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an econometric study of the impact of economic variables on adult obesity and food assistance program participation in the NLSY panel

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Abstract

Over the past thirty-five years, the U.S. adult obesity rate has more than doubled from roughly 15% to 35%, reflecting a general diffusion of obesity across all segments of the adult population (United States Department of Health and Human Services). The objective of this research is to identify the factors that influence adults' healthy weight, as reflected in body mass index (BMI) or being obese (having a body mass index of 30 or larger), the Food Stamp Program (or Supplemental Nutrition Assistance Program) participation, and the relationship of these two in longitudinal panel data.

The panel data was obtained by merging the individual-level national data for the U.S. adults from the National Longitudinal Survey of the Youth, 1979 Cohort (NLSY79), with external price data obtained from the American Chamber of Commerce Research Association (ACCRA) Cost of Living Index. Six rounds of NLSY79 survey were extracted at a 4-year interval from 1986 to 2006. Using the geocode information, the secondary data on local food, drinks and health care prices and labor market conditions were merged with the data on adults in the NLSY79.

We used three improved economic and econometric models to examine the effect of FSP (or SNAP) participation on women's BMI and likelihood of being obese. First, least squares instrumental variable (IV) estimation of our benchmark model suggests that women in households that currently participate in the FSP (or SNAP) have a higher BMI and a higher probability of being obese. Other things equal, participation in the FSP increases a woman's BMI by about 1.1%, and also increases her probability of being obese by about 2.6 percentage points. However, concerns are sometimes raised about least squares IV estimates being inconsistent because no account is taken of individual (or household) fixed (or random) effects.

Second, a new model of lifetime utility maximization is developed with perfect foresight, and the equations for BMI (and obesity) and FSP participation are estimated using the least squares estimator incorporating IV (for FSP and wage rate) and individual fixed effects. Results from this fitted model suggest that if a woman is in a household that decides to participate in FSP participation, it reduces her BMI by 15.67% and her probability of being

obese by 56.33 percentage points. Moreover, the estimates of the individual fixed effects have a frequency distribution that approximates a normal, and for a significant part of the sample, the individual fixed effects accounts for most of the explained variation in ln(*BMI*) and the probability of being obese.

Third, we next consider a model of lifetime utility maximization with updating and autocorrelation of BMI or the probability of being obese. These results suggest that if a woman is in a household that participates in the FSP program, it reduces here BMI by 1.12% and her probability of being obese by 3.76 percentage points, which is significantly lower than the results from the second model.

These latter two models have considerable appeal relative to the benchmark econometric model. Hence, we conclude that women in households that participate in the FSP participation have a lower BMI and a lower probability of being obese. Also, we conclude that individual-fixed effects play a large role in understanding obesity in women. These are key findings of this study.

Chapter 1. Introduction

Over the past thirty-five years, the U.S. adult obesity rate has more than doubled from roughly 15% to 35%, reflecting a general diffusion of obesity across all segments of the adult population (United States Department of Health and Human Services). Obesity is a concern because it increases the risk for cardiovascular diseases, diabetes, and most forms of cancer, except for lung. In addition, when adults are obese, their labor productivity and quality of life decline, medical expenditures increase dramatically and many die prematurely. The U.S. obesity rate is the highest in the world, and obese adults are a major financial burden to families and also the U.S. Medicare and Medicaid Programs. In 2008, medical costs associated with obesity were estimated at $147 billion; the per capita medical costs paid by third-party payers for people who are obese were $1,429 higher than those of normal weight (Ogden and Carroll 2010).

Earlier studies of obesity of U.S. adults have largely focused on data in a single cross-section or one round of a panel survey and tried to identify the factors that have great impacts on people's body weight. Among these factors, food prices are a major factor because they determine quantity demanded for food. Etilé (2008) used French food expenditures data to examine the effects of food prices in twenty-three product categories on individuals' body mass index (BMI) distribution for a sample of French adults. He found that the food price elasticity of BMI was negative and almost always significant for cereals, breaded proteins, and animal and vegetable fats. Around the median BMI, a higher price of seafood products (in brine and processed) increased BMI. The price elasticity of BMI for meats in brine was negative, and the price elasticity around the median for snacks and ready-meals was positive. For fruits and vegetables in brine, he found that a higher price increased BMI, but for processed fruits and vegetables, a higher price reduced BMI.

Auld and Powell (2009) used repeated cross-sectional data of adolescents drawn from the Monitoring the Future Survey to investigate the determinants of BMI. They showed that decreases in the relative price of energy dense foods increased adolescent body weight if the price of obtaining a calorie from dense food was lower than that of less dense food. Their results suggested that the price of high density food (fast food meals) was negatively related to body weight, whereas the price of low density food (fruits and vegetables) was positively associated.

In a recent study Chen (2009) showed that prices of food and drinks (for seven groups) contributed significantly to the explanation of adult decisions on physical activity and being obese for women in round 2004 of the NLSY79 data set but not for men. Also, a higher opportunity cost of time of women reduced their probability of obese, while a higher opportunity cost of time of men raised their probability of being obese. Women who had more education were more likely to be obese but men with more education were less likely to be obese. She also showed that early BMI (BMI at age 25) had a large positive and statistically significant impact on later BMI of both men and women.

Food from food assistance programs is one part of the food budget for some households --- mainly low income ones, thus affects the household members' nutrition intakes and body weight. Fox, Hamilton and Lin (2004) provided a summary of a comprehensive review and synthesis of published research on the impact of USDA's domestic food and nutrition assistance programs on participants' nutrition and health outcomes. Among them, a few studies have attempted to link an individual's participation in the Food Stamp Program (FSP), recently renamed the Supplemental Nutrition Assistance Program (SNAP), and obesity. The administration of the FSP with beginning-of-the-month payments to eligible households may lead participating households to over-consume at the beginning of the month and to starve at the end of the month. This cycling through "many mini feast and famine periods" could lead individuals to develop unhealthy eating habits, which in turn could contribute to obesity. The empirical evidence in these studies is that FSP participation increases the probability of being obese although the magnitude is quite different.

Gibson (2003) examined the relationship between FSP participation and obesity for low income individuals using data from the National Longitudinal Survey of Youth 1979 (NLSY79). Individual fixed-effects were used to take into account unobserved differences across individuals that did not vary over time. The results indicated that both current and long-term FSP participation were significantly related to the obesity of low income women, but not of low income men. Gibson (2004) used the same method to examine the relationship in children using data from the NLSY79 Child Sample. The models were estimated separately for younger (5-11 years old) and older (12-18 years old) children. The results indicated that long-term FSP participation was positively and significantly related to being overweight for young girls, and negatively and significantly related to being overweight for young boys, but not significantly related to being overweight for older children. However, these results are questioned because they did not consider the SNAP or FSP participation decision, which is endogenous.

Chen, Yean, and Eastwood (2005) used the data from the 1994-1996 Continuing Survey of Food Intakes by Individuals (CSFII) to examine the effects of FSP participation on two separate but related outcome measures: a continuous body mass index and a binary obesity indicator. For each measure, a simultaneous-equation system was used to accommodate the endogeneity of FSP participation. Their results indicated that FSP participation was positively related to bodyweight and the likelihood of being obese among low-income women, which suggested that women receiving FSP benefits were more likely to be obese due to their “distorted” food consumption caused by the food item eligibility restriction.

Meyerhoefer and Pylypchuk (2008) used the 2000-2003 Medical Expenditure Panel Survey (MEPS) and information on state-level FSP characteristics to estimate the impact of FSP participation on weight status and health care spending among non-elderly adults. Their results suggested that program participation by women led to a 5.9% increase in their likelihood of being overweight or obese and also to higher medical expenditures.

The literature reviewed above has provided some guidance on those factors that might affect adult decisions on a healthy weight and the Food Stamp Program participation, and also on the method of estimating the relationship between these two outcomes. An individual fixed-effects model using panel data is better than the estimations using a single cross-section or one round of a panel survey since it takes into account unobserved differences across individuals that did not vary over time. Also, the endogeneity between adult weight and the FSP participation should be corrected when estimating the effect of participation on weight.

The objective of this research is to identify the factors that affect adults’ healthy weight, as reflected in body mass index (BMI) or being obese (having a body mass index of 30 or larger), decision of a household to participate in the FSP (or SNAP), and the relationship of these two in longitudinal panel data. The factors we are also interested in include the prices of food and drinks, the opportunity cost of time, and past participation in the program.

We analyze household decision making from three different perspectives. For each perspective, an economic model of household decision making on food, other purchased goods, health, and leisure is developed, and then a corresponding econometric model is developed and estimated. In the first model, the household head makes decisions by maximizing household utility in each period separately while he/she does not update his/her decision-making process based on previous outcomes. The corresponding empirical econometric model is estimated by least squares with instrumental variables. Second, the household head maximizes household lifetime utility, but he/she does not update his/her decisions based on previous outcomes. Dynamic programming analysis of this utility maximization problem provides the fundamental structure of an econometric model with IVs and individual fixed-effects. Third, we extend the lifetime utility maximization problem by arguing that the household head takes account of previous health outcomes as he/she makes current decisions. An individual's previous health outcome, which is different from other consumption goods, affects his/her current decisions in that it limits his/her ability to conduct daily activities. The econometric model is least squares with IVs and with individual fixed effects and autocorrelation in the BMI or obesity equation.

The panel data we use is obtained by merging the individual-level national data for the U.S. adults from the National Longitudinal Survey of the Youth, 1979 Cohort (NLSY79), with external price data obtained from the American Chamber of Commerce Research Association (ACCRA) Cost of Living Index. Six rounds of NLSY79 survey were extracted at a 4-year interval from 1986 to 2006. With use of the geocode on each household, we are able to merge the secondary data on local food, drinks and health care prices and labor market conditions to the adults in the NLSY79.

The paper provides some new insights on adult obesity in the United States and makes contributions to the literature in the following ways. First, we develop economic models to support our empirical estimations. This step is missing in most previous studies. Second, most economists used data for a single cross-section or one round of a panel survey to examine the relationship between FSP participation and BMI or obesity. With our longitudinal panel data we can bring more information to bear on the relationship. Third, most findings in the literature are challenged because they did not control for the endogeneity between adult weight and participation in the FSP program, which is solved by an instrumental variable strategy in this paper.

The rest of the paper is organized as follows. In Chapter 2, we introduce the primary and secondary data sets to be used and define the variables. In Chapter 3, 4, and 5, we analyze the household decision making process from three different perspectives. In each chapter, we develop a theoretic model of decision making, describe the corresponding econometric model, discuss important hypotheses to be tested, and present empirical results. Chapter 6 concludes. Appendix I provides detailed information on the food items in each food category and gives an example of how to calculate the relative price of each food category. Appendix II is the questionnaires about non-cognitive abilities in NLSY79. Appendix III presents the regression results we use to predict the household non-wage income. The ordinary least squares estimations of the BMI/obesity equation are attached in Appendix IV.

Chapter 2. Data and Empirical Definitions of Variables

The primary data sources for the empirical analysis comes from the individual-level national data for the U.S. adults from the National Longitudinal Survey of the Youth, 1979 Cohort (NLSY79), merged with external price data obtained from the American Chamber of Commerce Research Association (ACCRA) Cost of Living Index.

The National Longitudinal Survey of the Youth, 1979 Cohort is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. The survey was conducted annually from 1979 to 1994 and has been conducted biennially since 1996. The most updated survey was conducted in 2006. Each round collected detailed information on the respondents' health status, number of family members, schooling, labor market behaviors, income and expenditures, and so on. We extract out a sample from 6 rounds at an interval of four years, i.e. 1986, 1990, 1994, 1998, 2002 and 2006, for two reasons. First, after 1986, all respondents were at least of age 21 and passed their juvenescent phase with a stable weight history. Second, the four-year interval helps reduce autocorrelation.

In 1979, the following three subsamples comprised the NLSY79 sample: (1) a cross-sectional sample of 6,111 respondents designed to be representative of the non-institutionalized civilian segment of young people living in the United States in 1979 and born between January 1, 1957, and December 31, 1964 (ages 14–21 as of December 31, 1978); (2) a supplemental sample of 5,295 respondents designed to oversample civilian Hispanic, black, and economically disadvantaged non-black/non-Hispanic youth living in the United States during 1979 and born between January 1, 1957, and December 31, 1964; (3) a sample of 1,280 respondents designed to represent the population born between January 1, 1957, and December 31, 1961 (ages 17–21 as of December 31, 1978), and who were enlisted in one of the four branches of the military as of September 30, 1978.

Following the 1984 interview, 1,079 members of the military subsample were no longer eligible for interview, while the rest randomly-selected 201 respondents remained in the survey. We excluded these respondents from our sample because their health status or BMI may be related to special training and thus are less representative. As a result, there are

11,406 respondents in our sample before dropping out those with missing values in key variables. Table 1 explains the abbreviations and a shot description of the variables to be used in the econometric model.

i) Body Mass Index (BMI) and Obesity

BMI is a simple index of weight-for-height and is commonly used to measure health in literature. It is defined as the individual's body weight (in kilograms) divided by the square of his or her height (in meters). According to the World Health Organization's classification, an adult's normal weight should be between 18.5 and 25. Persons with BMI<18.5 (kg/m^2) are classified as being underweight, persons with BMI>=25(kg/m^2) are classified as being overweight, and persons with BMI>=30(kg/m^2) are classified as being obese.

We construct two BMI variables: current BMI and BMI at age 20 (or put more accurately, BMI in the year that the respondent turned 20 years old). Respondents' self-reported weight was recorded in each round, but self-reported height was only available in round 1981, 1982, 1985 and 2006.

To calculate current BMI, we need to fix the problem of measurement errors and missing values in self-reported height. Because the respondents were still young (aged 14–21 as of December 31, 1978), their height may vary (normally increase) in the 1981, 1982, 1985 surveys. However, after close exam of these values, we find that some respondents have unreasonable height history. For instance, for some of them, the height in 1982 was much less than the value in 1981, or, the height in 1985 was much less than the value in 1982. Therefore, we use the maximum of all available height values up to the survey year as the respondent's height to calculate his/her BMI in this year. Specifically, for the observations in 1982, we use the maximum of the available height values in 1981 and 1982 to calculate current BMI in 1982. For the observations in 1986, 1990, 1994, 1998 and 2002, we use the maximum of the available height values in 1981, 1982 and 1985 to calculate BMI in these years. However, in order to keep the most updated information, for the observations in 2006, we use the height value in 2006 to calculate current BMI when it is available and use the foresaid method when it is not available.

To calculate BMI at age 20, we not only apply the same procedure to get the self-reported height, but also follow like rationale to approximate the missing values in self-reported weight. Because all respondents were born between January 1, 1957, and December 31, 1964, they turned 20 years old between year 1977 and 1984. For the respondents that were born before January 1, 1962, who turned 20 years old before January 1, 1982, we use their BMI in 1981 as their BMI at age 20. For the respondents that were born in 1962, we follow the following procedure to get their BMI at age 20. First, when their weight in 1982 is available, it is used to calculate their BMI at age 20. Second, when the respondent's weight is missing in 1982, we use the average of his/her weight values in 1981 and 1985 (when both are available) to approximate his/her weight in 1982. Last, if the respondent's BMI at age 20 still cannot be calculated by the second step due to the missing of weight values in 1985, we use their BMI in 1981 as BMI at age 20. Finally, for the respondents that were born after December 31, 1962, and turned 20 years old after December 31, 1982, we use their BMI in 1985 as their BMI at age 20.

ii) Food Stamp Program Participation

The survey asked the respondents about the detailed information on the Food Stamp program participation in all rounds. The questions covered the beginning date and the ending date of each period between the last interview and this interview in which the household received any food stamps, as well as the values of food stamps in each month during these periods. Therefore, we can get the total amount of the food stamps the respondents received during each year.

We constructed two variables representing the FSP: the index for current participation and the average annual amount of food stamps the respondent received between two survey years (referred shortly as lagged food stamps value). If the respondent received any food stamps during the reported year, the index for current FSP participation equals 1, otherwise it is 0. In order to check for dependence and recidivism of welfare program participation, we use the average annual amount of food stamps the respondent received in the last three calendar years between two survey rounds to represent the respondent's participation history. For instance, for the observations from round 1986, the lagged food stamps value is calculated as taking average of the annual food stamps that the respondents received in 1983, 1984 and 1985. Meanwhile, in order to check if missing previous participation history plays an important role in our estimations, a dummy variable is set to 1 if at least one of the annual food stamps values in the last three calendar years is missing, and set to 0 if all three values are available.

iii) ACCRA Prices of Food, Drinks, Fast Food and Health Care

To be consistent with the reported years of the NLSY79 data, we construct price indexes for food, drinks, fast food and health care in year 1985, 1989, 1993, 1997, 2001 and 2005. The American Chamber of Commerce Researchers Association (ACCRA) collects data on prices of 63 different items in 300 U.S. cities quarterly. These data provide useful information on prices of individual food items and can also be used to construct local cost of living indexes. The ACCRA data are collected at the establishment level and the basket of goods reflects a mid-management standard of living. The sample weight for each item is derived from expenditure shares in the U.S. Bureau of Labor Statistics' 1993 Consumer Expenditure Survey. We constructed prices of food, drink, fast food and health care using all of the price data included in the ACCRA data set. Although one can imagine creating better prices for some commodity groups, they would need prices on a much broader range of goods. The methodology we use has been applied by Chou, Grossman, and Saffer (2004), Powell et al. (2007), Auld and Powell (2008) for the price of fast food, Keng and Huffman (2007) for the price of alcohol, and Auld and Powell (2008) for the price of fruits and vegetables. Chen (2009) also used this method in her Ph.D. dissertation.

