedure

Participants signed up for their study session using the online SONA system, which allows for online posting of study time slots, sign ups, and credit granting. Each participant was assessed individually within a private room with the door closed. The

Multifactor Screener and IPAQ were given to the participants first as one survey and the researcher gave oral instructions that this part of the survey referred to the participants' current behavior and again reminded them that the survey was anonymous. After giving instructions the researcher closed the door and left the participant alone to complete the survey. Upon completion, the participant opened the door to signal to the researcher that he or she was ready to move on to the next part of the study. Next, the researcher gave the participant the HQ, with oral instructions that all of the questions referred to the participants' first seventeen years of life, while they were living with their parents or guardians. For both surveys, the researcher also gave oral instructions that the participant was free to leave any question blank should they choose. Again the door was closed to give the participant ample privacy while answering the questionnaire.

Upon completion of the HQ, the participant again opened the door to signal the researcher, who then took the participant into a separate room for the measurement of height and weight. Heights and weights were measured without shoes and participants were asked to remove any bags, backpacks, and/or heavy coats. The researcher recorded height and weight to the nearest tenth of inches and pounds, respectively, as well as time of day, experimental room (one of three available), and any questions or comments the participant voiced. Finally, the participant was debriefed and thanked for his/her time.

Analysis

Analysis of BMI was conducted first with Pearson Product-Moment Correlation Coefficients with each of the independent variables. In particular in this first analysis, the

relationship between childhood poverty (i.e., Participation in the School Lunch Program) and BMI as well as the relationship between BMI and physical activity, fat intake, and fruit and vegetable intake were examined. Next an initial large multiple regression analysis was conducted, which included all of the independent variables in one model. Finally, the main analysis was conducted using a series of hierarchical linear regression models. In every model covariates including Age, Gender, Race, Birth Weight, Paternal Obesity, Maternal Obesity, Mother Smoking Prior to Pregnancy, and Mother Smoking During Pregnancy and Participation in the School Lunch Program were entered in step one. Model 1 included Childhood Food Insecurity in step two. Model 2 included Time Receiving SNAP Benefits in step two. Model 3 incorporated Poor Neighborhood Quality in step two. Model 4 examined the interaction of Time Receiving SNAP Benefits and Poor Neighborhood Quality in step two. Model 5 included Cumulative Stress in step two. Finally, in model 6, step two included Childhood Food Insecurity, Time Receiving SNAP Benefits, Poor Neighborhood Quality, and the interaction of the latter two variables in step two and Cumulative Stress in step three.

For the analysis of Percent Energy from Fat and Servings of Fruits and Vegetables, the analysis was the same. As previously, Initial Pearson Product-Moment Correlation Coefficients were created followed by one large multiple regression analysis. The correlation analysis included all of the independent variables in the study. However the regression analyses excluded the fetal health items as there was not theoretical basis for their inclusion. Next, hierarchical regression models were created. Step one of all models included the demographic variables, Gender, Race, and Participation in the

School Lunch Program. The construction of the rest of the models was the same as that for BMI, noted above.

The analysis of Physical activity also started with initial Pearson Product-Moment Correlation Coefficient analysis, which included all of the independent variables. Due to results from this first correlational analysis, which are discussed in the next section, Cumulative Stress was also used in the subsequent regression analyses. The initial multiple regression analysis included Gender, Age, Race, Participation in the School Lunch Program, Poor Neighborhood Quality, and Cumulative stress in one model. Following this, hierarchical regression analysis included the same step one for the three models, which included Gender, Age, Race, and Participation in the School Lunch Program. Step two of Model 1 added Poor Neighborhood Quality to the model. Step two of Model 2 included Cumulative Stress. Finally, step two of Model 3 included both Poor Neighborhood Quality and Cumulative Stress.

Following these analyses, independent variables that were shown to be significant or trending predictors in previous models were then entered into another exploratory multiple regression, in order to identify the most parsimonious model related to these data. This post hoc step was taken in order to identify potential future directions for this research. Because of the increased probability of type 1 error in post hoc analyses such as these, any conclusions drawn from these models are taken with great caution.

RESULTS

Descriptives

Ninety-seven participants signed up for the study, 47 of which were part of the prescreened group (i.e.,, qualified as impoverished during childhood). Table 1 provides descriptive information and birth characteristics of the sample. Table 2 refers to descriptive information for the composite variables. The sample consisted 44 males and 53 females. For BMI, no one in the sample qualified as underweight. Slightly over half

Table 1 *Descriptive Statistics on Demographics and Birth Characteristics*

Measure	*N*	*%*
Demographics		
Race		
White/Caucasian	81	83.5
Hispanic/Latino	3	3.1
Native American/Alaskan Native	6	6.2
Asian/Pacific Islander	1	1.0
Middle Eastern	1	1.0
Multiracial	4	4.1
Gender		
Male	44	45.4
Female	53	54.6
Age		
18-25	86	88.7
>25	9	9.3
School Lunch Program Participants	47	48.5
Birth Characteristics		
Mother Overweight or Obese	3	3.1
Father Overweight or Obese	8	8.2
Mother Smoke Before Pregnancy	30	30.9
Mother Smoke During Pregnancy	6	6.2
Measure	*M*	*SD*
Birth Weight	7.04	1.92

Table 2 *Descriptive Statistics on Composite Scores*

Measure		*M*	*SD*
Independent Variables			
Childhood Food Insecurity	(0-6)	0.69	1.20
Poor Neighborhood Quality	(0-70)	6.01	8.78
Childhood Cumulative Stress		1.39	0.97
Abuse	(0-6)	0.61	1.20
Turmoil	(0-8)	1.63	1.84
Separation	(0-6)	1.30	1.27
Crowding		0.74	0.48
Noise	(0-4)	0.32	0.81
Housing	(0-8)	0.53	1.12
Dependent Variables			
BMI		25.40	5.01
Percent Energy Intake from Fat		34.28	2.94
Servings of Fruits and Vegetables		2.41	0.78
Physical Activity METs/week		6.48	5.26

the sample was determined to be of normal weight (55%) and nearly one third was overweight (30%). The remaining participants were obese class 1 (6%), obese class 2 (6%), and obese class 3 (1%). A large majority of the sample categorized themselves as Caucasian (84%) and between the ages of 18 and 25 years (89%). Among those who supplied their Birth Weight, the vast majority was born within the cutoffs for a healthy weight (78%). Few participants supplied a birth weight that would be considered low (9%) or high (14%). Due to a low number of participants within the other groups, racial groups were combined into a binomial variable defined as Caucasian or Other. Additionally, Maternal Overweight or Obesity was left out of the final analysis because only three participants provided an affirmative answer to this item. Time of day, researcher, and study room were not shown to have any influence on the dependent

variables, as shown by initial multiple regression models for each dependent variable, which included these and all independent variables.

In order to satisfy the assumption of normality of the outcome variables in the regression models, logarithmic transformations were performed on BMI, Servings of Fruits and Vegetables, and Physical Activity. In the subsequent sections and tables, please note that these variable names refer to the logarithmic values. Additionally, outliers were examined on a model by model basis and were only removed if they significantly affected the model as determined by a Cook's *d* of greater than 1.0. Furthermore, all models excluded missing variables pairwise. Multicollinearity was also assessed on a model by model basis using Variable Inflation Factor (VIF) collinearity diagnostics. In this study the assumption of multicollinearity was considered satisfied if all VIF values were below 10. Reliability analyses were conducted on the individual scores that made up Cumulative Stress as well as on the Poor Neighborhood Quality and Food Insecurity Scales. Good reliability was seen with most of the scales using a Chronbach's α cutoff of 0.70. The notable exceptions were the scales measuring Poor Neighborhood Quality (8 items; $\alpha = .45$) and Family Separation (6 items; $\alpha = .50$). The removal of any items from these scales was not shown to increase the reliability above the cutoff. In spite of this issue, these scales were retained for the analysis so as to maintain congruency with the previous literature. Because of this low reliability, interpretations from any results related to these scales must be treated with suspicion as this may indicate that the scale, or part of it, is measuring a different construct than expected.

For each of the 4 dependent variables (BMI, Percent Energy from Fat, Fruit and Vegetable Intake and Total Physical Activity), several regression models, based on predictions from the existing literature, were tested. The results of these analyses are presented separately below for each dependent variable.

Body Mass Index

In the investigation of BMI, an initial analysis was performed using Pearson product-moment correlation coefficients (Table 3). Initial correlational analysis showed

Table 3 *Pearson Product-Moment Correlations Between Independent and Dependent Variables*

	Dependent Variables			
	BMI	Fruit and Vegetable Intake	% Energy from Fat	Total Physical Activity
Independent Variables				
Gender	0.054	0.199	0.002	-0.148
Age	0.249*	-0.096	-0.004	0.097
Race (Categorical)	0.168	0.144	-0.155	0.242
Birth Weight	-0.216	-0.061	0.210	-0.020
Father Overweight/Obese	.294**	-0.121	-0.009	-0.159
Mother Smoke Before Pregnancy	0.138	0.046	0.005	0.042
Mother Smoke During Pregnancy	0.062	0.090	-0.037	-0.073
School Lunch Program Participation	0.018	0.016	-0.045	0.160
Childhood Food Insecurity	-0.166	0.064	-0.091	0.224
Amount of time receiving SNAP	0.005	0.205*	0.165	0.097
Poor Neighborhood Quality	0.1	-0.017	-0.129	-0.013
Time on SNAP X Neighborhood Interaction	0.033	0.047	0.073	0.012
Childhood Cumulative Stress	0.067	0.086	-0.025	0.256*

*$p < .05$ (2-tailed). ** $p < .01$ (2-tailed). ***$p < .001$ (2-tailed).

small positive correlations between BMI and Age (r = .25, n =93, p < .05) and Paternal Overweight (r = .29, n = 91, p<.01). Critically, BMI was not significantly correlated with Percent Energy from Fat, Fruit and Vegetable Intake, or Physical Activity. Hierarchical multiple regression was used to assess the ability of childhood circumstances (Childhood Food Insecurity, Poor Neighborhood Quality, Time Receiving SNAP Benefits, and Cumulative Stress) to predict body size (BMI) after controlling for demographic influences, health disparities at birth, and overall poverty (Age, Gender, Race, Birth Weight, Paternal Overweight, Maternal Smoking Before Pregnancy, Maternal Smoking During Pregnancy, and School Lunch Program Participation). Two age scores were removed from all of the models of BMI due to their consistent significant effect on the overall model. An initial multiple regression analysis (Table 4) was conducted with all variables included in the model, which explained 14.1% of the variance in BMI, (R^2 = 0.35 F[13, 40] = 1.67, p = .106). Within this model, significant predictors were Birth Weight (β = -0.34, p < .05), Paternal Overweight (β = 0.33, p<.05), and Age (β = 0.31, p < .05).

