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THREE ESSAYS IN FOOD CONSUMPTION AND HEALTH RELATED ISSUES

Fuad Mohammed Alagsam
University of Kentucky, fmalagsam@uky.edu
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THREE ESSAYS IN FOOD CONSUMPTION AND HEALTH RELATED ISSUES

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Agriculture, Food and Environment
at the University of Kentucky

By

Fuad Mohammed Alagsam

Riyadh, Saudi Arabia

Co-Directors: Dr. John Schieffer, Assistant Professor of Agricultural Economics
and Dr. Wuyang Hu, Professor of Agricultural Economics

Lexington, Kentucky

2017

ABSTRACT OF DISSERTATION

THREE ESSAYS IN FOOD CONSUMPTION AND HEALTH RELATED ISSUES

This dissertation consists of three essays that make contributions to the research on food consumption and health-related issues. Essay I elaborates on how the interactions of consumers' beliefs and actions influence Food-Away-From-Home (FAFH) consumption and tests whether consumers compensate for the high caloric intake typically associated with FAFH by changing their behaviors during other meals. Essay II studies consumers' choices related to time allocations for food consumption and tests how consumers' lifestyles moderate the effect of secondary eating (eating while doing other activities) on obesity. Lastly, Essay III examines intertemporal choices, through which individuals make trade-offs between immediate gratifications and future health, and tests the validity of the use of time preference proxies in the investigation of health outcomes.

KEYWORDS: Obesity, Food-Away-From-Home, Secondary Eating, Sedentary Lifestyle, Time Preferences

Fuad Mohammed Alagsam
Student's Signature

May 2, 2017
Date

THREE ESSAYS IN FOOD CONSUMPTION AND HEALTH RELATED ISSUES

By
Fuad Mohammed Alagsam

Dr. John Schieffer
Co-Director of Dissertation

Dr. Wuyang Hu
Co-Director of Dissertation

Dr. Carl Dillon
Director of Graduate Studies

May 2, 2017

To the spirit of my father
To my mother

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Chapter 1: Introduction

Since the mid-1970s, obesity has rapidly increased among U.S. consumers. Approximately two out of three adults are either overweight or obese (U.S. Department of Agricultural, 2016b). The high prevalence of obesity is a public health concern due to the high costs incurred by individuals and society. Obesity increases the risk for chronic diseases such as diabetes, cardiovascular diseases, musculoskeletal disorders, and cancer (World Health Organization, 2016). In 2008 dollars, the direct cost of obesity regarding medical expenditure was $147 billion (Finkelstein, Trogdon, Cohen, & Dietz, 2009). Food-Away-From-Home (FAFH), secondary eating, and time preferences are three of many factors blamed for obesity (Cawley, 2015; Rosin, 2008). This dissertation investigates these factors in three essays.

1.1. The Ability to Eat Food-Away-From-Home and Still Eat Healthy

FAFH consumption has rapidly increased since 1970. The proportion of food expenditure spent on FAFH increased from 25.9% in 1970 to 43.1% in 2012 (U.S. Department of Agricultural, 2016a). Previous research has attributed FAFH to poor diet quality in terms of high caloric intake (Beydoun, Powell, & Wang, 2009; J. K. Binkley, 2008; Bowman & Vinyard, 2004; Lin & Cuthrie, 2012; Mancino, Todd, & Lin, 2009; Taveras et al., 2005; Todd, Mancino, & Lin, 2010). The high demand as well as the high caloric intake associated with FAFH have led to the identification of FAFH as a factor that contributes to obesity. Although FAFH is high in calories, consumers might attempt to reduce caloric intake during other meals. To that end, Essay I tests whether consumers compensate for the high caloric intake typically associated with FAFH. The analysis uses data from the 2009-10 National Health and Nutritional Examination Survey (NHANES).

The NHANES is a food intake survey that provides detailed information for two non-consecutive days of food consumption.

Essay I makes two contributions to the existing literature. First, Essay I discusses how consumers change their behaviors on a meal-by-meal basis. For example, if a person eats an away from home breakfast, the analysis determines how his or her behavior changes during lunch and dinner to compensate for the high calories of the FAFH breakfast. The first essay also elaborates on the cognitive aspects of the compensating behavior. There is a consensus among consumers that FAFH is less nutritious than food cooked at home. Nonetheless, consumers demand FAFH because of price, taste, convenience, or socializing. We use the theory of cognitive dissonance to explain how negative beliefs about FAFH, which are contrary to the consumers' actions of eating FAFH, create a state of cognitive dissonance. To resolve cognitive dissonance, consumers compensate for FAFH by changing their behaviors during other meals.

1.2. The Mindlessness and the Mindfulness of Secondary Eating

Secondary eating is defined as eating while doing something else, such as reading or watching TV. While engaging in secondary eating, consumers might not be able to closely monitor the amount of food, leading to overeating and obesity (Wansink, 2007). Since the 1970s, the trend of secondary eating time has paralleled the trend of obesity, and secondary eating has been thus blamed for obesity. The second essay tests the effect of secondary eating on obesity. Studies that investigate the effect of secondary eating assume that secondary eating similarly affects every consumer. The contribution that the second essay makes to the literature is to relax this assumption, identifying situations when secondary eating increases body weight (termed "mindless secondary eating") and when secondary eating decreases body weight (termed “mindful secondary eating”). We hypothesize that lifestyle moderates the effect of secondary eating on obesity. Maintaining a sedentary lifestyle increases the odds of mindless secondary eating. On the contrary, maintaining an active lifestyle decreases the chances of mindless secondary eating.

Essay II uses data from the American Time Use Survey (ATUS). A subsample of participants from the Current Population Survey (CPS) was randomly selected to provide diaries of their activities for 24 hours, starting at 4:00 am the day before the interview. The Eating and Health Module contains information on secondary eating. We use two methods to account for lifestyle elements. The first method is to compare engagement in sedentary activities as well as physical activities. For example, watching TV for 4 hours increases the probability of mindless secondary eating as opposed to watching TV for half an hour. The second method is to compare secondary eating during different types of primary activities. In reality, secondary eating during working or driving might have a different effect from secondary eating while watching TV.

1.3. Validating the Use of Time Preference Proxies to Explain Effects on Health Outcomes

Food consumption and health-related issues are intertemporal choices that reflect trade-offs between immediate gratifications and future well-being. The rate of time preferences indicates the extent to which consumers can delay benefits. Patient individuals forgo present gratifications to obtain future benefits. Impatient people weigh present gratifications more than future well-being, so they are unable to delay benefits. To estimate the effect of time preferences on health outcomes, researchers either elicit the rate of time preference using monetary present-future trade-off questionnaires or use proxies. Essay III investigates the validity of using time preference proxies to estimate the effects on health outcomes, determining if variations in elicited discount rates correspond to variations in time preference proxies. The contribution of the third essay is methodological: to provide researchers who are interested in determining the effect of time preferences on health outcomes with guidance on how to measure time preferences. The analysis uses data from the National Longitudinal Survey of Youth (NLSY79). Before 2006, the NLSY79 provided information that can be used as proxies for time preferences. In 2006, the NLSY79 included two hypothetical monetary trade-off elicitation questions. The first question is over a month time horizon, and the second is over a year time horizon. These two time frames for the elicitation questions allow for investigating time preference proxies under the fixed exponential and hyperbolic preferences.

Chapter 2: The Ability to Eat Food-Away-From-Home and Still Eat Healthy

2.1. Introduction

Since 1970, U.S. consumer diets have shown an increased demand for Food-Away-From-Home (FAFH). FAFH expenditure rose from 25.9% of total food expenditure in 1970 to 43.1% by 2012 (U.S. Department of Agricultural, 2016a). Because of the high caloric intake, FAFH tends to be blamed for the obesity epidemic in the United States (Beydoun et al., 2009; J. K. Binkley, 2008; Bowman & Vinyard, 2004; Lin & Cuthrie, 2012; Mancino et al., 2009; Taveras et al., 2005; Todd et al., 2010). Approximately two adults in three are either overweight or obese (U.S. Department of Agricultural, 2016b).

Health advocates have called for FAFH regulations to improve people's diets and reduce obesity, in particular after FAFH became readily available (Cutler, Glaeser, & Shapiro, 2003), unavoidable for many reasons such as business meetings or social gatherings taking place at restaurants (Cohen & Bhatia, 2012), and increasingly tasty and visually appealing (Blechert, Klackl, Miedl, & Wilhelm, 2016). However, regulations focusing on FAFH are controversial. On the one hand, proponents of regulations argue that consumers lack both the ability to make healthy choices when eating away from home and the willpower to compensate during other meals for the excessive caloric intake associated with FAFH (Cohen & Bhatia, 2012). On the other hand, opponents of regulations argue that consumers can compensate for FAFH during other meals (Anderson & Matsa, 2011; Cutler et al., 2003). In order to illuminate the link between FAFH and obesity and the justification for such regulations, this paper elaborates on consumers' beliefs and behaviors relating to FAFH and tests whether consumers compensate by changing behavior during other meals for the high calories associated with FAFH.

Examples of FAFH regulations intended to develop better eating patterns and reduce obesity include: 1) The fast food ban in south Los Angeles, where obesity is highly prevalent, prohibiting the establishment of a stand-alone fast food restaurant (Sturm & Cohen, 2009); 2) The Healthy Eating Option Program in Watsonville, California, in which a permit approval for a new restaurant is conditional on providing healthier meals (Watsonville Municipal Code, 2010)[1]; 3) Standards for restaurant food accompanied by toys in San Francisco, California (Otten et al., 2014)[2]; and 4) The 2010 Patient Protection and Affordable Care Act, which requires chain restaurants with at least 20 branches to provide nutritional information (Swartz, Braxton, & Viera, 2011) so consumers can make informed choices.

In addition to nutrition, other factors come into play when choosing a meal, such as taste and convenience. In a survey of New Jersey households (Stewart, Blisard, & Jolliffe, 2006), respondents were asked to rank their preferences for FAFH on a scale of 1 (less preferred) to 5 (highly preferred) in terms of taste, nutrition, and convenience. On average, the responses were 4.5 for taste, 3.9 for nutrition, and 3.5 for convenience, indicating that when consumers dine away from home, they think about taste and convenience as important aspects of food consumption. Other studies drawn from the

[1] The approval of a new permit requires getting at least 6 out of 19 points. For example, 2 points are obtained by offering at least 4 choices of fruits or vegetables prepared in a low-fat way (e.g., green salad, baked potato) (Sturm & Cohen, 2009).
[2] For example, the maximum caloric intake per meal is 600 calories, and the maximum level of sodium per meal is 640 mg (Otten et al., 2014).

household production theory emphasize the importance of the convenience of FAFH. The assumption is that changes in socioeconomic factors, such as increased time at work, increase the opportunity cost of time. Consequently, the shift in consumers' preferences toward consuming more FAFH reflects their demand for convenience. McCracken and Brandt (1987) estimate the demand for FAFH based on the type of FAFH facilities (restaurants, fast food, and other commercial establishments). Their results show a significant effect of time value on FAFH expenditure. Yen (1993) finds that households with higher income and working wives are more likely to consume FAFH. J. K. Binkley (2006) and Stewart, Blisard, Bhuyan, and Nayga Jr (2004) also find hours worked outside the house to positively affect the demand for FAFH.

Studies that consider the association between FAFH and high caloric intake may ignore the ability of consumers to compensate for FAFH. Consumers sometimes act as if they have a caloric budget (Variyam, 2005). The excessive calories corresponding to FAFH are traded off at other meals. Cutler et al. (2003) explain that FAFH has no causal effect on obesity because typically, if one eats FAFH, they will compensate by eating less food later in the day.[3] Anderson and Matsa (2011) estimate the effect of FAFH on obesity and test for the compensating behavior. For their identification strategy, Anderson and Matsa (2011) use the placement of interstate highways in rural areas to obtain exogenous variations in FAFH prices to explain variations in obesity. They claim there is no causal effect of FAFH on obesity due to the compensatory behavior (Anderson & Matsa, 2011). To test for the compensatory behavior, Anderson and Matsa (2011) consider the

[3] Instead, Cutler et al. (2003) attribute the obesity epidemic to the low prices of FAFH wherein consumers with hyperbolic discounting and high preferences for high calories are most affected by the low prices.

difference between the effect of an away from home meal on the meal caloric intake and the daily caloric intake. A substantial effect of FAFH on calories at the meal level and a minimal effect on calories at the daily level demonstrates the compensating behavior. It is, however, unclear how consumers change their behavior during other meals to compensate for FAFH. For instance, if an away from home breakfast increases caloric intake, how do consumers compensate for the breakfast's excessive calories during lunch and dinner?

This paper also examines consumers' abilities to compensate for FAFH by changing their behaviors during other meals. We contribute to the existing literature by investigating how consumers change their behaviors on a meal-by-meal basis. For example, if a person eats an away from home breakfast, the analysis tests if behavior changes during lunch and dinner to compensate for the high calories from FAFH. We also contribute to the existing literature by elaborating on the cognitive aspects of the compensating behavior for FAFH. We use data from the 2009-10 National Health and Nutrition Examination Survey (NHANES). The NHANES is food intake data in which consumers provide information from two non-consecutive days about their food consumption. The Consumer Behavior Phone Follow-up Module provides information about consumers' beliefs. There is a consensus among consumers that FAFH is less nutritious than food cooked at home. Nonetheless, consumers demand FAFH because of price, taste, convenience, or socializing. We implement the theory of cognitive dissonance introduced by Festinger (1962) to explain how the negative beliefs about FAFH that are contrary to the consumers' actions of eating FAFH create a state of cognitive dissonance. To resolve cognitive dissonance, we hypothesize that consumers compensate for FAFH by changing behavior during other meals. The results support our hypothesis of the compensating behavior. For example, an away from home breakfast increases breakfast caloric intake by 378 calories, but consumers change their behavior during lunch by reducing lunch calories by 149 calories.

We perform two robustness consistency tests of our results with the theory of cognitive dissonance. We test the compensating behavior for the addictive components of FAFH. FAFH is high in sugar, carbohydrates, fat, and salt (Lin & Cuthrie, 2012; Todd et al., 2010), which are addictive components (Gearhardt, Corbin, & Brownell, 2009; Soto-Escageda et al., 2016). The implication is that if addiction prevents consumers from compensating for FAFH during other meals, the results are inconsistent with the theory of cognitive dissonance. We also perform a placebo test. It is impossible to imagine that drinking plain water has the same effect as FAFH. If so, then the results cannot be explained by the theory of cognitive dissonance. These tests indicate that our results are consistent with the theory of cognitive dissonance.

The results suggest redirecting policies toward increasing the efficacy of the compensatory behavior rather than restricting the availability of FAFH. There is no single type of food that can be the only assessment of diet quality. Eating FAFH does not automatically entail a poor diet, and eating food cooked at home does not ensure a better diet. The balance between foods from all sources due to the compensatory behavior is a better and more effective assessment of diet quality. The remainder of this essay is divided into five sections. Section 2.2 presents the data used for the analysis. Section 2.3 discusses the model. Section 2.4 reports the results. Section 2.5 checks the robustness of our results, and Section 2.6 concludes.

2.2. Data

We utilize data from the 2009-10 National Health and Nutritional Examination Survey (NHANES). For two non-consecutive days, the NHANES collected information on food intake. Consumers were personally interviewed on day one. On day two, consumers were interviewed by phone three to ten days later. The NHANES asked consumers about individual food intake regarding the type of food they had, from where it was obtained (e.g., a store, a table service restaurant, a fast food place), the name of the meal (e.g., breakfast, lunch, dinner), and the intake day of the week. Thus, the NHANES could calculate the amount of caloric intake for each item reported.

The Consumer Behavior Phone Follow-up Module provides information on beliefs about fast food and restaurant food in comparison to food cooked at home, so we restrict the sample to consumers from whom we could retain information on their beliefs regarding FAFH. The Consumer Behavior Phone Follow-up Module asks consumers the following questions:

> "Do you buy food from fast food or pizza places because it is cheaper than foods cooked at home?"
>
> "Do you buy food from fast food or pizza places because the foods there are more nutritious than cooking at home?"
>
> "Do you buy food from fast food or pizza places because the foods there taste better than foods cooked at home?"
>
> "Do you buy food from fast food or pizza places because it is more convenient than cooking at home?"
>
> "Do you eat at fast food or pizza places instead of cooking at home to socialize with family and friends?"

Consumers also answer the same questions regarding restaurant food, so we limited the analysis to FAFH from these two sources. The final sample consists of 7,538 observations. Panel A of Table 2.1 presents summary statistics of consumers' beliefs relating to FAFH. On average, only 2% of consumers consider fast food is more nutritious than food cooked at home, while only 4% of consumers think restaurant food is more nutritious than food cooked at home. In general, consumers are more likely to associate fast food with convenience and low prices and more likely to associate restaurant food with taste and socializing. Consumers' behaviors regarding FAFH are reported in Panel B of Table 2.1. The average daily FAFH consumption is equal to 0.6 meal, where the weekly FAFH consumption averages 4 meals.[4]

This link between beliefs and behaviors relating to FAFH reveals a general agreement among consumers that FAFH is less nutritious than food at home, but consumers continue to consume FAFH. We implement the theory of cognitive dissonance to explain how the inconsistency between beliefs and behaviors creates a state of cognitive dissonance. We hypothesize that consumers compensate for FAFH by changing behavior during other meals to resolve the dissonance.

Compensating for FAFH implies ingesting more calories when eating out, and then changing behavior during other meals, so we limit our sample to the three major meals, breakfast, lunch, and dinner. From an economic standpoint, the excessive calories associated with FAFH meals are optimal choices (Anderson & Matsa, 2011). This

[4] The average daily FAFH consumption is calculated from the two-non-consecutive day of food intake. The weekly FAFH consumption is calculated from consumers' responses to how many meals not home prepared consumed a week in the Diet Behavior and Nutrition Section in the National Health and Nutritional Examination Survey.

rationale is underlined by the assumption that the portion size of an away from home meal is larger than that cooked at home (Anderson & Matsa, 2011; Jeitschko & Pecchenino, 2006). Food cooked at home involves a sunk cost of food preparation and a price for groceries, while eating away from home involves only a sunk cost. At home, a consumer ingests calories until the marginal utility is equal to the price paid for groceries. When dining away from home, the consumer ingests calories until either finishing the meal, which is relatively larger, or being fully satiated at zero marginal utility. Hence, at the margin, consumers eat more food away from home than they do at home.

The excessive caloric consumption when eating FAFH is reported in Figures 2.1-3. Figure 2.1 demonstrates the effect of an away from home breakfast on caloric intake. The vertical axis is the average breakfast calories. The left bar is the average number of calories conditional on a food at home breakfast, and the right bar is the average number of calories conditional on a FAFH breakfast. In the calculation of the average breakfast calories conditional on an at home breakfast, we omit consumers who skipped breakfast to avoid an upward bias of the effect of FAFH on caloric intake. On average, consumers ingest 377 calories from an at home breakfast, but they ingest 692 calories from FAFH breakfast. Figure 2.2 demonstrates the effect of an away from home lunch. Lunch at home averages 525 calories while lunch away from home averages 803 calories. Similarly, at home dinner increases caloric intake by 730 on average compared to an away from home dinner, which increases caloric intake by 988 calories on average as shown in Figure 2.3.

2.3. Model

The model will first explain the theory of cognitive dissonance and its implications to determine the compensating behavior for FAFH by changing behavior during other meals. Then, the model will present the empirical counterpart to test our hypothesis of the compensating behavior.

2.3.1. Theoretical Model: Theory of Cognitive Dissonance

The theory of cognitive dissonance was developed by the social psychologist Leon Festinger (1962). Cognitive dissonance is defined as disutility that occurs when beliefs contradict behaviors. This theory hypothesizes that consumers tend to reject the state of cognitive dissonance and take steps to achieve cognitive consonance.[5] To resolve dissonance, consumers can change beliefs or behaviors or add a new cognition. For example, a person knows that smoking is bad but continues to smoke. He or she can resolve dissonance by thinking that the negative impacts of smoking are overstated, quitting smoking, or thinking that he or she will gain weight when quitting. Economists and other social scientists have implemented the theory of cognitive dissonance. For example, Akerlof and Dickens (1982) apply the theory of cognitive dissonance in their discussion of safety regulations in hazardous jobs.[6] Dickerson, Thibodeau, Aronson, and Miller (1992) use the theory of cognitive dissonance in their discussion of water conservation.

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[5] Consonance is the terminology used by Festinger. However, it is similar to cognitive consistency or cognitive equilibrium (Festinger, 1962).

[6] Akerlof and Dickens (1982) also use the theory of cognitive dissonance to discuss sources of innovation, advertising, social security, and economic theory of crime as other potential applications of the theory of cognitive dissonance.

The theory of cognitive dissonance predicts that the level of dissonance is proportional to the importance of the conflicting cognition, so that the greater the dissonance, the greater the actions to resolve it. Consumers consider a set of cognitions, nutrition, price, taste, convenience and socializing when eating FAFH. In general, price and nutrition can be the conflicting cognitions, but the investigation of offsetting calories considers nutrition as the conflicting cognition. When price is inconsistent with eating out, consumers do not necessarily resolve dissonance by reducing caloric intake during other meals. They might alter their behavior by consuming cheaper food regardless of calories.

There is a general agreement that FAFH is less nutritious than food at home, but consumers still eat it. The level of dissonance will be proportional to the importance of nutrition. If nutrition is important to consumers, dissonance is higher, and so is the intensity of their actions to compensate for FAFH during other meals to resolve the dissonance. In contrast, if nutrition is not important, dissonance is minimal, and consumers do not compensate for FAFH. Overall, the empirical analysis of estimating the compensating behavior will demonstrate the disagreement between nutrition and eating FAFH.

2.3.2. Empirical Model

To show how consumers would compensate for FAFH in an ideal world would require collecting a random sample. Consumers in this sample would have either positive or negative beliefs regarding the nutrition of FAFH in comparison to food at home. Those with negative beliefs would be assigned to a treatment group, and those with positive beliefs would be assigned to a control group. When all consumers ate FAFH, we would expect dissonance to be higher, and the compensatory behavior to be more pronounced for consumers in the treatment group than for those in the control group. In reality, such a randomized experiment is costly to conduct and might not be representative.

