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Secondary Eating and Obesity in the United States
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Master of Public Health

Epidemiology

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Secondary Eating and Obesity the United States

By

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B.S.
University of South Florida
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Abstract

Secondary Eating and Obesity in the United States
By Sarah Monson

Introduction: Obesity has become one of the United States' most pressing public health issues. Almost 35% of Americans are obese according to most recent prevalence data. Research on eating behaviors has shown that eating while distracted, or secondary eating, may cause people to consume more than they realize, with changes in awareness leading to lowered ability to self-regulate food consumption. This study assesses the relationship between BMI, obesity and reported secondary eating time and frequency during the day in the US adult population.

Methods: Data for this analysis on 11,369 adult respondents were taken from the 2008 American Time Use Survey, a cross-sectional survey conducted to obtain nationally representative estimates of Americans' time use. In 2008, the Eating and Health Module was included to obtain information directly related to eating behaviors. Linear and logistic regression models were run to observe the associations between BMI, obesity, and secondary eating time and frequency.

Results: Fifty-three percent of the population reported secondary eating during the day. Non-obese individuals reported 31.8 minutes of secondary eating on average, while obese individuals reported an average of 22.8 minutes. Those who were obese reported a mean of 0.78 secondary eating occasions per day compared to a mean of 0.93 secondary eating occasions among non-obese individuals. In logistic regression models adjusted for demographic characteristics education and selected time use variables like exercise time, those who reported more than 30 minutes of secondary eating had lower odds of obesity (OR = 0.81, 95% CI: 0.66-0.99) compared to those who did not report secondary eating at all. In unadjusted logistic regression models, those who reported one, or three or more, occasions of secondary eating had lower odds of obesity compared to those who did not report secondary eating at all.

Discussion: This is the first study to observe the associations between both secondary eating time and frequency and body composition in US adults. Secondary eating was associated with lower BMI and a lower likelihood of being obese. Future research on secondary eating should focus on describing energy intake during secondary eating events to further explore this behavior.

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Contents

I. Introduction/Statement of Need

Obesity has become one of the United States' most pressing public health issues. Between 1976/80 and 1988/94, obesity prevalence among adults in the US increased from 14.5% to 22.5%. The prevalence of obesity has risen an additional 12.4% since, with most recent estimates of obesity at 34.9%, or 78.6 million Americans that are obese [1].

The current level of obesity is a concern to public health practitioners for many reasons. The negative health effects of obesity have been well-documented and include conditions like coronary heart disease, myocardial infarctions and stroke, sleep apnea, diabetes, certain cancers, and other conditions associated with lower quality of life [2-5]. The most recently published annual medical costs for care associated with obesity were estimated at $190 billion in the United States [6].

There are a number of explanations for the rapid increase in obesity among adults, including increased availability and consumption of calorically dense foods and lower physical activity due to current transportation and labor trends [7-9]. There are many factors that may contribute to obesity, including genetic, social, environmental and behavioral determinants [10]. While genetic predispositions cannot be altered and social and environmental influences may be prohibitively challenging to modify, behavior and food consumption may be modifiable. Though the long-term impacts of behavioral changes on weight have not been extensively studied, small modifications in behavior and consumption habits have been argued to be more sustainable than large changes [11].

One behavior that could be contributing to obesity is secondary eating, or eating while one is engaged in another activity. Examples of secondary eating are consuming a granola bar while driving, snacking on popcorn while watching a movie, and eating crackers while working on a report. Engaging in this style of eating is different from primary eating, where a person focuses their attention on the meal or snack. Eating while distracted can cause people to consume more than they realize, and even small changes in awareness can lead to a lowered ability to self-regulate food consumption [12-15].

Many studies of secondary eating have been based in lab settings [12, 16-18]. However, eating behavior can also be observed in free-living society through time use surveys that record participants' activities over the course of a day. The American Time Use Survey (ATUS) has been conducted annually since 2003 by the Bureau of Labor Statistics to collect nationally representative data on how Americans spend their time. Despite infrequent use in health research, the ATUS can provide insight on behaviors that may affect weight and body mass, including time spent eating and drinking, time spent sedentary, time spent exercising, and other activities [19-22].

Using data from the 2008 ATUS, which is the most recent data wave to include the Eating and Health Module, this analysis aims to investigate the association between engaging in secondary eating and body composition. Particular interest will be paid to people with BMI $\geq$30, the current established cut-off for obesity. Exploration of other time use and demographic characteristics will also be conducted.

The goal of this analysis is to assess whether there is a relationship between BMI, obesity, and reported secondary eating in the US population. Specific aims are to answer the following research questions:

1) Does longer reported time engaged in secondary eating correlate to a higher BMI and odds of obesity?
2) Does more frequent reported engagement in secondary eating correlate to a higher BMI and odds of obesity?

It is expected that more time spent engaged in secondary eating and more frequent secondary eating will be associated with a higher BMI and higher odds of obesity in the US population. This hypothesized relationship is due to the potential for those who engage in secondary eating to consume more calories unknowingly, which could lead to higher BMI over time.

II. Literature Review

BMI Trends

In the US, overall weight and BMI have increased in adults over the past 40 years [29]. Increases in BMI were observed in Americans across all levels of income from 1970 to 2000 [30]. Mean age-adjusted BMIs rose steadily from the 1960's to early 2000's, with the mean BMI of 25.1 in males and 24.9 in females in 1960-62 increasing to mean BMI of 27.8 for males and 28.1 for females in 1999-2002 [31].

Obesity Measurement

In population studies, obesity is often assessed using the calculation of an individual's body mass index (BMI). BMI is a measure used by the Centers for Disease Control and Prevention (CDC) and World Health Organization (WHO) to assess health risks associated with levels of adiposity (body fat) [23, 24]. BMI is calculated by dividing weight in kilograms by height in meters squared and is used as a proxy measure for an individual's actual body fat percentage. The categories most commonly used for BMI are underweight (<18.5), normal weight (18.5-24.9), overweight (25-29.9) and obese (≥30)[25].

Although there are other measurements that can be used to assess obesity, such as waist-to-hip ratio or caliper measurements, BMI is used most frequently as it is simple to assess with no special equipment or training needed to calculate. The measure is accepted as generally being useful in assessing risk for adverse health outcomes, and comparison of BMI values to body fat scans shows acceptable concordance [26]. However, an individual's true body fat percentage is dependent on age and gender, and these factors should be considered when using BMI to more accurately assess body fat percentages [27].

While useful as an approximation for body fat in many cases, BMI has shortcomings in the ability to assess adiposity in those who have high muscle mass percentages [25]. Additionally, BMI does not perform uniformly to assess risk for adverse health outcomes across populations. For instance, it has been observed that Asian populations experience obesity-related diseases at lower BMIs than other racial and ethnic groups [28].

Energy Imbalance

In the human body, energy that is ingested in the form of food and caloric beverages can be used in one of two ways: burned as fuel with physical activity, or stored as potential energy in the form of body fat [32]. The equation for this energy balance is energy intake (energy in) – energy expenditure (energy out) = energy stored by the body. When one has a higher value for energy in than energy out over a prolonged period of time, weight gain, and potentially obesity, will result [33].

This energy gap - the positive balance of calories conserved above what is necessary to maintain weight - has been used to explain weight gain in individuals [34]. Past research has found that overweight individuals tend to underreport the number of calories they consume in a day, and this has been proposed as a reason to why some people do not lose weight when dieting [35]. More recent studies have found that people tend to underestimate the number of calories consumed regardless of BMI category, especially when consuming large meals [36]. This underestimation may be especially problematic in those consuming fast food items, which tend to be calorically-dense [37].

Through consuming excess calories or burning fewer than necessary to maintain an energy balance, people can gain weight over time. However, the energy gap for the population as a whole may be small, with one study concluding that a decrease in 100 kilocalories per day could prevent further increases in weight in around 90% of the US population [11]. Although the change in caloric intake necessary for reducing weight in the United States is not large, there are many factors that influence the number of calories that are consumed by Americans, including food availability and eating patterns. Each of these factors are discussed in more detail below.

Food availability for Americans has changed over the past 30 years. The rise in fast food restaurants coincided with the increase in BMI, and has been proposed as a contributing factor to the obesity problem due to the high calorie and fat content of the foods served [38]. Meals consumed away from the home made up 32% of total calories in American diets in the 1990's compared to 18% in the 1970s [39]. Meal portion sizes consumed both inside and outside of the home increased from 1977-1998 [40].