Step 1 of all subsequent hierarchical regression models (Table 5) included Gender, Age, Race (categorical), Birth Weight, Paternal Overweight, Mother Smoking Prior to Pregnancy, Mother Smoking During Pregnancy, and Participation in the School Lunch Program and accounted for 13.3% of the variance, (R^2 = 0.33, F[8, 45] = 2.01, p =.067). Step 1 of all the models included two significant predictor variables: Paternal Overweight (β = 0.33, p < .05) and Age (β = 0.31, p < .05). These variables were also significant in subsequent models.

Table 4 *Standardized Regression Coefficients (β), R^2 from Initial Multiple Regression Models for each Dependent Variable.*

	Dependent Variables			
	BMI	Fruit and Vegetable Intake	% Energy from Fat	Total Physical Activity
Independent Variables				
Gender	0.15	0.18	0.06	-0.13
Age	0.31*	-0.11	0.14	0.09
Race (Categorical)	0.09	0.16	-0.15	0.20
Birth Weight	-0.34*			
Father Overweight/Obese	0.33*			
Mother Smoke Before Pregnancy	0.10			
Mother Smoke During Pregnancy	0.04			
School Lunch Program Participation	0.18	0.01	-0.04	0.10
Childhood Food Insecurity	-0.28	0.03	-0.11	
Amount of time receiving SNAP	-0.20	-0.02	0.32	
Poor Neighborhood Quality	0.07	-0.26	-0.26	-0.28
Time on SNAP X Neighborhood	-0.03	0.41	-0.01	
Childhood Cumulative Stress	0.02	-0.05	0.06	0.31
R^2	0.35	0.17	0.13	0.17
F	1.67	1.82	1.37	1.95

*$p < .05$ (2-tailed). ** $p < .01$ (2-tailed). ***$p < .001$ (2-tailed).

Step 2 of Model 1 added Childhood Food Insecurity ($\Delta R^2 = 0.07$, $\Delta F[1, 44] = 4.67$, $p < .05$). The complete Model 1 accounted for 19.8% of the variance in BMI, ($R^2 = 0.33$, $F[9, 44] = 2.45$, $p < .05$), and included two additional variables that were statistically significant, which were Birth Weight ($\beta = -0.33$, $p < .05$) and Childhood Food Insecurity ($\beta = -0.32$, $p < .05$). Critically, the direction of this association is in the opposite direction of the literature and will be discussed below.

Step 2 of Model 2 included Time Receiving SNAP Benefits, which did not significantly predict BMI (ΔR^2 = .01, ΔF[1, 44] = 0.48, p = .492). The final model trended towards significance, accounting for 12.2% of the variance, (R^2 = 0.27, F[9, 44] = 1.82, p = .091 Step 2 of Model 3 included Poor Neighborhood Quality (ΔR^2 = 0.02, ΔF[1, 44] = 0.90, p = .348). The complete Model 3 approached significance, accounting for 13.1% of the variance in BMI, (R^2 = 0.28, F[9, 44] = 1.89, p = .08).

Model 4 included the lower order variables and interaction of Time Receiving SNAP Benefits and Poor Neighborhood Quality in step 2. Again, the addition of these variables resulted in a nonsignificant change to the model, (ΔR^2 = 0.02, ΔF[3, 42] = 0.38, p = .769). In the complete Model 4, the variance explained by the model was 9.5% (R^2 = 0.28, F[11, 42] = 1.56, p = .165).

Model 5 included Cumulative Stress in step 2, the addition of which resulted in a nonsignificant step (ΔR^2 = 0.02, ΔF[1, 44] = .97, p = .331). The variance accounted for by the overall Model 5 again approached significance at 13.2% (R^2 = 0.13, F[9, 44] = 1.90, p = .078). In Model 5 Birth Weight once again became an additional significant predictor in step two (β = -0.31, p < .05).

In the final Model 6, step two included Food Insecurity, Poor Neighborhood Quality, Time receiving SNAP Benefits, and the interaction of the latter two, yielding a nonsignificant (ΔR^2 = 0.07, ΔF [4, 42] = 1.17, p = .336). The BMI variance accounted for by step 2 of Model 6 was 14.5% (R2 = 0.34, F[11, 42] = 1.95, p = .060). Finally, Cumulative Stress was added in step 3, (ΔR2 = 0.00, ΔF [1, 41] = 0.00, p = .991). The

Table 5 Summary of Hierarchical Regression Analysis for Variables Predicting BMI (N=97)

	Model 1		Model 2		Model 3	
	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2
Variable						
Gender	0.11	0.12	0.11	0.11	0.11	0.12
Age	0.31*	0.29*	0.31*	0.31*	0.31*	0.35*
Race	0.11	0.09	0.11	0.11	0.11	0.13
Birth Weight	-0.27	-0.33*	-0.27	-0.27*	-0.27	-0.28
Paternal Overweight/Obesity	0.33*	0.35*	0.33*	0.34*	0.33*	0.35*
Mother Smoke Prior to Pregnancy	0.09	0.05	0.09	0.10	0.09	0.11
Mother Smoke During Pregnancy	-0.05	0.07	-0.05	-0.03	-0.05	-0.03
Participated in School Lunch Program	0.00	0.13	0.00	0.03	0.00	0.04
Childhood Food Insecurity		-0.32*				
Time Receiving SNAP				-0.10		
Childhood Neighborhood Quality						-0.15
SNAP Time x Neighborhood Quality						
Cumulative Stress						
Total R^2	0.26	0.33	0.26	0.27	0.26	0.28
F	2.01	2.45*	2.01	1.82	2.01	1.89
ΔR^2		0.07		0.01		0.02
ΔF		4.67*		0.48		0.90

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

Table 5 (Continued) Summary of Hierarchical Regression Analysis for Variables Predicting BMI (N=97)

	Model 4		Model 5		Model 6		
	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2	Step 3
Variable							
Gender	0.11	0.12	0.11	0.11	0.11	0.12	0.12
Age	0.31*	0.35*	0.31*	0.31*	0.31*	0.31*	0.31*
Race	0.11	0.13	0.11	0.14	0.11	0.10	0.10
Birth Weight	-0.27	-0.28	-0.27	-0.31*	-0.27	-0.33*	-0.34*
Paternal Overweight/Obesity	0.33*	0.36*	0.33*	0.36*	0.33*	0.35*	0.35*
Mother Smoke Prior to Pregnancy	0.09	0.10	0.09	0.08	0.09	0.07	0.07
Mother Smoke During Pregnancy	-0.05	-0.02	-0.05	0.03	-0.05	0.08	0.08
Participated in School Lunch Program	0.00	0.04	0.00	0.06	0.00	0.15	0.15
Childhood Food Insecurity						-0.31	-0.31
Time Receiving SNAP		0.03				-0.08	-0.08
Childhood Neighborhood Quality		-0.08				-0.09	-0.09
SNAP Time x Neighborhood Quality		-0.13				0.09	0.09
Cumulative Stress				-0.18			-0.00
Total R^2	0.26	0.28	0.26	0.28	0.26	0.34	0.34
F	2.01	1.51	2.01	1.90	2.01	1.75	1.57
ΔR^2		0.02		0.02		0.08	0.00
ΔF		0.38		0.97		1.16	0.00

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

variance explained by the complete model was 12.3% (R^2 = 0.34, F[12, 41]=1.74, p=.093). In the final model, only three variables were significant predictors of BMI: Paternal Overweight was the strongest (β = 0.36, p < .05), followed by Birth Weight (β = -0.33, p < .05), and Age (β = 0.31, p < .05).

An additional exploratory multiple regression model was created in order to assess the variables shown to be significant in the previous models. This model included Age, Birth Weight, Paternal Overweight, and Food Insecurity. Overall, this exploratory model was significant, accounting for 22.9% of the variance in BMI, (R^2 = 0.29, F[4, 49] = 4.94, p < .01). Within this model, significant predictors included Birth Weight (β = -0.36, p < .01), Paternal Overweight (β = 0.33, p < .01), and Age (β = 0.31, p < .05).

Because of the surprising nature of the negative association between BMI and Childhood Food Insecurity, additional Pearson product-moment correlation coefficients were calculated for both of the prescreened groups (i.e., School Lunch Program participants or not). Among those categorized as previously impoverished a moderate negative correlation between Childhood Food Insecurity and Current BMI was observed (r = -.31, n = 45, p < .05). No relationship was observed among those not categorized as previously impoverished (i.e., did not receive benefits from the school lunch program).

