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Testing an Ecological Model of Obesity Among School-Age Children: Identifying Targets for Tailored Intervention

Dorothy Mcleod Loren

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LOYOLA UNIVERSITY CHICAGO

TESTING AN ECOLOGICAL MODEL OF OBESITY AMONG SCHOOL-AGE CHILDREN: IDENTIFYING TARGETS FOR TAILORED INTERVENTION

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BY

DOROTHY MCLEOD LOREN

CHICAGO, IL

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ABSTRACT

Childhood obesity rates remain historically high in the US. One way to conceptualize the many factors that contribute to obesity is through the use of an ecological model. There is a particular need to adapt and test this type of comprehensive model among vulnerable racial/ethnic and socioeconomic groups. Using a large sample of US youth drawn from the ECLS-K:2011 (N=8,225), this project first investigated an ecological model of childhood obesity from kindergarten to second grade, including factors such as child physical activity, child screen time, child bedtime, family physical activity, family food insecurity, family meals, and neighborhood safety. Then, it compared the contributions of each individual factor across racial/ethnic, socioeconomic, and income-to-needs groups, concurrently and longitudinally.

Among the full sample, the largest standardized effect on weight was for income-to-needs ratio. Moving from above to below 200% of the poverty line resulted in an increase of 0.12 standard deviations in zBMI. Multigroup analyses indicated that there were no differences in model fit by socioeconomic status or sex. However, there was a significant difference in model fit based on race/ethnicity. Among Latino youth, income-to-needs ratio was a significant negative predictor of kindergarten zBMI; however, this effect was not significant among Black youth. Overall, findings highlighted the impact of income-to-needs ratio, as children of families who fell below 200% of the poverty line were more likely to weigh more.
CHAPTER ONE

INTRODUCTION

Since the turn of the millennium, childhood obesity has been labeled an “epidemic” in the United States (Kimm & Obarzanek, 2002), attracting attention in both medical research (e.g., Ebbeling, Pawlak, & Ludwig, 2002; Lobstein et al., 2015) and popular press (e.g., Kalb & Springen, 2005; Wallis, 2004). Despite increases in awareness and advocacy efforts, recent studies show that obesity rates remain historically high for school-aged children and continue to rise among adolescents (Ogden et al., 2016). Obesity is an immediate and longitudinal risk factor for a variety of negative health outcomes (Biro & Wien, 2010) and incurs huge individual and societal costs when occurring so early in life (John, Wenig, & Wolfenstetter, 2010). For example, obesity during childhood is associated with the development of childhood chronic diseases, such as sleep apnea, glucose intolerance, and hypertension (Dietz, 1998), and obesity during adulthood is correlated with the development of diabetes, heart disease, and certain cancers (Oza-Frank & Cunningham, 2010). Meanwhile, obesity during these two phases of life is connected: obesity in childhood and adolescence is one of the strongest risk factors for adult obesity, which is itself associated with mortality (Dietz, 1998). Even more troubling, studies have found that childhood obesity may be related to negative health outcomes later in life even when controlling for obesity in adulthood (Must, Jacques, Dallal, Bajema, & Dietz, 1992). In light of these concerns within both the individual and public health spheres, pinpointing determinants of youth obesity has become one of the highest priorities in child health (Story,
Sallis, & Orleans, 2009).

There are a multitude of factors theorized to contribute to early child obesity development. One way to conceptualize these many factors that contribute to the complex process of childhood obesity, in context, is through the use of an ecological model. When Bronfenbrenner published the first ecological model in 1979, he highlighted that child development is affected by everything in the child’s environment by dividing environmental aspects into five levels (e.g., microsystem, mesosystem, exosystem, macrosystem, and chronosystem), which were conceptualized as concentric spheres or layers of an onion with the most direct influences closer to the center. Although they did not utilize Bronfenbrenner’s proposed five levels, Davison and Birch (2001) were the first to publish a similar model applying ecological system theory to childhood obesity (see Figure 1). Their model uses the framework as a means to summarize the state of the research assessing various predictors of child overweight, with a similar concentric approach and levels indicating the least to most direct influences closer to the center of the “onion.” In their paper, the authors conclude that childhood obesity is indeed a phenomenon well explained through the use of an ecological systems lens, and that the representation of obesity development is incomplete without consideration for factors at the child, family, and community/demographic/societal levels. A decade after Davison and Birch first published their model, Harrison and colleagues (2011) expanded on the ecological model of child obesity by proposing the presence of six contextual levels (the “Six-C’s Model,” for “cell,” “child,” “clan,” “community,” “country,” and “culture;” see Figure 2). By further subdividing the ecological model into these six contextual levels, and by re-integrating Bronfenbrenner’s “chronosphere,” or the impact of the passage of time, these authors offer an expansion to the contextual factors that research on child obesity should consider as contributing factors.
Figure 1. Ecological model of childhood weight status (Davison & Birch, 2001)

Figure 2. Six c’s model of childhood obesity (Harrison et al., 2011)
The inclusion of the time variable in Harrison and colleagues’ (2011) model highlights the need to identify at which point in a child’s life the ecological model is applied, and how it can be tested longitudinally. In fact, there are several “critical periods” during which child obesity development may be the most predictive of persistent obesity and related complications. Among these critical periods is the so-called “adiposity rebound” between five and seven years of age (Dietz, 1998; Rolland-Cachera et al., 1984). This rise in adiposity that occurs around the child’s sixth year of life has been associated with more severe and harmful trajectories of obesity development (Dietz, 1998). Many studies have demonstrated that children who demonstrate earlier adiposity rebound are more likely to develop obesity, alongside other detrimental health outcomes such as insulin resistance, diabetes, and high blood pressure, in later child- and adulthood (Ip et al., 2017). However, other studies have called into question whether “early adiposity rebound” may simply indicate those children whose excess weight is developing fastest, those whose sex- and age-adjusted body mass index percentile is already high and increasing quickly (Cole, 2004). By either explanation, the first years of elementary school seem to be time during which weight development patterns are predictive of future obesity.

Furthermore, it has been suggested that the kindergarten age is a particularly impactful time for obesity intervention, as children’s obesogenic behaviors are thought to still be malleable and attendance in kindergarten itself presents the opportunity for widespread and standardized health promotion strategies (Manios et al., 2014). Therefore, all of the evidence suggests that the early elementary school years are a particularly salient time at which to apply ecological models in order to not only predict future weight patterns but also to identify key obesogenic factors on which to effectively intervene.
In addition to expanding the contexts that the ecological model contains, Harrison and colleagues (2011) also identify the need to adapt and test the model among high-risk populations, particularly those of vulnerable racial/ethnic or socioeconomic groups. Indeed, the idea that specific determinants of obesity should be identified as targets for tailored intervention within particularly vulnerable populations is a growing movement within the field (Caprio et al., 2008). However, despite the utility of these ecological models in detailing the various factors that describe how obesity develops and is maintained, and in creating the opportunity to draw large-scale comparisons across groups, there have been few studies that have actually empirically tested these theories. One exception is a study by Dev and colleagues (2013), who examined 22 risk factors, organized into an ecological framework, and their association with overweight/obesity development among children aged 2-5. These authors found that that child sleep duration, parental feeding style, and parent BMI were significantly associated with overweight. Another exception is an earlier study by O’Brien and colleagues (2007), who explored growth patterns of obesity over time and how these differed based on three levels of factors (sociocultural or demographic, quality of the child's home environment, and proximal child experience), finding that there were significant effects of home environment (i.e. overweight children were more likely to have less sensitive mothers) and child experience (overweight children were more likely to watched more television and less likely to engage in physical activity). However, these studies did not include the possibility of intercorrelations among the contributing factors or consider possible interaction effects by the racial/ethnic or socioeconomic groups, and to our knowledge, this has not been explored by any study to date.

Therefore, the current project aims to investigate the fit of a proposed ecological model of childhood obesity, measured using zBMI (see Figure 3), drawing on a large, national sample
of elementary school age children. The model proposed in the current study includes factors within the three innermost levels of an ecological model: individual, family, and community. Individual level factors include physical activity, sedentary behavior/screen time, and bedtime, while those that fall at the family level include family physical activity, family mealtimes, and family food insecurity. Finally, one factor that will be examined, neighborhood safety, falls at the community level. The literature that supports the inclusion of these factors in the proposed model is reviewed in subsequent sections. Furthermore, this study will examine the relative importance of each of these individual factors and levels of factors (i.e., individual, family, community) for \( z \text{BMI} \) development. Finally, in order to address the need to identify targets for tailored obesity intervention, this study will also consider how the proposed model fits among children who vary in terms of risk for obesity based on race/ethnicity, socioeconomic status/income-to-needs ratio, and sex.

Figure 3. Proposed ecological model of \( z \text{BMI} \) in the current study
Individual Factors

The individual child level contributors to obesity are perhaps the most studied. While factors at the family and community level almost certainly affect the behaviors discussed in this section, it is clear from an ecological standpoint that individual-level factors are those most closely and directly linked to childhood obesity. Some of the factors with the highest degree of research support, which will be tested for this study, are children’s physical activity, screen time/sedentary behavior, and bedtime/sleep habits. Notably, while Davidson and Birch (2001) include both child risk behaviors, such as these, and child characteristics, such as sex and age, at the individual level, they clearly distinguish between the influence of the two. These authors suggest that the behaviors (shown in upper case lettering in Figure 1) are the actionable risk factors, while the characteristics (shown in italic lettering in Figure 1) interact with child risk factors and contextual factors to influence the development of overweight as moderator variables. Therefore, this study utilizes child characteristics variables (e.g., racial/ethnic background, income-to-needs ratio, and sex) as both control variables and moderators at each level of the model, which is described in detail at the end of this section.

Physical Activity

One of the behaviors most commonly associated with childhood obesity is physical activity. This is conceptualized as a primary factor in obesity due to the theory that obesity results from extended periods of time in which an individual child carries a caloric imbalance or “energy gap”: i.e., consumes more calories than those that are calories burned (Koplan & Dietz, 1999). In this model, physical activity is acknowledged to provide a large component of the “calories burned” component of this equation (Wang, Gortmaker, Sobol, & Kuntz, 2006). Current guidelines for physical activity among early elementary children recommend moderate-
to-vigorous physical activity 1 or more hours per day (Landry & Driscoll, 2012), and those children who do not meet the current guidelines for physical activity may be at greater risk for obesity (Hills, Andersen, & Byrne, 2011) through a widening energy gap. In fact, studies of the energy gap demonstrate that weight gain leading to obesity status throughout the prepubertal period may have been avoided by reducing the daily energy gap by 110-165 kilocalories per day, or approximately 1-2 hours of physical activity (Wang et al., 2006). Indeed, among a sample of elementary-aged children, not meeting guidelines for physical activity was associated with 2.5 times the odds of obesity for girls and 3 times the odds of obesity for boys, as compared to children meeting the guidelines (Laurson, Lee, Gentile, Walsh, & Eisenmann, 2014). Notably, in the US and other Western countries, a large proportion of children and adolescents do not meet these recommended physical activity guidelines: while physical activity in early childhood is typically higher than it is in adolescence (Barr-Anderson et al., 2017), estimates of children in early childhood who meet these guidelines still range from only 42% for children aged 6-11 (Troiano et al., 2008) to 76% for children aged 6-8 (Fakhouri, Hughes, Brody, Kit, & Ogden, 2013). The protective effects of physical activity on obesity among early elementary aged children have been supported by a systematic review (Janssen & LeBlanc, 2010), and demonstrated both cross-sectionally and longitudinally. For example, Basterfield and colleagues (2014) examined current physical activity over a one-week period and zBMI among children aged 6-8 years, and found that 48% of healthy weight boys were categorized as “inactive” compared with 76% of overweight boys. However, only eight girls in total were in the active category, so these analyses were not possible; this is suggestive of a moderation effect of sex, which is explored further below. In another study of children in this age group, Sigmund and colleagues (2012) present evidence for the effects of physical activity over time by examining
children aged who were randomized to engage in a school-based physical activity intervention from ages 6 through 9. These authors found that one year after the start of the school-based physical activity, the odds of being overweight in the children who completed physical activity was almost three times lower than that of children in the control group, and that these odds steadily decreased with the duration of the physical activity across the second year. These statistics suggest physical activity is an essential factor to explore in determining how child obesity develops in this critical period.

