THREE ESSAYS ON THE IMPACTS OF PUBLIC POLICY
ON BEHAVIORAL HEALTH

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THREE ESSAYS ON THE IMPACTS OF PUBLIC POLICY

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This dissertation examines the impacts of public policies on the behavioral health of adults in the United States. The first essay entitled, "The Impact of Food Advertisements on Changing Eating Behaviors: An Experimental Study", examines how three types of food advertising (healthy food, unhealthy food, and anti-obesity) impact consumers' caloric and nutrient content selected in a lunch menu. The analysis is based on an economic experiment conducted with 186 adult non-undergraduate student subjects, each of which were randomly placed into either the control group or one of four treatments: (1) healthy food advertising, (2) anti-obesity advertising, (3) unhealthy food advertising, and (4) mixed (all three food) advertising. The results indicate that healthy, anti-obesity, and mixed food advertising reduced intakes of total calories, fat, sodium, and carbohydrates. Similarly, anti-obesity, healthy, and mixed food advertising results in increasing the probability of selecting more healthy items and fewer unhealthy items from a menu. Healthy food advertising has a stronger impact than anti-obesity or mixed food advertising.

The second paper, "Food Stamps, Food Insufficiency and Health of the Elderly", evaluates the efficacy of the Food Stamp Program (FSP) on improving the well-being of elderly Americans. The overarching objective of this study is to

determine whether and how elderly health status is affected by FSP participation, food insufficiency and other determinants. To carry out this goal, first a theoretical framework is developed to ascertain why so few eligible elderly households participate in the FSP, and how food intake affects health status. In addition, the model examines the main determinants of food insufficiency and how FSP participation and food insufficiency are linked to each other and then to health status. The data utilized in this study are a subset of the Health and Retirement Survey (HRS) from the year 2002. State-specific FSP criteria are used to determine the eligibility of elderly households in the sample. The method used to examine these linkages is a two-step econometric model with two instrumental variables for the endogeneity of food stamp program participation and food insufficiency. In the first step, a simultaneous multivariate Probit model of endogenous FSP participation and food insufficiency equations is estimated. Based on these results, probabilities of FSP participation and food insufficiency are predicted in Step One for use in Step Two. In Step Two, an Ordered Probit of health status is estimated as a function of the predicted FSP participation and predicted food insecurity, controlling for other determinants of health status. The estimating procedure extends the Murphy and Topel's (1985) standard error correction method to the case of two predicted explanatory variables. After correcting the standard errors, some coefficients lose their significance indicating the importance of the standard error correction procedure. Specifically, without the correction, FSP participation is found to worsen food insufficiency, but this relationship becomes insignificant after the correction. Conversely, being food insufficient significantly worsen health status with and without the correction procedure. The results suggest that FSP net benefits, though increasing food purchasing power, are inadequate to help elderly to achieve the minimum threshold of food intake that could significantly improve health status.

The third paper, “The relationship between Unemployment and Obesity: Evidence from NLSY 97 Survey Data”, investigates simultaneous relationship between unemployment and obesity in the U.S. The unemployment and obesity probit equations are estimated simultaneously using an instrumental variables approach to deal with the problem of endogeneity. The mother’s BMI and unemployment insurance are instrumented for obesity and unemployment, respectively. The results reveal unemployment significantly increases the likelihood of obesity, but not vice versa. This significant finding raises concerns on potential obesity-related health problems on unemployed individuals for policy makers. Although the results found no statistical evidence of weight discrimination, it is inconclusive that normal or underweight individuals would decrease their risks of unemployment due to no statistical difference in the probability of unemployment between obese and non-obese individuals.

BIOGRAPHICAL SKETCH

Pimbucha Rusmevichientong was born in Bangkok, Thailand and received her Bachelor's degree in Economics from Chulalongkorn University in 2005. She received Royal Thai Government Scholarship and completed her Master's degree in Agricultural Economics at Cornell University in 2007. After graduation, she returned to her post in Cooperative Promotion Department, Ministry of Agriculture and Cooperatives in Thailand where she was legally obliged to work. She was back to Cornell University in the pursuit of PhD in 2011.

To my family and friends

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CHAPTER 1

INTRODUCTION

Nearly half of all deaths occurring annually are the result of modifiable behavioral risk factors (McGinnis, 1992). These risk factors include uncontrolled hypertension and diabetes, smoking, physical inactivity, poor diet, alcohol abuse, violence, and risky sexual behavior (USDA and HHS, 2010, 2008). *Poor diet* contributes to many serious and costly health conditions. *Poor diet* includes under- or over-eating, lack of essential nutrients intake causing a prolonged nutritional deficiencies and *food insufficiency*, or consuming food and drink, which are high-energy dense i.e. fat, sugar and low nutrients i.e. fiber, vitamins, protein leading to *obesity*.

1.1 Economic Cost and Health Consequences of Obesity

Obesity results from a combination of causes and contributing factors, including individual factors such as behaviors and genetics. It has been increasingly cited as a serious health issue in recent decades in the U.S. because more than one-third (34.9% or 78.6 million) of U.S. adults in 2011-2012 were obese (Cynthia et al., 2014) and being obese puts one at risk for many physical health problems such as heart disease, stroke, type 2 diabetes and certain types of cancer. It may also trigger some mental or behavioral health[1] such as depression, eating disorders, distorted body

[1] Behavioral Health is a branch of interdisciplinary health, which focuses on the reciprocal relationship between the holistic view of human behavior and the well-being of the body as a whole entity. Behavioral health can have different outcomes by changing “behavior”. Behavioral health promotes the well being of individuals by intervening and preventing incidents of mental illness, substance abuse, or other entities in health (medanth.wikispaces).

image, and low self-esteem. Obesity costs society an estimated $117 billion in direct (preventive, diagnostic, and treatment services related to weight) and indirect (absenteeism, unemployment, loss of future earnings due to premature death) costs (Wolf, 2002). This exceeds health-care costs associated with smoking or problem drinking (Finkelstein et al., 2003) and accounts for 6% to 12% of all national health care expenditures in the United States in 2000 (Thompson et al., 2001). The economic cost of obesity to businesses in the United States is more than $12 billion per annum (Thompson et al., 1998). Obesity-related job absenteeism costs $4.3 billion annually (Cawley et al., 2007). Obesity is associated with lower work productivity (presenteeism), which costs employers $506 per obese worker per year (Gate et al., 2008). Many studies have found an association between obesity and unemployment. Both affect social and economics costs as well as a person's overall well-being. Obese individuals are more likely to suffer from social stigmatization and weight discrimination (NHLBI, 1998), which have been documented in a variety of settings including in the labor market (WHO, 1998). Conversely, prolonged unemployment can lead to reduced consumption of healthy food. Americans who have been out of work for a year or more are much more likely to be obese than those unemployed for a shorter time. The obesity rate rises from 22.8% among those unemployed for two weeks or less to 32.7% among those unemployed for 52 weeks or more (Gallup-Health ways Well-being Index, 2013). These two risk factors often occurred simultaneously. They are modifiable if the true effects are known.

1.2. Food advertising and a state-sponsored anti-obesity advertising

Much of the food that is advertised in the U.S. is for high-calorie and low nutrient food (Byrd-Bredbenner et al., 2000; Kuribayashi et al., 2001) and is targeted at children. U.S. food companies spent $3.5 billion in 2001 on fast-food advertisements and $5.8 billion on the separate food, beverage, and confectionary category, including $785.5 million for the top 5 soda brands (Welch, 2003). Exposure to food advertising on television leads to subsequent consumption of advertised food (Dietz, 1999) and the evidence shows that the consumption of advertised foods is higher than consumption of foods that are not advertised (Jeffrey et al., 2008; Boynton-Jarrett et al., 2003). Hence, successful food advertising could be one cause for the obesity crisis. As the most effective advertising medium, television advertising is extensively used in public health communication to convey health-related messages to the public, ranging from cancer prevention, seat-belt promotion, and oral health to drunk-driving prevention, anti-drug, and anti-tobacco campaigns. To the extent that obesity reflects modifiable risk behaviors that have similarities with smoking-related behaviors, anti-obesity advertising, which is state-sponsored, is aimed at reducing obesity (Emory, 2007). Generally, research has shown that such campaigns have small-to-moderate effects on attitudes, beliefs, and behaviors related to the primary message (Snyder et al., 2002; Derzon et al., 2002; Noar et al., 2006).

1.3 Food Stamps Program (SNAP), Food insufficiency, and Health of the Elderly

The Food Stamps Program, which was renamed the “Supplemental Nutrition Assistance Program” (SNAP) in 2008, is a federal nutrition entitlement program.

Although the program is administered by the U.S. Department of Agriculture, under the Food and Nutrition Service (FNS), the benefits are distributed by each U.S. state's Division of Social Services or Children and Family Services. The program is designed to help low-income households stretch their food budget, reduce their food insufficiency, and ultimately improve their health. Food insufficiency, which is defined as "an inadequate amount of food intake due to lack of resources" (Briefel et al., 1992), is found in all ages of the U.S. population. Yet, the low-income elderly population is the most vulnerable group to deficient health. Some elderly households may experience food insufficiency. The presence and degree of food insufficiency and the outcome of the Food Stamps Program participation decision may affect the health status of the elderly.

1.4 Objectives

The main objective of the dissertation is to contribute to our understanding of the behavioral health determinants and impacts of public policy on health. The specific objectives are to:

1. Evaluate the effectiveness of food advertisements i.e. unhealthy food ads, healthy food ads, a state-sponsored anti-obesity ads, and mixed ads on changing eating behaviors through changing total calories, macronutrients and healthy food items.

2. Estimate the effectiveness of the Food Stamps Program on improving health of the elderly and alleviating food insufficiency.

3. Examine why so few eligible elderly households choose to receive food stamps and what determines their level of food insufficiency.

4. Investigate the simultaneous relationship of modifiable risk factors contributing to social and economic costs and a person's overall likelihood of well-being - unemployment and obesity- during the economic recession in 2010.

1.5 Outline of Dissertation

The dissertation consists of three essays on behavioral health and the impacts of public policy on health. It is organized as follows: Chapter 2 presents the first essay: *The Impact of Food Advertisements on Changing Eating Behaviors: An Experimental Study*. The economic experiment is conducted to examine the impact of different types of food advertisements on consumers' purchases of lunch items; Chapter 3 presents the second essay: *Food Stamps, Food Insufficiency and Health of the Elderly*. The study develops a theoretical framework to understand the mechanism of the Food Stamps Program participation decision, food insufficiency, and these two factors impact on the health status of the elderly. A two-step econometric framework is developed to account for the endogeniety of food stamps program participation and food insufficiency. Chapter 4 presents the third essay: *The relationship between Unemployment and Obesity: Evidence from NLSY 97 Survey Data*. The study investigates the simultaneous relationship using an instrumental variable approach to understand how and whether obesity affects unemployment, and unemployment affects obesity at the same time.

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CHAPTER 2

THE IMPACT OF FOOD ADVERTISEMENTS ON CHANGING EATING BEHAVIORS: AN EXPERIMENTAL STUDY

2.1 Introduction

Obesity in the United States has become a serious health and economic problem. As reported in 2012, 34% of the population was obese and over 67% could be classified as overweight (WHO, 2011). A study by Lillis, 2010 put the cost of this problem in terms of increased health care at $150 billion per year. The obesity crisis has been fueled by reductions in physical activity, as well as by over-consumption of foods high in fat and sugar (Institute of Medicine [IOM], 2006). Although numerous factors play a role in obesity, the goal of this research was to examine the influence of food television advertisements on caloric and other nutrient intake from consumer choices of lunch items. Our main focus is on the impact of different types of food advertising on adult consumers' purchasing behavior. Specifically, we are interested in three types of advertising: unhealthy food advertising, healthy food advertising, and anti-obesity advertising.

Unhealthy food advertising, in this context, means television commercials that encourage consumption of products that are high in fat, sugar, and/or sodium. Previous studies have found that the majority of food advertisements aired on television promote unhealthy food products[2] (e.g., Cairns et al., 2009; Harris et al., 2009; Holt et al., 2007; Powell et al., 2007; Livingstone, 2005; Office of Communication, 2004; Hill and Radimer, 1997) and/or convey un- healthy nutritional messages that lead to greater preferences for and purchases of unhealthy products (Zimmerman and Bell, 2010; Galcheva et al., 2008; IOM, 2006; Brownell and Horgen, 2004; Story and French, 2004; Hastings et al., 2003; Boynton-Jarrett et al., 2003; Gamble and Cotugna, 1999; Lewis and Hill, 1998). Other studies have found exposure to food advertising to have a direct causal effect in increasing overall calorie consumption (Harris et al., 2009; Epstein et al., 2008; Halford et al., 2004, 2007); lower fruit and vegetable consumption five years later (Barr-Anderson et al., 2009); and higher rates of obesity in children (Chou et al., 2008). These and other studies in this area have mainly relied on secondary and survey data, which may not allow for the observation of the directionality in the causal relation. That is, being obese might cause children to en- gage in more sedentary activities, including watching more television.

Because secondary and survey data have been used in the majority of these studies, no study has been able to explicitly gauge the magnitude of the impact of various kinds of food advertisements on eating behavior. Also, time spent viewing television has been used as a proxy for advertising exposure in which various kinds of advertising are lumped together. In addition, most studies have examined the impact of food advertising on adolescent obesity rather than adult obesity.

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[2] An exception to this is Desrochers and Holt (2007), whose study could neither refute nor confirm that the majority of food advertising aimed at children is for products low in nutritional content.

Campaigns for healthy food and anti-obesity advertising are far less common and far less studied for their ability to mitigate obesity. According to Emery et al., 2007, research has generally shown that campaigns with health-related messages have small-to-moderate effects on attitudes, beliefs, and behaviors related to the primary message in the ad. Most healthy food advertising relates to fruit and vegetables; however, the amount of such advertising is negligible next to unhealthy food advertising. The limited amount of research on healthy food advertising has indicated that such advertising has a small, but statistically significant effect, on increasing the consumption of fruits and vegetables (Liaukonyte et al., 2012; Pollard et al., 2008).

Anti-obesity advertising is primarily state-sponsored and is targeted at children (nationwide CDC's Verb campaign is the only anti-obesity media campaigns at the federal level). Similar to anti-tobacco advertising, anti-obesity advertising aims to shock particularly obese and overweight children (or their parents) into losing weight; however, the anti-obesity campaigns lag behind anti-tobacco campaigns both in terms of their implementation (first anti-obesity campaign started in 2000, compared to 1990 for anti-tobacco campaigns) and their exposure levels, which are much lower for the anti-obesity campaigns. Moreover, recent re- search suggests that a threshold level exists for the exposure of anti -tobacco advertising after which the campaigns become effective. But, the relatively modest levels of exposure to state sponsored anti-obesity ads might not result in measurable changes in obesity-related behavior (Emery et al., 2007). To our knowledge, no economic studies exist that examine the efficacy of this type of advertising.

The purpose of the research summarized here was to examine and compare how these three types of food advertising impacted consumers' purchases of lunch items for adult consumers. Specifically, we measured whether unhealthy food advertising had a negative dietary impact and healthy food advertising and anti-obesity advertising had a positive dietary impact. The analysis was based on an economic experiment conducted with 186 adult non-undergraduate student subjects, each of which was randomly placed into either the control group or one of four treatments. The four treatments comprised anti-obesity advertising, healthy (fruit and vegetable) food advertising, unhealthy food advertising, and mixed (all three) food advertising. By conducting this laboratory experiment, our aim was to individually assess and compare the potential of each type of food advertisement to impact dietary and food purchasing behavior. The main contribution of this re- search is that it provides the only measure and comparison (to our knowledge) of the relative efficacy of three broad types of food advertising on nutritional intake of adult subjects. This information is important for the policy debate over designing effective anti- obesity polices.

2.2 Theories of how advertising effects consumer behavior

Advertising messages are usually constructed with the goal of influencing consumer's behavior (Cacioppo and Petty, 1983). There are different views on how advertising achieves this goal, but most research agrees that both a "central cognitive route" and a "peripheral route" are used. The central cognitive route is usually associated with careful consideration of the advertising message, while the "peripheral route” is more connected to emotions and use of behavioral heuristics and cues for decision making (Chaudhuri and Buck, 1995).

The Elaboration Likelihood Model (ELM–Petty and Cacioppo, 1996) is widely applied in advertising analysis, and implies that the more personally relevant the product becomes, the more persuasive an informative advertising becomes, while in the case of low personal relevance products advertising that allows a consumer to rely more on simple cues or emotions becomes more effective. Within this framework, healthy foods advertising that contains information about healthy diets would be more effective among consumers considering a change in their diet; for people unconcerned with their current diet, healthy foods advertising that appeals to emotions would be more effective.

Somewhat connected to the concept of the “peripheral route” in the ELM is the concept of the “behavioral nudge” which is a change to environmental cues that would prompt the desired behavior, or “any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives” (Thaler and Sunstein, 2008). In this framework, advertising primes consumption through affective cues that are unrelated to conscious influences such as, for example, reported hunger in case of food ads (Harris et al., 2009); advertising can thus unconsciously trigger healthier food consumption patterns though use of such cues (Marteau et al., 2001). In our research, the unhealthy advertising works as a “nudge” to encourage consumption of unhealthy items, while anti-obesity ads should nudge people towards healthier diets.

While there are various theories of how advertising affects consumer choices, it is outside the scope of this paper to disentangle the reasons behind the effectiveness of advertising. Both of the above models suggest that advertising can influence consumer behavior. We have selected a range of existing real world advertising clips that represent both informative messages and emotional appeals, and estimate the effect of those representative ads on participant behavior. We elaborate on possible behavioral motivations behind the estimated results further in the discussion section.

2.3 Methodology

2.3.1 Experimental design

A total of 186 adult non-undergraduate student subjects participated in the economic experiment. Subjects were paid $15 cash for participation and additionally offered a $10 food voucher that could be spent exclusively on food items selected from our menus. During the experiment, the subjects completed a series of computerized menus interspersed with television show excerpts and several advertising clips that were different based on the treatment.

At the beginning of the experiment, subjects were informed that they would be filling out a series of computerized lunch me- nus with $10 endowment for each menu. Subjects were instructed that in cases where their menu choices exceed $10, they would need to pay the excess from their $15 participation payment. How- ever, if they spent less than their $10 endowment on their menu choices, they would not receive the difference back in cash. The subjects were told that one of the menus was randomly drawn before the start of the experiment and would be disclosed at the end of the experiment. The choice of lunch items on that particular menu became binding for the subjects.

The experiment began with the first menu presented to subjects on their computer screens, and the subjects were asked to type the number of servings they wanted next to the desired item. The total cost of all of the selected items was displayed at the bottom of the menu. Table 2.1 provides the list of the items on the menu, the prices offered, and the nutrition information (however, the nutritional information was not presented to the subjects in the experiment). After completing the first menu, the subjects watched television show excerpts from "Portlandia" and the 2012 Emmy Awards for approximately 16 mins. A second menu identical to the first one was then presented to the subjects. After the second menu was completed, subjects were asked to complete a questionnaire disclosing their attitudes towards organic food, their health habits, and some demographic information (see Appendix Table A.1 for the list of questions).

The experiment had one control group in which the subjects viewed only the television shows, and did not see any advertisements. The first treatment used healthy food advertising in which, after completing the first menu, the subjects viewed the television show excerpts interspersed with six thirty-second healthy fruit and vegetable advertisements. The six healthy food advertisements all involved promoting fruit and vegetable consumption, and included the following commercials: (1) "Eat more fruits and vegetables," sponsored by Produce for Better Health and Syngenta, (2) "Eat 2 fruit + 2 veggies every day for good health!" sponsored by the Health Promotion Board, Tote Board, Singapore, (3) "Emma's Healthy Snack," sponsored by

Fresh Food, Kids, Woolworths, Australia (http://freshfoodkids.com.au), (4) "Eat More", sponsored by the Department of Health and Aging, Australia, Go for 2and5 campaign (http://www.gofor2and5.com.au/), (5) "Looking Good," sponsored by the Department of Health and Aging, Australia, Go for 2and5 campaign, and (6) "Mummy, I'm hungry," sponsored by the Department of Health and Aging, Australia, Go for 2and5 campaign. The second treatment was the anti-obesity advertising treatment that comprised four thirty-second and one sixty-second anti-obesity advertisements designed to discourage the consumption of unhealthy foods. They included: (1) "What Did You Eat Today?," sponsored by Obesity P.S.A. (http://www.obesity.org), (2) "This is Joe," sponsored by Center for Disease Control and Prevention, Safer Healthier Life, (3) "Don't Drink Yourself Fat," sponsored by NYC Department of Health, (4) "Fat Lane," produced for Participant Productions in support of the marketing campaign of the film "Fast Food Nation," and (5) "Cost of Obesity Pinwheel," sponsored by the Stone Agency for Blue Cross and Blue Shield of North Carolina. The third treatment featured unhealthy food advertising and included four advertisements (totaling three minutes) of savory and sweetened unhealthy foods.

The commercials included (1) "Pepperidge Farm – Chocolate" (http://www.youtube.com/watch?v=es-TbGGfNVMandfeature=player_detailpage), (2) "Papa John's Pizza," (3) "Quizno's | Toasty Torpedo," and (4) "Coke 2012 Commercial: Catch" StarringNE_Bear (http://www.youtube.com/watch?v=S2nBBMbj S8w). The final treatment had mixed food advertising that featured a combination of healthy foods (two thirty-second ads), anti-obesity (two thirty-second ads), and unhealthy food advertisements (two thirty-second ads).

2.4 Econometric model and estimation

Two econometric models were used to examine the impacts of the treatments. First, a set of difference-in-differences (DID) regression models was estimated to determine whether any of the treatments had a statistically significant impact on caloric and other nutrient intakes. These models provided a measure of the magnitude and significance of the various advertising treatments on nutritional contents of the lunch. Second, an ordered pro- bit model was used to estimate whether and by how much the advertising treatments changed the number of healthy items from Menu 1 to 2. This model was estimated in order to determine how the various types of advertising impacted consumers' purchases of items generally perceived as healthy or unhealthy.

2.4.1 A difference-in-differences model

A difference-in-differences regression model was used to deter- mine whether any of the treatments were statistically significant. To estimate the treatment effect, the DID estimator can be written as $(y_{11} - y_{10}) - (y_{01} - y_{00})$ where y_{it} is the outcome of interest for group i for period t. Alternatively, a regression-based estimator can use the level of the outcome variable to estimate the model:

$$y_{it} = \alpha + \gamma T_t + \theta C_i + \beta D_i + \delta D_i T_t + \varepsilon_{it}, \tag{2.1}$$

where y_{it} is the outcome of interest for group i for period t. The D_i is a group dummy variable that takes the value of one if the individual is in the treatment and zero if they are in the control. The T_t is a dummy variable for a time period that takes the value of one if it is in the post-treatment period and zero in the pre-treatment period, C_i is a demographic variable for each individual, and $D_i T_t$ is an interaction between the group and the time variable. The ordinary least squares (OLS) estimate of the coefficient, δ, for the interaction term is interpreted as a consistent estimator of the treatment effect. The dependent variable in this research, y_{it}, was the intake of total calories (or other nutrients as discussed below) for group i for period t, which was calculated as the summation of the product of the number of servings selected times the total calories of each serving based on the USDA nutrition database. Table 2.1 lists the food items with their nutrition information.

Table 2.1: List of food items with their respective prices on the lunch menu and USDA nutrition database

Food items	Prices	Calories	Calories from Fat	Total Fat (g)	Sat Fat (g)	Tran Fat (g)	Cholesterol (mg)	Total Carb (g)	Fiber (g)	Sugar (g)	Protein (g)	Sodium (mg)
Diet Pepsi	2.00	0	0	0	0	0	0	0	0	0	0	60
Pepsi	2.00	250	0	0	0	0	0	69	0	69	0	55
Gatorade Low Calorie	2.33	45	0	0	0	0	0	12	0	12	0	270
Mountain Dew	2.00	290	0	0	0	0	0	77	0	31	0	100
Unsweetened Iced Tea LIPTON	2.15	0	0	0	0	0	0	0	0	0	0	0
Original Iced Tea LIPTON	2.15	150	0	0	0	0	0	39	0	39	0	0
Tropicana Lemonade	2.59	300	0	0	0	0	0	72.5	0	70	0	50
Bottled Water	1.95	0	0	0	0	0	0	0	0	0	0	0
Green Salad with Sesame Oriental/Balsamic Dressing	7.03	137	0	12	2	0	0	7	1	6	1	744
Green Salad and Tuna with Sesame Oriental/Balsamic Dressing	7.03	316	0	13	2	0	46	7	1	6	40	1265
Veggie Cup with Hummus or Light Ranch	4.32	84	27	3	0	0	0	13	3	10	1	156
Cheese Pizza (6"pan)	5.18	517	189	21	9	0	46	60	3	0	23	1013
Pepperoni Pizza (6" pan)	5.83	530	207	23	9	0	52	57	3	0	12	1151
Local Bacon Cheeseburger	7.52	683	369	41	17	0	120	41	3	0	38	1655
Lean Turkey Whole Grain Sandwich	6.16	329	99	11	2	0	67	26	1	0	29	565
Macaroni & Cheese	4.53	491	198	22	9	0	39	54	3	0	19	945
Doritos Nacho Cheese	1.55	294	117	13	2	0	0	40	3	0	4	211
Fresh Apple	1.00	72	0	0	0	0	0	19	3	0	0	1
Fresh Banana	1.00	105	0	0	0	0	0	27	3	0	1	1
Fresh Orange	1.00	62	0	0	0	0	0	15	3	0	1	0
Chocolate Chip Cookies	2.20	108	54	6	2	0	7	13	1	0	1	79
Brownie Bar	1.94	224	72	8	2	0	21	37	1	0	3	88

Note: Food menu and prices are from a dining hall "Trillium" that participants can easily go for lunch after the experiment.

