Summer 2021

The Relationship of Structured Environments With Children's Body Composition and Obesogenic Behaviors

Ethan T. Hunt

THE RELATIONSHIP OF STRUCTURED ENVIRONMENTS WITH CHILDREN'S BODY COMPOSITION AND OBESOGENIC BEHAVIORS

by

Ethan T. Hunt

Bachelor of Science
Slippery Rock University, 2013

Master of Public Health
Indiana University-Bloomington University, 2016

Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Exercise Science

The Norman J. Arnold School of Public Health

University of South Carolina

2021

Accepted by:

Robert G. Weaver, Major Professor

Michael W. Beets, Committee Member

Bridget Armstrong, Committee Member

Gabrielle M. Turner-McGrievy, Committee Member

Marco Geraci, Committee Member

Tracey L. Weldon, Interim Vice Provost and Dean of the Graduate School

DEDICATION

This dissertation is dedicated to the University of South Carolina's Department of Exercise Science.

ACKNOWLEDGEMENTS

I would like to acknowledge several people that have helped me throughout my doctoral degree. First, and foremost, I would like to thank my Fiancé, Whitney, for her continuous love and support. I would also like to thank my parents John and Lynnie Hunt for always supporting my decisions. I would like to thank my mentor, Dr. Weaver, for providing me with a rich research experience and for his continuous feedback and guidance which has helped me grow and develop as an independent researcher. I would also like to thank Dr. Beets for his support and mentorship over the past four years. Last but not least, I would like to thank my dissertation committee members: Drs. Armstrong, Turner-McGrievy, and Geraci for their expertise and support throughout this entire process.

ABSTRACT

Recent nationally representative data show among children and adolescents aged 2 to 19 years, the prevalence of obesity is 17.0% (95CI= 15.5%-18.6%). Further, rates of obesity are disproportionately high among minoritized youth. The prevalence of children and adolescents with obesity is lower among White children compared to Black children (14.7% vs. 19.5%) or Hispanic children (14.7% vs. 21.9%). Disparities by socioeconomic status exist as well. Prevalence of children with obesity from households with an income that is >350% of the federal poverty threshold (after accounting for household size) is significantly less compared to children from households with an income that is <130% of the federal poverty threshold (10.9% vs 18.9%). Disparities exist by location as well. A recent systematic review concluded that children who reside in rural areas are 2.6 times more likely to have obesity when compared to their urban counterparts. Although children in rural areas have more obesity, this prevalence might differ based on the definition of rural used. Finally, evidence shows children gain 3-5 times the amount of weight and lose cardiorespiratory fitness (CRF) during summer compared to the 9-months of the school year. Notably, this trend is more pronounced in children who are already overweight or obese going into summer and/or from low-income or minoritized households. To our knowledge, no studies have examined summer weight gain by location or rurality status (i.e., exurban vs urban).

The purpose of study 1 was to examine accelerations in body composition (BMI, age-sex specific zBMI, and 95th percentile of BMI [%BMIp95] gain) during the summer

months by school locality (i.e., urban, suburban, exurban). This study utilized the Early Childhood Longitudinal Study Kindergarten Class of 2010-2011 (ECLS-K:2011), a complex multistage probability sample from the population of U.S. children who were enrolled to attend kindergarten in the fall of 2010. ECLS-K:2011 data were restricted to those participants with height and weight measured within specific time periods (August/September and April/May) to appropriately examine accelerations in body composition gain during the summer months and school year. A total of 1,549 children (48% female, 42% White) had at least two consecutive measures that occurred in August/September or April/May. Among all locale classifications (i.e., urban, suburban, and exurban), children from high income households comprised the largest proportions for each group (31%, 39%, and 37%) respectively. Among urban and suburban locations, Hispanic children comprised the largest proportions for both groups (43% and 44%) respectively. Among exurban locale classifications, the majority of children were white (60%). Children from suburban and exurban schools experienced significantly less accelerations in monthly zBMI gain compared to their urban counterparts -0.038 (95CI= -0.071, -0.004) and -0.045 (95CI= -0.083, -0.007) respectively. Children from exurban schools experienced significantly less acceleration in monthly %BMIp95 during the summer months when compared to the school year -0.004 (95CI= -0.007, 0.000). This is the first study to examine summer weight gain by school location. Summer appears to impact children more negatively from urban schools when compared to their suburban and exurban counterparts.

The purpose of study 2 of this dissertation is to evaluate children’s proportion of days meeting behavior guidelines: moderate-to-vigorous physical activity (MVPA) ≥60

minutes/day, sleep (10-13 hours/night for 5 years, 9-12 hours/night for 6-12 years), and screen-time (<2 hours/day) during the school year compared to summer vacation by race and free/reduced-priced lunch (FRPL) eligibility. Children (n=268, grades=K-4, 44.1%FRPL, 59.0% Black) attending three schools participated. Children's activity, sleep, and screen-time were collected during an average of 23 school days and 16 days during summer vacation. During school, both children who were White and eligible for FRPL met activity, sleep, and screen-time guidelines on a greater proportion of days when compared to their Black and non-eligible counterparts. Significant differences in changes from school to summer in the proportion of days children met activity (-6.2%, 95CI=-10.1%,-2.3%; OR=0.7, 95CI=0.6, 0.9) and sleep (7.6%, 95CI=2.9%,12.4%; OR=2.1, 95CI=1.4, 3.0) guidelines between children who were Black and White were observed. Differences in changes in activity (-8.5%, 95CI=- 4.9%, -12.1%; OR=1.5, 95CI=1.3, 1.8) were observed between children eligible vs. ineligible for FRPL. Summer vacation may be an important time for targeting activity and screen-time of children who are Black and/or eligible for FRPL.

This complete dissertation works to further the literature exploring childhood obesity, and its behavioral mechanisms that may help to curb prevalence rates that continue to be a public health concern. Obesity prevalence by location has been established in the literature. However, less is known regarding summer weight by school location. Further, I explore the behavioral mechanisms contributing to obesity by examining the proportion of days children meet behavior guidelines during summer vacation and the school year.

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CHAPTER ONE: INTRODUCTION

Excess adiposity in children is linked with numerous chronic diseases in adulthood ranging from diabetes, cardiovascular disfucntion, and metabolic syndrome.[1,2] The CDC defines overweight or obesity for youth (2-20 years) as having a body mass index (BMI) at or above the 85th percentile or 95th percentile, respectively, in relation to sex-specific CDC BMI-for-age growth charts.[3] Recent nationally representative data show among children and adolescents aged 2 to 19 years, the prevalence of obesity was 17.0% (95CI= 15.5%-18.6%).[4] Further, among children aged 6 to 11 years, obesity has increased from 11.3% (95CI= 9.40%-13.40%) to nearly 20.0% over the past two decades. [4] Further, rates of obesity are disproportionately high in minoritized children and children from low-income households. Data show that the prevalence of children and adolescents with obesity is lower among children who are White when compared to children who are Black (14.7% vs 19.5%). Further, the prevalence of children and adolescents with obesity is lower among children who are White when compared to children who are Hispanic (14.7% vs 21.9%).[4] In addition to disparities by race/ethnicity, disparities by socioeconomic status exist as well. Recent statistics show that the prevalence of children with obesity from households with an income that is >350% of the federal poverty threshold after accounting for household size is significantly less when compared to those children from households with an income that is <130% of the federal poverty threshold (10.9% vs 18.9%).[5] Further, the prevalence of children with obesity from households with an income that is >350% of the federal poverty threshold after accounting for household size is significantly less when compared to those children from families with an income that is >130% to 350% of the federal poverty threshold (10.9% vs. 19.9%).[5] Disparities exist by location as well. Children who are considered “exurban” or live in rural or areas other than “urban” areas are more likely to have obesity when compared to their urban counterparts.[6]

A large and growing body of evidence has shown that accelerations in weight gain and reductions in fitness occur during the summer months (June-August) in elementary aged children (6-11 yrs.).[7-15] Specifically, von Hippel and colleagues analyzed data from the Early Childhood Longitudinal Study Kindergarten (ECLS-K) Cohort 2010-2011 to examine weight gain during the summer compared to the school year. Increases in BMI accelerated during summer vacation when compared to the school year.[10] Chen and colleagues examined 1,651 elementary aged children’s weight trajectories from K-5th grade in a single Texas school district and found increases, regardless of initial weight status, in the prevalence of overweight and obesity occurred primarily during the summer months.[16] Further, evidence has demonstrated that accelerated summer weight gain impacts minority and overweight or obese children to a greater extent than their White or normal weight counterparts.[8,10,17] For instance, von Hippel and colleagues found that gains in BMI during the summer months were greater for children who are Black, Hispanic, and children who were overweight or obese when they entered kindergarten using data from the Early Childhood Longitudinal Study-Kindergarten Cohort 1998.[10] This finding was replicated in a follow up analysis of the Early Childhood Longitudinal Study-Kindergarten Cohort 2011.[18] Finally a recent systematic review examining trajectories of weight gain in children during the summer versus school year concluded that 86% of the studies that examined summer weight gain found an increased effect in summer weight gain acceleration for Black and Hispanic children compared to their White peers.[17]

Understanding the reasons and mechanisms for why summer weight gain is occurring is somewhat novel. Because of this, gaps in the literature remain. To better understand the mechanisms of summer weight gain, a further exploration into the childhood obesity is necessary to fill gaps in the literature. This dissertation works to do so by explaining potential relationships between locality and summer weight gain, and by examining the ability of children to meet behavior guidelines during the summer months compared to the school year. It is important to build off the previous literature to understand what has been done and what gaps remain. One possible explanation is that a child's day during the school year is dramatically different than the summer in which he/she is not enrolled in school. The presence of a consistent, structured day with adult supervision during the school year could be contributing to children's engagement in more healthy behaviors. The Structured Days Hypothesis (SDH) posits that a typical school day, or a day that is pre-planned, segmented, and adult supervised protects children against engaging in negative obesogenic behaviors, and, ultimately, prevents the occurrence of negative health-outcomes, in this case accelerated weight gain.[19] On the opposite end of the spectrum, summer, in which there is less structure and adult supervision, children engage in more unhealthy obesogenic behaviors (decreases in PA, increased in screen-time, etc.), which can contribute to gains in unhealthy weight throughout the summer months.[19-21] For example, during the school year, children are required to be at school at a certain time, which in turn would regulate when children wake in the morning and go to bed the previous night. Evidence has shown that early to bed and early to wake sleep schedules are protective against overweight and obesity and engagement in unhealthy behaviors.[22,23]

This “health gap” during the summer may play a crucial role in the widening of disparities in childhood obesity that have been discussed. Education literature has long examined the impact that summer vacation may have on academic outcomes.[24,25] Findings suggest that gaps in academic performance widen for children from low-income households compared to their middle-and-upper-income peers during the summer.25 The Health Gap hypothesis suggests that, similar to the academic literature, children from low-income households experience a similar amount of weight gain during the school year, then greater amount of weight gain during the summer compared to their high-income peers, resulting in a widening disparity in prevalence rates of obesity.[26] The lack of accessibility for structured programs during the summer may be driving these disparities. This hypothesis can be supported by America Camp Association data that highlights unequal access to summer programming in that 71% of summer day camp attendees are children who are White, and at least middle-income.[27] Thus, this dissertation project will explore these issues with the following three studies.