**Screen Time**

Although some may conceptualize physical activity and sedentary behavior on the same continuum, researchers have found that studying the two as separate variables provides important insight into the ways that child obesity may develop. Screen time and television viewing make up one important facet of sedentary behavior for children in the modern world. As with physical activity, children who adhere to the recommended guidelines for screen time viewing in childhood (<2 hours per day), are at decreased risk for obesity. Fakhouri and colleagues (2013) found that, among 6-8 year olds in the National Health and Nutrition Examination Survey, only 59% of children met these guidelines, and that not meeting the guidelines was associated with obesity. For example, Jackson and Cunningham (2017) examined obesity development in children from kindergarten through fifth grade utilizing the first Early Childhood Longitudinal Study, and found that that TV viewing was associated with increases in zBMI in over time. Specifically, a one hour increase in daily TV viewing was associated with a 0.04 increase in BMI z-score in the subsequent grade. In fact, after accounting for zBMI at the first time point, these authors found that TV viewing was the single most influential of those examined, which also included dietary factors and physical activity. Therefore, evidence suggests that it is important to
examine sedentary behaviors, such as television viewing, separately from physical activity. Several other studies have supported the idea that television viewing during the early elementary years is associated with obesity in later childhood (Jago, Baranowski, Baranowski, Thompson, & Greaves, 2005; Krahmstoever Davison, Marshall, & Birch, 2006; Proctor et al., 2003). Interestingly, evidence suggests that patterns of greater-than-recommended early childhood television viewing is maintained through childhood (Certain & Kahn, 2002), which may help explain why television viewing at age 5 is predictive of adult obesity (Viner & Cole, 2005). This evidence presents the importance of examining screen time, particularly television viewing, during early elementary ages as an important factor for obesity development during childhood.

**Bedtime**

Sleep behaviors have often been associated with obesity in early childhood, with theorists proposing that the hormones that regulate appetite and metabolism may be negatively affected by insufficient sleep, or sleep hours that occur outside of the natural circadian rhythm (Golley, Maher, Matricciani, & Olds, 2013; Snell, Adam, & Duncan, 2007). For example, a meta-analysis of sleep duration and obesity found that, among children and adolescents of all ages, increases in sleep duration were associated with decreases in rates of overweight and obesity (Chen, Beydoun, & Wang, 2008). More specifically, these authors found that there was a dose-response relationship between hours of sleep and obesity among children under the age of 10. While short sleep duration is one often-studied factor in obesity across the lifespan, it may not be the only or the most important measure of sleep health for childhood obesity—bedtime itself may also be an important and often underappreciated measure of sleep health for overweight. Indeed, recent studies have suggested that sleep timing may be a better predictor of obesogenic dietary intake than sleep duration (Fleig & Randler, 2009). To illustrate, Sekine and colleagues (2002)
examined sleep behaviors and obesity among a sample of over 8,000 children between the ages of 6 and 7. While the authors’ report focuses on the increase in odds for obesity based on sleep duration (children who received 9-10 hours of sleep had a 1.49 increase in odds of obesity as compared to those who received 10 hours of sleep or more), a similar or even stronger trend exists for bedtime, with children who went to bed after 11pm having a 2.43 increase in odds of obesity compared to those who went to bed before 9pm. In fact, a later bedtime alone has been found to be associated with obesity above and beyond the effects of sleep duration: indeed, one study found that among a sample of over 2,000 children aged 9 through 16, children who had later bedtimes and later rise times were more likely to report both higher BMI and more obesogenic dietary preferences (higher intake of energy-dense, nutrient poor foods; fewer fruits and vegetables), even while controlling for sleep duration (Golley et al., 2013). This association has been highlighted not only on a cross-sectional basis, but also longitudinally: Anderson and colleagues found that, among a group of preschool aged children, weekday bedtime strongly influenced the odds of developing obesity as adolescents. Specifically, preschool-aged children with early weekday bedtimes were half as likely to be obese as adolescents (Anderson, Andridge, & Whitaker, 2016). Other studies have also supported this conclusion. For example, Snell and colleagues (2007) examined bedtime among a sample of over 3,000 children aged 3-12 (at baseline) and its relation to BMI five years later. These authors found that for each additional hour a given child stayed awake at baseline, their BMI at the five-year timepoint increased by .12 standard deviations. Additionally, these authors found that the protective effect of earlier bedtimes was particularly relevant for children in the younger half of their those studied (ages 3-8 years), suggesting that shifts to later bedtimes among this age range may be particularly detrimental and impactful for long-term obesity risk (Snell et al., 2007). In conclusion, it is
apparent that sleep behaviors, specifically children’s bedtimes during the early elementary years, is an important factor for obesity development over time.

**Relative Importance of Individual Factors**

Overall, there is strong evidence that each of these individual-level factors—physical activity, screen time, and sleep—is important for obesity development during the adiposity rebound period. While there are few researchers that have compared the relative importance of each of these factors, one of two notable exceptions is Jackson and Cunningham (2017), who found that sedentary behavior in the form of television viewing was the most influential factor among physical activity, sedentary behavior, and diet. However, this study did not include sleep variables, so it is less known how their influence may compare to that of physical activity and sedentary behavior. One study that did examine all three of the individual variables included in this study was conducted by Laurson and colleagues (2014), and found that of the three posited predictors, the strongest predictor of obesity was physical activity. With what might be called a more direct impact on obesity, it is possible that physical activity and sedentary time may both have a stronger effect on obesity than sleep factors.

**Family Factors**

Beyond the level of the individual behaviors, the next context of a child’s life that has particular relevance for obesity and related behaviors is their family environment. The family environment appears to be particularly salient among young children in that it shapes their diet, physical activity, media use, and sleep (Ash, Agaronov, Young, Aftosmes-Tobio, & Davison, 2017). However, here the child’s own physical activity, sedentary behavior/screen time, and sleep are categorized at the individual level, given that these are activities that the child may engage in separately from their family members. On the other hand, there are several types of
family-level activities and opportunities, such as exercise with a family member, eating together as a family, and having access to high-quality, desirable foods, that specifically occur in the context of the family unit. These factors are discussed in more detail below as they relate to children’s obesogenic environment.

**Physical Activity**

In addition to a child’s individual engagement in physical activity (PA), it has been shown that parental and family activity impact children’s health. For example, family-based treatment for obesity has accumulated support following a 2007 Institute of Medicine report describing parents as integral targets for childhood obesity prevention, not only because of parenting practices directly related to obesogenic behaviors, but also because of the overall environment of physical activity that parents create in a child’s life (Koplan, Liverman, Kraak, & Wisham, 2007). In fact, a review and meta-analysis of parental effects on child physical activity indicated that there were positive associations between parental support and activity across children of all ages, and that associations between parent and child PA approached a medium effect size (Yao & Rhodes, 2015). However, these authors highlight that parental effects on physical activity may be particularly strong during the pre-adolescent phase, when the opportunity to establish norms of physical activity is presented (Yao & Rhodes, 2015). Several aspects of parental influence, including modeling physical activity and encouraging physical activity, may impact child zBMI, largely through increasing child physical activity. Another systematic review supported the idea that both parent encouragement of physical activity and parent modeling influenced physical activity among early elementary children, with moderate to strong evidence for connections between both variables and children’s PA (Xu, Wen, & Rissel, 2015). The vast majority of these studies have been conducted cross-sectionally, though there is
also evidence that this relation holds longitudinally for children of ages 5-7. Gubbels and colleagues found that the restriction of sedentary time/encouragement of physical activity by parents at age 5 was significantly related to lower zBMI at age 7 (Gubbels et al., 2011). Therefore, overall, it seems that during the adiposity rebound phase, parental effects on physical activity significantly impact obesity development, such that greater parental attention to or modeling of physical activity leads to healthier zBMI development.

**Food Security**

Availability of food as a result of existing monetary resources, called “food security” throughout this paper, represents another family-level variable that may impact a child’s weight. Food security has somewhat paradoxical link to childhood obesity, with many studies showing increased obesity rates among children who demonstrate the least food security (also conceptualized as the most “food insecurity”). The mechanism of action for a food insecurity-obesity link among children aged 2-13 has been hypothesized to center on food access. For example, Nackers and Applehans (2013) found that food insecurity among families with children aged 2-13 was associated with more obesity-promoting foods in the home, and greater access to less healthful foods in the kitchen. However, findings between food security and weight itself are at times complicated: a systematic review found that some studies demonstrated no effects, some studies demonstrated positive effects, and some studies demonstrated negative effects (Eisenmann, Gundersen, Lohman, Garasky, & Stewart, 2011). On the other hand, Eisenmann and colleagues highlight that, despite these mixed results, food insecurity and overweight certainly co-exist, such that the prevalence of overweight remains relatively high in food-insecure children.
Within the early childhood age group (2-5 years old) specifically, the link between food insecurity and obesity has been established longitudinally among an exceptionally large (>25,000) sample (Metallinos-Katsaras, Must, & Gorman, 2012). These authors found that food insecurity measured in infancy was associated risk for obesity at age 5, particularly if mothers were overweight or underweight. However, to our knowledge, there are no studies on this scale that examine the relation among children during the adiposity rebound period. Therefore, while findings are less clear than for other factors, these studies suggest that food insecurity is another variable of interest in examining the development of obesity during the adiposity rebound period, with the most theorized direction being that food insecurity may lead to greater obesity.

**Family Mealtimes**

A final family-level factor that may contribute to childhood obesity is that of regular family mealtimes. A meta-analysis by Hammons and Fiese (2011) reviewed studies investigating the impact of family mealtimes on obesity among children aged 3-17 and found that elementary-aged children who shared family meals three or more times per week are more likely to be in a normal weight range and have healthier dietary and eating patterns than those who share fewer than three family meals together. Similarly, among children aged 5-12, Fiese and colleagues (2012) found that family mealtimes and importance placed on mealtimes predicted lower child BMI status. The process by which family mealtimes may impact obesity during the adiposity rebound period has been suggested to be complex, and include family engagement, positive communication, and modeling (Fiese, Hammons, & Grigsby-Toussaint, 2012). Regardless of the mechanism, what is clear is that family mealtimes do impact obesity development for children in the early elementary age range.
Relative Importance of Family Factors

In conclusion, family physical activity, food insecurity, and family mealtimes all are supported as potential factors impacting obesity development during the adiposity rebound period. However, no studies to our knowledge have examined the relative importance of each of these family factors or proposed that one of the three may be more or less important than the others. Given the efforts being made to develop effective interventions for childhood obesity, it is important to identify these most influential factors in order to prioritize them in intervention development. Therefore, this study will also examine the relative importance of each of these factors for obesity development during this critical period.