While an increase in total caloric intake reflects increased food consumption, the increase is not necessarily an indication of unhealthy food consumption. Therefore, other additional nutrition elements were taken into account to capture the change in consumption patterns; including total fat, carbohydrates, protein, added sugar, and sodium that are generally viewed as over-consumed nutrients. The zero-one dummy variables were defined for the treatments of the healthy food advertisement (D_1), the anti-obesity advertisement (D_2), the unhealthy food advertisement (D_3) and the mixed food advertisement (D_4). The pre- (T_0) and post-treatment (T_1) dummy variables were conducted with the same participant. The statistical significance of each treatment was measured based on the estimated δ coefficients (i.e., healthy food advertising ($\hat{\delta}_1$), anti-obesity advertising ($\hat{\delta}_2$), unhealthy food advertising ($\hat{\delta}_3$), and mixed food advertising ($\hat{\delta}_4$) in the following regression model:

(2.2) $$y_{it} = \alpha_i + \gamma_i T_t + \theta_i C_i + \sum_{d=1}^{4} \beta_d D_d + \sum_{d=1}^{4} \delta_d D_d T_t + \varepsilon_{it},$$

2.4.2 Results from DID model

Table 2.2 presents a detailed numeric summary of the socio-economic and demographic information of participants across all treatments. In this table, since the characteristics are measured as zero-one dummy variables, the values represent the proportion of the sample in each respective category. The sample characteristics are listed for all subjects combined, as well as for the control and four treatments. As is clear by this table, there were differences in the demographic and social preference composition among the control and treatment groups. To control for these differences, a vector of participant characteristics dummy variables were included in the regression models.

Table 2.2: Descriptive statistics (mean) of demographic variables by treatments

Cate-gories	Variables	All	Control	Healthy Food Ads	Anti-Obesity Ads	Unhealthy Food Ads	Mixed Food Ads
			Treatments				
Gender	Male	0.263	0.558	0.227	0.135	0.379	0.190
	Female	0.737	0.441	0.773	0.865	0.621	0.810
Age	Age 21-30 years old	0.419	0.676	0.181	0.270	0.413	0.595
	Age 31-40 years old	0.155	0.088	0.250	0.162	0.137	0.119
	Age 41-50 years old	0.198	0.58	0.272	0.270	0.275	0.119
	Age 51 years old up	0.225	0.176	0.295	0.297	0.172	0.166
Educa-tion	High school	0.112	0.147	0.091	0.135	0.137	0.071
	College	0.398	0.470	0.409	0.270	0.414	0.429
	Associate/Graduate	0.489	0.382	0.500	0.595	0.448	0.500
Income	$30,000 – $39,999	0.231	0.382	0.227	0.216	0.241	0.119
	$40,000 – $79,999	0.425	0.264	0.386	0.514	0.448	0.500
	$80,000 up	0.280	0.264	0.341	0.162	0.276	0.333
	Decline to answer	0.064	0.090	0.045	0.108	0.034	0.047
Marital Status	Single	0.468	0.735	0.318	0.297	0.379	0.619
	Married	0.414	0.235	0.523	0.514	0.448	0.333
	Divorced	0.188	0.029	0.159	0.189	0.172	0.047
Health related habit	Smoke	0.053	0.058	0.0455	0.0541	0.0690	0.047
	Not smoke	0.947	0.942	0.9545	0.9459	0.931	0.952
	Drink alcohol	0.769	0.735	0.818	0.784	0.862	0.667
	Not drink alcohol	0.231	0.265	0.182	0.216	0.138	0.333
	Buy organic foods	0.376	0.294	0.455	0.378	0.448	0.310
	Not buy organic foods	0.624	0.706	0.545	0.622	0.552	0.690
Weight Consider	Obese	0.026	0	0.045	0.054	0.034	0
	Over weight	0.156	0.029	0.250	0.162	0.310	0.047
	Slightly over weight	0.188	0.235	0.205	0.216	0.137	0.143
	Under weight	0.048	0.147	0.022	0	0.034	0.047
	Normal weight	0.580	0.588	0.477	0.567	0.482	0.762
Race	Asian	0.258	0.323	0.068	0.216	0.172	0.500
	Hispanic	0.032	0.058	0.045	0.027	0.034	0
	Africa	0.037	0.088	0.045	0	0.069	0
	Caucasian	0.651	0.529	0.795	0.757	0.655	0.500
	Native American	0.005	0	0	0	0.034	0
	Other	0.016	0	0.045	0	0.034	0
Number of obs		186	34	44	29	37	42

Table 2.3: Food advertisement effects with DID model

	Total Calories Intake	Total Fat Intakes (g)	Saturate Fat Intakes (g)	Sodium Intakes (mg)	Carb Intake (g)
Healthy Food Ads ($\hat{\delta}_1$)	-134.36**	-7.64**	-2.79*	-258.02**	-9.65
	(64.635)	(3.326)	(1.575)	(113.661)	(9.108)
Anti-Obesity Ads ($\hat{\delta}_2$)	-93.04*	-5.08*	-1.81	-192.99*	-8.02
	(57.767)	(3.150)	(1.475)	(109.395)	(8.581)
Unhealthy Food Ads ($\hat{\delta}_3$)	19.43	3.76	2.57	145.73	-4.24
	(65.456)	(3.331)	(1.588)	(107.239)	(11.175)
Mixed Food Ads ($\hat{\delta}_4$)	-90.29*	-3.17	-0.60	-130.28	-8.46
	(54.89)	(3.163)	(1.512)	(108.366)	(9.739)
Constant	658.81***	29.42***	12.53***	1,288.6***	75.58***
	(134.647)	(7.279)	(3.210)	(271.824)	(19.098)
N=186 and R^2	0.22	0.14	0.15	0.15	0.19
Chi-square	114.74	69.57	76.80	73.08	83.63

Values in parenthesis are the standard errors and the ***, **, and * are 99%, 95%, and 90% confidence intervals respectively.

Table 2.3 presents the difference-in-differences results for the treatment variables[3]. Healthy food, anti-obesity, and mixed food advertising all reduced the total caloric intake relative to those of the control. Specifically, the treatment group for healthy food advertising consumed 134.4 fewer calories compared to the control, which represented a 22.9% decrease compared to the control. This result was the most statistically significant at the 5% level. The anti-obesity treatment group consumed 93 fewer calories than the control, which represented a 15.8% reduction. This result was statistically significant at the 10% level. The mixed advertising group, which featured all three types of advertising, consumed 90.3 fewer calories than the control group (15.4%).

[3] While not shown in Table 2.3, some of the socio-economic and demographic variables were statistically significant. For example, in the regression model with caloric intake as the dependent variable, the following characteristics were statistically significant: females consumed 95.2 fewer calories, people who drink alcohol consumed 64.7 more calories, consumers who purchase organic products consumed 52.7 fewer calories, and participants who indicated they were under-weight consumed 136.1 fewer calories.

When given equal exposure, the effect of healthy and anti-obesity advertising outweighed the effect of un- healthy advertising, thus decreasing the total caloric intake. This result was statistically significant at the 10% level. However, in reality, television advertisements are overwhelmed with loads of unhealthy advertising that dwarfs the amount of healthy and anti-obesity advertising in the media. As expected, the treatment for unhealthy food advertising had a higher caloric intake than the control; how- ever, this intake was not statistically significant. One explanation for unhealthy food advertising not having an impact is that subjects already viewed a tremendous amount of this type of advertising in real life and therefore the marginal impact of viewing a bit more in the laboratory was minimal. In summary, both healthy food and anti-obesity advertising have a significant effect on reducing caloric intake, but healthy food advertising had a stronger impact (see further discussion later on).

Next, we discuss the impact of different types of advertising on the overconsumption of various other nutrients that is associated with obesity. Healthy food advertising had the most impact on reducing total fat intake. The subjects in this treatment group consumed 7.6 less grams of fat than the control group, which represented a 34% reduction. This result was statistically significant at the 5% level. The subjects in the anti-obesity advertising treatment also consumed 5.1 grams less total fat than the control. Further, the subjects in the mixed advertising group consumed, on average, less total fat as well but the result was not statistically significant. Thus, while mixed advertising reduced the total intake, it did not have a statistically significant impact on fat intake. Similar to the results for the caloric intake, unhealthy food advertising increased the fat intake relative to the control group but this result was not statistically significant. Again, this lack of significance likely reflected a zero marginal impact because of the high saturation level of this type of advertising. The saturated fat results, as displayed in Table 2.3, were consistent with the total fat results.

The impact of the advertising treatments on sodium intake was similar to the results for the total and saturated fats. The healthy advertising treatment resulted in the largest reduction in the sodium intake relative to the control. The subjects in this treatment consumed 258 (24.1%) less milligrams of sodium than the subjects in the control. This amount was statistically significant at the 5% level. The anti-obesity advertising also had a statistically significant and negative impact on the sodium intake. The subjects in this advertising treatment consumed 193 less grams of sodium, a reduction of 18%. The mixed advertising treatment had a lower sodium intake than the control but was not statistically significant.

Interestingly, none of the four treatments had a statistically significant impact on the carbohydrates consumed. This was probably because of the relatively low degree of variation in the level of carbohydrates in the ''healthy'' versus ''unhealthy'' menu items. An interesting finding of our research was that while healthy and anti-obesity advertising were both significant in terms of reducing caloric and other nutrient intake, the former had a stronger effect than the latter. For example, healthy advertising had a 44.5% stronger impact on reducing calories than anti-obesity advertising (over 50% regarding fat and 33% regarding sodium), which was statistically significantly different (p-value < 0.05). There are two related explanations for this suggested by previous studies. First, some research suggests that negatively-framed advertising messages that are aimed at changing peoples' behavior can have the unintended consequence of inducing resistance and reducing the probability of self-change, especially when advertising is emotive, as well as framed and perceived as a health threat (Brown, 2001; Brown and Locker, 2009). The use of "fear appealing," emotive messages with information on possible health risks aimed at scaring recipients into changing their behavior to a healthier one, is generally not recommended in health promotion campaigns (Ruiter et al., 2001).

Second, and relatedly, previous research suggests that public health messages that focus on inducing behavioral changes in a non-stigmatizing way (e.g., positive healthy advertising) are more effective than messages that have the potential to stigmatize people (e.g., anti-obesity advertising). For example, Puhl et al., 2013 found that health messages that omitted the term "obesity" were rated as inducing more self-efficacy in engaging in healthy behavior than those containing "obesity." This finding is also consistent with Piggin and Lee, 2011 regarding the omission of the word "obesity" from the United Kingdom's 'Change4lLife' campaign and indicates the importance for future research to more rigorously test how weight-related terminology influences public response to healthy messages. These results suggest that more positive-based advertising such as encouraging healthy foods is more effective in changing behavior than more negative-based advertising, which is aimed at discouraging unhealthy foods, but may turn some people off due to the perceived stigmatizing nature of the ads.

The results from the DID regression model provided evidence that healthy food and anti-obesity advertising had a positive impact on changing the subjects' purchases towards healthier choices. By estimating the difference between the pre- and post- treatments (and between the control and treatment groups) in nutrient elements, we found reductions in most nutrients in response to healthy food, anti-obesity, and mixed food advertising. However, these numerical calculations can sometimes be at odds with the general food perceptions. For instance, some items in the menu, generally perceived as healthy such as tuna salad, actually had higher sodium contents than a small cheese pizza. Fruits have more carbohydrates than do cookies, and Diet Pepsi has a higher sodium content than does regular Pepsi or Tropicana lemonade. In order to see how the various types of advertising impacted consumers' purchases of items generally perceived as healthy or unhealthy, we estimated an ordered probit model in the next section.

2.4.3 Ordered Probit model

The food items offered in the lunch menu were clearly divided into two categories: healthy (e.g., fruit and veggie platter) and unhealthy (peperoni pizza)[4]. Therefore, we constructed the ordered probit model as follows. First, the change in the number of healthy items chosen from Menu 1 to 2 was computed. The dependent variable was constructed based on the change in healthy items and took on three

[4] Definitions of the term "healthy foods" vary depending on the source and context. Healthy food, here, is defined based on the definition used by the Federal Drug Administration (FDA). Under the FDA, a label may say "healthy" if the food is (i) low in fat and saturated fat (ii) limited in amount of sodium and cholesterol and (iii) provides at least 10 percent of one or more of Vitamin A, Vitamin C, iron, calcium, protein, and fiber (for single-item foods). The beverages with zero calories are considered as a healthy drink and those with positive calories are considered unhealthy.

discrete values. If the number of healthy items increased from Menu 1 to 2, then the dependent variable was equal to two; and if there was no change in the number of healthy items, then the dependent variable was equal to one. If the number of healthy items decreased, then the dependent variable was equal to zero.

Table 2.4: Number of subjects selecting more healthy items in Menu 2

Eating pattern	#Good items	Number of Subjects				
		Whole Menu	Entrée	Drink	Snack	Snack &Drink
Less Healthy[a]	-2	4	2	0	18	2
	-1	26	19	16	0	23
Neutral[b]	0	89	124	152	131	117
Become	1	51	40	18	34	39
Healthier[c]	2	14	1	0	3	3
	3	1	0	0	0	2
	4	1	0	0	0	0
% of change		51%	33%	22%	29.5%	37.1%
- To less healthy		30%	34%	47%	32%	36%
- To become healthier		70%	66%	53%	68%	64%
Total # of subjects		186	186	186	186	186

[a]A negative # of good items means a subject selected fewer good items in Menu 2 than Menu 1. The eating habit is assigned "Less Healthier".
[b]A zero # of good items means a subject selected # of good items in Menu 2 equal to Menu 1. The eating habit is assigned "Neutral or Unchanged".
[c]A positive # of good items means a subject selected more good items in Menu 2 than Menu 1. The eating habit is assigned "Become Healthier".

Table 2.4 summarizes the number of subjects who selected more healthy items in Menu 2. Because this was a non-linear model, the ordered probit results were interpreted in terms of a change in the probability of selecting a healthy item. The structure of the difference-in-differences model could still be used in the ordered probit model as follows[5]:

[5] The ordered probit model is more efficient than a linear OLS in dealing with an ordered discrete variable.

(2.3) $$E[Y_i|D,X] = \Phi[\alpha + \theta C_i + \sum_{d=1}^{4} \beta_d D_d + \varepsilon_i] = \Phi[u],$$

where Y_i equaled 0, 1, or 2 for "less healthy," "unchanged," and "healthier." The dummy variables for the healthy food, anti-obesity, unhealthy food, and the mixed food advertising treatments were denoted as D_1, D_2, D_3, and D_4 respectively.

Table 2.5: Food advertisement effects with the ordered probit model (the Whole Menu)

	Marginal Effects		
	Pr(Y=0)	**Pr(Y=1)**	**Pr(Y=2)**
Healthy Food Ads	-0.099*	-0.055*	0.154*
	(0.055)	(0.033)	(0.085)
Anti-Obesity Food Ads	-0.092*	-0.051*	0.144*
	(0.055)	(0.031)	(0.087)
Unhealthy Food Ads	-0.011	-0.006	0.017
	(0.072)	(0.040)	(0.112)
Mixed Food Ads	-0.148**	-0.079*	0.229**
	(0.060)	(0.041)	(0.095)
N= 186, R-square = 46.45			

Pr(Y=0) is the probability of being "less healthy" after the treatment. Pr(Y=1) is the probability of having a "unchanged" eating pattern before and after the treatment. Pr(Y=2) is the probability of being " healthier" after the treatment.
Values in parenthesis are the standard errors and the ***, **, and * are 99%, 95%, and 90% confidence intervals respectively.

Table 2.5 presents the results of the ordered probit model. All types of advertising, except for the unhealthy food advertising, had significant impacts on changing food purchase decisions from Menu 1 to 2. The mixed food advertising had the largest impact. The subjects in this treatment had a 14.8% lower probability of increasing their purchases of unhealthy items from Menu 1 to 2 and had a 23% higher probability of increasing their purchases of healthy items. The healthy food advertising treatment had similar, though somewhat smaller effects: the subjects in this treatment had a 9.9% lower probability of increasing their purchases of unhealthy items and a 15.4% higher probability of increasing their purchases of healthy items from Menu 1 to 2. The anti-obesity advertising also had a statistically significant impact on reducing the probability of increasing their purchases of unhealthy items and raising the probability of increasing their purchases of healthy items, but the magnitudes were somewhat smaller. It is again interesting to note that the more positive type of healthy advertising had a stronger impact than the negative anti-obesity advertising in raising (lowering) the probability of purchasing healthier (unhealthier) food.

Some of the demographic variables (not shown in Table 2.5) were also statistically significant. For instance, subjects with income levels over $80,000 had a 17.7% higher probability of increasing their purchases of unhealthy items from Menu 1 to 2 and a 27.4% lower probability of increasing their purchases of healthy items. A similar, but less impactful result occurred for subjects with income levels between $40,000 and $80,000. Subjects who were married had a 22.1% lower probability of increasing their purchases of unhealthy items from Menu 1 to 2 and a 34.4% higher probability of increasing their purchases of healthy items. The subjects that indicated they were overweight had a 9.3% higher probability of increasing their purchases of unhealthy items from Menu 1 to 2 and a 14.4% lower probability of increasing their purchases of healthy items.

The ordered probit model was also estimated separately for each of the three food categories: beverages, entrées, and snacks. The results are presented in Table 2.6. The most significant changes originated in the beverages category. For instance, the subjects who viewed the anti-obesity advertising had a 12.1% lower probability of increasing their purchases of unhealthy beverages from Menu 1 to 2 and a 14% higher probability of increasing their purchases of relatively healthy beverages. Hence, the subjects made the most of their adjustments in response to the advertising in their selection of beverages. Indeed, none of the treatments, except for the unhealthy food advertising, had an impact on changing the probability of the food selection in the entrée category.

Table 2.6: Food advertisement effects with the ordered probit model for each food category

	Consider only Entrées			Consider only Beverages			Consider only Snacks		
	Marginal Effect			Marginal Effect			Marginal Effect		
	Pr(Y=0)	**Pr(Y=1)**	**Pr(Y=2)**	**Pr(Y=0)**	**Pr(Y=1)**	**Pr(Y=2)**	**Pr(Y=0)**	**Pr(Y=1)**	**Pr(Y=2)**
Healthy Food Ads	0.008	0.004	-0.012	-0.084*	-0.013	0.097*	-0.068*	-0.043	0.111*
	(0.051)	(0.028)	(0.080)	(0.048)	(0.023)	(0.056)	(0.049)	(0.034)	(0.079)
Anti-Obesity Food Ads	-0.017	-0.09	0.026	-0.121**	-0.019	0.140**	0.000	0.000	-0.000
	(0.051)	(0.028)	(0.078)	(0.053)	(0.032)	(0.061)	(0.050)	(0.032)	(0.082)
Unhealthy Food Ads	0.080*	0.042	-0.123*	-0.088*	-0.014	0. 101*	0.036	0.023	-0.059
	(0.046)	(0.034)	(0.074)	(0.052)	(0.023)	(0.059)	(0.053)	(0.034)	(0.085)
Mixed Food Ads	-0.022	-0.012	0.035	-0.093*	-0.014	0.107*	-0.093*	-0.059*	0.152**
	(0.055)	(0.031)	(0.086)	(0.048)	(0.024)	(0.055)	(0.050)	(0.035)	(0.078)
N=186, R-square		38.08			33.40			24.53	

Pr(Y=0) is the probability of being "less healthy" after the treatment .
Pr(Y=1) is the probability of having a " unchanged" eating pattern before and after the treatment.
Pr(Y=2) is the probability of being " healthier" after the treatment.
Values in parenthesis are the standard errors and the ***, **, and * are 99%, 95%, and 90% confidence intervals respectively.

2.5 Conclusions

This research focused on the impact of different types of food advertising on consumers' purchasing behavior. In particular, we examined the impact of three broad types of advertising on adult food consumption: unhealthy food advertising, healthy food (fruits and vegetables) advertising, and anti-obesity advertising. To investigate these impacts, the study implemented an economic experiment in which 186 adult, non-undergraduate student subjects chose items from a lunch menu, and then, depending upon which treatment they were assigned to, were shown short clips of television shows interspersed with one of the three types of ads (or no ads for the control group), then asked to resubmit their menu choices. To determine whether any of the treatments had a significant impact on intake of various nutrients including total calories, a difference-in-differences regression model was estimated, which included demographic and socioeconomic variables to control for heterogeneity among treatments. In addition, because individual perceptions of the healthiness of food items might have a downward bias for their nutritional composition results, we estimated an ordered probit regression model to analyze how various types of advertising impact consumers' purchases of items generally perceived to be healthy or unhealthy.

The results indicated that exposure to both healthy food and anti-obesity advertising resulted in a significant decrease in caloric intake. That is, after controlling for differences in demographic and socioeconomic factors, subjects in the healthy advertising treatment consumed 134.4 (22.9%) fewer calories and those in the anti-obesity treatment consumed 93 (15.8%) less calories than subjects in the control (noadvertising) group. We also found that the treatment in which all types of ads were intermixed (healthy, un- healthy, and anti-obesity) resulted in a reduction of 90.3 (15.4%) calories, suggesting that the positive healthy food and anti-obesity advertising effect outweighs the negative effect of unhealthy food advertising on caloric intake. Similar results were also found for other nutrients such as total fat, saturated fat and carbohydrates. In addition, the results based on the ordered-probit regression indicated that all types of advertising, except for the unhealthy food advertising, had significant impacts on changing food purchase decisions from Menu 1 to 2. The mixed food advertising had the largest impact; subjects in this treatment had a 14.8% lower probability of increasing their purchases of unhealthy items from Menu 1 to 2 and had a 22.9% higher probability of increasing their purchases of healthy items. The healthy food advertising treatment had similar, though somewhat smaller effects: the subjects in this treatment had a 9.9% lower probability of increasing their purchases of unhealthy items and a 15.4% higher probability of increasing their purchases of healthy items from Menu 1 to 2. The anti-obesity advertising also had a statistically significant impact on reducing the probability of increasing their purchases of unhealthy items and raising the probability of increasing their purchases of healthy items, but the magnitudes were somewhat smaller.

The main conclusions of our experiment that have policy implications are three-fold. First, increasing the frequency of exposure to healthy food advertising would nudge people towards reducing caloric and unhealthy nutrient food intake. Second, increasing the frequency of anti-obesity advertising would have similar, but less significant effects. Third, limiting the exposure to unhealthy food advertising would also reduce caloric and unhealthy nutrient intake. The fact that healthy food advertising had a substantially stronger (over 50% in terms of reducing fat) effect than the anti-obesity advertising is consistent with findings by other researchers and may be due to anti-obesity advertising producing a negative fear-emotive or stigmatizing effect on the target audience, which may turn some people off and thereby water-down the effect of the message. This finding has an important policy implication for framing and crafting advertising messages to address obesity. That is, healthy food advertising might have a broader and more effective reach to the American public than anti-obesity advertising. Crafting a message that is more positive in encouraging healthy food consumption may be a more effective strategy in nudging people to eat healthier and consume fewer calories than the potentially stigmatizing nature of negative, anti-obesity advertising.

The main policy implication of this research is that the government should explore policy options to increase the frequency of healthy and anti-obesity advertising. Past research has concluded that the magnitude of exposure to unhealthy food advertising is substantially higher than that of the other two types of advertising (e.g., Cairns et al., 2009; Harris et al., 2009; Holt et al., 2007; Powell et al., 2007; Livingstone, 2005; Office of Communication, 2004; Hill and Radimer, 1997). We find the opposite impacts for healthy food and anti-obesity advertising. Therefore, providing consumers with a more balanced set of advertisements on food choices should be a policy option for reducing obesity.

An important caveat of this study is that it was conducted in a laboratory setting. Consequently, the results should be viewed as upper bound estimates for the various advertising impacts. The food advertising exposure presented to the participants in the laboratory was different from what occurs in real life. In reality, television viewers are inundated with unhealthy food advertising and seldom view either healthy food or anti-obesity ads. Also, in a laboratory setting, participants know that their decisions are thoroughly investigated, which is not like everyday life, and it can influence the decision-making process of participants even though they are assured of the anonymity of their actions. With the high degree of scrutiny applied in the lab and the relatively high stakes provided to subjects ($25 participation payment plus $10 in food endowment), participants might view the task with more responsibility and feel obligated to alter their behaviors. Therefore, subjects might conform to typical social norms to avoid high moral costs (Levitt and List, 2007). Thus, the results from the laboratory experiment should be generalized to the field with caution.

Despite some limitations, the results from this study still con- tribute to the literature examining the economic effect of food advertising on consumers' purchasing behavior. To our knowledge, this is the first study to measure the causality and direct exposure to all three types of food advertising. Despite the limitations outlined above, our study shows the potential of both healthy and anti-obesity advertising. Our research provides some information on the actual change in the selection of nutrient con- tents and food items in a lunch meal. Further research should examine the long-term effects and observe the nutrient change across all meals in a day for an extended period of time. Overall, the results suggest that a well-designed anti-obesity and healthy food advertisement might be an effective means for reducing obesity.

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APPENDIX A

Table A.1: Socio-demographic questions and answer option list

#	Question	Answer Options/Description
1	What is your gender?	Drop-down list: - Male - Female
2	What is your age?	Drop-down list: - 20 or less - 21-30 - 31-40 - 41-50 - 51 or more
3	What is the highest level of education you have achieved?	Drop-down list: - High School - Undergraduate degree - Associate degree - Graduate degree or higher
4	How would you describe yourself?	Drop-down list: - Caucasian - African American - Asian/Asian American - Hispanic - Native American - Other
5	What is your family household income?	Drop-down list: - Less than $40,000 - $40,001-$80,000 - $80,001-$120,000 - $120,001-$160,000 - Over 160,000 - Decline to answer
6	What is your marital status?	Drop-down list: - Single - Married - Divorced
7	How many children do you have?	Drop-down list: - No - One - Two - Three - Four - More than four
8	Do you smoke?	Drop-down list: - Yes - No
9	Do you drink alcoholic beverages?	Drop-down list: - Yes - No
10	How would you describe your health condition?	Drop-down list: - Underweight - Normal weight - Slightly overweight - Overweight - Obese
11	Do you often buy organic products?	Drop-down list: - Yes - No
12	On a scale of 1-5, please rate your preferences on the television segments and advertisements you have just watched. (1 - dissatisfied and 5 - very satisfied): a) TV Show b) Menu variety c) Price	Points (a) to (c) are rated from 1 to 5.