The dependent variable is the caloric intake at a given meal, breakfast, lunch, and dinner as shown in Equations 2.1, 2.2, and 2.3, respectively.[7] (Cameron & Trivedi, 2005) (Cameron & Trivedi, 2005) (Cameron & Trivedi, 2005) (Cameron & Trivedi, 2005) (Cameron & Trivedi, 2005)

$$C_{it1} = \beta_{01} + \beta_{11}B_{it} + \beta_{21}L_{it} + \beta_{31}D_{it} + X'_{it}\beta_{k1} + \alpha_i + \epsilon_{it1}, \tag{2.1}$$

$$C_{it2} = \beta_{02} + \beta_{12}B_{it} + \beta_{22}L_{it} + \beta_{32}D_{it} + X'_{it}\beta_{k2} + \alpha_i + \epsilon_{it2}, \tag{2.2}$$

$$C_{it3} = \beta_{03} + \beta_{13}B_{it} + \beta_{23}L_{it} + \beta_{33}D_{it} + X'_{it}\beta_{k3} + \alpha_i + \epsilon_{it3}. \tag{2.3}$$

where C_{itm} denotes calories ingested by consumer i on day t for meal m, B denotes an away from home breakfast, L denotes an away from home lunch, D denotes an away from home dinner, X denotes other controls, α_i denotes unobserved heterogeneity, and ϵ denotes the error term. β's are the coefficients to be estimated. i and t are the subscripts for consumers and the day of food intake; $i = 1,2, \dots, N$ and t is equal to 1 for the first day of food intake and 2 for the second day of food intake. $m = 1,2$, and 3 are for

[7] The percentages of those who did not have breakfast, lunch, and dinner are 17, 25, and 10%, respectively. We treat skipping a meal as true zero, not as censored.

breakfast, lunch, and dinner, respectively. k is the subscript for other control variables' coefficients, $k > 3$. Since consumers tend to eat differently on weekends (McCracken & Brandt, 1987), we add a dummy variable that equals 1 if the day of intake was either Friday, Saturday, or Sunday. Some days, consumers might experience a different eating pattern such as when traveling, so we control for a day fixed effect (whether day one or two).

Estimating equations 2.1-3 using OLS provides inconsistent estimates due to sample selection bias that results from the correlation between unobserved heterogeneity and independent variables.[8] Those who have strong preferences for high-calorie meals tend to eat more FAFH and compensate less. Failing to control for unobserved heterogeneity will underestimate the compensatory behavior. We estimate equations 2.1-3 using a fixed effect model to control for unobserved heterogeneity.[9]

Breaking down the calories eaten for breakfast, lunch, and dinner allows determining the effect of FAFH on caloric intake occasion within equations and allows determining how consumers change their behavior during other meals. Another advantage is to investigate the ability of consumers to pre-compensate and post-compensate for FAFH. For example, can a consumer pre-compensate for an away from home lunch at breakfast and post-compensate at dinner?

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[8] We do not estimate equations 2.1, 2.2, and 2.3 as a system of equations because we have the same set of independent variables in each equation. Thus, the results of the system of equations are similar to those of estimating the equations separately (Cameron & Trivedi, 2005).
[9] Equations 2.1-3 can be estimated using a first difference OLS. However, since each panel has only two observations a fixed effect estimator and first difference estimator generate the same results (Cameron & Trivedi, 2005).

Different demographic groups exert different eating patterns regarding FAFH. Male and obese consumers tend to eat more FAFH than female and non-obese consumers (J. K. Binkley, 2006; McCracken & Brandt, 1987). Mancino et al. (2009) estimate the effect of FAFH on caloric intake for males compared to females, and obese consumers compared to the healthy weight consumers. Their results indicate that the effect is higher among male and obese consumers. We estimate equations 2.1-3, separately, for males and females, and separately, for obese and healthy weight consumers. We expect dissonance to be higher among males and obese, as well as the compensatory behavior.[10] To measure obesity, we use the Body Mass Index (BMI), defined as weight in kilograms divided by the square of height in meter (kg/m^2).[11] Obese consumers are those with BMI ≥ 30, and healthy weight consumers are those with BMI < 25. Panel C of Table 2.1 provides summary statistics for these groups. On average, the sample is 48% male, 36% obese and 31% healthy weight. The share of obese consumers compared to the share of healthy weight consumers indicates the high prevalence of obesity.

The frequency of eating FAFH is expected to affect dissonance and compensating for FAFH during other meals. We expect consumers with a high frequency of eating FAFH to experience greater levels of cognitive dissonance and compensate more. The NHANES provides information on the frequency of the weekly away from home meals consumed, with a median equal to three FAFH meal/week. Since there is no measure calling for the high frequency of eating FAFH, we consider eating more than three FAFH

[10] Other groups that are less likely to eat FAFH might also compensate more. For example, age and education are negatively correlated with FAFH (J. K. Binkley, 2006; Stewart et al., 2004), but as consumers grow older or obtain more knowledge, they are expected to compensate more.
[11] Weight and high are measured, not self-reported.

meals a week as defining the high frequency of FAFH, and eating fewer than three FAFH meal/week as defining the low frequency of eating FAFH.

2.4. Results

The results indicate that people compensate for FAFH by changing their behaviors during other meals. In Table 2.2, we estimate equations 2.1-3 using OLS as appearing in columns 1-3 and a fixed effect estimator as appearing in columns 4-6. The dependent variable is the number of calories ingested at a given meal. To compensate for FAFH, consumers would simply ingest more calories when eating FAFH. The results in Table 2.2 show evidence of overeating. FAFH increases breakfast energy by 378 calories, lunch energy by 442 calories, and dinner energy by 394 calories. To test our hypothesis of the compensating behavior, we compare the effect of FAFH meals across regressions as reported in Table 2.2. On average, consumers forgo 149 calories at lunch to compensate for FAFH breakfast. To compensate for FAFH lunch, consumers forgo 37 calories at breakfast and 144 calories for dinner. Because the NHANES does not provide food intake information for consecutive days, we cannot determine post-compensation for an away from home dinner, although the results show evidence of pre-compensating for a FAFH dinner by 79 calories during lunch.

For breakfast and lunch equations, the OLS results underestimate the compensatory behavior because consumers' preferences for high caloric intake are negatively correlated with their compensatory behavior. We use a fixed effect estimator to account for the unobserved heterogeneity. For all three equations, we perform the Hausman test to determine correlations between the unobserved heterogeneity and independent variables. For breakfast and lunch equations, we reject the null hypothesis of no correlation. However, for dinner, we fail to reject the null hypothesis of no correlation between the independent variables and the unobserved heterogeneity, though this might be because of our inability to determine post-compensation for FAFH dinners.

We hypothesized that consumers compensate for FAFH by changing behavior during other meals. The results provide evidence for the compensating behavior. Consumers either pre-compensate or post-compensate or both. Pre-compensation for FAFH is not a surprising result because there are many situations when eating FAFH is planned, such as social meetings held in restaurants. Expecting to eat out does not necessarily imply that consumers know in advance the exact meal they will eat. As a result, post-compensation for FAFH is greater in magnitude than pre-compensation.

The results indicate partial compensation for FAFH: There are two reasons why these results do not state full compensation. First, reducing caloric intake during other meals is not the only mean to offset FAFH. A person can engage in physical activities to make up for the excessive calories. Second, not all restaurants provide nutritional information, unlike eating at home where most food items come with nutritional labels and consumers even control all ingredients. This issue of asymmetric information away from home might make offsetting FAFH insufficient.

Some might relate the compensating behavior to satiety and argue that when exceeding the desired caloric intake due to eating FAFH, satiety makes people reduces energy consumption in the following meals (Anderson & Matsa, 2011). However, the theory of cognitive dissonance is superior to satiety in demonstrating the compensating behavior. Satiety might explain post-compensating for FAFH but cannot justify pre-compensating. Our results based on the theory of cognitive dissonance show that consumers either pre-compensate or post-compensate or both. Satiety also differs based on protein, carbohydrates, and fat, restricting offsetting FAFH to meals that contain highly satiating components (protein > carbohydrates > fat) (Chambers, McCrickerd, & Yeomans, 2015). Nonetheless, the theory of cognitive dissonance does not impose any restriction on different combinations of protein, carbohydrates, and fat.

The results in Table 2.2 also show that FAFH compensation occurs either at the immediate following or the immediate previous meal. For example, eating an away from home breakfast has a negative and significant effect on lunch but not on dinner. The reason is that choosing a meal is a difficult process, which involves many factors such as biological factors (e.g., hunger), economic factors (e.g., income), social factors (e.g., family, religion), and knowledge (e.g., beliefs) (The European Food Information Council, 2005). This difficulty might deplete the cognitive ability to compensate for a meal that was eaten far earlier in the day.

The differences between males and females regarding compensating for FAFH are reported in Table 2.3. Columns 1-3 indicate the three meal occasions for males and columns 4-6 indicate the three meal occasions for females. Males overeat when eating a FAFH breakfast by 413 calories but compensate for it during lunch by 191 calories. When eating a FAFH lunch, males overeat by 518 calories but pre-compensate by 41 calories during breakfast and post-compensate during dinner by 173 calories. For males, a FAFH dinner also increases caloric intake by 480 calories but decreases lunch calories by 104 as an indication of pre-compensation. Similarly, for females, FAFH exerts a positive effect on breakfast, lunch, and dinner energy consumption by 325, 362, and 301 calories, respectively. However, females pre-compensate for a FAFH lunch during breakfast by 31 calories and post-compensate during dinner by 106 calories. Females pre-compensate for a FAFH dinner during lunch by 43 calories. The results in Table 2.3 have the expected patterns. As predicted, the compensating behavior is more pronounced in males than females for two reasons. First, being a male is associated with higher FAFH consumption. Second, males ingest more calories than females when eating FAFH. Both reasons arouse cognitive dissonance and intensify the actions of compensating for FAFH.

Given the accusation that FAFH contributes to obesity, we estimate the compensatory behavior for consumers with a healthy weight (BMI < 25) and obese (BMI ≥ 30) as appearing in Table 2.4. Regardless of the weight status, consumers ingest more calories when eating away from home, indicating a consistency with the economic justification of overeating away from home mentioned earlier. Because of the high association of FAFH with obesity, we expected the compensatory behavior to be more pronounced among obese consumers. The results in Table 2.4 meet our expectations. Obese consumers compensate for FAFH eaten at breakfast, lunch, and dinner, whereas healthy weight consumers only compensate for FAFH lunch.

Finally, we estimate differences in the compensatory behavior based on the frequency of eating FAFH. High frequent FAFH consumers experience a higher level of dissonance than low frequent consumers do. We estimate equations 2.1-3 for low frequent FAFH consumers, eating fewer than three FAFH meal/week, and high frequent FAFH consumers, eating more than three FAFH meal/week. The results in Table 2.5 meet our expectations. High frequent FAFH patrons excessively ingest more calories when eating away from home than low frequent FAFH consumers do. Nevertheless, the compensatory behavior is more pronounced in high frequent FAFH patrons. For example, high frequent FAFH consumers compensate for FAFH breakfast by 191 calories while low frequent FAFH consumers do not compensate for FAFH breakfast.

2.5. Robustness check

FAFH is high in sugar, carbohydrates, fat, and salt (Lin & Cuthrie, 2012; Todd et al., 2010). These components are addictive (Gearhardt et al., 2009; Soto-Escageda et al., 2016). If addiction prevents consumers from compensating for FAFH during other meals, the results mentioned in the earlier section of the paper cannot be consistent with the theory of cognitive dissonance. There might be a systemic error, even after controlling for the individual fixed effect, which is correlated with FAFH meals and differently affects energy levels for breakfast, lunch, and dinner. We estimate equations 2.1-3 for fat, sugar, carbohydrates, and sodium to determine whether addiction prevents the compensatory behavior. Fat, sugar, and carbohydrates are measured in grams (gm). Sodium is measured in milligrams (mg).

Table 2.6 demonstrates the results of compensating for FAFH fat. The dependent variable is the amount of fat in gm. One gm of fat has 9 calories. For all three meals, consumers increase fat consumption when eating FAFH but compensate for the high fat consumption associated with FAFH. For example, FAFH breakfast increases fat consumption by 20 gm but consumers compensate for it by eating 6 gm less of fat during lunch. The results of compensating for FAFH sugar appear in Table 2.7, where 1 gm of sugar contains 4 calories. For breakfast, lunch, and dinner, consumers ingest more sugar when eating FAFH but compensate for the excess amount of sugar associated with FAFH during other meals. To illustrate, FAFH breakfast increases the sugar consumption by 12 gm. However, consumers compensate for it by reducing the amount of sugar by 7 gm during lunch.

Table 2.8 shows the results for compensating for FAFH carbohydrates, in which a gm of carbohydrate contains 4 calories. For all meals, the results indicate that consumers ingest more carbohydrates when eating FAFH and compensate for their overconsumption of carbohydrates during other meals in the day. For instance, when eating FAFH breakfast, consumers increase carbohydrate consumption by 33 gm but compensate for it later during lunch by eating 18 gm less of carbohydrates. The results of compensating for FAFH sodium appear in Table 2.9. For all three meal occasions, consumers' behaviors demonstrate an overconsumption of sodium as a result of eating FAFH as well as the compensating behavior by altering their consumption patterns during other meals. For example, eating a FAFH breakfast increases sodium consumption by 771 mg, but consumers reduce lunch sodium by 332 mg.

Compensating for FAFH fat, sugar, carbohydrates, and sodium indicates that addiction does not prevent consumers from altering their behavior during other meals. The results are consistent with the theory of cognitive dissonance, and not due to a systemic error that is correlated with FAFH meals and has different effects on breakfast, lunch, and dinner energy consumption. Furthermore, we run a placebo test as appearing in Table 2.10. The dependent variable is the number of calories consumed at a particular meal. It is impossible to imagine that drinking water has the same effect as FAFH. We use the amount of plain water measured in gm instead of a FAFH breakfast in equation 2.1, instead of a FAFH lunch in equation 2.2, and instead of a FAFH dinner in the equation 2.3. Hence, there is no effect of water on energy consumption. In sum, our placebo test shows more evidence that FAFH, which is contrary to beliefs, creates a state of cognitive dissonance.

2.6. Conclusion

Food-Away-From-Home (FAFH) appears to be of poor diet quality because it is high in calories; thus, it is often blamed for the high prevalence of obesity in the United States. We hypothesize that consumers compensate for FAFH by changing their behaviors during other meals. To test this hypothesis, we use data from the 2009-10 National Health and Nutrition Examination Survey (NHANES). The results support our hypothesis of the compensating behavior. Consumers are able to reduce energy consumption during other meals to trade off the excessive caloric intake typically associated with FAFH. Consumers can change their behaviors either before or after eating FAFH or both. For example, consumers change their behaviors during breakfast and dinner to compensate for FAFH lunch.

Restricting FAFH is less warranted when consumers can compensate for the excessive caloric intake from the consumption of FAFH during other meals. FAFH restrictions might affect consumers' welfare for four reasons. First, restricting FAFH implies considering only nutrition. Besides nutrition, a food shopper simultaneously considers other aspects of food consumption such as price, taste, and convenience, weighs the utility of each, and then considers the one that gives him or her the most utility. For example, imagine that a health-conscious consumer forgets to bring lunch to work. The only options are to return home and get it or to buy a high-calorie meal from the workplace cafeteria. In this situation, convenience will outweigh nutrition more if the opportunity cost of time is high, and the consumer will offset the high caloric intake of lunch by eating a lower-calorie dinner later at home. Second, restricting FAFH implies revising the advancements in food processing, which might be socially desirable (Cawley, 2015). Third, there is no single type of food that can be the only assessment of diet quality. Eating FAFH does not automatically entail a poor diet, and eating food at home does not ensure a better diet. Finally, food environment regulations such as zoning, taxing, or portion control (Sturm & Cohen, 2009) are not anticipated to become implemented nationwide because these regulations interfere with consumers' rights to decide on their health and restrict the rights of businesses to expand and differentiate themselves. For instance, the state of Mississippi passed a law in 2013 that prevented controlling food portions (Fox News, 2013).

We also elucidate the cognitive aspects of the compensating behavior. Consumers believe that FAFH is less nutritious than food at home, but they still demand it because of price, taste, convenience, or socializing. We implement the theory of cognitive dissonance introduced by Festinger (1962) to explain how the negative beliefs about FAFH conflict with consumers' actions of eating FAFH and thus, create a state of cognitive dissonance. To resolve cognitive dissonance, consumers compensate for consumption of FAFH by altering behavior during other meals.

Since the compensating behavior is an action to resolve dissonance, we suggest redirecting policies toward manipulating cognitive dissonance rather than restricting the availability of FAFH. As an illustration of dissonance manipulation, in their discussion of water conservation, Dickerson et al. (1992) arouse cognitive dissonance in their experiment subjects, varying their mindfulness in water wasting behavior and their pro-commitment to society by asking them to inspire others to conserve water. The procommitted and mindful subjects experienced a greater dissonance and thus took shorter showers as opposed to the uncommitted subjects.

Increasing the intensity of dissonance after eating FAFH to induce the compensatory behavior is one avenue policymakers should consider to promote healthy eating and reduce obesity. Regulations that are based on dissonance manipulation can nudge consumers to improve their dietary choices without dictating their choices (R. H. Thaler & Sunstein, 2009). Mandating the nutritional information on menus at restaurants and fast food establishments can influence dissonance. Even if consumers do not use the nutritional information to decide on what to eat, just knowing the number of calories ingested can arouse dissonance after eating and increase the efficacy of compensating for FAFH. Menu labeling could also be supplemented by providing the nutritional information as a reference for a meal purchased, such as printing the nutritional information on the back of the receipt.

A limitation of this study is its focus on whether or not consumers compensate for the high caloric intake from FAFH, without assessing the efficacy of their compensation. To gauge the effectiveness of compensating would require information on food intake and physical activities for consecutive days to account for calorie consumption as well as expenditure. Not considering the availability of healthy food is also another limitation. Individuals who do not have enough access to healthy food like those who live in food desert areas might compensate less for FAFH. These limitations are left for future research.

Table 2.1: Summary statistics of the analysis of compensating for Food-Away-From-Home

Variables	Mean	S.D.
A: Beliefs relating to Food-Away-From-Home		
Fast food/pizza more nutritious	0.02	0.15
Fast food/pizza cheaper than cooking	0.16	0.36
Fast food/pizza tastes better	0.15	0.36
Fast food/pizza more convenient	0.86	0.34
Eat at fast food places to socialize	0.47	0.50
Restaurant food more nutritious	0.04	0.19
Restaurant food cheaper than cooking	0.06	0.23
Restaurant food tastes better	0.33	0.47
Restaurant food more convenient	0.69	0.46
Eat at a restaurant to socialize	0.85	0.36
B: Actions relating to Food-Away-From-Home		
Daily away from home meals	0.58	0.71
Away from home breakfast	0.08	0.27
Away from home lunch	0.24	0.43
Away from home dinner	0.26	0.44
Weekly away from home meals	4.00	3.92
C: Subgroups		
Male	0.48	0.50
Healthy weight	0.31	0.46
Obese	0.36	0.48