Community Factors

Beyond the level of the family, the child’s community environment has also been shown to have an impact on their obesogenic behaviors and weight. One of the most well-supported among these is the safety of the neighborhood in which the child lives. In contrast to the built environment in which the child lives, which may also have an effect on obesity, neighborhood safety is part of a community’s “social environment,” which Franzini and colleagues (2009) define as representing neighborhood safety and cohesion. One way that a safer, more cohesive neighborhood environment is proposed to decrease childhood obesity is through increased access to physical activity. For example, Franzini and colleagues found that, among a sample of fifth-grade students, the neighborhood social environment, which included variables such as social contact and perceived safety, was positively associated with physical activity, which itself was negatively associated with obesity. Similarly, Datar, Nicosia, and Shier (2013) also found cross-sectional and longitudinal associations between perceived neighborhood safety and physical activity, but not with zBMI, among first, third, and eighth graders. Alternatively, Burdette and
Whitaker (2005) suggest that, at least among preschool-aged children, decreased neighborhood safety is associated with increased television time, which may present another avenue for this factor to influence obesity, particularly among young children. In conclusion, neighborhood safety is a predictor of childhood obesity with strong support during the adiposity rebound period, such that children who live in neighborhoods rated as more safe are less likely to be obese or develop obesity over time.

**The Role of Demographic Characteristics**

Although testing the proposed ecological model (see Figure 3) capturing three levels of factors contributing to obesity (e.g., individual, family, community) may help inform obesity prevention and treatments, it does little to facilitate the development of *tailored* obesity interventions, which experts have recommended in the face of the growing childhood obesity epidemic (Barkin, Gesell, Po’e, Escarfuller, & Tempesti, 2012; Taylor et al., 2015). The idea of developing tailored interventions includes intervention components that can be emphasized or replaced based on evidence for the role demographic variables play in the development of obesity. These demographic factors, such as race/ethnicity, income-to-needs status, and sex may impact obesity in several ways, and will be dealt with in two separate manners, first as covariates and then as moderators, for the purposes of this study.

First, these demographic factors may act as “main effects” for obesity or related factors. This means that these factors may directly influence obesity development through biologic or other unaccounted processes—for example, sex influencing obesity development directly based on norms of adiposity—or they may influence the amounts that children are exposed to individual obesogenic factors—for example, income-to-needs ratio influencing the extent to which children live in neighborhoods that are deemed “unsafe,” which itself impacts obesity. In
order to account for these main effects, when they are not being explored otherwise, these variables will be included as covariates for the models proposed in the current study.

Notably, these factors may also influence the extent to which these obesogenic behaviors or situations lead to obesity development in the manner of a moderating variable—for example, physical activity decreasing obesity more for boys than girls. This avenue is particularly interesting, as it provides additional information beyond what is already known regarding race/ethnicity, income-to-needs ratio, sex and obesogenic behaviors, and would allow for creating relevant combinations of important factors. Unfortunately, the moderation effects of these variables are considerably less studied than the main effects model of demographic factors described above. Therefore, although this study will first test these variables as “covariate” or “control” variables for obesity and its related factors, it will also explore this relatively less common moderation pathway in order to determine how the components of the ecological model may vary and be differentially influential across demographic groups.

**Race/Ethnicity**

Though rates of obesity seem to be rising across demographics, there is evidence that it is particularly prevalent in some racial/ethnic groups, such as non-Hispanic black and Hispanic youth (Hales, Carroll, Fryar, & Ogden, 2017). A position statement by Caprio and colleagues (2008) outlines the many factors that may contribute to this distinction, including biologic and cultural influences. Biologic factors may indeed be part of the explanation, and offer evidence that race/ethnicity should be considered as a control variable in models predicting obesity. However, cultural factors offer a more actionable route to decreasing obesity among these populations, and may direct racial/ethnic differences in the child obesity epidemic through attitudes, preferences, and access to physical activity or sedentary activity (Barr-Anderson et al.,
2017; Johnston, Delva, & O’Malley, 2007), which represent “main effects” of race/ethnicity on other obesogenic factors within the model. Several studies suggest these “main effects” of cultural influences on obesogenic factors among racial/ethnic groups: for example, it has been suggested that there are racial/ethnic differences in physical activity overall, such that Hispanic children aged 6-11 participate in the least physical activity (Fakhouri et al., 2013). Other studies have indicated that Black children participate in the most physical activity (among Black, Latino, and White children), particularly at younger ages (Barr-Anderson et al., 2017). Furthermore, at the community level, there is evidence for a main effect of race/ethnicity on neighborhood safety (Singh, Siahpush, & Kogan, 2010). These studies indicate that race/ethnicity does appear to impact obesity directly through access to resources and activities; however, they do not consider whether these same factors would be particularly influential for obesity development among children of different racial/ethnic groups.

There is also some evidence for true moderation effects of race/ethnicity on the effects of obesogenic factors. Berge and colleagues (2015) examined the possibility of a racial/ethnic moderation effect of family mealtimes on obesity among older adolescents. These authors found that family meals had a stronger protective effect for obesity among Black as compared to White adolescents. To our knowledge, however, studies of moderating factors do not consider these processes among elementary school age children, and further, no studies consider the moderation effects of the individual, family, or community factors examined in this study.

**Income-to-Needs Ratio**

Socioeconomic factors such as income-to-needs ratio, a number representing the monetary resource of a family unit as compared to the number of individuals supported by the family unit, may contribute to the racial/ethnic disparities in obesity. Several studies suggest
avenues for a “main effect” of income-to-needs on obesity itself. Indeed, in the US, obesity prevalence tends to decrease as income increases (Shrewsbury & Wardle, 2008; Wang, 2001). Furthermore, there is also some evidence of main effects of income-to-needs on certain obesogenic factors. For example, Fiese and colleagues (2012) posit that income-to-needs ratios may have a negative direct effect on family mealtimes overall due to increased chaos in the homes as a result of lower resources. Similarly, income-to-needs ratios have been demonstrated to have an effect on many of the factors examined in this study, including screen time (Certain & Kahn, 2002), sleep duration (Appelhans et al., 2014), food insecurity (Franklin et al., 2012), and community safety (Singh et al., 2010).

On the other hand, to our knowledge, no studies have examined moderation effects of income-to-needs ratios among any of the factors studied here. However, one study by Appelhans and colleagues (2014), which specifically examined children aged 6-13, found that sleep duration may be particularly salient for childhood obesity for low-income families. In fact, in this study, sleep duration was the only health behavior associated with child overweight. However, this study did not examine sleep as a true moderator due to the fact that these were the only families included. What is clear from a review of the literature is that a vast majority of studies examine income-to-needs ratio as a control factor rather than a moderator. Therefore, this is an important avenue to consider in developing tailored interventions among these families.

Sex

Finally, obesity rates and predictors may differ based on the sex of the youth studied. In general, there is some evidence of a “main effect” of sex on obesity, such that rates of obesity are higher in females than in males, although this has not held to be true of youth in the United States (Ogden, Carroll, Kit, & Flegal, 2014). This is possibly because the use of the sex- and age-
adjusted zBMI in many studies of child obesity. Similar to racial/ethnic influences, direct sex differences in obesity may stem from biology or cultural differences in weight-related factors. Again, the biological contributors to sex differences in obesity are likely less actionable than those differences stemming from culture. These more targetable cultural differences may include obesogenic behaviors, such as those examined in this study. Several studies have found “main effects” of sex on the different obesogenic factors explored here. For example, many suggest that there are significant differences in rates of engagement in physical activity by sex, such that boys are more likely to engage in physical activity (Craggs, Corder, van Sluijs, & Griffin, 2011; Troiano et al., 2008). Indeed, girls’ rates of physical activity are shown to decrease early in childhood, leading to lower levels of physical activity among girls and women overall (Fakhouri et al., 2013).

Interestingly, the “moderation effects” that have been suggested, both in a cross-sectional study of 6-8 year old children (Basterfield et al., 2014) and in a systematic review of children of all ages (Janssen & LeBlanc, 2010), are that the relation between physical activity and odds of overweight may be significant only for boys, though mechanisms for this moderation are unknown. Furthermore, sex may act as a moderator for sleep’s effects of obesity, such that sleep deficits may be particularly problematic among male children (Chen et al., 2008; Sekine et al., 2002). In addition, one study has suggested that sex moderates the relation between food insecurity and obesity, such that food insecurity is associated with weight gain in early elementary school girls, but not boys (Jyoti, Frongillo, & Jones, 2005). Finally, at the community level, there is some evidence that sex may moderate the relation between neighborhood safety and obesity, such that the relation is stronger for girls than boys. Bacha and colleagues (2010) found that, from the third to fifth grade years, lower neighborhood safety ratings were associated
with an increased risk of obesity in general, but were only associated with increases in BMI $z$-scores among girls. In conclusion, sex is one the most studied moderating variables for obesogenic variables, with evidence for effects on physical activity, sleep, food insecurity, and community safety.

Altogether, many studies have examined demographic variables as “main effects” by measuring influence of these variables on obesity itself or on individual obesogenic factors. However, relatively fewer have looked to determine the influence of race/ethnicity, income-to-needs ratio, and sex as moderators of obesogenic factors among children. Furthermore, to our knowledge, none have examined the moderating influence of these variables on multiple of these influential variables at once with an adequately large sample size to do so. Therefore, this study will examine (1) the fit of the ecological model, controlling for the known main effects of demographic characteristics on obesity and related factors and (2) the fit of the proposed model, and how it may differ through moderation, for groups with varying demographic characteristics, such as race/ethnicity, income-to-needs status, and sex.

**Specific Aims and Hypotheses**

Utilizing a sample of US youth (ECLS-K: 2011) followed from kindergarten through second grade, this study seeks to examine the impact of individual, family, and community factors on obesity, measured by $z$BMI, in kindergarten and second grade. The study will address the following aims:

1. **Assess the fit of an ecological SEM model of $z$BMI concurrently and longitudinally.** This study will design and test a model of $z$BMI based on existing theoretical ecological models (see Figure 3) using kindergarten-age predictors to model $z$BMI both in kindergarten and second grade. For this aim, the model will control for race/ethnicity and income-to-needs
ratio, by allowing them to correlate with both the outcome variable and independent variables. It is predicted that the model will provide acceptable fit.

2. **Assess the contributions of individual factors, as well as each level of factors, to zBMI concurrently and longitudinally.** This study will then examine the relative contributions within and across levels of the ecological model: i.e., the importance of each factor within a level, and each level of factors itself, to zBMI in kindergarten and second grade. For this aim, the model will again control for race/ethnicity and income-to-needs ratio by allowing these variables to correlate with both the outcome variable and independent variables. Based on the evidence reviewed, it is hypothesized that, among the individual factors, physical activity and sedentary time will have stronger effects on zBMI than sleep. Furthermore, based on the concentric rings of influence within the ecological model, it is predicted that the individual factors will contribute most directly to kindergarten and second grade zBMI.