Study 1- Differences by School Location in Summer and School Monthly Weight Change: Findings from a Nationally Representative Sample

Given the literature base regarding summer weight gain in children, further exploration of this phenomenon among children from different economic and environmental backgrounds is needed. Understanding the social and ecological distal risk factors and how they may contribute to summer weight gain is important for public health because different approaches for different settings may be important when designing large scale obesity prevention programs. Therefore, I propose to examine the summer weight gain phenomenon by exploring the association of geographic school location with accelerations in body composition gain during the summer in elementary aged children. Past work utilizing large nationally representative datasets have examined summer weight gain in children by race/ethnicity and socioeconomic status, and found that children from minority and low-income households experience greater accelerated summer body composition gain.[18] The Early Childhood Longitudinal Study Kindergarten Class of 2010-2011 (ECLS-K:2011) is a complex multistage probability sample from the population of U.S. children who were enrolled to attend kindergarten in the fall of 2010. ECLS-K:2011 provides rich data on children's early school experiences beginning in kindergarten and following through fifth grade.[28] Measures of height and weight were collected from October-November each fall and February-March each spring. To understand summer weight change, measures need to be collected as close to the beginning and end of the school year as possible. I propose to restrict participants to those only measured within specific time periods (August/September and April/May), while accounting for complex survey design. Therefore, the purpose of Study 1 is to examine accelerations in body composition (BMI, age-sex specific zBMI, and 95th percentile of BMI (%BMIp95)) during the summer months by school locality (i.e., urban, suburban, exurban).

Study 2- Differences in Proportion of Children Meeting Behavior Guidelines During Summer & School & by Socioeconomic Status and Race

As mentioned previously, there is evidence regarding the summer weight gain phenomenon among youth. Less is known regarding the proximal behavioral mechanisms (PA, sedentary/screen-time, diet, and sleep) that contribute to this phenomenon. There is a lack of appropriate data on children's obesogenic behaviors during school versus summer. Specifically, data investigating the proportion of days children meet obesogenic behavior guidelines during the summer months and school year. Therefore, the purpose of this study is to evaluate the proportion of days meeting behavior guidelines (moderate-to-vigorous physical activity (MVPA≥60 minutes/day)[29], sleep (9-12 hours/night for 6-12-year-olds)[30], and screen-time (<2 hours/day)[31,32]) during the school year compared to summer vacation by race and free/reduced-price lunch (FRPL) eligibility.

CHAPTER TWO: MANUSCRIPT 1

DIFFERENCES BY SCHOOL LOCATION IN SUMMER AND SCHOOL MONTHLY WEIGHT CHANGE: FINDINGS FROM A NATIONALLY REPRESENTATIVE SAMPLE

Hunt, E.T., Beets, M.W., Armstrong, B.A., Turner-McGrievy, G.M., Geraci, M., R.G., Weaver, R.G. To be submitted to Childhood Obesity

Abstract

Objectives: To examine changes in accelerations of Body Mass Index (BMI), age-and-sex specific body mass index (zBMI), and 95th percentile of BMI (%BMIp95) during the summer months and school year by school location designation (i.e., urban, suburban, exurban). This study utilized the Early Childhood Longitudinal Study Kindergarten Class of 2010-201.

Methods: Of the 18,174 children in the ECLS-K:2011 dataset, I restricted participants to those with at least two consecutive measures that occurred August/September or April/May. Mixed-effect regression analyses estimated differences in monthly change in BMI, zBMI, and %BMIp95 between the summer and school year while accounting for the ECLS-K coplex sampling design. Models also examined differences in the magnitude of BMI, zBMI, and %BMIp95 change between the summer and school year by school location. Post-hoc Benjamini-Hochberg (BH) procedure set at 10% false discovery was incorporated to account for multiple comparisons.

Results: A total of 1,549 children (48% female, 42% White) had at least two consecutive measures that occurred in August/September or April/May. Among all locale classifications (i.e., urban, suburban, and exurban), children from high income households comprised the largest proportions for each group (31%, 39%, and 37%) respectively. Among urban and suburban locations, children who are Hispanic comprised the largest proportions for both groups (43% and 44%) respectively. Among exurban locale classifications, children who are White comprised the largest proportion of children (60%). Children from suburban and exurban schools experienced significantly less accelerations in monthly zBMI gain when compared to their urban counterparts -

0.038 (95CI= -0.071, -0.004) and -0.045 (95CI= -0.083, -0.007) respectively. Children from exurban school experienced significantly less acceleration in monthly %BMIp95 during the summer months when compared to the school year -0.004 (95CI= -0.007, 0.000).

Conclusions: This is one of the first studies to examine summer weight gain by school location. Summer appears to impact children more negatively from urban schools when compared to their suburban and exurban counterparts.

Introduction

Childhood obesity is a major public health concern.[5] Obesity is linked to a variety of chronic diseases and disorders such as heart disease, cancer, insulin resistance, and cardiovascular disease.[33,34] Where children live and attend school can be major contributors to obesity.[35,36] In recent years, there has been a substantial body of research examining the relationship between school location (i.e., urban, suburban, exurban) and risk for childhood obesity.[6]

While there are many ways to define locality, the United States (U.S.) Census defines urbanized areas as areas with a population of 50,000 or more which are either adjacent to densely populated areas, or other areas close in proximity with densely populated areas.[37] Areas directly outside urban areas are defined as suburbs. Suburbs include incorporated areas or census designations with at least 2,500 inhabitants, usually outside of urban areas. Exurban (i.e., town and rural locations) areas encompass localities outside of both urban and suburban areas.[38] Children who live in exurban settings are significantly more likely to have overweight/obesity when compared to their urban counterparts. [36,39] One recent meta-analysis concluded that children (2-19 years) in exurban settings have more than 25% greater odds of obesity compared to urban children.[6]

There is a limited amount of research which specifically examines childhood obesity prevalence in suburban settings. The limited research that does exist indicates that both females and males[40] in suburban areas, have lower rates of obesity compared to their same sex peers in urban or exurban settings. The underlying mechanisms driving these differences are likely multifaceted. Counterintuitively, it appears that children in rural settings engage in more physical activity (PA) than their urban counterparts, despite having higher rates of obesity.[41-43] In addition, differences in access to community resources may play a role. Specifically, more deprived exurban areas have less access to community resources such as healthcare and recreational facilities, supermarkets, and other essential services compared to their urban and suburban conterparts.[44-46]

Summer vacation from school may exacerbate disparities in access to resources for children in exurban areas compared to urban and suburban children. For instance, food insecurity is a risk factor for obesity in children.[47] During summer vacation, food security decreases in states providing small numbers of Summer Food Service Program meals and summertime school lunches than in other states.[48] Although the United States Department of Agriculture's Summer Food Service Program provides free meals for at risk children during the summer,[49] not all children can access this service. Lack of transportation and long distances to program sites are barriers to children in exurban areas accessing these services,[50] but may not be a barrier for children in more densely populated urban and suburban areas. These findings suggest that the removal of school may partially explain disparities in childhood obesity that exist by geographic location.

A large body of evidence indicates children's body mass index (BMI) accelerates, and the prevalence of children with obesity increases during the months of summer.[8,16,18,51-53] Previous studies have shown that Black children and children from low-income households experience greater increases in summer BMI gain compared to their White and high-income counterparts.[54] These disparate rates of accelerated summer BMI gain may also contribute to the disproportionately high rates of overweight and obesity observed among Black and low-income children.[55,56] Disparate rates of overweight and obesity by locality may be similarly explained by disproportionate rates of accelerated summer BMI gain. However, no studies to date have examined rates of children's accelerated summer BMI gain by locality. Thus, the current study aimed to examine accelerations in body composition during the summer months by school locality (i.e., urban, suburban, exurban).

Methods

This project utilized publicly available data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-11 (ECLS-K:2011).[28] ECLS-K:2011 is a complex multistage probability sample from the population of U.S. children who were enrolled to attend kindergarten in the fall of 2010. ECLS-K:2011 is designed to provide data on children's early school experiences beginning in kindergarten and following through fifth grade. Sampling for participants followed a multistage design, which took place in three primary steps. In the first step, the United States was divided into Primary Sampling Units (PSUs), and 90 of these PSUs were sampled. Second, public and private schools were sampled within each of the 90 PSUs. Third, children enrolled in kindergarten programs in those schools were sampled.[28] Each primary sampling unit was a large county or group of adjacent and demographically similar small counties.[28] The ECLS-K:2011 includes both public and private schools. Asian/Pacific Islander children were over-sampled to assure that the sample included enough students of this race/ethnicity to be able to make accurate estimates for these participants as a group.[28] Sampling weights were used to adjust for differential probabilities of selection at each sampling strata and adjust for the effect of nonresponse on parameter estimates.[57] The complete dataset consists of 18,174 children in 970 schools and 90 primary sampling units.