Overall, the predictions related to BMI were not supported. First, the prediction that increased BMI would be related to increased fat intake, decreased fruit and vegetable intake, and decreased physical activity was not supported. Indeed, no relationship was observed between any of these variables and BMI. Furthermore, no relationship was observed between childhood poverty and adult BMI, which was an important initial

assumption in this study. Finally, none of the predictions made by any of the models were supported. Indeed evidence against the FCCM was observed, as the results showed, increased childhood food insecurity was predictive of decreased BMI. This unexpected result will be considered further below.

Percent Energy from Fat

Scores for the Percent Energy from Fat (PEF) were calculated from the Multifactor Screener (NCI, 2011). One participant's age was left out of the analysis due to its significant individual influence on the model. Initial analysis for PEF scores were again Pearson product-moment correlation coefficients, shown in Table 3. This initial analysis showed no significant correlations. However, variables approached significance, Race (r = -.16, n = 95, p = .066) and Time Receiving SNAP Benefits (r = .17, n = 93, p = .057). Additionally, one overall multiple regression analysis was performed that included all of the predictor variables (Table 4). The variance predicted by this model was 3.5% (R^2 = 0.13, F [9, 82] = 1.37, p = .217). Within the model only Time Receiving SNAP Benefits was a significant predictor (β = 0.31, $p < .05$).

` A series of hierarchical regression analyses (Table 6) were performed once again in order to ascertain the predictive value of each composite IV (Childhood Food Insecurity, Poor Neighborhood Quality, Time Receiving SNAP, SNAP x Neighborhood interaction, and Childhood Cumulative Stress) over and above that of the demographic variables (Age, Gender, Race, and School Lunch Program Participation). Birth data were excluded from the analyses of Percent Energy from Fat, Servings of Fruits and

Table 6 Summary of Hierarchical Regression Analysis for Variables Predicting Percent Energy from Fat (N=95)

	Model 1		Model 2		Model 3	
	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2
Variable						
Gender	0.01	0.02	0.01	0.02	0.01	0.03
Age	0.10	0.10	0.10	0.08	0.10	0.14
Race	-0.16	-0.16	-0.16	-0.18	-0.16	-0.13
Participated in School Lunch Program	-0.04	-0.01	-0.04	-0.11	-0.04	-0.00
Childhood Food Insecurity		-0.08				
Time Receiving SNAP				0.21		
Childhood Neighborhood Quality						-0.15
SNAP Time x Neighborhood Quality						
Cumulative Stress						
Total R^2	0.04	0.04	0.04	0.07	0.04	0.05
F	0.79	0.71	0.79	1.36	0.79	0.93
ΔR^2		0.01		0.04		0.02
ΔF		0.43		3.56		1.47

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

Table 6 (Continued) Summary of Hierarchical Regression Analysis for Variables Predicting Percent Energy from Fat (N=95)

	Model 4		Model 5		Model 6		
	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2	Step 3
Variable							
Gender	0.20	0.05	0.20	0.01	0.20	0.06	0.06
Age	-0.09	0.15	-0.09	0.10	-0.09	0.14	0.14
Race	0.16	-0.14	0.16	-0.17	0.16	-0.14	-0.15
Participated in School Lunch Program	0.02		0.02	-0.06	0.02	-0.04	-0.04
Childhood Food Insecurity						-0.09	-0.11
Time Receiving SNAP		-0.07				0.34	0.32
Childhood Neighborhood Quality		0.37				-0.25	-0.26
SNAP Time x Neighborhood Quality		-0.25				-0.01	-0.01
Cumulative Stress				0.04			0.06
Total R^2	0.07	0.12	0.07	0.04	0.07	0.13	0.13
F	1.71	1.71	1.71	0.64	1.71	1.54	1.37
ΔR^2		0.09		0.00		0.09	0.00
ΔF		2.88*		0.11		2.25	0.13

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

Vegetables, and Physical Activity due to a lack of theoretical justification for their inclusion. The age of one participant was excluded from all of the models due to its consistently affecting the models. In every model, step 1 included Gender, Age, Race (categorical), and School Lunch Program Participation. The variance in PEF accounted for by step 1 was -0.9% (R^2 = 0.04, F [4, 88] = 0.79, p = .535). There were no significant individual predictors of PEF within step 1 of the models.

In Model 1, step 2 included Childhood Food Insecurity (ΔR^2 = 0.01, ΔF [1, 87] = .430, p = .615). The variance accounted for by Model 1 as a whole was -0.02% (R^2 = 0.04, F[5, 87] = .714, p = .615). Model 2 added Time Receiving SNAP Benefits in step 2 (ΔR^2 = 0.04, ΔF[1, 87] = 3.56, p = .063). Model 2 as a whole accounted for -1.9% of the variance in Percent Energy from Fat, (R^2 = 0.07, F[5, 87] = 1.36, p = .247). In step 2, two variables approached significance in predicting PEF: Race (β = -0.178, p = .091) and Time Receiving SNAP Benefits (β = 0.208, p = .063). Step 2 of Model 3 added Poor Neighborhood Quality to the model, (ΔR^2 = 0.02, ΔF (1, 87) = 1.47, p = .229). The variance accounted for by the complete Model 3 was -0.40% (R^2 = 0.05, F[5, 87] = 0.93, p = .466). Model 4 added Time Receiving SNAP Benefits and Poor Neighborhood Quality along with their interaction, (ΔR^2 = 0.09, ΔF[3, 85] = 2.88, p < .05). Overall, model 4 accounted for 5.2% of the variance in Percent Energy from Fat, (R^2 = 0.12, F[7, 85] = 1.71, p = .117). Step 2 of model 5 added Cumulative Stress, (ΔR^2 = 0.00, ΔF[1, 86] = 0.12, p = .744). Overall, model 5 accounted for only -2.0% of the variance in PEF, (R^2 = 0.04, F[5, 86] = 0.64, p = .670).

Model 6, the full model, added Childhood Food Insecurity, Time Receiving SNAP Benefits, and Poor Neighborhood Quality in step 2 ($\Delta R^2 = 0.09$, $\Delta F[4, 87] = 3.04$, $p < .05$). Step 2 accounted for 4.5% of the variance in PEF ($R^2 = 0.12$, $F[8, 83] = 1.78$, $p = .102$). Step 3 added Cumulative Stress to the model ($\Delta R^2 = 0.00$, $\Delta F[1, 82] = 0.13$, $p = .717$). The variance accounted for by the full model 6 was 3.5% ($R^2 = 0.13$, $F[9, 82] = 1.37$, $p = .217$).

A final exploratory multiple regression analysis was conducted in order to examine the predictive value of Race, Poor Neighborhood Quality, and Time Receiving SNAP Benefits for Percent Energy from Fat. The variance explained by the model was 6.9% ($R^2 = 0.10$ $F[3, 89] = 3.28$, $p < .05$. Within the model, Time Receiving SNAP Benefits was the best predictor ($\beta = 0.29$, $p < .05$), followed by Childhood Neighborhood Quality ($\beta = -.24$, $p < .05$).

Overall, the results for fat intake did not support any of the models examined. Indeed, no significant results were observed for this dependent variable. The post hoc exploratory model showed increased time receiving SNAP and better neighborhood quality predicting increased fat intake. This result, though post hoc, is in line with the FCCM and somewhat similar to the results found by Vartanian and Houser (2012). This is also in opposition to NAM, which predicted those growing up in lower quality neighborhoods would currently have greater fat intake. These findings will be discussed further below.

Fruit and Vegetable Intake

Servings of fruits and vegetables per day were also calculated from the Multifactor Screener (NIH, 2011). The logarithm of this variable was used for this analysis in order to satisfy the assumption of normality for the dependent variable. Furthermore, one participant's score for the interaction of Time Receiving SNAP Benefits and Neighborhood Quality was removed due to its consistent influence on the models. Please refer to Table 3 for Pearson product-moment correlation coefficients from the initial analysis. There were significant correlations observed between Servings of Fruits and Vegetables and Time Receiving SNAP Benefits ($r = 0.21$, $n = 94$, $p < .05$) and Servings of Fruits and Vegetables the Time Receiving SNAP Benefits and Neighborhood Quality interaction ($r = 0.24$, $n = 93$, $p < .05$). Furthermore, the variance explained by the initial overall multiple regression analysis (Table 4) was 4.8% ($R^2 = 0.14$, $F[9, 82] = 1.52$, $p = .156$). Within this model significant predictors were Gender ($\beta = 0.22$, $p < .05$) and Time Receiving SNAP Benefits ($\beta = 0.31$, $p < .05$).

For a summary of the hierarchical regression analysis, refer to Table 7. The first step in all the models included Gender, Age, Race (categorical), and Participation in the School Lunch Program. Step 1 accounted for 3.0% of the variance in Fruit and Vegetable Intake ($R^2 = 0.07$, $F[4, 89] = 1.71$, $p = .155$). None of the predictor variables included in this step were significant. Step 2 of Model 1 included Childhood Food Insecurity ($\Delta R^2 = 0.00$, $\Delta F[1, 88] = 0.00$, $p = .811$). The overall variance accounted for by Model 1 was 1.9% ($R^2 = 0.07$, $F[5, 88] = 1.36$, $p = .246$).