Beyond portion size, there are other factors that can influence the amount a person consumes, including the size of the plate or bowl that food is served in, the size of food packaging, and the presence or absence of other people while eating [13]. Socializing has the potential to influence eating habits and can incite individuals to eat more depending on how their eating companions eat, though many people are unaware of the influence that others have on their behaviors

[41]. In one experiment, researchers paired participants with a partner and observed the way they ate. Participants' eating behaviors such as speed and the amount consumed were highly correlated to the behaviors of their assigned partner. When asked about what influenced their eating behavior during this session, many related the way they ate during experiments to other factors, such as their hunger, and not the influence of their eating companion [42].

Lack of awareness of caloric intake may also influence the amount that individuals consume in a day. Recent analyses suggest that even when people are made aware of the calories in foods served in restaurants through menu labeling, they may not understand how to use this information in making food choices, and in certain cases, do not eat lower calorie foods [43-45].

Eating Patterns

Americans' eating patterns shifted to more frequent eating occasions during the day, with the time between each occasion decreasing by one hour from the late 1970's to the early 2000's [8]. Some researchers have attributed to more frequent snacking, or grazing, to fewer hours of leisure time, referred to as "time poverty" [20]. With less time to relax, one may not want to prepare meals, and instead eat what is quick and convenient.

A study analyzing 2006 and 2007 ATUS data explored eating habits among workers and non-workers. Workers spent less time engaged in eating than non-workers, and their intervals of eating time were shorter [46]. There was also more grazing done by higher wage earners. This eating pattern could be attributed to more value being placed on the time and less value placed on eating.

Some psychological research on grazing has argued that non-discrete eating occasions throughout the day may be related to binge eating disorder in obese individuals [47]. In a study of over 5,000 middle-aged subjects, obese individuals participated in snacking significantly more than non-obese comparison subjects, with snacking positively correlated with a higher energy intake for the day [48].

Although these studies suggest that snacking is associated with increased weight, inverse associations between body weight and the number of snacking occasions during the day have also been observed. A cross-sectional study of 2,372 adolescent girls observed fewer snacking occasions per day by those with higher BMIs and waist circumferences [49]. Another year-long study of 499 adults' food diaries observed lower odds of obesity in those who ate more frequently [50].

Overall, there is not conclusive evidence relating meal frequency to obesity. A meta-analysis of 15 meal frequency studies found a link between meal frequency and lower body mass, but concluded that the relationship was distorted due to one study producing a stronger effect than the others included in the review [51]. A 2009 literature review of 25 eligible studies on eating frequency and weight found no consistent evidence that eating more often had an effect on body weight [52]. The authors noted that the relationship between eating frequency and body weight could be confounded by the calories consumed during eating occasions.

Eating Rate

How quickly or slowly people eat has been explored as a possible factor in obesity, with a faster eating rate suggested as a contributor to overeating. Eating quickly may not give the brain enough time to acknowledge satiety cues, and modifying eating rate has been promoted as behavioral therapy for overeating since the 1960's [53]. There is evidence to suggest that eating rate is a heritable behavior, with children's eating rate correlated to the eating rate of their parents [54].

Eating rate has been mostly examined in controlled settings where it is directly manipulated by researchers. One study manipulating eating speed found that energy intake did not differ when participants were instructed to eat slowly rather than quickly, but that desire to eat was lower one hour following the meal in those who ate more slowly [55]. Another study found that eating more slowly decreased overall food intake for male subjects, but food intake was the same for female participants regardless of how fast they ate [56]. However, another study with female-only subjects that manipulated speed, number of bites, and amount of chewing found that eating more slowly decreased energy intake among participants [57]. Additionally, a 2014 meta-analysis of 22 studies that manipulated eating rate found that eating slower was significantly associated with an overall lower energy intake [58].

Beyond these experiments, other studies have observed correlations between eating speed and BMI in the free-living population. A study comparing the current BMIs of 4,742 middle-age Japanese civil servants to their BMIs from

20 years prior found that higher self-reported rates of eating were associated with an increased BMI over the time period of interest [59]. A 2011 cross-sectional study of 1,601 women from New Zealand found similar results, with faster self-reported eating rates correlated to higher BMI in the study population [60].

Distracted Eating

Eating while distracted may influence people to consume more during each eating event, lead to an underestimation of how much they have eaten, and quiet satiety cues that would normally signal fullness and the end of an eating occasion [13]. One of the most common and studied forms of distraction is television viewing, which has been explored many times as a contributing factor to obesity. Several studies have examined the effect that distraction by television has on overall caloric intake. One longitudinal study of 1,059 men and women in the U.S. observed increased television viewing as a predictor of weight gain in women, and that time spent watching TV was positively associated with caloric intake and higher fast food consumption [38]. However, men did not experience this effect.

Other studies have examined the influence television viewing has on immediate consumption. A controlled study of 20 undergraduates found participants ate between 36-71% more food when they ate while watching television compared to when they ate while listening to a symphony [61]. In addition to the increased volume of food eaten, participants also ate for a longer duration of time during the television session. Another study of seventy-four overweight women found that those who snacked while watching TV ate more calories during the day, regardless of the number of meals consumed [17].

Beyond television, researchers have examined how general distraction may influence both the amount of food eaten and the perception of food tastes. A 2001 study observed eating patterns for women who each ate in four different settings with varying levels of distraction. Although provided the same amount of food in each setting, the number of calories women ate were higher when they were distracted compared to the amount eaten during silent, solitary meals or meals eaten in a group of other women [12]. The authors attributed this higher consumption to a drop in cognitive restraint due to their distraction by a single stimulus.

Another controlled study of 88 undergraduate females found that self-reported levels of satiety were inversely related with levels of distraction while eating. Higher levels of distraction were related to less satisfaction and less satiety when consuming the same type and amount of food as the non-distracted group [16]. Similar results were found in a study of 20 students, with the ability to detect flavor in very sweet and salty foods decreasing with increasing levels of mental taxation imposed on subjects. These participants also ate significantly more when they were exposed to more distraction, potentially due to the inability to focus as much on food taste and satiety cues while focused on a concurrent, more mentally-demanding activity [18].

Distracted eating seems to be especially detrimental for those trying to lose weight. Restrained eaters are those who actively try to restrict calories, and it has been observed that these type of eaters consume more during periods of distraction than non-restrained eaters [62]. Analysis from a study that examined time use and caloric intake of 400 women found that "high calorie" days coincided with more time spent eating while doing other activities in overweight women, but this relationship was not present in women of normal weight [63]. It has been suggested that will-power is a finite resource, and those who actively restrain themselves throughout the day deplete their will-power more quickly, leaving them with a lowered ability to control their eating in distracted situations [14].

Despite the limitations of these studies, including small sample sizes and focus on female participants, the evidence consistently highlights the deleterious effect that distraction has on the ability of one to regulate their food intake. A meta-analysis of 22 weight intervention studies found evidence that high levels of self-monitoring by participants was associated with greater weight loss, indicating mindfulness can be an important tool in reversing weight gain [64].

Commuting

Passive commuting done by bus or car has been associated with obesity. A 2004 study of over 10,000 adults in Atlanta found a 6% increase in the odds of obesity for every hour spent passively commuting in a day [65]. This could be due to low levels of physical activity for individuals who passively commuted, as an opposite effect was seen for those in the study population who spent more time actively commuting by walking.

The same association was observed in an Australian cross-sectional study of 6,810 driving-aged adults, with commuting by driving positively correlated to being overweight or obese [66]. Those who drove to work did not meet recommended physical activity levels, and this inadequate exercise time was also related to being overweight or obese. Another study using census and state data from California observed higher BMI among those with more vehicle miles travelled [7]. Results from this study suggest a trade-off between commuting and physical activity, with a lack of physical activity, longer commute time, and obesity significantly correlated.

Sleep

Sleep is another factor previously linked to obesity. Several studies have found that fewer hours of sleep may be a risk factor for obesity in both adults and children [67, 68]. Analysis of NHANES data on over 24,000 participants indicate that those who sleep less than 7 hours had higher BMIs, and were more likely to be obese when compared to those who slept more than 7 hours per night [69]. Analysis of the 2004-2005 US National Health Interview Survey on 56,507 adults found that sleeping too few (less than 7) or too many (more than 8) hours was associated with increased obesity [22].

One meta-analysis of 45 sleep studies determined the loss of one hour of sleep per day is associated with a 0.35 increase in unit of BMI [69, 70]. Another meta-analysis of 35 published controlled experimental studies observing the effects of alcohol, sleep deprivation, and television viewing on obesity found sleep deprivation strongly associated with higher food intake, which could contribute to obesity [71].

Conceptual Framework

Based on previous research on distracted or secondary eating and the amount that one consumes, the hypothesis for this study is that more time spent engaged in secondary eating and more frequent secondary eating during the day will be associated with a higher BMI and higher odds of obesity in the adult US population. Limiting one's awareness during eating occasions may influence the amount one consumes, especially when other factors like portion size already influence this amount [12, 16, 18]. With lack of awareness of how much is being consumed, a person may also fail to account for the number of calories already eaten when balancing other food choices for the rest of the day.