Observations are weighted using the NHANES sample weights.
N = 7,538

Figure 2.1: The effect of an away from home breakfast on caloric intake

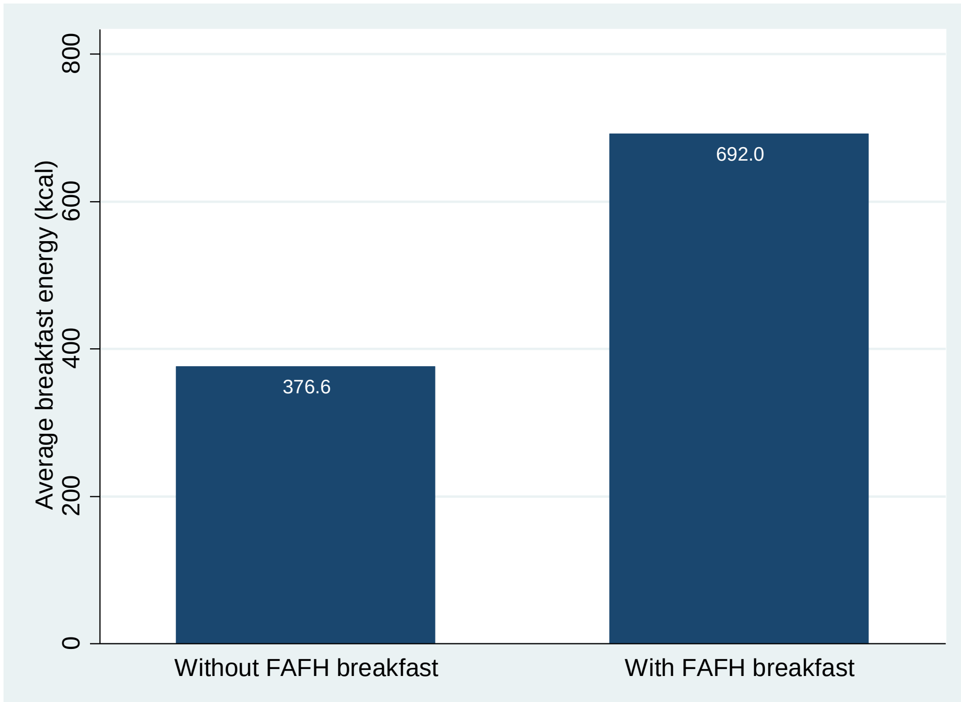

Figure 2.2: The effect of an away from home lunch on caloric intake

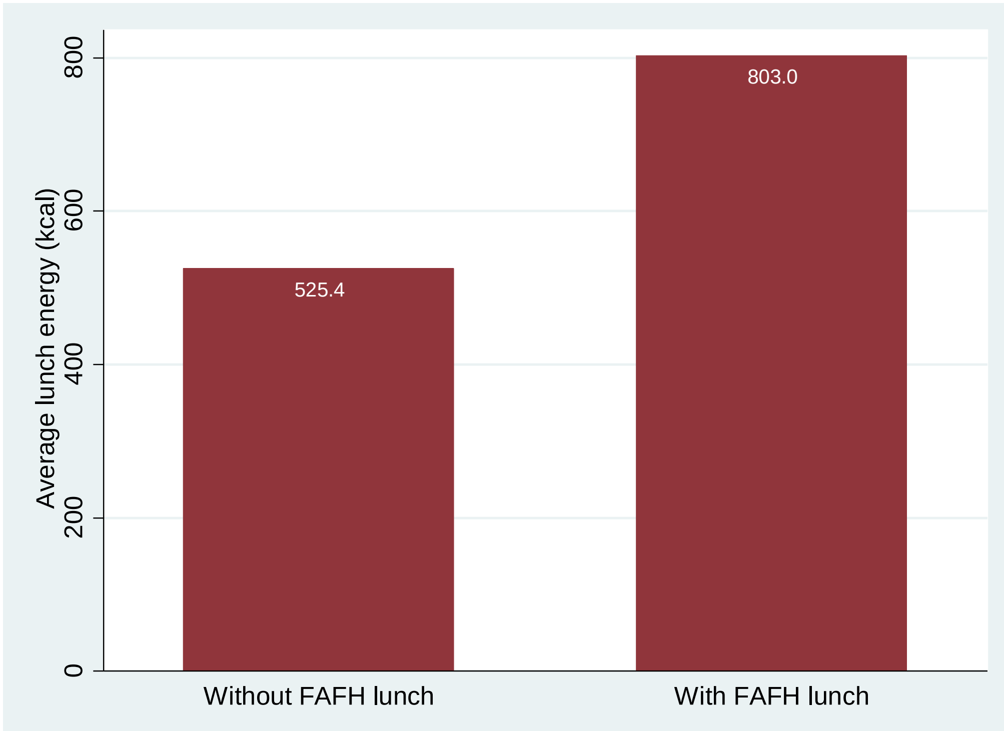

Figure 2.3: The effect of an away from home dinner on caloric intake

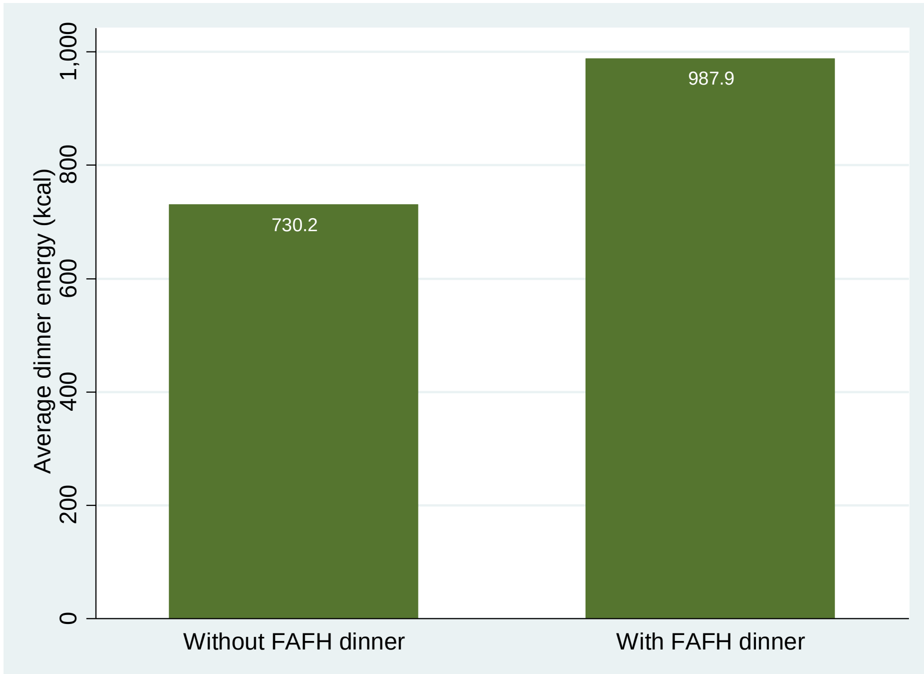

Table 2.2: The results of compensating for Food-Away-From-Home calories during other meals

	OLS			Fixed Effect		
	Energy (kcal)			Energy (kcal)		
Variables	Breakfast	Lunch	Dinner	Breakfast	Lunch	Dinner
	(1)	(2)	(3)	(4)	(5)	(6)
Away from home breakfast	385.299***	-112.258***	5.929	378.490***	-149.248***	-68.706
	(23.052)	(25.814)	(36.245)	(27.364)	(39.111)	(47.822)
Away from home lunch	-33.377***	456.021***	-125.054***	-36.516**	441.819***	-143.969***
	(10.654)	(18.193)	(19.683)	(14.737)	(25.252)	(29.179)
Away from home dinner	-36.719***	-52.524***	364.830***	-12.737	-78.830***	394.283***
	(10.195)	(15.026)	(23.598)	(13.277)	(21.050)	(30.903)
Weekend	38.165***	-11.979	-9.846	45.850***	-13.348	6.308
	(10.405)	(13.517)	(18.011)	(9.800)	(14.939)	(17.770)
Day fixed effect	-39.023***	-14.567	-7.040	-39.355***	-14.615	-8.122
	(8.614)	(11.918)	(15.286)	(8.609)	(11.910)	(15.296)
Constant	328.436***	388.000***	667.607***	320.270***	401.707***	663.660***
	(8.978)	(10.985)	(14.825)	(6.899)	(9.579)	(12.842)
Observations	7,538	7,538	7,538	7,538	7,538	7,538
R-squared	0.116	0.196	0.089	0.143	0.203	0.124

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.3: The results of compensating for Food-Away-From-Home calories during other meals among male and female consumers

Variables	Males			Females		
	Energy (kcal)			Energy (kcal)		
	Breakfast	Lunch	Dinner	Breakfast	Lunch	Dinner
	(1)	(2)	(3)	(4)	(5)	(6)
Away from home breakfast	412.966***	-191.251***	-74.394	324.752***	-71.717	-75.208
	(38.113)	(54.973)	(71.647)	(34.575)	(49.264)	(54.615)
Away from home lunch	-41.468*	518.419***	-172.798***	-31.182*	361.720***	-106.208***
	(23.234)	(42.017)	(47.919)	(18.117)	(25.086)	(31.551)
Away from home dinner	-21.039	-104.368***	480.024***	-6.409	-43.231*	301.318***
	(20.762)	(34.133)	(52.209)	(16.043)	(22.724)	(29.890)
Weekend	58.258***	1.756	13.027	35.146***	-25.600*	0.073
	(16.393)	(27.494)	(31.901)	(11.425)	(14.516)	(17.504)
Day fixed effect	-45.020***	-5.373	-1.828	-32.897***	-24.515*	-12.588
	(14.630)	(20.545)	(26.849)	(9.465)	(12.606)	(15.636)
Constant	356.094***	445.392***	793.349***	286.656***	356.012***	543.349***
	(12.293)	(16.411)	(23.475)	(7.416)	(10.650)	(12.867)
Observations	3,614	3,614	3,614	3,924	3,924	3,924
R-squared	0.157	0.219	0.139	0.122	0.195	0.113

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.4: The results of compensating for Food-Away-From-Home calories during other meals among healthy weight and obese consumers

Variables	Obese (BMI ≥ 30 (kg/m^2))			Healthy weight (BMI < 25 (kg/m^2))		
	Energy (kcal)			Energy (kcal)		
	Breakfast	Lunch	Dinner	Breakfast	Lunch	Dinner
	(1)	(2)	(3)	(4)	(5)	(6)
Away from home breakfast	386.837***	-149.284***	-77.221	393.443***	-121.823	29.899
	(39.784)	(48.079)	(64.556)	(63.426)	(79.815)	(67.342)
Away from home lunch	-68.429***	450.347***	-149.315***	-15.412	448.071***	-101.626**
	(25.801)	(39.294)	(46.050)	(31.221)	(40.692)	(42.500)
Away from home dinner	-12.435	-113.237***	343.017***	-27.051	-19.031	300.799***
	(23.242)	(34.824)	(51.944)	(25.430)	(36.790)	(43.643)
Weekend	44.403***	-12.818	30.256	34.410*	-14.241	-8.708
	(15.813)	(24.873)	(28.519)	(18.725)	(25.321)	(27.085)
Day fixed effect	-18.809	-10.218	-24.096	-67.227***	-18.056	12.917
	(13.510)	(17.849)	(27.104)	(16.195)	(21.287)	(23.294)
Constant	321.657***	397.238***	693.696***	333.004***	375.623***	618.709***
	(11.438)	(13.998)	(21.133)	(13.137)	(17.686)	(18.793)
Observations	2,892	2,892	2,892	2,196	2,196	2,196
R-squared	0.175	0.241	0.097	0.136	0.198	0.090

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: The results of compensating for Food-Away-From-Home calories during other meals among high and low frequent Food-Away-From-Home consumers

Variables	< 3 away from home meal/week			> 3 away from home meal/week		
	Energy (kcal)			Energy (kcal)		
	Breakfast	Lunch	Dinner	Breakfast	Lunch	Dinner
	(1)	(2)	(3)	(4)	(5)	(6)
Away from home breakfast	362.327***	-37.400	-86.301	390.362***	-190.968***	-48.788
	(44.927)	(57.088)	(78.380)	(34.193)	(53.962)	(65.677)
Away from home lunch	-17.132	395.040***	-124.365***	-58.697**	479.421***	-157.509***
	(19.302)	(36.920)	(45.693)	(23.567)	(38.750)	(43.485)
Away from home dinner	-4.297	-70.679***	354.999***	-22.346	-74.497**	419.505***
	(17.232)	(26.940)	(42.469)	(21.024)	(35.243)	(50.845)
Weekend	45.125***	-26.949	11.052	57.242***	-4.514	-15.058
	(13.407)	(21.004)	(23.742)	(16.989)	(25.824)	(30.716)
Day fixed effect	-51.154***	-24.546	10.771	-34.081**	-1.734	-13.779
	(11.023)	(16.216)	(20.400)	(15.580)	(20.315)	(26.498)
Constant	318.956***	399.804***	632.601***	326.488***	400.898***	690.904***
	(7.444)	(10.458)	(15.304)	(14.698)	(19.382)	(25.062)
Observations	3,704	3,704	3,704	2,758	2,758	2,758
R-squared	0.111	0.139	0.102	0.176	0.261	0.142

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.6: The results of compensating for Food-Away-From-Home fat during other meals

Variables	Fat (gm)		
	Breakfast	Lunch	Dinner
	(1)	(2)	(3)
Away from home breakfast	19.799***	-5.781***	-3.581
	(1.619)	(1.932)	(2.216)
Away from home lunch	-1.207	17.046***	-8.298***
	(0.758)	(1.146)	(1.407)
Away from home dinner	-0.092	-4.436***	17.101***
	(0.689)	(1.047)	(1.495)
Weekend	2.610***	0.424	0.598
	(0.476)	(0.782)	(0.863)
Day fixed effect	-0.920**	-0.033	0.778
	(0.450)	(0.604)	(0.763)
Constant	10.163***	18.545***	29.128***
	(0.374)	(0.481)	(0.664)
Observations	7,538	7,538	7,538
R-squared	0.137	0.132	0.107

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.7: The results of compensating for Food-Away-From-Home sugar during other meals

Variables	Sugar (gm)		
	Breakfast	Lunch	Dinner
	(1)	(2)	(3)
Away from home breakfast	11.604***	-6.663**	-2.551
	(2.306)	(2.742)	(2.256)
Away from home lunch	-2.264*	15.354***	-1.304
	(1.312)	(1.957)	(1.652)
Away from home dinner	0.002	-3.911**	11.048***
	(1.189)	(1.736)	(1.676)
Weekend	1.330	-0.406	1.266
	(0.891)	(1.165)	(1.072)
Day fixed effect	-1.822***	0.229	1.008
	(0.684)	(0.852)	(0.842)
Constant	24.387***	19.768***	24.002***
	(0.592)	(0.671)	(0.720)
Observations	7,538	7,538	7,538
R-squared	0.028	0.064	0.031

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.8: The results of compensating for Food-Away-From-Home carbohydrates during other meals

Variables	Carbohydrate (gm)		
	Breakfast	Lunch	Dinner
	(1)	(2)	(3)
Away from home breakfast	32.877***	-17.609***	-7.814
	(3.707)	(5.125)	(4.987)
Away from home lunch	-6.138***	40.195***	-8.396***
	(2.202)	(3.278)	(2.990)
Away from home dinner	-2.089	-8.951***	32.927***
	(1.946)	(2.914)	(3.335)
Weekend	3.041**	-0.645	2.578
	(1.410)	(1.950)	(2.070)
Day fixed effect	-6.144***	0.410	2.837*
	(1.218)	(1.511)	(1.693)
Constant	51.795***	52.687***	72.528***
	(1.020)	(1.211)	(1.422)
Observations	7,538	7,538	7,538
R-squared	0.070	0.123	0.069

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.9: The results of compensating for Food-Away-From-Home sodium during other meals

Variables	Sodium (mg)		
	Breakfast	Lunch	Dinner
	(1)	(2)	(3)
Away from home breakfast	771.141***	-332.376***	-70.085
	(59.823)	(85.649)	(103.480)
Away from home lunch	-57.037**	718.608***	-295.434***
	(25.219)	(53.673)	(63.108)
Away from home dinner	-25.150	-168.435***	550.753***
	(22.516)	(47.438)	(64.494)
Weekend	101.663***	4.015	30.597
	(18.319)	(35.085)	(39.228)
Day fixed effect	-46.985***	-18.393	47.433
	(15.674)	(28.164)	(34.243)
Constant	425.075***	1,000.999***	1,506.076***
	(12.575)	(22.289)	(28.463)
Observations	7,538	7,538	7,538
R-squared	0.152	0.111	0.060

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.10: The results of the placebo test

	Energy (kcal)		
	Breakfast	Lunch	Dinner
Variables	(1)	(2)	(3)
Plain water (gm)	-0.003	0.016	-0.030
	(0.009)	(0.016)	(0.022)
Away from home breakfast	No	Yes	Yes
Away from home lunch	Yes	No	Yes
Away from home dinner	Yes	Yes	No
Controls	Yes	Yes	Yes
Observations	7,538	7,538	7,538
R-squared	0.025	0.022	0.014

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Chapter 3: The Mindlessness and Mindfulness of Secondary Eating

3.1. Introduction

Since 1975, the prevalence of obesity in the U.S. has rapidly increased; approximately two in three adults are either overweight or obese (U.S. Department of Agricultural, 2016b). In response, researchers have investigated the factors driving excess body weight. Secondary eating is one of those factors. Especially since the mid-1970s, secondary eating has increased along with obesity (Zick & Stevens, 2011). Secondary eating is defined as eating while doing something else like working or driving. Someone who is secondarily eating might not be able to monitor the quantity (Wansink, 2007). Bellisle and Dalix (2001) show that secondary eating, unlike primary eating, leads to overeating.

The objective of this paper is to investigate the effect of secondary eating on obesity. Becker's household production theory explains consumers' choices regarding time allocation (Becker, 1965), and health production (Chen, Shogren, Orazem, & Crocker, 2002; Grossman, 1972, 2003; Huffman, 2011; Kalenkoski & Hamrick, 2013). Based on the household production theory, health production and time allocated to eating are affected by economic factors. A high wage increases the opportunity cost of time, suggesting that those consumers engage in secondary eating to save time (Hamermesh, 2010). In addition, a high wage increases the expected value of future income (J. Binkley, 2010) suggesting that consumers maintain a healthier lifestyle to preserve their income-earning capacity.

The literature discusses secondary eating time from several angles. Some studies investigate the effect of economic factors on secondary eating time (Senia, Jensen, & Zhylyevskyy, 2014). Other studies investigate the effect of secondary eating time on body weight (Bertrand & Schanzenbach, 2009; Hamermesh, 2010; Kolodinsky & Goldstein, 2011; Zick, Stevens, & Bryant, 2011). Studies that investigate the effect of secondary eating on obesity are inconclusive. Some studies find a negative effect of secondary eating on body weight (Hamermesh, 2010; Zick et al., 2011), whereas other studies find a positive effect (Bertrand & Schanzenbach, 2009). Except for Bertrand and Schanzenbach (2009), previous studies assume that secondary eating similarly affects all consumers, leading to overeating and obesity. This paper relaxes the assumption that secondary eating similarly affects consumers, identifying situations when secondary eating has a positive relationship with body weight, which we call "mindless," and situations when secondary eating has an inverse relationship with body weight, or "mindful." We hypothesize that lifestyle moderates the effect of secondary eating on body weight. Inactive consumers are more likely to engage in mindless secondary eating than those who are physically active.

We use data from the 2006-08 American Time Use Survey (ATUS). A subsample of consumers who participated in the Current Population Survey (CPS) was randomly selected to provide diaries of all activities starting from 4:00 am the day before the interview. The Eating and Heath Module contains information on secondary eating. There are two avenues in which lifestyle moderates the effect of secondary eating on obesity. First, the analysis controls for sedentary leisure activities and physical activities. For example, watching TV for four hours increases the odds of mindless secondary eating more than watching TV for half an hour does. Second, the analysis controls for the type of the primary task. The intuition is that the effect of eating while driving might differ from eating while watching TV.

The results provide evidence that lifestyle moderates the effect of secondary eating on obesity. Maintaining a sedentary lifestyle increases the odds of mindless secondary eating, and therefore contributes to the obesity epidemic. Consumers who eat while doing stationary activities are susceptible to mindless secondary eating as opposed to those who eat while doing less stationary activities. Our findings resolve the issue of the mixed results of previous studies that focus on the effect of secondary eating on obesity. Moreover, our results inform policies to better target people who have a sedentary lifestyle, to help them develop a healthier one.

The remainder of this paper is organized as follows. Section 3.2 explains the data used for the analysis and the model. Section 3.3 provides the results, and Section 3.4 concludes.

3.2. Data and Model

We use data from the 2006-8 American Time Use Survey (ATUS). A proportion of participants in the Current Population Survey (CPS) aged 15 years or older was selected to provide diaries of all activities for 24 hours, starting at 4:00 am the day before the interview. The Eating and Health Module provides information on secondary eating and drinking and on weight and height. After reporting all activities, participants were asked if they ate while doing other activities. The same questions were asked about secondary drinking. Consumers were asked about drinking beverages other than plain water while doing something else. Obesity is measured by Body Mass Index (BMI) which is weight in kilograms divided by the square of height in meters (kg/m^2). BMI is calculated from self-reported height and weight, so there might be some measurement errors. Even though it is not uncommon to use self-reported BMI (Hamermesh, 2010; Zick et al., 2011), there is no consensus on the validity of self-reported height and weight. Kuczmarski, Kuczmarski, and Najjar (2001) find that self-reported BMI is valid for younger adults. Merrill and Richardson (2009) and Cawley and Burkhauser (2006) find self-reported BMI to be underestimated. To correct self-reported BMI, Cawley and Burkhauser (2006) suggest using information from the National Health and Nutritional Examination Survey (NHANES). For each observation, the NHANES provides two values of weight and height; one is self-reported, and the other is measured. Courtemanche, Heutel, and McAlvanah (2015) follow this correction method but find that both the self-reported and corrected BMI provide almost the same results. Thus, we consider the issue of self-reported BMI as trivial.

A BMI under 18.5 is classified as underweight, between 18.5 and 24.9 is classified as normal weight, between 25 and 29.9 is classified as overweight, and 30 and above is classified as obese (Centers for Disease Control and Prevention, 2015). These classifications are for adults age 20 years and older, so we limit the sample to this age group. Retired and unemployed individuals might differ in their time allocations, so we omit people older than 65 years as well as those who are not working.

It should be noted that being underweight, like being overweight, has negative impacts on health, so we omit underweight consumers. Leisure sedentary activities are those that require more lying and sitting (Sugiyama, Healy, Dunstan, Salmon, & Owen, 2008), including watching TV, reading, computer use, video and board games, and sedentary commute (Dunton, Berrigan, Ballard-Barbash, Graubard, & Atienza, 2009).[12] Physical activities include all activities under the category of "sports, exercise, and recreation" coded in the Lexicon of the ATUS as 1301xx, in addition to active commute, walking and biking (Bureau of Labor Statistics 2016). To ensure health generation, we consider only sports with a Metabolic Equivalent Rate (MET) of 3 and above (Dunton et al., 2009). The MET measures the intensity of activities. One MET is defined as the energy to sit or lay (Tudor-Locke, Washington, Ainsworth, & Troiano, 2009). To do any sport with MET of 3 and above, a person has to spend at least three times more energy than that required for sedentary activities. We define secondary eating as the total sum of secondary eating and secondary drinking that occurred while doing other activities. The total time of secondary eating and drinking was also calculated using the procedure suggested by the U.S. Department of Agriculture (2016).

We use dummy variables to control for male, black, Hispanic, and other race individuals. The omitted groups are white and female individuals. We control for age and being married/cohabitating. We also control for education: high school, some college, or a college degree and beyond. The omitted groups are single and the education entailment of less than high school. We add a dummy variable that takes a value of 1 if family income is greater than 185% of the poverty income level and 0 otherwise. We add another dummy variable to control for households with missing income. Since time allocations and eating habits differ on weekends, in different seasons, and on holidays,

[12] Due to low variation, we omit other leisure activities: tobacco and drug use; television (religious); listening to the radio; listening to playing music (not radio); arts and crafts; hobbies, except arts and crafts and collecting; writing for personal interest and not other specified activities.

we add dummy variables to control for whether the interview day was during weekend day, summer, or holiday. Finally, we control for the number of children ages 0-5 years old and 6-17 years old.

The total number of observations is equal to 19,328. Table 3.1 presents the weighted summary statistics of the consumers' characteristics. The average BMI is equal to 28 (kg/m^2), which highlights the high prevalence of obesity. The average age of the sample is 41 years old. The sample consists of 56% male, 11% black, 13% Hispanic, 6% from other races, and 65% married individuals. Seventy-eight percent are from high-income households. The percentages of individuals with a high school degree, some college, or a college degree or above is equal to 29, 29, and 34%, respectively. The average number of children between 0-5 years old is 0.27 child, and the average number of children between 6-17 years old is 0.57 child. The average percentage residing in the Northeast, Midwest, and West regions is 18, 25 and 22%, respectively. Also, on average, 83% of individuals reside in metropolitan areas.

We hypothesize that lifestyle moderates the effect of secondary eating on obesity. Secondary eating does not have a direct effect on obesity. An active person is less inclined to engage in mindless secondary eating, whereas an inactive person is more inclined to do so. We use the time that someone spends on leisure sedentary activities, physical activities, paid work, and sedentary commute to control for lifestyle. Leisure sedentary activities include watching TV, reading, playing games, using a computer, and socializing with others. These activities are considered to be more habitual than others (Neal, Wood, & Quinn, 2006). Ignoring other activities might bias our results. Other activities might not be as habitual, but they vary in the level of sedentariness and the odds of secondary eating, such as attending a football game. Thus, in other specifications, we include all activities to reduce any possibility of omitted variable bias.