The following prices for commodity groups were created: price of fresh fruits and vegetables (*PR_FFruVeg*), price of processed fruits and vegetables (*PR_PFruVeg*), price of meat and fish (*PR_Meat*), price of dairy foods (*PR_Dairy*), price of alcoholic drinks (*PR_Alco*), price of non-alcoholic drinks (*PR_NAlco*), price of fast food (*PR_FF*), and price of health care (*PR_HC*). *PR_FFruVeg* is derived from prices of bananas, potatoes, and iceberg lettuce. *PR_PFruVeg* is derived from prices of frozen corn, fresh orange juice, canned peaches, and canned sweet peas. *PR_Meat* is derived from prices for T-bone steak, ground beef or hamburger, sausage, frying chicken, and chunk light tuna. *PR_Dairy* is derived from the prices for the whole milk, eggs, margarine, and grated parmesan cheese.

PR_Alco is derived from prices for beer and wine. *PR_NAlco* is derived from prices for vacuum-packed coffee and Coca Cola. *PR_FF* is derived from prices for a McDonald's Quarter-Pounder with cheese, an 11"-12" thin crust cheese pizza at Pizza Hut or Pizza Inn, and fried chicken (thigh and drumstick) at Kentucky Fried Chicken or Church's Fried Chicken. And the price of health care (*PR_HC*) is derived from the prices of a doctor visit, a dentist visit, ibuprofen (or an antibiotic in some years). (See Appendix I for more details on the list of items included in each component and the units priced.)

To eliminate locational noise in the price data and to solve the problem of different units among purchased items, a relative price for each item was created by dividing an item's price in a particular location by its average price among all the participating locations, and this real price was used to generate weighted consumer prices for each commodity group. Suppose there are I cities in total. Let P_{ki} denote the price of consumption category k in city i, P_{kji} denote the price of consumption item j ($j = 1,2,..., J$) in category k in city i, and P_{kj} denote the average price of consumption item j in category k across all participating cities in ACCRA (i.e. $P_{kj} = \sum_i P_{kji} / I$). W_{kji} denotes the expenditure weight of consumption item j in category k in city i where $\sum_j W_{kji} = 1$ for any k and i. Then the price of consumption category k in city i is:

$$P_{ki} = (P_{k1i} / P_{k1})W_{k1i} + (P_{k2i} / P_{k2})W_{k2i} + ... + (P_{kJi} / P_{kJ})W_{kJi} \qquad \textit{for any } k \textit{ and } i$$

where J is the total number of items belonging to consumption category k. See Appendix I for an example showing how the weighted price for a food group in a particular city is derived.[1]

Not all NLSY respondents lived in an ACCRA cost of living index (CLI) participating city, so a different strategy was developed to obtain prices for respondents who lived in these

[1] There are several differences in our method for constructing food and drinks prices relative to ones use in other studies. First, households purchase food and drinks to produce various nutritional, social and psychological outcomes, and, hence, not just for calories. Second, as in Chen (2009), I include a disaggregated but relatively comprehensive set of six food and drinks prices rather than one or two prices. Third, I disaggregate fruits and vegetables into fresh and processed because the latter contain, on average, significant added sugar and less fiber, which makes them less healthful. Fourth, non-labor income and the wage are deflated using the ACCRA cost of living index, which is consistent with the food, drinks, and health care price data.

areas. First, the price index was calculated for all ACCUR CLI participating cities in the same state as the respondent's residence, and then a simple average price was created across them. This average price for a commodity group was then used for the price that respondents faced in all non-ACCRA participating cities in that state. Because most ACCRA cost of living index (CLI) participating cities are urban areas in federally designated Standard Metropolitan Statistical Areas (MSAs), this average price would be less representative for respondents in suburbs within MSAs or in non-MSAs. To correct for this problem, we will add in some variables to control for the differences in economic status between these areas, such as the dummy variables that index urban areas or MSAs. This methodology allows us to keep all observations rather than deleting ones outside of ACCRA cost of living cities. It has been applied by Keng and Huffman (2007) for the price of alcohol.

iv) Labor Market Variables

The NLSY79 collects detailed information about an individual's employers in each reported year. A series of variables provide information on (1) time spent with an employer, i.e., start and stop dates for each job, hours, tenure, type of shift worked; (2) time spent away from an employer either on unpaid or paid leave, i.e., gaps within jobs; and (3) periods not working, i.e., gaps between jobs. Based on this information, the total hours that a respondent spent on work in the reported year were provided in each round. If the respondent reported no working hours, the index for labor market participation equals 0, otherwise it is 1.

All respondents were also asked about earnings received from working in each survey, including military income, wages, salaries, tips, farm income, and business income. The wage income we use here is the sum of wages, salaries and tips. We then compute the hourly wage rate by dividing total wage income by total working hours in the reported year. The real wage in each cross-section is computed by dividing the hourly wage by the ACCRA cost of living index for the location where the individual resides.

v) Noncognitive Abilities.

We are also interested in whether an individual's non-cognitive abilities affect labor market outcomes. Psychologists suggest that an individual's psychological traits, such as motivation and self control, affect his or her behaviors (Dunifon and Duncan 1998).

However, economists have generally ignored these factors. Starting in the late 1990's, researchers have included these noncognitive factors in the models for labor market, and their findings confirm that noncognitive abilities seem to matter for achievement in children as reflected in completed schooling which in turn affects later earnings.

Cawley, Heckman, and Vytlacil (2001) used the High School and Beyond (HSB) data set and defined nine behavioral problems as measured by social skills in the 10th grader. Their results suggested that when controlling for cognitive ability, these social skills were correlated with later earnings. They operated primarily through an individual's decisions on schooling attainment.

Groves (2005) used the National Longitudinal Survey of Young Women in U.S. and women from the National Child Development Study in U.K. to explore the value of incorporating psychological traits into wage determination models and found that some were statistically significant factors. Her results indicated that white women in the labor market were penalized for externality, aggression and withdrawal.

Muller and Plug (2006) also adopted the Five-Factor Model of personality structure to explore how personality affected the earnings of a large group of men and women who graduated from Wisconsin high schools in 1957 and were re-interviewed in 1992. Their results indicated that all five basic traits had statistically significant positive or negative earning effects and the overall effects were comparable to those commonly found for cognitive abilities. They also suggested that different traits were rewarded by different magnitudes for men and women.

Heckman, Stixrud, and Urzua (2006) presented an analysis of the effects of both cognitive and noncognitive skills on wages, schooling, work experience, occupational choice, and participation in a range of adolescent risky behaviors. They showed that a model with one latent cognitive skill and one latent noncognitive skill explained a large array of diverse behaviors.

The noncognitive measures we use are the Rotter Internal-External Locus of Control Scale that was administered in round 1979, and the Rosenberg Self-Esteem Scale that was administered in round 1980. Groves (2005) uses the Rotter Scale in her analysis of the return to personality. Heckman, Stixrud, and Urzua (2006) use the standardized average of the person's scores on the Rotter and Rosenberg scales as a measure of noncognitive skills.

The Rotter Internal-External Locus of Control Scale is a four-item abbreviated version of a 23-item forced-choice questionnaire adapted from the 60-item Rotter Adult I-E scale developed by Rotter (1966). The scale was designed to measure the extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal control) as opposed to the extent that the environment (i.e., chance, fate, luck) controls their lives (external control). The score for each item ranges from 1 to 4 in the external direction: the higher the score, the more external the individual. Since literature has found that people usually benefit from internal control, we construct a scale for internal control by reversing the score for each item. As a result, the minimal possible total score of the internal control scale is 16, indicating highest internal control, while the minimum possible total score is 4, indicating highest external control.

The Rosenberg Self-Esteem Scale was designed to measure the self-evaluation that an individual makes and customarily maintains. It describes a degree of approval or disapproval toward oneself (Rosenberg 1965). It contains 10 statements of self-approval and disapproval with which respondents are asked to strongly agree, agree, disagree, or strongly disagree. The scale for each statement ranges from 1 to 4, and is scored in the self-approval direction: the higher the score, the higher self-esteem. The maximum possible score is 40 while the minimum possible score is 10. The scale is widely used, and has accumulated evidence of validity and reliability.

The Rosenberg Self-Esteem Scale was also administered in 1987. We do not use it because personality is also affected by the success or failure in the labor market. By using the scales before labor market outcomes, we can treat the noncognitive skills as exogenous. See Appendix II for detailed information about questions for the Rotter Internal-External Locus of Control Scale and the Rosenberg Self-Esteem Scale.

In some regressions, we also use a comprehensive index for noncognitive abilities instead of two separate noncognitive scales. We derive this comprehensive index by dividing the internal control scale and the Rosenberg Self-Esteem Scale by their own sample standard deviations first, and then taking the sum of these two standardized scales. Nyhus and Pons (2005) also use the standardized average of the person's scores on the Rotter and Rosenberg scales as a measure of noncognitive skills.

vi) Basic Demographic Information and Family Background

Round 1979 provided each respondent's basic demographic information such as gender and race-ethnicity. It also recorded detailed information about each respondent' parents and growth history, from which we get father's and mother's education level, urban residence at age 14, and geographic region at age 14. Each round of NYSL79 updates information on the respondent's own education, marriages status, as well as the number of all biological and non-biological children and the age of each of them.

Each round also provides detailed information on the household income. Household real non-labor income in a given cross section is computed as total household income less the respondent's earnings divided by the ACCRA cost of living index for the area where the respondent resides. In the survey, only about 70 percent of respondents provided complete information on the household income, thus missing values of non-labor income are a major problem. In order to keep as many observations as possible in the sample, we use predicted household real non-labor income instead of reported household real non-labor income by regressing reported household real non-labor income on all available exogenous variables about demographic information and family background for female sample and male sample separately. Please see Appendix III for detailed regression results.

vii) The Temporal Price Deflator

Since the purchasing power of family non-labor income and wage rates is affected by inter-temporal price level, the real cross-sectional income and wage rates will be adjusted for temporal price changes by using the implicit price deflator for personal consumption expenditures from the U.S. Department of Commerce's GNP accounts (GNPDEF). This deflator is marginally better than the consumer price index of the U.S. Bureau of Labor Statistics (CPI) because the CPI is based upon a basket of goods and services while the GNPDEF incorporates all of the final goods produced by an economy. This allows the GNPDEF to more accurately capture the effects of inflation since it is not limited to a smaller subset of goods.

Table 1: Variable Definition

Variable	Definition
BMI	Body Mass Index, defined as weight/square of height (in kg/m^2)
BMI20	BMI in the year that the respondent turned 20 years old
D(Obese)	=1 if the individual was obese (BMI$\geq$30); =0 otherwise
D(FSP)	=1 if the individual participated in the Food Stamp Program; =0 otherwise
LagFS	The average annual Food Stamps the individual received during the three calendar years between two reported years (in 1,000 dollars)
LagMiss	=1 if at least one of the annual food stamps values in the last three calendar years is missing; =0 otherwise
Wage	The individual's average hourly real wage rate
D(empl)	=1 if the individual worked for pay; =0 otherwise
PR_FFruVeg	Price of fresh fruits and vegetables
PR_PFruVeg	Price of processed fruits and vegetables
PR_Meat	Price of meat and fish
PR_Dairy	Price of diary food
PR_Alco	Price of alcoholic drinks
PR_NAlco	Price of non-alcoholic drinks
PR_FF	Price of fast food
PR_HC	Price of health care
Edu	The highest grade completed by the individual
Rotter Scale	The Rotter Internal-External Locus of Control Scale
Internal Scale	Reversed Rotter Internal-External Locus of Control Scale
Rosenberg Scale	The Rosenberg Self-Esteem Scale
Noncog Scale	Comprehensive index for non-cognitive abilities
Inc	Predicted household real non-labor income (in 1,000 dollars)
Height	The individual's maximum height record for observations before 2006, height in 2006 for observations in 2006 (in centimeters)
Age	Age of the individual
Married	=1 if the individual was married and the spouse was present; =0 otherwise
Kids	Number of children in the household

Table 1: (Continued)

Variable	**Definition**
Black	=1 if the individual was black; =0 otherwise
Raceoth	=1 if the individual was neither white nor black; =0 otherwise
Ed_Fath	The highest grade completed by the individual's father
NoEdF	=1 if *Ed_Fath* is missing; =0 otherwise
Ed_Moth	The highest grade completed by the individual's mother
NoEdM	=1 if Ed_Moth is missing; =0 otherwise
Urban	=1 if the individual lived in an urban area; =0 otherwise
MSA	=1 if the individual lived in a metropolitan statistical area; =0 otherwise
Urban_14	=1 if the individual lived in an urban area at age 14; =0 otherwise
South_14	=1 in the individual lived in south at age 14; =0 otherwise
Region	
NE	=1 if the individual lived in northeast; =0 otherwise
NC	=1 if the individual lived in north central or middle west; =0 otherwise
South	=1 in the individual lived in south; =0 otherwise
West	=1 if the individual lived in west; =0 otherwise
preg	=1 if the female respondent was pregnant; =0 otherwise
t	Time trend, =1 for observations in 1986, =2 for observations in 1990, and so on

Chapter 3. Period Decisions without Information Updating

In this chapter, we exam the representative household's decisions on health status and the FSP participation under the assumption that the household head makes the decisions at the beginning of each period while he/she does not update his/her decision-making-process based on previous outcomes. The corresponding empirical econometric model is least squares with IVs, which differs from cross-sectional studies in that FSP participation is treated as being endogenous.

3.1 Theoretical Model

The theoretical model is based on the productive household models of health by Huffman et al. (2006), Grossman (2000), and Rosenzweig and Schultz (1983). In each period, the representative household makes the decisions on adult labor supply, leisure activities, consumption (including food, medical care and other consumption goods), and participation in the Food Stamp Program (FSP) simultaneously. Because the household head does not update the decision making decision based on previous outcomes, the decision making processes for all periods are independent from each other, and the state variables that affect the outcomes are all of current values except that the adult's health status at the very beginning would affect the decisions of all periods.

The agent is assumed to have a period utility function of the form

$$U_{it} = U(F_{it}, C_{it}, H_{it}, LP_{it}, LO_{it}; Z_{it}, \phi_{it}) - FSP_{it} * V(G_{it}, Z_{it}, \phi_{it}).$$

This utility function consists of two parts. $U(\cdot)$ is a quasi-concave utility function in which F represents the food and drinks consumed, C represents all other consumption goods excluding purchased medical care, H represents the adult's health status, LP represents physically active leisure time, and LO represents other types of leisure time. Z denotes the household's observable characteristics, such as the household head's gender, race, education, family structure, urban residency and so on, and ϕ denotes other unobservable factors affecting the household's preferences. The household also makes the decision to participate in the Food Stamp Program, which is represented by an indicator FSP. $V(\cdot)$ is the disutility function associated with FSP participation since the literature has attributed a part of the decline in the Food Stamp Program participation to the welfare-reform-related stigma. The level of disutility is affected by the household's own observable and unobservable characteristics (i.e. Z and ϕ) as well as by a variety of world factors in the environment (all represented by G), such as laws and regulations and people's attitude to welfare programs.

The household can improve the adult's health status by consuming food and drinks, working out and purchasing medical care (denoted by M). Specifically, the health production function is given by

$$H_{it} = H(F_{it}, LP_{it}, M_{it}; H_e, Z_{it}, \varphi_{it}),$$

where H_e denotes original health status at the very beginning and φ denotes other unobservables that affect the adult's efficiency in accumulating good health, for instance genetic disposition and distress.

The household faces three constraints. First, the food and drinks consumed is either purchased by using the household's cash income or provided by the Food Stamp Program,

$$F_{it} = X_{it} + FSP_{it} * FSB(Y_{it}; Z_{it}, G_{it}).$$

Here, X represents the food and drinks the household purchases from its cash income, and FSB represents the benefits provided by the Food Stamp Program, which depend on the household total income (denoted by Y), the household head's observable characteristics Z (such as age, being disable, being a single mother, etc.) and environmental factors G (mainly laws and regulations). Hence, foods purchased from cash income and from food stamps are treated as perfect substitutes.

Second, the household purchases all goods subject to his/her cash income constraint. Let P denote the cost of goods with subscripts representing different goods and W denote the nominal wage. Then, with P_X being the price of directly purchased food and that acquired by the FSP, the cash income constraint is

$$P_{X,t}(F_{it} - FSP_{it} * FSB(Y_{it}; Z_{it}, G_{it})) + P_{C,t}C_{it} + P_{M,t}M_{it} - FSP_{it} * FSC(G_{it}) = Y_{it} = W_{it}L_{it} + V_{it},$$

where L is the time spent for wage work, V is the non-wage income, and FSC is the monetary costs of participating in the Food Stamp Program (for example, transportation costs).