As shown in Figure 1, secondary eating by its very nature is influenced by other behaviors. Engaging in secondary eating means that one must concurrently be participating in another activity, and this can be seen essentially as distracted eating. Television viewing, working and commuting are three activities that have been linked to obesity, and also may be activities that people can be doing while secondary eating [7, 17, 38, 61, 65, 72].

Television viewing has been repeatedly linked with higher BMI [17, 38, 61]. Researchers have noted that beyond acting as a potential cue for a person to eat, it can take away from available time that could be used for physical activity. As one snacks while watching television, one is increasing their energy imbalance by ingesting more and burning less.

The time one spends working and the time it takes to get to work are both opportune periods to engage in secondary eating. Previous transportation research found longer times spent commuting correlated with higher body weights [7]. Additionally, working longer hours has also been linked to having a higher BMI [72].

Conversely, exercise is seen as both a prevention and as a treatment for obesity. Exercise can shift the energy gap from positive to negative, and allow for weight loss or weight maintenance. This activity could possibly counteract the effects that secondary eating may have on obesity.

Obesity prevalence varies by age, race/ethnicity characteristics, and these factors have therefore been added to the framework for obesity in Figure 1. Though the pathways that these factors can influence obesity are not known, they are important demographic components that may have associations with body weight.

Goals of this analysis are to observe the relationship between secondary eating and BMI, and determine if behaviors differ between participants who are obese and those who are not obese. The primary hypothesis is that those who report more time engaged in secondary eating, and those report more frequent secondary eating during the day, are more likely to have a higher BMI and be obese than those who do not report engaging in this behavior.

III. Methods

Study Design

Data for this analysis were obtained from the publicly available American Time Use Survey (ATUS), a nationally-representative study conducted by the US Census Bureau and sponsored by the US Bureau for Labor Statistics [73]. The Survey collects information in a 24-hour day diary format. The first ATUS was conducted in 2003, and since then has been administered annually to obtain estimates for how Americans spend their time during a day. For the years 2006-2008, the ATUS included a supplemental Eating and Health Module that collected information on respondents' BMI and other health-related characteristics.

Study Population

Designed using complex sampling methods, recruitment of participants for ATUS is done in a way to accurately reflect the population of the United States. Participants in ATUS are a subsample of the Current Population Survey's (CPS) larger sample. The CPS population includes all civilian, non-institutionalized individuals aged 15-85 in the United States [73]. Military personnel and otherwise institutionalized persons, such as prisoners or those living in nursing homes, are excluded from the study population.

ATUS households are stratified based on race and ethnicity, the presence and age of children, and the number of adults living in households without children. Following stratification, a single member from each of the chosen households is selected to participate in the ATUS phone interview. To be eligible, the household member must be between 15 and 85 years of age.

Once participant selection is complete, potential respondents are grouped into scheduled times to be called to complete the ATUS interview. Months and days of the week in which the respondents are contacted are randomly assigned. Half of those contacted will be asked to report on their activities for a weekday, and the other half of those contacted will be asked to report on their activities for a weekend. For the year 2008, there was a 54.6% response rate for the ATUS questionnaire, which is comparable to response rates from other years of the survey. The sampling process for the survey is shown in Figure 2.

Of the 12,708 eligible participants who responded to the EH Module, we excluded 614 persons under 18 years of age due to reduced ability to make food choices as minors, leaving only participants aged 18-85. Our sample further excluded 725 people who did not have valid reported height or weight, thus making BMI calculation impossible. The final sample for our analysis consisted of 11,369 participants.

Data Collection

Data for the ATUS are collected by computer assisted telephone interviewing (CATI), and assessed during and after the interview for both response and coding errors to ensure data quality [73]. Participants report on their time use over a 24-hour period and include the type of activities they participate in, how long each of these activities took place, where the activities occurred, and who else was present for each of these activities. All reported activities are recorded in the ATUS data files as six-digit numeric codes. The first two numbers describe the major category for the activity, with added details further classifying the activity coded within the next two tiers. For example, vacuuming is generally considered a "household activity," and coded with the major category of "02". The second tier of the activity is further classified in "housework" which is coded with the second tier code of "01". The third tier of the activity is coded as "01", "interior cleaning." Thus, the entire activity is coded by the interviewer as "020101".

From 2006-2008, the ATUS day diary included a supplemental Eating and Health (EH) Module. In addition to the questions administered in the day diary portion, the EH Module contained questions related to participants' general health and eating habits. Self-reported height, weight, and overall health were questions included in this supplement.

Measures

Outcome Variable

The main outcomes in this study were continuous BMI and obesity, defined as having a BMI greater than or equal to 30 kg/m^2. BMI was collected through self-report of height and weight during the EH Module. The highest and lowest reportable weights were 330 lbs. and 98 lbs. respectively, which was meant to preserve the confidentiality of those who participate in the ATUS [73]. There were 105 individuals who had these top- and bottom-coded values and were excluded from analysis. Continuous BMI and dichotomous obese/non-obese characterizations of body mass were examined.

Exposure Variable

Secondary eating was the exposure of interest in this study. During the EH Module, interviewers posed the following question to obtain information on secondary eating:

*"Yesterday, you reported eating or drinking between *read times below.* Were there any other times you were eating any meals or snacks yesterday, for example while you were doing something else?"* [74]

The number of reported secondary eating occasions were queried for those who said they had eaten during other times during the day, and the sum of these separate eating events was used for analysis. Total time spent secondary eating during these occasions were also summed and observed as a continuous variable.

Categorical variables for secondary eating in both time and frequency were created for logistic regression models. Secondary eating occasions were coded in four categories: no secondary eating, one secondary eating occasion, two secondary eating occasions, and 3 or more secondary eating occasions. These categories were coded as dummy variables (0/1). The same method was used to categorize total time spent secondary eating: no engagement in secondary eating, 0 to 15 minutes engaged in secondary eating, more than 15 and less than 30 minutes engaged in secondary eating, and more than 30 minutes engaged in secondary eating. These categories were determined based on the distribution of time and number of occasions of secondary eating in the sample.

Covariates

The following variables were treated as possible confounders and controlled for in analysis examining the relationship between secondary eating and obesity. These factors were selected based on previous literature.

Primary Eating and Drinking

Time spent primary eating and drinking was reported as a single time use variable in the ATUS. Information on this behavior was collected during the day-diary in line with all other main reported activities. All separate instances of primary eating and drinking time were summed and reported as total time. This variable was included due to the influence that eating has on BMI.

Secondary Drinking

Information on secondary drinking was obtained in a similar manner to secondary eating. During the EH Module, interviewers asked participants the following:

> *"Not including plain water, were there any other times yesterday when you were drinking any beverages?"[74]*

Time spent engaged in secondary drinking was examined as a continuous variable. All time spent drinking any beverage other than water was recorded as secondary drinking time. This variable was included because primary eating and drinking times were reported as a single variable by ATUS, and inclusion of secondary drinking allows to further analyze consumption behaviors.

Sleep Time

Sleep time was recorded for each participant in the ATUS day diary as a single continuous variable. This variable captured only time spent sleeping, and did not include leisure time spent in bed. This variable was included due to observed correlations between sleep duration and obesity [22, 75].

Commute Time

Commute time was collected as time related to travel. In ATUS, each travel event is categorized in relation to the activity that occurs after the travel event. For example, if an individual reports driving for 45 minutes and then reports working for the hours following, the travel component is coded as “travel related to work.” The exception to this rule is homebound trips, as those are coded relative to the action that precedes the trip home; so, driving home from work would still be coded as driving related to work. Work-related travel activities were classified into multiple categories and included “travel related to working”, “travel related to work-related activities” and “travel related to income-generating activities.” These three distinct activities were combined to create the continuous commuting variable. This was included based on previous studies showing positive associations between commute time and obesity [65, 66].

Exercise Time

Activities in this category included time spent engaged in “Sports, Exercise, and Recreation/Participating in Sports, Exercise, or Recreation/specific sport”. There were 37 activities ranging from playing basketball to participating in martial arts, and time spent participating in these activities was used to calculate overall time spent engaged in physical activity. This variable was included as a covariate for its potential to influence BMI [76].

Television Viewing

Television viewing was separated into two activities: “television and movies (not religious)” and “television (religious).” These two activities were summed to create one continuous variable. Television watching was included to account for viewing being linked to both the exposure of secondary eating, as well as the outcome of obesity [17, 61].