The ATUS provides information about 438 primary activities (Tudor-Locke et al., 2009). There are 19 major categories. Each category contains several subcategories. For example, the major category of the “household activities” encompasses 10 subcategories such as “housework.” Examples of activities under “housework” are interior cleaning and doing laundry. Tudor-Locke et al. (2009) develop a compendium of activities, which maps each activity in the ATUS to a value of a MET (Washington, 2016).

To control for all time allocations, we use this compendium by dividing all activities into three groups. The first group consists of activities with ($1.5 \geq$ MET). The second group consists of activities with ($1.5 <$ MET < 3). Activities with (MET ≥ 3) are contained in the third group. The rationale for choosing these thresholds is that activities with ($1.5 \geq$ MET), such as attending performing arts, playing video or board games, watching TV, and listening to music, are light. Light activities increase the odds of mindless eating. Activities with ($1.5 <$ MET < 3) are less sedentary than the activities of the first group but still require more movement, such as driving an automobile. Activities with (MET ≥ 3) generate health; these include activities like interior or exterior cleaning, playing with children (not sports), and sports in general. It is implausible to expect engagement in secondary eating while doing the activities of the latter group increases body weight.

To account for primary tasks, we break down secondary eating time into eating while doing the primary activities. The implication is that the effect of secondary eating on body weight will depend on the main activity. For example, eating while watching TV might increase the odds of mindless secondary eating more than eating while working or driving. We control for all primary activities estimating the effect of secondary eating time while doing activities with ($1.5 \geq$ MET) and activities with ($1.5 <$ MET < 3). We expect secondary eating while doing activities of the first group to have a positive and relatively high effect on BMI, whereas activities of the second group to have a positive and relatively low effect on BMI.

Table 3.2 presents the summary statistics of time allocations. Panel A reports the summary statistics for lifestyle regarding time allocations. On average, people spend 620 minutes doing activities with ($1.5 \geq$ MET) and 560 minutes doing activities with ($1.5 <$ MET < 3). More specifically, people allocate 12 minutes to socializing, 126 minutes to watching TV, 7 minutes to playing video or board games or to using a computer, and 14 minutes to reading. On average, people also allocate 323 minutes to work at their main jobs, 76 minutes to sedentary commute, and 16 minutes to physical activity. On average, consumers spend 80 minutes per day eating while doing other activities as shown in Panel B. The average secondary eating time is equal to 27 minutes while doing activities with ($1.5 \geq$ MET). Eating while doing activities with ($1.5 <$ MET < 3) averages to 50 minutes. The average time spent on secondary eating while doing activities of the latter group is higher, which highlights the importance of relaxing the assumption that secondary eating similarly influences body weight. If on average, people eat while doing activities that require movement, then it is implausible to assume that secondary eating has a direct effect on obesity.

For primary identification, we compare time allocations based on obesity status. Figure 3.1 presents the BMI kernel density distributions based on secondary eating. The dotted line plots the BMI distribution for those who report that they were engaging in secondary eating, and the solid line plots the BMI distribution of those who did not. No variations in secondary eating time explain variations in BMI. Figure 3.2 provides an example of the effect of lifestyle on obesity. Depending on watching TV, we plot the BMI distributions. The median amount of time spent watching TV time is 100 minutes. We categorize individuals who spend more than the median amount of time into the watch-more-TV group (dotted line), and those who spent less than the median time into the watch-less-TV group (solid line). Unlike the BMI distributions based on secondary eating, Figure 3.2 indicates that variations in time spent watching TV explain variations in obesity. Those who watch more TV are less likely to be at a healthy weight and more likely to be at an unhealthy weight. Table 3.3 presents the secondary eating mean differences between individuals who are obese and those who are at normal weight. On average, there are no statistically significant differences in secondary eating time by body weight. We compare the means of lifestyle regarding time allocations for obese and normal weight individuals as appearing in Table 3.4. On average, obese individuals are more likely than healthy weight individuals to maintain a sedentary lifestyle. For example, obese individuals spend an average of 30 more minutes watching TV every day. Overall, Figure 3.3 summarizes the information provided in Figures 3.1-2 and Tables 3.3-4, which we use for the primary identification. There is no direct effect on secondary eating on obesity. The effect is indirect, moderated by lifestyle. A sedentary lifestyle increases the odds of mindless secondary eating, and the opposite applies for an active way of life.

We apply OLS to test how lifestyle explains the effect of secondary eating on BMI. Our dependent variable is BMI, and our main independent variable is secondary eating time.

$$BMI = \beta_0 + \beta_1 S + X'\delta + \epsilon, \tag{3.1}$$

where S denotes secondary eating time, X denotes a vector of controls, and ϵ denotes the error term. β_0, β_1, and δ are the coefficients to be estimated. Equation 3.1 ignores the aspects of lifestyle. Then, we test the null hypothesis that secondary eating does not affect BMI. Rejecting the null hypothesis indicates that secondary eating has an adverse relation with BMI. We expand equation 3.1 to control for aspects of lifestyle.

$$BMI = \beta_0 + \beta_1 S + Z'\delta + \epsilon, \tag{3.2}$$

where Z denotes a vector of controls and includes aspects of lifestyle. These aspects are time spent on socializing, watching TV, playing games, using a computer, reading, working, sedentarily commuting, and being physically active. To determine the effect of lifestyle, we test the null hypothesis of no effect of secondary eating on BMI. Failing to reject the null hypothesis supports our hypothesis that lifestyle explains the effect of secondary eating on body weight. For robustness checking, we jointly test whether these aspects of lifestyle are different from zero. We perform several tests to confront various combinations of lifestyle elements. For example, we test whether socializing and watching TV are jointly different from zero. We also test whether socializing, watching TV, playing games, using a computer, and reading are different from zero. If the model in Figure 3.3 is correct, we reject the null hypotheses that the combinations of lifestyle aspects are jointly equal to zero. In another specification, we extend equation 3.1 by adding two variables to control for all aspects of lifestyle. The first added variable is the sum of the time that someone spends doing activities with ($1.5 \geq$ MET) and the second is the sum of the time that someone spends doing activities with ($1.5 <$ MET < 3). The omitted group consists of activities with (MET ≥ 3) since all three groups sum up to 24 hours. Failure to reject the null hypothesis that secondary eating has no effect on body weight further demonstrate the robustnesses of our results.

We also control for primary activities; estimating the effect of secondary eating while doing activities with ($1.5 \geq$ MET) and activities with ($1.5 <$ MET < 3). Finally, we estimate how lifestyle moderates the effect of secondary eating on obesity among males and females to account for gender differences. A large proportion of secondary eating time takes place while working. Different job environments might affect secondary eating. For instance, having a desk job might increase secondary eating time, whereas working on a farm or doing construction might not. To account for these differences, we divide individuals into three groups based on their occupations: white collar, blue collar, and service occupations (Courtemanche et al., 2015).[13]

[13] White collar occupations: Management occupations; business and financial operations occupations; computer and mathematical science occupations; architecture and engineering occupations; life, physical, and social science occupations; legal occupations; education, training, and library occupations; healthcare

3.3. Results

For all specifications, observations are weighted using the Eating and Health Module sample weights. Table 3.5 presents the OLS estimates of equation 3.1, estimating the effect of secondary eating time on BMI. Columns 1-4 present different specifications. In the first specification, we control for demographic factors. In the second specification, we add socioeconomic factors. In column 3 we control for geographic factors. We control for year fixed effect, and whether the interview was on the weekend, in summer, or on a holiday. Holding other variables constant, secondary eating has a positive effect on BMI. Although the significance level is marginal, the results hold among different specifications.

To test how the ways in which lifestyle moderates the effect of secondary eating on obesity, we estimate equation 3.2, which controls for different aspects of lifestyle, including socializing, watching TV, playing games, using a computer, reading, working, sedentarily commuting, and being physically active. Table 3.6 presents the OLS estimates using equation 3.2. Once we control for aspects of lifestyles, secondary eating becomes statistically insignificant. This supports our hypothesis that lifestyle moderates the effect of secondary eating on obesity. As reported in Table 3.6, the time that someone spends watching TV, playing games, using a computer, working, and sedentarily commuting is positively associated with BMI. In contrast, the time that someone spends on physical

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practitioner and technical occupations; healthcare support occupations; and office and administrative support occupations. Blue collar occupations: Arts, design, entertainment, sports, and media occupations; farming, fishing, and forestry occupations; construction and extraction occupations; installation, maintenance, and repair occupations; production occupations; and transportation and material moving occupations. Service occupations: Community and social service occupations; protective service occupations; food preparation and serving related occupations; building and grounds cleaning and maintenance occupations; personal care and service occupations; and sales and related occupations.

activities is negatively associated with BMI. To test the relevance of these lifestyle aspects, we perform joint hypothesis tests. Table 3.7 shows the F-values of these tests. The large magnitude of F-values supports the relevance of lifestyle elements. For example, we test the null hypothesis that socializing, watching TV, playing games, using a computer, and reading are jointly equal to zero. The F-value is equal to 13.06 and statistically significant at 1%, so we reject the null hypothesis. We run the same regression to demonstrate how lifestyle moderates the effect of secondary eating for demographic subgroups as reported in Table 3.8. Columns 1-2 show the results for males and females, and columns 3-5 show the results for white collar, blue collar, and service occupations. Among men and women, controlling for lifestyle aspects explains the effects of secondary eating on BMI. For blue collar and service occupations, controlling for lifestyle aspects also explains the effect of secondary eating. In among white collar individuals, secondary eating has a positive and significant effect on BMI even with controlling for lifestyle aspects. The white collar occupations are sedentary with a higher opportunity cost of time.

According to the household production theory, a high opportunity cost of time encourages secondary eating to save time (Hamermesh, 2010) and encourages physical activity to maintain earning capacity (J. Binkley, 2010). The results are consistent with the household production theory. The negative and statistically significant coefficient of physical activities is six times higher in magnitude, which is more than enough to offset the effect of secondary eating.

To test if these results are affected by omitted variable bias, we control for all activities by adding two variables of the total sum of time doing activities with (1.5 ≥

MET) and (1.5 < MET < 3), as appearing in Table 3.9. Except for the female group, the results in Table 3.9 are consistent with the previous findings. The results in Table 3.9 have the expected patterns. For all groups, the effects of activities with (1.5 ≥ MET) are higher in magnitude than those of activities with (1.5 < MET < 3) since the latter are less sedentary.

To control for all primary activities, we divide secondary eating time into eating while doing activities with (1.5 ≥ MET) and doing activities with (1.5 < MET < 3). The results show that eating while doing activities of the first group increases the odds of mindless secondary eating (Table 3.10). The opposite is true for doing activities of the latter group, which are less sedentary and require some movement.

Overall, secondary eating has no direct effect on obesity. We hypothesize that lifestyle moderates the effect of secondary eating on obesity. The results support this hypothesis and state two avenues in which lifestyle modulates the effect of secondary eating. The first avenue is through stationary activities. People who spend more time socializing, watching TV, reading, using a computer, playing video or board games, working in sedentary jobs, and sedentarily commuting are more likely to engage in mindless secondary eating. The second avenue is the type of primary activities in which secondary eating occurs. The analysis distinguishes between highly-and-less sedentary activities. Those who engage in secondary eating while doing activities of the former type are more susceptible to mindless secondary eating. In contrast, consumers who eat while doing activities of the latter type are less vulnerable.

3.4. Conclusion

Since the mid-1970s, obesity has rapidly increased in the U.S.; approximately two in three adults are either overweight or obese. Secondary eating is one factor that has been blamed for obesity. Secondary eating is defined as eating while doing something else such as reading or watching TV. While engaging in secondary eating, consumers might not be able to monitor the amount of food eaten, leading to overeating and obesity. Previous studies have assumed that secondary eating affects body weight similarly and shown mixed results of the effect of secondary eating. Our contribution was to relax this assumption, identifying situations in which “mindless secondary eating” positively affects body weight and situations where “mindful secondary eating” negatively affects body weight.

We hypothesize that lifestyle moderates the effect of secondary eating on obesity. Using data from the 2006-8 American Time Use Survey (ATUS), the results show that spending more time doing sedentary activities increases the odds of mindless secondary eating, leading to overeating and obesity. Furthermore, the analysis also demonstrates that eating while doing highly sedentary activities increases the chances for mindless secondary eating, but eating while doing less sedentary activities discourages it.

Our findings resolve the issue of the mixed results of previous studies, which consider secondary eating mindless (not mindful) leading to overeating and obesity. When we control for lifestyle, secondary eating time becomes statistically insignificant. Thus, policies that aim at reducing obesity should consider lifestyle as the real issue (not secondary eating), targeting individuals with sedentary lifestyles to help them develop an active way of life. For example, improving sidewalks and running tracks might encourage people to be more active and discourage mindless secondary eating.

Although we control for all activities in the ATUS, there might be an endogeneity issue: A sedentary lifestyle increases the odds of mindless secondary eating and obesity, but obesity also increases the chances of sedentary activities and secondary eating. Future research should consider using different data, which are less challenging to obtain valid Instrumental Variables or similar strategies to identify a causal relationship. We also did not directly measure mindless secondary eating, where people do not pay attention to the quantity, and mindful secondary eating, when they do so. To measure mindless and mindful secondary eating would require information of food environment. The ATUS is only a time use data that does not have information on food environment.[14] Accordingly, we focus on aspects of lifestyle. Future researchers should directly measure mindless and mindful secondary eating. To illustrate, suppose two people have desk jobs and enjoy snacking on potato chips while working. One person brings a small bag of potato chips every day, but the other keeps a family size bag in the office. If both rely on external cues to feel satiated (Wansink, 2007), secondary eating is supposed to be mindless when food is plenty and mindful when food is limited.

[14] Bellisle and Dalix (2001) and Bertrand and Schanzenbach (2009) use data that have information on time use and food intake, but their data focus on females and are not nationally representative.

Table 3.1: Summary statistics of consumers' characteristics

Variables	Mean	S.D.
Body Mass Index (kg/m^2)	27.51	5.44
Age (year)	40.82	11.93
Male	0.56	0.5
Black	0.11	0.31
Other race	0.06	0.23
Hispanic	0.13	0.34
Married	0.65	0.48
Income > 185% of Income Poverty Level	0.78	0.41
Missing income	0.13	0.33
High school	0.29	0.45
Some college	0.29	0.45
College degree and beyond	0.34	0.47
Number of children age 0-5 years	0.27	0.62
Number of children age 6-17 years	0.57	0.93
Northeast	0.18	0.38
Midwest	0.25	0.43
West	0.22	0.42
Metropolitan area	0.83	0.38
Weekend	0.42	0.49
Summer	0.24	0.43
Holiday	0.02	0.13
White caller occupations	0.50	0.50
Blue caller occupations	0.25	0.44
Service occupations	0.25	0.43

Observations are weighted using the Eating and Health Module sample weights.
N = 19,328

Table 3.2: Summary statistics of lifestyle and secondary eating

Variables (Time allocations are in 10 minutes' intervals)	Mean	S.D.
Panel A		
Activities with (1.5 ≥ MET)	62.85	31.37
Activities with (1.5 < MET < 3)	55.51	25.74
Socializing	1.15	4.11
Watching TV	12.62	13.13
Video/board games	0.74	3.9
Computer use	0.67	3.21
Reading	1.4	4.15
Work	32.73	25.42
Sedentary commute	7.57	6.85
Physical activities	1.63	5.03
Panel B		
Secondary eating	7.92	18.39
Secondary eating while doing activities with (1.5 ≥ MET)	2.65	8.42
Secondary eating while doing activities with (1.5 < MET < 3)	5.4	14.64

Observations are weighted using the Eating and Health Module sample weights.
N = 19,328

Figure 3.1: The BMI Kernel density functions based on secondary eating

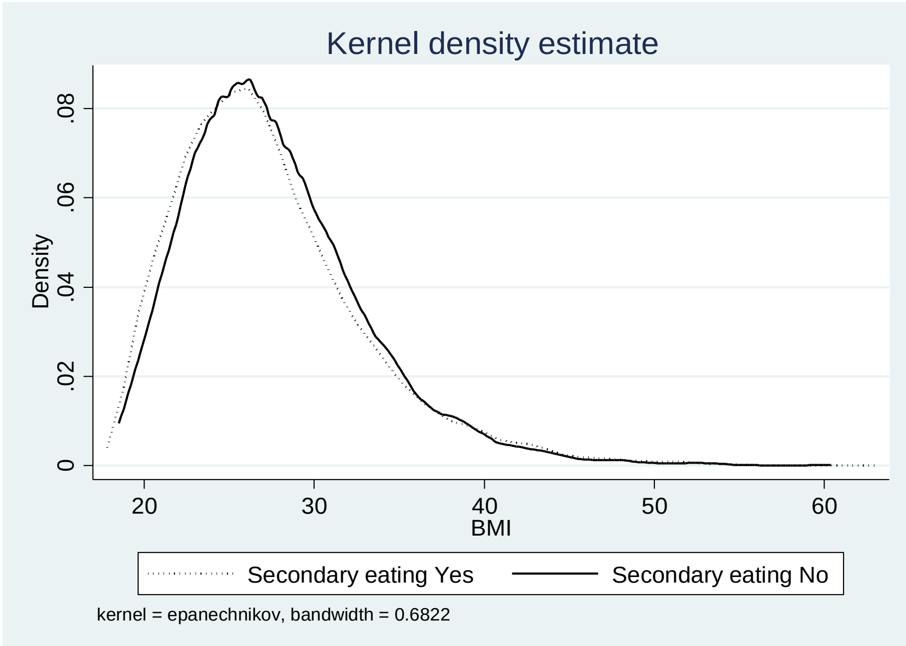

Figure 3.2: The BMI Kernel density functions based on watching TV

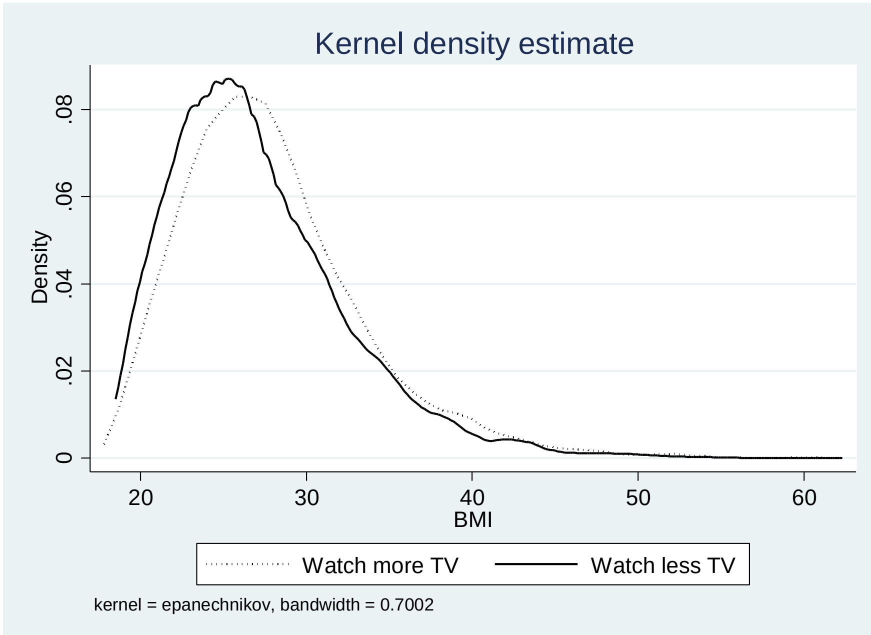

Table 3.3: Secondary eating mean differences between obese and normal weight individuals

Variables	Obese BMI ≥ 30[a]	Normal weight BMI < 25[b]	Mean difference
(Time allocations are in 10 minutes' intervals)	Mean	Mean	
Secondary eating	8.34	8.32	0.02
Secondary eating while doing activities with ($1.5 \geq$ MET)	3.29	2.87	0.42^{**}
Secondary eating while doing activities with ($1.5 <$ MET < 3)	5.34	5.39	-0.05

*** p<0.01, ** p<0.05, * p<0.1

a: N = 5,255

b: N = 6,772

Table 3.4: Summary statistics of lifestyle based on obesity status

Variables	Obese BMI ≥ 30[a]	Normal weight BMI <25[b]	Mean difference
(Time allocations are in 10 minutes' intervals)	Mean	Mean	
Activities with ($1.5 \geq$ MET)	66.92	64.22	2.70***
Activities with ($1.5 <$ MET < 3)	51	52.64	-1.64***
Socializing	1.30	1.03	0.27***
Watching TV	15.02	11.67	3.35***
Video/board games	0.90	0.60	0.30***
Computer use	0.74	0.69	0.05
Reading	1.39	1.74	-0.35***
Work	26.43	24.74	1.69***
Sedentary commute	7.35	7.42	-0.06
Physical activities	1.22	1.90	-0.68***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

a: N = 5,255

b: N = 6,772

Figure 3.3: Model

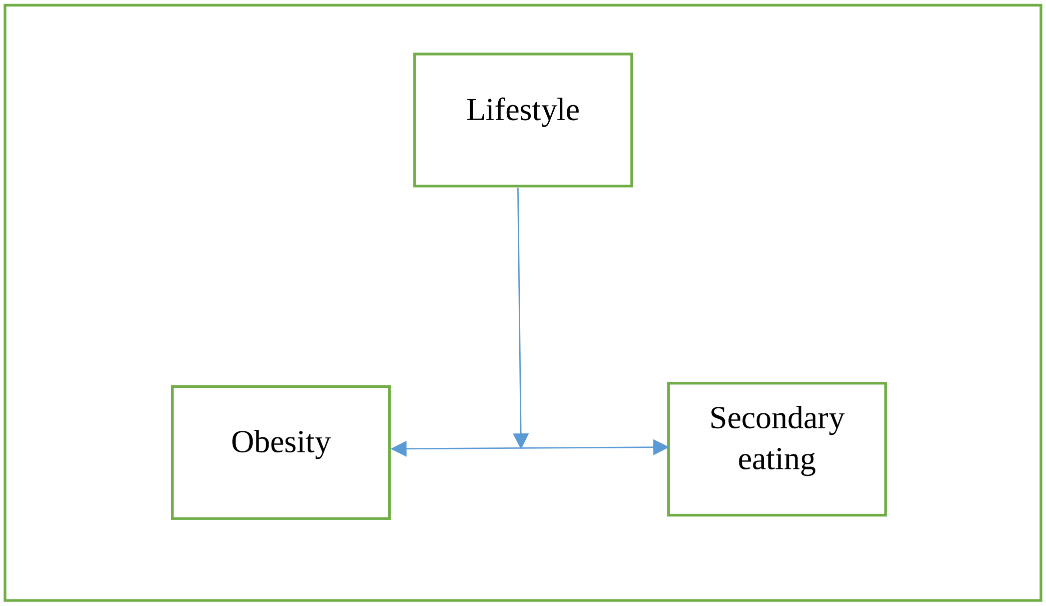

Table 3.5: The effect of secondary eating on BMI

Variables	(1)	(2)	(3)	(4)
Dependent variable is Body Mass Index (BMI)				
Secondary eating	0.006*	0.006**	0.006*	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.050***	0.055***	0.055***	0.055***
	(0.005)	(0.005)	(0.005)	(0.005)
Male	1.204***	1.182***	1.195***	1.194***
	(0.107)	(0.106)	(0.106)	(0.106)
Black	1.871***	1.634***	1.592***	1.591***
	(0.168)	(0.172)	(0.174)	(0.174)
Hispanic	1.052***	0.664***	0.763***	0.764***
	(0.159)	(0.170)	(0.173)	(0.173)
Other race	-0.854***	-0.721***	-0.620***	-0.620***
	(0.230)	(0.225)	(0.228)	(0.228)
Married		0.123	0.088	0.090
		(0.125)	(0.125)	(0.125)
Income > 185% of Income poverty level		-0.454***	-0.419***	-0.417***
		(0.145)	(0.145)	(0.145)
Income missing		-0.258	-0.257	-0.252
		(0.175)	(0.175)	(0.175)
High school		0.436*	0.426*	0.424*
		(0.230)	(0.229)	(0.230)
Some college		0.266	0.289	0.287
		(0.233)	(0.232)	(0.233)
College degree and beyond		-1.070***	-1.006***	-1.005***
		(0.228)	(0.228)	(0.229)
Number of children age 0-5 years		0.149*	0.154*	0.153*
		(0.086)	(0.086)	(0.086)
Number of children age 6-17 years		0.123**	0.128**	0.130**
		(0.054)	(0.054)	(0.054)