3. **Assess the relative importance of individual, family and community factors’ influence on zBMI in kindergarten and second grade for different demographic groups.**

   a. **Assess the contributions of individual, family, and community factors to zBMI in the second grade for racial/ethnic groups.** This study will examine the importance of factors’ contributions to zBMI among racial/ethnic groups, including White, Black, Latino, and Asian American/Pacific Islander/Native American youth. Based on the literature review presented above, it is predicted that family mealtimes will have a more protective effect for zBMI among Black youth than the other racial/ethnic groups.
b. Assess the contributions of individual, family, and community factors to zBMI in the second grade for income-to-needs groups. This study will examine the importance of factors’ contributions to zBMI income-to-needs ratio groups (i.e., those families above and below 200% of the poverty line). Though there is not current evidence for moderation effects of income-to-needs ratios on these relations, it is possible that sleep will have more impact on zBMI among children from families of lower income-to-needs ratios.

c. Assess the contributions of individual, family, and community factors to zBMI in the second grade for boys versus girls. This study will examine the importance of factors’ contributions to zBMI among boys and girls. Based on the literature review presented above, it is predicted that physical activity and sleep duration will contribute more to zBMI among boys, and that food insecurity and neighborhood safety will contribute more to zBMI among girls.
CHAPTER II

METHOD

Participants and Procedures

Data for the current study were drawn from the Early Childhood Longitudinal Study: Kindergarten Class of 2011 (ECLS-K:2011), a national study sponsored by the National Center for Education Statistics (NCES). The participants included in the ECLS-K:2011 constitute a nationally representative sample from both public and private schools. Participation in the study was voluntary and consisted of questionnaire and anthropomorphic data collected from parents/guardians, teachers, school administrators, and children. The study’s data collection points fell during fall (2010) and spring (2011) of the kindergarten year, fall (2011) and spring (2012) of the first grade year, fall (2012) and spring (2013) of the second grade year. Parents/guardians provided information on their children via interviews at each time point. The majority of parent interviews were conducted by telephone, though interviews were conducted in person for parents who did not have telephones, who were difficult to contact by telephone, or who preferred an in-person interview. School (teacher and administrator) data was not utilized by this study and therefore the school data collection process is not described here. Child anthropomorphic data was obtained during in-person cognitive and physical assessments at each study time point.

Because of the very large sample size available for analysis, and because utilizing complete case analysis (i.e., listwise deletion) with weight-related variables in large
epidemiological datasets has been proven to be a reliable and valid methodology (e.g., Razzaghi et al., 2016), participants with missing data were eliminated using listwise deletion. Therefore, for the present study, participants with full and complete anthropomorphic and survey data in both kindergarten and second grade (n=8,225, 62% of the full sample) are included. Confirmatory chi-square testing revealed no demographic differences between the full and analytic samples with regard to race/ethnicity ($\chi^2=0.90; p=0.97$), sex ($\chi^2=0.11; p=0.99$), or income-to-needs status ($\chi^2=0.40; p=0.94$). At baseline, participants were approximately evenly distributed by sex (51% male). When participants were categorized into the four proposed racial/ethnic groups, these were distributed in a manner that reflects the overall U.S. population (U.S. Census Bureau, 2018): 58.2% identified as White, 12.1% identified as Black, 21.4% identified as Hispanic/Latino, and 8.4% identified as another racial/ethnic category (Native American, Asian American, Pacific Islander). Families were also approximately evenly distributed above and below 200% of the federally defined poverty line for their size, with 57.2% of families falling at or above 200%.

**Measures**

**Body Mass Index**

Children's height and weight were measured at each round of data collection (e.g., the spring of kindergarten (2010-11), the fall and spring of first grade (2011-12), and the fall and spring of second grade (2012-13). Assessors recorded the children’s height in inches and weight in pounds using a Shorr board and a digital scale. Each measurement was taken twice to ensure reliable measurement (Tourangeau et al., 2015). Because only BMI (unadjusted for age and sex) was provided in the original NCES dataset, child zBMI during the spring of kindergarten and second grade was calculated in SAS using a procedure developed by the Center for Disease
Control (CDC) utilizing this organization’s own growth charts for children aged 0 to 20 (Centers for Disease Control, 2016).

**Child Physical Activity**

Children’s physical activity per week was measured via the parent interview in the spring of each year, and was measured using a single question: “In a typical week, on how many days does {CHILD} get exercise that causes rapid breathing, perspiration, and a rapid heartbeat for 20 continuous minutes or more?” Answers were recorded in number of days per week. This question was created for the ECLS-K, including previous rounds of ECLS-K data collection (e.g., in 1998) and therefore has been utilized in several previous examinations of physical activity (Datar et al., 2013; Stevens, To, Stevenson, & Lochbaum, 2008).

**Child Screen Time**

Children’s screen time per day was measured via the parent interview in the spring of each year using two questions. The first question was: “On any given weekday, how many hours of television, videotapes, or DVDs on average does {CHILD} watch at home?” Parents were then prompted to list the hours of screen time before 8:00 a.m., between 8:00 a.m. and 6 p.m., and after 6 p.m. The second question was: “How about on Saturday and Sunday? How many hours does {CHILD} watch television, videotapes, or DVDs at home on Saturday/Sunday?” Answers were recorded in number of hours. For the purposes of this study, total screen time/week was calculated by multiplying weekday screen time by five and weekend screen time by two, then adding these numbers together. This question was created for the ECLS-K:2011 and has been utilized in previous studies of television viewing (Peck, Scharf, Conaway, & DeBoer, 2015).
Child Bedtime

Bedtime was assessed within the parent interview in the spring of the kindergarten and first grade years. Parents were asked “About what time does {CHILD} usually go to bed?” Answers were recorded in hours and minutes. Notably, wake time was not assessed. However, bedtime has been frequently demonstrated to be a valid indicator of sleep quality and duration for the purpose of measuring effects of weight (Golley et al., 2013).

Family Physical Activity

Family physical activity was assessed via the parent interview in the spring of each year using a single question. The question was, “Now I'd like to talk with you about {CHILD}'s activities with family members. In a typical week, how often do you or any other family members do the following things with {CHILD}: Play a sport or exercise together?” Answers were coded on a Likert scale indicating 1=not at all, 2=once or twice per week, 3=3-6 times per week, and 4=every day. This question was created for the ECLS-K, including prior rounds of data collection, and has been utilized in previous examinations (Beets & Foley, 2008).

Family Food Insecurity

Adult- and child-level food insecurity was assessed during the parent interview during the spring of the kindergarten year. The National Center for Educational Statistics recommends parents’ reports of their own food insecurity as a measure of food-insecurity rather than child-level food insecurity, as child-level insecurity is very infrequently endorsed; therefore, this study will use household food insecurity for this measure. In the interview, the responder was asked eight questions relating to adult or household-level food insecurity, including “In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food?” and “In the last 12 months, were you ever hungry but didn't eat because there wasn't
enough money for food?” The National Center for Educational Statistics provides a composite score reflecting the mean of the responses to household-level food insecurity items, which will be utilized in the present analyses. This measure of family food security has been utilized in previous studies of the ECLS-K:2011 (Lee, Scharf, & DeBoer, 2018; Morrissey, Oellerich, Meade, Simms, & Stock, 2016).

**Family Mealtimes**

Frequency of family evening mealtimes was also assessed during the parent interview in the spring of each year utilizing two questions. The first question was, “In a typical week, please tell me the number of days your family eats the evening meal together.” The second question was, “In a typical week, please tell me the number of days your family eats breakfast together.” For the purposes of this study, both answers were combined into a single value approximating the number of family meals eaten together per week. This question was created for the ECLS-K, including previous versions, and has been utilized in prior studies (Burdette & Whitaker, 2005; Miller, Waldfogel, & Han, 2012).

**Neighborhood Safety**

Neighborhood safety was assessed via the parent interview in the spring of the kindergarten year. Perceived neighborhood safety was assessed using a single item: “How safe is it for children to play outside during the day in your neighborhood?” Responses were recorded on a Likert scale ranging from 1=not at all safe to 3=very safe. This question was created for the ECLS-K, including previous rounds of data collection, and has been utilized in prior research studies (Beets & Foley, 2008; Datar et al., 2013).
**Race/Ethnicity**

Race/ethnicity was assessed using data from the parent interview during spring of the kindergarten year. First, parents were asked whether they would identify themselves and/or the child as “Hispanic/Latino.” Then, parents were asked to identify their own/the child’s race. Answers were coded using the following options: 1=American Indian/Alaska Native, 2=Asian, 3=Black/African American, 4=Native Hawaiian or other Pacific Islander, and 5=White. For the present study, because of our interest in cultural influences on child weight and in order to maintain adequate sample size among groups, race/ethnicity will be conceptualized as a single variable and stratified into four groups: White, Black/African American, Hispanic/Latino, and Other Race/Ethnicity (e.g., American Indian, Asian American, Native Hawaiian or other Pacific Islander).

**Income-to-Needs**

Family’s income-to-needs status was calculated by the Center for National Education Statistics by comparing total family income to the poverty threshold for a family of the appropriate size. Parents reported on total household income in the spring of each year: answers were recorded in terms of dollars. Parents also reported on number of individuals who made up the “household.” Then, the NCES used these data to create three income-to-needs groups, with families categorized as falling (1) below the poverty threshold for their size, (2) at 100-200% of the poverty threshold for their size, or (3) greater than or equal to 200% of the poverty threshold for their size (Mulligan, Hastedt, & McCarroll, 2012). Because of the evidence that falling below 200% of the poverty line delineates families who are “low income,” and who experience the health effects of lack of resources (Lynch et al., 1998), in this study, families’ income-to-needs
will be dichotomized as above or below 200% the poverty threshold for their relative size (Diep, Baranowski, & Kimbro, 2017).

**Sex**

Data on child sex was obtained during the parent interview in the spring of the kindergarten year. Responses were recorded as “male” or “female” (Mulligan et al., 2012).
CHAPTER THREE

ANALYTIC PLAN

Data were first examined for evidence of outliers and skewness (Tabachnick & Fidell, 2013) and outliers and missing values were addressed. Next preliminary descriptive analyses were conducted for each of the independent and dependent variables, including assessment of means, standard deviations, and bivariate correlation analyses. Finally, structural equation modeling (SEM) techniques (path analyses, multigroup path analyses) were conducted in LISREL 8.80 software.

SEM was chosen to examine the aims presented in this paper for several reasons: (1) when utilized properly, it allows for full flexibility in analysis despite the limitations of ordinal and categorical data, (2) it allows simultaneous examination of multiple time points, and (3) it provides the option for multigroup analyses, which can be utilized as an efficient and concise method of testing multiple moderation analyses at once. SEM provides the possibility of two types of models (and the combination thereof): structural models, indicating links between endogenous and exogenous variables; and measurement models, indicating links between relations between latent, or unmeasured variables, and their measured indicators (Kline, 2015). Structural models, or path models, are the best technique to capture multiple levels of influence from a group of measured variables, such as those found in this study. Therefore, this study utilized this approach, harnessing structural, or path models, to examine the contribution of
(1) individual factors and (2) group-level factors (e.g., individual-level, family-level) to childhood zBMI, and comparing these models among demographic groups.
CHAPTER FOUR

RESULTS

Data Preparation

Data were first examined in SPSS for the influence of outliers, kurtosis, and skewness (Tabachnick & Fidell, 2013). Several variables were found to be non-normally distributed, including zBMI in second grade, which evidenced a skewness value of -7.44 (SE=.03) and a kurtosis value of 144.42 (SE=.05); food security in kindergarten, which evidenced a skewness value of 3.04 (SE=.03) and a kurtosis value of 8.93 (SE=.05); and number of television hours watched per week, which evidenced a skewness value of 14.81 (SE=.03) and a kurtosis value of 257.91 (SE=.05). Accordingly, outliers for continuous variables were removed when values were greater than three standard deviations from the mean (Cousineau & Chartier, 2010), for a total of 34 outliers based on zBMI and 24 outliers based on television/week, whose extreme recorded values suggested measurement error (for example, a majority of the removed television hours/week outliers reported watching television 385 hours/week, which is not mathematically possible). Upon elimination of these outliers, both zBMI in second grade and number of television hours watched per week were normally distributed. Because food security was measured on an ordinal scale from 1-3, the high degree of skewness and kurtosis indicated that there were very few families who reported the maximum level of household food security, a problem acknowledged by the National Center for Education Statistics (Tourangeau et al., 2015); therefore, as indicated by this body, the food security variable was condensed from a 1-3 ordinal
scale to a dichotomous variable, with 1 indicating full food security and 2 indicating some level of food insecurity. Upon completion of this transformation, food security was distributed within the bounds of normality. All other variables were normally distributed without removal of outliers.