CHAPTER 3

FOOD STAMPS, FOOD INSUFFICIENCY, AND HEALTH OF THE ELDERLY

3.1 Introduction

For elderly Americans, President Lyndon Johnson's War on Poverty legislation was remarkably successful. Poverty rates for the elderly fell from nearly 25 percent in 1968 to just less than 10 percent in 2013[6]. Even so, there still are a large number of poor and near-poor elderly citizens, who live in households that are unable to purchase the minimum level of necessities for their household members. Many others face that risk, but the percent is substantially higher among the elderly. It has been estimated that 23 (21) and 36 (30) percent of the elderly (nonelderly) have incomes below 150 and 200 percent of the federal poverty level (FPL) thresholds, respectively (Clark *et. al.*, 2004). Over three-year-period study from 2009 to 2011, Gould and Cooper (2013) found there is a disproportionately large group of elderly Americans with incomes between the FPL and 200 percent of the FPL accounting for 25.1 percent of elderly adults compared with only 16.6 percent of non-elderly adults.

[6] The Census Bureau has reported that poverty rates among the elderly (those ages 65 and older) are higher under the supplemental poverty measure (15 percent) than under the official poverty measure (9 percent), which is due in large part to the fact that the former deducts health expenses from income.

Even though they are not officially classified as being in poverty, Gould and Cooper concern that modest income levels could leave them dangerously vulnerable to changes in federal social programs. Many need assistance from the only universal nation-wide welfare program for the poor and near poor in this country, the Food Stamp Program (FSP)[7], which has been renamed to the Supplemental Food Assistance Program These households are the focus of this study.

Despite the limitations they face in purchasing food and other necessities, participation in the FSP by eligible elderly households remains low, roughly half the rate of all eligible households. Wilde and Dagata (2002) indicate that about one-third of eligible elderly people over age 60 receive Food Stamps despite the program's special provisions for them, particularly with respect to out-of-pocket medical expenses. Rosso (2001) confirm that, finding elderly participation rates of 32 percent in 1999 and 31 percent in 2002, respectively. Cunnyngham (2010) considers state-level trends in FSP participation among elderly individuals. Although there was variation across states and between consecutive years, the change in elderly participation rates from 2002-2006 was also positive in every state. Nationally, the estimated elderly FSP participation rate – the percentage of eligible elderly individuals participating in the program – increased steadily from 25 percent in 2002 to 34 percent in 2006. The Supplemental Nutrition Assistance Program (SNAP), formerly the Food Stamp Program, is the primary nutrition assistance program aimed at reducing food-related hardship.

[7] Because our data cover period with the original name, we use that name herein.

Although increasing over time, the level of participation is still low. Eligible nonparticipants may not have enough resources to purchase a minimally nutritionally adequate diet. Further, some elderly households may experience food insufficiency, where insufficiency is defined as needing to skip or skimp on meals because there is not enough food in the house or enough money to buy necessary food. The presence and degree of food insufficiency and the outcome of the FSP participation decision may affect the health status of the elderly. These linkages are not well understood and this research attempts to fill this knowledge gap in the literature.

Our overarching goal is to examine whether and how elderly health status is affected by FSP participation, food sufficiency, and other determinants. To do so we first ascertain (1) why so few needy elderly households choose to receive food stamps; (2) what determines their level of food insufficiency and finally; (3) how FSP participation and food insufficiency are linked to each other and then to health status? The insights gained are particularly timely and useful due to a tripartite set of changes. More specifically, policy makers need appropriate information and tools to buffer the elderly from the impacts of these changing demographics, economic realities, and other policy pressures.

The major demographic changes are: (1) as a group, the elderly make up an increasing share of the total population, and (2) life spans are increasing over time. Both of these trends are expected to continue. Based upon U.S. Census Bureau projections in 2012, the population of age 65 and older is expected to more than double from 43.1 million in 2012 to 92 million by 2060. The increase in the number of the "oldest old" would be even more dramatic - those 85 and older are projected to more than triple from 5.9 million to 18.2, reaching 4.3 percent of the total population. In 2056, for the first time, the older population, age 65 and over, is projected to outnumber the young, age under 18. A consequence of longer life spans is that savings for retirement, once thought to be ample, may prove inadequate. As the elderly age, the odds of running through personal resources increase, as do the associated odds of becoming poor and staying poor through extended old age. Given that one requirement for FSP eligibility is that countable assets be below a certain threshold, we should expect more elderly to become asset eligible for food stamps as they age.

Since 1970, approximately 90 percent of elderly Americans have received Social Security benefits. Porter et al., 1999, analysts at the Center on Budget and Policy Priorities, indicate that if it were not for those benefits, the elderly (65+) poverty rate would have been 47.6 percent in 1997 rather than the actual 11.9 percent. According to Center on Budget and Policy Priorities, in 2012, for nearly two-thirds (65 percent) of elderly beneficiaries, Social Security provides the majority of their cash income. For one-quarter (24 percent) of elderly beneficiaries, Social Security is the sole source of retirement income. Any policy changes that reduce real benefit levels to Social Security recipients would hit low-income and very old elderly Americans hard. Gould and Cooper (2013) estimate that the reduction in Social Security benefits arising from a proposed shift to indexing cost-of-living adjustments to the chained consumer price index[8] would boost the share of 70- to 75-year-olds

[8] The Chained Consumer Price Index is a time series measure of price levels of consumer goods and services created by the Bureau of Labor Statistics as an alternative Consumer Price Index. It measures living costs differently because it assumes that when prices for one thing go up, people sometimes settle for cheaper substitutes. Cost-of-living adjustments would be lower with the chained CPI than with the plain old CPI through the reduction of the quality of consumed goods (Keister 2013).

below two times the supplemental poverty threshold by 1.2 percentage points, resulting in 132,000 more "economically vulnerable" [9] seniors.

Another important national program for the elderly is Medicare, which has an age eligibility requirement of 65 years and older. Medicare plays a vital role in providing financial security to older people and for those with disabilities. In fiscal year 2013, it provides federal health insurance to 54 million people who are elderly, or permanently disabled, or have end-stage renal disease (KFF, 2014). Out-of-pocket spending tends to increase with age. In 2010, beneficiaries aged 85 and older spent three times more out-of-pocket spending on medical service, on average, than beneficiaries aged 65 to 74 (Cubanski et al., 2014). Thus, medical expenses have a real potential for crowding out spending on other necessities such as food. The crowding-out would be even more severe if Medicare benefits were reduced. Regardless, low income elderly Americans may have to choose between skipping medicines or doctor's appointments and skipping or skimping on meals[10]. Because the FSP uniquely deducts out-of-pocket medical expenses for the elderly when determining eligibility and food stamp benefits, the program can be a buffer and reduce the pressure to make such difficult tradeoffs among necessities[11]. For this reason alone, many elderly now need assistance from the FSP, and many more are likely to need it

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[9] "Economically vulnerable " is defined as having an income that is less than two times the supplemental poverty threshold (a poverty line more comprehensive than the traditional federal poverty line).

[10] We note another documented tradeoff low-income households must make (Bhattacharya *et. al*. 2003), particularly in parts of the country with very cold winters, food and home fuel. These Americans face a tradeoff between paying to heat the home in the winter months and paying for food. We do not account for this relationship in our research.

[11] A further buffer was included in the 2008 Farm Bill. A provision was enacted to remove the cap on the dependent care deduction for all food stamp applicants. This provision will be a boon for the elderly, particularly those utilizing elder day care programs or in-home elder day care. Removing the cap enhances the likelihood of FSP eligibility and increases FSP benefits for participants.

in the future.

The remainder of the paper is organized as follows. First, this research is placed in the context of extant relevant economic, nutrition, obesity, health and policy economic literatures. Then, a more detailed description of data sources for this study is presented. The major data source is the 2002 panel of the Health and Retirement Survey (HRS). Next we discuss our economic and econometric models and develop our estimation protocol. We construct and estimate an econometric model that accounts for the possible simultaneity between FSP participation and food insufficiency, and corrects the covariance matrix for the use of these two predicted probabilities as explanatory variables in the health status equation. Finally, we present results and implications, and conclusions and suggestions for further research.

3.2 Literature Review

The literature summarized below is divided into three parts. First, we review the numerous studies that have identified and examined various factors that influence the health status of elderly people. Second, previous studies that have examined the impact of the FSP on food consumption, nutrition intake, and elderly health are discussed. Finally, research on food sufficiency and security, the linkages to FSP Participation, and elderly health is summarized.

3.2.1 Research on Health

Although linkages among income, nutrition, obesity and health have been extensively studied in the health economics literature, relatively less research on this area has focused on the elderly. Deaton and Paxson (1998a, 1998b) have conducted research on life cycle patterns of health and nutrition-related indicators (e.g., self-reported health status and body mass index) and their relationships with income. The authors provide strong evidence on the suitability of using such indices in longitudinal analyses, and show that health status is positively correlated with income. They also show that this correlation is weakest among the youngest, and increases up to age 60 before decreasing. Their findings are consistent with Smith and Kington (1997), who apply the concept of a socioeconomic status-health gradient to show that health produces contemporaneous and long run feedbacks on economic status, implying simultaneity between these variables.

Other income-nutrition-health status studies have focused on the more vulnerable elderly given their economic and health conditions (e.g., Zhang, 1999; Stum et al., 1998; Smith and Kington, 1997; von Weizsacker, 1996). For instance, Zhang (1999) addresses the effect of income in determining health status among U.S. elderly Medicare beneficiaries. Stum et al., 1998 use the National Long-Term Care Survey to examine whether medical expenses are financially burdensome for disabled elders and to determine what factors are likely to put disabled elderly at risk of financial burden. Smith and Kington (1997) investigate the health outcomes resulting from alternative sources of income including the implications for gender, racial, and ethnic differences. In short, the health economics literature indicates that: (1) there is strong evidence that income is positively correlated with health status; (2) this relationship is simultaneous and changes during the life cycle; and (3) the most vulnerable groups (i.e. low income and/or deficient health) are likely to be at risk and therefore policy intervention is required. Finally, this literature suggests the importance of understanding the linkages between economic variables and nutrition and health outcomes in order to effectively improve the welfare of the elderly via public policy. Since 1991, rates of obesity have increased dramatically. Substantial increases among adults of all ages suggest that obesity among older Americans is likely to become a greater problem in the future. More than one-third of adults aged 65 and over were obese in 2007-2010 (Fakhouri et al., 2012). Consequently, an increase in the proportion of older adults who are obese negatively affects general elderly health condition and increase health care spending.

While the data we use in this study do not allow a detailed examination of food intake, previous studies have shown that food expenditures decrease as people get older and their need for more nutrient dense food increases, which suggests the incidence of nutrient-insufficient health problems could worsen health status among the elderly. Studies along these lines by Harris and Blisard (2002) confirm the decline in food expenditures as the elderly age. They indicate that households with heads of ages 65-74 and older than 75 spend \$41.44 and \$32.11 per capita per week, respectively. This decline generates a further concern regarding composition and sufficiency of the diets of the elderly. The quality of the diet among elderly people could be affected by food insecurity due to limited access to a variety of foods, or to the capacity to purchase food (Lee and Frongillo, 2001; Sharkey, 2004). Common low-income households adjust their food budget, reduce their food intake, and alter the type of food served when they experience inadequate resource to afford food (Bickel et al., 2000; Kendall et al., 1996; Olson, 1999; Tarasuk et al., 1999). Dietary variety decreases and consumption of energy-dense foods increases. These energy-dense foods, including refined grains, added sugars, and added saturated/trans fats, tend to be of poor nutritional quality and less expensive on a per calorie basis than alternatives (Drewnowski et al., 2005 and Monsivais et al., 2007). This is known as the "food insecurity – obesity paradox"(Brewer et al., 2010). McNamara et al., 1999 identify the gaps between food intakes and the Food Pyramid recommendation of the U.S. population and found that elderly individuals (age 60 and above) met the recommendations for only one of the five food groups, vegetables. The largest gap was in the dairy group, with the elderly consuming, on average, only 57 percent of the recommended amount. Further, Ranney and McNamara (2002) found the cost of attaining a healthier diet is relatively high for low-income households to afford, especially those containing the elderly.

3.2.2 Research on the Food Stamp Program

The goal of the Food Stamp Program (or Supplemental Nutrition Assistance Program, SNAP) is described by Nord and Golla (2009, p,iii), as, "SNAP [FSP] benefits are intended to increase the access of low-income households to food and a nutritious diet to improve their food security." There is a long history of research on the FSP by many disciplines. Economists are perplexed and challenged by the persistence of this major in-kind transfer program. Microeconomic theory implies that in kind benefits are restrictive and that giving assistance in cash would expand the choice set for recipients. Even so, a reasonable projection from the past to the foreseeable future suggests changing to cash benefits is not politically feasible or likely. Nutritionists view this large food assistance program as a major opportunity to enhance the amount and composition of food intakes and thereby enhance the health and well-being of lower-income people. Given the longevity and magnitude of the program, much research has been done. Nutritionists, economists, other researchers, and policy makers undertake analyses of how the program is working and how it might be redesigned to best achieve its objectives. While they primarily focus on the entire U.S. population and only rarely on the elderly, these studies often relate program participation to a variety of other outcomes such as food demand, food intake, nutritional status, labor supply, food sufficiency and food security.

Over time there have been at least three major reviews of the food stamp program literature. One focused on how food stamps affected food consumption (Fraker, 1990). Another reviewed the literature on how food assistance and nutrition programs affected nutrition and health (Fox et. al., 2004). The large body of research reviewed in these two studies indicates that FSP benefits increase food spending. It also shows that the program may affect household food supplies by enhancing nutrient availability, but is unclear about whether individual nutritional intake is improved (Wilde, 2007). These reviews were conducted before the major advent of food insecurity - food stamp research. The more recent review, by Wilde (2007) addresses this literature and will be discussed in the next section.

3.2.3 Research on Food Sufficiency and Security and Linkages to FSP Participation

The similarities and differences between food security and food sufficiency require clarification. First, these terms are often found in their negative forms, insecurity and insufficiency, respectively, as in our title. Second, various surveys have yielded slightly different definitions for food insufficiency based upon the number and wording of insufficiency related questions included in the questionnaire. Herein, we define a household to be food insufficient if household member(s) skipped or skimped on meals because they did not have enough food in the house. The actual questions asked in the HRS survey instrument are listed in Appendix D Part I. Food sufficiency questions preceded the development of the official food security measure.

The conceptual definition of food security is that all household members have access at *all times* to enough food for an active healthy life (Nord et. al., 2009). The official measure of the food security status of a household is calculated from their answers to questions in the Food Security Supplement (FSS) to the December Current Population Survey (CPS). Unlike food sufficiency, there is only one method for calculating food security. There are 18 specific questions asked; only ten if there are no children in the household. These questions are delineated in Appendix D Part II. Based upon the answers, the household is identified as having high, marginal, low, or very low food security. If the scoring yields high or marginal, the household is considered food secure while low or very low indicate food insecurity (USDA 2008a). When respondent burden is of particular concern, there is also a 6-question version of the FSS and an associated scale (USDA 2008b). It is interesting to note that the fourth question is almost identical to the question we use to define food sufficiency. In that sense and temporally, food sufficiency can be considered a precursor to the development of the measurement of food security.

Wilde (2007, pp. 307-309) presented a categorization of the research on how the FSP affects food security and hunger. He developed a set of seven categories to describe the research approaches used to quantify the effects on food stamps on food insecurity. Those include: (1) controlling for other observable variables; (2) jointly modeling the effect of food stamps on foods insecurity and vice versa; (3) using longitudinal or panel data; (4) using propensity score matching; (5) using a "dose-response" approach; (6) exploiting "natural experiments"; and (7) using random-assignment research design.

Our research falls squarely in Wilde's second approach, that of modeling FSP participation jointly with food insufficiency/insecurity using alternative simultaneous equation models to handle the endogeneity between participation and food security. As reported by Wilde, the findings vary. Compared to naïve models, Gundersen and Oliveira's (2001) approach eliminated the troublesome positive relationship between participation in FSP and food insufficiency. Jensen (2002) found a negative relationship between participation and insecurity. Huffman and Jensen (2008), after adding in a labor supply equation to the simultaneous system, found that food insecurity with hunger positively affects FSP participation, but that FSP participation has no effect on food insecurity. Yen et al., 2008, which was published after Wilde (2007), also falls within this category. They account for endogeneity with an instrumental variable (IV) approach and find that FSP participation reduces food insecurity. Wilde's third research category relates to using longitudinal or panel data, and that research is beginning to yield some interesting results. The research by Wilde (2007) indicated some reductions in troublesome results, but did not put an end to those problems. A later article by Nord and Golla (2009) is suggestive and may provide the clearest view of the relationships of interest, showing that food insecurity is reduced shortly after reenrolling in the FSP. Given that the HRS data is a panel data set, it certainly could be used in that fashion in the future. This study utilizes, however, a cross section from the HRS in 2002.

While our research does fit within Wilde's second research approach, our modeling and policy contributions go beyond the research reviewed therein. It is worth nothing that there are relatively few studies on this area focusing on the elderly. The similar study of Greenhalgh-Stanley and Fitzpatrick (2013) uses the same dataset, a restricted HRS data, pooled from 2000 to 2010 to examine the effect of food stamp participation on food insufficiency and diet-related disease among the eligible elderly. They estimate one directional effect of the FSP participation on food insufficiency with an instrumental variable approach, but not vice versa; and they independently estimate the effect of FSP participation on reported health and diet-related diseases. They found FSP participation significantly increases self-reported very good health status. Wu (2009) examine the effects of FSP participation on elderly outcomes such as food spending and nutritional intake. He found that elderly eligible nonparticipants are, on average, more food sufficient, spend more on food consumption, and eat more nutritious food than participants. Nicholas (2011) studied the relationship between food stamp recipient and diabetes health outcomes and found no significant difference in Medicare spending, outpatient utilization, diabetes hospitalizations and blood sugar (HbA1c) levels between recipients and eligible non-recipients after controlling for a detailed set of covariates including individual fixed effects and measures of diabetes treatment compliance. Neither study fully accounts for the endogeneity of FSP participation. Ziliak et al., 2008 estimate the effect of food insecurity on health outcome using NHANES and PSID data; however, they do not address potential endogeneity of food insecurity. They found a strong negative effect of food insecurity on reporting very good or excellent health status.

Our study first accounts for the possibility of simultaneity of FSP participation and food insufficiency on eligible elderly household following Gundersen and Oliviera's (2001) method. Second, we estimate the effect of both FSP participation and food insufficiency on the health status of the elderly in the two-step econometric model. To our knowledge, none of the related studies that use two-step estimation has a correction of second-step test statistics. As literature showing mixed evidence of the effect of FSP participation, food insecurity and elderly health outcome, we think it is very important to provide a correction of the covariance matrix in order to assure accurate statistical inference. Third, we extend and modify Murphy and Topel's (1985) procedure to be appropriate for two predicted variables. The corrected covariance matrix of the estimators lead to a more accurate conclusion of whether FSP participation and food sufficiency encourage better health outcomes.

3.3 Data

The data utilized in this study are the Health and Retirement Survey from the year 2002 panel from the Health and Retirement Study (HRS). This is a national panel with an initial sample of about 22,000 residents in the United States over the age of 55. The survey includes detailed information on demographics, health care utilization, health status, employment, family structure, income, expenditures, participation in government programs, and event histories.

Data from 18,167 respondents with no relevant missing information were allocated to their respective households and weighted to reflect U.S. households with a head of age 60 years or more. Selected descriptive statistics regarding FSP participation of these households are presented in Table 3.1.

Table 3.1: Food Stamp Program (FSP) participation by Single Person and Low-Income Elderly Households[1]

Characteristic	Number and Percent of Households
Elderly households	36,457,956
FSP participants	1,451,731
Percent participating	4.0
Elderly single-person households	16,737,945
FSP participants	1,021,642
Percent participating	6.1
Low-income elderly households[2]	13,446,749
FSP participants	1,316,267
Percent participating	9.8
Low-income elderly single-person households[2]	8,460,582
FSP participants	945,328
Percent participating	11.2

[1]These statistics come from a sample of 18,167 residents, less than the full sample of some 22,000. Residents were then assigned to their households. Residents or households were dropped from their respective samples if they had missing values for any of the variables included in the table. The final unweighted sample included 12,350 households.

[2] Low-income = gross income less than or equal to 200 percent of U.S. department of Health and Human Services (DHHS) poverty level.

Source: 2002 Health and Retirement Survey weighted data

It is important to note that FSP participation rates begin with only four percent of all elderly households and rises to 11.2 percent of low-income elderly single-person households. Actual eligibility was not calculated for the weighted data in this table. This and other studies show that approximately 30 percent of ***eligible*** elderly households participate in the program. Most studies have found that primary reason eligible elderly households fail to participate FSP is that they do not think they are eligible for the program. Many mistakenly believe their income and assets are too high (Accius, 2008).

The ideal estimation sample would be drawn from the population of elderly households eligible for food stamps. However, precisely which households are eligible is not known *a priori*. Determination of eligibility is complicated especially after the 1996 welfare reform statutes were enacted at the state level. Even so, we do determine whether each of the households in the survey is eligible for food stamps by matching the state of residence for each HRS household to state-level eligibility rules from the Urban Institute's waiver database and from the Center on Budget and Policy Priorities reports.

Our precise method for determining program eligibility is specified in detail in Appendix B. After following this method, we find 1,608 HRS households with financial respondents of age 60 or greater to be eligible for food stamps and 1,357 of the households having complete information on the variables utilized in our analyses. These constitute our eligible estimation subsample. Table 3.2 contains variable definitions and descriptive statistics for this group.

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Table 3.2: Variable Definitions, Means & Standard Deviations

Variable Categories and Names	Variable Definitions	Mean	Std. Deviation
DEPENDENT			
Participation	Food Stamp Program participation = 1 if household participated sometime in the past two years and 0 otherwise	0.314	0.464
Insufficiency	Food Insufficiency = 1 if household member(s) skipped meals or ate less than they wanted to because they didn't have enough food in the house sometime over the past two years.	0.168	0.374
Health[1]	Self-reported health status = 0 if poor, 1 if fair, 2 if good, 3 if very good, and 4 if excellent	1.407	1.094
INDEPENDENT			
Health related [1]			
Mom's age	= Mom's current age or Mom's age when she died	72.750	17.359
Obese	= 1 if BMI>=30	0.320	0.467
Smoke	= 1 if smoke, 0 otherwise	0.177	0.382
Exercise	= 1 if exercise, 0 otherwise	0.208	0.406
Drink alcohol	= 1 if drink alcohol, 0 otherwise	0.207	0.405
Age[1]			
Age 70-79	= 1 if age is from 70-79, 0 otherwise	0.281	0.450
Age 80-89	= 1 if age is from 80-89, 0 otherwise	0.206	0.404
Age 90 +	= 1 if age is 90 +, 0 otherwise	0.048	0.214
	omitted category is respondent's age ≤ 69		
Marital status[1]			
Divorced	= 1 if divorced, 0 otherwise	0.192	0.394
Widowed	= 1 if widowed, 0 otherwise	0.439	0.496
	omitted category = married.[2]		
Employment status[1]			
Economically active	= 1 if working, 0 otherwise	0.074	0.261
Retired	= 1 if retired, 0 otherwise	0.503	0.500
Disabled	= 1 if disabled, 0 otherwise	0.261	0.439
	omitted variable is homemaker		

Table 3.2 (cont'd)

Variable Categories and Names	Variable Definitions	Mean	Std. Deviation
Place of residence			
Rural	= 1 if rural 0 otherwise	0.329	0.470
Suburban	= 1 if suburban, 0 otherwise	0.287	0.453
	omitted category is URBAN		
Regions			
Midwest	= 1 if reside in midwest, 0 otherwise	0.164	0.370
South	= 1 if reside in south, 0 otherwise	0.259	0.438
West	= if reside in west, 0 otherwise	0.151	0.358
	omitted category is EAST		
Race/Ethnicity[1]			
Hispanic	= 1 if Hispanic, 0 otherwise	0.211	0.409
Nonhispanic black	= 1 if non-Hispanic black, 0 otherwise	0.330	0.470
Nonhispanic other	= 1 if non-Hispanic other, 0 otherwise	0.035	0.183
	omitted category is nonhispanic white		
Economic			
Income	= Annual household income (in thousands)	0.164	24.622
Receive SSI	= 1 if someone in the household receives SSI income, 0 otherwise	0.831	0.375
Own home	= 1 if home is owned, 0 otherwise	0.378	0.485
Own vehicle	= 1 if own at least 1 vehicle, 0 otherwise	0.436	0.496
Other			
Household size	= Household size	2.000	1.365
High School[1]	= 1 if earned high school diploma or greater, 0 otherwise	0.312	0.463
Skip medicines[1]	= 1 if skipped medicines due to financial constraints, 0 otherwise	0.030	0.171
Female[1]	= 1 if female, 0 otherwise	0.674	0.469
IADLA[1]	Instrumental activities of daily living equals to the sum of three binary variables that indicate whether the respondent has some difficulty of using the phone, managing money and/or taking medicines. The variable ranges from 0 to 3.	0.334	0.718

[1] All these person-specific variables relate to the household financial respondent.

[2] There is one other category, never married. There were no observations in our eligible subsample with that marital status.

Source: 2002 Health and Retirement Survey

3.4 Theoretical Framework

Our theoretical framework assumes that individuals maximize utility subject to their budget constraint. Utility is a function of food (F), health (H), other goods and services (Z), leisure time (L), if a person participated in the Food Stamp Program, and stigma (S) will be accrued with participation (FS). Aside from transaction costs associated with establishing and maintaining eligibility, stigma or lack of information explains why people might not participate. Stigma associated with welfare programs in general (Moffitt, 1983) and the Food Stamp Program (FSP) in particular (Ranney and Kushman, 1986) not only affects participation, but also might be the most important factor, given the implication of economic theory that people should always accept additional un-stigmatized income. Stigma can be modeled as a latent variable manifested through non-participation. Lack of knowledge of the FSP could lead eligible individuals not to apply. A few people, especially, isolated and immobile older people, or those with disabilities, might find the non-monetary cost of application too high. We model FSP participation, food insufficiency and health following Grossman's (1972) human capital model. Individuals do not demand medical services, but better health. Therefore, Grossman (1972) uses various health-related inputs such as nutrition (N) and medical services (M) in the health production function (H).