Table 3.5: Continued

Variables	(1)	(2)	(3)	(4)
Dependent variable is Body Mass Index (BMI)				
Northeast			-0.469***	-0.470***
			(0.152)	(0.152)
Midwest			-0.092	-0.094
			(0.137)	(0.137)
West			-0.442***	-0.441***
			(0.144)	(0.144)
Metropolitan area			-0.336**	-0.336**
			(0.144)	(0.143)
Weekend				0.016
				(0.101)
Summer				0.112
				(0.120)
Holiday				0.368
				(0.487)
The year of 2007				0.121
				(0.127)
The year of 2008				0.056
				(0.125)
Constant	24.467***	24.695***	25.110***	25.012***
	(0.226)	(0.337)	(0.353)	(0.364)
Observations	19,328	19,328	19,328	19,328
R-squared	0.037	0.055	0.057	0.058

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.6: The effect of secondary eating on BMI: Adjusting for aspects of lifestyle

	All
	(1)
Dependent variable is Body Mass Index (BMI)	
Secondary eating	0.004
	(0.003)
Socializing	0.014
	(0.010)
Watching TV	0.034***
	(0.005)
Playing games	0.058***
	(0.017)
Computer use	0.034*
	(0.020)
Reading	0.015
	(0.020)
Work	0.011***
	(0.003)
Sedentary commute	0.022***
	(0.008)
Physical activities	-0.035***
	(0.009)
Age	0.054***
	(0.005)
Male	1.032***
	(0.108)
Black	1.501***
	(0.175)
Hispanic	0.781***
	(0.172)
Other race	-0.608***
	(0.228)
Married	0.101
	(0.124)
Income > 185% of Income poverty level	-0.394***
	(0.145)
Income missing	-0.267
	(0.173)

Table 3.6. Continued

	All
	(1)
Dependent variable is Body Mass Index (BMI)	
High school	0.428*
	(0.229)
Some college	0.349
	(0.233)
College degree and beyond	-0.873***
	(0.230)
Number of children age 0-5 years	0.210**
	(0.087)
Number of children age 6-17 years	0.164***
	(0.054)
Northeast	-0.413***
	(0.152)
Midwest	-0.058
	(0.136)
West	-0.398***
	(0.141)
Metropolitan area	-0.380***
	(0.143)
Weekend	0.081
	(0.117)
Summer	0.172
	(0.119)
Holiday	0.581
	(0.494)
The year of 2007	0.122
	(0.126)
The year of 2008	0.046
	(0.125)
Constant	24.030***
	(0.386)
Observations	19,328
R-squared	0.066

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Joint hypothesis tests

<table>
<tr><th></th><th colspan="7">Joint hypothesis tests
F-value</th></tr>
<tr><th>Variables</th><th>(1)</th><th>(2)</th><th>(3)</th><th>(4)</th><th>(5)</th><th>(6)</th><th>(7)</th></tr>
<tr><td>Socializing</td><td rowspan="2">27.17
(0.000)</td><td rowspan="3">21.04
(0.000)</td><td rowspan="4">16.31
(0.000)</td><td rowspan="5">13.06
(0.000)</td><td rowspan="6">11.38
(0.000)</td><td rowspan="7">9.77
(0.000)</td><td rowspan="8">11.14
(0.000)</td></tr>
<tr><td>Watching TV</td></tr>
<tr><td>Playing games</td><td></td></tr>
<tr><td>Computer use</td><td></td><td></td></tr>
<tr><td>Reading</td><td></td><td></td><td></td></tr>
<tr><td>Work</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Sedentary commute</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Physical activities</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

p-value in parentheses

Table 3.8: The effect of secondary eating on BMI: Adjusting for aspects of lifestyle among different groups

	Male	Female	White collar occupation	Blue collar occupation	Service occupation
	(1)	(2)	(3)	(4)	(5)
Dependent variable is Body Mass Index (BMI)					
Secondary eating	0.001	0.006	0.010**	-0.005	-0.001
	(0.004)	(0.005)	(0.004)	(0.006)	(0.006)
Socializing	0.011	0.017	0.015	0.010	0.013
	(0.012)	(0.017)	(0.017)	(0.017)	(0.018)
Watching TV	0.031***	0.038***	0.045***	0.023***	0.025***
	(0.006)	(0.007)	(0.007)	(0.008)	(0.009)
Playing games	0.048**	0.086***	0.101***	0.025	0.033
	(0.020)	(0.032)	(0.030)	(0.031)	(0.027)
Computer use	0.030	0.046	0.045	0.064	0.005
	(0.024)	(0.035)	(0.029)	(0.045)	(0.022)
Reading	0.008	0.020	0.018	0.059	-0.029
	(0.039)	(0.016)	(0.015)	(0.083)	(0.027)
Work	0.010***	0.010**	0.011***	0.017***	0.004
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Sedentary commute	0.023**	0.020	0.031***	-0.015	0.042**
	(0.010)	(0.014)	(0.010)	(0.015)	(0.019)
Physical activities	-0.016	-0.111***	-0.060***	0.001	-0.034*
	(0.011)	(0.017)	(0.013)	(0.017)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	9,877	9,451	10,442	4,351	4,535
R-squared	0.042	0.092	0.081	0.041	0.080

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.9: The effect of secondary eating on BMI: Adjusting for aspects of lifestyle among different groups

Variables	All	Male	Female	White collar occupation	Blue collar occupation	Service occupation
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is Body Mass Index (BMI)						
Secondary eating	0.005	0.002	0.008*	0.011***	-0.005	-0.001
	(0.003)	(0.004)	(0.005)	(0.004)	(0.007)	(0.006)
Activities with ($1.5 \geq$ MET)	0.022***	0.015***	0.039***	0.029***	0.013*	0.025***
	(0.004)	(0.005)	(0.007)	(0.006)	(0.006)	(0.008)
Activities with ($1.5 <$ MET < 3)	0.014***	0.011***	0.024***	0.018***	0.013**	0.016***
	(0.003)	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,328	9,877	9,451	10,442	4,351	4,535
R-squared	0.060	0.036	0.086	0.071	0.032	0.075

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.10: The effect of secondary eating on BMI: Adjusting for primary tasks among different groups

Variables	All	Male	Female	White collar occupation	Blue collar occupation	Service occupation
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is Body Mass Index (BMI)						
Secondary eating while doing activities with (1.5 ≥ MET)	0.027***	0.032**	0.023**	0.034**	0.021	0.021
	(0.009)	(0.013)	(0.012)	(0.014)	(0.018)	(0.013)
Secondary eating while doing activities with (1.5 < MET < 3)	0.002	-0.002	0.005	0.004	-0.009	0.001
	(0.005)	(0.005)	(0.008)	(0.007)	(0.010)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,328	9,877	9,451	10,442	4,351	4,535
R-squared	0.060	0.036	0.086	0.071	0.032	0.075

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Chapter 4: Validating the Use of Time Preference Proxies to Explain Effects on Health Outcomes

4.1. Introduction

Variations in time preferences help explain variations in health-related behaviors such as smoking, caloric intake, physical activities, and obesity. Impatient individuals discount the future more, weighing present gratification more than future well-being. The opposite is true for patient individuals. The rate of time preference measures the ability to delay benefits in this present-future trade-off. Many researchers elicit the rate of time preference using questionnaires for monetary gains and losses (Fuchs, 1980; Khwaja, Silverman, & Sloan, 2007), asking, for example, to choose between receiving $5 today and $10 in a week. Others use proxies for the rate of time preferences (Lawless, Drichoutis, & Nayga Jr, 2013). Huston and Finke (2003) use the level of education, exercise, and the use of nutritional labels as proxies for time preferences to investigate the effect of time preferences on diet choices. Smith, Bogin, and Bishai (2005) use dissaving as a proxy to estimate the effect of time preferences on obesity. Cavaliere, De Marchi, and Banterle (2013) use the consideration of taste vs. nutrition when food shopping as a proxy when investigating obesity. In their investigation of obesity, Zhang and Rashad (2008) use the lack of self-control to lose weight and Ikeda, Kang, and Ohtake (2010) use debt and the degree of procrastinating over homework assignments during school vacations as proxies for time preferences.

These proxies reflect intertemporal choices in which individuals make trade-offs between the present and the future. For example, the consideration of nutrition involves forgoing the present gratification of tasty food to improve future health. Thus, these studies find that impatience is associated with a negative health outcome. For instance, Ikeda et al. (2010), find that an increase in the degree of procrastinating over homework assignments during school vacations is associated with a 2.81% increase in the probability of being obese.

In their investigation of the effect of time preferences on obesity, Borghans and Golsteyn (2006) examine the use of their time preference proxies by determining correlations between the proxies used and elicited discount rates. They conclude that the relationship between obesity and time preferences strongly depends on the choice of proxies. The validation of using proxies to explain the effect of time preferences on health outcomes has not been exhaustively investigated. The objective of this paper is to scrutinize the use and validity of such proxies for time preferences in investigations of health outcomes. This paper's emphasis is on the methodology rather than on policy implications. The results will provide researchers interested in determining the effect of time preferences on health outcomes with guidance on how to measure time preferences, specifically those who use secondary data.

For health outcomes, we focus on obesity. The prevalence of obesity has rapidly increased. Approximately two-thirds of the U.S. adult population are either overweight or obese (U.S. Department of Agricultural, 2016b). In an effort to understand the factors that contribute to obesity, researchers have shown interest in estimating the effect of time preferences on obesity, either by eliciting or using proxies for the rate of time preference. We utilize data from the National Longitudinal Survey of Youth (NLSY79), which is a nationally representative database from the Bureau of Labor Statistics. In 1979, the NLSY79 started interviewing youths between 14-22 years old, and then continued to interview them annually until 1994 and biennially afterward. Before 2006, the NLSY79 provided information that can be used as proxies for time preferences. Our choice of proxies comes from the studies of Cadena and Keys (2015); Courtemanche et al. (2015); DellaVigna and Paserman (2005) that are most recent and use the NLSY79. The investigated proxies are: "The interviewer remarks whether the participant was patient," having a bank account, declaring bankruptcy, maxing out a credit card, smoking, joining vocational clubs in high school, life insurance, and the Armed Forces Qualification Test (AFQT). We term the interviewer remark the "patience" proxy. The AFQT is an IQ test that determines military entrance and was given to the NLSY79 participants. In 2006, the NLSY79 added two hypothetical monetary present-future trade-off questions to its survey. The first question informs the participants about winning $1,000, then asks them to state the additional amount they will accept to receive the prize in a month. The second question is similar except the time horizon is a year rather than a month. The NLSY79 also contains information on body weight and height, enabling us to measure obesity. Given these two elicitation questions as well as information to measure obesity, we compare the elicited rates of time preference to the various proxies to validate the use of proxies in the estimation of the effect of time preferences on obesity.

The standard economic assumption is that people discount the future at a constant rate of time preference, which is characterized by an exponential functional form (Samuelson, 1937). Recent evidence suggests that the rate of time preference is relatively low in the near future and relatively high in the far future, characterized by a quasi-hyperbolic functional form (Laibson, 1997). Because the elicitation questions cover two-time frames, we investigate the hyperbolic discounting rate as an alternative to the constant exponential discount rate, in relation to the proxy measures. We use the concentration indices (CIs). The CIs rank the population by a measure of time preferences and calculate the overall concentration of the cumulative percentage of obesity against the cumulative percentage of the population (Wagstaff, O'Donnell, Van Doorslaer, & Lindelow, 2007). The CIs are superior to OLS because the CIs consider variations in the ranking rather than variations in the time preference measure, so the results are insensitive to outliers or different proxy scaling. The individual will have the same ranking regardless of outliers and different scaling among our proxies, simplifying the validation of our proxies and providing a value judgment to guide practitioners who are interested in using proxies to estimate health outcomes.

The results support the validity of time preference proxies to explain variations in time preference. Ranking the population by different time preference measures indicates the obesity concentration among impatient individuals. Under hyperbolic discounting, the proxies of patience, smoking, life insurance, and joining vocational clubs in high school are validated. In contrast, under the exponential discounting, the proxies of patience, maxing out a credit card, bankruptcy, smoking, life insurance, and joining vocational clubs are also validated. Other proxies overestimate patience by 5% under hyperbolic discounting and by 4% under exponential discounting. We also test the performance of our proxies among demographic subgroups, including males vs. females, highly educated vs. less educated, and white vs. nonwhite individuals to further guide practitioners who are targeting a specific demographic group.

The rest of this essay is divided into five sections. Section 4.2 explains the concept of time preferences and the difference between the exponential and hyperbolic discounting. Section 4.3 presents the data used for the analysis, demonstrating the computation of the rates of time preferences and providing more details for our proxies. Section 4.4 explains the model regarding the use of the CIs to validate time preference proxies. Section 4.5 reports the results, and section 4.6 concludes the discussion.

4.2. Time Preference

The intertemporal choices reflect a trade-off between present gratifications and future well-being. Impulsive behaviors involve a cost of forgoing the present gratification now and receiving the benefit later. For example, dieting involves a cost of forgoing the present gratification of tasty food to generate better health in the future. The rate of time preference measures the ability to delay benefits. In technical terms, let U be the utility. For a finite time T, the discounted utility model is equal to,

$$U = u_t + \delta u_{t+1} + \delta^2 u_{t+2} + \cdots \quad ; t = 0,1,2, \ldots T. \tag{4.1}$$

The standard economic assumption is that the economic agent is rational, discounting the future at a constant rate of time preference, and the exponential functional form characterizes the rate of time preference (Samuelson, 1937),

$$\delta^t = \left(\frac{1}{1+\rho}\right)^t,$$

where δ is the discount factor, ρ is the discount rate, and δ^0=1.

Other studies indicate a conflict between the rate of time preference today and in the future (Laibson, 1997; R. Thaler, 1981). An example from (R. Thaler, 1981) explains such conflict (time inconsistency). Suppose an individual faces two sets of choices, (A) and (B) as follows:

(A)	Choose between:	(A.1)	One apple today.
		(A.2)	Two apples tomorrow.
(B)	Choose between:	(B.1)	One apple in one year.
		(B.2)	Two apples in one year plus one day.

Source: (R. Thaler, 1981)

This individual might choose (A.1) over (A.2) and (B.2) over (B.1). The consistency in time preferences implies that in 364 days, the individual still prefers (B.2) over (B.1). However, preferences reflect time-inconsistency if reconsidering (B.1).

Heath behaviors such as smoking, exercising, and dietary choices might reflect time-inconsistency in discounting. For example, someone prefers exercising in a week over exercising now. A week later, he or she procrastinates maybe to the following week and so on, drawn on the present bias. In this situation, the exponential functional form fails to explain individuals' behaviors. Laibson (1997) suggests that quasi-hyperbolic discounting resonates with the inconsistency in time preference. Hyperbolic discounting means that the individual discounts the near future at a high rate and discounts the far future at a low rate. Shapiro (2005) finds that food stamp program (currently called the Supplemental Nutrition Assistance Program (SNAP)) recipients experience a decline in caloric intake in months in which they receive benefits. Food stamp recipients impatiently increase their caloric intake at the beginning of the month but patiently decrease their caloric intake toward the end of the month. Richards and Hamilton (2012) investigate the effect of time preferences on risk behaviors including obesity and find that hyperbolic discounting provides a better fit of their data. Following Laibson (1997) the discounted utility model is equal to,

$$U = u_t + \beta\delta u_{t+1} + \beta\delta^2 u_{t+2} + \cdots \quad ; t = 0,1,2, \dots T, \tag{4.2}$$

where β is the present bias, $\beta < 1$ implies time-inconsistency, and $\beta = 1$ implies time-consistency in which the discount factor takes the exponential functional form. Nevertheless, The NLSY79 provides two elicitation questions over two time frames. The first-time frame is over a month and the other is over a year. The empirical model uses the hyperbolic discount factor and the constant exponential discount factor in relation to the proxy measures. The following section explains the data used for the analysis, demonstrating the elicitation procedure and the logic for our proxies.

4.3. Data

We use data from the National Longitudinal Survey of Youth (NLSY79), which is a nationally representative database from the Bureau of Labor Statistics. In 1979, NLSY79 interviewed 12,686 youths between 14-22 years. The same individuals were then interviewed annually until 1994 and biennially after 1994. We omit observations with missing information. The final sample consists of 6,094 observations.

Before 2006, the NLSY79 provided information that could be used to proxy for time preferences. However, in 2006, the NLSY79 added two hypothetical present-future trade-off questions to its survey. In the first question, the time horizon is a month. In the second question, the time horizon is a year. The hypothetical monetary questions asked in the NLSY79 are:

> "Suppose you have won a prize of $1000, which you can claim immediately. However, you can choose to wait one month to claim the prize. If you do wait, you will receive more than $1000. What is the smallest amount of money in addition to the $1000 you would have to receive one month from now to convince you to wait rather than claim the prize now?"
>
> "Let me ask the same question but with a one year wait instead of one month. Suppose you have won a prize of $1000, which you can claim immediately. However, you have the alternative of waiting one year to claim the prize. If you do wait, you will receive more than $1000. What is the smallest amount of money in addition to the $1000 you would have to receive one year from now to convince you to wait rather than claim the prize now?"

4.3.1. The Calculation of Discount Factors

We exploit the different time frames of the elicitation questions to compute the constant exponential discount factor and the hyperbolic discount factor (Courtemanche et al., 2015). Let a_1 denote the answer to the first hypothetical monetary question over a month time horizon. The annualized discount factor, DF_1, is

$$DF_1 = \left(\frac{1{,}000}{1{,}000 + a_1}\right)^{12}. \tag{4.3}$$

Let also a_2 denote the answer to the second hypothetical monetary question over a year time horizon. The annualized discount factor, DF_2, is

$$DF_2 = \left(\frac{1{,}000}{1{,}000 + a_2}\right), \tag{4.4}$$

DF_1 is equal to the hyperbolic discount factor, $\beta\delta$ in equation 4.2, and DF_2 is equal to the exponential discount factor, δ in equation 4.1.

4.3.2. Time Preference Proxies

Our choice of proxies comes from Cadena and Keys (2015); Courtemanche et al. (2015); DellaVigna and Paserman (2005). These studies are most recent and use time preference proxies from the NLSY79.[15] Cadena and Keys (2015) estimate the effect of time preference on investments in human capital. Impatient individuals invest less in human capital and earn 13% less over their lifetimes compared to patient individuals (Cadena & Keys, 2015). Cadena and Keys (2015) also find that impatient individuals are less likely to save money and more likely to smoke, excessively drink, attrit the NLSY79 that they had previously agreed to participate in, and exit the military early. DellaVigna and Paserman (2005) use proxies to estimate the effect of time preference on job search by the unemployed. Impatient individuals make fewer efforts searching for a job, exiting unemployment later. Courtemanche et al. (2015) study the interactions of time preferences and food prices and their effects on obesity. Impatient individuals are more

[15] Courtemanche et al. (2015) and Cadena and Keys (2015) provide online supporting material. We use their codes to clean the data and utilize the sample.

responsive to low food prices, which leads to the overconsumption of food and obesity. Courtemanche et al. (2015) find that the elicited discount factors are correlated with other proxies that reflect intertemporal choices. For example, the elicited discount factors are positively correlated with the AFQT and negatively correlated with maxing out a credit card, smoking, and declaring bankruptcy (Courtemanche et al., 2015). Our analysis uses the following proxies:

Patience: After each survey, the interviewer remarks on the general attitude of the survey participant: whether the participant was friendly and interested, cooperative but not particularly interested, impatient and restless, or hostile. We use the interviewer remarks to generate a proxy for time preference that we term “patience.” The patience proxy is equal to 1 if the individual is friendly and interested, and zero if otherwise. The patience proxy also was implemented by DellaVigna and Paserman (2005) and Cadena and Keys (2015). However, our interpretation of patience/impatience differs from that in DellaVigna and Paserman (2005) and Cadena and Keys (2015). We consider “cooperative but not interested” as impatient, whereas DellaVigna and Paserman (2005) and Cadena and Keys (2015) consider them otherwise. The reason is that DellaVigna and Paserman (2005) and Cadena and Keys (2015) were interested in measuring patience/impatience using the interviewer remarks in the period of 1980-1985. At that time, the participants were much younger (15-28 years). However, we are interested in using the interviewer remarks in 2006 when participants are much older (41-49 years old). Younger individuals are more inclined to express their impatience directly, but social norms promote older individuals to be less inclined to do so. As a result, we consider as impatient those whom interviewers identify as cooperative but not particularly interested.