Demographic Characteristics

Demographic characteristics examined included highest educational attainment, employment status, income in relation to the Federal Poverty Line, and race/ethnicity. These demographic covariates were included based on existing literature showing the relationship of these characteristics with BMI.

Education Level

Highest education level was collected by the Current Population Survey and included in the CPS-ATUS linking file. Levels of educational attainment were reported in 16 different categories. These categories were condensed into five categories of educational attainment: less than a high school diploma, high school diploma, some college, college diploma, and advanced degree. This variable was included due to observed associations between lower levels of education and higher BMI [77].

Employment Status

Employment status was collected as “labor force status” and reported for each participant as employed, unemployed, or not in labor force, with multiple options for employed and unemployed, such as “unemployed – on layoff.” The detailed responses were collapsed into the two broad categories of employed or unemployed for analysis. This variable was included since studies have found that working longer hours is associated with increased odds of obesity [72, 78].

Poverty Level

Respondents' income relationship to the Federal Poverty Line (FPL) was determined based on annual income and household size for each respondent. For analysis, this was coded as a dichotomous variable of being at or below 130% of the FPL or above 130% of FPL. Being at or below 130% of the FPL determines Supplemental Nutritional Assistance Program (food stamp) eligibility [79]. This variable was included in analysis based on previous evidence of a positive association of BMI with receiving SNAP benefits [80].

Self-Rated Health

Self-rated health status was reported in the EH module. Participants were asked to rate their health on a five-point scale from poor to excellent. These categories of self-rated health were retained in analysis. This variable was included due to evidence of an inverse relationship between levels of obesity and self-rated health [81].

Race/Ethnicity

Race and ethnicity were collected by CPS and reported in the ATUS Activity File. There were 21 different options for respondents to report their race, and Hispanic ethnicity was reported as either 'yes' or 'no'. These options were collapsed into four categories to reflect racial options commonly used in other research and to avoid having very small numbers in certain categories. The categories included were non-Hispanic white, non-Hispanic black, Hispanic and other races. This variable was included as a covariate to control for variations in obesity prevalence between races and higher rates of obesity in the Hispanic population [29, 82, 83].

Analysis

All analyses were conducted using SAS Version 9.4. Analyses accounted for the complex nature of the ATUS by using provided statistical weights included in the EH Module dataset, and cluster and strata variables found in the ATUS-CPS file. These variables were used in all steps of analysis to provide accurate estimates for the population.

There were eight steps involved in this analysis. First, demographic characteristics of the population were obtained through univariate analysis. Demographic characteristics were then examined stratified by obese or non-obese status. Chi-square analyses were performed to test the differences in demographic characteristics between the two strata.

Second, the distribution of BMI among the population was measured. Weighted mean and median BMI were calculated, as well as the range of BMI among all respondents.

Third, the distribution of secondary eating occasions was calculated. Eating occasions were stratified by obese/non-obese, and calculations were performed to explore secondary eating occasions both in the total population and by only those who participated in secondary eating.

Fourth, time use estimates for the total population were calculated using weighted equations by summing total time use in minutes for all participants and dividing this number by the sum of the ATUS-provided EH Module statistical weights. Average time per day in hours, as well as the percentage of the sample that took part in each activity, was calculated for the total population. Then, the average time per day in hours was calculated for only those who reported participation in each of the activities during the day. The sample was then stratified by obesity status and t-tests were conducted to evaluate time use differences between the two strata.

Fifth, unadjusted linear regression analyses were conducted to explore the relationships between continuous BMI and secondary eating time and other selected demographic and time use variables. For each model, continuous BMI was used as the outcome and each demographic or time use characteristic was used as a single predictor.

Sixth, multivariate linear regression analyses were conducted. First, a full model with all selected predictor variables was run with continuous BMI as the outcome. Next, two separate multivariate linear regression models, also using continuous BMI as the outcome, were selected using backwards elimination. One model considered total secondary eating time as the primary predictor, while the other considered the number of secondary eating occasions as the primary predictor. Starting with all selected time use and demographic covariates used in the full model, variables not meeting statistical significance of $\alpha = 0.05$ were eliminated in a stepwise fashion. Weighted adjusted R-square and root MSE were considered with each variable eliminated, until final models were chosen that optimized both.

Seventh, logistic regression models were run to obtain unadjusted odds of obesity for each categorical variable, including sex, race/ethnicity, employment status, and income in relation to the federal poverty line.

Eighth, six logistic regression models were run to obtain unadjusted and adjusted odds of obesity for both the exposure of secondary eating time, and secondary eating occasions. After unadjusted models containing only the exposure were run for secondary eating time and secondary eating occasion categories, two additional adjusted logistic regression models were run. The first of these models considered only the secondary eating dummy variables as exposure and the demographic covariates of sex, age, race/ethnicity, highest education level, income in relation to FPL, employment status, and self-rated health. The second model used the same exposure variables and included the demographic characteristics of age, sex, race/ethnicity, highest level of education, respondents' income in relation to FPL, employment status, self-rated health, and the time use covariates of TV watching time, commute time, primary eating time, secondary drinking time, working time, and exercise time.

First weighted multivariate logistic regression model with secondary eating time as the primary exposure:

$$\mathbf{P\ (OB=1|X) = \beta_0 + \beta_1 SEC\_EAT1 + \beta_2 SEC\_EAT2 + \beta_3\, SEC\_EAT3 +}$$

$$\mathbf{\beta_4 AGE + \beta_5 SEX + \beta_6 NHBLACK + \beta_7 HISPANIC + \beta_8 OTHER +}$$

$$\mathbf{\beta_9 EDU + \beta_{10} FPL + \beta_{11} EMPL + \beta_{12} HEALTH}$$

Second weighted multivariate logistic regression model with secondary eating time as the primary exposure:

$$\mathbf{P\ (OB{=}1|X) = \beta_0 + \beta_1 SEC\_EAT1 + \beta_2 SEC\_EAT2 + \beta_3\, SEC\_EAT3 + \beta_4 AGE + \beta_5 SEX + \beta_6 NHBLACK + \beta_7 HISPANIC + \beta_8 OTHER + \beta_9 EDU + \beta_{10} FPL + \beta_{11} EMPL + \beta_{12} HEALTH + \beta_{13} TV + \beta_{14} COMM + \beta_{15} PRIEAT + \beta_{16} SECDRINK + \beta_{17} WORK + \beta_{18} EXERCISE}$$

Third multivariate logistic regression model with secondary eating occasions as the primary exposure:

$$\mathbf{P\ (D{=}1|X) = \beta_0 + \beta_1 SEC\_OCC1 + \beta_2 SEC\_OCC2 + \beta_3\, SEC\_OCC3 + \beta_4 AGE + \beta_5 SEX + \beta_6 NHBLACK + \beta_7 HISPANIC + \beta_8 OTHER + \beta_9 EDU + \beta_{10} FPL + \beta_{11} EMPL + \beta_{12} HEALTH}$$

Fourth weighted multivariate logistic regression model with secondary eating occasions as the primary exposure:

$$\mathbf{P\ (OB{=}1|X) = \beta_0 + \beta_1 SEC\_OCC1 + \beta_2 SEC\_OCC2 + \beta_3\, SEC\_OCC3 + \beta_4 AGE + \beta_5 SEX + \beta_6 NHBLACK + \beta_7 HISPANIC + \beta_8 OTHER + \beta_9 EDU + \beta_{10} FPL + \beta_{11} EMPL + \beta_{12} HEALTH + \beta_{13} TV + \beta_{14} COMM + \beta_{15} PRIEAT + \beta_{16} SECDRINK + \beta_{17} WORK + \beta_{18} EXERCISE}$$

Where OB = 1 if BMI $\geq$30, 0 if <30

Where D = 1 if BMI $\geq$30, 0 if <30

SEC_EAT1 = 1 for 0-15 minutes engaged in secondary eating, 0 for other

SEC_EAT2 = 1 for >15 and ≤ 30 minutes engaged in secondary eating, 0 for other

SEC_EAT3 = 1 for > 30 minutes engaged in secondary eating, 0 for other

SEC_OCC1 = 1 for 1 reported secondary eating occasion, 0 for other

SEC_OCC2 = 1 for 2 reported secondary eating occasions, 0 for other

SEC_OCC3 = 1 if 3 or more reported secondary eating occasions, 0 for other

AGE = continuous age

SEX = 0 for male, 1 for female

NHBLACK = 1 for Non-Hispanic black race, 0 for other

HISPANIC = 1 for Hispanic, 0 for other

OTHER = 1 for "other race", 0 for other

EDU = 1 if less than high school;

2 if high school degree/GED;

3 if some college;

4 if college degree;

5 if Master's degree or greater

FPL = 1 if < 130% Federal Poverty Line, 0 other

EMPL = 1 if employed;

2 if unemployed;

3 if not in labor force

HEALTH = 1 if poor self-rated health;

2 if fair self-rated health;

3 if good self-rated health;

4 if very good self-rated health;

5 if excellent self-rated health

TV = continuous time watching TV

COMM = continuous time commuting

PRIEAT = continuous primary eating time

SECDRINK = continuous secondary drinking time

WORK = continuous time working

EXERCISE = continuous exercise time

Results

Weighted distribution of demographic characteristics for the non-institutionalized adult US population for the year 2008 are shown in Table 1. The population was fairly equally distributed between male (49.9%) and female (50.1%). The most common highest level of education for the population was a high school diploma or GED. The mean age of the population was 46.3 years and most (67.4%) were employed. Slightly more than 17% had incomes that were at or below 130% of the Federal Poverty Line. The majority of the population (34.6%) rated their health as "very good".