Table 7
Summary of Hierarchical Regression Analysis for Servings of Fruits and Vegetables (N=96)

	Model 1		Model 2		Model 3	
	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2
Variable						
Gender	0.20	0.19	0.20	0.20*	0.20	0.20
Age	-0.09	-0.09	-0.09	-0.11	-0.09	-0.08
Race	0.16	0.15	0.16	0.14	0.16	0.17
Participated in School Lunch Program	0.02	0.01	0.02	-0.05	0.02	0.04
Childhood Food Insecurity		0.03				
Time Receiving SNAP				0.23*		
Childhood Neighborhood Quality						-0.06
SNAP Time x Neighborhood Quality						
Cumulative Stress						
Total R^2	0.07	0.07	0.07	0.12	0.07	0.07
F	1.71	1.36	1.71	2.33*	1.71	1.42
ΔR^2		0.00		0.05		0.00
ΔF		0.06		4.53*		0.27

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

Table 7 (Continued) Summary of Hierarchical Regression Analysis for Servings of Fruits and Vegetables (N=96)

	Model 4		Model 5		Model 6		
	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2	Step 3
Variable							
Gender	0.20	0.18	0.20	0.19	0.20	0.18	0.18
Age	-0.09	-0.12	-0.09	-0.09	-0.09	-0.12	-0.11
Race	0.16	0.15	0.16	0.15	0.16	0.15	0.16
Participated in School Lunch Program	0.02	0.01	0.02	0.01	0.02	0.00	0.01
Childhood Food Insecurity						0.01	0.03
Time Receiving SNAP		-0.04				-0.04	-0.02
Childhood Neighborhood Quality		-0.27*				-0.27*	-0.26
SNAP Time x Neighborhood Quality		0.42				0.42	0.41
Cumulative Stress				0.03			-0.05
Total R^2	0.07	0.17	0.07	0.07	0.07	0.17	0.17
F	1.71	2.43*	1.71	1.35	1.71	2.05	1.82
ΔR^2		0.09		0.00		0.10	0.00
ΔF		3.24*		0.08		2.35	0.09

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

Step 2 of Model 2 included Time Receiving SNAP Benefits ($\Delta R^2 = 0.05$, $\Delta F[1, 88] = 4.53$, $p < .05$). Overall, Model 2 accounted for 6.7% of the variance in Fruit and Vegetable Intake ($R^2 = 0.12$, $F[5, 88] = 2.33$, $p < .05$). The two significant individual predictors of Fruit and Vegetable Intake were Time Receiving SNAP Benefits ($\beta = 0.23$, $p < .05$) and Gender ($\beta = 0.20$, $p < .05$).

Step 2 of Model 3 added Poor Neighborhood Quality ($\Delta R^2 = 0.00$, $\Delta F [1, 89] = 0.27$, $p = .607$). The overall variance accounted for by Model 3 was 2.2%, ($R^2 = 0.07$, $F[5, 89] = 1.42$, $p = .223$).

Model 4 included Time Receiving SNAP Benefits, Poor Neighborhood Quality and their interaction ($\Delta R^2 = 0.10$, $\Delta F[3, 85] = 3.25$, $p < .05$). As a whole, Model 4 predicted 9.8% of the variance in Fruit and Vegetable Intake ($R^2 = 0.17$, $F[7, 85] = 2.43$, $p < .05$). Furthermore, in this model, the only significant predictor was Poor Neighborhood Quality ($\beta = 0.27$, $p < .05$).

Step 2 added Cumulative Stress to Model 5 ($\Delta R^2 = 0.00$, $\Delta F[1, 87] = 0.08$, $p = .778$). The variance accounted for by the entire Model 5 was 1.9%, ($R^2 = 0.07$, $F[5, 87] = 1.35$, $p = .250$).

Model 6, step 2, included Time Receiving SNAP Benefits, Childhood Food Insecurity, Poor Neighborhood Quality, and the interaction of Time Receiving SNAP Benefits and Poor Neighborhood Quality, ($\Delta R^2 = 0.10$, $\Delta F[4, 82] = 2.53$, $p = .061$).

Overall, the variance explained by step 2 was 8.6% ($R^2 = 0.17$, $F[8, 82] = 2.05$, $p = .05$). Within step 2 the only significant predictor variable was Poor Neighborhood Quality ($\beta = -0.27$, $p < .05$). Step 3 of Model 6 added Cumulative Stress, ($\Delta R^2 = 0.00$,

$\Delta F[4, 82] = 0.09$, $p = .762$). Model 6, as a whole, predicted 7.5% of the variance in Fruit and Vegetable Intake ($R^2 = 0.17$, $F[9, 81] = 1.82$, $p = .078$). Furthermore, none of the variables in this model significantly predicted Servings of Fruits and Vegetables.

Once again, an additional exploratory multiple regression was performed in order to assess a potentially more parsimonious model. This model included Gender, Time Receiving SNAP Benefits, and Poor Neighborhood Quality and accounted for 7.8% of the variance in Servings of Fruits and Vegetables ($R^2 = 0.11$, $F[3, 90] = 3.61$, $p < .05$). Within this model significant predictors included Time Receiving SNAP Benefits ($\beta = 0.30$, $p < .05$) and Gender ($\beta = 0.22$, $p < .05$).

Overall, the results for fruit and vegetable intake support only one of the reviewed models. Increased time on SNAP was predictive of increased fruit and vegetable intake, which is in line with FFCM. Although this was no longer significant in the full model with all of the other independent variables, none of the other variables were shown to be superior predictors of fruit and vegetable intake. Neighborhood quality was a significant predictor of fruit and vegetable intake to the extent that those who grew up in low quality neighborhoods had higher fruit and vegetable intake. However, this result was only observed when both SNAP participation and the interaction of SNAP and Poor Neighborhood Quality were included in the model. As a further investigation of these conflicting results, an additional model was created that included only Gender, Time Receiving SNAP Benefits and Poor Neighborhood Quality. When only these variables were included in the model, neighborhood quality was no longer a significant predictor.

Overall, the results for fruit and vegetable intake provide moderate support for FFCM and tentative evidence against NAM.

Physical Activity

Scores for Total Physical Activity (PA) were calculated from the IPAQ (IPAQ, 2012). The Age of one participant was excluded from the analysis due to its consistent effect on the models. The number of participants in the PA models is considerably lower than that of the other dependent variables due to missing data. Initial Pearson product-moment correlation coefficients showed only Cumulative Stress to be associated with PA ($r = 0.26$, $n = 63$, $p < .05$). In order to further investigate this positive relationship between Cumulative Stress and PA, an additional hierarchical regression analysis was carried out. An initial multiple regression model (Table 4) included Gender, Age, Race (categorical), Participation in the School Lunch Program, Poor Neighborhood Quality, and Cumulative Stress. The variance in PA accounted for by this model was 8.4% ($R^2 = 0.73$, $F[6, 56] = 1.95$, $p = .089$). Within the model, Cumulative Stress was the only significant individual predictor of PA ($\beta = 0.31$, $p < .05$).

Step 1 of all the hierarchical regression models (Table 8) was the same and included Gender, Age, Race (categorical), and Participation in the School Lunch Program. The variance accounted for by step 1 was 3.4% ($R^2 = 0.10$, $F[4, 58] = 1.54$, $p = .202$). There were no significant predictor variables within step 1. Step 2 of Model 1 added Poor Neighborhood Quality to the model ($\Delta R^2 = 0.02$, $\Delta F[1, 57] = 1.01$, $p = .318$). As a whole, the variance predicted by Model 1 was 3.4% ($R^2 = 0.11$, $F[5, 57] = 1.44$, $p =$

Table 8 Summary of Hierarchical Regression Analysis for Physical Activity (N=64)

	Model 1		Model 2		Model 3	
	Step 1	Step 2	Step 1	Step 2	Step 1	Step 2
Variable						
Gender	-0.13	-0.11	-0.13	-0.15	-0.13	-0.13
Age	0.02	0.06	0.02	0.01	0.02	0.09
Race	0.23	0.25	0.23	0.18	0.23	0.20
Participated in School Lunch Program	0.13	0.17	0.13	0.06	0.13	0.20
Childhood Neighborhood Quality		-0.14				-0.28
Cumulative Stress				0.19		0.31*
Total R^2	0.10	0.11	0.10	0.13	0.10	0.17
F	1.54	1.44	1.54	1.62	1.54	1.95
ΔR^2		0.02		0.03		0.08
ΔF		1.01		1.86		2.59

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

.225). Furthermore, there were no significant predictor variables within Model 1. Cumulative Stress was added in step 2 of Model 2, ($\Delta R^2 = 0.03$, ΔF [1, 57] = 1.86, p = .178). Overall Model 2 predicted 4.8% of the variance in PA ($R^2 = 0.13$, F[5, 57] = 1.62, p = .169).

Model 3 included both Poor Neighborhood Quality and Cumulative Stress in step 2 ($\Delta R^2 = 0.08$, ΔF[2, 56] = 2.59, p = .084). Overall, Model 3 predicted 8.4% of the variance in PA ($R^2 = 0.17$, F[6, 56] = 1.95, p = .089). Within the model, the only significant predictor of PA was Cumulative Stress ($\beta = 0.31$, $p < .05$).

Once again, a further exploratory multiple regression model was created in order to find the most parsimonious option. This model included Race (categorical), Poor Neighborhood Quality, and Cumulative Stress and accounted for 8.8% of the variance in

PA (R^2 = 0.13, F[3,59] = 3.01, p < .05). Within this model, only Cumulative Stress was significantly predictive of PA (β = 0.04, p < .05).

Overall, these results were quite unexpected. No support for NAM was observed for physical activity. Indeed, though nonsignificant, the relationship between neighborhood quality and physical activity was opposite the prediction by NAM. Additionally greater Cumulative Stress was a consistent significant predictor of increased PA, which was not predicted by any of the models reviewed. Potential explanations for this observation will be discussed below.