Third, the adult assigns his/her time up to fixed time endowment T, i.e.,

$$L_{it} + LP_{it} + LO_{it} + FSP_{it} * FST(G_{it}) = T ,$$

where FST is the amount of time that the adult has to spend on the FSP participation.

Therefore, in period *t*, the representative agent *i*'s utility maximization problem is to

$$\begin{aligned}
Max \quad & U = U(F_{it}, C_{it}, H_{it}, LP_{it}, LO_{it}; Z_{it}, \phi_{it}) - FSP_{it} * V(G_{it}, Z_{it}, \phi_{it}) \\
s.t. \quad & H_{it} = H(F_{it}, LP_{it}, M_{it}; H_e, Z_{it}, \varphi_{it}) \\
& P_{X,t}(F_{it} - FSP_{it} * FSB(Y_{it}; Z_{it}, G_{it})) + P_{C,t}C_{it} + P_{M,t}M_{it} + FSP_{it} * FSC(G_{it}) = W_{it}L_{it} + V_{it} \\
& L_{it} + LP_{it} + LO_{it} + FSP_{it} * FST(G_{it}) = T \\
& F_{it} \geq 0, \quad C_{it} \geq 0, \quad LP_{it} \geq 0, \quad LO_{it} \geq 0, \quad L_{it} \geq 0, \quad M_{it} \geq 0
\end{aligned}$$

Since application for participation in the Food Stamp Program is a yes-or-no decision, the agent's utility maximization problem can be viewed as a two-step problem. In the first step, the agent maximizes his/her utility conditional on his/her decision on participation and gets a maximized indirect utility level. In the second step, the agent compares these two conditional indirect utilities and makes the decision on participation to get a higher level of utility.

In all, we can solve for an interior solution for the agent's optimal decision on the Food Stamp Program participation (FSP_{it}^*), optimal consumptions of different goods ($X_{it}^*, F_{it}^*, C_{it}^*, M_{it}^*$), optimal time allocation ($LP_{it}^*, LO_{it}^*, L_{it}^*$), and optimal health status (H_{it}^*) and obtain the following implicit functions

$$\begin{cases} FSP_{it}^{*} = FSP(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \\ X_{it}^{*} = X(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \\ F_{it}^{*} = F(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \\ C_{it}^{*} = C(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \\ M_{it}^{*} = M(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \\ L_{it}^{*} = L(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \\ LP_{it}^{*} = LP(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \\ LO_{it}^{*} = LO(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \\ H_{it}^{*} = H(W_{it}, V_{it}, P_{X,t}, P_{C,t}, P_{M,t}, H_e; G_{it}; Z_{it}, \varepsilon_{it}) \end{cases} ,$$

where ε_{it} includes ϕ_{it} and φ_{it} , i.e., all unobservable factors that affect the individual's preferences and efficiency in accumulating good health. These equations will be the basis of the econometric model.

3.2 Econometric Model

The NLSY data do not contain information on purchases of food, health care or time allocated to leisure. Hence, the econometric model focuses on adult choices of a healthy weight and Food Stamp Program participation. Since an adult's weight may affect his or her wage rate, and hence, the opportunity cost of time, I also fit a wage equation and use it to instrument an individual's price of time. Four equations are to be estimated, among which, Equation 1 and 2 are primary equations while Equation 3 and 4 are auxiliary equations. Please refer to Appendix IV for ordinary least squares estimations of Equation 1 without instrument variable strategies.

Equation 1: Demand for Health

Equation 1 is to explain an individual's demand for health as indexed by BMI or being obese. An individual's body weight is affected by net energy balance, which is the net difference between calories consumed in work and exercise versus calories intake. In the long run, if net energy balance is positive, individuals gain weight, and if it is negative, they lose weight. For some individuals, they may be in equilibrium with no net change in weight or BMI. Therefore, those factors that affect an individual's decision on energy intake and energy consumption are the determinants of his/her body weight.

$$
\begin{aligned}
\ln BMI_i[or\ Obese_i^*] &= X_{1i}\mathrm{B} + \mu_{1i} \\
&= \beta_1 + \beta_2 D(FSP)_i + \beta_3 \ln Wage_i + \beta_4 PR\_FFruVeg_i + \beta_5 PR\_PFruVeg_i + \beta_6 PR\_Meat_i \\
&\quad + \beta_7 PR\_Dairy_i + \beta_8 PR\_Alco_i + \beta_9 PR\_NAlco_i + \beta_{10} PR\_FF_i + \beta_{11} PR\_HC_i + \beta_{12} Edu_i \\
&\quad + \beta_{13} NonCog_i + \beta_{14} BMI20_i + \beta_{15} BMI20_i^2 + \beta_{16} Black_i + \beta_{17} RaceOth_i + \beta_{18} Inc_i + \beta_{19} Age_i + \beta_{20} Age_i^2 \\
&\quad + \beta_{21} Married_i + \beta_{22} Kids_i + \beta_{23} NC_i + \beta_{24} South_i + \beta_{25} Urban_i + \beta_{26} MSA_i + \beta_{27} preg_i + \mu_{1i}
\end{aligned}
$$

First of all, I am particularly interested in the effect of the FSP participation on a woman's body weight. Previously research has reported significant effects of the FSP participation on an individual's probability of being overweight although the effects tend to differ across subpopulations. Based on the review of the literature, we hypothesize that adults who participate in the FSP are more likely to be obese.

Most studies on FSP participation and obesity treat the FSP participation as exogenous to other individual and household decisions. However, overweight people are more likely to participate in the FSP or have higher benefits because they are more likely to suffer from health restrictions and some diseases, and thus to have a lower level of income. Even when income is controlled, FSP participation and BMI may still be correlated. Townsent et al. (2001) found that food insecurity was positively related to the likelihood of being obese for women. Meanwhile, food insecure people are more likely to participate in the FSP. Thus, failure to accommodate the possible endogeneity of the FSP participation decision can lead to biased estimates of the effects of FSP participation on BMI. Hence, I use Equation 2 to estimate the predicted probability of current FSP participation instead of the index for participation so that I can obtain consistent estimates.

Second, the opportunity cost of time is important to decisions on time and goods allocation. If an individual's price of time is high, then he or she will tend to conserve on time-intensive activities. Recreational exercise is a time-intensive activity, but it also contributes to a healthy weight. On the other hand, individuals with a higher opportunity cost of time may try to build their health more effectively and efficiently, if they spend some time on physical activities, by hiring professional trainers. Overall, we hypothesize that individuals who have a higher opportunity cost of time are more likely to be obese.

Third, individuals consume food and drinks to obtain nutrients (carbohydrates, fats, protein, vitamins and minerals), to feel good (i.e., comfort food), and to socialize. The prices of disaggregated food and drinks are one set of factors that are expected to affect choices of food and drinks as well as physical activities, and thus affect his/her body weight (Chen 2009). An increase in the price of fresh fruits and vegetables is expected to reduce an individual's consumption of these products and to lead to a higher BMI or probability of being obese. An increase in the price of processed fruits and vegetables, which generally contain significant amounts of added sugar, will reduce the consumption of these foods and lower BMI and the probability of being obese. An increase in the price of meats and fish is expected to reduce an individual's consumption of these foods, which tend to be calorie dense, and may lead to a lower BMI and probability of being obese. Similarly, since most fast foods are calorie dense, an increase in the price of fast foods is expected to reduce an individual's consumption of these foods and thus lead to a lower BMI and probability of being obese. I am uncertain about the effects of the prices of dairy products, alcoholic drinks and non-alcoholic drinks on BMI and the probability of being obese. A higher price of health care is expected to shift attention to lifestyle production of good health and reduce the probability that an individual is obese.

Fourth, an individual's education increases his/her labor market skills, and skills in general, for decision making (Schultz 1975, Huffman 2001, Speakman *et al.* 2005). I hypothesize that individuals with more education will make healthier lifestyle choices. However, added education increases the likelihood that an individual selects a sedentary job, which is a potential cause for overweight. Previous studies find that women with higher education are more likely to be obese while men with higher education are less likely to be obese (Chen 2009).

Fifth, as suggested in Heckman, Stixrud, and Urzua (2006), an individual's lifestyle choices may be affected by his/her non-cognitive abilities. If an individual exhibits internal control or high self-esteem, he/she will take responsibility for his/her own actions and pursue a healthy lifestyle, including maintain a healthy weight.

Sixth, to explore the possibility of a "long reach" of early events on an adult's later taste for a healthy weight, an individual's BMI at age 20 and race-ethnicity (dummy variables for being black or of other races) are hypothesized to be determinants of the current demand for health.

Seventh, the nonlabor income is found to have a negative effect on BMI by Chen (2009). A non-linear income effect will also be tested because, when the household income is extremely low, an individual could be underweight due to malnutrition, and when the income is relatively low, he/she could be overweight due to unbalanced diet.

Eighth, there is strong empirical evidence that BMI tends to vary with age, generally increasing from young adulthood to the 60s and then tending to decline. Hence, an individual's age is expected to have a non-linear effect on the probability that an individual is obese.

Ninth, an individual's lifestyle choices are affected by his/her family structure. Married individuals or individuals with more children are expected to live to older ages and to choose healthier lifestyles, including a normal weight.

Tenth, an individual's current urban (versus rural) residence and regional location may affect his/her health status because of the different costs of health production. For example, in more rural areas, space for physically active leisure is cheaper, and space and good soils are more likely to be available for a vegetable garden.

Finally, an indicator for being pregnant is added to the equation to control for the fact that women are expected to gain 20-35 pounds during a healthy pregnancy, which increases their BMI.

To operationalize the equation for the probability of an individual being obese, we define a latent variable for an individual being obese as $Obese_i^*$, and then the latent regression equation (Greene 2003) is defined as $Obese_i^* = X_{1i}\mathrm{B} + \mu_{1i}$. However, we observe the following variable:

$$D(Obese)_i = \begin{cases} 1 & if\ Obese_i^* > 0 \\ 0 & otherwise \end{cases}.$$

Now, the probability of the individual being obese can be expressed as

$$p_{1i} = \Pr(D(Obese)_i = 1) = \Pr(Obese_i^* < 0) = \Pr(-X_{1i}\mathrm{B} + \xi_{1i} < 0) = \Pr(\xi_{1i} < X_{1i}\mathrm{B}) = F(X_{1i}\mathrm{B})$$

Where $\xi_{1i} = -\mu_{1i}$ and $F(\cdot)$ is a cumulative distribution function for μ_{1i} evaluated at $X_{1i}\mathrm{B}$. If ξ_{1i} is a proper diffuse or uniform distribution centered at zero, it has a triangular cumulative distribution function indexed on $X_{1i}\mathrm{B}$. Hence, $p_{1i} = \Pr(D(Obese)_i = 1) = F(X_{1i}\mathrm{B}) = X_{1i}\mathrm{B}$ because of the special form of $F(\cdot)$. The linear probability model for obesity is then

$D(Obese)_i = X_{1i}\mathrm{B} + e_{1i}$, where $e_{1i} = \begin{cases} 1 - X_{1i}\mathrm{B} & \textit{with probability } X_{1i}\mathrm{B} \\ -X_{1i}\mathrm{B} & \textit{with probability } (1 - X_{1i}\mathrm{B}) \end{cases}$ *and* $E(e_{1i} = 0)\cdot$

Equation 2: Food Stamp Program Participation

Equation 2 is to identify an individual's decision on current FSP participation, and is used to provide the predicted probability of current participation for Equation 1. Most FSP rules are set at a federal level, but states do have a say about some administrative features such as the length of eligibility certification periods, the design of outreach programs and about any "workfare" requirements for participation in the program. Currently, the Food Stamp Program operates as follows: the FSP household is defined as either a person living alone or a group of people who live together and customarily purchase food and prepare meals together. Households have to go through an eligibility determination, and monthly cash income is the main determinant of eligibility.

The FSP uses both the household's gross monthly income and its net monthly income. Gross income includes all of the household's cash income from most sources, including income from welfare programs. Net income is derived by subtracting out a standard deduction, which is 20 percent of earned income, and also deductions for shelter and child care. Households must have a gross income that does not exceed 130 percent of the federal poverty guidelines, and a net monthly income that does not exceed the federal poverty line. Finally, household assets must be less than $2,000. Benefits are calculated by taking the maximum benefit level for a household of a certain size and subtracting 30 percent of the net income.

Some literature tried to identify the factors that would affect a household's decision on the FSP participation. For instance, Capps and Kramer (1985) compared Probit model and

Logit model to analyze the FSP participation decision of a nationwide sample of households from the 1972-73 Bureau of Labor Statistics, Consumer Expenditure Diary Survey (CEDS). Their results suggested that race, education level, income level, regions and the level of benefits were all significant factors

In the later 1990's, the FSP saw an unprecedented decline in participation from 27.5 million participants in 1994 to 18.2 million participants in 1999 (USDAFSP). After looking at those families who left the FSP, researchers found that most food stamp leavers had incomes that still left them eligible for these benefits and that former welfare recipients left the FSP at higher rates than families who had not received assistance before. As a result, there was a wave of research trying to identify those factors that caused the declines in participation.

Daponte, Sanders, and Taylor (1999) conducted an experiment to find out whether some eligible households failed to participate because of a lack of information concerning their eligibility, the level of benefits, or logistics of the application process. Their findings showed that among those non-participants truly eligible for food stamps, providing information caused a significant increase in participation. However, there was evidence that the initial lack of information was endogenous: eligible households that did not participate were generally entitled to small benefits.

In a report to USDA, Wilde et al. (2000) analyzed how a strong economy and changes in social welfare programs drove the decline in participation. Calculations using state-level data indicated that 35 percent of the caseload decline from 1994 to 1998 was associated with changing economic conditions and 12 percent with program reform and political variables. An analysis of household-level data from the Current Population Survey led to the conclusion that 28 percent of the total change in participation was associated with a decrease in the number of people with low income and 55 percent was due to a decline in the proportion of low-income people who participated. In another report on older participants, Wilde and Dagata (2002) reported that those low-income older Americans who faced the most severe concerns about their health and food security situation were more likely to take the necessary steps to participate in the Food Stamp Program.

Currie and Grogger (2001) tried to explain the declines in FSP participation by three factors: welfare reform, the stigma and the transaction costs associated with participation, and the economic boom. They found that both decreases in the unemployment rate and the occurrence of welfare reform contributed to the declines in FSP caseloads. Specifically, among households with incomes less than 300 percent of poverty, changes in unemployment accounted for 20 percent of the decrease in FSP participation between 1993 and 1998, while the welfare reform accounted for 30 percent.

Our equation for current FSP participation is based on an assumption about "reservation award". Similar to the reservation wage theory, we assume that an individual will participate in the Food Stamp Program when his/her potential award from participation is greater than his/her reservation award. Such awards may be measured either by money or by utility. Specifically, potential award and reservation award are determined by these two equations respectively:

$$
\begin{aligned}
PA_i &= \lambda_1 + \lambda_2 \ln Wage_i + \lambda_3 Inc_i + \lambda_4 Married_i + \lambda_5 Kids_i + \lambda_6 preg_i + t + \varepsilon_{1i} \\
RA_i &= \omega_1 + \omega_2 \ln Wage_i + \omega_3 PR\_FFruVeg_i + \omega_4 PR\_PFruVeg_i + \omega_5 PR\_Meat_i + \omega_6 PR\_Dairy_i \\
&\quad + \omega_7 PR\_Alco_i + \omega_8 PR\_NAlco_i + \omega_9 PR\_FF_i + \omega_{10} PR\_HC_i + \omega_{11} Edu_i + \omega_{12} NonCogAb_i \\
&\quad + \omega_{13} Age_i + \omega_{14} Age_i^2 + \omega_{15} Kids_i + \omega_{16} Urban_i + \omega_{17} MSA_i + \omega_{18} NC_i + \omega_{19} South_i + \omega_{20} Black_i + \omega_{21} RaceOth_i \\
&\quad + \omega_{22} Ed\_Moth_i + \omega_{23} NoEdM_i + \omega_{24} Ed\_Fath_i + \omega_{25} NoEdF_i + \omega_{26} Urban\_14_i + \omega_{27} South\_14_i \\
&\quad + \omega_{28} LagFS_i + \omega_{29} LagMiss_i + \omega_{30} DUM96 + \omega_{31} t + \varepsilon_{2i}
\end{aligned}
$$

The *PA* equation determines the potential award when the agent applies for food stamps. It includes all determinants of eligibility that are available in the data, such as wage income, non-wage income, family size (marriage status and number of children), and number of children that need childcare expenses. The error term ε_1 represents the unavailable determinants of eligibility and the unobservable approval process.

The *RA* equation measures the agent's reservation award and includes all the factors that would affect the monetary value of food stamps and also the satisfaction or disutility associated with participation. The error term ε_2 captures the unobservable heterogeneity across individuals.