Bank account: A bank account organizes spending in the present and saves money for the future. Patient consumers are more likely to possess a bank account. We use the 1985-2000 and 2004 waves to obtain information on having a bank account. For each year, we create a dummy variable indicating the possession of a bank account and assign participants the average dummies.

Maxing out a credit card: Impatient consumers are more likely to max out a credit card, although doing so raises the interest paid. We use the NLSY79 2004 wave, which asks consumers the total number of maxed out credit cards. This proxy is a dummy variable, which equals 1 if the person had never maxed out a credit card, and zero otherwise.

Bankruptcy: Patience lends itself to better financial management either through controlling impulsive spending, saving, or maintaining the earning source. In contrast, impatience lends itself to worse financial management, increasing the odds of bankruptcy. The NLSY79 asks participants whether they ever have declared bankruptcy. A dummy variable is added, which equals 1 if the individual had never declared bankruptcy, and zero otherwise.

Life insurance: Patient individuals are more likely to work for employers who provide life insurance. We use information from the NLSY79 1979-2004 waves. For each year, we create a dummy variable that indicates obtaining employer-provided life insurance, assigning each participant the average dummies.

Vocational clubs in high school: Patient students are more likely to obtain higher education and less likely to participate in a vocational club in high school. In 1984, the NLSY79 asked participants if they engaged in vocational clubs in high school. Similar to DellaVigna and Paserman (2005), we focus on seven vocational clubs. We create a dummy variable for not participating in each club and then assign each individual the average dummies. The vocational clubs are: The American Industrial Arts Association, Distributive Education Clubs of America, Future Business Leaders of America, Future Farmers of America, Health Occupations Student Association, Office Education Association which is now known as the Business Professionals of America, and Vocations Industrial Club of America (DellaVigna & Paserman, 2005).

Smoking: Given the negative health consequences smoking can cause, patience leads to forgoing the present gratification of cigarettes for future wellbeing. In 1992, 1994, and 1998, the NLSY79 asked participants whether they have smoked at least 100 cigarettes during their lives. We add a dummy variable that indicates if the participant has not smoked 100 cigarettes.

Armed Forces Qualification Test (AFQT): The AFQT is an IQ test that determines military entrance. In 1981, the NLSY79 participants took the AFQT test, regardless of their interest in serving in the military. Those participants who are future-oriented invest in human capital and score higher on the AFQT.

Table 4.1 reports the summary statistics for time preference measures. The average hyperbolic and exponential discount factor equals 0.28 and 0.59, respectively. On average, the hyperbolic discount factor indicates a lower level of patience, whereas the exponential discount factor indicates a higher level. One explanation for the difference between the discount factors is that the present bias, β, is high among hyperbolic discounters. On average, the NLSY79 interviewers remark on 87% of participants as patient. Seventy-five percent of the time, individuals report that they possess a bank account. Ninety-one percent never max out a credit card and 87% have never declared bankruptcy. Roughly 60% of individuals indicate having life insurance that was provided by their employers. Forty-three percent of individuals have not smoked 100 cigarettes in their lives, and 97% never participated in vocational clubs in high school. The average AFQT score equals 51%. Table 4.2 shows the pairwise correlations between time preference measures. The correlation between the exponential discount factor and the hyperbolic discount factor is 0.58. Both discount factors are positively correlated with other proxies, yet they are attenuated, maybe because these proxies are calculated from different waves of the NLSY79 (DellaVigna & Paserman, 2005).

We focus on obesity as the health outcome variable. Obesity is measured by the Body Mass Index (BMI), which is defined as weight in kilograms divided by the square of height in meters (kg/m^2). The obesity threshold is set to 30 (kg/m^2). Expressing the BMI distribution as a dichotomous variable neglects body weight beyond the obesity threshold (Bilger, Kruger, & Finkelstein, 2016), and so we consider body weight beyond the obesity threshold. Let h be the obesity outcome variable,

$$h = \begin{cases} (BMI - s) & if\ BMI \geq s \\ 0 & otherwise \end{cases}, \tag{4.5}$$

where s is the obesity threshold (hereafter, health outcomes are reverse to obesity and vice versa).

The above proxies present patience. The patience level increases in a non-descending order. For example, the bank account proxy consists of fractional values bounded between zero and one. A zero value means perfect impatience, and one means perfect patience. We estimate the predicted values of all proxies as well as the elicited discount factors controlling for age, gender, education, race, occupation, net family income, and risk. For the patience proxy, we also control for the interview length. For occupation, we categorize participants into white collar, blue collar, or service occupations (Courtemanche et al., 2015). For risk, we incorporate the certainty equivalent of a 50/50 chance gamble of winning $10,000 or nothing. Table 4.3 presents a summary of statistics for the individuals' characteristics. The average BMI equals 28, which indicates the high prevalence of obesity. The proportion of individuals who fall beyond the obesity threshold is equal to 29%. The average BMI beyond the obesity threshold equals 1.41 (kg/m^2). During the investigation, participants were middle aged, between 41 and 49 years old, with an average of 45 years old. The sample consists of 53% male, 6% Hispanic, 13% black, 81% white, and 64% married individuals.

Regarding education attainment, the share of high school graduates is 41%, and the share of individuals with some college is 24%. Twenty-eight percent have a college degree or beyond. On average, individuals work 36 hours per week. Fifty-five percent work in white-collar occupations, 23% work in blue-collar occupations, and 10% work in service occupations. The average net household income equals 8.29 (measured in

$10,000). On risk attitude, the certainty equivalent of a 50/50 chance gamble of winning $10,000 or nothing roughly averages $4,800.

Finally, the elicited discount factors as well as the proxies of bank account, vocational clubs, and life insurance proxies, contain fractional values bounded between zero and one. For a fractional dependent variable with extreme values at zero and one, Papke and Wooldridge (1996) suggest the use of a Generalized Linear Model (GLM) with a binomial family and a probit link to provide a better inference. We also estimate the probability of the patience, bankruptcy, smoking, and maxing out credit card proxies using probit models. The predicted values of the AFQT proxy are estimated using OLS.

4.4. Model

To validate the use of time preference proxies in estimating health outcomes, we employ the Concentration Indices (CIs). The CIs are widely used in poverty analysis to measure socioeconomic-health inequality. For example, Makate and Makate (2016) use the CIs to measure socioeconomic inequality in the utilization of maternal healthcare for the Zimbabwean population. Arnold et al. (2016) use the CIs to calculate socioeconomic inequalities in cancer incidence and mortality among 43 countries. Others such as Yiengprugsawan, Lim, Carmichael, Dear, and Sleigh (2010) estimate socioeconomic inequality in morbidity in Thailand, Wagstaff, Van Doorslaer, and Watanabe (2003) measure socioeconomic inequality in malnutrition in Vietnam in 1993 and 1998, Bilger et al. (2016) estimate the socioeconomic inequality in obesity for the U.S. population from 1971-2012, and Lindelow (2006) measures socioeconomic inequality in hospital visits, health center visits, complete immunizations, pregnancy control, and institutional delivery in Mozambique.

The CIs investigate the overall concentration of the cumulative percentage of the health outcome against the cumulative percentage of the population, ranked by a specified standard. Studies that focus on socioeconomic inequality in health rank the population by living standards. For example, they rank the population by poverty income ratio (Bilger et al., 2016), an asset index (Makate & Makate, 2016), monthly adult-equivalent household income (Yiengprugsawan et al., 2010), and an index of human development (Arnold et al., 2016). Because our interest is validating time preference proxies, we rank the population by a measure of time preference instead of a living standard. We rank the population by the hyperbolic discount factor, the exponential discount factor, and the other proxies. A statistically insignificant difference between the CIs based on the elicited discount factors and those based on a certain proxy validates the use of that proxy.

Another method to validate the use of time preference proxies is to use OLS, by separately regressing the health outcome variable on the elicited discount factors and other proxies with controlling for other observed factors. Across equations, we test the differences between the elicited discount factor coefficients and the coefficients of other proxies. Suppose that all time preference measures' coefficients have the expected patterns. Impatience is positively associated with poor health outcomes. A statistically insignificant difference between the elicited discount factor coefficient and a certain proxy coefficient validates the use of the proxy.

However, the CIs method is superior to OLS for two reasons. First, outliers affect the OLS estimates. For example, consider two cases. In the first case, someone has life insurance for 20 years, which is the highest value. In the second case, suppose the same person has life insurance for 6 years, and again this is the highest value. In both cases, the OLS might yield different results. Second, different proxy scaling prevents us from obtaining a value judgment. We assume that the elicited discount factors are the correct time preference measures. If bias between the elicited discount factor and time preference proxies exists, we are only able to determine its direction, but not the magnitude. As an illustration, suppose we run an OLS, and $\hat{\beta}_1$ is the elicited discount factor coefficient. Also, suppose we run another OLS regression of the health outcome on the life insurance proxy, and $\hat{\beta}_2$ is the proxy coefficient. Recall that for the life insurance proxy, we create 20 dummy variables. If bias exists, then the bias equals $\hat{\beta}_1 - \hat{\beta}_2$ when assigning each individual the average dummies and equals $\hat{\beta}_1 - \frac{\hat{\beta}_2}{20}$ when assigning each individual the summation of 20 dummies. Thus, different proxy scaling affects bias magnitude, $\hat{\beta}_1 - \hat{\beta}_2 \neq \hat{\beta}_1 - \frac{\hat{\beta}_2}{20}$.

Our contribution is methodological; we aim at providing practitioners who are interested in using time preference proxies to estimate health outcomes the guidance to do so. The CIs provide a value judgment, so we determine which proxy better explains variations in time preferences and provide practitioners with suggestions on how to adjust for bias when using imperfect proxies. Outliers and different scaling do not affect the CIs. The CIs consider the variations in ranking, not the variations in time preference measures (Wagstaff et al., 2007). It does not matter how we scale our proxies and whether outliers exist in the data; an individual has the same ranking.

The CI is defined as one minus twice the area under the concentration curve (CC) (Lindelow, 2006; Wagstaff et al., 2007; Wagstaff & Watanabe, 2003). The CC plots the cumulative percentage of the health outcome against the cumulative percentage of the population, ranked by a measure of a time preference as appearing in Figures 4.1 and 4.2. The 45-degree line is called the equality line, which indicates the situation when the health outcome is equal for all individuals regardless of their level of patience. If the CC appears above the equality line, the health outcomes are concentrated among the impatient as shown in Figure 4.1. In contrast, if the CC is below the equality line, the health outcomes are concentrated among the patient as shown in Figure 4.2. The CI measures concentration in health outcomes as,

$$CI = 1 - 2\int_0^1 CC(p)dp, \tag{4.6}$$

where CI denotes the concentration index, p is the fractional rank of the population below a specified threshold, and CC is the concentration curve.

For computational ease, the concentration index is equal to the covariance between the health outcome and the fractional rank, scaled by two and divided by the health outcome mean,

$$CI = \frac{2}{\mu_h} cov(h, r), \tag{4.7}$$

where $cov(h, r)$ denotes the covariance between the health variable, h, and the rank of the time preference measure, r. We can use a convenient regression to estimate equation

4.7 after rescaling the health outcome variable by twice the rank variance divided by the mean of the health outcome (Erreygers, Clarke, & Zheng, 2017; Lindelow, 2006; Wagstaff et al., 2007; Wagstaff et al., 2003).

$$\frac{2\sigma_r^2}{\mu_h} h = \alpha + \beta r + \epsilon, \tag{4.8}$$

The CI is equal to $\hat{\beta}$ in equation 4.8. For statistical inference, we use the standard error of $\hat{\beta}$. The CI is equal to $-1 \leq CI \leq 1$. A negative value admits the concentration of health outcome among impatient individuals, but a positive value admits the concentration of health outcomes among patient individuals. A zero CI means no variation in the health outcome.

The CIs can be sensitive to the choice of the ranking measure (Lindelow, 2006; Wagstaff et al., 2007; Wagstaff et al., 2003). Wagstaff and Watanabe (2003) study the CI's sensitivity to the choice of a living standard. Across 19 countries, they measure two outcomes of child malnutrition, being underweight or stunted, ranking the population by consumption and an asset index. For each child malnutrition outcome, at most 6 out of 19 countries show sensitivities to the choice of the living standard, concluding that both living standards generate the same CIs. Lindelow (2006) also uses both consumption and the asset index to measure socioeconomic inequality in four health outcomes. For all four health outcomes, the CIs show sensitivity to the living standard choice, contrasting with the results of Wagstaff and Watanabe (2003).

The CIs sensitivity to the choice of a ranking measure concerns practitioners whose focus is measuring socioeconomics inequality in health. However, we consider the CIs sensitivity to be a real strength in validating the use of time preference proxies in the estimation of health outcomes. Our main assumption is that the elicited discount factors are the correct time preference measures, and so we ask the following question- does a ranking by time preference proxy alter the CIs? To explain the situations when time preference proxy yields the same result as the elicited discount factor, suppose r_e and r_p are the rankings based on the elicited discount factor and time preference proxy, respectively. Also suppose CI_e and CI_p are the two CIs based on different rankings, then we rewrite equation 4.7 as follows,

$$\Delta CI = \frac{2}{\mu_h} cov(h, \Delta r), \tag{4.9}$$

where ΔCI is the difference between the two CIs, $\Delta CI = CI_e - CI_p$ and Δr is the difference between the rankings, $\Delta r = r_e - r_p$. For individuals to have the same ranking on both time preference measures, Δr=0, is a sufficient condition. The necessary condition is that the reranking does not covary with the health outcome even if they have different ranking points. We can use a convenient OLS regression,

$$\frac{2\sigma_{\Delta r}^2}{\mu_h} h = \alpha + \beta_1 \Delta r + \epsilon, \tag{4.10}$$

where $\sigma^2_{\Delta r}$ is the reranking variance. $\hat{\beta}_1$ in equation 4.10 is equal to ΔCI. For a statistical inference, we also use the standard error of $\hat{\beta}_1$. Finally, we use equation 4.8 to estimate the CIs, ranking the population by the elicited hyperbolic discount factor, the elicited exponential discount factor, and other proxies. Assuming that the elicited discount factors are the correct time preference measures, we use equation 4.10 to determine how reranking from the elicited discount factors to time preference proxies affect the CIs.

4.5. Results

Table 4.4 shows the results of validating time preference proxies in the estimation of health outcomes. Column 1 presents the estimates for obesity concentration using equation 4.8. The negative CIs indicate the predicted patterns in which obesity concentrates among impatient individuals. The CIs range from 0.105-0.178 in absolute value, wherein ranking by the patience proxy demonstrates the smallest pro-impatience obesity concentration and ranking by the bank account proxy demonstrates the largest pro-impatience obesity concentration. Given the high prevalence of obesity in which nearly one-third of the population are obese, a CI between 0.105-0.178 is relatively high.

Figure 4.3 plots the CCs based on ranking the population by the elicited discount factors. The dashed line indicates ranking by the hyperbolic discount factor, and the dotted line indicates ranking by the exponential discount factor. The solid line represents the equality line, which indicates the situation when all people have the same body weight. Both CCs appear above the equality line and demonstrate the obesity concentration among impatient individuals. An example of the CCs when ranking the population by the time preference proxies appears in Figure 4.4. The dashed line indicates the CC based on ranking the population by the patience proxy. The CC when ranking by the bank account proxy appears as a dotted line. Ranking by these two proxies demonstrates that obesity concentrates among impatient individuals. The CC of the bank account proxy lies above the CC of the patience proxy, which determines a higher concentration of obesity among impatient individuals.

To validate time preference proxies, we use equation 4.10 to test whether reranking from the elicited discount factors to the other proxies affects the CIs. Column 2 of Table 4.4 presents the differences in the CIs, ΔCI, when reranking from the hyperbolic discount factor to other proxies. Reranking to the proxies of patience, smoking, life insurance, or joining vocational clubs does not affect the CIs. In contrast, reranking from the exponential discount factor to the proxies of patience, maxing out a credit card, bankruptcy, smoking, joining vocational clubs, or life insurance does not affect the CIs appearing in column 3. The similarity between the CIs when reranking from the elicited discount factors to the other proxies validates the use of time preference proxies. Such similarities do not ensure the same ranking on different time preference measures but only suggest that reranking and obesity do not correlate. We strongly suggest employing the proxies of patience, maxing out a credit card, bankruptcy, life insurance, and vocational clubs when assuming exponential time preferences. When assuming hyperbolic time preferences, we strongly suggest employing the proxies of patience, smoking, life insurance, and vocational clubs.

Figure 4.5 presents an example of the difference between two CCs when reranking the population from the hyperbolic discount factor to the patience proxy. The solid line presents the equality line, the dashed-and-dotted line presents the CC when ranking by the hyperbolic discount factor, and the dashed line presents the CC when ranking by the patience proxy. By visual inspection, these two CCs are quite similar. The dotted line presents the CC based on reranking to the patience proxy. Since the two CCs from the hyperbolic discount factor and the patience proxy are quite similar, the reranking CC lies on the equality line for the most part. Figure 4.6 presents an example of the difference between two CCs when reranking the population from the hyperbolic discount factor to the bank account proxy. The dashed-and-dotted line indicates the CC based on the hyperbolic discount factor and the dashed line presents the CC based on the rank of the bank account proxy. The former CC slightly lies below the latter. The dotted line demonstrates the difference in both CCs, which slightly lies above the equality line for some parts.

Other proxies that exert statistically significant differences between the CIs overestimate patience. Under hyperbolic time preferences, the proxies of bank account, maxing out a credit card, bankruptcy, and the AFQT overestimate patience by 6, 5, 4.4, and 5.5%, respectively. Under exponential time preferences, the bank account proxy overestimates patience by 4.1% and the AFQT proxy overestimates patience by 3.6%. When practitioners are interested in using other proxies, we suggest that they should adjust their estimates by 5% (the average bias) against patience under hyperbolic discounting, and by 4% (the average bias) under exponential discounting.

The performance of time preference proxies among males and females is reported in Table 4.5. The first three columns present the results for males. Column 1 indicates that obesity concentrates among impatient men. Column 2 shows the validity of our proxy when reranking from the hyperbolic discount factor. Except for the life insurance proxy, other proxies are also valid when reranking from the exponential discount factor as shown in column 3. Columns 4-6 in Table 4.5 present the validity of time preference proxies to explain variations in time preferences among females. As expected, obesity concentrates among impatient women as shown in column 4. Reranking from the hyperbolic discount factor to the proxies of patience, smoking, life insurance, or vocational clubs has no significant effect on the differences between the CIs as reported in column 5. Column 6 also shows that reranking from the exponential discount factor to the proxies of patience, maxing out a credit card, smoking, life insurance, or vocational clubs does not affect the differences between the CIs.

Proxies that exert significant differences in the CIs when reranking from the elicited discount factors underestimate patience for men but overestimate patience for women. Among men, reranking from the exponential discount factor to the life insurance proxy underestimates patience by at least 6%. For women, reranking from the hyperbolic discount factor to the proxies of bank account, maxing out a credit card, bankruptcy, and the AFQT overestimates patience by 12.1, 5.6, 7.6, and 7.7%, respectively. Under the exponential discounting, reranking to the proxies of bank account, bankruptcy, and the AFQT overestimates patience by 10.5, 5.9, and 6.1%, respectively.

We suggest that practitioners who focus on men should use the proxies of patience, bank account, maxing out a credit card, bankruptcy, smoking, life insurance, the AFQT, and vocational clubs. Other proxies can be used without adjustment needed under hyperbolic discounting, but under exponential discounting, we suggest adjusting estimates by 6% against impatience. If the focus is on women, we suggest using the proxies of patience, smoking, life insurance, and vocational clubs, under hyperbolic discounting. Under exponential discounting, we suggest using the proxies of patience, maxing out a credit card, smoking, life insurance, and vocational clubs. If practitioners want to employ other proxies, we recommend that they should adjust their estimates by 8% against patience under exponential and hyperbolic discounting.

Table 4.6 presents the performance of time preference proxies among the highly educated and less educated groups. We identify highly educated as those with a college degree and beyond and the less educated as those with a high school degree or less. Column 1 presents the CIs for the less educated group. Ranking by the elicited discount factors does not explain obesity concentration. However, ranking by the proxies of bank account, maxing out a credit card, bankruptcy, and the AFQT explain obesity concentration among the impatient. Columns 2 and 3 validate all proxies under hyperbolic and exponential discounting. Column 4 reports the CIs for the highly educated group. Except for the patience proxy, other time preference measures indicate the obesity concentration. Column 5 demonstrates that reranking from the hyperbolic discount factor to the proxies of bank account, maxing out a credit card, bankruptcy, life insurance, or the AFQT does not affect the CIs' differences. Also, reranking from the exponential discount factor to the proxies of bank account, maxing out a credit card, life insurance, or the AFQT does not change the CIs as shown in column 6.

If practitioners target the less educated individuals, all proxies are valid. If targeting the highly educated individuals, we suggest using the proxies of bank account, maxing out a credit card, bankruptcy, life insurance, or the AFQT for hyperbolic discounting. For exponential discounting, we suggest using the proxies of bank account, maxing out a credit card, life insurance, or the AFQT. Other proxies can be used to explain variations in time preferences. Among the less educated individuals, we detect no bias based on the differences between the CIs. Nonetheless, for the highly educated group, proxies that exert significant differences when reranking from the elicited discount factors to other proxies underestimate patience by 10%, on average. Accordingly, we suggest adjusting bias against impatience.

We test the performance of time preference proxies among the white and nonwhite groups as reported in Table 4.7. Column 1 shows the CIs for the nonwhite group. Except for the patience and smoking proxies, other time preference measures have the expected patterns. Obesity is common for the nonwhite impatient individuals. Column 2 shows that reranking from the hyperbolic discount factor to the proxies of bank account, maxing out a credit card, bankruptcy, smoking, life insurance, vocational clubs, or the AFQT exerts no statistically significant differences between the CIs. Reranking from the exponential discounting to the proxies of bankruptcy or vocational clubs also does not change the CIs as shown in column 3. The CIs for the white race are reported in column 4. The negative and statistically significant CIs state the concentration of obesity among the impatient. Reranking from the hyperbolic discount factor validates the patience and life insurance proxies as shown in column 5. Column 6 demonstrates that reranking from the exponential discount factor validates the proxies of patience, maxing out a credit card, life insurance, and vocational clubs.