ECLS-K:2011 collected fall measurements from August to December and spring measurement from March to June.[18] A measurement occasion (i.e., month height/weight was collected) variable was included in the ECLS-K:2011 dataset. Because our aim was to estimate monthly school and summer change in body composition, we restricted our analytical sample to children who were measured in August/September and April/May. This approach allowed us to examine differences in body composition change during school (more-structured) and summer (less-structured) without employing analytical methods that would predict all children's height/weights at one specific time period. After restricting the dataset to the defined months, we had an analytical sample of 1,549 children. Figure 1.1 shows the flow of exclusions from the complete sample to the analytic sample.

Measures

Body Composition

On each measurement occasion, height and weight were measured twice, using a Shorr board stadiometer and a Secca Bella 840 flat electronic scale.[28] Children were asked to remove shoes, hats, and jackets.[28] BMI was calculated using the standard formula BMI=kilograms/meter2. BMI-z score was then transformed into age-and-sex specific BMI-z score.[58] In addition, we calculated percentage of the 95th percentile of BMI (%BMIp95). %BMIp95 is the ratio of individual BMI relative to the sex- and age-specific Center for Disease Control and Prevention 95th percentile BMI multiplied by 100. Thus, a %BMIp95 > 100% indicates that an individual child is obese.[59] %BMIp95 is included as an additional measure as it may be more appropriate than zBMI change for tracking change in age and sex specific BMI over time, especially for those children with extreme zBMI values and does not differ soley due to differences in sex and age as zBMI may.[60]

Location

To measure school locality, ECLSK:2011 categories correspond to the 2006 system National Center for Education Statistics (NCES) location variables which were constructed in combination with the United States Census Bureau classification system.[37,61] Geocoding technology and the Office of Management and Budget defined metro areas that rely less on population size and county boundaries than proximity of an address to an urbanized area.[62] NCES school location designations and definitions are as follows: city, suburb, town, and rural. Cities consist of areas inside an urbanized area and inside a principal city (i.e., the core city in a metropolitan area) with population of 250,000 or more. Suburbs consist of areas outside a principal city and inside an urbanized area with population of 250,000 or more. Towns consist of areas inside an urban cluster that is less than or equal to 10 miles from an urbanized area. Rural area consists of Census-defined rural territory that is less than or equal to 5 miles from an urbanized area, as well as rural territory that is less than or equal to 2.5 miles from an urban cluster. For this study, we chose to categorize school locations as urban, suburban, and exurban, in that schools in "towns", and "rural settings" are defined as exurban.[38]

Covariates

Race/Ethnicity

Race and ethnicity of children was measured via parent proxy report. Consistent with previous work using ECLSK:2011 datasets,[63,64] we designated children into five racial/ethnic categories (i.e., non-Hispanic White, Black, Hispanic, Asian, and “Other”). Children whose parent/guardians designated them as non-Hispanic White were categorized as White. Children whose parent/guardians designated them as non-Hispanic Black were categorized as Black. Children whose parent/guardians designated them as Hispanic were categorized as Hispanic. Children whose parent/guardians designated them as Asian or Pacific Islander were categorized as Asian. All other children whose parents identified them as any other racial/ethnic category other than non-Hispanic White, were classified as Other.

Income-to-Poverty Ratio

Parent/guardians reported their total household income for the previous year to the nearest thousand during the parent interview portion of data collection.[28] Income-to-poverty ratio was calculated by dividing the total reported household income by the Department of Health and Human Services’ poverty threshold,[65] where lower scores represent greater unmet need. For example, an poverty-to-income ratio (PIR) of 0.5, indicates that a household is earning an equivalent of 50% the amount of income as the federally established poverty threshold, while an income-to-poverty ratio of 1.5 indicates that a household is earning 150% of the federally established poverty threshold. For this study, each participant was classified as above 200% PIR, and below 200% PIR based upon their household income-to-poverty ratio. Classifications align categories defined by the ECLS-K:2010-11 database[63] and were created as follows. If a child's household received an income-to-poverty ratio of 0.00-1.99, the child was classified as below 200% PIR. Children living in a household with an income-to-poverty ratio of >2.00 were classified as above 200% PIR.

Parental Employment Status and Education

Parent/guardians reported their employment status for the previous week during the parent interview portion of data collection.[28] Employment status was specific to "job for pay," in that parents were asked a dichotomous (yes or no) "during the past week, did you work at a job for pay?" Similarly, parent/guardians reported their highest education received. Education was categorized as the following: high school, but no diploma, high school diploma, vocational/technical program after high school, some college but no degree, associate degree, bachelor's degree, professional degree after bachelor's degree, or "other."

Analysis

All statistical analyses were performed using Stata software version 16 (StataCorp, College Station, TX, USA). After restricting the sample to children with measurements in August/September for fall and April/May for spring, descriptive statistics were calculated for both the full sample of participants and restricted analytical dataset.

To account for the potential bias introduced by large amounts of missing data in analyses of complete-case data, multiple imputation was performed to estimate missing values.[66] Specifically, missing covariate values of poverty status and parental education were imputed using the chained equations methodology and generated ten imputed data sets.[67] Poverty status (via poverty threshold) and parental education were chosen to examine because descriptively, it was shown to have high proportions of missing within these covariate variables (>25%). To do this, a stepwise approach occurred as follows. First, because of the large dataset, missing cases of covariate data were identified by performing a missing value analysis pattern test by employing Little's missing cases at random (MCAR) test.[68,69] Using Stata, the mcartest command implements the chi-square test of MCAR, which tests whether significant differences exist between the means of different missing-value patterns. The test statistic takes a form similar to the likelihood-ratio statistic for multivariate normal data and is asymptomatically chi-square distributed under the null hypothesis that there are no differences between the means of different missing-value patterns. Rejection of the null provides sufficient evidence to indicate the data are MCAR.[69] The relationship between all covariates in the analytical models were explored via a chi-square test. These tests indicate that other covariates included in analyses (i.e., school designated location and race/ethnicity) were related to poverty status and parental education. Relationships of covariate variables are as follows: (location vs. parental education, $p < 0.00$), (sex vs. parental education, $p = 0.20$), race/ethnicity vs. parental education, $p < 0.00$), (location vs. poverty status, $p = 0.02$), (sex vs. poverty status, $p = 0.18$), and (race/ethnicity vs. poverty status, $p < 0.00$).

After examining descriptive data and examining missingness utilizing the Little MCAR and chi-square test, it was determined that parental education and poverty status were not MCAR, thus multiple imputation of said missingness would be conducted prior to final analyses. This was done by incorporating multiple imputation while accounting for the complex survey design using study weights. The included weighting variable accounted for non-response at the school, child, and parent level. The ECLSK analytical handbook recommends incorporating a weighting variable that includes the most cases to produce estimates that are representative of the cohort of children who were in kindergarten in 2010-2011. For this reason, the weighting variables W2SCH0 and W7CF7P_7 were included. W2SCH0 accounts for nonresponse at the school level. W2SCH0 ecompasses the child base weight adjusted for nonresponse associated with child assessment/child questionnaire data from all seven rounds from kindergarten through third grade, as well as parent data from all seven rounds from kindergarten through third grade. Multiple imputation in Stata involves three steps. First, Stata is informed that multiple imputation will be conducted by "setting the dataset". Next, it is indicated which variables with missing observations will be imputed by "registering" them. To reproduce these results, Stata recommends setting a seed with a random number otherwise Stata will draw different samples every time it runs the imputation procedure and replication will not be possible. Finally, a specified number of times the missing values should be replaced is conducted, producing ten datasets while accounting for weighting variables using weights that include adjustments for nonresponse. All of the datasets were combined into one single multiple-imputation dataset. Finally, the imputed datasets now available to estimate various models, including regression models. To run a regression model using this imputed dataset, stata instructs to add the following rule (mi estimate, dots) before the command. When initiating an analysis, Stata now produces an output for the pooled dataset with ten imputations. Following imputation, separate multilevel mixed effects linear regressions nested at the child level estimated differences in monthly BMI, zBMI, and %BMIp95 change. Monthly change scores for the school year BMI, zBMI, and %BMIp95 were created by subtracting a child's fall measure from the spring and dividing by the number of months between each child's fall and spring measure. The same process for the summer by subtracting the spring measure from the subsequent fall measure and dividing by the number of months between each child's spring and subsequent fall measure. Monthly change was selected as the outcome measure to account for the difference in time period for a school year (i.e., 9-months) and summer (i.e., 3-months). In addition to the dependent variable (monthly BMI, zBMI change, or %BMIp95), separate models were constructed to examine the impact of monthly change in body composition by our independent variables: race/ethnicity, poverty status, and location. Each separate model then included post-estimation interactions that allowed us to examine within group summer vs school change and between group difference in summer change using the lincom post-estimation procedure for multilevel and longitudinal modeling in STATA.[70] All models included sex, age, parents employment status, parents education, race, and poverty-to-income ratio as covariates. Finally, to correctly estimate variance taking into account the clustered, multistage sampling design and the use of differential sampling rates to oversample targeted subpopultions, standard errors were estimated using the Taylor series method and weighting variables were included.[71] The same sampling weights used in the mulitiple imputation were included in all models.[28] Finally, a post-hoc Benjamini-Hochberg (BH) procedure set at 10% false discovery was incorporated to account for multiple comparisons.[72]

Results

Demographics and sample sizes are presented in Table 1.1 A total of 1,532 children (52% female, 42% White) were included in the final analytic sample. Raw monthly changes in BMI, zBMI, and %BMIp95 during the school year and summer months are presented in Table 1.2. Model based estimates examining within and between group difference in change by rurality can also be found in Table 1.2. Model based within group differences, examining differences between monthly changes during the school year and summer months by BMI, zBMI, and %BMIp95, increased by 0.095 (95CI= 0.074, 0.117), 0.016 (95CI= -0.004, 0.027), and 0.001 (95CI= 0.000, 0.002) more during the summer compared to the school year respectively. For children from urban schools, school change in raw BMI, zBMI, and %BMIp95 was 0.028 (SD= 0.193), 0.002 (SD= 0.074), and -0.001 (SD= 0.010) respectively. For children in urban schools, summer change in raw BMI, zBMI, and %BMIp95 was 0.071 (SD= 0.230), 0.007 (SD= 0.126), and 0.000 (SD= 0.012) respectively.