Chi-square analyses revealed significant differences in obesity status by race/ethnicity ($\chi^2 = 23.3$, p-value <0.01), highest education level obtained ($\chi^2 = 20.3$, p-value <0.01), employment status ($\chi^2 = 3.2$, p-value <0.01), respondents' income in relation to FPL ($\chi^2 = 35.8$, p-value <0.01) and self-rated health ($\chi^2 = 99.6$, p-value <0.01). There was no significant difference in obesity between males and females ($\chi^2 = 2.48$, p-value = 0.12).

Mean BMI for the sample was 27.4 kg/m^2 and ranged from 12.9 kg/m^2 to 62.7 kg/m^2. Nearly one-third of the population was obese (Table 2).

Mean reported occasions of secondary eating per day were 0.89, and ranged from no occasions to 45 occasions (Table 3). Among all who reported any secondary eating, mean occasions were 1.68. Non-obese individuals reported a mean of 1.73 secondary occasions per day compared to a reported mean of 1.55 occasions per day for obese individuals.

Roughly half of the population engaged in secondary eating, and the average time for this activity was slightly under half an hour (Table 4). Among those who reported any secondary eating, average time was just under one hour. Fewer people (37.7%) reported secondary drinking than secondary eating, with an average time of 1.41 hours spent secondary drinking for the total sample. Those who reported any secondary drinking did so for an average of 3.84 hours.

American adults spent an average of 1.13 hours engaged in primary eating and drinking, 8.46 hours sleeping, 2.84 hours watching television, and 3.58 hours working. Only 16.4% of the population engaged in exercise during the day, with the average time of 0.26 hours. Among those who participated in exercise, mean time was 1.55 hours.

Sleeping, working, and secondary drinking times were not statistically different between obese and non-obese individuals (Table 5). However, obese individuals spent an average of half an hour longer watching TV than non-obese individuals. Non-obese individuals engaged in exercise nearly twice as long as obese individuals did, and non-obese individuals also spent longer engaged in secondary eating on average than obese respondents.

Table 6 shows linear regression analysis results of continuous BMI with selected demographic and time use variables. Secondary eating time had a statistically significant negative relationship with continuous BMI ($\beta = -0.12$, p-value <0.01). Age, identifying as non-Hispanic black, Hispanic ethnicity, being unemployed, income at or below 130% of FPL, secondary drinking, and TV watching were positively correlated with BMI. Self-rated health was most strongly correlated with continuous BMI, with lower BMI significantly related to higher levels of self-rated health. Time spent commuting and time spent sleeping were negatively correlated with BMI, but were not significant at $\alpha = 0.05$ significance level.

Table 7 displays the multivariate linear regression model between continuous BMI and all selected predictor variables. Secondary eating time was significantly and negatively associated with BMI ($\beta = -0.16$, p-value <0.01), and secondary eating occasions were slightly associated with BMI, though not significantly ($\beta = 0.02$, p-value = 0.75). Approximately 11% of the variability in BMI is explained by this regression model.

Table 8 displays the final multivariate linear regression model using secondary eating time as the main exposure. All variables in this model were statistically significant due to the backwards elimination process of variable selection. Primary and secondary eating were both inversely related to BMI, with each hour engaged in primary eating associated with a 0.35 decrease in unit of BMI. Each hour of secondary eating was associated a 0.16 decrease in unit of BMI.

Age was slightly correlated to BMI, with each increase in year of age corresponding to a 0.02 increase in unit of BMI. Identifying as non-Hispanic black was associated with a 1.32 increase in unit of BMI, and identifying as 'other' race was associated with a 1.78 unit decrease in unit of BMI. The strongest predictor of BMI was self-rated health, with each increase in level of self-rated health associated with a 1.50 decrease in unit of BMI. Ten percent of BMI variability can be explained by this model.

Table 9 displays the final multivariate linear regression model using secondary eating occasionss as the exposure of interest. Again, all variables in this model were statistically significant due to backwards elimination of variables. The number of secondary eating occasions was negatively associated with BMI, with each additional secondary eating occasion associated with a 0.11 decrease in unit of BMI. Identifying as non-Hispanic black was positively associated with BMI and Hispanic ethnicity was negatively associated. Self-rated health was again the variable most strongly associated with BMI, with each increase in level of self-rated health associated with a 1.50 unit decrease in BMI. This model also explained 10% of the variability in BMI.

Table 10 shows the crude odds ratios for all categorical variables in the association with obesity. The odds of being obese did not significantly differ between genders (OR = 0.91, 95% CI: 0.82-1.02). Statistically significant differences in odds of obesity were observed between non-Hispanic blacks and 'other' races compared to the referent non-Hispanic white group. Odds of obesity did not differ significantly between employment statuses. Odds of obesity were significantly higher in those with incomes at or below 130% of the FPL referent to those above 130% (OR = 1.59, 95% CI: 1.38-1.83). Those with a high school education had significantly higher odds of being obese than those with less than a high school education (OR = 1.31, 95% CI: 1.15-1.48), and odds of obesity were significantly lower in those with college and graduate or higher degrees compared to those with less than a high school degree (OR = 0.68, 95% CI: 0.59-0.79 and OR 0.55, 95% CI: 0.45-0.67). Odds of obesity were significantly different at all levels of self-rated health in comparison to "poor" self-rated health, with "very good" and "excellent" self-rated health inversely associated with obesity.

The odds of obesity by exposure of time spent engaged in secondary eating are shown in Table 11 in three weighted logistic regression models. The unadjusted odds of obesity for those who spent fifteen minutes or less (OR = 0.85, 95% CI: 0.75-0.97), or more than 30 minutes (OR = 0.80, 95% CI: 0.67-0.95), engaged in secondary eating were significant. Thus, those with longer reported times of secondary eating had lower odds of being obese compared to those who do not engage in secondary eating at all.

In the second model adjusting for the demographic covariates of age, sex, race/ethnicity, highest level of education, income relationship to FPL, employment status, and self-rated health, none of the levels of secondary eating time remained significantly associated with obesity (OR = 0.88, 95% CI: 0.77-0.99 for 0-15 minutes; OR = 1.01, 95% CI = 0.84-1.22 for 15-30 minutes; OR =0.81, 95% CI: 0.68-0.97 for 30+ minutes). In the final multivariate model adjusting for demographic characteristics as well as time spent watching television, commute time, primary eating time, secondary drinking time, working time, and exercise time, only the exposure of more than 30 minutes spent engaged in secondary eating remained significant (OR = 0.81, 95% CI: 0.66-0.99).

Table 12 displays the odds of obesity by number of secondary eating occasions in three logistic regression models. The unadjusted odds of obesity for those engaged in one occasion of secondary eating (OR = 0.86, 95% CI: 0.76-0.97), and three or more occasions of secondary eating (OR = 0.71, 95% CI: 0.55-0.95), were significant compared to those who did not engage in any secondary eating. Thus, those engaging in secondary eating one time per day, or three or more times per day, have lower odds of being obese compared to those who do not engage in secondary eating at all. Secondary eating frequency was not significantly associated with obesity in either of the adjusted models. In both partially and fully adjusted models, reported secondary eating occasions were not significantly associated with obesity, though there appeared to be a pattern of lower odds of obesity for those who engaged in 1 occasion or 3 or more occasions of secondary eating during the day compared to the referent of no secondary eating in a day.

IV. Discussion

This study set out to analyze the relationships between BMI, obesity, and the behavior of secondary eating. This is the first study to observe the associations between both secondary eating time and frequency and body composition in US adults. Although it was hypothesized that BMI and odds of obesity would be higher in those who reported more frequent and longer secondary eating occasions, evidence from these analyses suggested otherwise.