We suggest that practitioners who target nonwhite individuals should use the proxies of bank account, maxing out a credit card, bankruptcy, smoking, life insurance, vocational clubs, or the AFQT, under hyperbolic discounting. When assuming exponential time preferences, we suggest using the bankruptcy or the vocational clubs proxy. For the white race, we suggest using the patience or life insurance proxy under hyperbolic time preferences and using proxies of patience, maxing out a credit card, life insurance, or vocational clubs under exponential time preferences. Other proxies generate bias, underestimating patience for the nonwhite race, by an average of 8 and 5% under hyperbolic and exponential discounting, respectively. Among the white race, other proxies also generate bias, overestimating patience by 8 and 6% under hyperbolic and exponential discounting, respectively. Accordingly, we suggest fixing bias when using other proxies.

Table 4.8 provides a summary of the validated time preference proxies. However, the above discussion raises the question, why do these proxies explain variations in time preferences? One possible explanation is that current situations either in the financial domain or the health domain lead to the uncertainty about the future, reducing the cost of forgoing future benefits. Over the health domain, being obese, for example, reduces life expectancy and so reduces the cost of forgoing future benefits. As a consequence, obese individuals engage in other impulsive behaviors. We test this theory by changing the obesity threshold from 30 (kg/ m^2) to 25, 35, and 40 (kg/ m^2) and investigate the performance of our time preferences measures as shown in Tables 4.9-11. The premise for testing this theory is that the magnitudes of the CIs and the number of valid proxies increase as the obesity threshold increases. Table 4.12 shows the differences between the magnitude of the CIs and the number of valid proxies for different obesity thresholds. The incremental increases in the CIs and the number of valid proxies as we increase the obesity threshold support our theory that being obese reduces the cost of forgoing future benefit, so individuals engage in other impulsive behaviors.

Over the financial domain, low income is also supposed to reduce the cost of forgoing future benefits. J. K. Binkley and Golub (2011) investigate the choices between healthy and unhealthy types of breakfast cereal, milk, bread, and soft drinks. To control for the possibility that low-income households cannot afford the healthy options, the prices within these products are almost identical. The results show that low-income households choose unhealthy options even if there is no cost incurred to choose the healthy ones (J. K. Binkley & Golub, 2011). This also explains why smoking is common among low-income individuals. Despite a cost incurred to buy cigarettes, low-income individuals think there is nothing to lose in the future in general (J. Binkley, 2010).

Finally, we test whether individuals discount future health outcomes hyperbolically or exponentially. Table 4.13 shows the reranking from the hyperbolic discount factor to the exponential discount factor for different obesity thresholds. At 25 (kg/ m^2) obesity threshold, reranking from the hyperbolic discount factor to the exponential discount factor does not affect the difference between the CIs. At 30, 35, and 40 (kg m^2) obesity thresholds, individuals with hyperbolic time preferences deviate toward patience by 2, 4, and 6%, respectively. In other words, the present bias, β, decreases. The positive and significant difference support hyperbolic discounting, although the increase is minimal. Table 4.14 shows the differences between the hyperbolic and exponential discount factors for males vs. females, highly educated vs. less educated, and nonwhite vs. white. Reranking from the hyperbolic discount factor to the exponential discount factor suggest that males do not deviate, but females deviate toward patience by 2%. Regarding education entitlement, neither group deviates. The results for race show that nonwhite and white consumers deviate toward patience by 3%.

4.6. Conclusion

Risky health behaviors reflect trade-offs between present gratification and future benefits. For example, dieting involves a cost of forgoing tasty food to improve future health. The rate of time preference measures the ability of individuals to delay benefits. Patient individuals delay benefits, whereas impatient individuals do not. Studies that investigate the effect of time preferences on health outcomes either elicit or use proxies for the rate of time preference. The objective of this paper is to validate the use of time preference proxies. For health outcomes, we focus our analysis on obesity. We use data from the National Longitudinal Survey of Youth (NLSY79), which contains information that we use as proxies and two hypothetical monetary elicitation questions. The first question is for a month time horizon, and the second question is for a year time horizon. Exploiting these two time horizons for the elicitation questions, we investigate hyperbolic discounting in addition to the constant exponential discounting. The results validate the use of time preference proxies. Under hyperbolic discounting, we validate the proxies of patience, smoking, life insurance, and joining vocational clubs in high school. In contrast, under the exponential discounting, patience, maxing out a credit card, bankruptcy, smoking, life insurance, and joining vocational clubs are also validated as proxies. Other proxies overestimate patience by 5% under hyperbolic discounting and by 4% under exponential discounting.

Our proxies are calculated from different years on the NLSY79 and are validated to explain the effect of time preferences on current obesity status. This suggests that time preferences might be stable over time (Meier & Sprenger, 2015). Evidence shows that four-year-olds who delay benefits achieved better scholastic performance and better frustration management skills later in life (Mischel, Shoda, & Rodriguez, 1989). The validity of our proxies also indicates that impulsive health-related behaviors might be substitutes, so past smoking explains current obesity, and vice versa (Cawley, 2015). The stability of time preference over time and the substitutability between health-related risk behaviors suggest a policy that oriented people delay benefits, so they can invest more in health rather than quit one risky health behavior such as smoking just to cope with another such as obesity (Cawley, 2015).

An ongoing discussion is whether individuals discount the future exponentially or hyperbolically. The results show that individuals deviate toward patience by 2%, supporting hyperbolic discounting. A two percent deviation is very low, given that the sample consists of individuals in their mid-ages (41-49 years old). There are two types of hyperbolic discounters. The first is a naïve agent who is not aware of the conflict between the rate of time preferences in the near and far future, acting in a way similar to the exponential discounter. The second is a sophisticated agent who is fully aware of the inconsistency in time preferences and who uses commitment devices such as not bringing soda home or shopping more frequently and buying a small amount of food each time (Scharff, 2009). Our analysis cannot determine whether individuals are naïve and need to be educated or sophisticated and need to have better commitment devices. However, this small deviation warrants future research. A limitation of this paper is the focus of obesity as the health outcome with the uncertainty that the applicability of the results extends to other health outcomes. Another limitation is assuming that the elicited discount factors are the correct measures of time preference. These elicited discount factors might be sensitive to the question formats (Lawless et al., 2013). However, validating the use of time preference proxies to explain other health outcomes, as well as validating proxies in relation to elicited discount factors based on different question formats, also warrant future research.

Table 4.1: Summary statistics for time preference measures

Variable	Mean	S.D.
Hyperbolic discount factor (DF1)[a]	0.28	0.34
Exponential discount factor (DF2)[a]	0.59	0.25
Patience[b]	0.87	0.34
Bank account[c]	0.75	0.30
Max credit card[d]	0.91	0.28
Bankruptcy[e]	0.87	0.34
Smoking[f]	0.43	0.50
Life insurance[g]	0.59	0.30
Vocational clubs[a]	0.97	0.07
Armed Forces Qualification Test (AFQT)[h]	51.24	28.91

Observations are weighted using the National Longitudinal Survey of Youth sample weights.

a: N = 6,094
b: N = 5,879
c: N = 6,091
d: N = 5,763
e: N = 5,818
f: N = 6,059
g: N = 6,033
h: N = 5,876

Table 4.2: Correlations between time preference measures

Variables	DF1	DF2
Hyperbolic discount factors (DF1)	---	---
Exponential discount factors (DF2)	0.58***	---
Patience	0.01	0.01
Bank account	0.10***	0.11***
Max credit card	0.06***	0.05***
Bankruptcy	0.00	0.02*
Smoking	0.01	0.03**
Life insurance	0.05***	0.04***
Vocational clubs	0.03**	0.03**
Armed Forces Qualification Test (AFQT)	0.11***	0.13***

*** p<0.01, ** p<0.05, * p<0.1, observations are weighted using the National Longitudinal Survey of Youth sample weights.

Table 4.3: Summary statistics of individuals' characteristics

Variables	Mean	S.D.
Body Mass Index (BMI)	28.04	5.58
Obesity prevalence	0.29	0.46
BMI beyond 30 (kg/m^2)	1.41	3.36
Age (years)	44.86	2.30
Male	0.53	0.50
Hispanic	0.06	0.24
Black	0.13	0.34
White	0.81	0.40
High school degree	0.41	0.49
Some college	0.24	0.42
College graduate and above	0.28	0.45
Married	0.64	0.48
Average working hours per week	35.81	19.56
Net household income ($10,000)	8.29	8.40
White collar occupation	0.55	0.50
Blue collar occupation	0.23	0.42
Service occupation	0.10	0.30
Certainty equivalent	4796.28	3258.23

Observations are weighted using the National Longitudinal Survey for Youth sample weights. N = 6,094

Figure 4.1: The concentration curve for the impatient

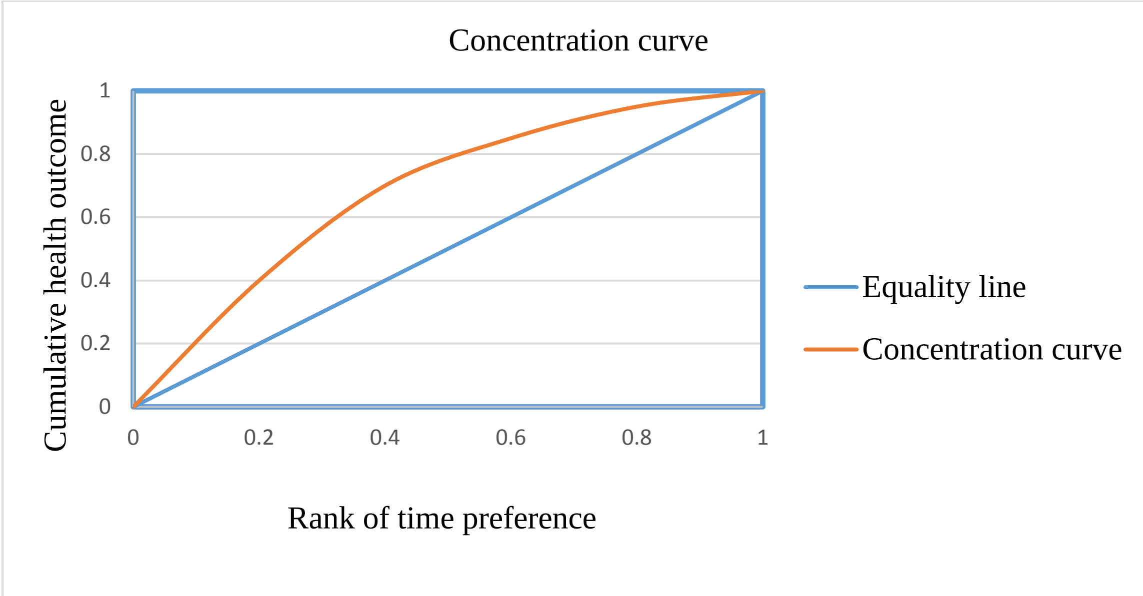

Figure 4.2: The concentration curve for the patient

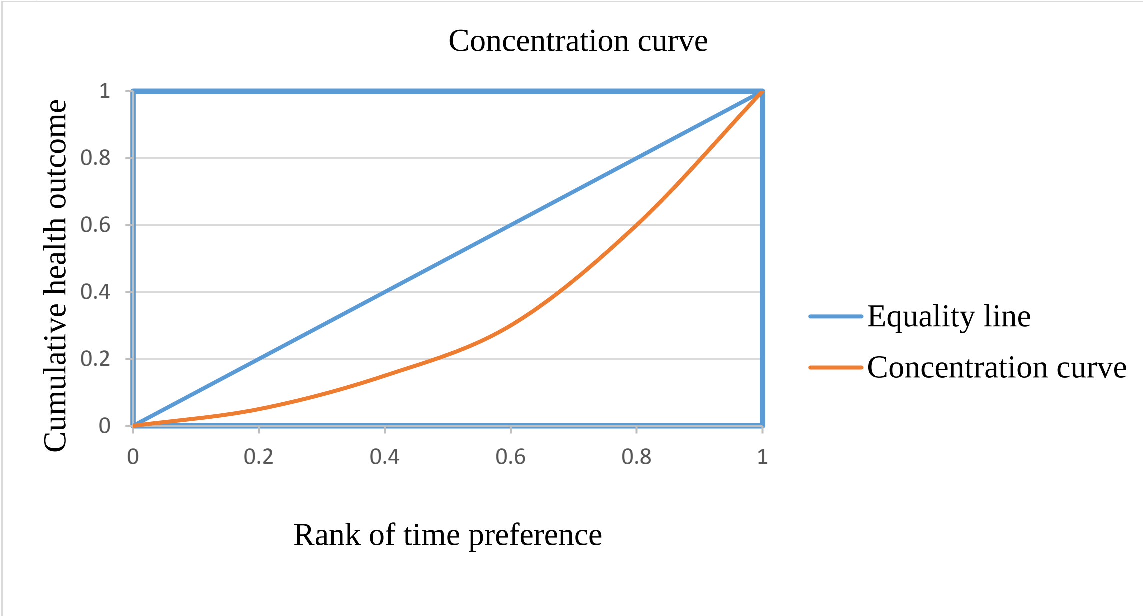

Table 4.4: Validating time preference proxies

Time preference measures	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies
	CI	ΔCI	ΔCI
	(1)	(2)	(3)
Hyperbolic discount factor (DF1)	-0.118***	---	---
	(0.018)		
Exponential discount factor (DF2)	-0.138***	---	---
	(0.017)		
Patience	-0.105***	-0.013	-0.032
	(0.019)	(0.022)	(0.022)
Bank account	-0.178***	0.060***	0.041**
	(0.018)	(0.022)	(0.018)
Max credit card	-0.168***	0.050**	0.031
	(0.018)	(0.021)	(0.019)
Bankruptcy	-0.162***	0.044*	0.025
	(0.019)	(0.024)	(0.020)
Smoking	-0.107***	-0.012	-0.031
	(0.020)	(0.025)	(0.021)
Life insurance	-0.106***	-0.012	-0.031
	(0.020)	(0.026)	(0.022)
Vocational clubs	-0.114***	-0.005	-0.024
	(0.019)	(0.030)	(0.030)
Armed Forces Qualification Test (AFQT)	-0.174***	0.055***	0.036**
	(0.018)	(0.021)	(0.017)

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$
N = 6,094

Figure 4.3: The concentration curves based on ranking the population by the hyperbolic and exponential discount factors

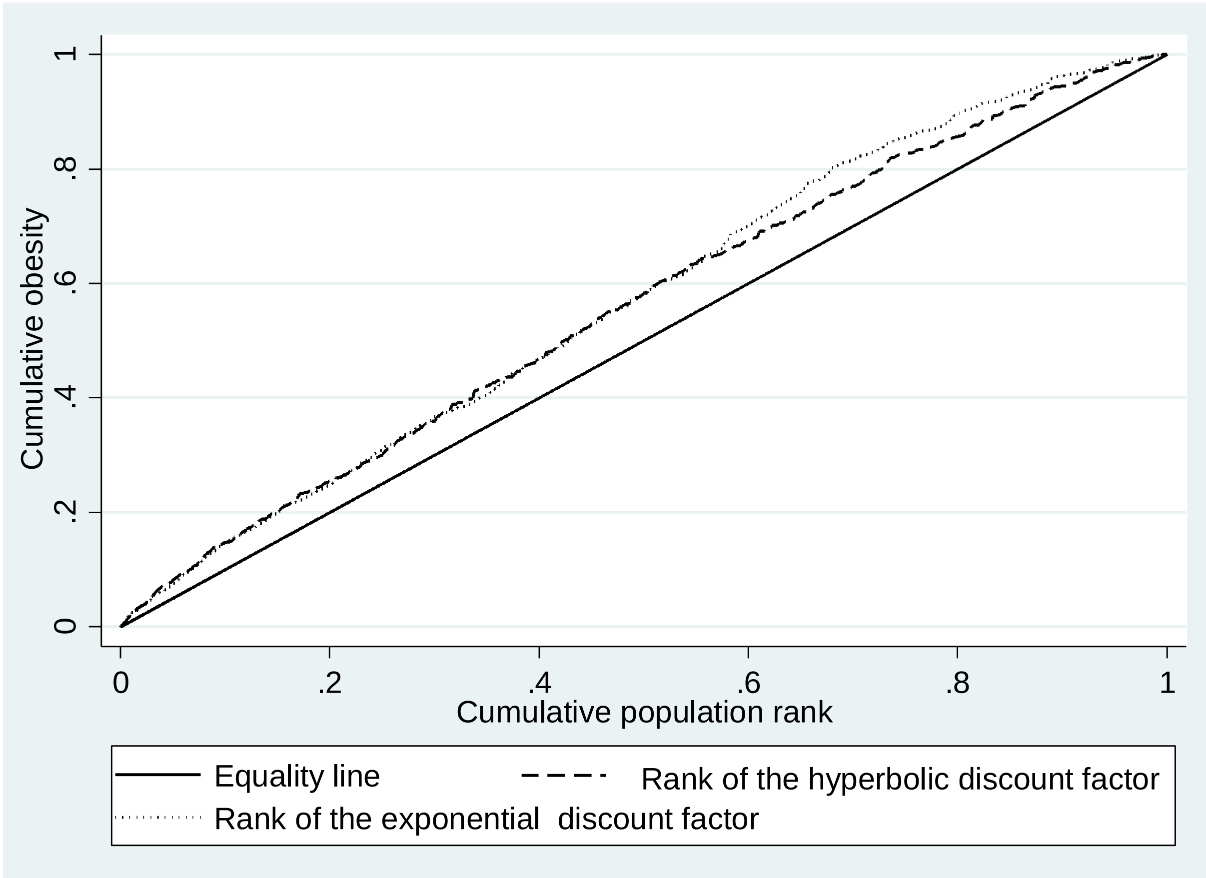

Figure 4.4: The concentration curves based on ranking the population by the patience and bank account proxies

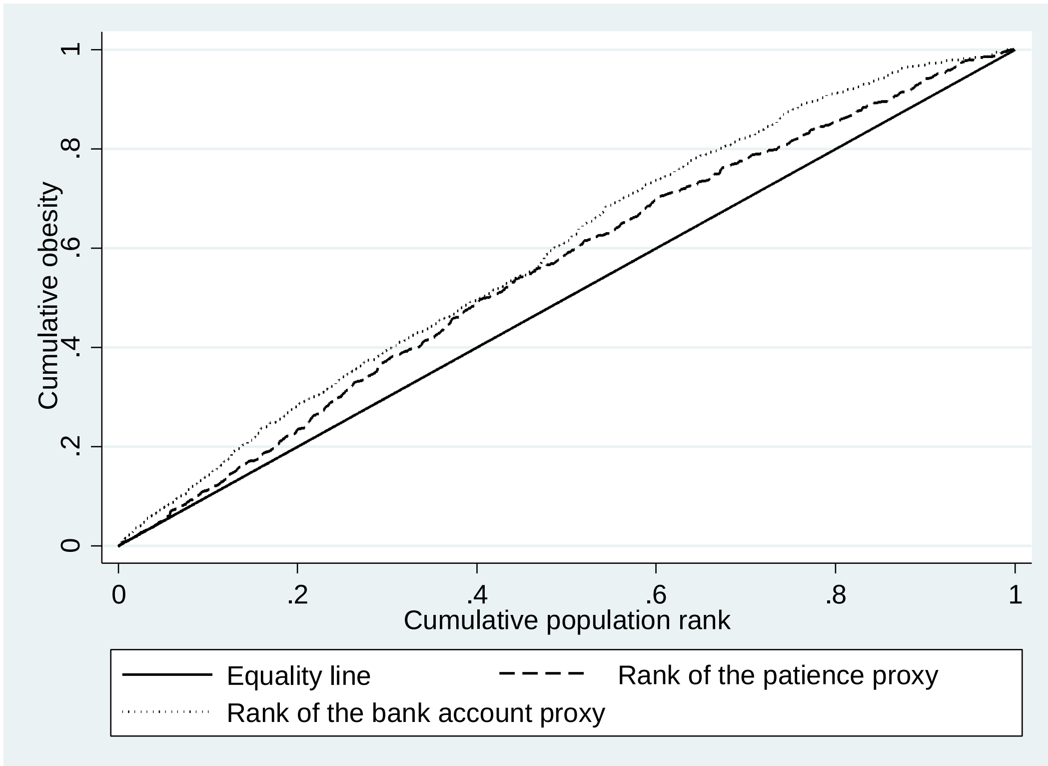

Figure 4.5: The difference in the concentration curves based on reranking the population from the hyperbolic discount factor to the patience proxy

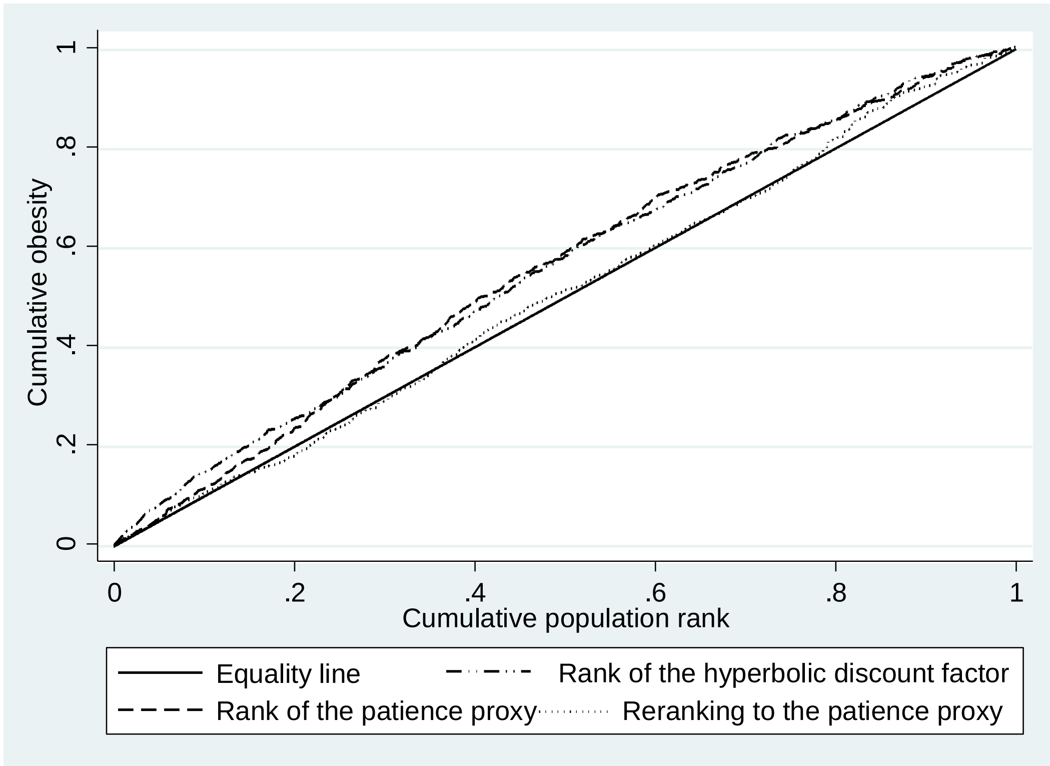

Figure 4.6: The difference in the concentration curves based on reranking the population from the hyperbolic discount factor to the bank proxy