For children from urban schools, model based within group differences during the summer reached statistical significance by BMI, and %BMIp95 at 0.083 (95CI= 0.049, 0.117), and 0.004 (95CI= 0.000, 0.006) respectively. For children from suburban schools, raw school change in BMI, zBMI, and %BMIp95 was 0.027 (SD= 0.158), 0.006 (SD= 0.076), and -0.001 (SD= 0.008) respectively. For children from suburban schools, summer change in raw BMI, zBMI, and %BMIp95 was 0.088 (SD= 0.202), 0.012 (SD= 0.098), and 0.001 (SD= 0.010) respectively. For children from suburban schools, within group differences in accelerations during the summer were statistically significant for BMI during the summer months 0.047 (95CI= 0.004, 0.090), but not zBMI, and

%BMIp95, 0.008 (95CI= -0.013, 0.029), and 0.002 (95CI= -0.000, 0.004) respectively. School location did not predict significant between group differences in BMI change during the summer, indicating that children's summer accelerations in BMI were not significantly different by school location.

Between group differences in summer zBMI gain were statistically significant between children from suburban and urban schools -0.035 (95CI= -0.062, -0.008), such that children from urban schools had significantly greater zBMI gain when compared to children from suburban schools. There were also significant differences in summer zBMI change between exurban and urban schools' zBMI -0.037 (95CI= -0.060, -0.014), such that from summer acceleration was significantly greater among urban children when compared to children from exurban schools.

Between group differences were not statistically significant for children from suburban schools during the summer months for %BMIp95 -0.002 (95CI= -0.005, 0.001), such that children from urban schools' difference in summer accelerations were not significantly different when compared to children from suburban schools. Further, between group differences were statistically significant for children from exurban schools during the summer months for %BMIp95 -0.002 (95CI= -0.005, 0.000), implying that children from urban schools' difference in summer accelerations was significantly greater when compared to children from exurban schools.

Discussion

This study sought to examine differences in accelerations of children's BMI during the summer months by school locality. Overall, children's BMI, zBMI, and %BMIp95 gain was statistically significantly greater during the summer months when compared to the school year. Across BMI and %BMIp95 children from urban schools experienced statistically significant accelerations during the summer months compared to the school year. Children from urban school's summer accelerations in zBMI appears to be statistically significantly greater when compared to children from suburban and exurban designated schools. Like zBMI, children from urban schools experienced significantly greater accelerations in %BMIp95 during the summer months compared to their exurban counterparts. These findings contradict past work that has found children from urban areas are less likely to be overweight/obese compared to children from exurban areas.[73,74]

Reasons for these contradictory findings could be the unbalancednature of the sample. First, in this sample, a higher proportion of children who reside in exurban settings were from high income households (>2.0 PIR) compared to urban settings (37% vs 31%) respectively. These differences in PIR could be contributing to the differences in summer acceleration presented herein. The Health Gap Hypothesis states that children from low-income households experience a greater amount of weight gain during the summer when compared to their high-income peers, because children from low-income households have less access to community programming during the summer.[26] High income children in exurban areas may not be affected by the distance and transportation barriers that low-income children in exurban areas experience. Thus, this may explain why they did not experience accelerated summer BMI gain at the same rate as their urban peers in this sample. Second, in this sample, a higher proportion of children who reside in urban settings are children who are from minority households (76% vs 40%) respectively. These differences in race/ethnicity could also explain the findings of this study. Studies have shown that children from minority households are more susceptible to accelerated summer BMI gain.[54] This may be due to the fact that children from minoritized racial groups are more likely to live in low resourced communities and experience unique stressors due to systemic racism.[75] This may explain the relatively higher rates of accelerated BMI gain in the urban children in the current sample. Finally, utilizing BMI as the primary outcome measure may be contributing to our findings. In this sample, White children make up the largest proportion of exurban children when compared to Black (60% vs.10%). Studies have shown that BMI is a poor indicator of excess body fat in Black or African American children, with between 30-60% of Black children misclassified as overweight or obese when they do not have excess body fat.[76-78]

Future studies of summer changes in body composition should include complimentary measures of body composition (e.g., bioelectrical impedance) beyond BMI. Adding these additional measures may help to better understand yearly trajectories of body composition given the limitations with BMI. BMI for youth is widely used as a surveillance and outcome measure of body composition in clinical trials because it is non-invasive, fast and easy to employ for weight status screening (i.e., underweight, normal or healthy weight, overweight, and obesity), and can be readily deployed in field-based research settings where measures of hundreds, if not thousands, of youth may occur (e.g., schools). [79] While evidence has shown that BMI is moderately correlated with children's body composition,[80-82] it provides no information on an individual's body composition. Rather, BMI is a simple ratio of an individual's height-to-weight. This can be problematic because individuals with the same BMI may have dramatically different body compositions. For instance, recent studies have demonstrated BMI's inability to distinguish fat from lean mass, which can lead to inappropriate diagnosis of excess adiposity in up to 25% of children.[83,84] Further, changes in children's BMI as they mature may be primarily driven by gains in fat free mass (FFM), not adiposity, especially for boys.[85] Because of these limitations, supplementing measures of BMI with non-invasive measures of body composition could better inform efforts to assess the prevalence of, and target intervention efforts towards addressing childhood obesity, all while producing greater certainty in measures of body composition in research studies.

The current study included several strengths. First, after restricting the sample, a large final sample is still included in analysis. Second, our study included the use of BMI, zBMI, and %BMIp95 to illustrate the differences and weaknesses provided by all three measures. Third, restricting the sample to those measured in August/September and April/May allowed us to explicitly examine school and summer changes without predicting the measures of children assessed outside these measurement windows. Finally, incorporating BH to account for Type-I error at a 10% false discovery rate allowed for multiple comparisons. After correcting for multiple comparison testing, all findings that originally reached statistical significance ($p<0.05$) remained in the post-hoc analysis. This study is also not without its limitations. The effects and clinical significance may be questioned as some BMI findings did reach statistical significance, although the magnitude and effect size of change were quite small. Past studies have concluded that reductions in mean zBMI of 0.15 and BMI standard deviations of 0.7-1.2 are associated with significant improvements in lipid, insulin, blood pressure, total cholesterol and low-density lipoprotein.[86,87] The findings presented herein are presented as monthly changes. When examining yearly trajectories and monthly changes in measures of BMI, it should be noted that small differences on a monthly level may be important as they compile over time. To continue multiple summers of slightly higher acclerations may be contributing to health outcomes over time.

Conclusion

BMI gain accelerated during the summer months when compared to the school year. Between group differences indicated that for children from urban schools, BMI accelerates at a greater rate during the summer months compared to suburban and exurban children. Interventions are needed that specifically address obesogenic behaviors during the summer months, especially for children in urban settings, who are more likely to be low-income and from racially minoritized groups.