In multiple weighted statistical models, both longer reported secondary eating time and more frequent reported secondary eating were associated with lower BMI. While longer reported secondary eating time was also associated with lower likelihood of being obese, more frequent reported secondary eating was associated with lower levels of obesity only in crude models. Though adjusted models were not significant, there appeared to be an overall pattern of lower likelihood of obesity in those who reported more frequent secondary eating during the day compared to those who did not report secondary eating.

The behaviors of interest for this study were collected in a cross-sectional manner. All reported time use was based on the previous day in each participant's life, and eating behavior was not manipulated in any way. Although experiments have observed higher food intake among participants in settings where distracted is imposed [12, 16, 18], people may behave differently outside of a controlled environment. Individuals who reported secondary eating may be consuming food more slowly during each eating occasion, allowing time to pick up on satiety cues and stop eating when they are full, instead of overeating. It is also possible that those who ate more frequently spread their caloric intake over the course of the day, with fewer calories consumed during each eating occasion.

The results of this study add to existing evidence that those who take more time to eat tend to have a lower BMI [56, 59, 60, 84]. However, without more detailed information on specific eating behaviors such as how fast or slow someone eats, it cannot be assumed that those who engaged in secondary eating for longer actually ate at a slower rate. Though there was weaker evidence that reported secondary eating frequency was associated with lower odds of obesity, the overall observed pattern supports previous findings that more frequent eating is associated with lower likelihood of being obese [49, 50]. However, these findings also come from cross-sectional study designs, so it is not possible for causal inference to be made in terms of eating frequency.

Some results of time use in our analyses were surprising. Previous research suggests that commute time is associated with a higher BMI [7, 66] – however, time spent commuting did not differ by obesity status in our study. Other time use variables aligned with previous research more closely. Obese participants spent more time watching TV than non-obese participants, which was expected due to previously observed correlations with TV viewing time and BMI [17, 38, 61, 85].

Most observed demographic factors aligned with existing literature. Results were consistent with previous literature that observed an association between being obese and lower self-rated health [81]. Higher levels of education were related to a lower likelihood of being obese [62]. Those who identified as

Hispanic or non-Hispanic black were more likely to be obese than those with other racial backgrounds [29, 82, 83].

Strengths

The ATUS is formulated to be nationally representative, and over 11,000 participants were included in this analysis, compared to small sample sizes in many eating behavior studies. Second, though ATUS respondents are asked to only report about one day in their lives, the sampling method accounts for the different days of the week should provide adequate coverage for different activities across the population. The BLS ensures adequate coverage of weekdays, weekends, and holidays to create a more complete picture of daily time use by Americans [73]. Third, variables included in the dataset are accompanied by calculated weights that ensure time estimates can be extrapolated to estimate the time an "average American" spends participating in activities during a day.

Fourth, the format of ATUS may reduce the influence of social desirability of reporting behaviors related to obesity, such as eating and exercise. As body weight and eating habits in general may carry some stigma, having the questions regarding dietary choices included in a time recall diary that asks about many activities and other details can lessen the influence of social desirability on given answers. When one is asked about an entire day worth of activities rather than specific eating behaviors there may be reduced reporting by participants [86].

Finally, the 24-hour time use diary may be easier for participants to report on compared to multi-day diaries. Although detailed, asking about only the day prior can make recollection of activities easier. The responses for this time period is also actively checked and verified for logical answers by ATUS staff, and interviewers can ask respondents about inconsistencies reported for that day.

Weaknesses

The amount of time spent eating may not be predictive of the number of calories that are consumed during an eating event. Depending on the foods being consumed, a person could eat a high number of calories in a short period of time (e.g. a candy bar), but could take longer to eat fewer calories from foods that take more time to chew (e.g. a piece of fruit high in fiber). However, it would be unreasonable for the survey inquiring on general activities to focus on nutrition without being prohibitively time-consuming for participants.

Next, secondary activities are often hard to capture, as it is the responsibility of the participant to not only report all activities, but to also prioritize which activity qualifies as their primary one. The Bureau of Labor Statistics has published a report detailing the ways that it is difficult to collect data on multitasking in a 24-hour time use survey when the information is volunteered rather than directly asked for by interviewers [87].

Third, recall bias may influence the way secondary eating is reported during the ATUS. Information on secondary eating was obtained in a separate module from the general questionnaire, removing context within the 24-hour time period. This could have caused underreporting of the amount of time respondents spent eating while doing other things, and it is also possible that they could have forgotten eating during another activity altogether. However, this bias should not have been differential between weight groups.

Fourth, while other variables that have been historically associated with obesity, such as age, sex, and exercise time were able to be controlled for in the linear and logistic regression models, numbers of calories consumed were not available and thus could not be accounted for.

Fifth, BMI was self-reported during the telephone interview. Women tend to under report their weight and men tend to over report height, which could skew the BMI calculation [88]. However, self-reported height and weight is commonly used in research so comparability of this variable to other data is still possible. Both high BMI and fear of being perceived negatively by interviewers are predictors for underreporting energy intake in both men and women participating in 24-hour dietary recalls [89]. Social desirability could also have influenced the reported weight, and it is possible that this is why the BMI in this study was 7.4% lower than the national estimate of obesity prevalence.

Future Directions

The ATUS, despite some limitations, has great potential to contribute to obesity knowledge and treatment efforts. Further research on eating patterns using time use data could be very useful for targeting obesity interventions. With emphasis placed on prompting recall of secondary eating, more information could be gathered about multi-tasking and eating. Concurrent inquiry into whether one has engaged in multitasking behaviors during the day diary may obtain higher response rate for secondary eating and drinking. Although it may create more response burden, asking ATUS participants after each activity if they had eaten during that time could be a way to capture secondary eating more thoroughly.

Beyond time use diaries, future research should be done to measure the composition of foods consumed during secondary eating occasions. It is important to see if differences exist between the types and calorie counts of foods consumed during primary eating occasions compared with secondary eating occasions, and how this nutritional content fits into a person's overall diet.

Another potential direction for future related research is to look more closely at secondary drinking. While few people reported secondary drinking in the 2008 EH Module, future iterations of the Module may be able to better parse out those who engaged in secondary drinking of liquids that may influence body mass, such as sugar sweetened beverages. Being able to differentiate between high calorie and no calorie beverages such as diet soft drinks may lead to further insight into this behavior.

Overall, this study adds to the evidence that longer eating time is more frequent eating may also be related to lower BMI. Despite some disadvantages in the way that information on secondary eating was obtained, this research presents insight into how obese and non-obese individuals spend their time, and the ways trade-offs in time use are associated with weight. It is within these time use choices that body mass can be affected, and it must be taken into consideration how an individual finds balance between many activities in their daily life. A deeper understanding of how Americans spend their time may be helpful in finding solutions to the obesity epidemic, and interventions that acknowledge the nuanced use of time may be more successful than those that do not.

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VI. Tables and Figures

Figure 1. Directed Acyclic Graph displaying the relationship between obesity and secondary eating.