Further Exploratory Analyses

Few of the results in this analysis supported the predictions of any of the reviewed models. Indeed, some of these results led to further questions about the data set. These analyses are post hoc and should be interpreted with great caution due to an increased risk of type 1 error. In order to ascertain if the relationship between Cumulative Stress and BMI was masked due to PA, another hierarchical regression was performed. Step one included Age, Birth Weight, and Paternal Obesity, all of which accounted for 9.7% of the variance in BMI (R^2 = 0.17, F[3,36] = 2.40, p = .08). Step 2 added Physical Activity to the model, which did not significantly change the model's predictive ability (ΔR^2 = 0.00, ΔF[1, 35] = 0.00, p = .995). The third step added Cumulative Stress, which also did not produce a significant change (ΔR^2 = 0.00, ΔF[1, 34] = 0.05, p = .831). The model, as a whole, predicted only 4.5% of the variance in BMI (R^2 = 0.17, F[5,34] = 1.37, p = .259). This model provides no additional evidence for CSM, which was also

not supported in the previous model. However, this model suggests that a relationship between BMI and Childhood Cumulative Stress is not masked by increased physical activity.

An additional analysis was conducted in order to examine the relationships between the independent variables related to poverty (Table 9). This correlational analysis included Childhood Food Insecurity, Time Receiving SNAP Benefits, Poor

Table 9 *Pearson Product-Moment Correlation Coefficients Between Measures Associated with Poverty*

Subscale	1	2	3	4	5	6	7	8	9
1. Abuse	--	.503**	.532**	.194	.281**	.179	.597**	.260*	.375**
2. Family Turmoil		--	.563**	.258*	.445**	.263*	.428**	.361**	.389**
3. Family Separation			--	.171	.190	.409**	.381**	.369**	.277**
4. Over Crowding				--	.429**	.227*	.347**	.277**	.282**
5. Noise					--	.215*	.373**	.333**	.540**
6. Substandard Housing						--	.240*	.564**	.305**
7. Food Insecurity							---	.353**	.367**
8. Time Receiving SNAP								--	.478**
9. Poor Neighborhood Quality									--

*p < .05 (2-tailed). ** p < .01 (2-tailed). ***p < .001 (2-tailed).

Neighborhood Quality, and the six factors from which Cumulative Stress was calculated, Abuse, Family Turmoil, Family Separation, Crowding, Noise, and Substandard Housing. Nearly all of these variables showed a significant positive

relationship. Notable among these relationships was that between Childhood Food Insecurity and Childhood Abuse ($r = 0.60$, $n = 95$, $p < .01$) and that between Poor Neighborhood Quality and Noise ($r = 0.54$, $n = 96$, $p < .01$). These significant positive associations begged the question of whether or not including the Childhood Food Insecurity scores and Poor Neighborhood Quality scores in the calculation of Cumulative Stress would be beneficial. In a further analysis, unreported here, this new composite variable was calculated and placed in the models; however, it did not have any significant impact on the pattern of results. Though this large composite did not provide additional insight into CSM, the correlations between the independent variables support an initial assumption of CSM, which is that stressful situations in poverty often occur together.

One final exploratory analysis split the data by gender in order to ascertain whether men and women display different relationships across these variables. Once again, any results obtained from this analysis would need to be interpreted with caution, because this further limits an already small dataset. As previously, this manipulation had no significant impact on the pattern of results. Interestingly, a marginal positive association was observed between Cumulative Stress and BMI among men ($r = 0.27$, $n = 43$, $p = 0.08$). This finding is in line with CSM and will be discussed further below.

DISCUSSION

The current study sought to investigate the influence of cumulative childhood stress on current BMI over and above that of childhood food insecurity, poor neighborhood quality, and the period of time receiving benefits from the SNAP program in childhood, and the interaction of the latter two variables. Additionally, this study sought to investigate the predictive value of each of these factors over that of health risks at birth. This was accomplished with a retrospective survey, in which college student participants were asked to self-assess their experiences from the first seventeen years of life. In addition to BMI, three other dependent variables were examined using hierarchical regression models. These were percent dietary energy intake from fat, servings of fruits and vegetables per day, and physical activity.

The results of this study were largely null and provided only tentative evidence for one model above the others. Initial correlational analyses revealed that the initial assumption on which the study was based, that childhood poverty was related to adult obesity, was not supported. The classification of childhood poverty was based on the participants' indication as to whether or not they had received free or reduced lunch through the School Lunch Program. Because this is a national program, based on income, it is a reasonable indicator of poverty. Furthermore, because we were able to include 47 participants that qualified as previously impoverished, it is unlikely that we observed these results because children growing up at higher SES tend not to attend college as adults. However, it may be the case that the poverty-obesity relationship is less consistent among a younger population and/or a lower weight population. Indeed,

with the exception of Wells and colleagues (2010), the large cohort studies reviewed above may be assuming a linear relationship that is apparent only because the results of the older/larger participants is so powerful. Wells and colleagues examined growth trajectories rather than differences in BMI. Future large cohort studies should separate their samples into age groups and examine the reliability of this relationship among younger persons. Without meeting the initial assumption of the poverty-obesity relationship, it is difficult to draw conclusions from the rest of the results. Nevertheless, the result of this study are discussed in the context of each model below.

In this study, the Cumulative Stress Model (CMS) was compared to three other models related to childhood poverty. The CSM predicted that cumulative stress during childhood and adolescence should increase both adult BMI and Percent Energy Intake from Fat (Wells et al., 2010). The hypothesis that Cumulative Childhood Stress would predict adult BMI over and above the other predictor variables was not supported by the results of the present study. Indeed, Cumulative Childhood Stress was neither significantly correlated with BMI, nor predictive of it in any of the hierarchical regression models. Additionally, Cumulative Stress was not correlated with, nor predictive of Percent Energy Intake from Fat in any model. An additional post hoc analysis that included only male participants did find a marginally significant positive relationship between childhood cumulative stress and adult BMI. Indeed, Wells and Colleagues (2010) did observe a stronger relationship between these two variables in men than in women. Though we may draw little evidence for CSM from this post hoc investigation,

this finding does provide an indication that a larger future study among men may be able to observe this relationship more reliably.

Examining this model from a different angle, one of the basic assumptions is that stressful experiences often occur together among impoverished children and that examining the cumulative effect of all of these variable is the most powerful way to predict health disparities. Although we did not find the predicted relationship with BMI, we did observe several significant correlation among the scores that made up the Cumulative Stress score as well as two other variables, which have not previously been examined. Indeed, suffering under food insecurity and/or living in a low quality neighborhood are likely also stressful experiences. Future research should consider the utility of including food insecurity and neighborhood quality in a cumulative stress score for predicting health outcomes.

Although not predicted by this model, Cumulative Stress was significantly, positively correlated with Physical activity. Physical activity has been shown to alleviate the negative physical consequences of chronic stress and to increase resilience against it. It may be the case that participants in this study, who have experienced a greater amount of Cumulative Stress, are more physically active because physical activity provides a measure of stress relief (McEwen, 2007).

The Food Choice Constraint Model (FCCM) was another model tested in the present study. The FCCM also predicted that Childhood Food Insecurity should lead to increased adult BMI, increased Percent Energy Intake from Fat, and decreased Servings of Fruits and Vegetables (Martin, 2005). The dietary fat and fruit/vegetable predictions

were not supported by the current results and food insecurity was not significantly correlated with nor predictive of either of these variables in any models tested. Food insecurity was shown to significantly predict adult BMI in one model, but the direction of this association was negative; thus greater food insecurity predicted a *lower* BMI score. Further correlational analysis of the relationship between Childhood Food Insecurity and BMI revealed a significant negative relationship only among those individuals prescreened as previously impoverished. Though far fewer, there were participants in the non-impoverished group that showed food insecurity. Further examination of the individual scores showed that this result is driven by four participants with BMI levels that were in the lowest quartile of the sample. Although these results are quite interesting and provocative, the sample size and the post hoc nature of these results limits the conclusions that may be drawn.

Future research should examine the relationship between childhood food insecurity and BMI in groups that include individuals at the lowest levels of food insecurity. Indeed, the current results may differ from those reported previously due to our sampling technique. The Short Form of the Household Food Security Scale is not designed to assess food insecurity associated with hunger (i.e., severe forms of food insecurity). However the screening procedure we used, which asked students if they had participated in the School Lunch Program as children, may have unintentionally selected those who had experienced severe food insecurity with hunger. This might explain the observed negative relationship we found between food insecurity and obesity. For these participants, food insecurity, which is a measure of one's concern or anxiety over food,

may be more indicative of childhood hunger experienced in the context of low income and School Lunch Program participation.. Food insecurity, which is a measure of one's concern or anxiety over food, may be more indicative of hunger if it is in the context of very low income, rather than the purchase of energy dense foods as the FCCM suggests.

The Neighborhood Affluence Model (NAM) was also tested in the present study. It predicted that Poor Neighborhood Quality should predict increased adult BMI, increased percent energy from fat, decreased fruit and vegetable intake, and decreased physical activity (Black & Macinko, 2008). Nevertheless, this model was also not supported by these data, as Neighborhood quality did not significantly predict any of these DVs in the predicted direction. Though not consistent in all models, low neighborhood quality was predictive of *lower* percentages of energy intake from fat and *higher* fruit and vegetable intake. These findings are not supported in the literature, however results inconsistent with NAM are not unprecedented. As noted above, Vartanian and Houser (2012) showed increased adult BMI for those who had an increased amount of time on SNAP and *higher* neighborhood affluence. Unlike the current study, a main effect of neighborhood quality was not observed in Vartanian and Houser's study (2012). Few conclusions may be drawn from this result because it was quite weak and inconsistent. However, future research should continue this inquiry. Whereas past literature has examined the effect of neighborhood affluence on concurrent BMI or diet quality, these two studies examined childhood neighborhood quality, and adult BMI and adult diet quality. The relationship between *childhood* neighborhood

quality and *adult* health may take a very different shape than the relationship between concurrent neighborhood quality and health.