Data were next examined for missing values. As discussed within the Methods section, listwise deletion was utilized when preparing the analytic sample, such that there were no participants with any missing values for any of the included variables within the analytic sample (n=8225). Furthermore, as described above, the analytic sample did not differ significantly based on demographic characteristics from the full sample.

**Descriptive Statistics**

Preliminary descriptive analyses were run with all study variables, including means, standard deviations, and bivariate Spearman correlations. The results are presented in Table 1. Overall, the sample evidenced average \( z \)BMI values at both T1 (M=.45) and T2 (M=.49) that would be categorized as “healthy weight” based on standard guidelines (<-2 = underweight, >1 = at risk of overweight, >2 = overweight, >3 = obese; Anderson et al., 2017). However, the sample also demonstrated considerable variability with regard to \( z \)BMI, with standard deviations of over 1 standardized unit of body mass at each time point, indicating that at one standard deviation above and below the mean, participants would be categorized as overweight. Participants were relatively evenly divided by sex (51% male) and the majority of the sample (58%) were of white/Caucasian racial/ethnic background. Among individual-level variables, families reported that the children received exercise for 20 minutes for, on average, 4.5 days out of the week, that the children watched 14.5 hours of television per week, and that the average bedtime of the included children was slightly past 8:30pm. Among family-level variables, families reported that
Table 1. Correlations Between zBMI, Child Characteristics, and Obesity-Related Factors

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</thead>
<tbody>
<tr>
<td>1. Kindergarten zBMI</td>
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<tr>
<td>2. Second Grade zBMI</td>
<td>.779**</td>
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<tr>
<td>3. White Race/Ethnicity</td>
<td>.065**</td>
<td>.074**</td>
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<tr>
<td>4. Male Sex</td>
<td>-.020</td>
<td>-.037**</td>
<td>.028**</td>
<td>-</td>
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<tr>
<td>5. Income-to-Needs Ratio &gt; 200% Poverty Line</td>
<td>-.126**</td>
<td>-.132**</td>
<td>-.265**</td>
<td>.006</td>
<td>-</td>
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<tr>
<td>6. Exercise</td>
<td>.002</td>
<td>-.006</td>
<td>-.190**</td>
<td>-.093**</td>
<td>.064**</td>
<td>-</td>
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<tr>
<td>7. Screen Time</td>
<td>.088**</td>
<td>.107**</td>
<td>.077**</td>
<td>.001</td>
<td>-.216**</td>
<td>-.064**</td>
<td>-</td>
<td></td>
<td></td>
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<tr>
<td>8. Bedtime</td>
<td>.082**</td>
<td>.098**</td>
<td>.264**</td>
<td>-.023*</td>
<td>-.176**</td>
<td>-.087**</td>
<td>.233**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>9. Family Exercise</td>
<td>.033*</td>
<td>.032**</td>
<td>-.081**</td>
<td>-.088**</td>
<td>-.025*</td>
<td>.159**</td>
<td>-</td>
<td>.051**</td>
<td>-.048**</td>
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<tr>
<td>10. Food Security Status = Food Secure</td>
<td>.065**</td>
<td>.068**</td>
<td>.115**</td>
<td>-.015</td>
<td>-.309**</td>
<td>-.015</td>
<td>.101**</td>
<td>.094**</td>
<td>.022</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11. Family Meals</td>
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<td>-.085**</td>
<td>-.107**</td>
<td>-.016</td>
<td>.129**</td>
<td>.080**</td>
<td>-</td>
<td>-.180**</td>
<td>.107**</td>
<td>-.094**</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>12. Neighborhood Safety</td>
<td>-.057**</td>
<td>-.069**</td>
<td>-.265**</td>
<td>-.030**</td>
<td>.269**</td>
<td>.110**</td>
<td>-</td>
<td>-.138**</td>
<td>.077**</td>
<td>-.199**</td>
<td>.110**</td>
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</table>

Mean: .45, .49, 58%<sup>a</sup>, 51%<sup>a</sup>, 57%<sup>a</sup>, 4.55, 14.48, 8.54, 2.81, 88.4%<sup>a</sup>, 9.75, 2.69

SD: 1.12, 1.06, --, --, --, 2.35, 8.51, .74, .85, --, 3.18, .53

N: 8225, 8225, 8225, 8225, 8225, 8225, 8225, 8225, 8225, 8225, 8225, 8225

<sup>a</sup>Pct (categorical variable)

*p≤0.05 level; **p≤0.01 level
on average, the family exercised together for 3-6 hours per week, that the majority (88.4%) of families did not experience food insecurity, and that families ate approximately nine meals together per week. Finally, the average neighborhood safety level was reported as falling between “more safe than unsafe” and “very safe.” Furthermore, many of the contributing variables evidenced significant correlations, as expected within a dataset of this size among conceptually-related variables. This is because, assuming that the true (population) correlation coefficient is non-zero, a large sample size gives more than adequate power to detect a significant correlation, and a weak but stable sample correlation is considered “significant.”

**Aim 1: Applying the Ecological Model to zBMI in Kindergarten and Second Grade**

For the first aim, in order to assess the fit of an ecological model of zBMI development in both kindergarten and in second grade, a path model was constructed using the cleaned data. To construct a path model that would produce accurate parameter estimates despite having a combination of continuous and ordinal (i.e., non-normally distributed) variables, Robust Diagonally Weighted Least-Squares (DWLS) estimation was used for all analyses. This type of SEM analysis analyses the correlation matrix of the variables, rather than the covariance matrix, and produces parameter estimates that are not inflated by the non-normality of any ordinal data. For this first aim, in accordance with existing psychometric procedures (Brockway, Carlson, Jones, & Bryant, 2002), it was originally proposed that the total sample would be randomly divided in half, with the first half of the data utilized to develop the model (the *development* sample), and the second half utilized to confirm its fit (the *confirmation* sample). However, after examination of the proposed theoretical path model, based on the number of elements that were desired to be estimated in the model, it was determined that the ideal model for the proposed relations was “just-identified”—i.e., a model with exactly as many parameters to be estimates as
there are elements in the covariance matrix that is being analyzed. This type of model has 0 degrees of freedom and provides a perfect fit by default; therefore, it was not necessary to attempt to maximize fit by testing the model with development and confirmation samples.

Proposed indices of absolute fit for all analyses included root mean square estimation (RMSEA), standardized root mean square residual (SRMR), and indices of relative fit included comparative fit index (CFI). Acceptable model fit was defined as RMSEA <.08 (Browne & Cudeck, 1993), SRMR <.08 (Hu & Bentler, 1998), CFI >.90 and (Marsh, Hau, & Grayson, 2005). Parameter estimates, factor loadings, and error terms were also examined as indicators of appropriate model fit. For the baseline model, race/ethnicity and income-to-needs ratio were included by allowing these variables to correlate with both $z_{BMI}$ in kindergarten and second grade, as well as any independent variables. Because the outcome variable, $z_{BMI}$, is adjusted for both age and sex, sex was not utilized as a control variable. Furthermore, all independent variables were allowed to correlate within the baseline model for both kindergarten and second grade, as selectively correlating independent variables does not improve model fit (i.e., although a correlation coefficient for theoretically uncorrelated variables was estimated in the model, there is no negative effect of this on the overall model).

Results from the fit-testing of the originally proposed path model within the full sample demonstrated perfect fit, as anticipated. This model demonstrated an RMSEA value of 0.00, an SRMR value of 0.00, and a CFI of 1.00. These fit indices do not indicate that the model is an exact representation of $z_{BMI}$ development, but rather that it is estimating every possible parameter in the model (e.g., all of the relations among all of the variables, as well as their unique and shared error variances). In and of itself, the perfect fit of the model does not provide any interpretable findings; however, it serves as a satisfactory point from which to examine the
relative importance of factors and the possibility of moderation based on demographic factors (e.g., the remaining aims of this study). Therefore, analyses proceeded as planned.

**Aim 2: Examining Relative Importance of Factors and Levels**

Examining relative importance of individual factors. For this aim, the path model was examined to determine each factor’s “importance” for zBMI in kindergarten and second grade. This was first accomplished by assessing the standardized coefficient for which of the factors a change of one standard deviation most impacts zBMI. Note that in SEM, these values are labeled as gamma ($\gamma$), whereas they are commonly referred to as betas ($\beta$) in multiple regression. In SEM, betas instead refer to the path coefficients between two endogenous or dependent variables. A diagram of the path model with gammas for each of the independent variables (and the beta between the dependent variables) is provided in Figure 4, while a table of standardized coefficients and their p-values is presented in Table 2. These p-values were computed using a standard calculator for two-sided z-value significance and the z-values provided by LISREL for each of the individual predictors.

As examination of the standardized coefficients does not provide information about the impact an individual factor has on the total $R^2$ of the model, or the amount to which an individual factor explains the variance observed in zBMI, further analytic steps were taken to obtain this information. To do this, the $R^2$ values were compared across two sets of models: first, for a baseline model which included only the control variables and tiers of variables that were not of interest; next, for separate models in which each additional factor from their tier of interest was freed to be estimated. This data is presented in Table 3.
Figure 4. Baseline path model with labeled standardized coefficients ($\gamma$) for both T1 and T2, significant pathways in bold

Table 2. Standardized regression coefficient values ($\gamma$) and their significance at T1 and T2; significant p-values in bold

<table>
<thead>
<tr>
<th>Variable</th>
<th>T1 $\gamma$</th>
<th>T1 $\gamma$ SD</th>
<th>T1 p-value</th>
<th>T2 $\gamma$</th>
<th>T2 $\gamma$ SD</th>
<th>T2 p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PA/Week</td>
<td>0.02</td>
<td>0.03</td>
<td>0.56</td>
<td>0.00</td>
<td>0.02</td>
<td>1.00</td>
</tr>
<tr>
<td>Screen time/Week</td>
<td>0.04</td>
<td>0.12</td>
<td>0.73</td>
<td>0.02</td>
<td>0.07</td>
<td>0.72</td>
</tr>
<tr>
<td>Bedtime</td>
<td>0.04</td>
<td>0.02</td>
<td>0.12</td>
<td>0.02</td>
<td>0.01</td>
<td>0.20</td>
</tr>
<tr>
<td><strong>Family PA/Week</strong></td>
<td>0.04</td>
<td>0.01</td>
<td><strong>0.006</strong></td>
<td>0.01</td>
<td>0.01</td>
<td>0.16</td>
</tr>
<tr>
<td>Food Insecurity</td>
<td>0.01</td>
<td>0.01</td>
<td>0.37</td>
<td>0.00</td>
<td>0.01</td>
<td>0.74</td>
</tr>
<tr>
<td>Family Meals/Week</td>
<td>-0.04</td>
<td>0.04</td>
<td>0.39</td>
<td>-0.02</td>
<td>0.03</td>
<td>0.44</td>
</tr>
<tr>
<td>Neighborhood Safety</td>
<td>0.00</td>
<td>0.01</td>
<td>0.87</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.10</td>
</tr>
<tr>
<td>Income-to-needs ratio</td>
<td>-0.12</td>
<td>0.03</td>
<td>&lt;0.001</td>
<td>-0.02</td>
<td>0.02</td>
<td>0.28</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td>0.01</td>
<td>0.01</td>
<td>0.37</td>
<td>0.01</td>
<td>0.01</td>
<td>0.34</td>
</tr>
</tbody>
</table>
Table 3. Change in $R^2$ among individual- and family-level factors at T1 and T2