The maximization problem for the consumer is expressed below:

$$\text{(3.1)} \qquad \mathrm{Max\ U(F, H(N(F), O(F), M), S(FS), Z, L)}$$

$$\text{(3.2)} \qquad s.t.\ \mathrm{Tw + A + B_{fs}FS - C_{fs}FS = p_m M + p_f F + Z + wL}\,,$$

where H is health production function, which includes nutrition (N) and obesity (O) functions; and nutrition (N) and obesity (O) are a function of food (F). Food consumption could increase the level of nutrition intake to improve health status, but also, if over consumed, could cause obesity that deteriorates health status. Stigma (S) is a function of food stamp program participation (FS) in which FS =1 if an individual participates the program, and zero otherwise. Nutrition, obesity, medical services, and FSP participation do not directly affect utility. Z represents other goods and services; L is non-labor market/leisure time; T is total time available; (T-L)*w is labor income based on and individual's wage rate (w); A is non-labor income; B_{fs} is the benefit of FSP participation; C_{fs} is the monetary cost of FSP participation such as the cost of application, certification and re-certification for food stamps; p_m is average unit cost of medical services, and p_f is average unit price of food. All prices and the wage rate are normalized by the price of other goods and services (p_z), thus $p_z = 1$. Some assumptions are imposed for utility maximization such as food (F), medical services (M), other goods and services (Z), leisure time (L) are normal goods, continuous, and differentiable. Food stamp (FS) is an inferior good and is a binary variable. The stigma (S) is assumed to be a linear function of FS, that is, $S(FS) = \varsigma FS$; $\varsigma > 0$. The first partial derivatives of all arguments are $U_F, U_H, U_Z, U_L, H_N, H_M, N_F, O_F > 0$, $H_O < 0$, and $U_S = -s$ where $s > 0$. The second partial derivatives are $N_{FF}(F < \tilde{F}) > 0$, $N_{FF}(F > \tilde{F}) < 0, O_{FF}(F < \tilde{F}) < 0$, $O_{FF}(F > \tilde{F}) > 0, H_{OO} > 0$ and $H_{NN} < 0$. $\tilde{F}$ is a threshold of food consumption that increases the rate of obesity and decrease the rate of nutrition intake if $F > \tilde{F}$. This can be graphically expressed as in Figure 3.1:

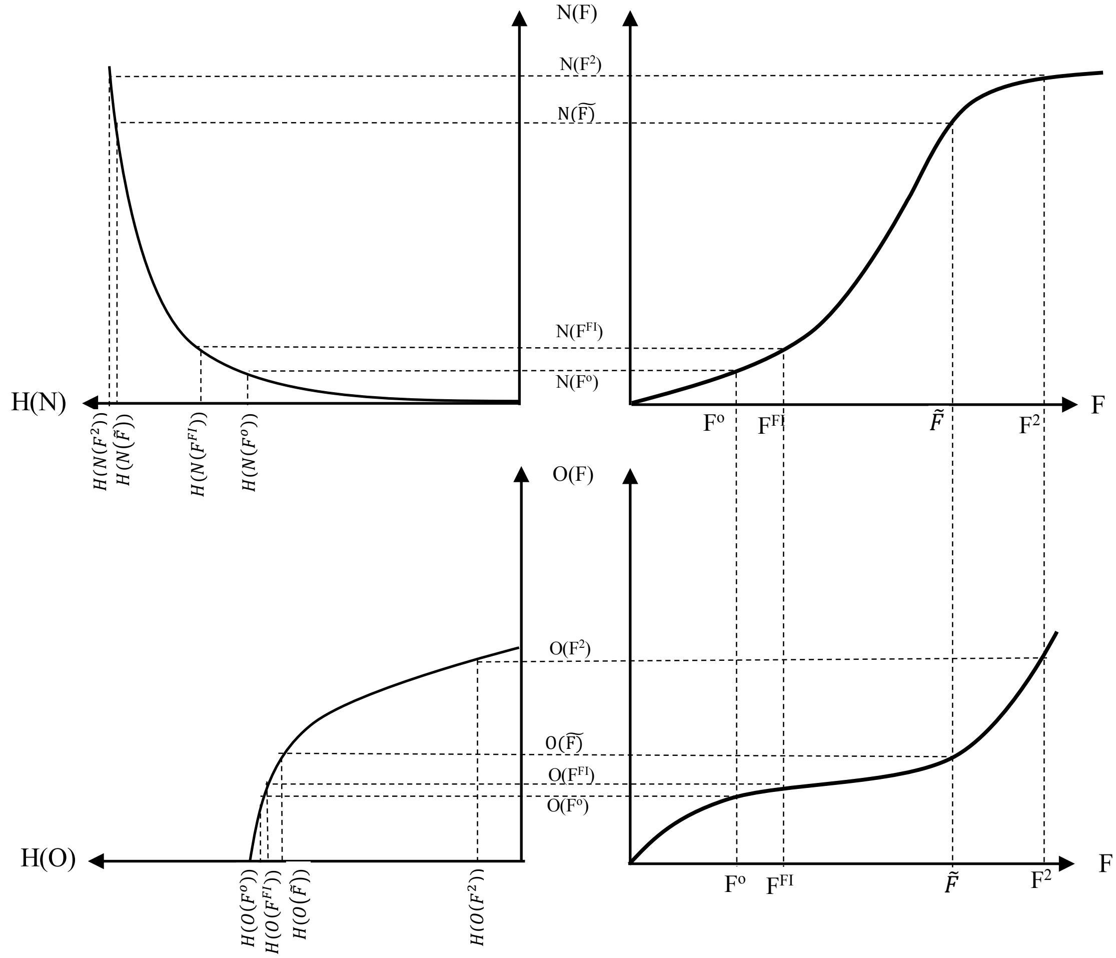

Figure 3.1: The relationship of health status (H), nutrition (N), obesity (O) and food intake (F)

F^{FI} is a food insufficiency threshold. For example, an individual who consumes $F^{o} < F^{FI}$ has health derived from food consumption $[H(F^{o}) = H(N(F^{o})) + H\ (O(F^{o}))]$ that is less than individual who consumes at $\tilde{F}$ where $\tilde{F} > F^{FI}$, thus $[H(\tilde{F}) = H\ (N(\tilde{F})) + H\ (O(\tilde{F}))]$. At the $H(F^{o})$ level, the individual does not have enough food to maintain good health, thus reporting poor or fair health status. However, if the individual consumes more than $\tilde{F}$ such as $F = F^{2}$, then the health derived from food consumption $[H(F^{2}) = H\ (N(F^{2})) + H\ (O(F^{2}))]$ might be lower than $H(F^{o})$ because the rate of obesity outweighs the rate of nutrition intake. Inversely, the consumer might report poor health status. Equations (3.1) and (3.2) yield the following Lagrangian expression:

$$(3.3) \qquad \mathrm{L} = \mathrm{U}(\mathrm{F}, \mathrm{H}(\mathrm{N}(\mathrm{F}), \mathrm{O}(\mathrm{F}), \mathrm{M}), \mathrm{S}(\mathrm{FS}), \mathrm{Z}, \mathrm{L}) +$$

$$\lambda(\mathrm{Tw} + \mathrm{A} + \mathrm{B}_{\mathrm{fs}}\mathrm{FS} - \mathrm{C}_{\mathrm{fs}}\mathrm{FS} - \mathrm{p}_{\mathrm{m}}\mathrm{M} - \mathrm{p}_{\mathrm{f}}\mathrm{F} - \mathrm{Z} - \mathrm{wL})$$

The first order conditions of equation (3.3) can be expressed as

$$(3.3.1) \qquad \frac{\partial \mathrm{L}}{\partial \mathrm{F}} = \mathrm{U}_{\mathrm{F}} + \mathrm{U}_{\mathrm{H}}\mathrm{H}_{\mathrm{N}}\mathrm{N}_{\mathrm{F}} + \mathrm{U}_{\mathrm{H}}\mathrm{H}_{\mathrm{O}}\mathrm{O}_{\mathrm{F}} - \lambda \mathrm{p}_{\mathrm{f}} = 0$$

$$(3.3.2) \qquad \frac{\partial \mathrm{L}}{\partial \mathrm{M}} = \mathrm{U}_{\mathrm{H}}\mathrm{H}_{\mathrm{M}} - \lambda \mathrm{p}_{\mathrm{m}} = 0$$

$$(3.3.3) \qquad \frac{\partial \mathrm{L}}{\partial \mathrm{FS}} = \mathrm{U}_{\mathrm{S}}\varsigma - \lambda(\mathrm{B}_{\mathrm{fs}} - \mathrm{C}_{\mathrm{fs}}) = 0$$

$$(3.3.4) \qquad \frac{\partial \mathrm{L}}{\partial \mathrm{Z}} = \mathrm{U}_{\mathrm{Z}} - \lambda = 0$$

$$(3.3.5) \qquad \frac{\partial \mathrm{L}}{\partial \mathrm{L}} = \mathrm{U}_{\mathrm{L}} - \lambda \mathrm{w} = 0$$

$$(3.3.6) \qquad \frac{\partial \mathrm{L}}{\partial \lambda} = \mathrm{A} + \mathrm{B}_{\mathrm{fs}}\mathrm{FS} - \mathrm{C}_{\mathrm{fs}}\mathrm{FS} - \mathrm{p}_{\mathrm{m}}\mathrm{M} - \mathrm{p}_{\mathrm{f}}\mathrm{F} - \mathrm{Z} - \mathrm{wL} = 0$$

$$(3.5) \qquad \frac{\mathrm{U}_{\mathrm{F}} + \mathrm{U}_{\mathrm{H}}\mathrm{H}_{\mathrm{N}}\mathrm{N}_{\mathrm{F}} + \mathrm{U}_{\mathrm{H}}\mathrm{H}_{\mathrm{O}}\mathrm{O}_{\mathrm{F}}}{\mathrm{p}_{\mathrm{f}}} = \frac{\mathrm{U}_{\mathrm{H}}\mathrm{H}_{\mathrm{M}}}{\mathrm{p}_{\mathrm{m}}} = \mathrm{U}_{\mathrm{Z}} = \frac{\mathrm{U}_{\mathrm{L}}}{\mathrm{w}} = \frac{-\mathrm{s} * \varsigma}{\mathrm{B}_{\mathrm{fs}} - \mathrm{C}_{\mathrm{fs}}} = \lambda,$$

where λ is the marginal utility of money. Equation (3.5) satisfies the equi-marginal principle that the marginal utility of food per dollar spent is equal to the marginal utility of spending on health, the marginal utility of other goods and services, and the marginal utility of leisure, respectively. If $\mathrm{U}_{\mathrm{F}} + \mathrm{U}_{\mathrm{H}}\mathrm{H}_{\mathrm{N}}\mathrm{N}_{\mathrm{F}} + \mathrm{U}_{\mathrm{H}}\mathrm{H}_{\mathrm{O}}\mathrm{O}_{\mathrm{F}} > 0$, this means food consumption increases marginal utility per dollar spent.

However, if $U_F + U_H H_N N_F + U_H H_O O_F \leq 0$, food consumption decreases marginal utility per dollar spent. The FSP participation decision involves a direct comparison between maximum utility with and without participation. Thus, a person participates FSP if

$$\text{(3.6)} \qquad U(F^{FS}, H^{FS}(N(F), O(F), M), S(FS), Z^{FS}, L^{FS}) - U(F^{NFS}, H^{NFS}(N(F), O(F), M), 0, Z^{NFS}, L^{NFS}) > 0,$$

where the binary superscripts relate to FSP participation status. FSP participation increases household incomes by $B_{fs} - C_{fs}$ and will also increase consumption of F, M, Z, and L, thus increasing overall utility. Specifically, an increase in food consumption is hypothesized to improve food insufficiency such that $F^{FI} - F^{FS} < F^{FI} - F^{NFS}$, where F^{FI} indicates a food insufficiency threshold below which at least some household member's meals are reduced in size or skipped, thereby jeopardizing nutritional status and health. In turn, F^{FS} is the level of food consumption when the individual participates in the FSP and F^{NFS} is the level of food consumption when the individual does not participate in the FSP. Because additional money from participating FSP could increase amount of food purchased, we, thus, assume that $F^{FS} > F^{NFS}$. Food insufficiency directly decreases household utility and indirectly decreases household utility through health (H) and nutrition function (N). The household will consider participating in the FSP to increase its utility as shown in equation (3.6). However, participating in the FSP can stigmatize the household, which in turn may decrease its utility. In the first order condition equations, the individual will participate in the FSP if the marginal utility of net benefit from FSP participation is greater than the disutility of stigma. In mathematical terms,

$$\lambda\,(B_{FS} - C_{FS}) > S, \tag{3.7}$$

where $S = -s * \varsigma$ is a disutility of stigma from participating the FSP and $\lambda > 0$. Thus, the individual is more likely to participate in the FSP if the stigma is relatively small, if the marginal utility of income (λ) is large, if the cost of participating is small, or if participation benefits are large. We assume that eligibility for the FSP is exogenous, i.e. not chosen by a person through labor supply or household formation decisions for this study of eligible households' behavior. The implication of this model is that FSP participation (FS), food insufficiency (FI) and health status (H) are derived from a utility maximization problem and that they are all function of parameters of the utility function and demographic factors that shift the utility function. First, we are interested in the relationship between FSP participation (FS) and food insufficiency (FI). FSP participation and food insufficiency are simultaneously determined. Participation in the FSP, for instance, could alleviate food insufficiency through providing more money from the FSP to buy more food. Food insufficiency could encourage individuals to participate in the FSP if households have food consumption that is low enough to be skipping meals. From first order condition, we can solve for F* and determine whether F* is greater or less than F^{FI}. FS* can be determined based on the FSP participation condition in (3.7). The prices and wage ratios are excluded in the estimation because we assume the ratios are the same for every low-income household. Both FSP participation and food insufficiency affect elderly's health status through the function H(•). These effects will be built into the health equation in the econometric framework presented below.

3.5 Econometric Framework

Our theoretical model leads to an estimation framework consisting of three equations estimated in two sequential steps. The equations are FSP participation (FS), food insufficiency (FI), and self-reported health status (H) in equations (3.8) through (3.10) below, respectively. The first two equations (3.8) and (3.9) are simultaneously estimated using Probit maximum likelihood estimation in Step One. In Step Two, we estimate self-reported health status in equation (3.10) using Ordered Probit maximum likelihood estimation with the predicted values of FS and FI among the independent variables. The equations are:

$$(3.8) \qquad \mathrm{FS}^* = \beta_{0,\mathrm{FS}}\mathrm{FI}^* + \mathbf{x}'_{\mathrm{FS}}\beta_{\mathrm{FS}} + \varepsilon_{\mathrm{FS}} \quad ; \mathrm{FS} = 1 \text{ iff } \mathrm{FS}^* \leq 0 \text{ and } \mathrm{FS} = 0 \text{ iff } \mathrm{FS}^* > 0$$

$$(3.9) \qquad \mathrm{FI}^* = \beta_{0,\mathrm{FI}}\mathrm{FS}^* + \mathbf{x}'_{\mathrm{FI}}\beta_{\mathrm{FI}} + \varepsilon_{\mathrm{FI}} \quad ; \mathrm{FI} = 1 \text{ iff } \mathrm{FI}^* \leq 0 \text{ and } \mathrm{FI} = 0 \text{ iff } \mathrm{FI}^* > 0$$

$$(3.10) \qquad \mathrm{H}^* = \beta_{0,\mathrm{H}}\mathrm{FS}^* + \beta_{1,\mathrm{H}}\mathrm{FI}^* + \mathbf{x}'_{\mathrm{H}}\beta_{\mathrm{H}} + \varepsilon_{\mathrm{H}}$$

In (3.10), the general observation mechanism for H = 0, 1,…,4 is :

$$\begin{aligned} \mathrm{H_i} &= 0 \text{ if } \mathrm{H_i} \leq \mu_o \\ &= 1 \text{ if } \mu_o < \mathrm{H_i} \leq \mu_1 \\ &= 2 \text{ if } \mu_1 < \mathrm{H_i} \leq \mu_2 \text{ and } \ldots. \\ &= \mathrm{j} \text{ if } \mathrm{H_i} > \mu_{j-1}. \end{aligned}$$

There are five categories of health status ordered from zero to four with zero indicating poor health and four indicating excellent health. The more specific definitions of the dependent and independent variables are presented in Table 3.2. The two-step framework arises from econometric difficulties that must be addressed both within and across steps. First, the FS equation (3.8) and the FI equation (3.9) contain endogenous explanatory variables, FI^* and FS^*, respectively. We follow Gundersen and Oliviera's (2001) framework, which is consistent with our theoretical model, and specify (3.8) and (3.9) first as independent equations and then as a simultaneous system. Specifically, a two-equation system of simultaneous-in-propensity program participation and food insufficiency is estimated with Probit equations. We also address the issue of identification in this first step of our two-step procedure. Two identification variables are whether household members skipped necessary medications due to financial constraints (SKIP MEDICINES) and whether any household member participates in the Supplemental Security Income (SSI) program (RECEIVE SSI). These two variables will be discussed in detail in the identification section. Gundersen and Oliviera (2001) found the simultaneous specification performs well when estimating food stamp program participation and food insecurity relationships with a sample of eligible American (nonelderly and elderly) households.

Step Two involves estimation of health status (H) in equation (3.10). Two variables from the first step, the predicted index values for FSP participation (FS^*) and food insufficiency (FI^*), are transformed into predicted probabilities and used as explanatory variables in the health status equation. This raises a second econometric issue because the variables are based on estimates from the simultaneous system in Step One. The standard two-step procedure fails to account for the fact that imputed repressors (predicted variables from the first stage) are measured with sampling error, so hypothesis tests based on the estimated covariance matrix of the second-step estimator are biased, even in large samples (Murphy and Topel, 1985). Thus, the use of predicted explanatory variables require that we modify a covariance correction method developed by Murphy and Topel (1985) to allow for two, rather than one, predicted explanatory variables (see Appendix E Part I for details).

3.5.1 Step One Estimation

The specifications and results of the independent and simultaneous FSP participation and food insufficiency equations are reported in Table 3.3. We follow Gundersen and Oliviera's (2001) method, which is from a general model developed by Maddala (1983, pp. 246-247). We start with a reduced form two-equation system, which consists of FSP participation and food insufficiency equations as follows:

$$\text{(3.11)} \qquad \mathrm{FS}^* = \boldsymbol{\pi}_{\mathbf{FS}}\mathbf{X} + \mathrm{v}_{\mathrm{FS}} \;;\; \mathrm{FS} \begin{cases} = 1 \text{ (participate in FSP) iff } \mathrm{FS}^* \leq 0 \\ = 0 \text{ (not participate in FSP) iff } \mathrm{FS}^* > 0 \end{cases}$$

$$\text{(3.12)} \qquad \mathrm{FI}^* = \boldsymbol{\pi}_{\mathbf{FI}}\mathbf{X} + \mathrm{v}_{\mathrm{FI}} \;;\; \mathrm{FI} \begin{cases} = 1 \text{ (food insufficiency) iff } \mathrm{FI}^* \leq 0 \\ = 0 \text{ (food sufficiency) iff } \mathrm{FI}^* > 0 \text{ ,} \end{cases}$$

where FS^* is a latent true value of FSP participation, $\mathrm{FI}^*$is a latent true value of food insufficiency, $\mathbf{X}$ is a vector of explanatory variables, $\boldsymbol{\pi}_{\mathbf{FS}}$ and $\boldsymbol{\pi}_{\mathbf{FI}}$ are vectors of corresponding parameter estimates, and v_{FS} and v_{FI} are error terms. The reduced form equations (3.11) and (3.12) are independently estimated by a Probit Maximum likelihood estimation. The predicted index values from those two reduced form estimations denoted as $\widehat{\mathrm{FI}}^*$ and $\widehat{\mathrm{FS}}^*$ are used as an explanatory variable in the structural equation (3.13) and (3.14), respectively as

$$\mathrm{FS}^{**} = \alpha_{0,\mathrm{FS}}\widehat{\mathrm{FI}}^* + \mathbf{X}'_{\mathrm{FS}}\boldsymbol{\alpha}_{\mathrm{FS}} + \mathrm{u}_{\mathrm{FS}} \tag{3.13}$$

$$\mathrm{FI}^{**} = \alpha_{0,\mathrm{FI}}\widehat{\mathrm{FS}}^* + \mathbf{X}'_{\mathrm{FI}}\boldsymbol{\alpha}_{\mathrm{FI}} + \mathrm{u}_{\mathrm{FI}}\ , \tag{3.14}$$

where FS^{**} and FI^{**} are the latent true values of FSP participation and food insufficiency in structural equations, respectively; $\mathbf{X_{FS}} \in \mathbf{X}$, $\mathbf{X_{FI}} \in \mathbf{X}$, $\mathbf{X_{FS}} \neq \mathbf{X_{FI}}$, $\alpha_{0,\mathrm{FS}}$, $\alpha_{0,\mathrm{FI}}$, $\boldsymbol{\alpha}_{\mathbf{FS}}$ and $\boldsymbol{\alpha}_{\mathbf{FI}}$ are vectors of corresponding parameter estimates, and u_{FS} and u_{FI} are error terms. Similar to the reduced forms, the FS^{**} and FI^{**} in structural equations are categorized in a binary form and the same order. $\mathbf{X_{FS}}$ and $\mathbf{X_{FI}}$ are vectors of explanatory variables which are not identical due to identifiable parameters in the simultaneous model. This will be discussed in the identification section below. Equation (3.13) and (3.14) are independently estimated by Probit maximum likelihood estimation. The predicted index values from these two structural equations are transformed into predicted probabilities denoted as $\widehat{\mathrm{FS}}^{**}$ and $\widehat{\mathrm{FI}}^{**}$, which are then used as explanatory variables in the health status equation in the second step. It is worth noting that the general model of Maddala (1983, pp. 246-247) that features a simultaneous Probit model requires a modified correction in the variance-covariance matrix for $\widehat{\mathrm{FS}}^{**}$ and $\widehat{\mathrm{FI}}^{**}$. The correction procedure is presented in the Appendix E

Part I. Before proceeding to the second step of the estimation, the issue of identification and endogeneity need to be addressed.

Table 3.3: Program Participation and Food Sufficiency Probit Estimates

Variables	Independent Probits: FSP Participation[1] (st. error)	Independent Probits: Food Insufficiency[1] (st. error)	Simultaneous Probits: FSP Participation[1] (st. error)	Simultaneous Probits: Food Insufficiency[1] (st. error)
Constant	-1.336*** (0.209)	-1.025*** (0.219)	-1.43*** (0.166)	-1.27*** (0.414)
Participation[2]	____	0.378*** (0.091)	____	-0.270 (0.291)
Insufficiency[2]	0.404*** (0.098)	____	-0.224 (0.213)	____
Skipped medicine	____	0.736*** (0.219)	____	0.626*** (0.186)
Receive SSI	0.344** (0.136)	____	0.296*** (0.097)	____
Income (in thousands)	0.153 (0.182)	0.063 (0.200)	0.185 (0.123)	0.138 (0.145)
Age 70-79	0.172* (0.096)	-0.253*** (0.097)	0.094 (0.087)	-0.181** (0.086)
Age 80-89	0.034 (0.120)	-0.290** (0.130)	-0.058 (0.105)	-0.260** (0.092)
Age 90 +	-0.179 (0.216)	-0.485* (0.257)	-0.344** (0.172)	-0.534*** (0.170)
Divorced	0.290** (0.118)	-0.119 (0.121)	0.270*** (0.088)	0.029 (0.144)
Widowed	-0.112 (0.103)	-0.396*** (0.113)	-0.229** (0.109)	-0.410*** (0.079)

Table 3.3: (cont'd)

Variables	Independent Probits FSP Participation[1] (st. error)	Independent Probits Food Insufficiency[1] (st. error)	Simultaneous Probits FSP Participation[1] (st. error)	Simultaneous Probits Food Insufficiency[1] (st. error)
Disabled	0.266 **	0.168	0.342 ***	0.289 **
	(0.096)	(0.109)	(0.093)	(0.126)
Economically active	0.093	-0.287	-0.001	-0.263 **
	(0.170)	(0.201)	(0.136)	(0.131)
Retired	-0.115	0.023	-0.116	-0.022
	(0.092)	(0.107)	(0.069)	(0.084)
Rural	0.398 ***	-0.167	0.344 ***	-0.030
	(0.102)	(0.111)	(0.079)	(0.132)
Suburban	0.064	-0.068	0.049	-0.049
	(0.104)	(0.106)	(0.071)	(0.080)
Female	0.257 ***	0.364 ***	0.392 ***	0.485 ***
	(0.099)	(0.108)	(0.112)	(0.123)
Hispanic	0.312 ***	-0.182	0.257 **	-0.082
	(0.120)	(0.128)	(0.090)	(0.127)
Nonhispanic black	0.148	0.207 **	0.222 **	0.268 **
	(0.102)	(0.097)	(0.084)	(0.091)
Nonhispanic other	0.051	-0.223	-0.019	-0.192
	(0.216)	(0.285)	(0.160)	(0.169)
Household size	0.073 **	-0.361	0.062 **	-0.011
	(0.031)	(0.034)	(0.025)	(0.030)
Highschool	-0.098	-0.005	-0.096	-0.035
	(0.088)	(0.104)	(0.062)	(0.073)

Table 3.3 (cont'd)

Variable	Independent Probits: FSP Participation[1] (st. error)	Independent Probits: Food Insufficiency[1] (st. error)	Simultaneous Probits: FSP Participation[1] (Corrected st. error)	Simultaneous Probits: Food Insufficiency[1] (Corrected st. error)
Midwest	0.062	-0.023	0.066	0.018
	(0.111)	(0.120)	(0.080)	(0.090)
South	-0.136	0.068	-0.114	0.020
	(0.101)	(0.121)	(0.074)	(0.088)
West	-0.502 ***	0.144	-0.461 ***	-0.048
	(0.137)	(0.124)	(0.086)	(0.166)
Own home	-0.248 ***	-0.044	-0.275 ***	-0.153
	(0.089)	(0.095)	(0.062)	(0.102)
Own vehicle	-0.068	-0.017	-0.072	-0.054
	(0.083)	(0.100)	(0.064)	(0.075)
Obese(BMI>=30)	0.099	-0.152 **	-0.056	0.164 **
	(0.081)	(0.092)	(0.065)	(0.069)
IADLA	-0.058	0.180 ***	-0.001	0.164 ***
	(0.059)	(0.058)	(0.055)	(0.046)
LOG LIKELIHOOD	-761.977	-561.691	-770.112	-569.921

[1] The superscripts *, ** and *** represent significant coefficients at the ten, five, and one percent level, respectively.
[2] For the independent Probit equations, the PARTICIPATION and INSUFFICIENCY variables are binary, while for the simultaneous Probits, they are index values predicted from the reduced form estimates. Those results are presented in Table C.1 in the appendices.