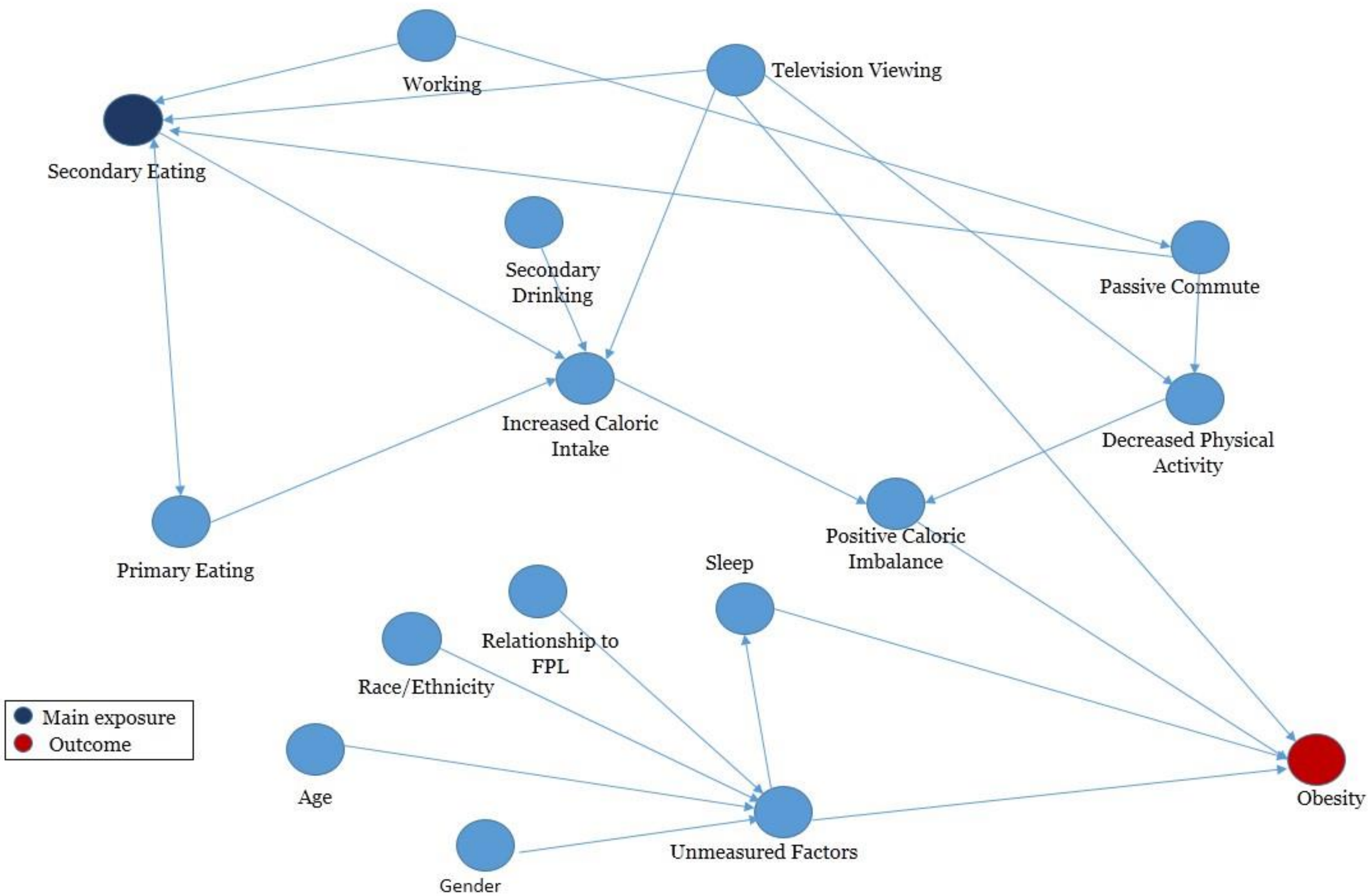
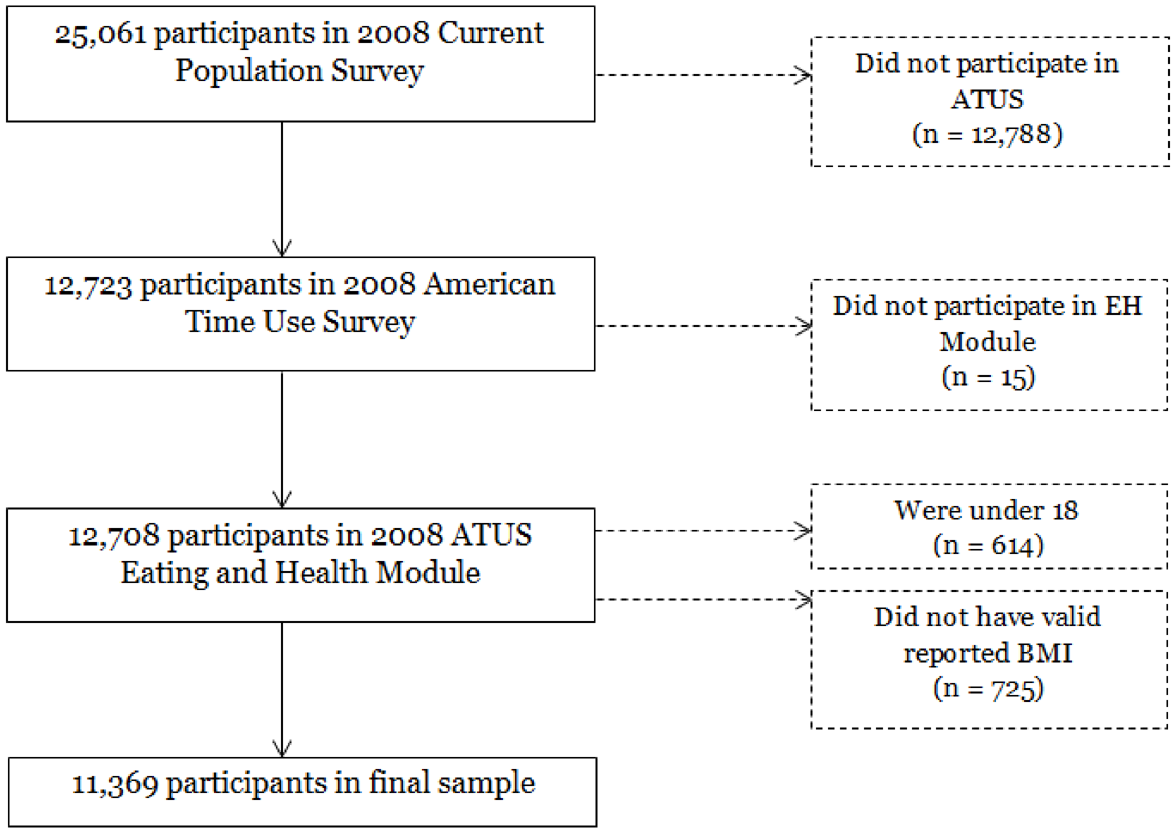


Figure 2. Study Participation in the 2008 Eating and Health Module Sample, n = 11,369



Dashed boxes indicate the reason for exclusion and number removed from the sample in each step.

Table 1.
Weighted distributions for the 2008 ATUS Eating and Health Module, n = 11,369

	Total n=11,369		Obese n = 3,186		Non-Obese n = 8,183		
	n	*%*	*n*	*%*	*n*	*%*	*χ² (p-value)*
Age							
Mean	46.3		47.6		45.8		
Standard Error	0.62		0.39		0.29		
Median	46		48		46		
Sex							2.48 (0.12)
Male	5,173	49.9	1,508	51.5	3,665	49.3	
Female	6,196	50.1	1,678	48.4	4,518	50.7	
Race/Ethnicity							**23.3 (<0.01)**
Non-Hispanic White	7,829	70.7	2,059	66.9	5,770	72.1	
Non-Hispanic Black	1,542	11.1	598	15.1	944	9.6	
Hispanic	1,450	12.8	426	14.0	1,024	12.3	
Other	548	5.5	103	3.9	445	6.1	
Education							**20.3 (<0.01)**
Less than High School	1,136	13.1	428	14.7	908	12.5	
High School/GED	3,103	30.9	981	35.1	2,122	29.3	
Some College	3,197	26.9	667	20.2	1,461	18.0	
College Degree	2,383	18.9	857	23.3	2,595	28.8	
Master's or Greater	1,350	10.1	253	6.7	1,097	11.5	
Employment Status							**3.2 (0.04)**
Employed	7,541	67.4	2,035	65.1	5,506	68.3	
Unemployed	436	4.6	141	5.3	295	4.3	
Not in Labor Force	3,392	28.0	1,010	29.6	2,382	27.4	
Income							**35.8 (<0.01)**
> 130% FPL	9,025	82.6	2,387	77.5	6,638	84.5	
< 130% FPL	2,068	17.4	741	22.5	1,327	15.5	
Self-Rated Health							**99.6 (<0.01)**
Excellent	2,085	18.4	219	7.2	1,866	22.7	
Very Good	3,946	34.6	906	28.8	3,040	36.7	
Good	3,415	30.9	1,212	38.9	2,203	28.0	
Fair	1,403	12.0	631	18.8	772	9.4	
Poor	511	4.0	215	6.3	296	3.2	
Refused/Don't Know	9	<0.1	3	<0.1	6	<0.1	

Bolded values of Chi-Square tests indicate significance at α = 0.05

Table 2.
Weighted distribution of BMI for 2008 ATUS Eating and Health Module, n=11,369

Mean (SE)		27.4 (0.075)
Median		26.6
Range		12.9-62.7
Obesity status	n	%
BMI <30 kg/m^2	8,183	72.6
BMI ≥30 kg/m^2	3,186	27.4

Table 3.
Weighted distribution of secondary eating occasions per day for the 2008 Eating and Health Module, n = 11,369

	Total Population	Among those who secondary ate
Obesity Status	**Mean (SE)**	**Mean (SE)**
Obese	0.78 (0.03)	1.55 (0.05)
Non-Obese	0.93 (0.03)	1.73 (0.05)
All	0.89 (0.23)	1.68 (0.04)
Median	0.09	1
Range	0 - 45	1 - 45

Table 4.
Weighted time use descriptive statistics for the 2008 Eating and Health Module, n = 11,369