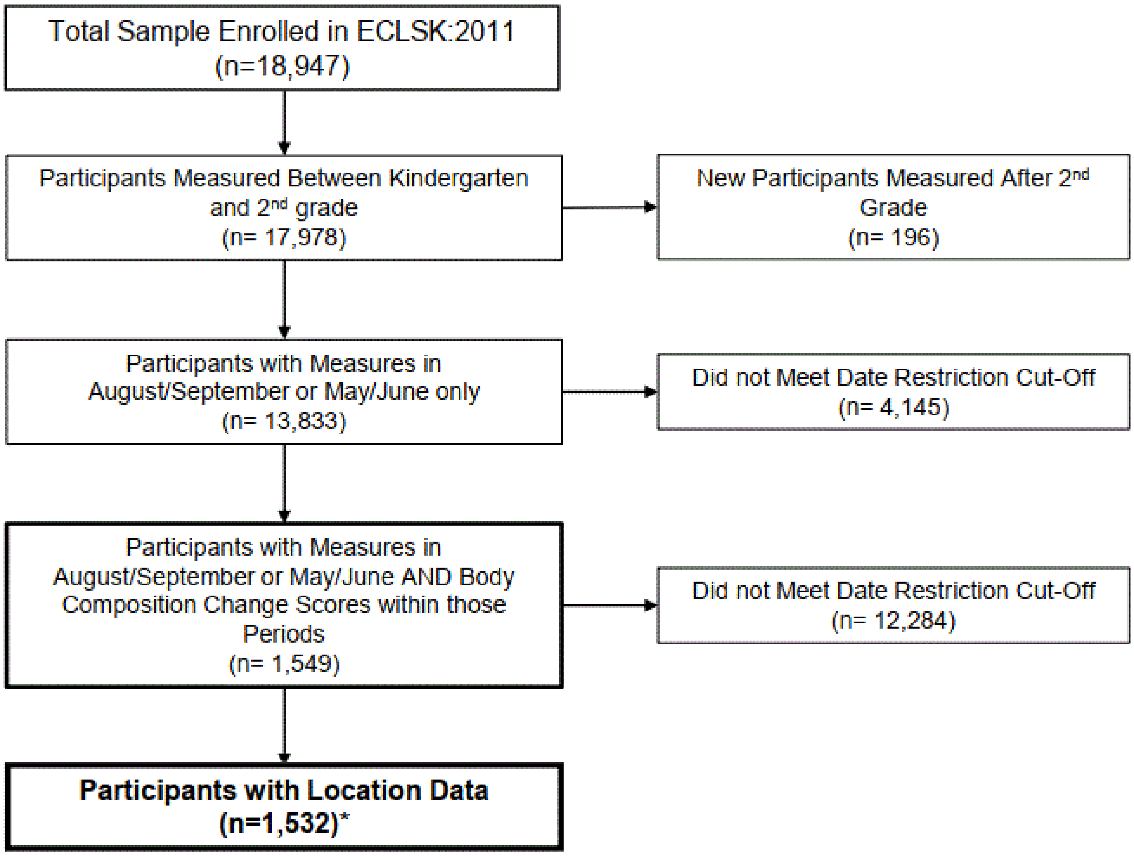

Figure 2.1 Flow Diagram of Participants Included

Table 2.1 Demographics of Analytical Sample and Full Sample

	Analytical Sample (N=1,532)						Full Sample (N=18,947)					
	Urban (n=550)		Suburban (n=468)		Exurban (n=514)		Urban (n=6,414)		Suburban (n=6,895)		Exurban (n=5,638)	
Income, n (%)												
Low (0.0-0.9 PIR)	132	24%	97	21%	101	20%	1,642	26%	1,113	16%	917	16%
Med (1.0-1.9 PIR)	83	15%	66	14%	97	19%	1,098	17%	1,061	15%	1,007	18%
High (>2.0 PIR)	173	31%	183	39%	192	37%	1,786	28%	3,179	46%	2,371	42%
Missing	162	29%	126	26%	124	24%	1,888	29%	1,542	22%	1,343	24%
Mean Age (± SD)	7.13	0.76	6.93	0.88	6.71	0.69	6.95	0.98	6.98	1.00	7.01	1.01
Mean BMI (± SD)	17.22	3.20	17.15	3.11	17.00	3.22	17.22	3.16	17.03	2.96	17.14	3.04
zBMI (± SD)	0.5055	1.10	0.5381	1.06	0.5107	1.08	0.5387	1.12	0.4740	1.09	0.5194	1.07
Sex, n (%)												
Boys	284	52%	241	51%	273	53%	3,209	50%	3,530	51%	2,952	52%
Girls	266	48%	227	49%	241	47%	3,192	50%	3,350	49%	2,674	47%
Race, n (%)												
White	134	24%	163	35%	308	60%	1,681	26%	3,197	46%	3,830	68%
Black	79	14%	36	8%	49	10%	1,256	20%	784	11%	475	8%
Hispanic	236	43%	204	44%	101	20%	2,219	35%	1,895	27%	811	14%
Asian	59	11%	43	9%	13	3%	839	13%	573	8%	187	3%
Other	38	7%	20	4%	43	8%	403	6%	420	6%	329	6%
Missing	4	1%	2	0%	0	0%	16	0%	26	0%	6	0%
Parent Employed, n (%)												

Yes	278	51%	282	60%	333	65%	2,492	39%	3,099	45%	2,791	50%
No	171	31%	209	45%	167	32%	1,789	28%	1,954	28%	1,639	29%
Missing	1	0%	0	0%	14	3%	2,133	33%	1,842	27%	1,208	21%
Parents Highest Education, n (%)												
High School or Less	147	27%	133	28%	164	32%	1,761	27%	1,394	20%	1,466	26%
Some College	52	9%	58	12%	72	14%	742	12%	856	12%	882	16%
Associates	18	3%	23	5%	46	9%	320	5%	468	7%	451	8%
Bachelors	77	14%	90	19%	76	15%	793	12%	1,378	20%	915	16%
Greater than Bachelors	41	7%	48	10%	41	8%	415	6%	723	10%	397	7%
Other	10	2%	18	4%	20	4%	242	4%	236	3%	314	6%
Missing	205	37%	98	21%	95	18%	2,141	33%	1,840	27%	1,213	22%

PIR = Poverty-to-Income Ratio
SD = standard deviation
BMI = Body Mass Index

Table 2.2 Mixed-Effect Linear Regression Models Estimating Difference in Monthly Change during the School Year and Summer

	Raw School Change			Raw Summer Change			Model Based Within Group Difference			Model Based Between Group Diff in Change		
	n	**Mean**	**SD**	**n**	**Mean**	**SD**	**Coef.**	**95CI**		**Coef.**	**95CI**	
BMI												
Full Sample	1214	0.028	0.193	710	0.071	0.230	**0.095**	**0.074**	**0.117**			
Urban	415	0.030	0.157	277	0.078	0.247	**0.083**	**0.049**	**0.117**	ref		
Suburb	369	0.027	0.158	213	0.088	0.202	**0.047**	**0.004**	**0.090**	-0.036	-0.090	0.018
Exurban	398	0.028	0.256	196	0.053	0.240	**0.039**	**0.009**	**0.070**	-0.044	-0.090	0.002
zBMI												
Full Sample	1209	0.002	0.074	710	0.007	0.126	**0.016**	**0.004**	**0.027**			
Urban	414	-0.001	0.074	277	0.014	0.140	0.043	0.026	0.060	ref		
Suburb	367	0.006	0.076	213	0.012	0.098	0.008	-0.013	0.029	**-0.035**	**-0.062**	**-0.008**
Exurban	396	0.002	0.075	196	-0.004	0.139	0.006	-0.009	0.021	**-0.037**	**-0.060**	**-0.014**
Percent of 95 Percentile Change												
Full Sample	1214	-0.001	0.010	710	0.000	0.012	**0.001**	**0.000**	**0.002**			
Urban	415	-0.002	0.008	277	0.001	0.013	**0.004**	**0.002**	**0.006**	ref		
Suburb	369	-0.001	0.008	213	0.001	0.010	0.002	0.000	0.004	-0.002	-0.005	0.001
Exurban	398	-0.001	0.013	196	-0.001	0.012	0.002	0.000	0.003	-0.002	-0.005	0.000

School and summer change estimates are presented as raw means and standard deviations
All models included sex, age, parents employment status, parents education, race, and poverty-to-income ratio as covariates.
Within and between group difference estimates are model based
Benjamini-Hochberg post-hoc analysis accounted for type-I error set at 10% false discovery rate
Bolded values p<0.05

CHAPTER THREE: MANUSCRIPT 2

DIFFERENCES IN PROPORTION OF CHILDREN MEETING BEHAVIOR GUIDELINES DURING SUMMER & SCHOOL & BY SOCIOECONOMIC STATUS AND RACE

Hunt, E.T., Beets, M.W., Armstrong, B.A., Turner-McGrievy, G.M., Geraci, M., R.G., Weaver, R.G. Accepted by *Obesity Science and Practice*

Abstract

Objective: Children who fail to meet activity, sleep, and screen-time guidelines are at increased risk for obesity. Further, children who are Black are more likely to have obesity when compared to children who are White, and children from low-income households are at increased risk for obesity when compared to children from higher-income households. The objective of this study was to evaluate the proportion of days meeting obesogenic behavior guidelines during the school year compared to summer vacation by race and free/reduced priced lunch (FRPL) eligibility.

Methods: Mixed-effects linear and logistic regressions estimated the proportion of days participants met activity, sleep, and screen-time guidelines during summer and school by race and FRPL eligibility within an observational cohort sample.

Results: Children (n=268, grades=K-4, 44.1%FRPL, 59.0% Black) attending three schools participated. Children's activity, sleep, and screen-time were collected during an average of 23 school days and 16 days during summer vacation. During school, both children who were White and eligible for FRPL met activity, sleep, and screen-time guidelines on a greater proportion of days when compared to their Black and non-eligible counterparts. Significant differences in changes from school to summer in the proportion of days children met activity (-6.2%, 95CI=-10.1%,-2.3%; OR=0.7, 95CI=0.6, 0.9) and sleep (7.6%, 95CI=2.9%,12.4%; OR=2.1, 95CI=1.4, 3.0) guidelines between children who were Black and White were observed. Differences in changes in activity (-8.5%, 95CI=- 4.9%, -12.1%; OR=1.5, 95CI=1.3, 1.8) were observed between children eligible vs. ineligible for FRPL.

Conclusions: Summer vacation may be an important time for targeting activity and screen-time of children who are Black and/or eligible for FRPL.

Introduction

There is growing evidence that the socioeconomic status of a child's family is a key risk factor for becoming obese.[88,89] Compelling evidence exists that school-aged children[90-94] and adults[95,96] from low-income families are at elevated risk for obesity. Recent data from the National Health and Nutrition Examination Survey show that 20% of children from families with a household income at ≤130% of the federal poverty threshold have obesity, while only 10% of children from families with incomes ≥350% of the federal poverty threshold have obesity.[5] Importantly, this gap has increased over time. Independent of income, Black children are at an increased risk for obesity when compared to children who are White.[56,92] This is most likely due to the well-documented effects of structural racism on health behaviors which underlie health disparities.[97]

Summer vacation from school is a critically important time for addressing obesity. A large body of evidence indicates that body mass index (BMI) gain accelerates during the summer.[8,16,18,51-53] Further, at least one study has shown that the prevalence of children with obesity increases during the months of summer.[18] This acceleration in BMI may be due to engagement in unhealthy behaviors during the summer. For instance, a growing number of studies demonstrate that children engage in less physical activity, spend more time sedentary, and spend more time on screens during the summer than during the school year.[14,98,99] Studies are also emerging that show children engage in healthier amounts of sleep and less variable sleep on nights prior to school days, compared to extended breaks from school, like summer.[98-100] The degradation of health behaviors during summer vacation likely leads to decreased rates of meeting activity,[29] sleep,[30] and screen-time guidelines.[31,32] Failing to meet these guidelines has been associated with increased risk for obesity, insulin resistance, cardiovascular and other diseases.[33]

The structured days hypothesis,[101] which posits that structure, defined as a pre-planned, segmented, and adult-supervised compulsory environment, plays a protective role for children against unhealthy behaviors and, ultimately, prevents the occurrence of negative health-outcomes, such as excessive BMI gain. The structured days hypothesis draws upon concepts in the 'filled-time perspective' literature, which posits that time filled with favorable activities cannot be filled with unfavorable activities.[102] This perspective leads to the hypothesis that children engage in a greater number of unhealthy behaviors that lead to increased BMI gain during times that are less-structured (e.g., summer days) than during times that are more structured (e.g., school days). Correspondingly, the Health Gap Hypothesis posits that children from low-income households and children who are Black have relatively less access to structured summer programming (e.g., summer camps) than their middle-to-high income and White counterparts due to financial barriers and insufficient community resources.[26] Thus, summer may disproportionately impact the health behaviors of children from low-income and Black households and ultimately lead to greater accelerated summer BMI gain in these children. Indeed preliminary evidence suggests that children who are Black and children from low-income households experience greater increases in summer BMI gain compared to other children.[54] Ultimately, greater accelerated summer BMI gain may partially explain the disproportionate risk for obesity born by children from low-income and Black households.