Source: 2002 Health and Retirement Survey

3.5.2 Identification

Our two candidate identification variables are whether household members skipped necessary medications due to financial constraints (SKIP MEDICINES), and whether any household member participates in the Supplemental Security Income (SSI) program[12] (RECEIVE SSI). Skipping needed medicines may be positively associated with food insufficiency and have no effect on food stamp participation. That is, skipping medicines is a mechanism for dealing with insufficient resources much like skipping meals. If the household receives SSI benefits, we hypothesize that most, if not all, the stigma associated with receiving welfare is incurred when applying for and receiving SSI benefits. Further, any stigma remnants associated with food stamps would not be participation barriers. Based on this hypothesis, then, receipt of SSI income would positively affect food stamp participation, but have no effect on food insufficiency.

While our reasoning seems sound, our identification expectations need to be tested. We do so by including RECEIVE SSI and SKIP MEDICINCES in the reduced form equations (3.11) and (3.12), respectively.[13] Therein, the variable RECEIVE SSI is positive and significant in the FSP participation equation, but insignificant in the food insufficiency equation. Similarly, the variable SKIP MEDICINES is positive and significant in the food insufficiency equation, but not significant in the FSP participation equation. Taken together, these reduced form statistical results support utilizing these two variables for identification purposes. Hence, we include these two

[12] The Federal Supplemental Security Income Program provides monthly cash assistance to people who are disabled, blind, or elderly and have little income and few assets. In 2013, nearly 8.4 percent million people collected SSI benefit. For nearly three-fifths of recipients, SSI represents their only source of income (SSA 2013).
[13] The reduced form estimates are presented in Table C.1 in the Appendix C.

variables in the appropriate equations of the independent and simultaneous formulations. The signs and significance of these variables are as hypothesized. That is, SKIP MEDICINES positively and significantly affects food insufficiency for both independent and simultaneous specifications as hypothesized. Similarly, RECEIVE SSI is positive and significant in both specifications of the food stamp participation equation as presented in Table 3.3. Specifically, individuals who skip medicine due to financial constraints have higher probability to experience food insufficiency (14.8 percent) and individuals who receive SSI have higher probability to participate in FSP (9.5 percent) than those who do not.

3.5.3 Endogeneity

The main reason Gundersen and Oliviera (2001) argue for the simultaneous model is because eligible households, who are more likely to participate in the FSP, may also be more likely to be food insufficient (2001, p. 879). Our bivariate statistics clearly show this to be true for our food stamp eligible sample. Based upon manipulation of information provided in Table 3.4, food stamp participants are almost twice as likely as nonparticipants to be food insufficient with 24.2 percent of food stamp participants and 13.4 percent of nonparticipants. When comparing food insufficient and food sufficient households, 45.2 percent of food insufficient households receive food stamps. The percentage for food sufficient households is lower, 28.6 percent. For the SIPP sample of the entire population utilized by Gundersen and Oliviera (2001), 40 percent of the eligible households participate in FSP, compared to 31 percent of the eligible elderly in our HRS sample.

Table 3.4: Bivariate Percent Distribution of Food Stamp Program Participation and Food Insufficiency

		Food Insufficiency (percent)	
		Yes	**No**
Food Stamp Program	**Yes**	7.6	23.8
Participation (percent)	**No**	9.2	59.4

Source: 2002 Health and Retirement Survey

Policy makers likely would be troubled by the bivariate statistics below and by the naïve independent estimates reported in columns 2 and 3 of Table 3.3. Note the positive and significant effects of food insufficiency on FSP participation and, in turn, FSP participation on food insufficiency. To compare those results to their counterpart coefficients in columns 4 and 5 where the endogeneity between FSP participation and food insufficiency are accounted for by the simultaneous system, both coefficients have negative signs, but are not significantly different from zero. Our simultaneous equation models with standard error correction removed the evidence of a significant positive association between food stamp participation and food insufficiency. While policy makers would prefer to see food stamp program participation reduce food insufficiency, at least our results show that the program has no significant effect and, in particular, does not increase food insufficiency.

3.5.4 Step One Estimation Results

We choose the simultaneous equation specification for FSP participation and food sufficiency as the preferred specification and discuss only those results. Similar to Gundersen and Oliveira’s (2001) results, both coefficients of FSP participation and food insufficiency are not significantly different from zero. Greehalgh-Stanley and Fitzpatirck (2013) and Huffman and Jensen (2008) found the same result that FSP participation did not significantly improve food insufficiency of the elderly. Unlike our results, Huffman and Jensen (2008) did find that food insecurity positively affected FSP participation.

The positive (+) and negative (-) significant demographic determinants of FSP participation are: receive SSI (+), age 90+ (-), divorced (+), disabled (-), rural (+), female (+), Hispanic (+), non-Hispanic black (+), household size (+), west (-), own house (-). The significant demographic determinants of food insufficiency are: skipped medicine (+), age (-), widowed (-), disabled (+), economically active (-), female (+), non-Hispanic black (+), obese (BMI>=30) and IADLA (+). The marginal effects of the variables in the simultaneous model of FSP participation and food insufficiency are presented in Table 3.5. The marginal effects tell us by how much FSP participation and food insufficiency changes when the variables change by one unit.

We focus on marginal effects of significant variables on both FSP participation and food insufficiency equations. Individuals living in the west and age 90+ are the least likely group to participate in FSP (-14.8 percent and -11.1 percent). Being female, being divorced compared to married, living in rural areas compared to urban, and being disabled tends to increase participation in FSP (12.6 percent, 8.7 percent, 11 percent and 11.1 percent, respectively). Previous literature has found that FSP participation is closely related to employment status and household composition, since unemployment and divorce often precede applications for food assistance (Gleason et al., 1998; Lubitz and Carr, 1985).

Table 3.5: Marginal Effects of the variables in simultaneous models of FSP Participation and Food Insufficiency

Independent Variable [2]	**FSP Participation**[3] **Marginal Effects**[1]	**Food Insufficiency**[3] **Marginal Effects**[1]
Participation	---	-0.068
Insufficiency	-0.072	---
Skip medicines	---	0.148***
Receive SSI	0.095***	---
Income (in thousands)	0.059	0.034
Age 70-79	0.030	-0.043**
Age 80-89	-0.018	-0.064**
Age 90+	-0.111**	-0.131***
Divorced	0.087***	0.009
Widowed	-0.073**	-0.096***
Disabled	0.110***	0.071**
Economically active	-0.0003	-0.061
Retired	-0.038	-0.007
Rural	0.111***	-0.003
Suburban	0.015	-0.009
Female	0.126***	0.117***
Hispanic	0.082**	-0.015
Nonhispanic black	0.071**	0.064**
Nonhispanic other	-0.006	-0.046
Household size	0.019**	-0.002
Highschool	-0.031	-0.009
Midwest	0.021	0.004
South	-0.036	0.004
West	-0.148***	-0.013
Own home	-0.089***	-0.037
Own vehicle	-0.023	-0.013
Obese	0.018	-0.025**
IADLA	-0.0002	0.037***

[1] Marginal effects for continuous variables are calculated as follows:
For continuous variables: $\frac{\partial E(Y)}{\partial X} = \frac{\partial F(*)}{\partial X}$, where F(•) indicates the standard normal distribution function.
For binary variables: the marginal effects are: Prob [y|x=1] – Prob [y|x=0]. See Greene (2002).
[2] The independent variables listed either have significant Probit coefficients or are members of categories of variables where at least one variable is significant in the relevant equation.
[3] The superscripts *, ** and *** represent significant coefficients at the ten, five, and one percent level, respectively.

The FSP participation rate is lower among employed individuals, who tend to have less time than unemployed individuals do and may find the application process burdensome (McKernan and Ratcliffe, 2003). Individuals who own a house compared to ones who do not exhibit lower probabilities of participation in the FSP (-8.9

percent). This might be associated to the absence of financial obligations. In addition, asset ownership may discourage participation among low-income households with assets below the FSP limit. These households may choose not to participate because program application and recertification incur high transaction costs for applicants with assets (Huang et al., 2010). The level of annual household income, however, has no significant impact on either FSP participation or food insufficiency. This is not surprising because one of the FSP eligibility criteria for elderly households is the net income test, in which the gross income is subtracted by standard deduction, earn income deduction, dependent care deduction and medical deduction. Therefore, these deductions leave out high income elderly from the sample. Race disparity plays an important role in determining the program participation. Hispanics and non-Hispanic black individuals tend to participate in FSP more than white individuals (8.2 percent and 7.1 percent, respectively).

For food insufficiency, the marginal effects suggest that individuals age 90+ are the lowest risk group in food insufficiency (-13.1 percent) compared to individuals at age less than 70 who are at the highest risk. Females and disabled individuals are more vulnerable to experience food insufficiency (11.7 percent, 7.1 percent, respectively) relative to the rest. Non-Hispanic blacks have the highest risk of being food insufficient (11.7 percent). IADLA index shows that individuals who have higher IADLA are more likely to experience food insufficiency (7.4 percent).

3.5.5 Step Two Estimation Results

This step focuses on exploring the determinants of the self-reported health status by financial respondents of food stamp eligible households in our sample. The health status ranges from zero (poor health) to four (excellent health). The mean self-reported health status (HS) in our sample is 1.54, which falls between good and fair. These statistics are derived from Table C.2 in Appendix C, which also details the frequencies and percent of the households reporting health status, FSP participation and food sufficiency categories.

The ordered dependent variable of the health status equation (3.10) is estimated using Ordered Probit maximum likelihood. We modify the ordered Probit equation (3.10) by including predicted probabilities of FSP participation and of food insufficiency estimated from the simultaneous estimation in the first stage rather than the original propensities. Because these predicted explanatory variables are used, Murphy and Topel's (1985) covariance correction method is required for each of the predicted variables. The procedure of the covariance correction is presented in Appendix E Part I.

With excellent health assigned a value of four, very good health with a value of three, good health with a value of two, fair health with a value of one, and poor health given a value of zero, the signs of variables with a positive (negative) coefficient mean that as the variables increases (decreases), health status increases (declines). We report parameter estimates of the health status equation in Table 3.6 along with the uncorrected and corrected standard errors. Based upon the uncorrected standard errors in the third column, there is a negative and statistically significant relationship between participation in the FSP participation and health status. That is, elderly participants in the FSP have a lower health status than FSP eligible nonparticipants. Also, the coefficient of the probability of being food insufficient is negative and significant, meaning that health status declines as food insufficiency increases.

Table 3.6: Self-Reported Health Status Ordered Probit Estimates with Uncorrected and Corrected Standard Errors

Variables	**Coefficient**	**Uncorrected Std. Error**		**Corrected Std. Error**	
Probability of participation.	-1.552	0.583	***	0.991	
Probability of food insufficiency.	-3.530	0.553	***	1.520	**
Mother's age	0.001	0.001		0.002	
Income	0.430	0.153	***	0.209	**
Divorce	0.129	0.118		0.172	
Age 70-79	-0.042	0.085		0.135	
Age 80-89	-0.138	0.099		0.132	
Age 90+	-0.162	0.165		0.232	
Widowed	-0.302	0.091	***	0.123	**
Economically active	0.268	0.130	**	0.161	*
Retired	0.055	0.087		0.128	
Rural	0.145	0.115		0.304	
Suburban	-0.003	0.074		0.103	
Female	0.481	0.095	***	0.143	***
Household size	-0.014	0.027		0.043	
High school	0.115	0.071	*	0.115	
Hispanic	0.045	0.098		0.130	
Nonhispanic black	0.362	0.088	***	0.127	***
Nonhispanic other	0.168	0.167		0.224	
Midwest	-0.065	0.078		0.135	
South	-0.220	0.089	***	0.173	
West	-0.205	0.121	*	0.245	
Own Home	-0.128	0.082		0.141	
Own Vehicle	0.022	0.067		0.091	
Smoke	-0.108	0.079		0.089	
Exercise	0.406	0.073	***	0.088	***
Drink Alcohol	0.163	0.073	***	0.096	
Obese	-0.195	0.064	***	0.088	**
Mu(1)	-1.460	0.266	***	0.365	***
Mu(2)	-0.432	0.266	*	0.352	
Mu(3)	0.410	0.263	*	0.355	
Mu(4)	1.277	0.271	***	0.367	***
Chi-Squared	256.188	--		--	
Prob[ChiSqd > value]	0.0000000	--		--	

The superscripts *, ** and *** represent significant coefficients at the ten, five, and one percent level, respectively.

Source: 2002 Health and Retirement Survey

However, the results change when using the Murphy and Topel's (1985) standard error correction method, which more than doubles the uncorrected standard errors displayed in the fourth column of Table 3.6. When the correct standard errors are used, while food insufficiency continues to lead to declining health status, participation in the FSP no longer has a statistically significant impact on health status. This result underscores the importance of the Murphy and Topel's (1985) method in hypothesis testing.

Our empirical result of negative effect of food insufficiency on health status is similar to several research in which individuals who are food insufficient will experience nutritional deprivation or substandard nutrition due to insufficient food intake (Gundersen and Kreider, 2009 (in children); Kursmark and Weitzman, 2009 (in children); Dixon et al., 2001 (in adults); Stuff et al., 2004 (in adults). Specifically, the food-insufficient elderly tend to consume lower quantities of a number of nutrients (Bhattacharya et al., 2004; Lee and Frongillo, 2001), in particular protiein, calcium, and vitamins A and B-6 (Rose and Oliveira, 1997a). Thus, it is difficult for them to maintain good health status (Ziliak et al., 2008) and more likely for them to report fair/poor health status (Lee and Frongillo, 2001). The insignificant effect of FSP participation contradicts our hypothesis that FSP participation should improve food insufficiency and thus promote better health.

We find that participating in FSP has no significant effect on health status. The same result is found in a study of Greenhalgh-Stanley and Fitzpatrick (2013). There are two theoretical possibilities for this result. First, many critics of the FSP have accused it of encouraging participants to buy more food, particularly unhealthy foods, which are relatively cheaper and contribute to weight gain. If true, then the participant would fail to achieve significant health improvement due to the negative health effect from obesity. Two studies found positive effect of FSP on obesity (Baum, 2011 and Meyerhoefer and Pylypchuk, 2008); however, Baum (2011) notes that the effects are relatively small. Without more information about the food preference of the FSP eligible household and the amount of food items purchased, Gundersen (2013) suggests that it is not clear whether the increased income due to the FSP will increase obesity. However, our empirical findings in the first step contradict this possibility because we found no association between FSP participation and obesity (see Table 3.4). Similar results are found in the majority of studies (Baum, 2012; Leung et al., 2011; Fan, 2010).

The second possibility is the additional money from the FSP neither increases obesity nor is sufficient for elderly households to purchase enough food to improve health condition. Several studies show elderly FSP participants have no better nutrient intake than non-eligible or eligible nonparticipating counterparts (Leung et al., 2011; Fey-Yensan, 2003; Weimer, 1998), or even found them spending less on food and consuming fewer proteins (Wu 2009) and nutrients (Butler 1996). This might result from high food prices particularly for healthy items such as fruits and vegetables. As a result, they face a "heat or eat dilemma" in which their food budget is sacrificed to keep the house warm and lights on (Thayer et al., 2008). Thayer et al., 2008 found that food stamp benefits are insufficient to improve food insufficiency; for example, even households receiving the maximum food stamp benefit would have to spend an additional $2,520 in Boston and $3,165 in Philadelphia annually to purchase the

TFP[14]. The average food stamp benefit is about \$750 per year and this amount would lead to an increase of \$180 in their annual food expenditure (Wu, 2009). The average FSP benefit for an elderly household was \$128 per month, which is a lower benefit than many other types of FSP households due to smaller household size (Leftin, 2010). Wu (2009) suggests that with this level of benefits, FSP benefits may be too low to reduce the incidence of food insufficiency. To investigate whether the level of food stamp benefits could affect the health status of the elderly, the weekly household expenditures from food stamps is used in the model as opposed to binary program participation. The positive correlation is found between health status and weekly household expenditures from food stamps (0.0437). This indicates that increasing food stamp expenditures is related to improving health status of low-income elderly. The weekly household expenditures from the food stamps equation are estimated simultaneously with food insufficiency equations in the first step. Due to zero expenditure for all non-participants, the food stamp expenditure dependent variable is zero-truncated. Thus, simultaneous tobit-probit equations are estimated. In the second step, the ordered probit health status equation is estimated with predicted values of food stamp expenditures and food insufficiency from the first step estimation. The key results are presented in Table 3.7.

[14] The US Department of Agriculture's Thrifty Food Plan (TFP) is the national standard for a "nutritious diet at a minimal cost." This cost- specific food plan for a family of four determines maximum food stamp benefits and was the basis for developing poverty thresholds in the US.

Table 3.7: The self-reported health status estimation results using a weekly household food stamp expenditures

Step 1 : Simultaneous tobit-probit estimations			
Food insufficiency	**Coefficient**	**Uncorrected Std. Error**	
Weekly household FS expenditures	-0.001	0.008	
+ Other covariates			
Weekly household FS expenditures	**Coefficient**	**Uncorrected Std. Error**	
Food insufficiency	-0.456	16.508	
+ Other covariates			
Step 2 : Ordered probit estimation			
Health status	**Coefficient**	**M&T Std. Error**	**Marginal Effect**
Food insufficiency	-1.449 ***	0.608	-0.087
Weekly household FS expenditures	0.017 ***	0.006	0.001
+ Other covariates			

[1] The superscripts *, ** and *** represent significant coefficients at the ten, five, and one percent level, respectively
[2] The full estimation results is available from the authors.
Source: 2002 Health and Retirement Survey

In the top panel of Table 3.7, weekly household food stamp expenditures have a negative effect on food insufficiency and vice versa. However, both simultaneous equations are not statistically significant. Weekly household food stamp expenditures have a positive and significant effect on the health status. A $1 increase in food stamp expenditures increases the probability of health improvement among low-income elderly by 0.001. The results reveal the importance of the level of food stamp expenditures in the household that could potentially affects the health of low-income elderly. Given the evidences of lower FSP benefits from many studies, participating stigma and application burden, the FSP eligible elderly are still rational to participate the program. Theoretically, individuals participate in the FSP if the marginal utility of net benefit from FSP is greater than the disutility of stigma, that is, $\lambda\ (B_{FS} - C_{FS}) > S$. As we know that marginal utility of income in low-income elderly households is relatively high ($\lambda \gg 0$). Stigma (S) has been shown to be one of the primary concerns of participation, accounting for 67 percent of eligible elderly (U.S. GAO, 2000 pp.26).

However, the majority of the FSP eligible elderly receive welfare from more than one program and those are presumably less stigmatized by participation. About 80 percent of the FSP eligible elderly in our HRS sample participated in Supplemental Security Income (SSI) program. Responses to PSID survey questions of nonparticipation reason suggest a significant portion of information barrier rather than stigma (Wu, 2009). With a large marginal utility of income and a relatively small stigma level, the low net benefits of the FSP are still positive; however, the level of net benefits, in fact, does not uniformly suffice for all eligible elderly to reach the significant level of food that improves health. Therefore, it follows that the insignificant effect of FSP participation on health improvement is due to the positive, but insufficient FSP net benefit amount.

We also observed levels of significance declining in other variables after correcting standard errors. The variables that maintain significance are: income (+), widowed (-), economically active (+), female (+), Non-Hispanic black (+), exercise (+) and obese (-). The sign of the non-Hispanic black coefficient is counterintuitive, indicating that being non-Hispanic black households are more likely to have better health outcome than the white counterparts. In general, non-Hispanic blacks on average have lower health than whites in the population. It is worth noting that our sample consists only eligible households, which may be the reason we get the counter-intuitive sign for non-Hispanic blacks.

We present the marginal effects on all five categories of health status in Table 3.8. The marginal effects on poor and very good health categories have the highest magnitudes.

Table 3.8 : Marginal Effects[2] of Selected Variables on Self-Reported Health Status

Independent Variable [1]	**Poor Health**	**Fair Health**	**Good Health**	**Very Good Health**	**Excellent Health**
Probability of participation	0.425	0.129	-0.196	-0.236	-0.122
Probability of food insufficiency*	0.967	0.294	-0.448	-0.535	-0.278
Income (in thousands)*	-0.117	-0.035	0.054	0.065	0.034
Widowed*	0.082	0.025	-0.038	-0.046	-0.024
Economically active*	-0.073	-0.022	0.034	0.041	0.021
Female*	-0.132	-0.040	0.061	0.073	0.038
Nonhispanic black*	-0.099	-0.030	0.046	0.055	0.029
Exercise*	-0.111	-0.033	0.052	0.061	0.032
Obese*	0.054	0.016	-0.025	-0.030	-0.015

*Significant coefficients in the health status equation based upon corrected covariances from Table 3.6.
[1]The independent variables listed either have significant Ordered Probit coefficients or are members of categories of variables where at least one variable is significant in the health equation.
[2] The full listing of marginal effects is available from the authors

Source: 2002 Health and Retirement Survey

We consider only the statistically significant variables. Individuals who are food insufficient have a higher probability to report poor health status up to 96 percent, and lower probability to report very good health by 53.5 percent compared to food sufficient counterparts. Our findings suggest that food insufficiency has a tremendous negative effect on elderly health. Obese individuals have higher probability to report poor health by 8.2 percent and lower probability to report very good health by 4.6 percent compared to non-obese counterparts. Widows are more likely to report poor health by 5.4 percent and less likely to report very good health by 3 percent compared to married counterparts. Females are less likely to report poor health by 13.2 percent and more likely to report very good health by 7.3 percent compared to male counterparts. Having vigorous exercise prevents worsen health status among elderly, that is, it decreases the likelihood of reporting poor health (-11 percent) and increases the likelihood of reporting very good health (7.3 percent). Each additional thousand dollars increase in annual elderly household income helps improve elderly health because individuals with those additional income are less likely to report poor health up to 11.7 percent and more likely to report very good health by 6.5 percent. Last, individuals who are still working at this age have lower probability to report poor health by 7.3 percent and higher probability to report very good health by 4.1 percent, compared to homemaker counterparts.

3.6 Summary, Conclusions and Implications for Future Research

The main purpose of this research was to investigate how health status is affected by FSP participation, food insufficiency, and other determinants. Our investigation sought to explain three important policy questions: (1) why so few needy elderly households choose to receive food stamps; (2) what determines their level of food insufficiency, and finally; (3) how FSP participation and food insufficiency are linked to each other and then to health status? The analysis was based on health information in the 2002 Health and Retirement Survey and state-specific FSP criteria.

In addition to the unique data used in the study, there are two main contributions of the econometric model used in the analysis. Our first step simultaneous multivariate Probit estimates of FSP participation and food insufficiency of the needy elderly qualitatively replicate Gundersen and Oliviera's (2001) earlier research based on SIPP[15] data for the entire population. That is, when the endogeneity of FSP participation and food insufficiency is accounted for, the significant positive effect of food insufficiency on FSP participation becomes statistically insignificant, as does the troubling significant positive effect of FSP participation on food insufficiency, which becomes negative, but insignificant.

The major econometric contribution is the correction of all health equation coefficient standard errors using Murphy and Topel's (1985) technique. This technique is necessary because of the use of two predicted values, the probabilities of FSP participation and food insufficiency, as explanatory variables in the health status equation. Use of the correct standard errors is important since, without the correction, FSP participation is found to worsen health status, which is clearly an undesirable policy outcome. When the corrected standard error is applied, however, FSP participation is found to not have a statistically significant impact on health status. Our theoretical framework explains one possibility for the insignificant effect of FSP participation on health status. The FSP net benefits, though increasing food purchasing power, are inadequate to help elderly to achieve the minimum threshold of food that could significantly improve health status. Even with the correction, as the probability of being food insufficient increases, health status worsens and significantly so.

In terms of future research there are two areas that merit further attention. Step One of this research can trace its heritage back to one of Wilde's (2007) approaches that FSP participation and food insecurity are jointly estimated. The link is even stronger given the nature of our results, that is most (not all) of the prior research using

[15] Survey of Income and Program Participation

this approach finds no effect of the FSP participation on food insecurity. A major reason for this finding could be because all these studies rely upon cross-section data. The dynamic model of FSP participation and food insecurity could better explain short-term and long-term impact of those two variables on health status; however, truly understanding could require longitudinal panel data. One other avenue for investigation is to exploit the fact that the surveys that measure food insecurity also measure food spending in detail. Explaining that spending in relation to the thrifty food plan[16] spending amount and the food security levels obtained may also yield new insults of use to policy makers.

[16] The Thrifty Food Plan (TFP) is one of four USDA-designed food plans specifying foods and amounts of foods to provide adequate nutrition. It is used as the basis for designing Food Stamp Program benefits. It is the cheapest food plan and is calculated monthly using data collected for the consumer price index (CPI).

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APPENDIX B

Food Stamp Program Eligibility Determination

To determine which households are eligible for food stamps and, hence, included in our estimation sample, we rely upon the regulations as reported in the *Characteristics of Food Stamp Households: Fiscal Year 2002* (USDA, 2003). We employ data from the HRS survey to establish categorical eligibility criteria as well as to conduct net income and countable assets eligibility tests.

Categorical Eligibility

Regulations establish that some households are categorically eligible for the FSP without income or asset considerations. Accordingly, we classify a household as eligible if all of its members receive Supplemental Security Income (SSI) or if the household receives welfare income (e.g., cash or in-kind Temporary Assistance to Needy Families (TANF) benefits.