Therefore, the agent would participate in the Food Stamp Program if his/her participation award is greater than his/her reservation award. We define a latent variable $FSP_i^* = RA_i - PA_i$, which has the following relationship in Equation 2:

$$\begin{aligned} FSP_i^* &= X_{2i}\Theta + \mu_{2i} \\ &= \theta_1 + \theta_2 \ln Wage_i + \theta_3 PR\_FFruVeg_i + \theta_4 PR\_PFruVeg_i + \theta_5 PR\_Meat_i + \theta_6 PR\_Dairy_i \\ &+ \theta_7 PR\_Alco_i + \theta_8 PR\_NAlco_i + \theta_9 PR\_FF_i + \theta_{10} PR\_HC_i + \theta_{11} Edu_i + \theta_{12} NonCogAb_i + \theta_{13} Inc_i \cdot \\ &+ \theta_{14} Age_i + \theta_{15} Age_i^2 + \theta_{16} Married_i + \theta_{17} Kids_i + \theta_{18} Urban_i + \theta_{19} MSA_i + \theta_{20} NC_i + \theta_{21} South_i \\ &+ \theta_{22} Ed\_Moth_i + \theta_{23} NoEdM_i + \theta_{24} Ed\_Fath_i + \theta_{25} NoEdF_i + \theta_{26} Black_i + \theta_{27} RaceOth_i \\ &+ \theta_{28} Urban\_14_i + \theta_{28} South\_14_i + \theta_{30} LagFS_i + \theta_{31} LagMiss_i + \theta_{32} preg_i + \theta_{33} DUM96 + \theta_{34} t + \mu_{2i} \end{aligned}$$

However, we observe the following variable:

$$D(FSP)_i = \begin{cases} 1 & if\ \ FSP_i^* > 0 \\ 0 & otherwise \end{cases}.$$

Now the probability of the individual participating in the FSP can be expressed as

$$p_{2i} = \Pr(D(FSP)_i = 1) = \Pr(FSP_i^* < 0) = \Pr(-X_{2i}\Theta + \xi_{2i} < 0) = \Pr(\xi_{2i} < X_{2i}\Theta) = F(X_{2i}\Theta),$$

where $\xi_{2i} = -\mu_{2i}$ and $F(\cdot)$ is a cumulative uniform distribution function for μ_{2i} evaluated at $X_{2i}\Theta$. If μ_{2i} is a proper diffuse or uniform distribution centered at zero, it has a triangular cumulative distribution function indexed on $X_{2i}\Theta$. Hence, $p_{2i} = F(X_{2i}\Theta) = X_{2i}\Theta$ because of the special form of $F(\cdot)$. The linear probability model for FSP participation is then

$D(FSP)_i = X_{2i}\Theta + e_{2i}$, where $e_{2i} = \begin{cases} 1 - X_{2i}\Theta & with\ probability\ X_{2i}\Theta \\ -X_{2i}\Theta & with\ probability\ (1 - X_{2i}\Theta) \end{cases}$ $and\ E(e_{2i}) = 0 \cdot$

Given that there is some time required to apply for and maintain FSP participation, individuals that have a higher opportunity cost of time are less likely to participate, other things equal. Since the FSP provides a substitute for some directly purchased food, an individual is expected to be more likely to participate in the program as the food prices increase.

I am uncertain whether an individual's cognitive skills and non-cognitive skills affect decisions on his/her household's FSP participation. But clearly, individuals in household with larger amounts of non-labor income will be less likely to participate in the Food Stamp Program, other things equal. Married individuals are expected to be less likely to participate in the Food Stamp Program because they could obtain financial support from their spouse, but individuals with more children are expected to be more likely to participate because of the heavier financial burden. Individuals in urban areas and more developed regions may be less likely to participate in the FSP because of the higher average income level and less friendly attitude toward the welfare programs. Women in non MSA areas may be less likely to participate in the FSP because of the added costs of participation.

Individuals who have participated in the FSP in the past are expected to be more likely to currently participate. The reorganization of the welfare program for needy families in 1996 caused a disturbance in the decisions of households to participate in welfare programs as well as the FSP. Hence, we include a dummy variable taking 1 in 1996 and later years (and zero otherwise). This will allow for a general change in willingness to participate by pre- and post-welfare reform. A time trend is added in the equation to capture the change of economy that is not captured by all other explanatory variables. Since these factors do not affect an individual's body weight, they also help to identify the FSP participation from the BMI or obesity equation.

We also include some variables to summarize family background effects and impacts of experiences in adolescence such as parents' education and residence at age 14. These variables may affect an individual's attitude towards welfare program. These variables also work for identification purpose besides their own affects on the FSP participation. An individual's family attributes and community environment during adolescence may have an effect on his/her current body weight by affecting his/her choice on lifestyle. However, because the BMI at age 20 should have captured all these effects, they could be deleted from the BMI and obesity equations after the BMI at age 20 is controlling for.

Equation 3 and 4: Hourly Wage Rate and Probability of Employment

We have each individual's reported hourly wage in the data. However, an individual's reported hourly wage is endogenous in Equation 1 and 2 because it may be affected by his/her health status or welfare program participation. For example, literature has proved that an adult's weight affects his or her wage rate (Baum and Ford 2004; Cawley 2004). Another possibility is that the hourly wage, health status, and welfare program participation are all affected by some factors that are not available in the data, for instance, an individual's occupation or working environment. Thus, we use Equation 3, the hourly wage equation, to estimate the predicted hourly wage rate, and use it instead of the reported hourly wage to index an individual's opportunity cost of time. This equation is not only interesting itself because it related an individual's human capital attributes to his or her wage, but it also facilitates keeping all observations in the data set together by providing a predicted wage for those who were not working or did not report working status. In these cases, the predicted wage is a proxy variable for the individual's opportunity cost of time.

$$\begin{aligned}\ln Wage_i &= \pi_1 + \pi_2 Edu_i + \pi_3 NonCogAb_i + \pi_4 Age_i + \pi_5 Age_i^2 + \pi_6 Black_i + \pi_7 RaceOth_i + \pi_8 Height_i \\ &+ \pi_9 BMI20_i + \pi_{10} BMI20_i^2 + \pi_{11} Married_i + \pi_{12} Urban_i + \pi_{13} MSA_i + \pi_{14} NC_i + \pi_{15} South_i \\ &+ \pi_{16} Ed\_Moth_i + \pi_{17} NoEdM_i + \pi_{18} Ed\_Moth_i + \pi_{19} NoEdM_i + \pi_{20} t + \mu_{3i}\end{aligned}$$

I expect an individual's wage to increase with cognitive skills (as indexed by education level) and non-cognitive abilities. An individual's age rather than his or her labor market experience is used to represent current and pass incentives to invest in experience, given schooling. I expect an individual's wage to increase but at a decreasing rate as he or she becomes older. Those who are black or of other races are expected to earn lower wages than white people. An individual's early BMI is also expected to affect his current wage although may work in different ways for different populations. Thus a non-linear effect is permitted. According to the wage compensation theory, married people may earn a higher hourly wage rate if they give up some non-wage compensation (for instance, health insurance) because they could get them through their spouse. Individuals in rural areas and less developed regions are expected to earn a lower hourly wage rate. The parents' education levels are expected to have a positive effect on a person's wage rate. Finally, a time trend is added in the equation to capture any trend in real wage rates over the sample period. Because people who are taller are expected to earn a higher wage rate, other things equal (Keng and Huffman 2007), we use an individual's height to identify the wage equation from Equation 1 and 2.

Individuals are assumed to work for a wage when the opportunity cost of their time (or the reservation wage) is less than their wage offer. Thus, working for pay is a rational decision leading to potential selection issues, and such decision must be controlled in fitting the wage equation (Heckman 1979). Under plausible assumptions this discrete outcome can be approximately estimated by the Probit equation on labor market participation (Equation 4).

We define a latent variable $empl_i^*$, which has the following relationship:

$$
\begin{aligned}
empl_i^* &= X_{4i}\Lambda + \mu_{4i} \\
&= \alpha_1 + \alpha_2 PR\_FFruVeg_i + \alpha_3 PR\_PFruVeg_i + \alpha_4 PR\_Meat_i + \alpha_5 PR\_Dairy_i + \alpha_6 PR\_Alco_i \\
&+ \alpha_7 PR\_NAlco_i + \alpha_8 PR\_FF_i + \alpha_9 PR\_HC_i + \alpha_{10} Edu_i + \alpha_{11} NonCogAb_i + \alpha_{12} Inc_i + \alpha_{13} Height_i \\
&+ \alpha_{14} BMI20_i + \alpha_{15} BMI20_i^2 + \alpha_{16} Age_i + \alpha_{17} Age_i^2 + \alpha_{18} Black_i + \alpha_{19} RaceOth_i + \alpha_{20} Married_i + \alpha_{21} Kids_i \\
&+ \alpha_{22} Ed\_Moth_i + \alpha_{23} NoEdM_i + \alpha_{24} Ed\_Fath_i + \alpha_{25} NoEdF_i + \alpha_{26} Urban_i + \alpha_{27} MSA_i + \alpha_{28} NC_i \\
&+ \alpha_{29} South_i + \alpha_{30} Urban\_14_i + \alpha_{31} South\_14_i + \alpha_{32} LagFSP_i + \alpha_{33} LagMiss_i + \alpha_{34} preg_i + \alpha_{35} t + \mu_{4i}
\end{aligned}
.
$$

However, we observe the following variable:

$$
D(empl)_i = \begin{cases} 1 & if\ empl_i^* < 0 \\ 0 & otherwise \end{cases}.
$$

Then the probability of the individual working for pay can be expressed as

$$
p_{4i} = \Pr(D(empl)_i = 1) = \Pr(empl_i^* < 0) = \Pr(-X_{4i}\Lambda + \xi_{4i} < 0) = \Pr(\xi_{4i} < X_{4i}\Lambda) = \Phi(X_{4i}\Lambda),
$$

where $\xi_{4i} = -\mu_{4i}$ and $\Phi(\cdot)$ is a cumulative normal distribution function for μ_{4i} evaluated at $X_{4i}\Lambda$. Hence, Equation 4 can be fitted as a Probit model.

Since Equation 4 is a reduced form equation, almost all signs are uncertain. However, if leisure is a normal good, the income effect should have a negative sign. From this equation, I can obtain the predicted probability of labor market participation, which is then used to get the inverse Mills ratio term in the wage equation. The selectivity-corrected wage equation is then fitted to those observations that reported positive hours of labor market work to get unbiased estimates. Since the fitted wage equations are now fixed up for selectivity, each individual's wage (whether they actually worked for pay or not) can be predicted by setting the probability of participating in labor market to one. This predicted wage is a proxy or indicator variable for the true opportunity cost of time of each individual (Greene 2003).

Heckman's two-stage estimation works better when the first-stage estimation includes good instrument variables for identification purpose. In our case, local prices, nonwage income, past FSP participation, residence at age 14, the number of children, and a dummy for being pregnant are used because they would affect a person's decision to participate in the labor market, but would not affect his/her real wage rate once he/she gets a job.

Hence, the above four equations are the focus of the econometric estimation for the first model. To summarize, I control for individual heterogeneity using data on observables or measured attributes, and also instrument for an individual's hourly wage rate and the probability that their household participates in the Food Stamp Program. Consequently, in this chapter, the estimation of the econometric model is best described as least squares with IVs. The labor force participation equation (Equation 4) is to be fitted to data for both those who work for a wage and those that do not, and the resulting coefficients are used to predict the probability of participation. This ties into the IV for Heckman sample selection correction term in the wage equation (Equation 3). Equation 3 is then fitted to obtain unbiased estimates of the wage equation, and after shutting down the sample selection effect, it is used to create an instrument for an individual's hourly wage covering both labor force participants and nonparticipants. After that, Equation 2 is estimated to learn about the determinants of a household's participation in the FSP, but also this equation is used the create an IV for a household's FSP participation. Finally, Equation 1 (ln(BMI) and probability of being obese) is estimated including instruments for the individual's wage and FSP participation.

The least squares IV estimation is often questioned in the literature because it fails to control for observed and unobserved fixed effects that may affect a household's and its members' lifestyle choices. Hence, these results are used as one benchmark for comparison of other modeling strategies. Please refer to Table 2 for expected effects of main independent variables in these four equations. To be consistent with later estimated models, the discrete choice models for labor force participation (Equation 1) and for FSP participation (Equation 2) are fitted using the linear probability model instead of the Probit model. Recall that a key property of these equations is that they generate a consistent but not necessarily efficient prediction (Greene 2003).

Table 2: Expected Effects of Main Independent Variables in Equation 1-4

Variable	***lnBMI/D(Obese)***	***D(FSP)***	***lnWage***	***empl****
D(FSP)	+			
lnWage	+	-		
Pr(D(empl)=1)			+	
PR_FFruVeg	+	+		+/-
PR_PFruVeg	-	+		+/-
PR_Meat	-	+		+/-
PR_Dairy	+/-	+		+/-
PR_Alco	+/-	+		+/-
PR_NAlco	+/-	+		+/-
PR_FF	-	+		+/-
PR_HC	-	+		+/-
Inc	-	-		-
LagFS		+		
Edu	+/-	+/-	+	+/-
NonCogAb	-	+/-	+	+/-
Married	-	-	+	+/-
Kids	-	+		+/-
DUM96		+		

3.3 Sample Description

To reduce measurement error problems, I limit the sample to individuals with a BMI between 16 and 40. Because of important biological differences, differences in past decisions on investments in human capital, and past labor force participation decisions, estimations are undertaken on male and female samples separately. Some women were pregnant in survey years, and to keep them in the sample, a dummy for pregnancy (*preg*) is included in the estimations for the female sample. Because I didn't find significant results for the male sample, the discussion in this paper focuses on the female sample.

There are a total of 20,750 observations in the female sample—20.4% of which came from round 1986, 19.5% from round 1990, 16.1% from round 1994, 15.6% from round 1998, 15.1% from round 2002 and 13.4% from round 2006. About 55.5% of female individuals are white, 28.3% are black, and 16.2% are of other races. Their average height was 164 centimeters (about 65 inches). The average BMI at age 20 was 22.1, while the average BMI in 1986 was 23.2 and increased to 27.3 in 2006 with a rate of about 0.2 units per year. Among these female individuals, 18.4% were obese and 11.5% ever participated in the Food Stamp Program. 82% of female adults worked for pay with an average hourly wage rate of 10.49 dollars. The female sample's average education level, the measure for cognitive abilities, was 11.5 years. As for measures for non-cognitive abilities, the mean of Internal Scale was 8.38, the mean of Rosenberg Scale was 32.1, and the mean of the comprehensive index for noncognitive abilities was 13.53. 53.6% were married, and the average number of children in the household was 1.38. 75.7% of female adults lived in urban areas and 56.1% lived in metropolitan statistical areas. Please see Table 3 for summary statistics of key variables for the female sample.

Table 3: Summary Statistics of Key Variables for Female Sample

Variable	Mean	Std. Dev.	Min	Max
BMI	25.27	5.02	16.04	39.94
D(Obese)	0.184	0.387	0	1
BMI20	22.07	3.42	16.14	39.94
D(FSP)	0.115	0.319	0	1
LagFS (in $1,000)	0.18	0.64	0	27.48
D(empl)	0.820	0.384	0	1
Wage (if worked for pay)	10.49	27.71	0	2,087
Inc (in $1,000)	20.9	20.6	-31.1	79.1
Height	164	6.73	132	193
age	36.88	7.15	21	50
Black	0.283	0.450	0	1
RaceOth	0.162	0.368	0	1
Edu	11.481	4.40	0	20
Rotter Scale	11.62	1.49	8	16
Internal Scale	8.38	1.49	4	12
Rosenberg Scale	32.10	4.07	16	40
Noncog Scale	13.53	1.56	7.61	17.66
Married	0.536	0.499	0	1
Kids	1.38	1.25	0	9
Ed_Moth	10.38	3.80	0	20
Ed_Fath	9.44	5.21	0	20
Urban	0.757	0.429	0	1
MSA	0.561	0.496	0	1
NC	0.252	0.434	0	1
South	0.421	0.494	0	1
South_14	0.390	0.488	0	1
Urban_14	0.791	0.407	0	1
preg	0.044	0.205	0	1

3.4 Estimation Results

The results from fitting the econometric model are reported in Table 4, in which most findings are consistent with our expectation.

The prices of meat and fish, alcoholic drinks, and health care services have a positive effect on women's participation in the labor market. On the contrary, the price of processed fruits and vegetables and the price of fast food have a negative effect, suggesting that higher prices of these substitutes for home prepared food reduce women's likelihood of working for pay. Women with higher non-wage income are more likely to participate in the labor market. Women whose household has in the past participated in the FSP are significantly less likely to work currently. Age has a reverse U-shaped effect on women's participation in the labor market, with a peak effect at age 33. Compared to white women, black women and women of other races are more likely to have a job. Education level and noncognitive skills have no significant effect on women's decision on the labor market participation. Married women or women with more kids are less likely to work for pay. Both parents' education level has a significant negative effect on the daughter's employment decision. Women living in MSAs are less likely to work for pay. Compared to women in Northeast and West, women living in the North Central region are more likely to participate in the labor market. Women who grew up in rural areas or in south are more likely to work. Finally, pregnant women are less likely to have a job.