The purpose of this study was to examine the proportion of days children met guidelines for moderate-to-vigorous physical activity (MVPA≥60 minutes/day),[29] sleep (10-13 hours/night for 5 year olds, 9-12 hours/night for 6-12 year olds),[30] and screen-time (<2 hours/day)[31,32] during the school year compared to the summer, and to examine if these rates differed by race and free/reduced priced lunch (FRPL) eligibility, a proxy of household income. It is hypothesized that 1) during the summer all children will meet physical activity, sleep, and screen-time guidelines on fewer days than during the school year, and 2) children who are eligible for FRPL and Black children will experience greater declines in the number of days that they meet physical activity, sleep, and screen-time guidelines than children who are not eligible for FRPL and children who are White.

Methods

Study Sample and Design

This study utilized data from a larger natural experiment that examined changes in BMI and fitness during the summer vacation and school year for children attending a year-round school and two match paired traditional schools.[103,104] Physical activity, sleep, and screen-time behavioral data were collected on a subset of (n=267) children participating in the larger study from Spring 2018-Fall 2019. This study presents obesogenic behavior data from school years (2017-2018, 2018-2019) and summers (2018, 2019). All kindergarten through third grade students participating were invited to participate in the behavioral data collection in the Spring of 2018. Measurements commenced in the spring semester of 2018 (i.e., April) and were completed in the fall academic semester of 2019 (i.e., August). Data collection occurred during three distinct one-month measurement periods while school was in session (March and October 2018, and March 2019) and two distinct three-month periods during the traditional summer vacation (May to August 2018 and 2019). For children in the traditional school, summer vacation lasted 11 weeks while summer vacation lasted 5 weeks for children in the year-round school. Prior to the completion of any measures a consent letter was sent home to parents describing study procedures. Parents who consented were asked to sign and return the letter. All protocols were approved by the University of South Carolina Institutional Review Board prior to enrollment of the first participant.

Measures

Race

Parents reported child's race on a single item screener once at enrollment into the study. Children whose parents reported a race other than White or Black were excluded from the current analysis (n=26).

Physical Activity and Sleep

Details fully describing the study can be found elsewhere.[104] Physical activity and sleep were measured using a Fitbit Charge 2TM (Fitbit Inc., San Francisco, California, USA). Fitbits were chosen because they provide good agreement with polysomnography and electrocardiography,[105] they use multiple heartrate and actigraphy channels to classify sleep which is superior to a single-channel actigraphy,[106] can be charged at home, and data is stored in the cloud allowing for data collection over extended periods of time (e.g., 3-month summer vacation). Data processing for physical activity and sleep were informed by the International Study of Childhood Obesity, Lifestyle and the Environment data processing protocols.[107] For this analyses, only nocturnal sleep was considered. A valid night of sleep was considered sleep onset that occurred between 5pm and 6am and lasted for greater than 240 minutes.[108] If sleep segments were separated by less than 20 minutes they were considered one continuous sleep segment.[109] Sleep duration was identified as the number of minutes that the Fitbit device classified a child as asleep during a sleep episode. To distill heartrate into activity intensity levels, each child's resting heartrate was calculated as the lowest mean beats-per-minute for 10 consecutive minutes each day.[110] Heartrates were distilled into activity intensity levels based on percent heart rate reserve (HRR). Intensity levels are classified as follows: 0.0-19.9% HRR equaled sedentary, 20.0-49.9% of HRR equaled light physical activity, and ≥50.0% equaled MVPA.111 An individual day of at least 10 hours of waking wear was considered a valid day.[107]

Screen-time

Screen-time was assessed via parent proxy-report. Parents completed a questionnaire with their child/children to report their children's screen-time twice per week during measurement periods. Parents were asked to report on their child's daily screen-time on at least 4 days during each 30-day collection period. Parents/children estimated total amount of time (hours and minutes) children spent in front of a screen that day (e.g., TV, computer, video game, smartphone, and tablet).

Household Income

Poverty-to-income ratio (PIR) was used as a measure of household income. PIR is the ratio of household income to poverty and is calculated by dividing the total reported household income accounting for household size by the Department of Health and Human Services' poverty threshold.[65] Parents/guardians were asked to select a household income as a single item in $10,000 increments. For this analysis, PIR was dichotomized by FRPL status according to the National School Lunch Program.[112] Children living in a household with a PIR <1.85 were classified as eligible to receive FRPL and a PIR ≥1.85 was classified as not eligible to receive FRPL.

Statistical Analyses

First, means and standard deviations of school and child characteristics were examined. Subsequently, regression analysis was used to assess the difference between meeting guidelines (dependent variable) on a school or summer day (independent variable). For each behavior, the dependent variable was operationalized as a binary variable (meeting vs not meeting the guidelines) or as the proportion of days a child met guidelines. The independent variable was also binary (i.e., school or summer day). Multi-level mixed effect logistic and linear regressions, respectively, were conducted to account for clustering (i.e., days nested within children and children nested within schools). One set of models included race and race-by-condition interactions while a second set of models included FRPL status (<1.85 PIR vs. ≥1.85 PIR) and FRPL-by-condition interactions. All models were adjusted for sex and grade. Analyses exploring the proportion of days children met guidelines by FRPL status included race as a covariate, and models estimating the proportion of days children met guidelines by race included FRPL status as a covariate. Analyses were carried out in Stata (v14.2, College Station TX).

Results

Characteristics of the participating children are presented in Table 2.1. A total of 267 children participated in the study with 58.1% identifying as Black and 33.0% identifying as White. A total of 51.3% of the participants identified as female and 44.4% eligible for FRPL. During the school year children engaged in 77.6 (SD=73.7), 470.2

(SD=68.2), and 100.2 (SD=89.0) minutes of MVPA, sleep, and screen-time, respectively. During the summer children engaged in 75.3 (SD=90.7), 486.3 (SD=91.7), and 145.3 (SD=120.2) minutes of MVPA, sleep, and screen-time, respectively.

Model based within- and between-group estimates (including covariates) of the proportion of days and odds of meeting MVPA, sleep, and screen-time guidelines during summer vacation and the school year are presented in Figure 2.1. Black children were less likely to meet MVPA guidelines in the summer compared to the school year (change=-6.2% [95CI=-8.7%, -3.7%]; OR=0.7 [95CI=0.6, 0.8]) while children who are White were just as likely to meet MVPA guidelines during the summer compared to the school year (change=0.0% [95CI=-3.0%, -3.0%]; OR=1.0 [95CI=0.9, 1.2]). This translated to Black children experiencing a -6.2% ([95CI=-10.1%, -2.3%]; OR=0.7, [95CI=0.6, 0.9]) greater decline in MVPA guideline adherence from school to summer when compared to children who are White. Black children were more likely to meet sleep guidelines in the summer compared to the school year (change=17.0% [95CI=13.8%, 20.1%]; OR=3.9 [95CI=3.0, 5.0]) while children who are White were also more likely to meet sleep guidelines during the summer compared to the school year (change=9.5% [95CI=5.9%, 13.2%]; OR=1.9 [95CI=1.4, 2.5]). This translated to Black children experiencing a 7.4% ([95CI=2.6%, 12.2%]; OR=2.0, [95CI=1.4, 2.9]) greater increase in sleep guideline adherence from school to summer when compared to children who are White. Black children were less likely to meet screen-time guidelines in the summer compared to the school year (change=-21.4% [95CI=-24.8%, -17.0%]; OR=0.3 [95CI=0.2, 0.4]) while children who are White were also less likely to meet screen-time guidelines during the summer compared to the school year (change=-19.4% [95CI=-

24.8%, -14.0%]; OR=0.3 [95CI=0.2, 0.5]). This translated to no statistically significant difference in school to summer change between Black and White children in screen-time guideline adherence (difference in change=-2.0% [95CI=-9.0%, 5.0%]; OR=0.8, [95CI=0.5, 1.2]).

Children eligible for FRPL were less likely to meet MVPA guidelines in the summer compared to the school year (change=-8.5% [95CI=-11.0%, -6.0%]; OR=0.7 [95CI=0.6, 0.8]) while children not eligible for FRPL were just as likely to meet MVPA guidelines during the summer compared to the school year (change=0.5% [95CI=-2.2%, -3.2%]; OR=1.0 [95CI=0.9, 1.1]). This translated to children who are eligible for FRPL experiencing a -9.0% ([95CI=-12.6%, -5.4%]; OR=0.6, [95CI=0.5, 0.8]) greater decline in MVPA guideline adherence from school to summer when compared to children not eligible for FRPL. Children eligible for FRPL were more likely to meet sleep guidelines in the summer compared to the school year (change=14.7% [95CI=11.6%, 17,7%]; OR=3.1 [95CI=2.4, 4.0]) while children not eligible for FRPL were also more likely to meet sleep guidelines during the summer compared to the school year (change=12.2% [95CI=9.0%, 15.3%]; OR=2.6 [95CI=2.0, 5.1]). This translated to children eligible for FRPL experiencing no statistically significant greater increase in sleep guideline adherence from the school to summer compared to children not eligible for FRPL (difference in change=2.5% [95CI=-1.9%, 6.8%]; OR=1.2 [95CI=0.9, 1.8]). Children eligible for FRPL were less likely to meet screen-time guidelines in the summer compared to the school year (change=-21.1% [95CI=-25.4%, -16.8%]; OR=0.3 [95CI=0.2, 0.3]) while children not eligible for FRPL were also less likely to meet screen-time guidelines during the summer compared to the school year (change=-20.7%

[95CI=-25.6%, -15.7%]; OR=0.3 [95CI=0.2, 0.4]). This translated to no statistically significant difference in school to summer change between children eligible for FRPL and children not eligible for FRPL (difference in change=0.5% [95CI=-6.1%, 7.0%]; OR=0.9 [95CI=0.6, 1.3]).