Net Income Test

Elderly households are exempt from the gross income test. Therefore, the only applicable income eligibility criterion is the net income test. We determined net income by subtracting deductions permitted under the FSP from monthly gross income. We employed the deductions allowed in year 2002. The following deductions from household's gross monthly income were used to arrive at net monthly income:

- Standard Deduction - Households receive a standard deduction based on location and household size. For example, a household with one to four members received a deduction of $134 in the contiguous United States in fiscal year 2002. The standard deduction for outlying states and territories varies to reflect price differences between these areas and the contiguous United States (Table B.1).
- Earned Income Deduction - Households received a deduction equal to 20 percent of the combined earnings of household members.
- Dependent-Care Deduction - Households with dependents receive a deduction for expenses involved in caring for dependents while other household members work, search for a job, or attend school. The HRS compiles information about home-care expenses in the household. Consequently, we deduct $175 per month per dependent, assuming that the dependent is older than two years old.
- Medical Deduction - Household with elderly members can employ a medical deduction. To calculate this deduction, we employ the monthly out-of-pocket medical expenses minus medical expenses covered by government insurance programs minus $35. The deduction is zero if the resulting number is less or equal than zero.
- Child Support Payment Deduction - This deduction is not taken into account in our analysis. We assume that elderly households do not pay for child support.

• Excess Shelter Expense Deduction - We create a housing expense variable that includes rent, mortgage payments, utility bills and property taxes. According to the regulations, households with elderly members can subtract the full value of shelter costs that exceed 50 percent of their adjusted income (i.e. after all other deductions have been made).

Table B.1: Value of Standard, Maximum Dependent-Care, and Excess Shelter Expense Deductions in the Continental United States and Outlying Areas in Fiscal Year 2002

Area	Standard[a]	Maximum Dependent-Care[b,c]	Excess Shelter
Continental United States…	$134	$200/$175	$354
Alaska …………………….	229	200/175	566
Hawaii …………..............	189	200/175	477
Guam ……………………..	269	200/175	416
Virgin Islands …………….	118	200/175	279

[a] Prior to fiscal year 1997, the standard deduction was adjusted each October to reflect changes in the CPI-U for nonfood items. Since fiscal year 1997, the standard deduction has been frozen at fiscal year 1996 levels.
[b] The household limit on the dependent-care deduction is equal to the maximum dependent-care deduction multiplied by the number of dependents in the household.
[c] The higher dependent-care deduction pertains to dependents under age 2; the lower deduction is for dependents age 2 or more.

Source: U.S. Department of Agriculture.
Source: Characteristics of Food Stamp Households, Fiscal Year 2002, Appendix C, Table C-4, page 82.

After calculating the net monthly income, we sort households into two categories, those whose net income is at or below the poverty line and above it. The poverty line varies by state and household size (Table B.2). To be eligible for the FSP, a household must have a net monthly income at or below 100 percent of the poverty guideline.

Assets Test

The second critical test is based on the value of countable assets. This test is applied if the household first passed the net income test. If so, an elderly household in our sample is eligible for FSP if its countable assets were less than $3,000 in 2002. Cash, liquid assets and vehicles are examples of countable assets. We summed the values of the following countable assets from the HRS survey: IRA accounts, value of stocks, value of bonds, checking and saving accounts, Treasury bills and government bonds.

Table B.2: HHS Poverty Income Guidelines for Fiscal Year 2002 FSP [a]

Household Size	Continental United States, Guam, and the Virgin Islands	Alaska	Hawai
1	$8,590	$10,730	$9,890
2	11,610	14,510	13.360
3	14,630	18,290	16,830
4	17,650	22,070	20,300
5	20,670	25,850	23,770
6	23,690	29,630	27,240
7	26,710	33,410	30,710
8	29,730	37,190	34,180
Each Additional Member	+3,020	+3,780	+3,470

[a] These numbers, which were used as poverty guidelines for the FSP in fiscal year 2002, were issued by the Department of Health and Human Services (HHS) and published in the February 2001 Federal Register. The Bureau of the Census establishes different poverty thresholds, which are used primarily for statistical purposes.

Source: 66 Federal Register 33, February 16, 2001.

The missing piece in the HRS data is the value of each vehicle. Only the total value of vehicles owned by household members is collected in the HRS. Another complication is vehicle asset regulations vary across states. For example, by August 2003, twenty one states had adopted policies that excluded the value of all vehicles from the asset test. Other states adopted policies that excluded the value of one vehicle per adult or per household or increased the allowable value of one or more vehicles. Only seven states were still using the federal FSP rules.

Our strategy to for implementing the vehicle variable was first to identify those cases in which it is possible to determine whether or not the household is eligible for FSP without knowing the specific vehicle information. In particular, we know that the household is eligible/ineligible in the following cases:

- When the HRS reported value for vehicles in the household is less than \$4,650 (this is the standard deduction for vehicle for each household) – asset eligible.
- When the state exempts all vehicles from countable assets – asset eligible.
- When countable assets without the vehicle values are greater than \$3,000 – asset ineligible.
- When the value of countable assets (including the value of vehicles) reported in HRS is less than \$3000 – asset eligible.
- When a household is categorically eligible because all members receive Supplemental Security Income (SSI) or the household receives cash or in-kind Temporary Assistance to Needy Families (TANF) benefits – assets irrelevant.
- When the household is ineligible based on the net income test – assets irrelevant.
- When household received food stamps in 2002 – eligible.

Final Eligibility Determination

To determine eligibility, the household has to pass both the net income and the countable assets tests. Based on this information we are able to sort out 97.1 percent of the households. The remaining 2.9 percent are excluded from the estimating sample. Thus, our estimation sample includes only elderly households in the HRS deemed to be eligible for food stamps.

APPENDIX C

Ancillary Statistics and Estimates

Table C.1: Reduced Form Probit Estimates of Food Stamp Participation and Food Insufficiency

Variables	FSP Participation[1] (st. error)		Food Insufficiency[1] (st. error)	
Constant	-1.228	***	-0.901	***
	(0.204)		(0.224)	
Skipped Medicinc	-0.153		0.680	***
	(0.223)		(0.217)	
Receive SSI	0.317	**	-0.093	
	(0.132)		(0.148)	
Income	0.164		0.098	
	(0.186)		(0.206)	
Age 70-79	0.146		-0.228	**
	(0.103)		(0.096)	
Age 80-89	-0.004		-0.277	**
	(0.119)		(0.228)	
Age 90 +	-0.233		-0.495	**
	(0.214)		(0.250)	
Divorced	0.280	**	-0.044	
	(0.117)		(0.125)	
Widowed	-0.146		-0.372	***
	(0.103)		(0.119)	
Disabled	0.292	***	0.222	**
	(0.096)		(0.109)	
Economically active	0.063		-0.284	
	(0.169)		(0.199)	
Retired	-0.118		0.006	
	(0.093)		(0.108)	
Rural	0.372	***	-0.124	
	(0.101)		(0.109)	
Suburban	0.060		-0.057	
	(0.103)		(0.106)	

Table C.1 (cont'd)

Variables	Reduced Form FSP Participation[1] (st. error)		Probit Estimates Food Insufficiency[1] (st. error)	
Female	0.300	***	0.416	**
	(0.099)		(0.109)	*
Household size	0.068	**	-0.030	
	(0.033)		(0.036)	
Highschool	-0.094		-0.009	
	(0.082)		(0.102)	
Hispanic	0.290	**	-0.147	
	(0.119)		0.125	
Nonhispanic black	0.171	*	0.227	**
	(0.103)		(0.097)	
Nonhispanic other	0.028		0.208	
	(0.213)		(0.280)	
Midwest	0.066		-0.001	
	(0.116)		(0.119)	
South	-0.126		0.053	
	(0.100)		(0.120)	
West	-0.480	***	0.083	
	(0.136)		(0.122)	
Own home	-0.255	***	-0.085	
	(0.088)		(0.094)	
Own vehicle	-0.063		-0.039	
	(0.084)		(0.101)	
IADLA	-0.038		0.171	**
	(0.059)		(0.057)	*
LOG LIKELIHOOD	-770.691		-569.920	

Note: ***, **, * = significance at 1 percent, 5 percent, 10 percent level, respectively.
Source: 2002 Health and Retirement Survey

Table C.2: Frequency and Percent of Food Stamp (FS) Participation Food Insufficiency (FI) and Health Status

Frequency of FS and FI by Health Status

Health Status	FS Only	FI Only	Both	Neither	Row Total
Excellent	9	9	0	35	**53**
Very Good	29	13	5	131	**178**
Good	80	24	19	225	**348**
Fair	135	44	38	251	**468**
Poor	70	35	41	164	**310**
Column Total	**323**	**125**	**103**	**806**	**1357**

FS and FI as a Percent of Health Status

Health Status	FS Only	FI Only	Both	Neither	Row Total
Excellent	17	17	0	66	100
Very Good	16	7	3	74	100
Good	23	7	5	65	100
Fair	29	9	8	54	100
Poor	23	11	13	53	100
Column Total	-	-	-	-	-

Health Status as a Percent of FS and FI

Health Status	FS Only	FI Only	Both	Neither	Row Total
Excellent	3	7	0	4	-
Very Good	9	10	5	16	-
Good	25	19	18	28	-
Fair	42	35	37	31	-
Poor	22	28	40	20	-
Column Total[17]	101	99	100	99	-

Source: 2002 Health and Retirement Survey

[17] Columns do not sum to 100 percent due to rounding.

APPENDIX D

Part I

Questions for Defining Food Insufficiency

There are two linked questions in the HRS that relate to food sufficiency.

1. In question HQ415 the household financial respondent is asked: Since the previous interview, have you always had enough money to buy the food you need?

2. Question HQ416 is only asked if the response to the previous question is inapplicable or not yes. That is, the response to question HQ415 was, “no,” “don’t know,” or “refused.” If so, respondent is asked: At any time since the previous interview have you skipped meals or eaten less than you felt you should because there was not enough food in the house? A “yes” response to this question means that the household is food insufficient.

APPENDIX D

Part II

Food Security

Questions used to assess the Food Security of Households in the CPS Food Security Survey

1. "We worried whether our food would run out before we got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?

2. "The food that we bought just didn't last and we didn't have money to get more." Was that often, sometimes, or never true for you in the last 12 months?

3. "We couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months?

4. In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (Yes/No)

5. (If yes to question 4), How often did this happen – almost every month, some months but not every month, or in only 1 or 2 months?

6. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? (Yes/No)

7. In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food? (Yes/No)

8. In the last 12 months, did you lose weight because there wasn't enough money for food? (Yes/No)

9. In the last 12 months did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food? (Yes/No)

10. (If yes to question 9), How often did this happen -- almost every month, some months but not every month, or in only 1 or 2 months?

(Questions 11-18 were asked only if the household included children age 0-18)

11. "We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food." Was that often, sometimes, or never true for you in the last 12 months?

12. "We couldn't feed our children a balanced meal, because we couldn't afford that." Was that often, sometimes, or never true for you in the last 12 months?

13. "The children were not eating enough because we just couldn't afford enough food." Was that often, sometimes, or never true for you in the last 12 months?

14. In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food? (Yes/No)

15. In the last 12 months, were the children ever hungry but you just couldn't afford more food? (Yes/No)

16. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (Yes/No)

17. (If yes to question 16), How often did this happen -- almost every month, some months but not every month, or in only 1 or 2 months?

18. In the last 12 months did any of the children ever not eat for a whole day because there wasn't enough money for food? (Yes/No)

Source: Nord M, Andrews M, Carlson S. 2009. Household Food Security in the United States, 2008. Washington, D.C.: U.S. Department of Agriculture, Economics Research Service, Report NO. ERR-83. 58 pp. November. Page 3.

APPENDIX E

Part I

Covariance Matrix Correction in Simultaneous Probit Equations

I. Likelihood Functions

The likelihood functions are taken from the general expression in Mallar (1997). The log likelihood Probit function for the structural FSP participation equation is

$$ln\mathcal{L}_{FS**} = \sum_{i=1}^{N}[FS_i \ln(Q_{FS,i}) + (1 - FS_i)(1 - Q_{FS,i})] ,$$

where $Q_{FS,i} = \int_{-\infty}^{I_{FS,i}} (2\pi)^{-1/2} e^{-t^2/2} dt$ and $I_{FS,i} = \alpha_{0,FI}\widehat{\boldsymbol{FI}}^{*} + \boldsymbol{X}'_{\boldsymbol{FI}}\boldsymbol{\alpha}_{\boldsymbol{FI}}$.

The log likelihood Probit function for the structural obesity equation is

$$ln\mathcal{L}_{FI**} = \sum_{i=1}^{N}[FI_i \ln(Q_{FI,i}) + (1 - FI_i)(1 - Q_{FI,i})] ,$$

where $Q_{FI,i} = \int_{-\infty}^{I_{FI,i}} (2\pi)^{-1/2} e^{-t^2/2} dt$ and $I_{FI,i} = \alpha_{0,FS}\widehat{\boldsymbol{FS}}^{*} + \boldsymbol{X}'_{\boldsymbol{FS}}\boldsymbol{\alpha}_{\boldsymbol{FS}}$.

II. Covariance Matrices

Based on Maddala (1983, pp243-247), we follow the steps as following:

Step 1: The reduced forms in (1) and (2) are estimated by Maximum Likelihood Probit Estimation, and get a predicted value of FS^* and FI^* denoted as $\widehat{FS}^*$ and $\widehat{FI}^*$ respectively.

(1) $$\boldsymbol{FS}^* = \boldsymbol{\Pi}^*_{\boldsymbol{FS}}\boldsymbol{X} + \boldsymbol{v}^*_{\boldsymbol{FS}} \quad , \boldsymbol{\Pi}^*_{\boldsymbol{FS}} = \frac{\boldsymbol{\Pi}_{\boldsymbol{FS}}}{\boldsymbol{\sigma}_{\boldsymbol{FS}}} \text{ and } \boldsymbol{v}^*_{\boldsymbol{FS}} = \frac{\boldsymbol{v}_{\boldsymbol{FS}}}{\boldsymbol{\sigma}_{\boldsymbol{FS}}}$$

(2) $$\boldsymbol{FI}^* = \boldsymbol{\Pi}^*_{\boldsymbol{FI}}\boldsymbol{X} + \boldsymbol{v}^*_{\boldsymbol{FI}} \quad , \boldsymbol{\Pi}^*_{\boldsymbol{FI}} = \frac{\boldsymbol{\Pi}_{\boldsymbol{FI}}}{\boldsymbol{\sigma}_{\boldsymbol{FI}}} \text{ and } \boldsymbol{v}^*_{\boldsymbol{FI}} = \frac{\boldsymbol{v}_{\boldsymbol{FI}}}{\boldsymbol{\sigma}_{\boldsymbol{FI}}} ,$$

where FS^* and FI^* are observed only a latent variable (zero and one). Thus, we can only estimate $\boldsymbol{\Pi}^*_{\boldsymbol{FS}}$ and $\boldsymbol{\Pi}^*_{\boldsymbol{FI}}$ **, not** $\boldsymbol{\Pi}_{\boldsymbol{FS}}$and $\boldsymbol{\Pi}_{\boldsymbol{FI}}$

Step 2: Substitute $\widehat{\boldsymbol{FI}}^*$ and $\widehat{\boldsymbol{FS}}^*$ into the structural forms in equation (3) and (4) respectively, and estimate both equations by Maximum Likelihood Probit Estimation.

(3) $$\boldsymbol{FS}^{**} = \alpha_{0,FS}\widehat{\boldsymbol{FI}}^* + \boldsymbol{X}'_{\boldsymbol{FS}}\boldsymbol{\alpha_{FS}} + \boldsymbol{\epsilon_{FS}}$$

(4) $$\boldsymbol{FI}^{**} = \alpha_{0,FI}\widehat{\boldsymbol{FS}}^* + \boldsymbol{X}'_{\boldsymbol{FI}}\boldsymbol{\alpha_{FI}} + \boldsymbol{\epsilon_{FI}},$$

where $\alpha_{0,FS}=\gamma_{FS}\frac{\sigma_{FI}}{\sigma_{FS}}$, $\alpha_{0,FI} = \gamma_{FI}\frac{\sigma_{FS}}{\sigma_{FI}}$, $\boldsymbol{\alpha_{FS}} = \frac{\boldsymbol{\beta_{FS}}}{\boldsymbol{\sigma_{FS}}}$, $\boldsymbol{\alpha_{FI}} = \frac{\boldsymbol{\beta_{FI}}}{\boldsymbol{\sigma_{FI}}}$, $\boldsymbol{\epsilon_{FS}} = \frac{\boldsymbol{\varepsilon_{FS}}}{\boldsymbol{\sigma_{FS}}}$, $\boldsymbol{\epsilon_{FI}} = \frac{\boldsymbol{\varepsilon_{FI}}}{\boldsymbol{\sigma_{FI}}}$

Step 3: Although equation (3) and (4) will give us an unbiased estimator, the covariance matrix is not correct. Let $a_{FS} = \frac{\phi_{FS}}{\Phi_{FS}(1-\Phi_{FS})}$ and $a_{FI} = \frac{\phi_{FI}}{\Phi_{FI}(1-\Phi_{FI})}$, where ϕ is a standard normal probability density (PDF) and Φ is a cumulative standard normal distribution (CDF) estimated of fitted values from reduced form equation (1) and (2), $A_{FS} = \phi_{FS} * a_{FS}$, $A_{FI} = \phi_{FI} * a_{FI}$, $\boldsymbol{Z}_{FS} = \begin{bmatrix}\Pi^*_{FI}\boldsymbol{X} \\ \boldsymbol{X_{FS}}\end{bmatrix}$ and $\boldsymbol{Z}_{FI} = \begin{bmatrix}\Pi^*_{FS}\boldsymbol{X} \\ \boldsymbol{X_{FI}}\end{bmatrix}$. The variance-covariance matrix for the $\boldsymbol{FS}^{**}$ equation is defined as

$$W_1^{-1}[W_1 - W_3W_2^{-1}W_4 - W_4'W_2^{-1}W_3' + W_3W_2^{-1}W_3']W_1^{-1}$$, where

$$W_1 = \frac{1}{N}\sum_{i=1}^{N} A_{FS}\boldsymbol{Z}_{FS}\boldsymbol{Z}'_{FS}$$

$$W_2 = \frac{1}{N}\sum_{i=1}^{N} A_{FI}\boldsymbol{X}_{FS}\boldsymbol{X}'_{FS}$$

$$W_3 = \frac{1}{N}\sum_{i=1}^{N} A_{FS}\,\alpha_{0,FS}\boldsymbol{Z}_{FS}\boldsymbol{X}'_{FS}$$

$$W_4 = \frac{1}{N}\sum_{i=1}^{N} a_{FS}a_{FI}\,E((FS-\Phi_{FS})(FI-\Phi_{FI}))\,\boldsymbol{X}_{FS}\boldsymbol{Z}'_{FS}$$

The variance-covariance matrix for the $\boldsymbol{FI}^{**}$ equation is defined as

$W_1^{-1}[W_1 - W_3 W_2^{-1} W_4 - W_4' W_2^{-1} W_3' + W_3 W_2^{-1} W_3'] W_1^{-1}$, where

$$W_1 = \frac{1}{N} \sum_{i=1}^{N} A_{FI} \boldsymbol{Z}_{FI} \boldsymbol{Z}'_{FI}$$

$$W_2 = \frac{1}{N} \sum_{i=1}^{N} A_{FS} \boldsymbol{X}_{FI} \, \boldsymbol{X}'_{\boldsymbol{FI}}$$

$$W_3 = \frac{1}{N} \sum_{i=1}^{N} A_{FI} \, \alpha_{0,FI} \boldsymbol{Z}_{FI} \boldsymbol{X}'_{FI}$$

$$W_4 = \frac{1}{N} \sum_{i=1}^{N} a_{FS} a_{FI} \, E((FS - \Phi_{FS})(FI - \Phi_{FI})) \, \boldsymbol{X}_{FI} \boldsymbol{Z}'_{FI}$$

APPENDIX E

Part II

Murphy and Topel's Standard Error Correction

From Green (2003, pp. 510), the Murphy and Topel (1985) correction of the asymptotic covariance matrix at the second step is given by

$$\widetilde{V_2} = \widehat{V}_2 + \widehat{V}_2(\hat{C}\widehat{V}_1\hat{C}' - \hat{R}\widehat{V}_1\hat{C}' - \hat{C}\widehat{V}_1\hat{R}')\widehat{V}_2,$$

where $\widehat{V}_2(pxp)$ is the asymptotic variance matrix of the second stage, $\widehat{V}_1(qxq)$ is the asymptotic variance matrix of the first stage, $\hat{C}$ and $\hat{R}$ matrices are based on the first derivative of the second- and first- stage log likelihood function with respect to the first- and second-stage parameter vectors $\hat{\theta}_1$ and $\hat{\theta}_2$. The $\hat{\theta}_1$ is an estimated parameter vector by maximum likelihood in the first stage. The $\hat{\theta}_2$ is an estimated parameter vector by maximum likelihood in the second stage, with $\hat{\theta}_1$ inserted in place of θ_1. The two-stage estimation consists of the two marginal distributions, $f_1(y_1|\boldsymbol{x}_1, \theta_1)$ and $f_2(y_2|\boldsymbol{x}_2, \theta_2, (\boldsymbol{x}_1, \hat{\theta}_1))$. Although θ_1 and θ_2 could be estimated jointly by Full Information Maximum Likelihood (FIML), fitting the models by using a two-step estimation procedure by Limited Information Maximum Likelihood (LIML) is less complicated and fairly straightforward (Green, 2003). The $\hat{C}$ and $\hat{R}$ matrices are presented as :

$$\hat{C}(pxq) = \left\{\sum_{i=1}^{N}(\frac{\partial \ln f_{i2}}{\partial \hat{\theta}_2})(\frac{\partial \ln f_{i2}}{\partial \hat{\theta}'_1})\right\}$$

$$\hat{R}(pxq) = \left\{\sum_{i=1}^{N}\left(\frac{\partial \ln f_{i2}}{\partial \hat{\theta}_2}\right)\left(\frac{\partial \ln f_{i1}}{\partial \hat{\theta}'_1}\right)\right\},$$

where f_{i2} and f_{i1} are observation i's contribution to the likelihood function of second-stage model and first-stage model, respectively. In our case, the second-stage model includes two predicted variables from the first-stage models. Because the first-stage model includes two simultaneous equations – FSP participation and food insufficiency equations, the two first-stage equations are independent from each other after taken account of simultaneity and corrected standard errors using Maddala's method (1983). If there are two generated variables and both are independent, the matrix $\hat{C}$= $[C_{FS} \quad C_{FI}]$, matrix $\hat{R} = [R_{FS} \quad R_{FI}]$ and $\hat{V_1} = \begin{bmatrix} \hat{V}_{FS} & 0 \\ 0 & \hat{V}_{FI} \end{bmatrix}$ where C_{FS} and $\hat{V}_{FI}$ belong to FSP participation equation, C_{FS} and $\hat{V}_{FI}$ belong to food insufficiency equation.

CHAPTER 4

THE RELATIONSHIP BETWEEN UNEMPLOYMENT AND OBESITY: EVIDENCE FROM NLSY 97 SURVEY DATA

4.1 Introduction

Unemployment and obesity are two significant problems afflicting millions of people in the United States today. The prevalence of adult obesity has nearly tripled since the 1960s, increasing from 13% in 1960-1962 to 36% in 2009-2010 (Flegal et al., 1998, 2012). It is well-documented that although obesity is high among the overall population, substantial disparities exist among racial/ethnic minorities and vary on the basis of socioeconomic status. For instance, unemployed individuals, who have lower incomes, are more likely to consume cheaper and more fattening food (Cawley, 2004). During the economic recession from 2007-2009, the unemployment rate hit its highest level since 1983. Average U.S. household annual income fell from \$55,627 to \$51,017 between 2007 and 2012. The increase in unemployment and reduction in incomes that occurred over this period resulted in many households choosing less expensive food budgets, which resulted in poorer nutrition and diet quality (Todd, 2014). While the association between unemployment and obesity has been extensively studied, the results of these studies are mixed in terms of the magnitude and the sign of the correlation. Some researchers have found a positive correlation between the unemployment rate and obesity or body weight status (Charles and DeCicca, 2008; Janssen et al., 2006; Bockerman et al., 2006). This finding may be due to unemployed people overeating as a way to comfort themselves (Zhang, 2014). Economic stress often results in eating cheaper, less healthful food, and stress alone can lead to overeating or other negative eating habits (Stoddard et al., 2009). People who are unemployed spend relatively more time on eating because they have more time to do so and frequently they turn to food to find a sense of fulfillment (Stringham et al., 2004)

However, not all studies have found a positive association between obesity and unemployment. For instance, Todd (2014) found that during the economic recession from 2009-2010, the overall quality of diet for working-age adults (20-59) improved slightly through lower total calories consumed from food away from home, as well as its share of daily calories. In addition, Ruhm (2000, 2005) used micro-data from the Behavioral Risk Factor Surveillance System (BRFSS) to examine the relationship between economic conditions and health, and found that individuals are more likely to be in the healthiest weight ranges during temporary economic downturns compared with more prosperous times and that obesity increases when the economy strengthens. Other studies suggest that economic upturns create more job stress and result in less time for self-care activities such as eating well or exercising (Neumayer, 2003; Tapia Granados, 2005; Gerdtham and Ruhm, 2006). While these results offer evidence of a strong relationship between unemployment and obesity, the causal direction is not clear.