<table>
<thead>
<tr>
<th>Model</th>
<th>T1 $R^2$</th>
<th>$\Delta R^2$</th>
<th>T2 $R^2$</th>
<th>$\Delta R^2$</th>
<th>Model</th>
<th>T1 $R^2$</th>
<th>$\Delta R^2$</th>
<th>T2 $R^2$</th>
<th>$\Delta R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline (Excludes All Individual Factors)</td>
<td>0.04</td>
<td>--</td>
<td>0.61</td>
<td>--</td>
<td>Baseline (Excludes All Family Factors)</td>
<td>0.05</td>
<td>--</td>
<td>0.61</td>
<td>--</td>
</tr>
<tr>
<td>PA Only</td>
<td>0.04</td>
<td>0.00</td>
<td>0.61</td>
<td>0.00</td>
<td>PA Only</td>
<td>0.04</td>
<td>-0.01</td>
<td>0.61</td>
<td>0.00</td>
</tr>
<tr>
<td>Screen time Only</td>
<td>0.05</td>
<td>0.01</td>
<td>0.61</td>
<td>0.00</td>
<td>Food Security Only</td>
<td>0.05</td>
<td>0.00</td>
<td>0.61</td>
<td>0.00</td>
</tr>
<tr>
<td>Bedtime Only</td>
<td>0.03</td>
<td>-0.01</td>
<td>0.61</td>
<td>0.00</td>
<td>Family Meals Only</td>
<td>0.05</td>
<td>0.00</td>
<td>0.61</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Cross-sectional models.** Analyses of the significance of standardized coefficients of the independent variables for $z$BMI in kindergarten indicated two significant effects: both family physical activity and income-to-needs ratio were significant at T1 ($p=.006$, $p<.001$, respectively). The gamma coefficient for family physical activity indicated that this variable was positively associated with $z$BMI, such that children whose parents reported greater family physical activity were more likely to evidence higher $z$BMI scores. The gamma coefficient for income-to-needs ratio indicated that this variable was negatively associated with $z$BMI scores, such that children whose family fell below 200% of the poverty line in terms of income were more likely to evidence higher $z$BMI scores.

Effect sizes of these standardized coefficients as a whole indicated that the majority of the predictors did not demonstrate strong standardized effects. In fact, the largest standardized effect by a factor of three was that of income-to-needs ratio, for which a change in one standard deviation (i.e., moving from above to below 200% of the poverty line) was found to result in an increase of .12 standard deviations in $z$BMI. For the remaining predictor variables, change in one...
standard deviation was found to result in changes of between 0 to 0.04 standard deviations, which, although effect sizes for simple standardized regression coefficients are rarely calculated, can be quantified as small effects (Nieminen, Lehtiniemi, Vähäkangas, Huusko, & Rautio, 2013).

Analyses of the change in $R^2$ and model fit based on incremental addition of individual variables indicated that no single individual variable significantly enhanced $R^2$ or changed model fit. However, it is possible to descriptively compare change in $R^2$ among the individual and family variables. To do so demonstrates that, among individual factors, screen time alone enhanced $R^2$, whereas $R^2$ remained constant with the addition of physical activity and decreased with the addition of bedtime. Similar analysis of the change in $R^2$ and model fit based on incremental addition of family-level variables indicated that no single family variable significantly enhanced $R^2$ or changed model fit. Interestingly, adding both food security and family meals to be estimated in the model did not affect $R^2$, whereas adding family physical activity, whose standardized coefficient was significant in the model, decreased $R^2$ by .01. Therefore, overall, screen time appears to be the most relatively important individual factor for explaining variance in $z$BMI, whereas no similarly impactful family variable was identified.

**Longitudinal models.** Findings indicated that no standardized coefficients of the predictor variables were significant at T2. In terms of the effect sizes of the standardized coefficients, all of the standardized coefficients, already small in size, decreased for second grade $z$BMI. As expected, the relation between $z$BMI in kindergarten and $z$BMI in second grade was strong, evidencing a standardized coefficient of .77, a highly significant and large effect, which likely contributes to the small size and significance of all of the other coefficients in the model.

Similarly, analyses of the change in $R^2$ based on incremental addition of individual and family variables indicated that no individual or family variable significantly enhanced $R^2$ of
second grade zBMI. Notably, the values of \( R^2 \) remained the same with or without the addition of any of the individual or family factors, likely again due to the high degree of \( R^2 \) explained by kindergarten zBMI. Therefore, as no individual or family variables improved or decreased fit at this timepoint, it is not possible to even descriptively compare change in \( R^2 \) among the individual and family variables at T2, and it can be concluded that no single individual or family factors helped to explain more of the variance in zBMI in second grade than any other.

**Examining relative importance of ecological levels.** Furthermore, for this aim, the overall cross-sectional and longitudinal models were assessed for the most important “level” of factors (e.g., individual, family, community). In order to do this, the predictors were allowed to intercorrelate while their regression coefficients (gammas) linked them to the DV fixed at zero. For this baseline model, again, only the “control” variables of income-to-needs ratio and race/ethnicity were freed to be estimated in the model. Then, sets of regression coefficients for different levels of predictors (i.e., “individual factors”) were then successively freed to be estimated in the model and the amount of change in the R-squared for the DV was observed (Joreskog & Sorbom, 1999). For each of the models within this aim, race/ethnicity and income-to-needs were again included as covariates.

**Cross-sectional models.** Analyses of zBMI in kindergarten indicated that both the individual and family level of predictors improved \( R^2 \) (although the change was not significant), whereas the community factor did not improve \( R^2 \). Because \( R^2 \) did increase with the addition of the “individual-level” and “family-level” sets of variables, it is possible again to descriptively compare change in \( R^2 \) among these sets of variables. To do so demonstrates that T1 \( R^2 \) was improved by .02 with the addition of the individual factors, whereas it was improved by .01 with the addition of the family factors; therefore it is suggested that individual factors were more
influential in explaining variance in zBMI than either family or community factors. However, it is important to note that this was not a statistically significant difference.

**Longitudinal models.** Analyses of zBMI in second grade indicated that no level of factors (individual, family, or community) improved $R^2$ appreciably. As when comparing longitudinal factors, $R^2$ remained the same with or without the individual, family, and community variables, likely due to the considerable influence of kindergarten zBMI. Therefore, it cannot be concluded that any level of factors was significantly more associated with second grade zBMI than any other level of factors. A summary of the results of change in $R^2$ across the levels of both the longitudinal and cross-sectional models is provided in Table 4.

Table 4. Change in $R^2$ among ecological levels of factors

<table>
<thead>
<tr>
<th>Model</th>
<th>$R^2$</th>
<th>$\Delta R^2$</th>
<th>$R^2$</th>
<th>$\Delta R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline (Covariates Only)</td>
<td>0.03</td>
<td>--</td>
<td>0.61</td>
<td>--</td>
</tr>
<tr>
<td>Individual Only</td>
<td>0.05</td>
<td>0.02</td>
<td>0.61</td>
<td>0.00</td>
</tr>
<tr>
<td>Family Only</td>
<td>0.04</td>
<td>0.01</td>
<td>0.61</td>
<td>0.00</td>
</tr>
<tr>
<td>Community Only</td>
<td>0.03</td>
<td>0.00</td>
<td>0.61</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Aim 3: Examining Differences in Model Fit by Demographic Variables**

For the third and final specific aim, multi-group SEM was utilized to assess for differences among the model’s fit within the overall sample, dividing participants by (1) race/ethnicity, (2) income-to-needs status, and (3) sex. The process of multigroup SEM involves the use of invariance testing to compare versions of the path model in which all structural coefficients are set to be invariant by a given variable against a baseline multi-group model in which no structural coefficients are invariant (Joreskog & Sorbom, 1999). For example, the
baseline, just-identified, model for both sexes was compared to a model wherein the gamma matrix (i.e., the matrix including all of the paths from x-variables to y-variables) was constrained to be equal across sexes. If this constrained model performed no worse than the baseline model, it was therefore interpreted that the GA matrices are invariant between sexes (i.e., that sex doesn't affect any of the predictive impacts). If, on the other hand, the constrained model did perform worse, it was interpreted that there is variance between sexes within the gamma matrix. In this case, a number of additional models were run to identify the source of the invariance.

Traditionally, invariance testing has been completed through the comparison of overall model fit chi-square values; in these models, given the use of DWLS estimation, the standard chi-square value is typically inflated and therefore it has been recommended to utilize the Satorra-Bentler adjusted chi-square. However, more recently, Cheung and Rensvold (2002) and later Chen (2007) have proposed an alternative method that has grown in popularity. This approach allows for the use of equality constraints, or invariance testing, by examining changes between the variant and noninvariant models based on model fit indices, such as the CFI and RMSEA. These authors’ examination found that these indices were well-suited for invariance testing and resistant to the effects of differences in sample size and invariance that is not uniformly distributed. Since its introduction, this method has been utilized in several recent studies utilizing structural equation modeling and equality constraints, or invariance testing (Joshanloo & Bakhshi, 2016; Scholten, Velten, Bieda, Zhang, & Margraf, 2017). Therefore, the aforementioned baseline and gamma-invariance models were created for each demographic grouping, and the reduction in the CFI and RMSEA was observed. As suggested by Chen (2007) for cases in which there is adequate sample size in each group (>300, a criterion that was met for all groups), cut-off values for significance when observing change in the CFI and RMSEA
values were set at a change in CFI of greater than or equal to .010 accompanied by a change in RMSEA greater than or equal to .015. A change of these proportions was interpreted as indicating a significant decrease in model fit and hence non-invariance (Chen, 2007). When it was determined for any of the demographic variables that coefficients were not equivalent, e.g., for males and females, individual equality constraints were then utilized to individually test each path coefficient for demographic differences. For any path coefficients determined to be non-equivalent across groups, the direction of the equivalence was noted, and conclusions were drawn regarding the relative importance of various individual factors on zBMI development in kindergarten and second grade across demographic groups. For each of these models, the demographic factors that were not being examined directly were controlled (e.g., in the sex differences model, the model controlled for income-to-needs and race/ethnicity).

**Differences in model fit by race.** As described, racial/ethnic groups included (1) White, (2) Black/African American, (3) Hispanic/Latino, and (4) Other (comprising American Indian, Asian, Native Hawaiian or other Pacific Islander). Because there were four categories of racial/ethnic identity, in order to complete the process of testing invariance among groups, it was necessary to test the invariance of each of the six possible combinations of two races. Therefore, utilizing the techniques described above, models were run testing the global invariance of the regression coefficients of the models describing (1) White children vs. Black/African American children, (2) White children vs. Hispanic/Latino children, (3) White children vs. American Indian, Asian, and Pacific Islander children, (4) Black/African American children vs. Hispanic/Latino children, (5) Black/African American children vs. American Indian, Asian, and Pacific Islander children, and (6) Hispanic/Latino children vs. American Indian, Asian, and
Pacific Islander children. The results of each of these six statistical processes are presented in Table 5.