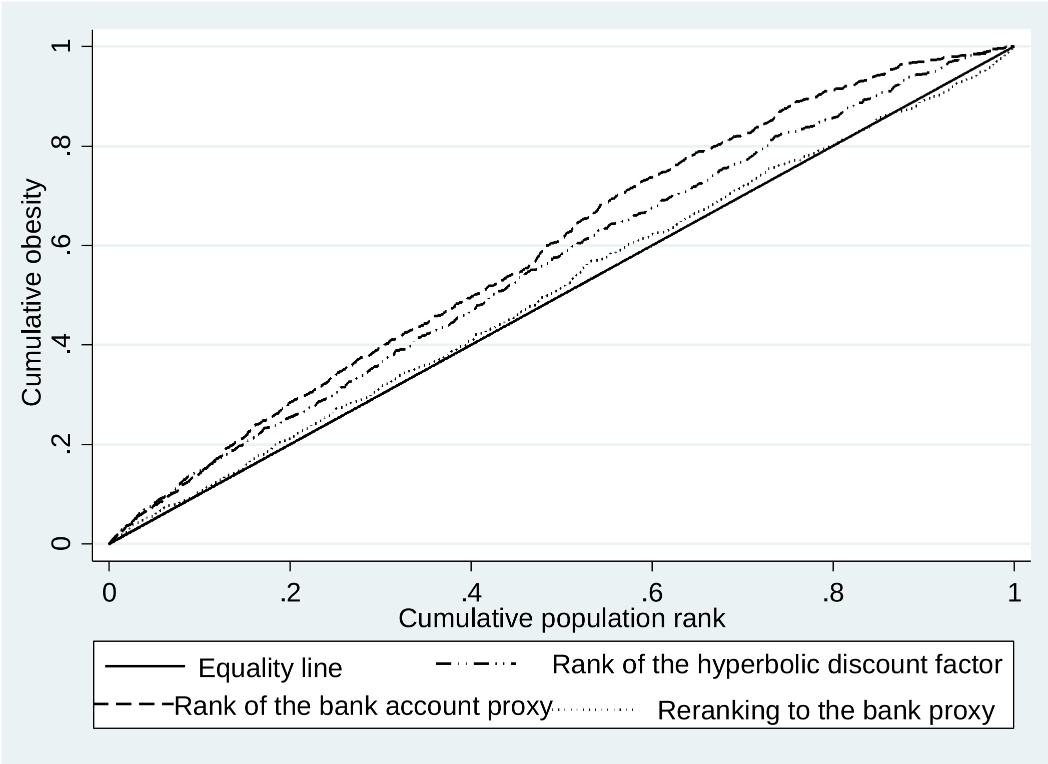

Table 4.5: Validating time preference proxies among males and females

Time preference measures	Male[a]			Female[b]		
	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies
	CI	ΔCI	ΔCI	CI	ΔCI	ΔCI
	(1)	(2)	(3)	(4)	(5)	(6)
Hyperbolic discount factor (DF1)	-0.112***	---	---	-0.117***	---	---
	(0.024)			(0.025)		
Exponential discount factor (DF2)	-0.115***	---	---	-0.133***	---	---
	(0.022)			(0.023)		
Patience	-0.114***	0.002	-0.000	-0.158***	0.041	0.025
	(0.022)	(0.027)	(0.023)	(0.024)	(0.030)	(0.026)
Bank account	-0.114***	0.002	-0.001	-0.238***	0.121***	0.105***
	(0.025)	(0.031)	(0.024)	(0.025)	(0.031)	(0.027)
Max credit card	-0.114***	0.003	-0.000	-0.173***	0.056**	0.040
	(0.023)	(0.030)	(0.028)	(0.023)	(0.026)	(0.025)
Bankruptcy	-0.108***	-0.004	-0.007	-0.192***	0.076**	0.059**
	(0.026)	(0.036)	(0.029)	(0.026)	(0.032)	(0.027)
Smoking	-0.109***	-0.002	-0.005	-0.106***	-0.011	-0.027
	(0.028)	(0.033)	(0.027)	(0.028)	(0.036)	(0.031)
Life insurance	-0.058**	-0.053	-0.056**	-0.131***	0.014	-0.002
	(0.028)	(0.034)	(0.028)	(0.026)	(0.036)	(0.032)
Vocational clubs	-0.128***	0.016	0.013	-0.096***	-0.021	-0.037
	(0.028)	(0.033)	(0.028)	(0.027)	(0.028)	(0.025)
Armed Forces Qualification Test (AFQT)	-0.144***	0.032	0.029	-0.194***	0.077***	0.061**
	(0.025)	(0.031)	(0.025)	(0.026)	(0.028)	(0.024)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
a: N = 3,059
b: N = 3,035

Table 4.6: Validating time preference proxies among highly and less educated

Time preference measures	Less educated[a]			Highly educated[b]		
	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies
	CI	ΔCI	ΔCI	CI	ΔCI	ΔCI
	(1)	(2)	(3)	(4)	(5)	(6)
Hyperbolic discount factor (DF1)	-0.024	---	---	-0.141***	---	---
	(0.023)			(0.036)		
Exponential discount factor (DF2)	-0.031	---	---	-0.160***	---	---
	(0.021)			(0.034)		
Patience	-0.029	0.005	-0.002	-0.028	-0.114***	-0.132***
	(0.022)	(0.031)	(0.030)	(0.027)	(0.043)	(0.044)
Bank account	-0.050***	0.026	0.020	-0.176***	0.035	0.016
	(0.019)	(0.030)	(0.024)	(0.031)	(0.046)	(0.038)
Max credit card	-0.071***	0.047	0.041	-0.158***	0.017	-0.002
	(0.023)	(0.030)	(0.027)	(0.029)	(0.039)	(0.032)
Bankruptcy	-0.056***	0.032	0.026	-0.089***	-0.053	-0.071**
	(0.021)	(0.034)	(0.028)	(0.018)	(0.038)	(0.030)
Smoking	0.003	-0.028	-0.034	-0.065***	-0.077*	-0.096**
	(0.018)	(0.032)	(0.027)	(0.025)	(0.045)	(0.037)
Life insurance	-0.010	-0.015	-0.021	-0.127***	-0.015	-0.034
	(0.023)	(0.034)	(0.028)	(0.045)	(0.063)	(0.053)
Vocational clubs	0.013	-0.038	-0.044	-0.045**	-0.096***	-0.115***
	(0.022)	(0.029)	(0.027)	(0.017)	(0.036)	(0.031)
Armed Forces Qualification Test (AFQT)	-0.046***	0.022	0.016	-0.116***	-0.025	-0.044
	(0.014)	(0.027)	(0.021)	(0.017)	(0.036)	(0.029)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

a: N = 3,059

b: N = 3,194

Table 4.7: Validating time preference proxies among white and nonwhite

Time preference measures	Nonwhite[a]			White[b]		
	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies
	CI	ΔCI	ΔCI	CI	ΔCI	ΔCI
	(1)	(2)	(3)	(4)	(5)	(6)
Hyperbolic discount factor (DF1)	-0.057*** (0.013)	---	---	-0.054** (0.022)	---	---
Exponential discount factor (DF2)	-0.088*** (0.016)	---	---	-0.084*** (0.021)	---	---
Patience	0.025 (0.019)	-0.082*** (0.022)	-0.113*** (0.023)	-0.091*** (0.026)	0.036 (0.029)	0.006 (0.029)
Bank account	-0.049*** (0.013)	-0.008 (0.016)	-0.039** (0.016)	-0.142*** (0.024)	0.088*** (0.030)	0.058** (0.024)
Max credit card	-0.057*** (0.011)	0.000 (0.017)	-0.031* (0.017)	-0.112*** (0.022)	0.058** (0.029)	0.028 (0.026)
Bankruptcy	-0.090*** (0.020)	0.033 (0.021)	0.002 (0.020)	-0.159*** (0.026)	0.105*** (0.032)	0.075*** (0.026)
Smoking	-0.029 (0.021)	-0.028 (0.022)	-0.059*** (0.021)	-0.151*** (0.026)	0.097*** (0.029)	0.067*** (0.025)
Life insurance	-0.046** (0.022)	-0.011 (0.023)	-0.042* (0.023)	-0.104*** (0.026)	0.050 (0.033)	0.020 (0.028)
Vocational clubs	-0.058*** (0.020)	0.001 (0.020)	-0.030 (0.020)	-0.112*** (0.026)	0.057** (0.027)	0.027 (0.025)
Armed Forces Qualification Test (AFQT)	-0.043*** (0.013)	-0.014 (0.016)	-0.045*** (0.016)	-0.132*** (0.024)	0.077*** (0.029)	0.047** (0.024)

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

a: N = 2,966

b: N = 3,128

Table 4.8: A summary of the validated time preference proxies

Time preference proxies	Discounting	All	Male	Female	Less educated	Highly educated	Nonwhite	White
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patience	Hyperbolic	Yes	Yes	Yes	Yes	No	No	Yes
	Exponential	Yes	Yes	Yes	Yes	No	No	Yes
Bank account	Hyperbolic	No	Yes	No	Yes	Yes	Yes	No
	Exponential	No	Yes	No	Yes	Yes	No	No
Max credit card	Hyperbolic	No	Yes	No	Yes	Yes	Yes	No
	Exponential	Yes	Yes	Yes	Yes	Yes	No	Yes
Bankruptcy	Hyperbolic	No	Yes	No	Yes	Yes	Yes	No
	Exponential	Yes	Yes	No	Yes	No	Yes	No
Smoking	Hyperbolic	Yes	Yes	Yes	Yes	No	Yes	No
	Exponential	Yes	Yes	Yes	Yes	No	No	No
Life insurance	Hyperbolic	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Exponential	Yes	No	Yes	Yes	Yes	No	Yes
Vocational clubs	Hyperbolic	Yes	Yes	Yes	Yes	No	Yes	No
	Exponential	Yes	Yes	Yes	Yes	No	Yes	Yes
Armed Forces Qualification Test	Hyperbolic	No	Yes	No	Yes	Yes	Yes	No
(AFQT)	Exponential	No	Yes	No	Yes	Yes	No	No

Table 4.9: Validating time preference proxies setting the obesity threshold equal to 25 (kg/m^2)

Time preference measures	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies
	CI	ΔCI	ΔCI
	(1)	(2)	(3)
Hyperbolic discount factor (DF1)	-0.074***	---	---
	(0.010)		
Exponential discount factor (DF2)	-0.075***	---	---
	(0.009)		
Patience	-0.090***	0.016	0.014
	(0.010)	(0.012)	(0.012)
Bank account	-0.110***	0.036***	0.034***
	(0.010)	(0.011)	(0.010)
Max credit card	-0.099***	0.025**	0.024**
	(0.010)	(0.012)	(0.011)
Bankruptcy	-0.096***	0.022*	0.021*
	(0.010)	(0.013)	(0.011)
Smoking	-0.063***	-0.011	-0.013
	(0.011)	(0.013)	(0.011)
Life insurance	-0.052***	-0.022*	-0.024**
	(0.011)	(0.013)	(0.011)
Vocational clubs	-0.081***	0.007	0.005
	(0.010)	(0.011)	(0.010)
Armed Forces Qualification Test (AFQT)	-0.109***	0.036***	0.034***
	(0.010)	(0.011)	(0.009)

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$
N = 6,094

Table 4.10: Validating time preference proxies setting the obesity threshold equal to 35 (kg/m^2)

Time preference measures	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies
	CI	ΔCI	ΔCI
	(1)	(2)	(3)
Hyperbolic discount factor (DF1)	-0.147***	---	---
	(0.029)		
Exponential discount factor (DF2)	-0.185***	---	---
	(0.027)		
Patience	-0.141***	-0.006	-0.044
	(0.034)	(0.039)	(0.037)
Bank account	-0.237***	0.090**	0.052*
	(0.032)	(0.040)	(0.031)
Max credit card	-0.182***	0.035	-0.003
	(0.031)	(0.037)	(0.031)
Bankruptcy	-0.192***	0.045	0.007
	(0.034)	(0.043)	(0.034)
Smoking	-0.153***	0.005	-0.032
	(0.035)	(0.045)	(0.038)
Life insurance	-0.162***	0.015	-0.022
	(0.035)	(0.046)	(0.038)
Vocational clubs	-0.113***	-0.034	-0.071**
	(0.033)	(0.037)	(0.033)
Armed Forces Qualification Test (AFQT)	-0.219***	0.072*	0.034
	(0.032)	(0.038)	(0.030)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
N = 6,094

Table 4.11: Validating time preference proxies setting the obesity threshold equal to 40 (kg/m^2)

Time preference measures	Obesity	Reranking from DF1 to other proxies	Reranking from DF2 to other proxies
	CI	ΔCI	ΔCI
	(1)	(2)	(3)
Hyperbolic discount factor (DF1)	-0.155*** (0.045)	---	---
Exponential discount factor (DF2)	-0.216*** (0.042)	---	---
Patience	-0.172*** (0.057)	0.016 (0.064)	-0.044 (0.059)
Bank account	-0.296*** (0.054)	0.140** (0.068)	0.080 (0.052)
Max credit card	-0.179*** (0.052)	0.024 (0.062)	-0.036 (0.050)
Bankruptcy	-0.210*** (0.057)	0.054 (0.073)	-0.006 (0.055)
Smoking	-0.208*** (0.061)	0.053 (0.077)	-0.008 (0.063)
Life insurance	-0.230*** (0.061)	0.074 (0.078)	0.014 (0.065)
Vocational clubs	-0.068 (0.054)	-0.088 (0.062)	-0.148*** (0.054)
Armed Forces Qualification Test (AFQT)	-0.254*** (0.055)	0.099 (0.064)	0.039 (0.049)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
N = 6,094

Table 4.12: The magnitude of the CIs and the number of valid proxies for different obesity thresholds

Obesity threshold	Concentration Index		The number of valid proxies	
	Maximum	Minimum	Hyperbolic	Exponential
	(1)	(2)	(3)	(4)
25 (kg/m^2) obesity threshold	-0.052	-0.109	3	3
30 (kg/m^2) obesity threshold	-0.105	-0.178	4	6
35 (kg/m^2) obesity threshold	-0.113	-0.219	6	6
40 (kg/m^2) obesity threshold	-0.155	-0.296	7	7

Table 4.13: Hyperbolic time preferences vs. exponential time preferences

Obesity threshold	Reranking from the hyperbolic to the exponential discount factor
	ΔCI
25 (kg/m^2) obesity threshold	0.002 (0.004)
30 (kg/m^2) obesity threshold	0.019** (0.008)
35 (kg/m^2) obesity threshold	0.038*** (0.014)
40 (kg/m^2) obesity threshold	0.060** (0.025)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
N = 6,094

Table 4.14: Hyperbolic time preferences vs. exponential time preferences for different groups

Obesity threshold	Reranking from the hyperbolic to the exponential discount factor
	ΔCI
Male[a]	0.003 (0.012)
Female[b]	0.016** (0.008)
Less educated[c]	0.006 (0.011)
Highly educated[d]	0.019 (0.017)
Nonwhite[e]	0.031*** (0.006)
White[f]	0.030*** (0.010)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
a: N = 3,059
b: N = 3,035
c: N = 3,059
d: N = 3,194
e: N = 2,966
f: N = 3,128

Chapter 5: Conclusion

This dissertation discusses three essays in food consumption and health-related issues. The first essay discusses Food-Away-From-Home (FAFH) consumption. We hypothesize that consumers compensate for the high caloric intake typically associated with FAFH by changing their behaviors during other meals. We use data from the 2009-10 National Health and Nutrition Examination Survey (NHANES). The NHANES provides information on food intake for two nonconsecutive days. On day one, consumers were personally interviewed, and on day two consumers were interviewed by phone. The NHANES asked consumers about their beliefs regarding FAFH, which allows us to elaborate on the cognitive aspects of the compensating behavior. There is a consensus among consumers that FAFH is less nutritious than food cooked at home. Despite this, consumers still demand FAFH for other reasons like price, convenience, or socializing. We use the theory of cognitive dissonance to explain how this inconsistency of consumers' beliefs and actions creates a state of cognitive dissonance. To resolve dissonance, consumers compensate for FAFH by changing their behaviors during other meals in the day.

We limit the analysis to individuals for whom we obtained information about beliefs and exploit the panel nature of the NHANES, employing a fixed effect estimator to control for unobserved heterogeneity. Failure to control for unobserved heterogeneity results in a downward bias for the compensatory behavior. The results show that consumers ingest more calories away from home than they do at home but compensate for the excessive caloric intake from FAFH during other meals.

We also run two tests for the robustness of the consistency of our results with the theory of cognitive dissonance. First, FAFH is high in addictive food components, sugar, salt, fat, and carbohydrates. If addiction prevents the compensating behavior, the results are inconsistent with the theory of cognitive dissonance. The analysis states the compensating behavior for the high amount of sugar, salt, fat, and carbohydrates from FAFH. Second, we perform a placebo test to estimate the effect of plain water on energy consumption. It is implausible to expect drinking water to create a conflict between beliefs and action like FAFH. The results for plain water are statistically insignificant. Overall, these two tests provide evidence of the consistency of our results with the theory of cognitive dissonance.

Essay II discusses the mindless and the mindfulness of secondary eating. Secondary eating is that which occurs while doing other activities like driving or watching TV. When someone engages in secondary eating, he or she might overeat and gain weight. Essay II tests the effect of secondary eating on obesity. We identify situations when secondary eating is positively related to obesity (mindless secondary eating) and cases where secondary eating is negatively related to obesity (mindful secondary eating). We hypothesize that lifestyle moderates the effect of secondary eating on obesity.

We use data from the American Time Use Survey (ATUS). A subsample of the Current Population Survey (CPS) was randomly selected to provide diaries for 24 hours. The Eating and Health Module contains information on secondary eating. The results show that spending more time doing sedentary activities that require lying and sitting increases the odds of mindless secondary eating. Furthermore, eating while doing highly sedentary activities that mostly involves lying or sitting increases the chances for mindless secondary eating as opposed to eating while doing less sedentary activities that require some movements.

Essay III validates the use of time preference proxies to estimate the effect of time preferences on health outcomes. To determine the effect of time preferences on health outcomes, researchers either elicit the rate of time preference or use proxies. This paper determines if variations in elicited discount rates correspond to variations in time preference proxies in the estimation of health outcomes. For health outcome, we focus our analysis on obesity. We utilize data from the National Longitudinal Survey of Youth (NLSY79), which provides information that can be used as proxies as well as two elicitation questions. The first elicitation question is over a month horizon, and the second is over a year horizon. We exploit the differences over time for the elicitation questions to validate proxies under the fixed exponential discounting and hyperbolic discounting. The results confirm the use of time preference proxies in the estimation of health outcomes. Under hyperbolic discounting, we validate the proxies of patience, smoking, life insurance, and joining vocational clubs in high school. Under exponential discounting, we also validate the proxies of patience, maxing out a credit card, bankruptcy, smoking, life insurance, and joining vocational clubs. Other proxies overestimate patience by 5% under hyperbolic discounting and by 4% under exponential discounting.

To reduce obesity, consumers must balance between energy consumption and expenditure. Eating FAFH does not entail a poor diet and obesity, and eating at home does not automatically assure a better diet and healthy weight. Similarly, it is of less importance whether eating is the primary or secondary task when consumers maintain a balanced diet. A balanced diet reflects the willpower to forgo present gratifications for future benefits. Understanding why consumers lack such willpower is essential to help people balance between energy consumption and expenditure. For example, if the present bias is relatively high, consumers might engage in some commitment devices, such as keeping healthy options at home to assure the compensating behavior for FAFH or preparing a limited amount of food to reduce any possibility of overeating when eating occurs while doing other activities. Finally, future research should consider the interdependence of FAFH, secondary eating, and time preferences in the examination of obesity causes. Since people eat several meals throughout the day, the rate of time preference might change from one meal to another, so they might overeat when the present bias is high and compensate when the present bias is low. The availability of FAFH may contribute to the increased time of mindless secondary eating. Perhaps, time preferences determine lifestyle as well as the effect of secondary eating on obesity.

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Vita

Fuad Mohammed Alagsam

Education

- Ph.D. in Agricultural Economics, University of Kentucky, United States, Expected August 2017
- M.S. in applied economics, Washington State University, United States, 2011
- B.S. in Agricultural Economics, King Saud University, Saudi Arabia, 2006

Work Experience

- Lecturer, Department of Agricultural Economics, King Saud University, 2012 (on leave for Ph.D. studies at the University of Kentucky).
- Teaching Assistant, Department of Agricultural Economics, King Saud University, 2007

Grants

- A scholarship for graduate studies from King Saud University, 2008
- A travel fund ($325) to Boston, MA, from the Graduate School at the University of Kentucky, 2016

Presentations

- "Unintended Consequences of Reading Nutrition Labels." The 2017 Southern Agricultural Economics Association, Mobile, Alabama
- "The Ability to Eat Food-Away-From-Home and Still Eat Healthy." 2016. A departmental seminar in the Department of Agricultural Economics at the University of Kentucky
- "The Mindlessness and Mindfulness of Secondary Eating." The 2016 Annual Meeting of the Agricultural and Applied Economics Association, Boston, Massachusetts
- "Validating the Use of Time Preference Proxies to Explain Effects on Health Outcomes." The 2016 Annual Meeting of the Agricultural and Applied Economics Association, Boston, Massachusetts

Service

- The graduate students' representative to the Graduate Program and Research Committee in the Department of Agricultural Economics at the University of Kentucky, Spring 2016-Spring 2017