The reverse directionality of unemployment and obesity impact has also been extensively studied. Morris (2007) investigated the impact of obesity on unemployment and the endogeneity of obesity and unemployment using three approaches: a univariate probit model; propensity score matching; and an instrumental variable regression with a recursive bivariate probit model. His findings show that obesity has a statistically significant and negative effect on employment. According to the American Obesity Association, obese persons are frequently stereotyped as emotionally impaired, socially handicapped, and as possessing negative personality traits, which lead them to be at greater risk of being laid off or experiencing job discrimination. Obesity may also reduce work productivity. The empirical evidence shows that weight increases the probability of health-related work limitations, and the probability of receiving disability-related benefit payments (Burkhauser and Cawley, 2004). Obesity may also increase the number of sick days or rates of absenteeism, which creates higher cost for employers, and more sick days may lead to job discrimination (Janssen et al., 2005). A stereotype some employers have is that obese individuals are less productive (Everett, 1990), or discrimination arises through uncertainty, or lack of knowledge about the productivity of obese workers (Pagan and Davila, 1997). There may be prejudice by employers, reflecting their dislike for obese workers and the psychological costs incurred when dealing with them (Moon and McLean, 1980). There is some evidence that overweight/obese job applicants face weight discrimination based on several experimental studies in the U.S. at every stage of employment, from the hiring decision through wage setting and promotion (Puhl and Brownel, 2001). A study by the Rudd Center for Food Policy and Obesity at Yale University in 2008 found that discrimination against overweight people-particularly women is as common as racial discrimination. In term of unemployment duration, the percentage of time spent being unemployed during working years is significantly higher for each BMI deviation from the median BMI attained at age 20, and the probability of re-gaining employment after a period of unemployment is significantly lower (Paraponaris et al., 2005). However, other studies (Sargent and Blachflower, 1994; Harper, 2000) have found an insignificant effect of obesity on employment.

The relationship between unemployment and obesity during times of economic stagnation is not well understood and the research reported here attempts to fill this knowledge gap in the literature. Unlike other non-modifiable risk factors contributing to social and economics costs and a person's overall likelihood of well-being, these two risk factors are modifiable if the true effects are known. A major challenge, however, in measuring the true effect of unemployment and obesity is the "confoundedness problem". Confoundedness is a condition where an extraneous variable, also known as a confounding variable, is correlated with both outcomes and treatment groups. Hence, the mis-estimation due to the failure to account for confounding variables causes a spurious relationship and omitted-variable bias. A random assignment can eliminate the problem in experimental studies; however, it is not plausible in survey data studies such as the present one. One example of a confounding variable in this case is a mental depression. One in every ten Americans deals with mental depression each year, according to the results of a nationwide survey by the Centers for Disease Control and Prevention (CDC). About 60-80 percent of people who live with mental illness are unemployed (NASMHPD, 2007) and for people living with the most severe mental illnesses, unemployment rates can be as high as 90 percent (National Governors Association, 2002). Unemployed people were four times as likely to live with severe mental illness as their employed counterparts

(Mental Health America, 2009). The apparent weight-mental health connection is found in several studies. People with major depression are twice as likely to be obese as those who do not suffer depression (McElroy, 2009). A positive association between mental depression and obesity has been found in most studies (Baumeister and Harter, 2007; Richardson et al, 2006; Johnston et al., 2004; Becker et al., 2001). Several US survey studies have observed gender differences in this relationship, with positive associations between obesity and depression among women, and either negative (Carpenter et al., 2000; Palinkas et al., 1996) or no associations among men (Istvan et al., 1992). Mental depression may cause obesity though overeating, making poor food choices, avoiding exercise, and becoming more sedentary (Hasler et al., 2005; Richardson et al., 2003; Goodman and Whitaker, 2002).

To measure the association between unemployment and obesity, we use an econometric technique to alleviate simultaneity and confoundedness problems to provide an unbiased estimate of the effects. Specifically, a two-equation system of unemployment and obesity probit equations is estimated simultaneously in the study. The identification issue is addressed and an instrumental variable approach is used. The two instrumental variables for unemployment and obesity equations are the number of months the individual received unemployment insurance (UI) in the past, and the mother's body mass index (BMI), respectively.

This research contributes to the literature on obesity and unemployment in several ways. First, we investigate not just a one directional relationship, but simultaneity between unemployment and obesity in the U.S. using an instrumental variable approach. This is useful because it provides a more accurate understanding of how and whether obesity affects unemployment, and unemployment affects obesity at the same time. Second, the study uses data during the economic recession in 2010 when the unemployment rate was at its peak level since 1983. The relationship between unemployment and obesity during times of economic stagnation is not well understood, and this research attempts to fill this knowledge gap in the literature. Third, the paper estimates the effect of unemployment and obesity for both males and females. Most previous studies using an instrumental variable approach have been limited to only one gender of the sample due to specific attribution of the instrumental variable, e.g. using a BMI of child as an instrument for individual's BMI where a BMI of child is only attached with female respondents (Cawley, 2000) or using age at onset of first menarche (first menstrual cycle) as an instrument for adult's BMI (Crouse, 2014).

The remainder of this paper is organized as follows. First, the econometric model is presented, which accounts for the possible simultaneity between unemployment and obesity and identification. Second, a detailed description of data sources for this study and the descriptive statistics are presented. The major data source is the 2010 National Longitudinal of Youth Survey 1997 (NLSY97). Finally, results, implications and conclusions are suggested for further research.

4.2 Econometric Modeling

The econometric model consists of two equations. To remedy econometric potential problems of simultaneity and confoundedness between unemployment and obesity, the endogenous unemployment and obesity of the individuals are estimated simultaneously using an instrumental variable approach.

The general model of Maddala (1983, pp. 246-247) is used in the estimation. The two-reduced form system consisting of unemployment and obesity equations is expressed as follows:

$$(4.1) \qquad L^* = \boldsymbol{\pi_L X} + v_L \; ; \qquad L = 0 \text{ (employed) } iff \;\; L^* \leq 0$$
$$= 1 \text{ (unemployed) } iff \; L^* > 0$$

$$(4.2) \qquad B^* = \boldsymbol{\pi_B X} + v_B \; ; \qquad B = 0 \; (\text{BMI} < 30) \; iff \;\; B^* \leq 0$$
$$= 1 \; (\text{BMI} \geq 30) \;\; iff \;\; B^* > 0 \, ,$$

where L^* is a latent true value of unemployment , $B^*$is a latent true value of obesity measured as a true Body Mass Index (BMI), $\boldsymbol{X}$ is a vector of explanatory variables, $\boldsymbol{\pi_L}$ and $\boldsymbol{\pi_B}$ are vectors of corresponding parameter estimates, and v_L and v_B are error terms. The latent value of unemployment is categorized in binary form taking the value one if the individual is unemployed and zero if the individual is employed. The BMI is a standard measurement of obesity based on height and weight that applies to adult men and women. According to CDC, 35% of the U.S. population of adults (aged 20 years or over) was categorized as obese or worse in 2011-2012, and since we are primarily interested in the upper level of the BMI scale in this study, these six categories of BMI[18] are re-categorized into two as: (1) $BMI < 30$ (overweight or below) and (2) $BMI \geq 30$ (obese or above).

[18] BMI is calculated as weight in pounds multiplied by 703 and divided by height in inches squared. The BMI scale is generally categorized into six categories: $BMI < 18.5$ (underweight), $18.5 \leq BMI < 25$ (normal weight), $25 \leq BMI < 30$ (overweight), $30 \leq BMI < 35$ (obese), $35 \leq BMI < 40$ (clinically obese) and $BMI \geq 40$ (dangerously obese).

Unfortunately, the latent true BMI in equation (4.2) is not observed due to the BMI in NLSY97 dataset being calculated from self-reported weight and height information. It has been documented that self-reported weight and height is subject to some degree of reporting errors, which may bias coefficient estimates (Cawley, 2004). Self-reporting may result in a mis-measurement of actual obesity and will introduce endogeneity bias if the measurement error is correlated with the self-reported values.

Specifically, respondents are known to declare higher height and lower weight than the actual measurement (Robert, 1995; Ziebland et al., 1996) resulting in lower BMI. Similar to Cawley (2004), the correction for self-reporting errors in this research uses the Third National Health and Nutrition Examination Survey (NHANES III), which includes both self-reported weight and height and independently measured weight and height. According to Lee and Sepanski (1995), if one has validation data, which in this case contains measured, and self-reported weight and height (and, therefore, BMI), one can regress the measured BMI on its self-reported value, and use the estimated coefficient to correct for self-reported bias. Specifically, the estimated OLS coefficient is multiplied by the self-reported BMI to create an estimate of true BMI. Measured BMI is regressed on self-reported BMI and its square (in deviation about race-gender group-specific means) in the sub-sample of NHANES III in which respondents aged 25-31 years old corresponding to respondents' age in the sample of the NLSY97. The BMI models fit the data very well judging by high R^2. The regression results are presented in Table F.1 in the Appendix F. The fitted value of BMI, after corrected for self-reporting errors, is used throughout the paper as the latent true BMI.

The reduced forms in equation (4.1) and (4.2) are independently estimated by a probit maximum likelihood estimation, respectively. The predicted index values from those two reduced form estimations denoted as $\hat{L}^*$ and $\hat{B}^*$ are used as an explanatory variable in the structural equation (4.4) and (4.3), respectively as

$$L^{**} = \alpha_{0,L}\hat{B}^* + \boldsymbol{X}_L'\boldsymbol{\alpha}_L + u_L \quad (4.3)$$

$$B^{**} = \alpha_{0,B}\hat{L}^* + \boldsymbol{X}_B'\boldsymbol{\alpha}_B + u_B\ , \quad (4.4)$$

where L^{**} are the latent true value of unemployment and B^{**} are the latent true values of obesity in structural equations, $\boldsymbol{X_L} \epsilon\, \boldsymbol{X}$, $\boldsymbol{X_B} \epsilon\, \boldsymbol{X}$, $\boldsymbol{X_L} \neq \boldsymbol{X_B}$, $\alpha_{0,L}$, $\alpha_{0,B}$, $\boldsymbol{\alpha_L}$ and $\boldsymbol{\alpha_B}$ are vectors of corresponding parameter estimates, and v_L and v_B are error terms. Similar to the reduced form equation (4.1) and (4.2), the L^{**} and B^{**} in structural equations are categorized in a binary form and the same order, respectively. $\boldsymbol{X_L}$ and $\boldsymbol{X_B}$ are vectors of explanatory variables which are not identical due to identifiable parameters in the simultaneous model (discussed in an identification section). Equation (4.3) and (4.4) are independently estimated by probit maximum likelihood estimation, respectively. It is worth noting that the general model of Maddala (1983, pp. 246-247) features a simultaneous probit model. Such a model requires a modified correction in the variance-covariance matrix for $\hat{L}^{**}$ and $\hat{B}^{**}$. The correction procedure is presented in the Appendix F.4.

4.2.1 Identification

The parameters of two-simultaneous equations are identified if both equations do not have an identical set of parameters. Thus, the identification of a simultaneous equation can be thought of in term of the possibility of instrumental variable estimation. The candidates for instrumental variable for unemployment and obesity respectively are the number of months the individual received unemployment insurance (UI) in the past, and the individual's mother's BMI, respectively. Previous research shows that the duration of unemployment insurance (UI) increases the probability of unemployment, mostly by increasing the reservation wage (the minimum wage at which a worker will accept employment) and by decreasing the cost of unemployment (Ehrenberg and Oaxaca, 1976). Meyer (1990) found that the UI has a negative effect on the probability of becoming employed. The extension of UI benefits during the recent recession raised the unemployment rate by 0.1 to 0.5 percentage points. About half of this effect was due to workers continuing to look for work rather than exiting the labor force (Rothstein, 2011). The advantage of using UI as an instrumental variable is it is strongly correlated with the individual's unemployment, but is exogenous to the individual's obesity.

The use of an individual's mother's BMI as an instrumental variable for obesity is based on the fact that parental weight is highly correlated with offspring weight due to genetics. A strong relationship has been observed between biologic parents-child pairs (Zonta et al., 1987) and twins (Poulsen et al., 2001) in regard to BMI. It is estimated that genetic factors explain approximately 40% of the variance in body fat (Bouchard et al., 1988) and up to 70% of variance in abdominal obesity

(Carey et al., 1996). In addition, previous studies (Stunkard et al., 1986; Maes et al., 1996; Grilo and Pogue-Geile, 1991) provide evidence that the correlation between parents' and a child's BMI may have little to do with shared environmental factors. However, in the NLSY97, the majority of individuals only included their mother's BMI information. Therefore we use only the mother's BMI as an instrument for individual's obesity. A weakness of using only the mother's BMI as a valid instrument is that it ignores the father's genetic makeup in terms of affecting the child's BMI. However, several medical studies on the genetic transmission from parents to their children's obesity have found that mother's obesity is more important than father's obesity in influencing the metabolic syndrome[19] or the insulin resistance syndrome in her child (Druet et al., 2006; Bjornholt et al., 2000; Dabelea et al., 2000; Pettitt et al., 1990). Although an obese mother can give birth to normal birth weight babies, these babies have a higher probability of later developing obesity and insulin resistance syndrome (Mingrone et al., 2008; Obregon, 2010) because the insulin resistance syndrome is developed in fetuses of the obese mother in utero (Catalano et al., 2009). Obesity is commonly associated with metabolic syndrome because obesity makes it more difficult for cells to respond to insulin. Abdominal obesity is ranked as the first risk factor of the metabolic syndrome prevalence in the U.S. (CDC, 2009).

The model is identified with two instruments for two endogenous repressors in simultaneous equations and the instruments are valid because they satisfied an exclusion restriction that the excluded instruments only directly affect its own

[19] The metabolic syndrome (MS) is also known as insulin resistance syndrome because most people who have metabolic syndrome have insulin resistance where the body inefficiently makes insulin to move glucose (sugar) into cells for use as energy. This syndrome is a cluster of conditions - increased blood pressure, a high blood sugar level, excess body fat around the waist (Abdominal obesity) and abnormal cholesterol levels - that occur together, increasing your risk of heart disease, stroke and diabetes (Mayo clinic).

endogenous regressors, but not directly affect the dependent variables. The model is a non-linear simultaneous equation system; the traditional F-Statistic test on instrument relevance[20] and the Hausman test on instrument exogeneity are not applicable. The correlation is simply employed to see the strong correlation between the instruments and endogenous regressors[21]. Ideally, the best candidate to be an instrumental variable is an exogenous variable that appears in other equations in the model because it is correlated with the endogenous regressor in the model via the reduced form equations, but it is not correlated with the error term in any equation. The two reduced forms in equation (4.1) and (4.2), which include both UI and mother's BMI variables are independently estimated. The regression results show that the UI variable is positive and statistically significant, but the mother's BMI variable is not significant in equation (4.1). In contrast, the mother's BMI variable is positive and statistically significant in equation (4.2), but the UI variable is not significant in that equation. The reduced form regression results presented in Table F.2 in the Appendix F validate the use of both instrumental variables. With respect to identification of the two-step estimation, we thus include these two instrumental variables in both reduced form equation (4.1) and (4.2). In the structural equations, the UI and the mother's BMI variables are included as an explanatory variable in equation (4.3) and equation (4.4), respectively.

[20] Instrument Relevance: Valid instruments are highly correlated with the endogenous regressors even after controlling for the exogenous regressors. This requirement can be empirically tested in the first stage regression.

[21] The correlation results found the unemployment insurance (UI) is statistically correlated with the unemployment status (0.3064), but not the individual's BMI whereas the mother's BMI is statistically correlated with the individual's BMI (0.2673), but not the individual's employment status.

4.3 Data and Descriptive Statistics

The National Longitudinal Survey of Youth 1997 (NLSY97) is designed to represent the entire population of American youth. All youths were between 12 and 16 years of age when the first of annual survey was conducted in 1997. Retention rates for those NLSY97 respondents remaining eligible for survey have remained close to 90 percent during the 16 years of surveys. The survey year of 2010 is a sample in our study. The 7,479 respondents were interviewed from October, 2010 to June, 2011. The respondent's employment status was recorded by week until the week of interview. The employment status at the week of interview is used as a respondent's current employment status. The study focuses on respondents who are currently working or currently unemployed. Thus, respondents who did not report their employment status at the week of their interview as "unemployed" or "working" were dropped from the sample. For example, respondents who reported being "out of labor force", "active military services", "not determined" or "no information" were dropped. The percentage distribution of employment status and obesity presented in Table 4.1 shows that the average BMI of unemployed respondents (30.09) is higher than that of the employed respondents (28.37). The 41% of unemployed respondents have BMI >=30 compared to 32 % of the employed counterparts.

Table 4.1: Percentage distribution of employment status and Body Mass Index (BMI)[1]

Body mass index (BMI)	Employment status Unemployed	Employed
Average BMI	30.09	28.37
BMI>=30	41%	32%
BMI<30	59%	68%
Observations	162	2,710

[1] The BMI, after corrected for self-reporting errors.

The final sample consists of 2,872 observations with 1,501 males and 1,371 females. The unemployed respondents account for 6% in the sample (Table 4.2). The self-reported BMI is calculated from respondent's self-reported weight and height at the interview date. The BMI, after corrected for self-reporting errors, is used throughout the paper as the respondent's true BMI. The average BMI of the respondents in the sample is 28.44 and the respondents who have BMI>=30 account for 33% of the sample (Table 4.2).

The instrumental variables for unemployment and obesity are indicator variables of the respondent who received unemployment insurance (UI) more than 6 months in the past 23 months and a mother's BMI >=30, respectively. The number of months the respondent received UI is calculated by accumulating self-reported UI reception by month during the past 23 months until the month of interview. During the recession in 2009-2011, Congress approved an extension of a program to provide unemployment benefits for up to 99 weeks (~23 months) - an addition of 73 weeks to the traditional 26 weeks (~ 6 months) offered by the states. However, the duration varies from state to state based on how bad the unemployment situation was in the regions. The 23-month unemployment benefit is used for a maximum UI duration for each respondent in the study. The UI benefit is categorized into two as: 1 if the respondent received UI benefit more than 6 months in the past 23 months and 0 if the respondent received UI 6 months or less or never received in the past 23 months. The respondents who received UI benefit more than 6 months accounts for 4% of the sample. The mother's BMI is calculated from mother's self-reported weight and height in 1997 and corrected for self-reporting errors using the sub-sample of NHANES III in which respondents aged 26-82 years old corresponding to mothers' age in the sample of the NLSY97 in 1997. The regression results are presented in Table F.1 in the Appendix. The average mother's BMI is 27.83. The mother's BMI is categorized into two as 1 if mother's BMI >=30 and 0 if otherwise. The respondent's mother who has BMI>=30 accounts for 29% of the sample.

The following socioeconomics repressors are included in the unemployment and obesity regression equations: age, age squared, gender, race (black, hispanic, white and mixed race), highest education degree obtained (graduate, college, high school and less than high school), region of residence (northeast, north central, west and south), marital status (married, never married, others (separated, divorced or widowed)), household size, have children, and income of other family members in the previous year which is calculated from the difference between gross family income and respondent's income in the past year. The summary statistics of the variables used in the study are presented in Table 4.2.

Table 4.2: Variable definition and descriptive statistics of the sample

Variables	**Definition of variables**	**Mean**	**Std. Dev.**	**Min**	**Max**
A. Endogenous Variables					
Employment Status	1 if respondent reported unemployed as of the survey date	0.06	0.23	0	1
BMI of respondent	BMI after corrected self-reporting errors	28.44	6.88	12.22	70.31
BMI >= 30	1 if respondent has BMI >=30	0.33	0.008	0	1
BMI < 30	1 if respondent has BMI < 30	0.67	0.008	0	1
B. Instrumental Variables					
BMI of respondent's mother	BMI of respondent's mother after corrected self-reporting errors	27.83	6.40	16.90	70.30
Mother's BMI >= 30	1 if respondent's mother has BMI >=30	0.29	0.45	0	1
Mother's BMI <30	1 if respondent's mother has BMI < 30	0.71	0.45	0	1
UI Benefit	Number of months respondent has received an unemployment insurance (UI) benefit [1]	0.80	2.74	0	23
More than 6 months	1 if respondent received UI benefit more than 6 months (~26weeks)	0.04	0.21	0	1
C. Demographic Variables					
Age	Age of respondent at the date of interview	27.90	1.44	25	31
Male	1 if respondent is male	0.52	0.50	0	1
Race					
Black	1 if respondent reported race "Black"	0.23	0.42	0	1
Hispanic	1 if respondent reported race "Hispanic"	0.19	0.39	0	1
White	1 if respondent reported race "Non Black and Non Hispanic"	0.57	0.50	0	1
Mixed race (base)	1 if respondent reported race "Mixed race (non-Hispanic)"	0.01	0.10	0	1
Education	The highest education the respondent has				
Graduate degree	1 if respondent has a graduate education	0.07	0.26	0	1
College degree	1 if respondent has a bachelor education	0.35	0.48	0	1
High school	1 if respondent has a high school education	0.53	0.50	0	1
None (base)	1 if respondent has lower high school education	0.05	0.22	0	1

Table 4.2 (cont.): Variable definition and descriptive statistics of the sample

Variables	**Definition of variables**	**Mean**	**Std. Dev.**	**Min**	**Max**
Region	Region of the residence as of the survey date [2]				
NE	1 if respondent resided in northeastern region	0.15	0.36	0	1
NC	1 if respondent resided in north central region	0.23	0.42	0	1
WE	1 if respondent resided in western region	0.22	0.41	0	1
SO (base)	1 if respondent resided in southern region	0.40	0.49	0	1
Marital status	Marital status as of the survey date				
Married	1 if respondent reported "Married"	0.36	0.48	0	1
Never Married	1 if respondent reported "Never Married"	0.56	0.50	0	1
Others	1 if respondent reported "Separated" or "Divorced" or "Widowed"	0.07	0.26		
Household size	Number of people living in the household as of the survey date	3.13	1.58	1	15
Children	1 if respondent has children	0.42	0.49	0	1
Income	Gross family income in the previous year	70,619.10	55,335.18	0	290,810
	Respondent's income in the previous year	33,165.85	23,216.27	0	130,254
	Income of other Family members	37,682.22	49,172.41	1	290,610
Number of observations		2,872			

[1] The number of months the respondent received UI are calculated by accumulating self-reported UI reception by month during the past 23-month period until the month of interview. During the recession (2009-2011), Congress approved an extension of a program to provide unemployment benefits for up to 99 weeks - an addition of 73 weeks to the traditional 26 weeks offered by the states. However, the duration varies from state to state based on how bad the unemployment situation is in the regions. The maximum extension 23 months is used in the calculation.

[2] Northeast (CT, ME, MA, NH, NJ, NY, PA, RI, VT) , North Central (IL, IN, IA, KS, MI, MN, MO, NE, OH, ND, SD), South (AL, AR, DE, DC, FL, GA, KY, LA, MD, MS, NC, OK, SC,TX, VA, WV), West (AK, AZ, CA, CO, HI, ID, MT, NV, NM, OR, UT, WA, WY)

[3] The income of other family members is set to one, assuming the respondents do not have other income from the family members because log of zero is undefined.

4.4 Estimation results

The results of the simultaneous unemployment and obesity equations are reported in Table 4.4. Before estimating the simultaneous equation models expressed in equations (4.3) and (4.4), we first estimate these two equations under the assumption that unemployment and obesity are exogenous to illustrate what the results would be under this incorrect assumption. In other word, the propensity of the individual to be unemployed has no influence on whether the individual is obese (BMI>=30) and the propensity of the individual to be obese has no influence on whether the individual is unemployed. In the univariate probit models, the variables for identification in the simultaneous equation models are also included in conjunction with other demographic regressors. The UI benefit and mother's BMI indicator variables are included in unemployment and obesity equations, respectively. The results from the univariate probit models are presented in Table 4.3. In these simplistic models, obese individuals are more likely to be unemployed (1.5%) and unemployed individuals are more likely to be obese (5.7%). Both of these variables are statistically significant at 90% confidence level.

Table 4.3: The unemployment and obesity univariate probit results

Variables	Unemployment			Obese		
	Coeff [1]	Std. Error	Marginal Effect	Coeff [1]	Std. Error	Marginal Effect
Unemployed [2]	--	--		0.167*	0.090	0.057
Obese (BMI >=30) [2]	0.141*	0.080	0.015	--	--	--
Age at survey date	0.438	1.169	-0.001	-0.411	0.719	-0.141
Age squared	-0.009	0.021	0.047	0.008	0.012	0.002
Male	-0.072	0.085	-0.007	-0.009	0.052	-0.003
Race (base : Mixed race)						
Black	-0.481	0.336	-0.005	0.404*	0.231	0.138
Hispanic	-0.190	0.372	-0.020	-0.095	0.263	-0.033
White	-0.350	0.337	-0.037	-0.081	0.258	-0.027
Education (base: Less than highschool)						
Graduate education	-0.708***	0.234	-0.076	-0.408***	0.152	-0.140
College education	-0.664***	0.159	-0.071	-0.250**	0.119	-0.085
Highschool Education	-0.395***	0.143	-0.042	0.006	0.113	0.002
Region (base : South)						
Northeastern region	-0.114	0.122	-0.001	-0.029	0.076	-0.009
Northcentral region	0.104	0.105	0.011	-0.030	0.066	-0.010
Western region	-0.108	0.115	-0.011	-0.058	0.070	-0.019
Marital status (base : Divorced,Separated,Widowed)						
Married	-0.483***	0.147	-0.052	0.029	0.106	0.010
Never married	-0.294**	0.142	-0.031	0.006	0.105	0.002
Household size	0.034	0.026	0.004	0.027	0.018	0.009
Have children	-0.145	0.101	-0.015	0.129**	0.063	0.044
Log income of other family members	0.001	0.010	0.0001	0.007	0.006	0.002
Constant	-5.762	16.255		4.288	10.308	
Pseudo-R^2	0.047			0.056		
Observations	2,872			2,872		

[1] The superscripts *,**,and *** represent significant coefficients at the 90% , 95% and 99% confidence level, respectively.
[2] For the univariate probit equations, the unemployed and obese variables are binary, while for the simultaneous probit equations; they are index values predicted from the reduced form estimates. Those results are presented in Table F.2 in the Appendix F.

The above approach assumes that obesity conditional on the covariates is independent of unemployment and vice versa. The associations between unemployment and obesity are positive and significant, but imprecisely measured due to omitted variable bias and possible reversed causality. An instrumental variable regression using a recursive bivariate probit model is used to control for the endogenity when the dependent variable and endogenous regressor are binary variable (Wooldridge, 2002, pp 477-8; Morris, 2007). The main IV recursive bivariate probit results are presented in Table 4.4.