	Average hours per day	Percent engaged in activity per day	Average hours per day among those who participated in activity
Primary Activities			
Primary Eating and Drinking	1.13	96.1	1.18
Commuting	0.29	31.3	0.73
Sleeping	8.46	99.9	8.47
Watching TV	2.84	81.6	3.48
Working	3.58	47.1	7.6
Exercising	0.26	16.4	1.55
Secondary Activities			
Secondary Eating	0.48	53.2	0.92
Secondary Drinking	1.41	37.7	3.84

Table 5.
Weighted time use comparisons of obese and non-obese respondents for 2008 ATUS Eating and Health Module, n = 11,369

	Average time per day (hours)		
	Obese (n = 3,186)	Non-Obese (n = 8,183)	t-test p-value
Primary Activities			
Primary Eating and Drinking	1.05	1.16	<0.01
Commuting	0.27	0.30	<0.01
Sleeping	8.48	8.45	0.52
Watching TV	3.21	2.69	<0.01
Working	3.54	3.59	0.57
Exercising	0.17	0.30	<0.01
Secondary Activities			
Secondary Eating	0.38	0.52	0.01
Secondary Drinking	1.45	1.40	0.44

Table 6.
Weighted unadjusted linear regression of continuous BMI with selected demographic and time use characteristics for 2008 ATUS Eating and Health Module, n = 11,369

Variable	**Regression Coefficient**	**p-value**	**R^2**
Age	0.03	<.001	0.01
Sex	-0.76	<.001	<0.01
Race/Ethnicity			
Non-Hispanic White	-0.66	<.001	<0.01
Non-Hispanic Black	1.87	<.001	0.01
Hispanic	0.54	0.01	<0.01
Other Race	-2.07	<.001	<0.01
Highest Education Level	-0.49	<.001	0.01
Employment Status	0.18	0.03	<0.01
Relationship to FPL	1.24	<.001	<0.01
Self-Rated Health	-1.52	<.001	0.08
Primary Eating Time	-0.47	<.001	<0.01
Secondary Eating Time	-0.12	0.00	<0.01
Secondary Eating Occasions	-0.12	<.001	<0.01
Secondary Drinking	0.03	0.11	<0.01
Commuting	-0.09	0.44	<0.01
Sleeping	-0.03	0.40	<0.01
Watching TV	0.21	<.001	0.01
Working	0.00	0.85	<0.01
Exercising	-0.40	<.001	<0.01

*Each line represents a separate unadjusted model

Table 7.
Weighted multivariate linear regression of continuous BMI with all selected demographic and time use variables for 2008 ATUS Eating and Health Module, n = 11,369

Variable	**Regression Coefficient**	**Standard Error**	**p-value**
Intercept	34.28	0.70	<0.01
Secondary Eating Time	-0.16	0.06	<0.01
Secondary Eating Occasions	0.02	0.05	0.75
Age	0.02	0.00	<0.01
Sex	-0.75	0.15	<0.01
Race/Ethnicity			
Non-Hispanic Black	1.35	0.24	<0.01
Hispanic	0.32	0.24	0.19
Other	-1.70	0.34	<0.01
Highest Education Level	-0.06	0.06	0.36
Employment Status	-0.45	0.10	<0.01
Relationship to FPL	0.20	0.23	0.38
Self-Rated Health	-1.47	0.08	<0.01
Primary Eating	-0.31	0.08	0.00
Secondary Drinking	0.05	0.02	0.02
Commuting	-0.22	0.13	0.10
Sleeping	-0.07	0.04	0.04
Watching TV	0.05	0.03	0.11
Working	0.03	0.02	0.20
Exercising	-0.21	0.06	<0.01

Multivariate model adjusted $R^2 = 0.11$

Table 8.
Weighted multivariate linear regression model of continuous BMI with selected variables with secondary eating time as primary exposure for 2008 ATUS Eating and Health Module, n = 11,369

Variable	Regression Coefficient	Standard Error	p-value
Intercept	34.72	0.54	<0.01
Secondary Eating Time	-0.15	0.03	<0.01
Age	0.02	0.00	<0.01
Sex	-0.79	0.14	<0.01
Race/Ethnicity			
Non-Hispanic Black	1.32	0.23	<0.01
Other	-1.78	0.33	<0.01
Employment Status	-0.39	0.09	<0.01
Self-Rated Health	-1.50	0.07	<0.01
Primary Eating	-0.36	0.08	<0.01
Secondary Drinking	0.05	0.02	0.02
Sleeping	-0.09	0.03	0.01
Exercising	-0.23	0.06	<0.01

Multivariate model adjusted $R^2 = 0.10$

Table 9.
Weighted multivariate linear regression model of continuous BMI with selected variables with secondary eating bouts as the primary exposure for 2008 ATUS Eating and Health Module, n = 11,369

Variable	**Regression Coefficient**	**Standard Error**	**p-value**
Intercept	34.75	0.55	<0.01
Secondary Eating Occasions	-0.11	0.03	<0.01
Age	0.02	0.00	<0.01
Sex	-0.77	0.14	<0.01
Race/Ethnicity			
Non-Hispanic Black	1.31	0.23	<0.01
Other	-1.80	0.33	<0.01
Employment Status	-0.40	0.09	<0.01
Self-Rated Health	-1.50	0.07	<0.01
Primary Eating	-0.36	0.08	<0.01
Secondary Drinking	0.04	0.02	0.04
Sleep	-0.09	0.03	<0.01
Exercising	-0.22	0.06	<0.01

Multivariate model adjusted $R^2 = 0.10$

Table 10.
Weighted crude logistic regression odds ratio estimates for obesity with selected categorical variables for 2008 ATUS Eating and Health Module, n = 11,369

		Confidence Interval	
	OR	95% Lower	95% Upper
Gender			
Male	Ref	-	-
Female	0.91	0.82	1.02
Race			
Non-Hispanic White	Ref	-	-
Non-Hispanic Black*	1.69	1.45	1.96
Hispanic	1.17	0.98	1.39
Other*	0.62	0.47	0.83
Employment Status			
Employed	Ref	-	-
Not Employed	1.25	0.94	1.68
Not in Labor Force	1.11	0.99	1.25
Income			
> 130% of FPL	Ref	-	-
≤ 130% of FPL*	1.59	1.38	1.83
Education			
Less than High School	Ref	-	-
High School*	1.31	1.15	1.48
Some College	1.12	1.00	1.27
College*	0.68	0.59	0.79
Graduate Degree or Higher*	0.55	0.45	0.67
Self-Rated Health			
Poor	Ref	-	-
Fair*	2.22	1.90	2.60
Good*	1.64	1.46	1.85
Very Good*	0.70	0.62	0.79
Excellent*	0.26	0.22	0.32

*Indicates p <0.05

Table 11.
Weighted multivariate logistic regression OR estimates for obesity by level of secondary eating time for 2008 ATUS Eating and Health Module, n=11,369

	Crude OR (95% CI)	Adjusted OR (95% CI)*	Adjusted OR (95% CI)**
No secondary eating	Ref	Ref	Ref
0 - 15 minutes secondary eating	**0.85 (0.75, 0.97)**	0.94 (0.82, 1.08)	0.90 (0.78, 1.04)
15-30 minutes secondary eating	0.92 (0.77, 1.10)	1.01 (0.84, 1.22)	0.97 (0.80, 1.18)
30+ minutes secondary eating	**0.80 (0.67, 0.95)**	0.87 (0.72, 1.05)	**0.81 (0.66, 0.99)**

Statistically significant point estimates are indicated in bold
* Adjusted for age, sex, race/ethnicity, highest level of education, relationship to FPL, employment status, and self-rated health
** Adjusted for age, sex, race/ethnicity, highest level of education, relationship to FPL, employment status, self-rated health, TV watching time, commute time, primary eating time, secondary drinking time, working time, and exercise time

Table 12.
Weighted multivariate logistic regression OR estimates for obesity by bouts of secondary eating for 2008 ATUS Eating and Health Module, n=11,369

	Crude OR (95% CI)	Adjusted OR (95% CI)*	Adjusted OR (95% CI)**
No secondary eating	Ref	Ref	Ref
1 bout of secondary eating	**0.86 (0.76, 0.97)**	0.92 (0.80, 1.04)	0.88 (0.77, 1.02)
2 bouts of secondary eating	0.90 (0.77, 1.08)	1.05 (0.87, 1.27)	0.99 (0.81, 1.20)
3 or more bouts of secondary eating	**0.71 (0.55, 0.95)**	0.87 (0.66, 1.15)	0.80 (0.60, 1.01)

Statistically significant point estimates are indicated in bold
* Adjusted for age, sex, race/ethnicity, highest level of education, relationship to FPL, employment status, and self-rated health
** Adjusted for age, sex, race/ethnicity, highest level of education, relationship to FPL, employment status, self-rated health, TV watching time, commute time, primary eating time, secondary drinking time, working time, and exercise time