Discussion

In the current study, all children met MVPA and screen-time guidelines on fewer days and sleep guidelines on more days during the summer when compared to the school year. However, Black children and children eligible for FRPL saw larger decreases in the proportion of days they met MVPA guidelines during the summer than children who are White and not eligible for FRPL. Further, Black children saw a larger increase in the proportion of days they met sleep guidelines during the summer when compared to their White counterparts.

The findings of the current study align with past studies that have found children are less active and engage in more screen-time during periods of less structure (i.e., summer, weekends, or holidays).[104,113-118] Given that Black children and children from low-income households experience more dramatic accelerations in BMI during the summer than their White and middle-to-high-income counterparts,54 the finding in this study that the summer negatively impacted the MVPA of Black children and children eligible for FRPL to a greater degree than White children or children not eligible for FRPL is important. This finding suggests a specific behavioral mechanism, decreased MVPA, that may partially explain the greater increases in BMI gain during the summer for Black children and children eligible for FRPL. Future interventions that target increasing the MVPA of Black children and children from low-income households during the months of summer may be warranted.

While the percent of children meeting sleep guidelines was low, it is consistent with past studies that have examined sleep guideline adherence with objective measures.119,120 Further, it is not surprising that children met sleep guidelines on more days during the summer when compared to the school year. Past studies have shown that children's total sleep time increases on weekends compared to school days and during the summer when compared to the school year.[99,104,121,122] However, these same studies show that children's bedtimes and wake times shift later and become more variable during the summer. While meeting sleep duration guidelines is protective against developing obesity,[123,124] sleep timing (i.e., late to bed, late to wake) and stability (i.e., keeping bed and wake time constant) have also been shown to be independent risk factors for obesity.[23] If children's sleep timing is shifted and becoming more variable during the summer in the current sample, the benefits of meeting sleep duration guidelines may be nullified by later and more variable sleep timing.

Given the findings of the current study coupled with evidence from past studies that show children engage in behaviors that negatively impact their weight status during the summer, intervention strategies to improve children's behaviors during summer are warranted, especially for Black children and/or eligible for FRPL. One possible public health strategy is to provide increased access to healthy structured summer programming. At least one study has tested the impact of providing children with access to structured summer programming. Children (n=94) were randomly assigned to either attend a structured summer camp or to experience a typical summer with no access to a structured program.[125] Children assigned to attend the summer program lost 0.03 BMI z-score units while those assigned to not attend gained 0.07 BMI z-score units over the summer. While the differences were not statistically significant they trended in the expected direction. Further children assigned to attend the summer program engaged in 2.3% more MVPA during the program compared to the school year while children not attending the program engaged in 1.9% less MVPA during the summer compared to the school year. This pilot study shows promise for the strategy of providing structured summer programming to enhance health behaviors and mitigate accelerated summer BMI gain.

This study has several strengths including the collection of data continuously for 30+ days during the school year and summer vacation, the within-person design (i.e., same children measured during the school year and summer), and the grounding in theoretical frameworks (i.e., Structured Days Hypothesis and health gap hypothesis). This study also has limitations that must be considered when interpreting the results. First, this study only included three schools in the southeastern United States. Thus, the generalizability of findings may be limited. Second, one of the three schools followed a year-round calendar. Thus, there may be systematic differences in the findings between school calendar types. Third, the study used Fitbit devices to quantify physical activity and sleep. While these devices have shown good agreement with electrocardiography assessment of heartrate and polysomnography assessment of sleep,[105,126,127] they have been sparsely used in physical activity and sleep. This limits the ability to compare the findings of this study with other studies.

Conclusions

During summer children are less likely to meet guidelines for physical activity and screen-time, providing partial support for the Structured Days Hypothesis.[19] This is particularly true for Black children or children eligible for FRPL, providing support for the Health Gap Hypothesis.[26] Interventions that target MVPA and screen-time during times of less structure (i.e., summer), may be warranted.

Table 3.1. Participant Demographic and Behavioral Data

	(N)	**%**
Overall sample	**267**	**100**
Race		
Black	155	58.1
White	86	33.0
Other	26	7.9
Sex		
Boys	137	48.7
Girls	130	51.3
Grades		
Kindergarten	17	6.4
1st	56	21.0
2nd	78	29.2
3rd	75	28.1
4th	42	15.7
Income Level		
Eligible for FRPL (≤1.85 PIR)	120	44.1
Not Eligible for FRPL (>1.85 PIR)	147	55.9
Total Weekday Behavior Data	**Minutes**	±
Moderate-to-Vigorous Physical Activity (n=267) (n=14,172 child days)	79.4	77.0
Sleep (n=209) (n=4,927 child days)	474.7	75.3
Screen-Time (n=195) (n=2831 child days)	120.8	105.9

Free/Reduced Price Lunch (FRPL)

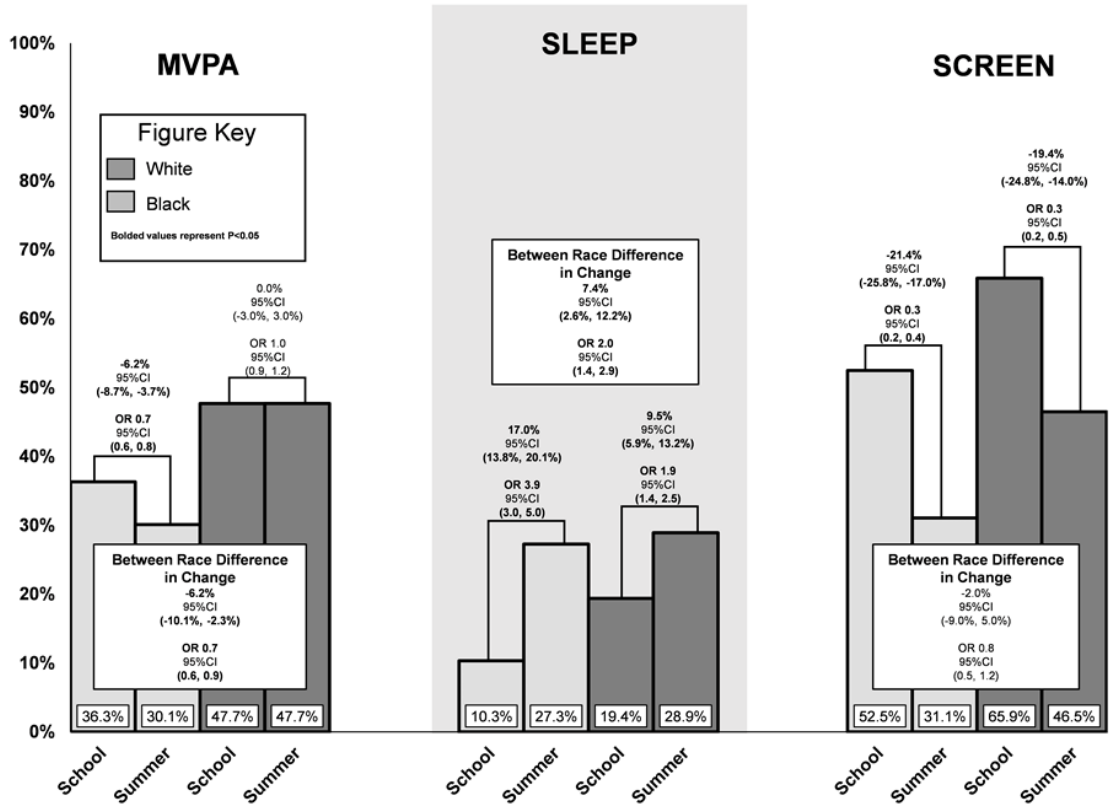

Figure 3.1a Proportion of Days Meeting Guidelines on School Days and Summer Vacation by Race

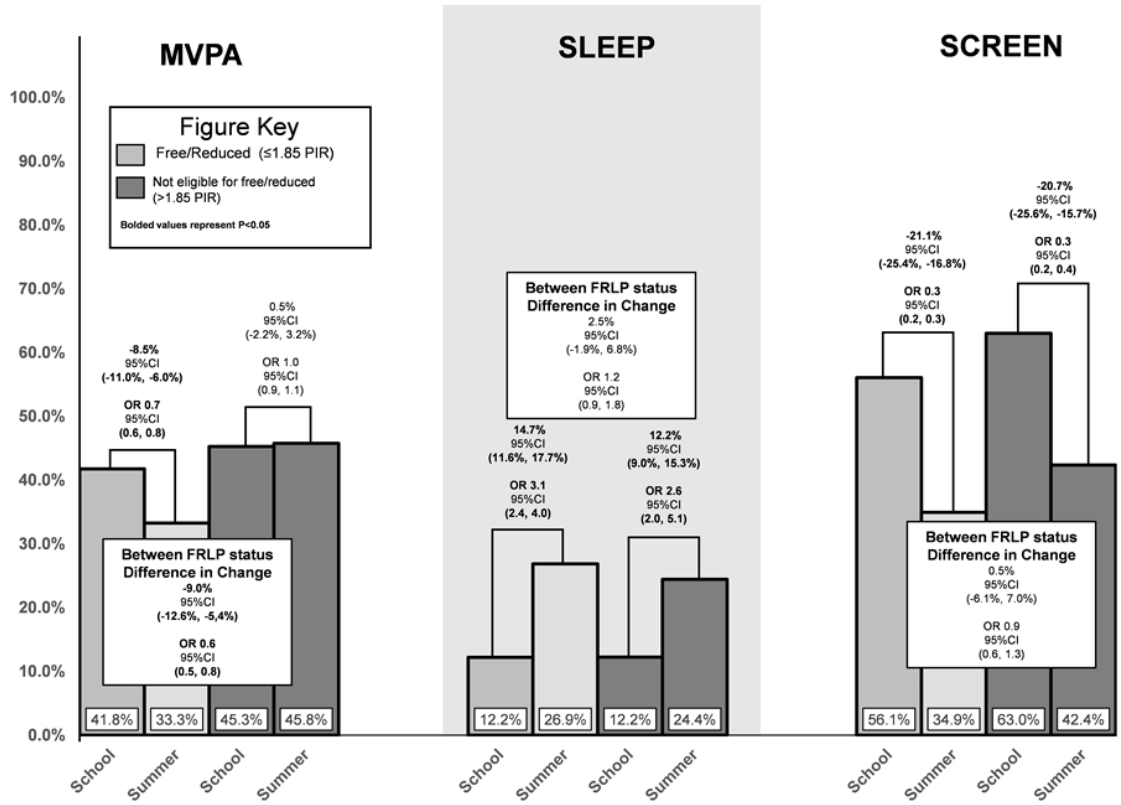

Figure 3.1b Percent of Days Meeting Guidelines on School Days and Summer Vacation by Free/Reduced Status