Table 5. Change in model fit estimates among racial groups; significant values bolded

<table>
<thead>
<tr>
<th>Model</th>
<th>DF</th>
<th>CFI</th>
<th>RMSEA</th>
<th>Satorra-Bentler Adjusted $\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. White vs. Black: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gamma-invariant Model</td>
<td>16</td>
<td>1.00</td>
<td>0.00</td>
<td>1.99</td>
</tr>
<tr>
<td>2. White vs. Hispanic/Latino: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gamma-invariant Model</td>
<td>16</td>
<td>1.00</td>
<td>0.00</td>
<td>1.48</td>
</tr>
<tr>
<td>3. White vs. Other: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gamma-invariant Model</td>
<td>16</td>
<td>1.00</td>
<td>0.00</td>
<td>1.35</td>
</tr>
<tr>
<td>4. Black vs. Hispanic/Latino: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gamma-invariant Model</td>
<td>16</td>
<td>0.99</td>
<td>0.04</td>
<td>50.71</td>
</tr>
<tr>
<td>5. Black vs. Other: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gamma-invariant Model</td>
<td>16</td>
<td>1.00</td>
<td>0.00</td>
<td>12.10</td>
</tr>
<tr>
<td>6. Hispanic/Latino vs. Other: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gamma-invariant Model</td>
<td>16</td>
<td>1.00</td>
<td>0.00</td>
<td>9.77</td>
</tr>
</tbody>
</table>

Findings indicated that there were no significant differences in fit between a majority of the racial/ethnic pairings, including Models 1, 2, 3, 5, and 6. However, fit indices did evidence a significant change in Model 4, comparing Black/African American youth to Hispanic/Latino youth, with a change of 0.01 units in CFI and a 0.04 units in RMSEA. This indicated that the fit of the combined regression coefficients between these two groups was not equivalent. Therefore, in order to better understand the possible source of this invariance (i.e. which independent variables were differentially related to zBMI), individual regression coefficients were then tested for invariance. A summary of these findings is presented in Table 6.
Table 6. Change in model fit between African American and Hispanic youth while constraining specific gamma coefficients

<table>
<thead>
<tr>
<th>Gamma Coefficient (Independent Variable, Dependent Variable)</th>
<th>DF</th>
<th>CFI</th>
<th>RMSEA</th>
<th>Satorra-Bentler Adjusted $\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0. Baseline Hispanic/Latino: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.003</td>
</tr>
<tr>
<td>Physical Activity/Week, T1 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.007</td>
</tr>
<tr>
<td>Screen time/Week, T1 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.10</td>
</tr>
<tr>
<td>Bedtime, T1 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.23</td>
</tr>
<tr>
<td>Family Physical Activity, T1 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.11</td>
</tr>
<tr>
<td>Food Security, T1 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.24</td>
</tr>
<tr>
<td>Family Meals/Week, T1 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.33</td>
</tr>
<tr>
<td>Income-to-needs Ratio, T1 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.64</td>
</tr>
<tr>
<td>Physical Activity/Week, T2 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.007</td>
</tr>
<tr>
<td>Screen time/Week, T2 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.006</td>
</tr>
<tr>
<td>Bedtime, T2 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.48</td>
</tr>
<tr>
<td>Family Physical Activity, T2 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.39</td>
</tr>
<tr>
<td>Food Security, T2 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>Family Meals/Week, T2 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.12</td>
</tr>
<tr>
<td>Income-to-needs Ratio, T2 zBMI</td>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Findings indicated that there were no significant differences in model fit for African American and Hispanic/Latino children based on a single regression coefficient. Therefore, it was concluded that multiple subthreshold differences in the strength or direction of individual coefficients were driving the observed significant difference in overall model fit. In order to more descriptively explore specific differences between the regression coefficients of these two models, a representation of the just-identified baseline path model was created for both Latino and African American youth separately. Each of these is presented in Figures 5 and 6 below.
Figure 5. Path model for Black/African American children (n=990) with labeled standardized coefficients for both T1 and T2; significant pathways in bold

Figure 6. Path model for Hispanic/Latino children (n=1759) with labeled standardized coefficients for both T1 and T2; significant pathways in bold
These models highlight that among Black/African American children, there were no statistically significant gamma or regression coefficients for either kindergarten or second grade zBMI, whereas among Hispanic/Latino children, as in the full model, income-to-needs ratio was a large and significant negative predictor of kindergarten zBMI, such that children below 200% of the poverty line were significantly more likely to evidence higher kindergarten zBMI. Furthermore, many of the non-significant coefficients differed considerably for Black versus Hispanic/Latino youth, including a stronger protective effect of family meals and a stronger detrimental effect of screen time for Black/African American children.

**Differences in model fit by income-to-needs ratio.** Income-to-needs groups included (1) Below 200% of the poverty line relative to family size, and (2) At or above 200% of the poverty line relative to family size. Because there were only two groups in this category, only one set of baseline and gamma-invariant models was needed to test for overall differences in model fit. The results of this testing are presented in Table 7.

Table 7. Change in model fit estimates among Income-to-Needs Ratio groups

<table>
<thead>
<tr>
<th>Model</th>
<th>DF</th>
<th>CFI</th>
<th>RMSEA</th>
<th>Satorra-Bentler Adjusted $\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Above vs. Below 200% PL: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gamma-invariant Model</td>
<td>16</td>
<td>1.00</td>
<td>0.00</td>
<td>2.13</td>
</tr>
</tbody>
</table>

There was no change in either CFI and RMSEA among the baseline and gamma-invariant models, indicating that there was no significant overall difference in the fit of the overall model between children whose income-to-needs ratio indicated that they fell above 200% of the poverty line for a family of that size and children whose income-to-needs ratio indicated they fell below 200% of the poverty line. Therefore, when assessing the overall model, income-to-needs ratio
did not emerge as a significant moderator of any of the links between the included obesity-relevant factors and either kindergarten or second grade zBMI.

**Differences in model fit by sex.** Sex groups included (1) Male and (2) Female. Because there were again only two categories to be tested, only one set of comparator models was run to test for overall differences in model fit. The results of this testing are presented in Table 8.

Table 8. Change in model fit estimates among sex groups

<table>
<thead>
<tr>
<th>Model</th>
<th>DF</th>
<th>CFI</th>
<th>RMSEA</th>
<th>Satorra-Bentler Adjusted $\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Boys vs. Girls: Baseline Model</td>
<td>0</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Gamma-invariant Model</td>
<td>18</td>
<td>1.00</td>
<td>0.00</td>
<td>2.69</td>
</tr>
</tbody>
</table>

Again, there was no change in either CFI or RMSEA among the baseline and gamma-invariant models, indicating that there was no significant overall difference in the fit of the overall model between boys and girls. Therefore, sex did not emerge as a significant moderator of any of the links between these obesity-relevant factors and either kindergarten or second grade zBMI.
CHAPTER FIVE

DISCUSSION

Given the increasing rates of obesity in school-age children and the significance of the adiposity rebound period in determining future weight, it is imperative to identify factors that contribute to this epidemic. While many studies have examined the influence of components of the ecological model (i.e., genetic individual, family, and community factors) on childhood obesity, relatively few have examined more than a few of these factors at once, and fewer still have compared their relative importance for obesity. No studies to date have expanded these models to compare how these complex relations differ based on demographic characteristics such as race/ethnicity, sex, and income-to-needs ratio. Therefore, this study is one of the first to empirically examine the ecological model of zBMI among school-age youth, as well as the first to explore moderation by demographic variables within this model.

The first objective of this study was to examine the fit of an ecological SEM model of zBMI between kindergarten and second grade among this large, national sample. Although two other studies have utilized an ecological framework to examine the influence of multiple factors on child obesity or zBMI (Dev et al., 2013; O’Brien et al., 2007), and another known study examined the fit of a structural equation model of factors in adult physical activity (Mama et al., 2015), to our knowledge, no prior studies have attempted to fit structural, or path models, to zBMI development in children utilizing the ecological model. In the current study, because of the “just-identified” method chosen to best represent the variables utilized, the baseline model
demonstrated a perfect fit, which served as a satisfactory point from which to examine the remaining aims of this study.

The second objective of this study was to examine whether there were particularly influential individual factors or levels of factors in this model of zBMI in kindergarten and the second grade. Based on a review of the literature, it was hypothesized that children’s physical activity and sedentary time would have the most significant impact on zBMI. However, the first finding within this aim highlighted that only two factors, family physical activity and income-to-needs ratio, were significantly associated with zBMI in kindergarten, such that a standard unit increase in each of these factors was associated with a significant unit increase in zBMI. The first of these factors, family physical activity, was positively associated with zBMI in kindergarten, indicating that increased reported family physical activity was associated with increased zBMI in kindergarten only. This finding is in the opposite direction of that which was hypothesized and predicted by earlier studies (Koplan et al., 2007; Xu et al., 2015; Yao & Rhodes, 2015). There are several possible explanations for this surprising finding, especially in light of its cross-sectional nature: the first is that families with overweight children may be aware of their child’s weight and therefore more likely to engage in proactive exercise. Although recognizing overweight in children this young is not expected among all parents (Katz, 2015), some parents may be aware of their child’s weight and use this information as a motivation to engage their family in regular physical activity (Beets et al., 2010; Davison, Cutting, & Birch, 2003). Indeed, given the data supporting its effectiveness in curbing childhood obesity, some families with overweight children may have been counseled by a medical provider to engage in regular family exercise. Similarly, this finding may also be partially explained by what is known about the genetics of obesity: estimates place heritability of obesity between 40 and 70% (Herrera &
Lindgren, 2010), and genes for overweight are shown to impact obesity even in early childhood (Dina et al., 2007; Zhao & Grant, 2011). Therefore, parents whose children are overweight are more likely to be overweight themselves, and it is possible that this finding may be explained not only by parents’ awareness of their child’s weight but also their awareness of their own weight. Perhaps, therefore, this cross-sectional finding is a product of which families choose to engage in regular family exercise at this young age. The fact that this finding did not emerge longitudinally supports this interpretation, as it presumes that children’s obesity and parental encouragement of physical activity are occurring concurrently rather than physical activity predicting later increases in zBMI.

The second, and perhaps the most compelling finding from this aim was that income-to-needs ratio evidenced the most clear relation with zBMI at T1, with a standardized coefficient more than three times that of any other factor. Other studies that have included income-to-needs ratio or similar poverty-related variables as predictors in models of obesity have found mixed effects. For example, Dev and colleagues (2013), one of the first to test an ecological framework to childhood obesity, examined several income-related variables such as WIC status and parental education, and did not find significant effects of these variables. Similarly, O’Brien and colleagues (2007), another example of an ecologically-informed study of childhood obesity, found that among demographic, household, and individual factors, demographic factors (which included income-to-needs ratio) were not significant predictors of weight trajectories. At the same time, many studies examining longitudinal pathways of both income status and obesity have demonstrated that low or decreasing income is associated with risk for obesity both cross-sectionally and over time throughout childhood (Demment, Haas, & Olson, 2014; Kendzor, Caughy, & Owen, 2012; Lee, Andrew, Gebremariam, Lumeng, & Lee, 2014). Therefore, it is
perhaps in some ways unsurprising that a relation between income-to-needs and obesity was identified in this study, despite contradicting other ecological studies of childhood obesity. However, what is surprising is the relative strength of this association in relation to the other predictors. Some other studies have reported that inclusion of individual or neighborhood poverty status in models of childhood obesity (i.e. “adjusted models”) has diluted the significance of the effects of other factors (Rossen, 2014), but to our knowledge, few studies have examined many factors and concluded that income-to-needs ratio made up the majority of the significant effects.

As this study included a considerably larger and more representative sample than many examinations of childhood obesity, this result bears repeating—poverty itself was the greatest predictor of weight. Indeed, given the relatively weaker associations in the model between poverty-related factors, such as food insecurity, and weight, it seems that these factors alone do not explain the relationship between income-to-needs and obesity risk. This begs the question, “what component of poverty is responsible for this association?” Beyond those related variables already explicitly measured for this study, the biggest contender may be dietary intake. Evidence demonstrates that children’s dietary intake pattern is significantly related to poverty (Bhattacharya, Currie, & Haider, 2004), such that families who live below 200% of the poverty line are significantly more likely to have access to energy-dense, nutrient-poor foods (Lorson, Melgar-Quinonez, & Taylor, 2009) or fast foods (Reidpath, Burns, Garrard, Mahoney, & Townsend, 2002). Dietary intake was perhaps the largest obesogenic factor missing from the present model, and it is possible that income-to-needs ratio served as a proxy for these effects.