Finally, a model based on the Feast and Famine Cycle (FFCM), presumed to result from participation in the SNAP program, was tested. The FFCM predicted that Time Receiving SNAP Benefits should increase adult BMI and potentially increase intake of both Percent Energy from Fat and Servings of Fruits and Vegetables. This follows the logic that having been on SNAP, one learns a consistent behavior of binging and/or overeating, regardless of energy density, when resources are plentiful. We presume with this prediction that the majority of those able to pay for a college course are also able to purchase a plentiful amount of food (Dinour et al., 2007). However, our results showed that length of SNAP participation was not significantly correlated with nor predictive of adult BMI in any of the models tested. Additionally, the planned hierarchical regression models for predicting Percent Energy Intake from Fat were nonsignificant. One model did show length of SNAP participation to be predictive of increased fruit and vegetable consumption, however this relationship became nonsignificant when other poverty indicators were added to the model. Further exploratory models with fewer predictors showed length of SNAP participation to be predictive of increased percentage of dietary energy from fat and increased fruit and vegetable intake. In summary, the present results provided modest support for the FFCM by showing that individuals who received increased SNAP benefits as children are currently eating increased amounts of both fat and fruits and vegetables. Indeed, this is the only model that would predict an increased intake of both types of food, which

reflects a general increase in eating when resources are plentiful. As noted above, we can make few conclusions from these models because they are post hoc and the sample is limited. However, these results are not entirely unprecedented. As noted above, Martin and colleagues (2012), showed experimental evidence that SNAP participants, in a variety of stores in Hartford, CT, purchased more fruits when they were made available than did nonparticipants. These models provide us with an indication of what best to examine in future research. FFCM's prediction remains ambiguous as to whether or not adults that were impoverished as children are more prone to simply overeating in general when resources are plentiful (e.g. when one has a meal plan on a college campus) or if a binging and restriction behavior is maintained in adulthood. Because binging behavior was not measured in this study, we cannot draw any conclusions as to the nature of this relationship. Future investigations of the Feast and Famine Cycle Model, as it applies to children, should include an assessment of adult binging behavior in order to better assess this model.

Additionally, the only consistently significant predictors of BMI were age, birth weight, and Father's overweight. In the case of Father's overweight, we are cautious in drawing any conclusions from these results since it is possible that those who are especially obese are simply more likely to categorize their parents as overweight. Furthermore, of the 97 participants in this study, a small minority reported Maternal (N = 3) and/or Paternal (N = 8) Overweight/Obesity, which does not reflect the rates of overweight and obesity in the adult Caucasian population. Birth Weight, by contrast, was reported by far more participants and there seem to be few alternative explanations for its

association with adult obesity. However, the current study found a *negative* relationship between reported Birth Weight and adult BMI, whereas previous research has typically reported a positive relationship (Parsons et al., 1999, Rooney, Mathiason, & Schauberger, 2010, & Morandi et al., 2012). However, the current sample included only 58 participants who reported their birth weight. Furthermore, only 8 of those participants reported a birth weight above the recommended cut off of 8.82 lbs. It is possible that the positive relationship would have been observed had there been more participants with higher birth weights. Low birth weight has been linked to an increased risk of abdominal obesity, which may also account for the relationship found in the present study (Laitinen, Pietilainen, Wadsworth, Sovio, & Jarvelin, 2004).

There were a number of limitations to this study. First and foremost, this study included a very small sample size given the large number of variables included in the analyses. This was unavoidable given the available subject pool. Few students met the prescreen criteria for impoverishment during childhood (N = 64), making a larger sample that maintained the oversampling of one group impossible. Furthermore, this study may have been limited by the young average age of the participants. Although we were specifically interested in studying childhood factors among college students, few previous studies have confirmed the poverty-obesity relationship among this, although it has been repeatedly confirmed in the general population. The original study, on which this one was based, showed this relationship among 17 year olds; however, that was a study of growth trajectories, not BMI between groups (Wells et al., 2012). Additionally, this study observed a consistent positive relationship between age and BMI. Therefore, it

may be reasonable to assume that an older participant sample, with higher average BMI scores, may be needed to demonstrate significant relationships among the variables proposed by the models we attempted to test. There was an additional limitation in the ability of this measure to access variables related to health at birth. Indeed, participants were unable or unwilling to characterize their parents as overweight or obese. This may result from a basic misunderstanding of the terms (i.e., the belief that "obese" categorizes a much larger body size than is accurate). However, it is also possible that participants did not want to categorize their parents in this way due to a negative social stigma associated with obesity (Crandall, 1994).

Future research should continue to investigate the predictive validity of these models and the poverty-obesity relationship that we attempted to test in the present study. However, based on the current results a larger sample, spanning a wider age-range, and including a wider range of adult BMIs, should be used. Additionally, future research in this area should investigate a superior method of examining health at birth, perhaps changing the language of the questions in a way that eliminates this social stigma. Another possibility would be to conduct this retrospective analysis in a hospital, which may have birth and other health records available. This would likely lead to more accuracy and maintain the goal of convenience in conducting these studies. As noted above, the results have left the relationship between childhood food insecurity and adult BMI quite unclear, potentially due to some participants being closer to an extreme level of food insecurity than we were able to measure. The USDA (2012a) has other, more extensive food insecurity scales available that are designed to assess food insecurity with

and without hunger, which may be of use in future research. Although there is certainly room for improvement, the method of assessment in this study remains a benefit in spite of these results. Using a survey like this allows for quick and convenient assessments. Future research should attempt administering this questionnaire, with improvements to two scales for better reliability, to an online sample with self-reported heights and weights in order to ascertain if it is reliable and useful in that format. Overall, in spite of our attempt to test a number of different theoretical models and to evaluate a broad range of potentially important predictors, many questions remain unanswered about the nature of the experiences of children who grow up in poverty and how this may impact adult overweight and obesity, and thereby adult health.

REFERENCES CITED

Bell, E. A. & Rolls, B. J. (2001). Energy density of foods affects energy intake across multiple levels of fat content in lean and obese women. *American Journal of Clinical Nutrition 73*(6), 1010-1018.

Black, J., & Macinko, J. (2008). Neighborhoods and obesity. *Nutrition Reviews*, *66*(1), 2-20.

Blumberg, S. J., Bialostosky, K., Hamilton, W. L., & Briefel, R. R. (1999). The Effectiveness of a Short Form of the Household Food Security Scale. *American Journal Of Public Health*, *89*(8), 1231-1234.

Centers for Disease Control and Prevention (CDC). Aug. 13, 2012. Overweight and Obesity: Adult Obesity Facts. Retrieved from: http://www.cdc.gov/obesity/data/adult.html.

Chen, Y., & Qian, L. (2012). Association between lifetime stress and obesity in Canadians. *Preventive Medicine*, *55*(5), 464-467. doi:10.1016/j.ypmed.2012.08.013

Craig, C. L., Marshall, A. L., Sjöström, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E.,…. Pekka, O. (2003). International Physical Activity Questionnaire: 12-Country Reliability and Validity. *Medicine & Science In Sports & Exercise*,*35*(8), 1381-1395.

Crandall, C. S. (1994). Prejudice Against Fat People – Ideology and Self – Interest. *Journal of Personality and Social Psychology 66*(5), 882-894. doi: 10.1037//0022-3514.66.5.882

Dallman, M. F., Pecoraro, N. C., & la Fleur, S. E. (2005). Chronic stress and comfort foods: self-medication and abdominal obesity. *Brain, Behavior & Immunity*, *19*(4), 275-280. doi:10.1016/j.bbi.2004.11.004

Dahri, S., Snoeck, A., Reusens-Billen, B., Ramacle, C., Hoet, J. J. (1991). Islet Function in Offspring of Mothers on Low-Protein Diet During Gestation. *Diabetes 40*(2), 115-120. Doi: 10.2337/diab.40.2.S115

Dinour, L. M., Bergen, D., & Yeh, M. (2007). The Food Insecurity–Obesity Paradox: A Review of the Literature and the Role Food Stamps May Play. *Journal Of The American Dietetic Association*, *107*(11), 1952-1961. doi:10.1016/j.jada.2007.08.006

Dong, M., Anda, R. F., Dube, S. R., Giles, W. H., & Felitti, V. J. (2003). The relationship of exposure to childhood sexual abuse to other forms of abuse, neglect, and household dysfunction during childhood. *Child Abuse & Neglect*, *27*(6), 625-639. doi:10.1016/S0145-2134(03)00105-4

Drewnowski, A., & Specter, S. E. (2004). Poverty and Obesity: The Role of Energy Density and Energy Costs. *American Journal of Clinical Nutrition 79*(1), 6 – 16.

Evans, G. W. (2003). A Multimethodological Analysis of Cumulative Risk and Allostatic Load Among Rural Children. *Developmental Psychology,39*(5), 924-933.

Evans, G. W. (2004). The Environment of Childhood Poverty. *American Psychologist, 59*(2), 77-92. doi:10.1037/0003-066X.59.2.77

Evans, G. W., & Wells, N. M. (2000). Housing Quality and Mental Health. *Journal Of Consulting & Clinical Psychology*, *68*(3), 526.

Felitti, V. J., Anda, R. F., Nordenberg, D., Williamson, D. F., Spitz, A. M., Edwards, V.,... Marks, J. S. (1998). Relationship of Childhood Abuse and Household Dysfunction to Many of the Leading Causes of Death in Adults: The Adverse Childhood Experiences (ACE) Study. *American Journal of Preventive Medicine 14*(4), 245-258. Doi: 10.1016/S0749-3797(98)00017-8

Flegal, K. M., Carroll, M. D., Ogden, C. L., Curtin, L. R. (2010). Prevalence and Trends in Obesity Among US Adults, 1999-2008. *Jama-Journal of the American Medical Association 303*(3), 235-241. DOI:10.1001/jama.2009.2014.