CHAPTER FOUR

OVERALL DISCUSSION

Discussion

Data representing U.S children and adolescents shows the prevalence of obesity was 17.0% (95CI= 15.5%-18.6%).4 Specifically, among children aged 6 to 11 years, obesity has increased from 11.3% (95CI= 9.40%-13.40%) to nearly 20.0% over the past two decades. [4] Rates of obesity are disproportionately high among children from minoritized racial groups and/or low-income households. This dissertation addresses gaps in the literature by exploring accelerations in children's summer weight gain, and exploring children's differences in the proportion of days meeting obesogenic behaviors guidelines during summer versus school. Currently, it is known that rates of obesity differ by income, locality, and race/ethnicity.4,6 To continue, more recent work has established that summer vacation may be negatively impacting children's weight status, in that elementary aged children gain significantly more unhealthy weight during summer vacation when compared to the school year.[8,18] Finally, the SDH posits that structured enivornments may be providing children with opportunities to engage in more healthy obesogenic behaviors which may be contributing to weight maintenance during the school year and non-school periods of structure.[19]

I sought to further obesity literature by examining the summer weight gain phenomenon and the SDH by examining differences in monthly BMI accelerations by school designated location and differences in children's ability to meet behavior guidelines during summer vacation compared to the school year by a measure of socioeconomic status and race. I found that across all school dersignated locations, children's accelerations of BMI increase during summer vacation when compared to the school year. This aligns with previous literature examining summer weight gain,[8,18] However this is to our knowledge the first study to examining monthly acceleration in weight gain, and the first to examine summer weight gain by school locality. I found that urban children appear to gain significantly more unhealthy weight during the summer compared to their suburban and exurban peers. Overall, weight prevalence appears to be worse in exurban children6, so this finding is slightly contradictory in nature. Additional cohort studies are needed to further examine differences in summer weight gain by location. One potential reason for the current findings are the unbalanced nature of the analytical sample examined. Urban children of low-income made up a larger proportion of the sample when compared to low-income exurban children. This could be driving the findings presented as past work has established that low-income populations are more likely to be overweight or obese.[5] Future work examining locality will need to equally distribute and sample by income to appropriately examine the phenomenon. To continue, I found children who are Black and eligible for free/reduced lunch (a measure of socioeconomic status) are less likely to meet MVPA guidelines during the summer months compared to their White and non-eligible counterparts. These findings align with the income literature previously mentioned regarding childhood obesity by income and race/ethnicity in that children who are Black and low-income are more likely to be obese.[5,128] Less is known regarding the behavioral mechanisms driving the obesity disparities presented. One possible public health strategy is to provide increased access to healthy structured summer programming. This precise and equitable effort to provide lower resourced areas with more affordable programming may be the key link needed to close disparities in childhood obesity.

This dissertation attempted to fill gaps in the literature by furthering the research examining summer weight gain and subsequent obesity contributing behaviors. Additional work is needed to continue to examine disparities in summer unhealthy weight gain by location, race/ethnicity, and income. To continue, additional work is needed to examine the obesity causing behaviors driving obesity (MVPA, sleep, dietary intake, and sedentary behaviors) during less-structured periods of time (i.e. summer vacation, holiday breaks, and weekends) among low -resourced and minoritized communities and school. As authors Link and Phelan stated in a seminal paper examining social conditions of disease, they concluded that distal risk factors such as socioeconomic status and social support are likely fundamental causes of disease, because they embody access to important resources.[129] The focus on proximal; risk factors of childhood obesity (physical activity, sedentary behaviors, sleep, and dietary intake) are important in research, however without proper examination of the distal fundamental causes of childhood obesity that are examined here may be limiting the ability to improve childhood obesity, and the subsequent disparities that currently exist.

Purpose

The objectives of the research conducted in this dissertation were to:

1) Examine accelerations in body composition (BMI, age-sex specific zBMI, and 95th percentile of BMI (%BMIp95)) during the summer months by school locality (i.e., urban, suburban, exurban).

2) Provide an evidence-based argument on the importance of summer vacations impact on children's ability to meet obesogenic behavior guidelines by examining the proportion of days children met guidelines for moderate-to-vigorous physical activity (MVPA≥60 minutes/day)[29], sleep (10-13 hours/night for 5 years, 9-12 hours/night for 6-12 years)[30], and screen-time (<2 hours/day)[31,32] during the school year compared to the summer, and to examine if these rates differed by race and free/reduced priced lunch (FRPL) eligibility, a proxy of household income.

Major Findings

Study 1 examined children's monthly accelerations in BMI by school location (urban, suburban, and exurban). One of the more widely cited papers examining the summer weight gain phenomenon utilized data from the ECLS-K:2011 to estimate accelerated summer BMI gain.[10,18] However, the majority of measures of height and weight were collected from October-November each fall and February-March each spring. I restricted the analytical sample to children who measured in August/September and April/May. This approach allowed me to examine the impact school (more-structured) and summer (less-structured) may have on change on monthly change in body composition estimates by geographically coded school location using National Center for Education Statistics (NCES) location variables which were constructed in combination with the United States Census Bureau classification system.[37,61] I found all children experienced significant increases in monthly accelerations in BMI, zBMI, and %BMIp95 during summer vacation when compared to the school year. Children from urban school's summer accelerations in zBMI appears to be statistically significantly greater when compared to children from suburban and exurban designated schools. These findings contradict past work noting obesity prevalence is higher among children in exurban locations.

Study 2 examined the proportion of days children met obesogenic behavior guidelines during the school year compared to the summer months. Children met MVPA and screen-time guidelines on fewer days and sleep guidelines on more days during the summer when compared to the school year. However, children who are Black and eligible for FRPL saw larger decreases in the proportion of days they met MVPA guidelines during the summer than children who are White and not eligible for FRPL. Further, children who are Black saw a larger increase in the proportion of days they met sleep guidelines during the summer when compared to their White counterparts. Researchers should continue to examine the summer weight gain phenomenon while creating large scale cohort studies that work to examine the disparities that exist and potentially compile over time or multiple summers in low-income and/or minoritized populations during the summer. Equitable access to summer opportunities is needed to help to begin to close the disparate rates of children's ability to meet behavior guidelines during summer vacation.

Implications and Considerations

In total, this dissertation has continued to explore the summer BMI gain phenomenon, while examining additional measurements of BMI (%BMIp95) and the exploration of school location (i.e., urban vs exurban). Further, this dissertation project explored potential behavioral mechanisms that contribute to unhealthy weight gain by examining children's proportion of days meeting obesogenic behavior guidelines during summer vacation and the school year. In total, this dissertation project provides evidence that continues to highlight the importance of several key intervention timepoints and levers. First, summer should be identified as a crucial time when intervening to address obesity in youth. This dissertation adds to the literature base that not only children are gaining more negative weight during the shorter summer months compared to the longer school year, but also those contributing obesogenic behaviors and children's ability to meet those obesogenic behavior guidelines is hindered, in that children who are Black or qualify for FRPL saw larger decreases in the proportion of days they met MVPA guidelines during the summer than children who are White and not eligible for FRPL. These findings highlight the broader definition of SDH in that times of "less structure" in a child's day or year may be negatively impacting their ability to engage in healthy behaviors, and thus subsequently contributing to unhealthy weight gain. SDH draws from concepts found in the 'filled-time perspective' which is based on the principal that time filled with favorable activities cannot be filled with unfavorable activities.102 SDH is an important concept that embodies both distal and proximal risk factors for childhood obesity in that it includes proximal obesity contributing behaviors, but also understands the need to provide access to equitable programming that will provide the structured opportunities to engage in positive health behaviors.

Limitations to Dissertation

However, this total dissertation is not without limitations. In Study 1, I explored accelerations in BMI gain during the summer months compared to the school year. However, as some findings did reach statistical significance, the magnitude and effect size of change were quite small, thus the clinical significance of those changes may be questioned. In Study 2, I examined the proportion of days children met obesogenic behavior guidelines during the school year compared to the summer months. This study only included three schools in the southeastern United States. Thus, the generalizability of findings may be limited. Second, one of the three schools followed a year-round calendar. Thus, there may be systematic differences in the findings between school calendar types. Finally, the study used Fitbit devices to quantify physical activity and sleep. While these devices have shown good agreement with electrocardiography assessment of heartrate and polysomnography assessment of sleep,[105,130] they have been sparsely used in physical activity and sleep. This limits the ability to compare the findings of this study with other studies.

Future Research

Studies that aim to examine yearly trajectories in weight gain in children should collect measurements at the appropriate times throughout the year to best estimate differences and changes in weight during the summer, as well as the school year. Researchers must be aware of the limitations of collecting BMI in the field, therefore should explore additional complimentary measures of non-invasively collecting body composition (i.e., bioelectrical impedance analysis). It appears that across most groups, accelerations in body composition are occurring a greater rate during the summer compared to the school year, albeit not reaching statistical significance. Interventions working to address obesogenic behaviors during the summer months should be explored. During summer children are less likely to meet guidelines for physical activity and screen-time, providing partial support for the Structured Days Hypothesis.[19] This is particularly true for children who are Black or eligible for FRPL, providing support for the Health Gap Hypothesis.[26] Interventions that target MVPA and screen-time during times of less structure (i.e., summer), may be warranted within these populations.

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