The estimated coefficient for *Pr(D(empl)=1)* is significantly differently from zero in the wage equation, implying that selection problem is important. Age has a reversed U-shaped effect on female workers' wage rate with a peak effect at age 39. Compared to white women, black women earn much less (by 7.9%) while women of other races earn much more (by 9.1%). Women who have more education or higher noncognitive abilities earn a significantly higher wage rate. Women who are taller earn significantly more, while early BMI does not affect current wage rate significantly. Both parents' education level has a significant positive effect on the daughter's wage rate. Women living in urban areas or MSAs earn a significantly higher wage rate. Compared to women in Northeast and West, women living in North Central or South earn much less.

Women with a higher opportunity cost of time are less likely to participate in the Food Stamp Program. The prices of fresh fruits and vegetables and fast food have a negative effect on the probability of participation, while the prices of dairy products and health care services have a positive effect. Women with a higher non-wage income are less likely to participate. Households that have been in the program are more likely to continue in the program. Age has a reversed U-shaped effect on the probability of participation with a peak effect at age 39. Education level does not have a significant effect on women's likelihood to participate in the FSP, while noncognitive abilities have a significantly positive effect. Married women or women with kids are more likely to participate in the program. Both parents' education level has a significant positive effect on the daughter's participation decision. Women living in urban areas or MSAs are more likely to participate than women in rural areas or non-MSAs. Compared to women in Northeast and West, women in North Central and South are less likely to participate. Pregnant women are more likely to participate. Households are more likely to participate in the FSP after 1996.

Women in the households that currently participate in the FSP have a higher BMI and also a higher probability of being obese. Other things equal, participation in the FSP would increase a woman's BMI by about 1.1%, and increase her probability of being obese by about 2.6 percentage points.

Higher prices of processed fruits and vegetables, alcoholic drinks and non-alcoholic drinks increase women's BMI and the probability of being obese. A higher price of dairy products reduces women's BMI and the probability of being obese. A higher price of fast food increases women's BMI, but does not have a significant effect on the probability of being obese. A higher price of health care reduces women's probability of being obese, but does not have a significant effect on their BMI.

Those women who earn a higher wage rate tend to have a higher BMI and a higher probability of being obese. Those women with a higher household non-wage income have a lower BMI, and they are also less likely to be obese. Given the age range of our sample, women's BMI increases as they get older, while their probability of being obese decreases as they grow to age 35 and increases after then. Compared to white women, black women have a larger BMI and a higher probability of being obese, while women of other races have a larger BMI but not necessarily a higher probability of being obese. Women with more education tend to have a higher BMI and a higher probability of being obese, but, on the contrary, women with higher noncognitive abilities tend to have a lower BMI and a lower probability of being obese. A woman with a higher early BMI tends to have a higher current BMI and also a higher probability of being obese. Married women, women with more children and pregnant women tend to have a higher BMI and a higher probability of being obese. Compared to women in Northeast and West, women in North Central and South tend to have a higher BMI and also are more likely of being obese.

To sum up, most estimation results are consistent with the literature, especially the positive effect of the FSP participation on women's BMI and probability of being obese. Some price effects are contrary to our expectations or common sense. It may be related to the limitation of our price data, or to the fact that we can not control for the physical activities in the body weight model. The estimate of the program effect on the body weight in this model is consistent because of the large sample size, but it is still usually questioned for failing to control some unobservable factors. For instance, although we use some observed characteristics to index an individual's attitude towards welfare program, they may not work well. To solve this problem, we will take advantage of the panel data and use the individual fixed-effects model to get a more accurate estimate.

Table 4: Least Squares IV Estimations for Female Sample

Variable	*lnBMI*	*D(Obese)*	*D(FSP)*	*lnWage*	*empl**
D(FSP)	0.011* (1.731)	0.026* (1.649)			
lnWage	0.082*** (5.003)	0.189*** (4.645)	-0.213*** (-5.362)		
Pr(D(empl)=1)				1.434*** (20.68)	
PR_FFruVeg	0.025 (1.533)	0.059 (1.430)	0.068** (2.096)		-0.121 (-0.604)
PR_PFruVeg	0.069* (2.403)	0.162** (2.274)	0.014 (0.243)		-1.179*** (-3.462)
PR_Meat	-0.017 (-0.631)	-0.110* (-1.677)	-0.018 (-0.337)		0.549* (1.676)
PR_Dairy	-0.057** (-2.551)	-0.122** (-2.217)	-0.093** (-2.174)		-0.028 (-0.105)
PR_Alco	0.051** (3.040)	0.071* (1.719)	-0.024 (-0.677)		0.375* (1.690)
PR_NAlco	0.067*** (3.252)	0.102** (2.000)	0.061 (1.514)		0.357 (1.428)
PR_FF	0.042* (1.797)	0.010 (0.178)	0.138*** (3.037)		-0.578** (-2.091)
PR_HC	0.023 (-1.478)	-0.042 (-1.048)	-0.056* (-1.806)		0.343* (1.776)
Inc	-0.002*** (-4.830)	-0.005*** (-4.576)	-0.011*** (-3.718)		0.054*** (2.926)
LagFS			0.241*** (79.80)		-0.382*** (-21.14)
LagMiss			0.125*** (5.954		-0.327*** (-2.912)
Age	-0.001 (-0.262)	-0.016** (-2.346)	0.011* (1.764)	0.140*** (16.10)	0.150*** (9.023)
Age^2	0.0000 (0.876)	0.0002*** (2.687)	-0.0001* (-1.714)	-0.0018*** (-14.60)	-0.0022*** (-9.694)
Black	0.044*** (13.68)	0.043*** (5.395)	-0.035* (-1.743)	-0.079*** (-5.143)	0.390*** (3.185)
RaceOth	0.025*** (6.830)	0.005 (0.546)	0.008 (1.148)	0.091*** (4.797)	0.161*** (4.002)
Edu	0.001*** (2.305)	0.002** (2.216)	0.003 (1.598)	0.008*** (5.308)	-0.010 (-0.900)
NonCog Scale	-0.001* (-1.932)	-0.006*** (-3.380)	0.011*** (3.510)	0.039*** (9.910)	0.000 (0.006)
Height				0.004*** (4.375)	0.001 (0.361)

Table 4: (Continued)

Variable	*lnBMI*	*D(Obese)*	*D(FSP)*	*lnWage*	*empl**
BMI20	0.096*** (41.69)	0.020*** (3.414)		0.001 (0.068)	0.027 (1.012)
BMI20^2	-0.001*** (-26.42)	0.001*** (6.825)		-0.000 (-0.777)	-0.001 (-1.266)
Married	0.069*** (6.125)	0.141*** (5.102)	0.250*** (2.935)	0.066*** (5.427)	-1.598*** (-3.034)
Kids	0.006*** (5.109)	0.011*** (3.836)	0.046*** (8.471)		-0.274*** (-8.159)
Ed_Moth			0.010*** (3.835)	0.016*** (6.411)	-0.034** (-2.180)
NoEdM			0.092*** (4.335)	0.173*** (4.350)	-0.338*** (-2.806)
Ed_Fath			0.010*** (3.838)	0.017*** (8.216)	-0.044*** (-2.719)
NoEdF			0.108*** (4.450)	0.146*** (5.315)	-0.521*** (-3.585)
Urban	-0.003 (-1.246)	0.0002 (0.400)	0.013* (1.670)	0.065*** (4.231)	0.032 (0.704)
MSA	0.001 (0.597)	0.003 (0.504)	0.068*** (6.269)	0.052*** (3.842)	-0.225*** (-3.444)
NC	0.010*** (3.025)	0.016** (2.002)	-0.084*** (-5.031)	-0.136*** (-8.678)	0.398*** (4.108)
South	0.015*** (4.992)	0.024*** (03.390)	-0.058*** (-5.488)	-0.104*** (-7.359)	0.102* (01.704)
Urban_14			0.004 (0.786)		-0.148*** (-5.187)
South_14			-0.031*** (-3.687)		0.162*** (3.140)
DUM96			0.046*** (4.702)		
Preg	0.064*** (14.09)	0.045*** (4.027)	0.061*** (7.133)		-0.151*** (-2.959)
Time Trend			0.086*** (4.425)	0.254*** (23.14)	-0.222** (-2.199)
Constant	1.378*** (28.21)	-0.841*** (-6.965)	-0.410** (2.238)	-4.287*** (-15.42)	0.258 (0.242)
Number of Observations	20,750	20,750	20,750	15,691	20,750
R^2	0.5299	0.2996	0.3917	0.4242	0.1007

Notes: (1) z-statistics in parentheses. (2) *** represents statistical significant level in 1%, ** represents statistical significant level in 5%, and * represents statistical significant level in 10%.

Chapter 4. Forward-Looking Decisions without Information Updating

In this chapter, we develop a model of decision making by the head of a household who is forward-looking but does not update current and future decisions as information is accumulated on past outcomes. Hence, the household head maximizes the household's lifetime utility, not one period utility, assuming no uncertainty. She/he makes decisions on life styles at the beginning of life and sticks to them in each period afterwards despite past outcomes. The corresponding empirical econometric model is least squares IV with individual fixed-effects. This model has become fairly common in the labor literature.

4.1 Theoretical Model

The theoretical model is based on the multi-period model of labor supply reviewed by Blundell and McCurdy (1999). In this model, marginal-utility-of-wealth-constant labor supply functions, known as Frisch functions, provide an extremely useful method for analyzing lifecycle decision problems, and also lay out the theoretical foundation for using individual fixed effects in an econometric model.

The representative household makes its lifetime decisions on labor supply, leisure activities, consumption (including food, medical care and other consumption goods), demand for health status and the participation in the Food Stamp Program according to the value function at time *t* with κ representing the household's utility discount factor:

$$V(A_t, t) = \max\left[U(F_t, C_t, H_t, LP_t, LO_t; Z_t, \phi) + S(FS_t; Z_t, \phi) + \kappa V(A_{t+1}, t+1)\right]^2$$

Here $U(\cdot)$ is a strictly concave utility function of goods consumed, in which F_t represents the food and drinks consumed in period *t*, C_t represents all other consumption of goods excluding purchased medical care in period *t*, H_t represents the current health status of the household members in period *t*, LP_t represents physically active leisure time in period *t*, LO_t represents other types of leisure time in period *t*, Z_t denotes the observable characteristics of the household, such as the household head's gender, race, education, family structure, urban

[2] Note that this value function implies two underlying assumptions. First, it assumes intertemporal strong separability of preferences. Second, the household can completely predict its income, the value of food stamps it receives and adult health status in each period.

residency and so on, and ϕ denotes other unobservable factors affecting the household's preferences. In the utility function, food and drinks, other consumption goods, current health, and other types of leisure time are assumed to provide a positive marginal utility, while physically active leisure time is assumed to provide a negative marginal utility. We also assume that participation in the Food Stamp Program has a disutility, represented by $S(\cdot)$, since the literature has attributed a part of the decline in participation to the welfare-reform-related stigma. Specifically, with FS_t representing the value of food stamps the household receives in period *t*, the disutility function satisfies the following conditions:

$$\begin{cases} S(0;Z_t,\phi)=0, \quad S(FS_t;Z_t,\phi)\to c_1<0 \text{ if } FS_t\to 0, \quad S(FS_t;Z_t,\phi)\to 0 \text{ if } FS_t\to\infty \\ \dfrac{dS}{dFS_t}\to c_2>0 \text{ if } FS_t\to 0, \quad \dfrac{dS}{dFS_t}\to 0 \text{ if } FS_t\to\infty, \quad \dfrac{d^2S}{dFS_t^2}\le 0 \end{cases}$$

In other words, if the household doesn't participate in the program, the disutility associated with participation is 0. If the household participates in the program, the disutility associated with participation is lower bounded by a constant $c_1<0$, and increases as the value of food stamps increases, which implies a positive marginal disutility. To permit a corner solution for FS_t, we also impose an upper bound $c_2>0$ for marginal disutility.

The household can improve the adult's current health status by its choices of food and drinks, physical exercise and medical care services (denoted by M). Specifically, the adult's health production function is a strictly concave function given by

$$H_t = H(F_t, LP_t, M_t; Z_t, H_e, \varphi),$$

where H_e denotes the early health status of the household member, and φ denotes other unobservable factors that affect the adult's efficiency in accumulating good health, for instance distress and genetic predisposition for good/bad health. Some foods, for instance, fresh fruits and vegetables that are high in fiber, vitamins and minerals, are called healthy foods because they have a positive marginal product on health output. Some foods, like alcoholic beverages, nonalcoholic beverages and fast food that contain added sugar, and added salt and fat, are called unhealthful foods when they have a negative marginal product on health output. Finally, in each period, the household receives an endowment of time T

that is allocated to work for pay L_t, physically active leisure LP_t, and other types of leisure LO_t, i.e., $L_t + LP_t + LO_t = T$.

By setting the price of goods C as 1, let P denote the cost of goods with subscripts representing different goods and W denote the real wage rate. Then, the household intertemporal budget constraint can be represented by the time path of assets, A, as

$$A_{t+1} = (1+r_{t+1})[A_t + B_t + W_t L_t - C_t - P_{F,t}(F_t - FS_t) - P_{M,t} M_t]$$

where A_{t+1} is the real value of assets at the beginning of period $t+1$, r_{t+1} is the real rate of return earned on assets between t and $t+1$, and B_t represents unearned-non-asset income. Note that since the food stamps can be used to purchase food and drinks, $(F_t - FS_t)$ is the amount of food and drinks that the household purchases out of its own pocket.

Therefore, the representative household chooses consumption, leisure and labor supply by maximizing the value function

$$V(A_t, t) = \max\left[U(F_t, C_t, H(F_t, LP_t, M_t; H_e, Z_t, \varphi), LP_t, LO_t; Z_t, \phi) + S(FS_t; Z_t, \phi) + \kappa V(A_{t+1}, t+1)\right]$$

subject to

$$A_{t+1} = (1+r_{t+1})(A_t + B_t + P_{F,t} FS_t + W_t T - W_t LP_t - W_t LO_t - C_t - P_{F,t} F_t - P_{M,t} M_t)$$

Thus, we have the Lagrange equation

$$\begin{aligned} L_t &= U(F_t, C_t, H(F_t, LP_t, M_t; H_e, Z_t, \varphi), LP_t, LO_t; Z_t, \phi) + S(FS_t; Z_t, \phi) + \kappa V(A_{t+1}, t+1) \\ &\quad + \lambda_t [A_t + B_t + P_{F,t} FS_t + W_t T - W_t LP_t - W_t LO_t - C_t - P_{F,t} F_t - P_{M,t} M_t - \frac{A_{t+1}}{1+r_{t+1}}] \end{aligned}$$

Standard dynamic programming techniques yield the following first-order conditions:

$$\begin{cases} \dfrac{\partial U_t}{\partial F_t} + \dfrac{\partial U_t}{\partial H_t} \cdot \dfrac{\partial H_t}{\partial F_t} = \lambda_t P_{F,t} \\ \dfrac{\partial U_t}{\partial C_t} = \lambda_t \\ \dfrac{\partial U_t}{\partial H_t} \cdot \dfrac{\partial H_t}{\partial M_t} = \lambda_t P_{M,t} \\ \dfrac{\partial U_t}{\partial LP_t} + \dfrac{\partial U_t}{\partial H_t} \cdot \dfrac{\partial H_t}{\partial LP_t} = \lambda_t W_t \\ \dfrac{\partial U_t}{\partial LO_t} = \lambda_t W_t \\ \dfrac{dS}{dFS_t} + \lambda_t P_{F,T} \le 0,\ FS_t \ge 0,\ FS_t(\dfrac{dS}{dFS_t} + \lambda_t P_{F,T}) = 0 \\ \dfrac{\partial V_{t+1}}{\partial A_{t+1}} = \dfrac{\lambda_t}{\kappa(1+r_{t+1})} = \lambda_{t+1} \end{cases} .$$

Basically, these first-order conditions imply that the household chooses such that the marginal returns from these choices equal the marginal costs associated with them. Specifically, the first-order condition with respect to FS_t indicates that the household would choose not to participate in the Food Stamp Program when the marginal return from participation $\lambda_t P_{F,t}$ is less than the marginal disutility $-\dfrac{dS}{dFS_t}$, and vice versa. The last equation is also called the Euler equation, in which λ_t is the Lagrange multiplier of the intertemporal budget constraint, representing the marginal utility of wealth $\partial V_t / \partial A_t$ by the Envelope theorem.

These first-order conditions imply that the demand functions for different goods (F^*, C^*, M^*), time allocation of adults (LP^*, LO^*, L^*), food stamps FS_t and adult health status (H^*) are of the form

$$\begin{cases} F_t^* = F(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \varepsilon) \\ C_t^* = C(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \varepsilon) \\ M_t^* = M(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \varepsilon) \\ L_t^* = L(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \varepsilon) \\ LP_t^* = LP(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \varepsilon) \\ LO_t^* = LO(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \varepsilon) \\ FS_t^* = FS(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \varepsilon) \\ H_t^* = H(F_t^*, LP_t^*, M_t^*; Z_t, H_e, \varphi) = H(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \varepsilon) \end{cases},$$

where ε includes ϕ and φ, i.e., all the unobservable factors that affect the household's preferences and efficiency in accumulating good health of adults.