Table 4.4: The unemployment and obesity IV recursive bivariate probit results[1]

Variables	Unemployment		Obese	
	Coeff [2]	Std.Err	Coeff [2]	Std.Err
Unemployed [3]	--	--	0.324	0.275
Obese (BMI >=30) [3]	0.026	0.330	--	--
+ Other covariates				
ρ	0.742	0.206	-0.087	0.141
Wald test ρ=0 [p-value]	$\chi^2(1)$=0.126 [0.719]		$\chi^2(1)$=0.376 [0.539]	

Impact of the instrument on	Unemployment		Obese	
	Coeff [1]	Std.Err	Coeff [1]	Std.Err
Mother's BMI >=30	--	--	0.665***	0.052
UI Benefit				
More than six months of UI	1.610***	0.126	--	--
+ Other covariates				

[1] The IV bivariate probit regressions are conditional on other covariates i.e. age, gender, races, educations, regions, marital status, household size, number of children, income of other family members in the past year.
[2] The superscripts *,**,and *** represent significant coefficients at the 90% , 95% and 99% confidence
[3] For the bivariate probit equations, the unemployed and obese variables are binary

In the top panel of Table 4.4, one can see that obesity has a positive effect on unemployment and unemployment has a positive effect on obesity, but neither relationship is statistically significant. Similar to Lindeboom et al., 2010; Cawley, 2000, and Norton and Han, 2008, this study finds no evidence that obesity causes unemployment using an instrumental variable model, but is contrary to the results obtained by Morris (2007). Cawley (2000) suggested that the observed correlation between body mass index and unemployment may be due to unemployment instead causing weight gain or unobservable factors causing both unemployment and weight gain. Current unemployment may affect current obesity. For example, individuals may be obese because they perform poorly in the labor market (Pagan and Davila, 1997). The ρ in a recursive bivariate probit unemployment equation is positive. This means that unexplained factors that affect unemployment are positively correlated with unexplained factors that affect obesity. A Wald test for both the unemployment and obesity equations fail to reject the hypothesis that $\rho=0$. This suggests that, assuming the instrument is valid, the endogeneity of obesity and unemployment do not significantly affect the univariate probit estimates. The bottom panel reports the significance of the instruments. As expected, even after controlling for the full set of covariates, unemployment insurance (UI) and mother's BMI are positive and highly significant predictors of unemployment and obesity, respectively, indicating that the instruments satisfy the non-weakness requirement.

An instrumental variable regression using a recursive bivariate probit model cannot fully capture potential unobserved factors causing both unemployment and obesity or reversed causality. This may cause the insignificant effects. The simultaneous probit model is an appropriate model to estimate the simultaneity of unemployment and obesity. The results of the simultaneous probit models are presented in Table 4.5. The standard errors of simultaneous probit models are corrected following Maddala's method (1983, pp. 246-247; presented in the Appendix F.4). It is worth mentioning that the unemployed and obese explanatory variables in simultaneous probit equation models in Table 4.5 are not binary. They are index values, which are predicted from the reduced form estimation in equation (4.1) and

(4.2). The interpretation of these two variables is different from the other explanatory variables. Thus, we only focus on the directionality of the effect of these two variables in the simultaneous equation models. Unemployed individuals are more likely to be obese than employed individuals and it is statistically significant at the 95% confidence level. Obese individuals are more likely to be currently unemployed compared to non-obese individuals; however, the result is not statistically significant.

The marginal effects of the explanatory variables in the simultaneous probit equation models are presented in Table 4.5. The forth column shows the marginal effect of the characteristics of individuals on the likelihood of unemployment. The UI benefit is positively associated with unemployment. Individuals receiving UI benefits for more than 6 months during the past 23 months have a 14.9% higher probability to be currently unemployed than individuals who received UI benefits 6 month or less in the past 23 months. The characteristics of individuals, which have the highest probability of unemployment, are mixed race, less than high school education, southern region, divorced, separated, or widowed, and have no children. White individuals have the lowest probability to be unemployed (-5%). Educational attainment plays a very significant role in determining the likelihood of unemployment. Individuals with a graduate degree have the lowest probability to be unemployed (-6.4%).

Table 4.5: The unemployment and obesity simultaneous probit results

Variables	Unemployment			Obese		
	Coeff [1]	Corr Std.Err	Marginal Effect	Coeff [1]	Corr Std.Err	Marginal Effect
Unemployed [2]	--	--	--	0.103**	0.047	0.033
Obese (BMI >=30) [2]	0.002	0.066	0.0002	--	--	--
Mother's BMI >=30	--	--	--	0.695***	0.035	0.227
UI Benefit (base : never or less than six months of UI)						
More than six months of UI	1.605***	0.100	0.149	--	--	--
Age at survey date	0.623	0.592	0.058	-0.711	0.452	-0.231
Age squared	-0.012	0.010	-0.001	0.013	0.008	0.004
Male	-0.150***	0.042	-0.014	-0.008	0.033	-0.002
Race (base : Mixed race)						
Black	-0.251	0.221	-0.023	0.437**	0.167	0.142
Hispanic	-0.349	0.220	-0.032	-0.047	0.166	-0.015
White	-0.537**	0.216	-0.050	0.087	0.166	0.028
Education (base: Less than highschool)						
Graduate education	-0.689***	0.126	-0.064	-0.263**	0.101	-0.085
College education	-0.679***	0.102	-0.063	-0.150*	0.084	-0.048
Highschool Education	-0.432***	0.096	-0.040	0.058	0.076	0.018
Region (base : South)						
Northeastern region	-0.154**	0.062	-0.014	-0.005	0.048	-0.001
Northcentral region	0.077	0.054	0.007	-0.015	0.042	-0.005
Western region	-0.187***	0.057	-0.017	0.006	0.044	-0.002
Marital status (base : Divorced,Separated,Widowed)						
Married	-0.511***	0.088	-0.047	0.046	0.071	0.015
Never married	-0.332***	0.087	-0.031	-0.00008	0.068	-0.00002
Household size	0.054***	0.015	0.005	0.021	0.012	0.006
Have children	-0.197***	0.051	0.018	0.152***	0.041	0.049
Log family income of other family members	-0.016 **	0.005	-0.0015	0.007 *	0.004	0.002
Constant	-8.014***	1.114		8.209***	0.855	
Pseudo-R2	0.095			0.180		
Observations	2,872			2,872		

[1] The superscripts *,**,and *** represent significant coefficients at the 90% , 95% and 99% confidence level, respectively.
[2] For the univariate probit equations, the unemployed and obese variables are binary, while for the simultaneous probit equations; they are index values predicted from the reduced form estimates. Those results are presented in Table F.2 in the Appendix F.

Individuals with a college degree prominently decrease the probability of unemployment by 2% from attaining high school degree. People living in the northeastern and western regions have a 1.4% and 1.7% respectively lower probability to be unemployed than individuals living in the southern region. Married individuals have the lowest probability to be unemployed (-4.7%). Marriage is still seen as a normative developmental milestone in American culture (DePaulo and Morris, 2005; Morris et al., 2007). Single people are perceived as less mature, and less well adjusted than married people (Etaugh and Birdoes, 1991; Morris et al., 2008). Thus, the stereotypes of single people might be seen as less committed to their jobs compared to married people, and might thus be discriminated against in employment decisions (Jordan and Zitek, 2012). One additional person in the household increases the probability of the individual being unemployed by 0.5%. Individuals with children, however, are less likely to be unemployed (-1.8%) than individuals without children. There is more of an imperative to take a job, any job, if individuals have dependents (Harknett). People with low-income working families are often taking jobs with lower wages and less job security, compared with the middle-class jobs they held before the economic downturn (NELP, 2012). The log incomes of other family members show significant and negative but small effect on unemployment (-0.1%).

The marginal effects of the characteristics of individuals on the likelihood of obesity are presented in the seventh column in Table 4.5. The mother's BMI is strongly associated with individual's BMI. The individuals who have an obese mother (BMI>=30) are more likely to be obese (22.7%) than individuals who have a non-obese mother. African Americans are the most likely to be obese (14.2%). This finding corresponds with the Gallup-Healthways Well-being survey in 2012 that African Americans are among the most likely in the United States to be very obese, with about 9% falling into obese class II and 6% obese class III -- the highest Body Mass Index (BMI) categories. Our results show that individuals with a graduate degree are the least likely to be obese (-8.5%) following by a college degree (-4.8%). Individuals with a high school degree are the highest risk group of being obese. The individuals with children, however, are more likely to be obese (4.9%) than individuals without children. The log incomes of other family members show significant and positive but small effect on obesity (-0.2%). The rest of the explanatory variables are not statistically significant in the simultaneous equation models.

Note that the univariate probit equation estimations indicate positive and significant effects of obesity on unemployment and, in turn, unemployment on obesity. In the instrumental variable regression based on a recursive bivariate probit model, obesity has not statistically significant effect on unemployment and vice versa. However, the results of the simultaneous probit equation estimations, for which the endogeneity between unemployment and obesity is accounted for, found that only unemployment has a positive and significant effect on obesity. It is worth noting that without correction of standard errors, this simultaneous estimation method yields insignificant effect of both unemployment and obesity. The evidence here indicates that obesity and unemployment are not independent and suggests in order to find true effects of each one, both should be estimated simultaneously. Our results suggest that unemployment positively impacts obesity, but not vice versa.

The study uses data in the period of economic recession in 2010 where a post-dismissal traumatic stress disorder is presumably ubiquitous and much more pronounced than other normal periods. One potential confounder is a mental depression that could potentially correlate with both unemployment and obesity and could create a spurious relationship if the estimate fails to account for. In addition to a multivariate model, which could handle large numbers of covariates such as age, sex, ethnicity and control potential confounders simultaneously, the estimation includes a mental depression covariate in a simultaneous equation system. The process of accounting for covariates is also called adjustment and comparing the results can clarify how much the suspected confounders in the model distort the relationship between exposure and outcome (Pourhoseingholi et al. 2012). The adjusted model with a potential confounder, mental depression, in the estimation shows that its inclusion does not impact the previous results for the variables of interest, unemployment and obesity (Table F.3 in the Appendix F). Thus, the exclusion of the mental depression variables does not appear to invalidate the model. In addition, the different BMI values close to the principal cut off point of obesity i.e. BMI >= 29 or BMI >=32 are chosen to estimate in the regression models for robustness check of the model. The results are statistically consistent.

4.5 Conclusions and Policy Implications

Unemployment could affect weight gain through over-eating as a means to cope with unemployment stress, or due to more time for eating and the consumption of cheaper, more fattening food. Alternatively, obesity could affect unemployment. In 1995-1996, 7% of US adults reported at least one time experience of weight discrimination, and in 2004-2006, that percentage rose to 12% of adults, which was a 66% increase (Andreyeva et al., 2008). Friedman and Puhl (2012) reported that overweight and obese job applicants are viewed as having poor self-discipline, low supervisory potential, poor personal hygiene, and less ambition and productivity. The perpetuating negative cycle of joblessness and obesity will occur in the situation in which unemployment may cause some people to engage in binge eating that leads to obesity and pre-existing obesity may make it harder for others to find and keep work at the same time.

To estimate the true simultaneous effects of unemployment and obesity on each other, the impact of unemployment on probability of obesity and the impact of obesity on probability of unemployment are simultaneously estimated with Maximum Likelihood probit estimations using an instrumental variable approach. The results show that unemployment increases the likelihood of obesity, but not vice versa. The univariate probit and bivariate probit models are also estimated to see the effect. Without correcting for endogeneity, the univariate probit results reveal a significant and positive impact of obesity on unemployment, and vice versa. An instrumental variable regression with a recursive bivariate probit model used to account for endogeniety, but not simultaneity, found insignificant results. Our contribution in simultaneous estimation and properly adjusting the standard errors is not only warranted in our econometric application, but also in policy implication. The results underscore the importance of the standard error correction in hypothesis testing. Our results find that being unemployed increases the likelihood of being obese. However, we find no effect of obesity on employment status, which contradicts the evidence of weight discrimination.

Notwithstanding insignificant impact of obesity on unemployment status, other results from the study suggest future researchable issues. First, the study found that being unemployed significantly contributes to the probability of being obese. The impact of extended periods of unemployment on weight gain should be further investigated because obesity-related health consequences would become more prominent and raise a concern for policymakers. Second, although the results found no statistical evidence of weight discrimination, it is inconclusive that normal or underweight individuals would decrease their risks of unemployment due to no statistical difference in the probability of unemployment between obese and non-obese individuals. Last, the results of this study affirm that the influence of several socio-economics characteristics heavily affect the probability of being unemployed and/or obese. This suggests importance of socioeconomic status in explaining employment and obesity status.

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APPENDIX F

Table F.1: The regression results of measured BMI on self-reported BMI using NHANES III (1999-2010) [1,2]

Male respondents aged 25-31years old

Measured BMI	**Black**	**Hispanic**	**White**	**Mixed Race**
Self-reported BMI	1.046***	0.932***	1.019***	0.971***
	(0.026)	(0.026)	(0.013)	(0.008)
Adj R-squared	0.9	0.83	0.93	0.90
Observations	317	466	659	80

Female respondents aged 25-31years old

Measured BMI	**Black**	**Hispanic**	**White**	**Mixed Race**
Self-reported BMI	1.064***	1.032***	1.007***	1.048***
	(0.022)	(0.023)	(0.015)	(0.076)
Adj R-squared	0.90	0.83	0.88	0.83
Observations	378	556	882	94

Female respondents aged 26-82 years old

Measured BMI	**Black**	**Hispanic**	**White**	**Mixed Race**	**All**
Self-reported BMI	1.024***	1.027***	1.031***	1.061***	1.028***
	(0.009)	(0.010)	(0.005)	(0.027)	(0.004)
Adj R-squared	0.89	0.83	0.92	0.84	0.89
Observations	2,525	2,985	6,015	483	12,008

[1] Controlled by age, age squared, the squared deviation from gender-race mean BMI
[2] Standard errors in the parentheses

Table F.2: The unemployment and obesity reduced form probit results

Variables	**Employment Status**		**Obese**	
	Coeff [1]	Std.Error	Coeff [1]	Std. Error
Mother's BMI >=30	-0.014	0.087	0.67***	0.052
UI Benefit (base: never or less than six months of UI)				
More than six months of UI	1.363***	0.115	0.14	0.109
Age at survey date	-0.325	1.151	-0.74***	0.052
Age squared	0.005	0.021	0.01	0.697
Male	-0.039	0.086	-0.04***	0.012
Race (base: Mixed race)				
Black	-0.390	0.335	0.40	0.251
Hispanic	-0.366	0.336	-0.10	0.253
White	-0.600*	0.331	0.00	0.248
Education (base: Less than high school)				
Graduate education	-0.525	0.331	-0.31**	0.153
College education	-0.497*	0.250	-0.18	0.119
High school Education	-0.285*	0.166	0.03	0.111
Region (base: South)		0.146		
Northeastern region	-0.120	0.126	-0.04	0.075
North central region	0.054	0.105	-0.03	0.065
Western region	-0.110	0.115	-0.02	0.069
Marital status (base: Divorced,Separated,Widowed)				
Married	-0.464***	0.147	-0.02	0.098
Never married	-0.308*	0.137	-0.07	0.096
Household size	0.035	0.026	0.02	0.018
Have children	-0.240*	0.101	0.13**	0.061
(base: Income>$50,000)				
Income<= $5,000	0.889***	0.198	0.15	0.119
$5000< Income<= $10,000	0.767***	0.204	0.15	0.125
$10,000 < Income<= $25,000	0.357**	0.177	0.20**	0.084
$25,000 < Income<= $50,000	0.242	0.174	0.17**	0.078
Constant	4.480	15.981	8.63	9.709

[1] The superscripts *, **, and *** represent significant coefficients at the 90%, 95% and 99% confidence level, respectively.

Table F.3: The unemployment and obesity simultaneous probit results including a mental depression variable as an explanatory variable

	Employment Status			Obese		
	Coeff [1]	Corr Std.Err	Marginal Effect	Coeff [1]	Corr Std.Err	Marginal Effect
Unemployed				0.090*	0.049	0.030
Obese (BMI >=30)	0.0005	0.066	0.00004			
Mother's BMI >=30	-	-	-	0.697***	0.036	0.226
UI Benefit (base : never or less than six months of UI)						
More than six months of UI	1.59***	0.101	0.148	-	-	-
Mental Depression	0.138**	0.051	0.012	0.198**	0.039	0.064
Age at survey date	0.592	0.595	0.055	-0.766*	0.463	-0.248
Age squared	-0.011	0.010	-0.001	0.015*	0.008	0.005
Male	-0.142***	0.042	-0.013	-0.001	0.034	-0.0003
Race (base : Mixed race)						
Black	-0.229	0.222	-0.021	0.466**	0.171	0.151
Hispanic	-0.325	0.221	-0.030	-0.019	0.172	-0.006
White	-0.513**	0.217	-0.047	0.199	0.170	0.038
Education (base: Less than highschool)						
Graduate education	-0.682***	0.126	-0.063	-0.237**	0.103	-0.076
College education	-0.660***	0.102	-0.061	-0.126	0.086	-0.040
Highschool Education	-0.421***	0.096	-0.039	0.074	0.077	0.024
Region (base : South)						
Northeastern region	-0.157**	0.062	-0.015	-0.005	0.049	-0.001
Northcentral region	0.071	0.055	0.006	-0.018	0.043	-0.005
Western region	-0.188***	0.057	-0.017	0.006	0.045	0.001
Marital status (base : Divorced,Separated,Widowed)						
Married	-0.491***	0.088	-0.046	0.068	0.073	0.022
Never married	-0.318***	0.087	-0.029	0.015	0.069	0.004
Household size	0.053***	0.015	0.005	0.020	0.012	0.006
Have children	-0.193***	0.054	-0.018	0.156***	0.042	0.051
Log family income of other family members	-0.016***	0.005	-0.001	0.007*	0.004	0.002
Constant	-7.679***	1.209		8.874***	0.804	
Pseudo-R^2	0.182			0.095		
Observations	2,872			2,872		

[1] The superscripts *,**,and *** represent significant coefficients at the 90% , 95% and 99% confidence level, respectively.

F.4 Covariance Matrix Correction in Simultaneous Probit Equations

I. Likelihood Functions

The likelihood functions are taken from the general expression in Mallar (1997). The log likelihood probit function for the structural umployment equation is

$$ln\mathcal{L}_{L**} = \sum_{i=1}^{N}[L_i \ln(Q_{Li}) + (1 - L_i)(1 - Q_{Li})] \ ,$$

where $Q_{Li} = \int_{-\infty}^{I_{Li}}(2\pi)^{-1/2}e^{-t^2/2}dt$ and $I_{Li} = \alpha_{0,Bi}\widehat{\boldsymbol{B}}^{*} + \boldsymbol{X}_{\boldsymbol{B}}'\boldsymbol{\alpha}_{\boldsymbol{B}}$.

The log likelihood probit function for the structural obesity equation is

$$ln\mathcal{L}_{B**} = \sum_{i=1}^{N}[B_i \ln(Q_{Bi}) + (1 - B_i)(1 - Q_{Bi})] \ ,$$

where $Q_{Bi} = \int_{-\infty}^{I_{Bi}}(2\pi)^{-1/2}e^{-t^2/2}dt$ and $I_{Bi} = \alpha_{0,Li}\widehat{\boldsymbol{L}}^{*} + \boldsymbol{X}_{\boldsymbol{L}}'\boldsymbol{\alpha}_{\boldsymbol{L}}$.

II. Covariance Matrices

Based on Maddala (1983, pp243-247), we follow the steps as following:

Step 1: The reduced forms in (1) and (2) are estimated by Maximum Likelihood Probit Estimation, and get a predicted value of L^* and B^* denoted as $\widehat{L^*}$ and $\widehat{B^*}$ respectively.

(1) $$\boldsymbol{L}^{*} = \boldsymbol{\Pi}_{\boldsymbol{L}}^{*}\boldsymbol{X} + \boldsymbol{v}_{\boldsymbol{L}}^{*} \quad , \boldsymbol{\Pi}_{\boldsymbol{L}}^{*} = \frac{\boldsymbol{\Pi}_{\boldsymbol{L}}}{\boldsymbol{\sigma}_{\boldsymbol{L}}} \text{ and } \boldsymbol{v}_{\boldsymbol{L}}^{*} = \frac{\boldsymbol{\nu}_{\boldsymbol{L}}}{\boldsymbol{\sigma}_{\boldsymbol{L}}}$$

(2) $$\boldsymbol{B}^{*} = \boldsymbol{\Pi}_{\boldsymbol{B}}^{*}\boldsymbol{X} + \boldsymbol{v}_{\boldsymbol{B}}^{*} \quad , \boldsymbol{\Pi}_{\boldsymbol{B}}^{*} = \frac{\boldsymbol{\Pi}_{\boldsymbol{B}}}{\boldsymbol{\sigma}_{\boldsymbol{B}}} \text{ and } \boldsymbol{v}_{\boldsymbol{B}}^{*} = \frac{\boldsymbol{\nu}_{\boldsymbol{B}}}{\boldsymbol{\sigma}_{\boldsymbol{B}}} \ ,$$

where L^* and B^* are observed only a latent variable of unemployment status and obesity, respectively (zero and one). Thus, we can only estimate $\boldsymbol{\Pi}_{\boldsymbol{L}}^{*}$ and $\boldsymbol{\Pi}_{\boldsymbol{B}}^{*}$ **, not** $\boldsymbol{\Pi}_{\boldsymbol{L}}$and $\boldsymbol{\Pi}_{\boldsymbol{B}}$

Step 2: Substitute $\widehat{\boldsymbol{B}}^{*}$ and $\widehat{\boldsymbol{L}}^{*}$ into the structural forms in equation (3) and (4) respectively, and estimate both equations by Maximum Likelihood Probit Estimation.

(3) $$\boldsymbol{L}^{**} = \alpha_{0,L}\widehat{\boldsymbol{B}}^{*} + \boldsymbol{X}_{\boldsymbol{L}}'\boldsymbol{\alpha}_{\boldsymbol{L}} + \boldsymbol{\epsilon}_{\boldsymbol{L}}$$

(4) $$\boldsymbol{B}^{**} = \alpha_{0,B}\widehat{\boldsymbol{L}}^{*} + \boldsymbol{X}_{\boldsymbol{B}}'\boldsymbol{\alpha}_{\boldsymbol{B}} + \boldsymbol{\epsilon}_{\boldsymbol{B}}\ ,$$

where $\alpha_{0,L} = \gamma_L \frac{\sigma_B}{\sigma_L}$, $\alpha_{0,B} = \gamma_B \frac{\sigma_L}{\sigma_B}$, $\boldsymbol{\alpha}_{\boldsymbol{L}} = \frac{\boldsymbol{\beta}_{\boldsymbol{L}}}{\boldsymbol{\sigma}_{\boldsymbol{L}}}$, $\boldsymbol{\alpha}_{\boldsymbol{B}} = \frac{\boldsymbol{\beta}_{\boldsymbol{B}}}{\boldsymbol{\sigma}_{\boldsymbol{B}}}$, $\boldsymbol{\epsilon}_{\boldsymbol{L}} = \frac{\boldsymbol{\varepsilon}_{\boldsymbol{L}}}{\boldsymbol{\sigma}_{\boldsymbol{L}}}$, $\boldsymbol{\epsilon}_{\boldsymbol{B}} = \frac{\boldsymbol{\varepsilon}_{\boldsymbol{B}}}{\boldsymbol{\sigma}_{\boldsymbol{B}}}$

Step 3: Although equation (3) and (4) will give us an unbiased estimator, the covariance matrix is not correct. Let $a_L = \frac{\phi_L}{\Phi_L(1-\Phi_L)}$ and $a_B = \frac{\phi_B}{\Phi_B(1-\Phi_B)}$, where ϕ is a standard normal probability density (PDF) and Φ is a cumulative standard normal distribution (CDF) estimated of fitted values from reduced form equation (1) and (2) , $A_L = \phi_L * a_L$, $A_B = \phi_B * a_B$, $\boldsymbol{Z}_L = \begin{bmatrix} \Pi_B^{*}\boldsymbol{X} \\ \boldsymbol{X}_{\boldsymbol{L}} \end{bmatrix}$ and $\boldsymbol{Z}_B = \begin{bmatrix} \Pi_L^{*}\boldsymbol{X} \\ \boldsymbol{X}_{\boldsymbol{B}} \end{bmatrix}$. The variance-covariance matrix for the $\boldsymbol{L}^{**}$ equation is defined as

$$W_1^{-1}[W_1 - W_3W_2^{-1}W_4 - W_4'W_2^{-1}W_3' + W_3W_2^{-1}W_3']W_1^{-1}\text{ , where}$$

$$W_1 = \frac{1}{N}\sum_{i=1}^{N} A_L\boldsymbol{Z}_L\boldsymbol{Z}_L'$$

$$W_2 = \frac{1}{N}\sum_{i=1}^{N} A_B\boldsymbol{X}_L\boldsymbol{X}_L'$$

$$W_3 = \frac{1}{N}\sum_{i=1}^{N} A_L\, \alpha_{0,L}\boldsymbol{Z}_L\boldsymbol{X}_L'$$

$$W_4 = \frac{1}{N}\sum_{i=1}^{N} a_L a_B\, E((L - \Phi_L)(B - \Phi_B))\, \boldsymbol{X}_L\boldsymbol{Z}_L'$$

The variance-covariance matrix for the $\boldsymbol{B}^{**}$ equation is defined as

$[W_1 - W_3 W_2^{-1} W_4 - W_4' W_2^{-1} W_3' + W_3 W_2^{-1} W_3'] W_1^{-1}$, where

$$W_1 = \frac{1}{N} \sum_{i=1}^{N} A_B \boldsymbol{Z}_B \boldsymbol{Z}_B'$$

$$W_2 = \frac{1}{N} \sum_{i=1}^{N} A_L \boldsymbol{X}_B \, \boldsymbol{X}_{\boldsymbol{B}}'$$

$$W_3 = \frac{1}{N} \sum_{i=1}^{N} A_B \, \alpha_{0,B} \boldsymbol{Z}_B \boldsymbol{X}_B'$$

$$W_4 = \frac{1}{N} \sum_{i=1}^{N} a_L a_B \, E((L - \Phi_L)(B - \Phi_B)) \, \boldsymbol{X}_B \boldsymbol{Z}_B'$$