IPAQ: International Physical Activity Questionnaire. January 12, 2012. Downloadable Questionnaires: Short Last 7 Days Self-Administered Format. Retrieved from: https://sites.google.com/site/theipaq/questionnaire_links.

Jansson, T. & Powell, T. L. (2007). Role of the placenta in fetal programming: underlying mechanisms and potential interventional approaches. *The Biochemical Society 113*, 1-13. Doi: 10.1042/CS20060339.

Jilcott, S. B., Wall-Bassett, E. D., Burke, S. C., & Moore, J. B. (2011). Associations between Food Insecurity, Supplemental Nutrition Assistance Program (SNAP) Benefits, and Body Mass Index among Adult Females. *Journal Of The American Dietetic Association,111*(11), 1741-1745. doi:10.1016/j.jada.2011.08.004

Kilmer, R. P., Cowen, E. L., Wyman, P. A., Work, W. C., & Magnus, K. B. (1998) Differences in Stressors Experienced by Urban African American, White, and Hispanic Children. *Journal of Community Psychology 26*(5), 415-428.

Laitinen, J., Pietilainen, K., Wadsworth, M., Sovio, U., & Jarvelin, M. R. (2004). Predictors of Abdominal Obesity among 31 – Y – Old Men and Women Born in Northern Finland in 1966. *European Journal of Clinical Nutrition 58*(1), 180 – 190. doi:10.1038/sj.ejcn.1601765.

Larson, N. I., & Story, M. T. (2011). Food Insecurity and Weight Status Among U.S. Children and Families: A Review of the Literature. *American Journal Of Preventive Medicine*, *40*(2), 166-173. doi:10.1016/j.amepre.2010.10.028

Ledikwe, J. H., Blanck, H.M., Khan, L. K., Serdula, M. K., Seymour, J. D., Tohill, B. C., & Rolls, B. J. (2006). Dietary energy density is associated with energy intake and weight status in US adults. *American Journal of Clinical Nutrition 83*(6), 1362-1368.

Martin, K., Havens, E., Boyle, K., Matthews, G., Schilling, E., Harel, O., & Ferris, A. (2012). If you stock it, will they buy it? Healthy food availability and customer purchasing behaviour within corner stores in Hartford, CT, USA. *Public Health Nutrition*, *15*(10), 1973-1978. doi:10.1017/S1368980011003387

Martin, S. S. (2005) From Poverty to Obesity: Exploration of the Food Choice Constraint Model and the Impact of an Energy-Dense Food Tax. *The American Economist 49*(2), 78-86.

McEwen, B. S. (2007). Physiology and Neurobiology of Stress and Adaptation: Central Role of the Brain. *Physiological Reviews 87*(3), 873 – 904. doi: 10.1152/physrev.00041.2006.

Mendoza, J. A., Drewnowski, A., Cheadle, A., & Christakis, D. A. (2006). Dietary Energy Density Is Associated with Selected Predictors of Obesity in U.S Children. *Journal Of Nutrition*, *136*(5), 1318-1322.

Morandi A, Meyre D, Lobbens S, Kleinman K, Kaakinen M, et al. (2012) Estimation of Newborn Risk for Child or Adolescent Obesity: Lessons from Longitudinal Birth Cohorts. *PLoS ONE 7*(11): e49919. doi:10.1371/journal.pone.0049919

National Cancer Institute. August 3, 2011. Applied Researcher: Multifactor Screener in the 2000 NHIS Cancer Control Supplement (CCS). Retrieved from: http://appliedresearch.cancer.gov/surveys/nhis/multifactor/.

Oken, E. & Gillman, M. W. (2003). Fetal Origins of Obesity. *Obesity Research 11*(4), 496-506.

Olson, C. M., Bove, C. F., & Miller, E. O. (2007). Growing up poor: Long-term implications for eating patterns and body weight. *Appetite*, *49*(1), 198-207. doi:10.1016/j.appet.2007.01.012

Pearson, N., Timperio, A., Salmon, J., Crawford, D., & Biddle, S. J. H. (2009). Family influences on children's physical activity and fruit and vegetable consumption. *International Journal of Behavioral Nutrition and Physical Activity 6*, 34. DOI: 10.1186/1479-5868-6-34.

Parsons, T. J., Powers, C. C., Logan, S. S., & Summerbell, C. D. (1999). Childhood predictors of adult obesity: a systematic review. *International Journal Of Obesity & Related Metabolic Disorders*, *23*S1-S107.

Poulton, R., Caspi, A., Milne, B., Thomson, W., Taylor, A., Sears, M., & Moffitt, T. (2002). Association between children's experience of socioeconomic disadvantage and adult health: a life-course study. *Lancet*, *360*(9346), 1640.

Rooney, B. L., Mathiason, M. A., & Schauberger, C. W. (2010). Predictors of Obesity in Childhood, Adolescence, and Adulthood in a Birth Cohort. *Matern Child Health J 115,* 1166 – 1175. doi: 10.1007/s10995-010-0689-1.

Senese, L. C., Almeida, N. D., Fath, A. K., Smith, B.T., & Loucks, E. B. (2009). Associations Between Childhood Socioeconomic Position and Adulthood Obesity. *Epidemiologic Reviews 31*(1), 21 – 51. DOI: 10.1093/epirev/mxp006.

Thompson, F. E., Midthune, D., Subar, A. F., Kahle, L. L., Schatzkin, A., & Kipnis, V. (2004). *Public Health Nutrition 7*(8), 1097-1106. DOI: 10.1079/PHN2004642.

Townsend, M. S., Peerson, J., Love, B., Achterberg, C., & Murphy, S. P. (2001). Food Insecurity Is Positively Related to Overweight in Women. *Journal Of Nutrition*, *131*(6), 1738.

United States Census Bureau. March 31, 2011. American Housing Survey (AHS): Codebook for the American Housing Survey. Retrieved from: http://www.huduser.org/portal/datasets/ahs/AHS_Codebook.pdf.

United States Department of Agriculture (USDA). August 15, 2012a. Food Security in the US: Survey Tools. USDA Economic Research Service. Retrieved from: http://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-us/survey-tools.aspx.

United States Department of Agriculture (USDA). September 04, 2012b. Food Security in the U.S.: Definitions of Food Security. USDA Economic Research Service. Retrieved from: http://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-us/definitions-of-food-security.aspx#.UUIEHRysiSo.

Vartanian, T., & Houser, L. (2012). The Effects of Childhood SNAP Use and Neighborhood Conditions on Adult Body Mass Index. *Demography*, *49*(3), 1127-1154. doi:10.1007/s13524-012-0115-y

Wells, N. M., Evans, G. W., Beavis, A., & Ong, A. D. (2010). Early Childhood Poverty, Cumulative Risk Exposure, and Body Mass Index Trajectories Through Young Adulthood. *American Journal Of Public Health*, *100*(12), 2507-2512. doi:10.2105/AJPH. 2009.184291

Williamson, D. F., Thompson, T. J., Anda, R. F., Dietz, W. H. & Felitti, V. (2002). Body Weight and Obesity in Adults and Self-Reported Abuse in Childhood. *International Journal of Obesity 26*, 1075 – 1082.

APPENDICES

APPENDIX A

BEHAVIORAL QUESTIONNAIRE

PART 1. Please think about what you usually ate or drank during the past month, that is, the past 30 days. Please read each question carefully and:

- **Report how many times per day, week, or month you ate each food.**
- **Choose the best answer for each question.**
- **Mark only one response for each question.**

1. How many times per **day**, **week**, or **month** did you **usually** eat **cold cereals**?

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

2. How many times per **day**, **week**, or **month** did you use **milk**, either to drink or on cereal?

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

2a. What kind of milk did you **usually** use? (Pick the one you used most often).

1. Whole milk
2. 2% fat
3. 1% fat
4. 1/2% fat
5. Non-fat or skim
0. DID NOT DRINK MILK IN PAST MONTH.

3. How many times per **day**, **week**, or **month** did you **usually** eat **bacon or sausage**, not including low fat, light, or turkey varieties?

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

4. How often did you eat **hot dogs** made of beef or pork?

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

5. How often did you eat **whole grain bread** including toast, rolls, and in sandwiches? Whole grain breads include whole wheat, rye, oatmeal, and pumpernickel.

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

6. How often did you drink **100% fruit juice** such as orange, grapefruit, apple, and grape juices? Do **not** count **fruit drinks** such as Kool-Aid, lemonade, cranberry juice cocktail, Hi-C, and Tang.

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

7. How often did you eat **fruit? Count** fresh, frozen, or canned fruit. **Do not count** juices.

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

8. How often did you use **regular fat salad dressing or mayonnaise**, including on salad and sandwiches? Do **not** include low-fat, light, or diet dressings.

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

9. How often did you eat **lettuce or green leafy salad**, with or without other vegetables?

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

10. How often did you eat **French fries, home fries,** or **hash brown potatoes**?

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

11. How often did you eat **other white potatoes**? **Count** baked potatoes, boiled potatoes, mashed potatoes, and potato salad. Do **not** include yams or sweet potatoes.

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

12. How often did you eat **cooked dried beans**, such as refried beans, baked beans, bean soup, and pork and beans?

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

13. How often did you **usually** eat **other vegetables**?

COUNT:
- Any form of vegetable—raw, cooked, canned, or frozen.

DO NOT COUNT:
- Lettuce salads
- White potatoes
- Cooked dried beans
- Rice

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

14. How many times per **day**, **week**, or **month** did you **usually** eat **any kind of pasta**? **Count** spaghetti, noodles, macaroni and cheese, pasta salad, rice noodles, soba, and any other kind of pasta.