The above set of functions reveals the set of variables that are to explain the above seven behavioral outcomes, and also provides the structural model for our empirical analysis. Goods consumption, labor supply and health status merely depend on components observed in the current period: the current prices of food and drinks $P_{F,t}$, the current price of medical services $P_{M,t}$, the current wage rate W_t, the household current observable characteristics Z_t, as well as λ_t which summarizes the relevant information from all other periods. Variables such as future wealth, wages, or personal characteristics affect current behavioral outcomes only through the change of λ_t.

The Euler equation implies a time path for λ of the form

$$\ln \lambda_{t+1} = -\ln(\kappa(1 + r_{t+1})) + \ln \lambda_t = b_t + \ln \lambda_t .$$

Repeat substitutions yield

$$\ln \lambda_t = \sum_{j=0}^{t-1} b_j + \ln \lambda_0 .$$

where $b_t = -\ln(\kappa(1 + r_{t+1}))$. Hence, λ_t in the outcome functions can divided into two parts: λ_0, which can be treated as an unobservable individual fixed effect, plus b_t, which depends on the interest rate and the household's utility discount rate that can be captured by observable individual characteristics (age and its squared term by Blundell and McCurdy [1999]). This provides the fundamental structure of the individual fixed effects model that is incorporated into our second econometric model of obesity and FSP participation.[3]

Comparative static results for the model are difficult to derive because substitution effects and income effects of various foods and consumption goods are unclear and also because it is hard to specify the characteristics of health production function. For example, if the household participates in the FSP in period t, λ_t will fall because of the diminishing marginal utility of wealth while all future $\lambda_{t'}, t' > t$ remain the same. Holding other factors constant, the household would increase adult's other leisure time and consumption of other goods in the current period. But it is hard to predict the changes in food consumption and physically active leisure time, and thus health status as a result.

For another instance, if the household does not participate in the FSP and the price of medical care services increases marginally, holding other factors constant, the household will reduce consumption of medical services, and resort to a healthier diet (with eating more healthy foods and less unhealthy foods) and more physical excises to build up good health. The household will also increase the labor supply to compensate for the higher living cost, and as a result, the time for other leisure activities would decrease. But we do not know for sure whether the adult's health status will be better, be worse, or even remain unchanged, or whether the consumption of other goods would change at all. When the household does participate in the FSP, since the food stamps can be used to purchase more healthy foods and less unhealthy food, it becomes more difficult to predict the effect of a change in the price of medical services.

A marginal increase in the price of healthy foods will have stronger negative effects since the declined consumption of healthy foods does not only worsen the health status but also directly decreases the household utility. The household will attempt to increase income and input of medical care services and physical activities to build up good health. Again, for the households that participate in the FSP, if they can somehow offset the negative effects by

[3] This economic model provides one plausible rationale for using individual fixed effects to represent random individual effects at the beginning of the decision making period. However, other research might develop other rationales for using individual fixed effects models.

using the food stamps more wisely, the changes in their consumption behavior and health status may be moderated.

The effects of an increase in the price of unhealthy foods are more complicated. A marginal increase in the price of healthy foods reduces consumption, which directly decreases the household's utility, but also increases the household's utility indirectly by health benefits. Thus, the net change in utility depends on which effect is dominant. Some unhealthy foods, such as nonalcoholic drinks, can be purchased using the food stamps. As a result, their price effects will be different for households that participate in the FSP and those that do not. On the other hand, some unhealthy foods, such as alcoholic, can not be purchased using the food stamps. Thus their price effects will be the same irrespective of whether the household participates in the FSP.

Now let us take a look at the individual fixed-effect term λ_0. Inserting the optimal demand functions into the intertemporal budget constraint gives us

$$A_{t+1} = (1 + r_{t+1})[A_t + B_t + W_t L_t^* - C_t^* - P_{F,t}(F_t^* - FS_t^*) - P_{M,t} M_t^*],$$

which is an implicit function for λ_t or λ_0. Although we cannot obtain the explicit function of λ_0, we at least know that it depends on the household's asset values at the beginning and at the end of each period, the unearned-non-asset income, the cost of goods, the real wage rate and all the unobservable factors that affect the household's preferences and efficiency in accumulating good health of adults.

Although we can make some predictions about household behaviors based on normal assumptions as discussed above, we cannot draw explicit conclusions. Hence, the theoretical model provides only a broad framework for viewing household decisions on the economics of health and other choices.

4.2 Econometric Model

The econometric model focuses on adults' choice of health status (Equation 5) and the decision on the FSP participation (Equation 6). Based on the economic model, a system of these two equations is estimated with a focus on the effect of the FSP participation on the adult health status -- BMI and being obese. An instrumental variable strategy is used because of the endogeneity of the decision on the FSP participation.

When estimating the system, we still need to control for the endogeneity of the opportunity cost of time measured by the hourly wage rate. Hence, we fit an hourly wage rate equation (Equation 7) to estimate the predicted hourly wage rate and use it to index an individual's opportunity cost of time.

In the ordinary least square estimation of the wage equation, *Pr(D(empl)=1)* is included to control for selection. However, in the individual fixed-effects model, which is assumed to be constant over all time, this variable will drop out. Thus, we do not need to estimate the labor market participation equation.

Equation 5: Health Status Equation

Equation 5 is to explain the household's demand for an individual's health without information updating. Based on the theoretical model, an adult's health status depends on the household's decision to participate in the FSP, his/her current wage rate, the current prices of local food and medical services, current observable characteristics (including marriage status, the number of kids in the household and current residence region), his/her age and age squared, and an individual fixed effects.

$$\begin{aligned}\ln BMI_{it}[or\ D(Obese)_{it}] &= \beta_1 + \beta_2 D(FSP)_{it} + \beta_3 \ln Wage_{it} + \beta_4 PR\_FFruVeg_{it} + \beta_5 PR\_PFruVeg_{it}\\ &+ \beta_6 PR\_Meat_{it} + \beta_7 PR\_Dairy_{it} + \beta_8 PR\_Alco_{it} + \beta_9 PR\_NAlco_{it} + \beta_{10} PR\_FF_{it} + \beta_{11} PR\_HC_{it} + \beta_{12} Age_{it}\\ &+ \beta_{13} Age_{it}^2 + \beta_{14} Married_{it} + \beta_{15} Kids_{it} + \beta_{16} Urban_{it} + \beta_{17} NC_{it} + \beta_{18} South_{it} + \beta_{19} West_{it} + \beta_{20} preg_{it} + \delta_{1i} + \varepsilon_{it}\end{aligned}$$

Among all these factors, we are particularly interested in the effect of the decision of the household to participate in the Food Stamp Program. Based on a review of the literature, we hypothesize that adults who live in household that participate in the Food Stamp Program are more likely to be obese.

Second, an adult's opportunity cost of time is important to decisions on time and goods allocation. If an individual's price of time is high, then he/she will tend to conserve on time-intensive activities. Recreational exercise is a time-intensive activity, but it also contributes to a healthy weight. On the other hand, individuals who have a higher opportunity cost of time may try to build their health more effectively and efficiently, if they spend some time on physical activities, by hiring professional trainers. Overall, we hypothesize that individuals who have a higher opportunity cost of time are more likely to be obese.

Third, individuals consume food and drinks to obtain nutrients (carbohydrates, fats, protein, vitamins and minerals), to feel good (i.e., comfort food), and to socialize. The local prices of disaggregated food and drinks are one set of factors that are expected to affect a household's choices of food and drinks as well as it adult's physical activities, and thus affect their body weight (Chen 2009). An increase in the price of fresh fruits and vegetables is expected to reduce an individual's consumption of these products and to lead to a higher BMI or probability of being obese. An increase in the price of processed fruits and vegetables, which generally contain significant amounts of added sugar, will reduce the consumption of these foods and lower BMI and the probability of being obese. An increase in the price of meats and fish is expected to reduce an individual's consumption of these foods, which tend to be calorie dense, and may lead to a lower BMI and probability of being obese. Similarly, since most fast foods are calorie dense, an increase in the price of fast foods is expected to reduce an individual's consumption of these foods and thus lead to a lower BMI and probability of being obese. We are uncertain about the effects of the prices of dairy products, alcoholic drinks and non-alcoholic drinks on BMI and the probability of being obese. A higher price of health care is expected to shift attention to lifestyle production of good health and reduce the probability that an individual is obese.

Fourth, there is strong empirical evidence that BMI tends to vary with age, generally increasing from young adulthood to the 60s and then tending to decline. Hence, an individual's age is expected to have a non-linear effect on ln(BMI) and the probability that an individual is obese.

Fifth, an individual's lifestyle choices are affected by his/her family structure. Married individuals or individuals with more children are expected to live to older ages and to choose healthier lifestyles, including a normal weight.

Sixth, an individual's current urban (versus rural) residence and regional location may affect his/her health supply because of the different costs of health production. In more rural areas, including the North Central, West and South, space for physically active leisure is cheaper, and space and good soils are more likely to be available for a vegetable garden.

Finally, pregnant women tend to have a higher BMI or a higher probability of being obese.

Equation 6: Food Stamp Program Participation

Equation 6 is to explain a household's decision to participate in the FSP, which is hypothesized to depend on local prices of food and drinks, the price of medical services, age of adults, marriage status of adults, and the number of kids at home.

This equation is of interest itself but also to provide predicted probabilities of FSP participation for Equation 5. Two instrumental variables, an index of residence in a metropolitan statistical area and the household non-wage income, are used for identification purpose based on policies that set the rules for the Food Stamp Program. We are not sure about the sign of the effect of residing in a MSA. On one hand, individuals who live in MSAs may be less likely to participate in the FSP because of the higher average income level and less friendly attitude toward the welfare programs. One the other hand, local governments probably are able to provide support for more people because they have more resources, thus resulting in a higher participation rate. We expect that households with a higher household non-wage income are less likely to participate in the FSP.

$$\begin{aligned} D(FSP)_{it} &= \theta_1 + \theta_2 PR\_FFruVeg_{it} + \theta_3 PR\_PFruVeg_{it} + \theta_4 PR\_Meat_{it} + \theta_5 PR\_Dairy_{it} + \theta_6 PR\_Alco_{it} \\ &+ \theta_7 PR\_NAlco_{it} + \theta_8 PR\_FF_{it} + \theta_9 PR\_HC_{it} + \theta_{10} Age_{it} + \theta_{11} Age_{it}^2 + \theta_{14} Married_{it} + \theta_{15} Kids_{it} \\ &+ \theta_{15} MSA_{it} + \theta_{16} Inc_{it} + \delta_{2i} + \mu_{it} \end{aligned}$$

Since the Food Stamp Program provides a substitute for some directly purchased food, an individual is expected to be more likely to participate in the program as the prices of healthy food increase. However, we are uncertain about the effects of local prices of unhealthy food because they depend on the tradeoff between the reduced utility from less consumption and the increased utility from better health.

Retirement-aged adults are expected to be in household that more likely to participate in the Food Stamp Program because they usually have less current income. However, because they can obtain social security and Medicare when they turn aged 65, a non-linear effect of an adult's age is permitted in the model to capture life-stage effects.

Married individuals are expected to be less likely to participate in the Food Stamp Program because they could get financial support from their spouse, but individuals with more children are expected to be more likely to participate because of the heavier financial burden.

Equation 7: Hourly Wage Rate Equation

Equation 7 is the hourly wage equation for adults, and it is also used to generate estimates of the opportunity cost of time for Equation 1.

$$\ln Wage_i = \pi_1 + \pi_2 Age_{it} + \pi_3 Age_{it}^2 + \pi_4 Age_{it} * Edu_{it} + \pi_5 Age_{it} * NonCogScale_{it} + \pi_6 South_{it} + \delta_{3i} + \omega_{it}$$

An individual's age rather than his or her labor market experience is used to represent current and pass incentives to invest in experience, given schooling. We expect an individual's wage to increase but at a decreasing rate as he or she becomes older.

Other studies have found that an individual's wage increases with more cognitive skills (as indexed by education level) and noncognitive abilities. In our data set, all the respondents were at least 22 years old in the first sampling year. Hence their education level rarely changed as they became older. Also, the noncognitive abilities scales were administrated far before the first sampling year, so they are fixed during all the sampling years. Therefore, the interaction terms of age and education as well as age and noncognitive abilities are used in Equation 7 for two purposes. First, the cognitive skills and non-cognitive abilities work as instrumental variables in Equation 7. Second, the interaction terms allow for us to examine whether their effects increase or decrease with more labor market experience.

At last, an index of residence in southern areas is used in the equation because individuals that currently live in a poorer area are expected to earn less.

4.3 Sample Description

We use a balanced sample in which each individual has complete records in all six sampling years.[4] There are a total of 1,638 individuals with 6 observations per individual in the female balanced sample (please see Table 5 for the summary statistics of key variables). About 56.5% of females are white, 28.8% are black, and 14.7% are of other races. At age 20, these females had an average BMI of 21.74, and 2.2% of them were obese. The female sample has an average education level of almost 13 years. As for measures for non-cognitive abilities, the mean of Rosenberg Scale is 32.09, the mean of Internal scale is 8.35, and the mean of Noncog Scale is 13.70.

From year 1986 to year 2006, the average BMI of these women increased by over 19% from 22.64 to 27, while their obesity rate also increased by over 20 percentage points. This trend is consistent with the increasing obesity rate in the U.S. over that last twenty year. During the same period, the Food Stamp Program participation rate increased steadily to 1994 and then dropped sharply. The average annual amount of food stamps the household received in the last three calendar years also shows the same pattern except for a small increase in 2006. We believe that these phenomena may be related with the welfare reform in 1996.

The proportion of women who are married increased in the first two sampling years and remained steady thereafter. The number of kids in the household increased until 1998 and decreased thereafter. The proportion of pregnant women fluctuated at a higher level in the first three sampling years and then kept at a much lower level in the last three sampling years. We believe that all these changing patterns are normal as the respondents aged.

The hourly real wage rate and the predicted annual real non-wage income both kept rising during these twenty years. The residence location of these respondents didn't change much except that the proportion of respondents living in metropolitan statistical areas more than doubled in the last two sampling years. We are not sure if it is because more respondents moved to MSAs or because the U.S. Census Bureau revised the standards for MSAs in year 2000.

[4] Just as in the least squares estimations with IV strategies, no significant effects of participation in the FSP on body weight or the probability of being obese are found for male adults in the data set although the instrumental variable strategy works well. Therefore, our empirical analyses focus on the female sample.

Table 5: Summary Statistics for Female Balanced Sample

Part 1: Summary Statistics of Key Demographic Variables

Variable	Mean	Std. Dev.	Min	Max
BMI20	21.74	3.04	16.14	39.48
age (in 1986)	24.56	2.23	21	29
Black	0.288	0.453	0	1
RaceOth	0.147	0.354	0	1
Edu	12.79	2.10	0	20
Rosenberg Scale	32.09	3.97	19	40
Internal Scale	8.35	1.49	4	12
Noncog Scale	13.70	1.55	9.41	17.89

Part 2: Means of Variables in each sampling year

Variable	1986	1990	1994	1998	2002	2006
BMI	22.64	23.79	24.77	25.67	26.37	27.00
D(Obese)	4.46%	8.55%	13.98%	18.86%	23.44%	26.50%
D(FSP)	13.37%	14.96%	16.24%	10.19%	7.57%	6.11%
LagFS	119.45	201.19	288.20	234.32	120.57	152.72
LagMiss	0.18%	0.37%	0.55%	0.49%	0.49%	0.43%
Wage (if worked for pay)	5.99	9.57	10.43	13.62	17.22	19.49
Married	44.44%	55.31%	56.47%	56.65%	58.55%	57.88%
Kids	0.89	1.37	1.55	1.73	1.57	1.32
preg	7.14%	6.29%	8.42%	1.59%	0.98%	0.24%
Urban	79.30%	78.57%	77.84%	68.74%	75.34%	68.32%
NC	28.51%	29.55%	29.61%	29.30%	29.18%	29.12%
South	41.09%	40.72%	41.39%	41.94%	41.94%	42.06%
West	18.75%	18.50%	18.19%	18.19%	18.01%	18.19%
MSA	49.82%	48.66%	44.63%	30.40%	79.61%	91.94%
Inc (in 1,000 dollars)	5.90	15.16	15.39	26.34	33.69	38.71

4.4 Estimation Results

The econometric model is least squares with IVs and individual fixed-effects model, and estimates of this model are reported in Table 6. Estimation of the wage equation differs here relative to the benchmark model because variables that do not change over time are excluded and captured in the estimate coefficients of the individual fixed effects. A woman's age has a reversed U-shaped effect on her hourly wage rate, peaking at age of 55, but given the age range of our sample, older female workers tend to earn more. When both women's cognitive skills and non-cognitive abilities are controlled in the wage equation, noncognitive abilities have a significant positive effect on hourly wage rate, while cognitive skills have no significant effect although still with a positive sign.[5] This means that for women, non-cognitive abilities affect their hourly wage instead of their cognitive skills, and the magnitude of such effect increases as they get older. No North-South regional differences exist in women's real wage rates in the fixed-effects model.