This study also aimed to compare the influence of factors within tiers, to determine whether a particular individual- or family-level factor might hold more importance for weight
than the others. It was hypothesized that screen time and physical activity would be more influential than sleep in influencing child zBMI. Partially consistent with this hypothesis, findings demonstrated that, among individual factors, screen time alone enhanced the total model in explaining the variance in zBMI at T1. This finding suggests that, among the individual factors captured here, screen time was the one that most contributed to explaining children’s weight. As was reviewed above, conceptualizing sedentary time as a separate element of time use from exercise has recently been proposed in the literature (Fakhouri et al., 2013; Melkevik, Torsheim, Iannotti, & Wold, 2010), and the influence of screen time in this model supports this idea. In addition to simply suggesting a higher proportion of sedentary time, screen time per week may also be suggestive of other factors that may lead to child weight, such as increased eating of high-calorie foods while watching (Ciccone, Woodruff, Fryer, Campbell, & Cole, 2013; Santaliestra-Pasías et al., 2012), exposure to low-nutrient food and beverage marketing that influences children’s preferences, requests, and eating habits (Chamberlain, Wang, & Robinson, 2006), and dysregulated sleep cycles (Chahal, Fung, Kuhle, & Veugelers, 2013; Hale & Guan, 2015). Therefore, of the individual variables measured in this study, screen time per week may capture the most complex and relevant data for weight status, and therefore have the largest impact on overall variance in weight of the three.

A final component of the second aim of the study to compare each level of predictors—individual, family, and community—and their respective influences on child zBMI. Based on the concentric rings of influence within the ecological model, it was predicted that the individual factors would contribute most directly to kindergarten and second grade zBMI. Consistent with this hypothesis, individual predictors helped to explain the variance in zBMI to a greater degree than family or community factors. There are several clear explanations for this finding—
physiologically, research indicates that, beyond genetics, individual factors have the most direct impact on weight. For example, a child’s use of sedentary screen time directly relates to the amount of calories that they burn (or do not burn) in a given day (Thivel, Aucouturier, Doucet, Saunders, & Chaput, 2013), and as weight is a factor of calories consumed to calories burned, this directly impacts adiposity (Wang, Orleans, & Gortmaker, 2012). Meanwhile, family and community factors are likely to have more distal and mediated paths in their influence on obesity: for example, community safety is hypothesized to impact physical activity, which itself impacts obesity (Franzini et al., 2009; Singh et al., 2010). While testing mediation in this way is beyond the scope of this model, it helps demonstrate the finding that individual factors likely have a greater impact on $z$BMI variance than family or community factors.

Finally, it is important to note that, throughout analyses for the second aim, all of the significant findings in terms of relative importance of individual factors or levels of factors were found in kindergarten only. This trend is almost certainly due to the amount of variance in second grade $z$BMI that is explained directly by kindergarten $z$BMI. This expected finding is due to a number of factors: first, the genetic contribution to obesity, mentioned above, is likely at least somewhat captured by this relation. Children who are genetically more likely to be overweight in kindergarten are also more likely to be overweight in second grade. Even beyond genetics, other factors in a child’s environment may influence obesity that were not captured by this model (i.e., diet) would also be expected to be fairly consistent between kindergarten and second grade and could lead to the strong consistency of $z$BMI between these two points in the adiposity rebound period.

The third objective of this study was to explore and identify differentially influential factors for separate demographic groups, such as race/ethnicity, income-to-needs ratio, and sex.
For a majority of these groupings, including sex and income-to-needs ratio, the model demonstrated similar fit between groups. The finding that the fit of the model did not differ based on sex indicates that for both male and female children, among the factors examined, the predominant driver of obesity was income-to-needs status. This sobering finding suggests that the ways in which income-to-needs or poverty status may impact weight, summarized above, may be relatively consistent for boys and girls. Furthermore, the fact that income-to-needs ratio, found to be such an strong correlate of weight at T1, did not moderate any of the findings when examined in multigroup SEM, suggests that this being above or below 200% of the poverty level did not change the way in which individual, family, and community factors influence obesity. This null finding can be framed in a more hopeful light—children of both lower and higher income-to-needs were both impacted in a similar way by these factors, including the many of those that were demonstrated to be neutral or protective when it comes to weight status. While neither of these null findings suggest options for creating tailored obesity interventions, they do support the idea that interventions can be broadly applied and affect change in a similar manner, at least for boys and girls and lower and higher income-to-needs ratios and among the factors included here.

Notably, while it was found that there were no differences in model fit for the majority of racial/ethnic group pairs, for one set of racial/ethnic groups, the findings highlighted a difference in fit between African American and Hispanic/Latino youth. Although the follow-up analyses did not pinpoint a specific factor that entirely explained the difference in model fit among these youth, descriptive examination of the models between the two groups seem to suggest that the main influential factor in the overall model—income-to-needs ratio—was more influential for Hispanic/Latino children than it was for African American children. Recent studies of similarly
large national datasets have suggested that increased income is not as protective for African American children as it is for Caucasian children with regard to obesity (Assari, 2018); this study extends this finding to include that perhaps a higher income-to-needs ratio is particularly protective for Hispanic/Latino children. If poverty is indeed a relatively more influential factor in Hispanic/Latino child obesity, this is key public health information, given that Hispanic/Latino children are also the group that are most disproportionately likely to be obese (Ogden et al., 2014).

**Limitations and Future Directions**

This study, while informative, is not without its limitations. First, given the nature of the public-use dataset utilized, the availability of measures to capture each of the possible obesogenic factors within an ecological model was limited. Most notably, and as has been mentioned above, the ECLS-K:2011 does not include any direct measures of dietary intake, which is a very well-established contributor to childhood obesity via the energy gap hypothesis as explained in the introduction (see Koplan & Dietz, 1999). Although it is not possible to test directly, this limitation may be part of the reason that results were so strongly centered around poverty status. Furthermore, because the ECLS-K:2011 is a broad study not designed as an examination of childhood obesity, the measures that were available for many of the included independent variables often comprise only one or few items, and therefore may not capture the full variability present in the sample with regard to these factors. However, these measures have been utilized in other studies (Beets & Foley, 2008; Burdette & Whitaker, 2005; Datar et al., 2013; Lee et al., 2018; Miller et al., 2012; Morrissey et al., 2016), and were purposefully chosen by the NCES to represent these constructs in the most efficient manner possible (Mulligan et al., 2012).
Another characteristic of the data available through the ECLS:K-2011 is that each of the measures about child/family environment and activities is based on caregivers’ report, another possible source of bias. Parental estimates of their children’s activities (e.g., physical activity, sleep) are understood to be less reliable than objectively measured data such as ecological momentary assessment and actigraphy monitoring (Dayyat, Spruyt, Molfese, & Gozal, 2011; Sallis, Taylor, Dowda, Freedson, & Pate, 2002). However, to our knowledge, no studies of this magnitude to date have been able to measure behavioral data in these more objective ways. Furthermore, although there is a recent push toward child-report questionnaires of health behaviors (Combs et al., 2019), there is no evidence supporting the idea that children between kindergarten and second grade are accurate reporters of health behaviors.

It is a strength of the study that the Structural Equation Modeling methods chosen (Diagonally Weighted Least Squares modeling) maximized reliability of the parameter estimates in light of the considerable number of ordinal variables. However, these same analyses precluded applying the sampling weights provided by the NCES in order to help the sample racially/ethnically reflect the overall U.S. kindergarten population at the time of data collection. Particularly due to the multigroup nature of the main analyses and concerns that sampling weights, which serve to weight data based on demographic characteristics, would render these comparisons uninterpretable, this tradeoff was intentionally chosen in order to maximize validity. However, a limitation is therefore that the provided conclusions are less generalizable than another type of analysis that could fully utilize these weights. In spite of this, the large sample size available for the analysis likely indicates relatively good generalizability of these results. Both of the preceding paragraphs suggest that future national studies of weight among children should include more multi-dimensional measures of obesogenic behaviors in order to
maximize validity, and avoid ordinal variables in order to improve generalizability through the use of the provided weights.

Although not a limitation per se, it is important to acknowledge that even for the strongest “statistically significant” effect of income-to-needs ratio within the full sample, there remains the question of clinical significance. The standardized coefficient of .16 suggests that for each standard deviation increase in income-to-needs ratio, zBMI increases by .18. Although there are not published standards of demonstrating clinical significance via zBMI increase or decrease among children in this age range, it is possible to consider how the change in zBMI that might be observed as children switch between income-to-needs groups compares to participation in an obesity intervention. For example, an average decrease in zBMI of .20 has been reported after a 10-week, four hour/week comprehensive family-based obesity intervention among 6-13 year old children (Law et al., 2014) suggesting that the impact of poverty on zBMI in this model has approximately the same effect as this length and intensity of intervention. Future research on clinical significance of zBMI increase or reduction in terms of its later health effects is certainly warranted and would make such interpretations more meaningful for future studies.

A final potential weakness of this study is highlighted by the contrast between the strong correlations found between nearly each of the variables (see Table 1) and the relatively fewer significant findings that arose analyzing this data in a single large model. This contrast reveals one of the downsides of testing large, comprehensive models such as this partial ecological model: assuming that only some portion of the variance in zBMI is explained by the total tested ecological factors, this variance is necessarily divided among many (often themselves correlated) variables, and therefore each variable is associated with only a small portion of the total variance. Although this study appropriately utilized a path modeling approach to this question in
order to handle a complicated set of measured variables and time points, the end statistical model is similar to a regression model with nine predictors each entered on the same step. In these scenarios, as in the model presented here, it is likely that removing some variables from the equation would increase the relative variance explained by the remaining variables, possibly boosting some into statistical significance. Therefore, although the study’s design was determined to be the best suited for answering the given questions—regarding relative influence of factors and levels of factors—it presents somewhat fewer “significant” findings than a more targeted study. This also alludes to a possible reason why relatively few former studies have utilized a similar approach: because of the pressures to public significant results, and the increase in likelihood of significant results among more concise models, these ecological models may be less “publishable.” However, this more comprehensive approach presents results that may reflect something closer to the whole and complex truth of child obesity development.

**Conclusions**

The current study aimed to propose and test the fit of an ecological model of child obesity, including individual, family, and community factors, among a large, national sample of children in the critical adiposity rebound period. Furthermore, it attempted to clarify which of these factors, both within and between levels, may be most influential for child obesity development. Overall, income-to-needs ratio was a particularly influential factor in obesity during kindergarten, such that children whose families fell below 200% of the poverty line were more likely to weigh more. In addition, these findings suggested that, among individual, family, and community factors, individual factors were most influential, and that screen time was the most influential of these. Finally, this study advanced the literature by exploring how the fit of this model may differ among children of differing demographic characteristics, finding that
income-to-needs ratio was particularly influential for weight among Hispanic/Latino children as opposed to Black/African American Children. All in all, this study serves to drive home the structural, public health origins and implications of the child obesity epidemic. While obesity is often thought of as the burden of individuals or families, it is clear that more distal demographic factors are key as well as—and perhaps more than—the most proximal individual factors, particularly for some racial/ethnic minority groups.


Peck, T., Scharf, R. J., Conaway, M. R., & DeBoer, M. D. (2015). Viewing as little as 1 hour of TV daily is associated with higher change in BMI between kindergarten and first grade. *Obesity, 23*(8), 1680-1686. https://doi.org/10.1002/oby.21132


VITA

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