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

15. How often did you eat **peanuts**, **walnuts**, **seeds**, or **other nuts**? Do **not** include peanut butter.

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

16. How often did you eat **regular fat potato chips, tortilla chips, or corn chips**? Do **not** include low-fat chips.

☐	☐	☐	☐	☐	☐	☐	☐	☐
NEVER	1-3 times last month	1-2 times per week	3-4 times per week	5-6 times per week	1 time per day	2 times per day	3 times per day	4 or more times per day

We are interested in finding out about the kinds of physical activities that people do as part of their everyday lives. The questions will ask you about the time you spent being physically active in the **last 7 days**. Please answer each question even if you do not consider yourself to be an active person. Please think about the activities you do at work, as part of your house and yard work, to get from place to place, and in your spare time for recreation, exercise or sport.

Think about all the **vigorous** activities that you did in the **last 7 days**. **Vigorous** physical activities refer to activities that take hard physical effort and make you breathe much harder than normal. Think *only* about those physical activities that you did for at least 10 minutes at a time.

1. During the **last 7 days**, on how many days did you do **vigorous** physical activities like heavy lifting, digging, aerobics, or fast bicycling?

   _____ **days per week**

   ☐ No vigorous physical activities → ***Skip to question 3***

2. How much time did you usually spend doing **vigorous** physical activities on one of those days?

   _____ **hours per day**

   _____ **minutes per day**

   ☐ Don't know/Not sure

Think about all the **moderate** activities that you did in the **last 7 days**. **Moderate** activities refer to activities that take moderate physical effort and make you breathe somewhat harder than normal. Think only about those physical activities that you did for at least 10 minutes at a time.

3. During the **last 7 days**, on how many days did you do **moderate** physical activities like carrying light loads, bicycling at a regular pace, or doubles tennis? Do not include walking.

   _____ **days per week**

   ☐ No moderate physical activities → ***Skip to question 5***

4. How much time did you usually spend doing **moderate** physical activities on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

Think about the time you spent **walking** in the **last 7 days**. This includes at work and at home, walking to travel from place to place, and any other walking that you have done solely for recreation, sport, exercise, or leisure.

5. During the **last 7 days**, on how many days did you **walk** for at least 10 minutes at a time?

_____ **days per week**

☐ No walking → ***Skip to question 7***

6. How much time did you usually spend **walking** on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

The last question is about the time you spent **sitting** on weekdays during the **last 7 days**. Include time spent at work, at home, while doing course work and during leisure time. This may include time spent sitting at a desk, visiting friends, reading, or sitting or lying down to watch television.

7. During the **last 7 days**, how much time did you spend **sitting** on a **week day**?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

APPENDIX B

HISTORY QUESTIONNAIRE

History Questionnaire

The following survey will ask you a variety of questions about childhood experiences. All of these questions pertain to when you were growing up, which entails the first seventeen years of your life. Please be aware that you may leave any question blank if you wish. If you are unsure of which answer to pick, please pick the **BEST** answer available that most closely represents your experience.

Thank you for your participation!

All of the following questions refer to while you were growing up, during the first 17 years of your life. Circle the BEST answer.

Did a parent or other adult in the household frequently swear at, insult, or put you down?

Yes No

Did a parent or other adult in the household frequently act in a way that made you afraid that you would be physically hurt?

Yes No

Did a parent or other adult in the household frequently push, grab, shove, or slap you?

Yes No

Did a parent or other adult in the household frequently hit you so hard that you had marks or were injured?

Yes No

Did an adult or person at least 5 years older than you ever touch or fondle you in a sexual way?

Yes No

Did an adult or person at least 5 years older than you ever have you touch their body in a sexual way?

Yes No

All of the following questions refer to while you were growing up, during the first 17 years of your life. Circle the BEST answer.

Did you live with anyone who was a problem drinker or alcoholic?

Yes No

Did you live with anyone who used street drugs (This refers to any illegal intoxicants or pharmaceuticals not prescribed by a physician)?

Yes No

Was a household member depressed or mentally ill?

Yes No

Did a household member attempt suicide?

Yes No

Was one or both of your parents (or stepparent, caregiver, etc.) sometimes, often, or very often pushed, grabbed, slapped, or had something thrown at him/her/them?

Yes No

Was one or both of your parents (or stepparent, caregiver, etc.) ever threatened with, or hurt by, a knife or gun?

Yes No

Did a household member ever go to prison?

Yes No

Did your parents or guardians often or very often have arguments or fights?

Yes No

All of the following questions refer to while you were growing up, during the first 17 years of your life. Circle the BEST answer.

Did a close family or household member die while you were living at home?

Yes No

Did your parents get divorced?

Yes No

Was your family ever known to protective/preventive services?

Yes No

While you were growing up, did you take care of other children in the family?

Yes No

Have you been in a foster home?

Yes No

While you were growing up, did you live with a relative or a friend?

Yes No

All of the following questions refer to while you were growing up, during the first 17 years of your life. Circle the BEST answer.

Please indicate how many rooms were in your household while you were growing up? (if you moved or resided in more than one house, please refer to wherever you lived the longest). This could include bedrooms, bathrooms, kitchens, dens, dining rooms, living rooms, and/or any regularly used room in the home.

Number of rooms in household _____

How many people resided in the home you indicated in the previous question? (if some people moved out please indicate the highest number that you ever experienced)

Number of people in household _____

Did you often hear neighbors through the floors, walls or ceilings of your home?

Yes No

Did your neighborhood have bothersome street noise or heavy traffic?

Yes No

Was the loudness of the noise inside of your home bothersome?

Yes No

Was the loudness of the noise around the outside of your home bothersome?

Yes No

All of the following questions refer to while you were growing up, during the first 17 years of your life. Circle the BEST answer.

In the inside walls or ceilings of your home, were there any open holes or cracks wider than the edge of a dime that persisted for six months or longer?

Yes No

Did any of the windows in your home have broken glass that persisted for six months or longer?

Yes No

While you were living there did water ever leak into your home DIRECTLY FROM THE OUTSIDE that persisted for six months or longer? (For example, through the roof, outside walls, basement or any closed windows or skylights during inclement weather)?

Yes No

While you were living there, did water leak in from broken pipes, water heaters, backed up plumbing, or other equipment failure inside your home that persisted for six months or longer?

Yes No

Did the common stairways located inside, or attached to the outside, of your home have any loose, broken or missing steps that persisted for six months or longer?

Yes No

Did the roof surface of your home sag or appear uneven for six months or longer?

Yes No

Did the outside walls of your home slope, lean, buckle or slant for six months or longer?

Yes No

Was any of the electrical wiring in the finished areas of your home exposed from the walls for six months or longer? (Exclude appliance cords, extension cords, chandelier cords, phone, antenna, cable TV wires, etc.)

Yes No

All of the following questions refer to while you were growing up, during the first 17 years of your life. Circle the BEST answer.

In any 12 month period, did the food that your family bought just not last and you did not have money to get more?

Never True Sometimes True Often True

In any 12 month period, could your family not afford to eat balanced meals?

Never True Sometimes True Often True

In any 12 month period, did your family ever cut the size of your meals or skip meals because there was not enough money for food?

Yes No

If you answered yes to the previous question above, how often did this happen?

Not Applicable In only 1 or 2 months Some months but not every month Almost every month

In any 12 month period, did you ever eat less than you felt you should because there was not enough money for food?

Yes No

In any 12 month period, were you ever hungry but did not eat because there was not enough money for food?

Yes No

While you were growing up, did your family ever receive benefits from the Supplemental Nutrition Assistance Program (also known as SNAP or Food Stamps)?

Yes No

If you answered yes to the previous question, for approximately how long did you receive these benefits?

Years_____ Months_____

All of the following questions refer to while you were growing up, during the first 17 years of your life. Circle the BEST answer.

In your opinion, was the tap water in your home safe for cooking and drinking?

Yes No

Were there any open spaces, such as parks, woods, farms or ranches within a block ($1/8^{th}$ of a mile) of your home?

Yes No

Were there any youth recreational organizations within 15 minutes of your home (for example YMCA, youth center, boys and girls club, or church affiliated youth program)?

Yes No

Was there safe public transportation available for your neighborhood?

Yes No

Did you have a satisfactory grocery store within 15 minutes of your home?

Yes No

To the best of your knowledge, did your neighborhood tend to have a high crime rate, for example, burglary, robbery, theft, rape, or murder?

Yes No

Did there tend to be a significant amount of trash, litter, or junk in the area within a block ($1/8^{th}$ mile) of your home?

Yes No

How would you rate your neighborhood overall on a scale of 1-10?

1 = worst, 10=best _____

Please indicate the best answer the following questions to the best of your knowledge.

Gender: Male Female

Please indicate your age: _____ years

Which of the following best describes your race/ethnicity (circle one)?

- White/Caucasian
- African American
- Hispanic/Latino
- Native American or Alaskan Native
- Asian/Pacific Islander
- Middle Eastern
- Multiracial

What did you weigh when you were born?

- Birth weight _____ pounds
- Do not know

While attending grade school, did you ever receive free or reduced lunch through the School Lunch Program?

Yes No

To the best of your knowledge was your mother overweight or obese when you were born (aside from weight gained during pregnancy)?

Yes No Do not know

To the best of your knowledge was your father overweight or obese when you were born?

Yes No Do not know

To the best of your knowledge did your mother smoke <u>before</u> she became pregnant with you?

Yes No Do not know

To the best of your knowledge did you mother smoke <u>while</u> she was pregnant with you?

Yes No Do not know

APPENDIX C

RESEARCHER QUESTIONNAIRE

Researcher questionnaire

Your name _____

Subject number _____

Study number_____

Study room number _____

Participant Height_____

Participant Weight_____

Time_____

Any questions the participant asked?

_____

_____

_____

_____

_____

Additional Comments

_____

_____

_____

_____

_____