Women's household FSP participation decision is shown to be sensitive to the local prices of fresh fruits and vegetables, fast food and dairy products, but not to the local prices of other food and services. As we expected, a one dollar increase in the price of fresh fruits and vegetables increases the participation probability by about 11 percentage points, and a one dollar increase in the price of fast food increases the participation probability by almost 20 percentage points. But contrary to our expectation, a one dollar increase in the prices of dairy product decreases the probability of her household's participation probability by almost 16 percentage points. A woman's age has a reversed U-shaped effect on her household's FSP participation rate, peaking at age 56. Women with more kids are more likely to participate in the Food Stamp Program, which is consistent with the facts that, as in 2006, 52% of food stamp households included children; but contrary to our expectation, married women are also more likely to participate in the program although single-parent families are a mainly target group for the program.

Both instrumental variables in the FSP equation, the dummy for MSA residence and the

[5] The regressions using the internal scale and the Rosenberg scale instead of the comprehensive noncognitive scale show that female individuals with higher internal control earn on average more than those with lower internal control, which is consistent with the findings of literature.

non-wage household income, are statistically significant: women living in MSAs are more likely to participate in the Food Stamp Program than those not living in MSAs, and women with higher non-wage household income are less likely to participate in the Food Stamp Program than those with lower non-wage household income. The test for weak instruments also suggests that these two instruments are fairly strong since the F-statistics for joint significance is bigger than 10 (Stock and Yogo 2005).

As for the BMI equation and obesity equation, the signs of most variables are the same across the two equations, but the significant levels are usually different. Women with a higher opportunity cost of time are less likely to be obese. Women currently participating in the Food Stamp Program have a lower BMI or a lower probability of being obese on average than those who are not in the program. But the magnitude of the effects is much larger than usual expectations. Specifically, participation reduces women's BMI by 15.67% and the probability of being obese by 56.33 percentage points.

The price of dairy products has a negative effect on women's BMI and the probability of being obese, suggesting that low price and popular use of dairy product may be a reason for obesity in the U.S.. The price of alcoholic drinks has a positive effect on women's BMI, while the price of non-alcoholic drinks has a positive effect on both women's BMI and the probability of being obese. Contrary to popular belief, the price of fast food has a positive effect on women's BMI, but not on the probability of being obese. This result needs to be interpreted carefully because the food items we used in the category "fast food" do not include those frozen ready-to-eat meals available in supermarkets.[6] The price of medical services has a negative effect on women's BMI, but not on the probability of being obese.

Women's BMI increases as they grow older until about age 48, and then BMI decreases gradually with each passing year. Given the age range of women in our sample, their probability of being obese increases as they get older. Married women have a higher BMI on average than unmarried women, but not a significantly different probability of being obese. Women with more kids or being pregnant usually have a higher BMI or a higher probability of being obese. Those living in urban areas tend to have a lower BMI, but the probability of

[6] More and more female adults, especially those working for pay, purchase ready-to-eat meals instead of preparing meals using all fresh materials, which is believed to be a reason of obesity.

being obese is not significantly different for residing in urban areas or in rural areas. Compared with women living in Northeast, those living in the Midwest and West have a larger BMI, and those living in South have a lower probability of being obese.

MaCurdy (1981) has shown that estimates of individual fixed effects contain useful information, not some much in their values, but in their distribution. Now let us take a look at the individual fixed effects in the BMI equation and the obesity equation. Figure 1 presents a plot of the estimate of the individual fixed effects in the ln(BMI) equation. We can see that their distribution is looks similar to a normal distribution with a mean close to 0. In Figure 2, we can see that the frequency plot of actual BMI and predicted BMI are similar, so the model of ln(BMI) does a good job in prediction except that the predicted values are a little more condensed than the actual values, especially in the upper tail. As a result, for those women that have a large BMI, the predicted BMI is less than their actual BMI. This under-prediction of extreme values is common in econometric models.

Figure 3 presents the distribution of estimated individual fixed effects, and it has two obvious features. First, the negative mean means that on average, the individual fixed effects tend to reduce women's probability of being obese. Second, the long upper tail suggests that unobservable fixed effects of some women make them very likely of being obese. We also calculate two predicted probability of being obese. The first one is the individual probability of being obese predicted by a woman's own characteristics and her individual fixed effect. The second one is the average probability of being obese predicted by the sample's "average" characteristics and a woman's own individual fixed effect. These values are plotted in Figure 4 and their coincidence in the upper tale suggests that for some women, the individual fixed effect is the main factor explaining their being obese. Put differently, for these women, the non-fixed effect variables are a minor part of the explanation of them having a large BMI or probability of being obese. Hence, policies targeted to change these non-fixed effect variables would help little to decrease their body weight, while policies targeted to change individual fixed effects would work better.

Table 6: Individual Fixed-Effects Estimations for Female Balanced Sample

(sample size of 9,828 = 6*1,638)

Variable	*lnBMI*	*D(Obese)*	*D(FSP)*	*lnWage*
D(FSP)	-0.1567** (-2.14)	-0.5633** (-2.42)		
lnWage	-0.0312 (-0.72)	-0.3485** (-2.54)		
PR_FFruVeg	0.0283 (1.24)	0.1107 (1.53)	0.1090* (1.77)	
PR_PFruVeg	0.0381 (1.19)	0.1119 (1.11)	-0.0401 (-0.43)	
PR_Meat	-0.0304 (-0.92)	-0.1084 (-1.03)	0.0699 (0.73)	
PR_Dairy	-0.0593** (-1.97)	-0.3078*** (-3.23)	-0.1591** (-1.97)	
PR_Alco	0.0644** (2.38)	0.0626 (0.73)	-0.0243 (-0.32)	
PR_NAlco	0.0562** (2.06)	0.2056** (2.37)	0.0834 (1.10)	
PR_FF	0.0913*** (3.29)	0.1395 (1.58)	0.1993*** (2.88)	
PR_HC	-0.0436* (-1.85)	0.0095 (0.13)	0.0663 (1.05)	
Age	0.0190** (2.52)	0.0706*** (2.96)	-0.0113*** (-2.43)	0.1535*** (12.24)
Age^2	-0.0002*** (-2.79)	-0.0006*** (-2.93)	0.0001*** (1.52)	-0.0014*** (-9.74)
Married	0.0099* (1.68)	-0.0140 (-0.74)	0.0604* (1.90)	
Kids	0.0082** (2.00)	0.0270** (2.06)	0.0614*** (15.58)	
Preg	0.0652*** (13.96)	0.0291* (1.96)		
Urban	-0.0059* (-1.98)	0.0056 (0.60)		

Table 6: (Continued)

Variable	***lnBMI***	***D(Obese)***	***FSP***	***lnWage***
NC	0.0259** (2.11)	-0.0298 (-0.76)		
South	0.0164 (1.55)	-0.0601* (-1.79)		-0.0574 (-1.09)
West	0.0209* (1.66)	-0.0130 (-0.33)		
*Age*Edu*				0.0000 (0.66)
*Age*Noncog Scale*				0.0018*** (2.73)
MSA			0.0326*** (3.96)	
Inc			-0.0047*** (-4.29)	
Constant	2.6821*** (26.09)	-1.0361*** (-3.18)	0.1179* (1.76)	-2.4590*** (-14.77)
Test for Weak Instruments			11.86	3.94
Test for Overidentification in FSP Equation				
Sargan Statistics	0.3838	2.2082		
P-Value	0.5356	0.1373		
R^2	0.402	0.105	0.061	0.531

Notes: (1) z-statistics in parentheses.
(2) *** represents statistical significant level in 1%, ** represents statistical significant level in 5%, and * represents statistical significant level in 10%.

Figure 1: Density Plot of Predicted Individual Fixed-effects for BMI Equation

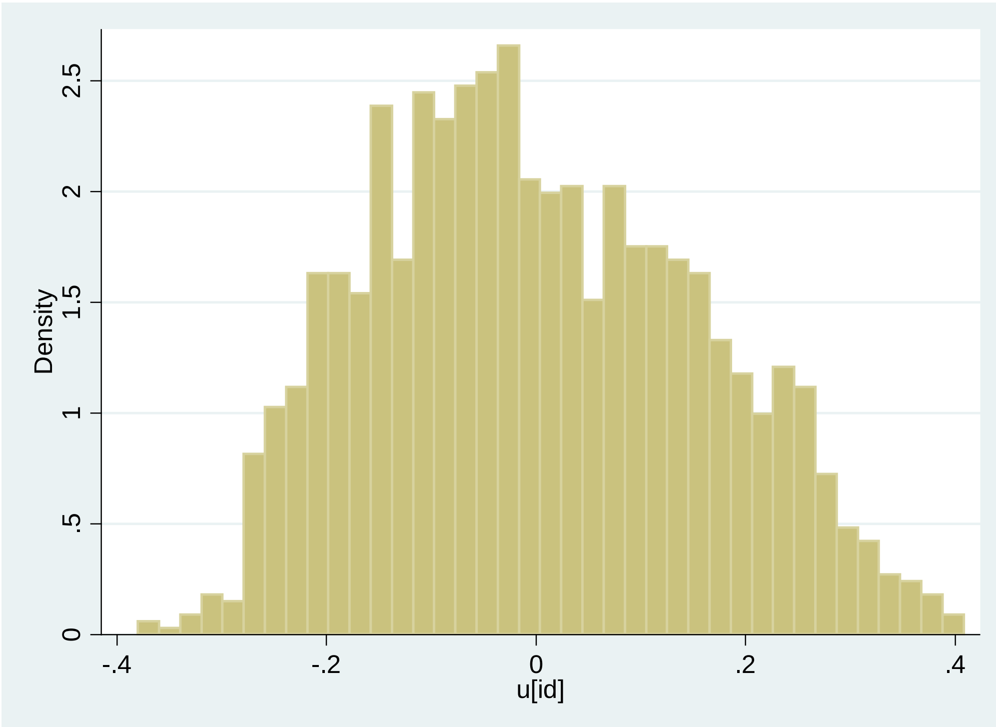


Figure 2: Frequency Plot of Predicted BMI

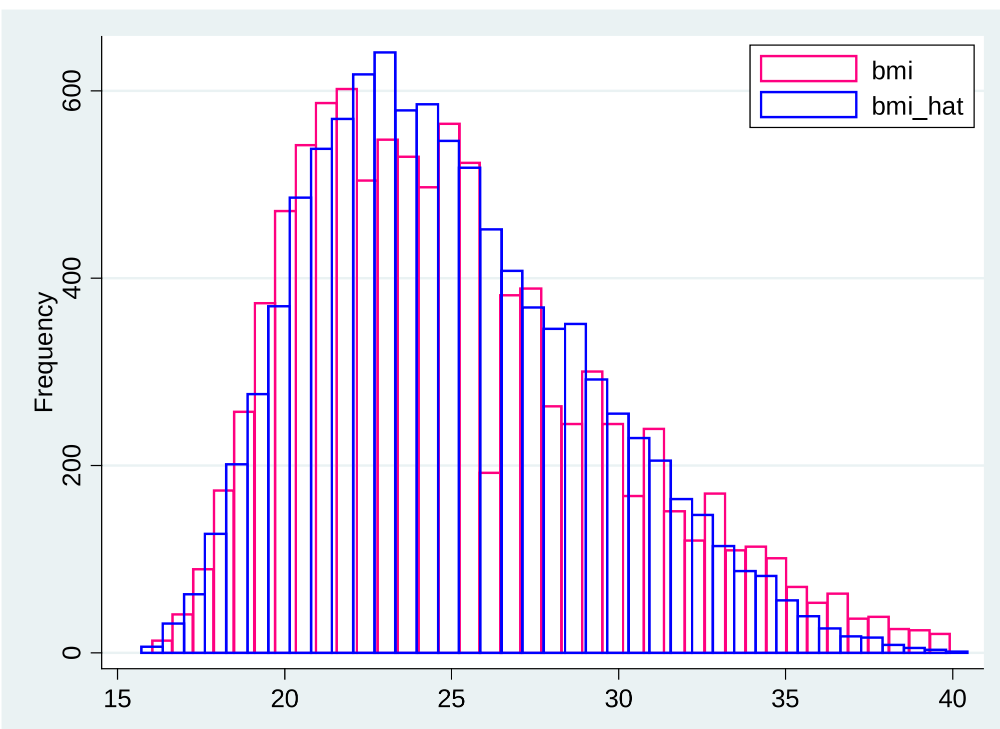


Figure 3: Density Plot of Predicted Individual Fixed-effects for Obesity Equation

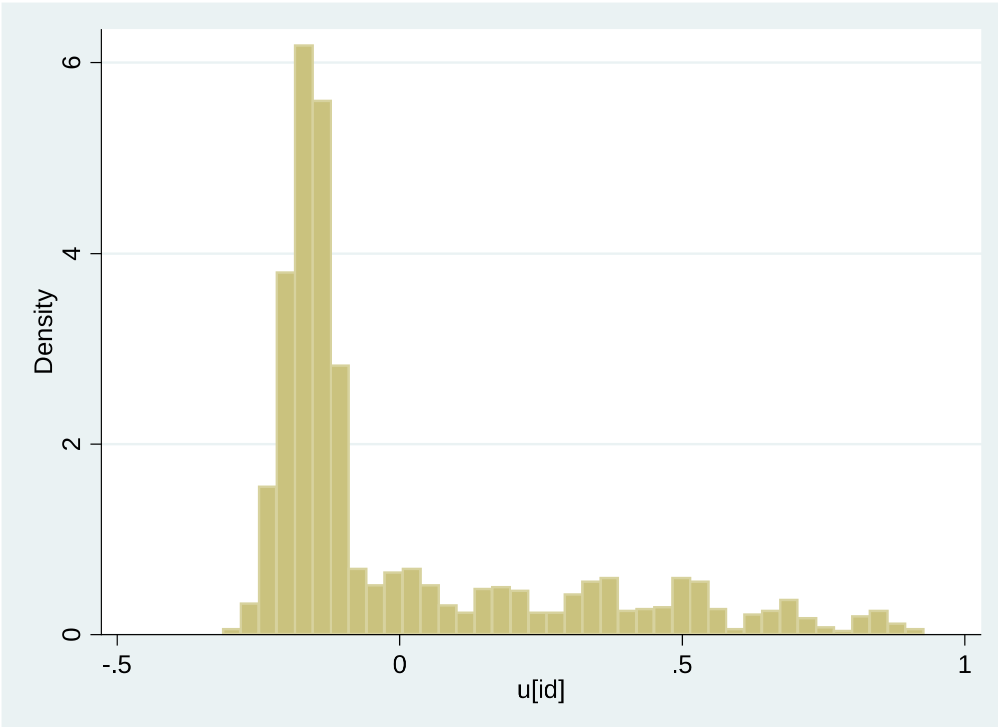
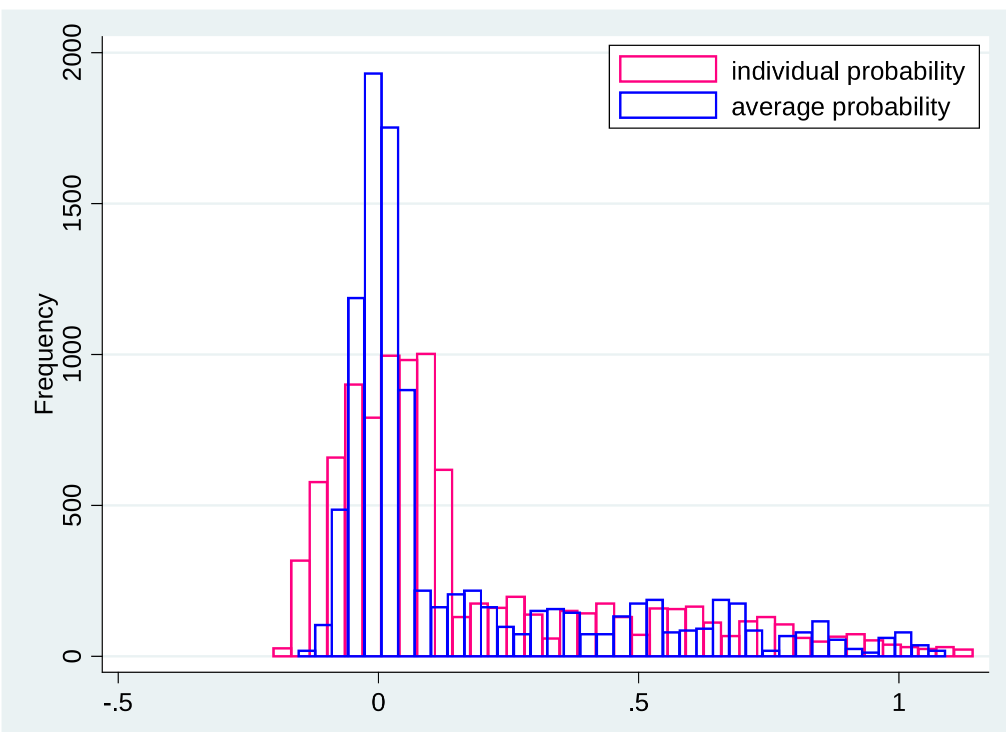


Figure 4: Frequency Plot of Predicted Probability of Being Obese



Chapter 5. Repeated Period Decisions with Information Updating

In this chapter, we continue with a similar framework as in the previous chapter except in each period, the household head updates his/her decisions based on adult health outcomes in previous periods. This assumption may seem more realistic for two reasons. First, health status at the beginning of the period directly affects an individual's ability to conduct some activities, such as consuming food and engaging in leisure activities. Two adults facing exactly the same income constraint may make totally different decisions on consumption and daily activities if their health status is different. Second, an individual's current health status is a result of an especially complex process, including genetic characteristics (for instance, a small share of individuals were born at unusually high birth weights), long-term habits (like diet and exercise), and short-term health shocks. In Chapter 4, individual fixed effects capture the effects of those genetic characteristics and long-term habits that are constant over time, but they can not tell us about the short-term health shocks. Instead, last period's health status can in part reflect the effect of those health shocks. Therefore, a rational person would take advantage of the most recent information in repeating her decisions.

The corresponding empirical econometric model is still the individual fixed-effects model, but as we will discuss later, some complications need to be solved for estimation.

5.1 Theoretical Model

We assume that the adult health status at the beginning of each period affects the decisions by limiting changes in current health. As a result, at period t, given A_t and H_{t-1}, the representative household head chooses consumption, leisure and labor supply by maximizing the value function

$$\begin{aligned}&V(A_t, H_{t-1}, t)\\&= \max\left[U(F_t, C_t, H(F_t, LP_t, M_t, H_{t-1}; Z_t, \varphi), LP_t, LO_t; Z_t, \phi) + S(FS_t; Z_t, \phi) + \kappa V(A_{t+1}, H_t, t+1)\right]\end{aligned}$$

subject to

$$A_{t+1} = (1 + r_{t+1})(A_t + B_t + P_{F,t} FS_t + W_t T - W_t LP_t - W_t LO_t - C_t - P_{F,t} F_t - P_{M,t} M_t)$$

Standard dynamic programming techniques yield the first-order conditions as follows.

Compared with the set of first-order conditions in Chapter 4, current health status directly changes the marginal cost of food consumption, medical services, and physical activities by its effects on future utility $\partial V_{t+1} / \partial H_t$ although it doesn't directly affect the marginal cost of other good consumption, other leisure activities and food stamps. Obviously, it also becomes more difficult to predict how these decisions would change in response to exterior shocks. However, the last equation, *i.e.* the Euler equation, remains the same, which means we can still use the individual fixed effects in our econometric model.

$$\begin{cases} \dfrac{\partial U_t}{\partial F_t} + (\dfrac{\partial U_t}{\partial H_t} + \kappa \dfrac{\partial V_{t+1}}{\partial H_t}) \cdot \dfrac{\partial H_t}{\partial F_t} = \lambda_t P_{F,t} \\ \dfrac{\partial U_t}{\partial C_t} = \lambda_t \\ (\dfrac{\partial U_t}{\partial H_t} + \kappa \dfrac{\partial V_{t+1}}{\partial H_t}) \cdot \dfrac{\partial H_t}{\partial M_t} = \lambda_t P_{M,t} \\ \dfrac{\partial U_t}{\partial LP_t} + (\dfrac{\partial U_t}{\partial H_t} + \kappa \dfrac{\partial V_{t+1}}{\partial H_t}) \cdot \dfrac{\partial H_t}{\partial LP_t} = \lambda_t W_t \\ \dfrac{\partial U_t}{\partial LO_t} = \lambda_t W_t \\ \dfrac{dS}{dFS_t} + \lambda_t P_{F,T} \le 0,\ FS_t \ge 0,\ FS_t(\dfrac{dS}{dFS_t} + \lambda_t P_{F,T}) = 0 \\ \dfrac{\partial V_{t+1}}{\partial H_t} = \dfrac{\partial U_{t+1}}{\partial H_{t+1}} \cdot \dfrac{\partial H_{t+1}}{\partial H_t} \\ \dfrac{\partial V_{t+1}}{\partial A_{t+1}} = \lambda_{t+1} = \dfrac{\lambda_t}{\kappa(1+r_{t+1})} \end{cases}$$

These first-order conditions imply the functions of consumption demands for different goods (F^*, C^*, M^*), time allocation of adults (LP^*, LO^*, L^*), demand for food stamps FS_t and adult health status (H^*) of the form

$$\begin{cases} F_t^* = F(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \varepsilon) \\ C_t^* = C(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \varepsilon) \\ M_t^* = M(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \varepsilon) \\ L_t^* = L(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \varepsilon) \\ LP_t^* = LP(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \varepsilon) \\ LO_t^* = LO(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \varepsilon) \\ FS_t^* = FS(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \varepsilon) \\ H_t^* = H(F_t^*, LP_t^*, M_t^*, H_{t-1}; Z_t, \varphi) = H(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \varepsilon) \end{cases},$$

where ε includes ϕ and φ, i.e., all the unobservable factors that affect the household's preferences and efficiency in accumulating good health of adults. In these demand functions, H_{t-1} captures all the information from previous decisions and affects the household's current decisions on consumption, leisure and participation in the Food Stamp Program.

5.2 Econometric Model

The econometric model in this chapter focuses only on women's choice of health status -- ln(BMI) or being obese (Equation 8). Based on the theoretical model, a woman's health status depends on the household's decision to participate in the FSP, her health status in the last period, her current wage rate, the local current prices of food and medical services, her current observable demographic characteristics (including marriage status, the number of kids and current residence region), her age and age squared, and an individual fixed-effects term.

Equation 8: Health Status Equation

$$\begin{aligned} \ln BMI_{it}[or\ D(Obese)_{it}] = {} & \beta_1 + \beta_2 D(FSP)_{it} + \beta_3 \ln BMI_{it-1}[or\ D(Obese)_{it-1}] + \beta_4 \ln Wage_{it} + \beta_5 PR\_FFruVeg_{it} \\ & + \beta_6 PR\_PFruVeg_{it} + \beta_7 PR\_Meat_{it} + \beta_8 PR\_Dairy_{it} + \beta_9 PR\_Alco_{it} + \beta_{10} PR\_NAlco_{it} + \beta_{11} PR\_FF_{it} \\ & + \beta_{12} PR\_HC_{it} + \beta_{13} Age_{it} + \beta_{14} Age_{it}^2 + \beta_{15} Married_{it} + \beta_{16} Kids_{it} + \beta_{17} Urban_{it} + \beta_{18} NC_{it} + \beta_{19} South_{it} \\ & + \beta_{20} West_{it} + \beta_{21} preg_{it} + \delta_{4i} + \varepsilon_{it} \end{aligned}$$

Some complications arise when estimating this equation. First, we need to control for the endogeneity of the opportunity cost of time measured by the hourly wage rate. Hence, we still fit an hourly wage rate equation (using Equation 7 in Chapter 4) to estimate the predicted hourly wage rate and use it to index an individual's opportunity cost of time.

Second, as the economic model shows, the current decision on FSP participation is endogenous even when the lagged health status is controlled for. Thus, as in Chapter 4, we use non-wage household income and the indicator for MSA residence to instrument current participation.

Third, the presence of lagged health status causes potential autocorrelation. To incorporated this feature of the econometric model, we adopt the Arellano-Bond "difference GMM estimator" (Arellano and Bond 1991). This method uses first-differences to eliminate individual fixed effects term, and then uses Generalized Method of Moments estimation by instrumenting the first-differenced lagged dependent variables by its past levels. This estimator is especially designed for situations with 1) "small *T*, large *N*" panels; 2) dependent variable that depends on its own past realizations; 3) independent variables that are not strictly exogenous; 4) fixed-individual effects; and 5) possible heteroskedasticity and autocorrelation within individuals but not across them.

5.3 Sample Description

We use the same balanced sample as in Chapter 4. However, because of the mechanism of the Arellano-Bond difference GMM estimator, one observation per woman is lost in differencing and another observation is lost due to using lagged health status to instrument for the change in health status. Therefore, the size of sample is now reduced to including only observations from 1994 to 2006, *i.e.*, 4 observations per person. Specifically, for observations in 1994, the dependent variable becomes the change of health status between 1990 and 1994, the independent variable becomes the change of health status between 1986 and 1990, and the health status in 1986 is used as instrument. For observations in 1998, the dependent variable becomes the change of health status between 1994 and 1998, the independent variable becomes the change of health status between 1990 and 1994, and the health status in 1986 and 1990 is used as instruments. For observations in 2002, the dependent variable becomes the change of health status between 1998 and 2002, the independent variable becomes the change of health status between 1994 and 1998, and the health status in 1986, 1990 and 1994 is used as instruments. For observations in 2006, the dependent variable becomes the change of health status between 2002 and 2006, the independent variable becomes the change of health status between 1998 and 2002, and the health status in 1986, 1990, 1995 and 1998 is used as instruments.

5.4 Estimation Results

Table 7 presents the new econometric results. Women who had a larger BMI in the previous period experience a larger BMI decline, and women who were obese in the previous period have a larger reduction in the probability of being obese currently. Specifically, a 10 percent increase in a woman's last period's BMI results in a 3.7% reduction in her BMI in the current period. Other things equal, compared to a woman that was not obese in the last period, the current probability of being obese of a woman that was obese in the last period is lower by about 20 percentage points. Because after controlling for individual fixed effects, last period's health status mainly captures previous health shocks, these results indicate that there is adjustment to partially off-set the effects of previous health shocks.

When a woman's household participates in the FSP, she experiences a significant reduction in her current BMI and probability of being obese. Compared to the results in Chapter 4, the magnitude of this effect is much smaller. If her household participates in the FSP program, it lowers her BMI by 1.12% instead of 15.67%, and reduces her probability of being obese by 3.76 percentage points instead of 56.33 percentage points.

Women who have a higher hourly wage rate have a larger BMI, but not necessarily a higher probability of being obese. A higher price of processed fruits and vegetables results in a larger BMI and a higher probability of being obese, while a higher price of dairy produces results in a lower BMI and a lower probability of being obese. A higher price of fast food increases BMI, but does not affect the probability of being obese. For our sample, women's BMI decreases as they get older. Married women have a larger BMI and are more likely to be obese. But the number of kids in the household does not affect her BMI or the probability of being obese. Pregnant women have a larger BMI, but not a higher probability of being obese. Unfortunately, because the Arellano-Bond difference GMM estimator differences out the individual fixed-effects term before the estimations, we can not get more information about the individual fixed effects.

Table 7: Arellano-Bond Difference GMM Estimations for Female Balanced Sample (sample size of 6,552 = 4*1,638)

Variable	*lnBMI*	*Obesity*
Lag.lnBMI/Lag.Obesity	-0.3716*** (-31.49)	-0.1987*** (-7.51)
D(FSP)	-0.0112** (-2.35)	-0.0376** (-2.35)
lnWage	0.4450*** (2.99)	-0.1274 (-0.26)
PR_FFruVeg	-0.0076 (-0.33)	-0.0135 (-0.17)
PR_PFruVeg	0.0712** (2.15)	0.2197** (1.99)
PR_Meat	-0.0185 (-0.48)	0.0785 (0.61)
PR_Dairy	-0.0578* (-1.85)	-0.3368*** (-3.23)
PR_Alco	0.0390 (1.25)	0.0705 (0.68)
PR_NAlco	0.0149 (0.54)	0.0367 (0.40)
PR_FF	0.1469*** (3.11)	0.1374 (0.87)
PR_HC	0.0060 (0.23)	-0.0187 (-0.21)
Age	-0.0543** (-2.08)	0.0454 (0.52)
Age^2	0.0004* (1.95)	-0.0003 (-0.51)
Married	0.0248*** (7.54)	0.0304*** (2.78)
Kids	0.0006 (0.38)	-0.0003 (-0.05)
Preg	0.0367*** (7.04)	0.0011 (0.06)
Urban	-0.0022 (-0.72)	0.0007 (0.07)

Table 7: (Continued)

Variable	***lnBMI***	***D(Obese)***
NC	0.0226 (1.45)	-0.0119 (-0.23)
South	0.0445*** (2.72)	0.0112 (0.21)
West	0.0116 (0.74)	0.0326 (0.62)
Arellano-Bond test for AR(1) in first differences:		
p-value	0.000	0.000
Sargan test of over-identification restrictions:		
p-value	0.000	0.000

Notes: (1) z-statistics in parentheses.
(2) *** represents statistical significant level in 1%, ** represents statistical significant level in 5%, and * represents statistical significant level in 10%.
(3) The Arellano-Bond test for AR(1) in first differences is to test the autocorrelation over a 4-year rather than a one year period.

Chapter 6. Conclusion

In this paper, we use longitudinal panel data to examine the effects of participation in the Food Stamp Program (SNAP) on women's weight and probability of being obese. We lay out the household utility maximization problem and the econometric models from three different perspectives and also conduct the empirical analyses consistent with these models. An instrumental variable strategy is used to control for the endogeneity of FSP participation, the previous period's weight and the opportunity cost of women's time.

The effects of the FSP (SNAP) on body weight have been an important aspect in assessing the program's impacts because the FSP (SNAP) is available to most people who meet income and resource standards and thus affects a quite broad and diverse population. Our review of the literature discovered mixed effects of a woman's household participating in the FSP (SNAP) on her being obese. Although the earlier studies contained methodological limitations, they were still cited as evidence of the questionable value of the FSP (SNAP) program.

We used three improved economic and econometric models and longitudinal data in our analysis of the effects of FSP (SNAP) participation on women's BMI and likelihood of being obese. Results from fitting the benchmark model, which is an annual model of decision making and close to those appearing in the literature, suggest that women in the households that currently participate in the FSP have a higher BMI and a higher probability of being obese. Other things equal, if the woman's household participates in the FSP, she has a higher BMI by about 1.1% and probability of being obese by about 2.6 percentage points. Two criticisms of this model are that it is not life-time or long-run decision making and does not provide a rationale for including individual fixed effects. These deficiencies can undermine confidence in these results.

In the second and third models, decisions are made in a life-time utility maximization framework and the logical econometric model contains individual fixed effects, which gets free of the main problems of the benchmark model. In the second model, a woman is in a household that participates in the FSP has a 15.67% reduction in BMI and 56.33 percentage points reduction in the probability of being obese. Hence, the FSP participation reduces BMI and probability of being obese in life time utility maximization, which quite different from the first model.

In the third theoretical model, decisions are updated each period based on the previous period's health or health shock. The associated econometric model contains both individual fixed effects and autocorrelation in the health equation. These results suggest that if a woman is in a household that participates in the FSP, it lowers her BMI by 1.12% and her probability of being obese by 3.76 percentage points. Hence, in this third empirical model as in the second, FSP participation also reduces BMI and the probability of being obese.

Although we still do not understand the underlying mechanism causing the weight loss, we believe that models two and three are preferred—when a woman is in a household that participates in the FSP (SNAP) program, she has a lower BMI and a lower probability of being obese. Given the significant cost of the SNAP program, reducing obesity of women can be counted as one of its benefits, rather than an added cost, in policy discussions.

We also find that prices of processed fruits and vegetables, dairy product, alcoholic drinks, non-alcoholic drinks and fast food, play an important role in women's weight. Our results suggest that an increase in the price of processed fruits and vegetables, alcoholic drinks, non-alcoholic drinks, and fast food increases women's weight and probability of being obese, while a higher price of dairy products reduces them. Because the demand schedule for fast food is expected to be negatively sloped, we expected an increase in its price to reduce demand and contribute to reduced obesity, but our findings were in the opposite direction. A possible explanation for our findings is that we did not control for physical activities in our model because of the limitation of our data. Because a change in the price would have an income effect causing a person to adjust his/her demands for leisure, which includes physical activities, the resulting change in body weight is hard to predict or interpret.

These price effects suggest some policies that manipulate food prices to move women to a healthier weight. For instance, if the program were to subsidize those healthy foods where a lower price increases the demand for them, this could lower women's BMI and probability of being obese. Also, the foods that are of the type where a higher price reduces obesity might be designed as excluded from food stamp (SNAP) purchases. This circumvents the resistance by the general public to directly taxing food.

Another important finding of this study is that for some women, the individual fixed effect is the main factor explaining their being obese, or put differently, for these women, the non-fixed effect variables are a minor part of the explanation of them having a large BMI or a higher probability of being obese. Hence, policies targeted to change these non-fixed effect variables would help little to decrease their body weight. For example, for women who currently have a large BMI or are obese, on average it may be very difficult to manipulate prices or other things in their environment to significantly reduce their weight. On the contrary, policies targeted to change individual fixed effects would work better. Because the individual fixed-effects term mainly reflects the effects of genetic characteristics (which are hard to change) and long-term habits, healthy weight programs should target to the early development of self control, healthy eating, and persistent exercise patterns. For instance, the USDA launched the SNAP-Ed in an attempt to help FSP participants make healthier food choices. Although our results covering the period before SNAP-ED, this education program should make some efforts to help obese women improve self control and pursue a healthy lifestyle. This would especially help those young obese women.

Appendix I: Prices of Food and Drinks

1. Food and Drinks Items in Each Food Group

Category	Item	Weight	Description
PR_FFruVeg	Fresh Bananas	0.509678	Price per pound
	Fresh Potatoes	0.245161	10 lb., white or red
	Fresh Iceberg lettuce	0.245161	Head, approximately 1.25 pounds
PR_PFruVeg	Frozen corn	0.083624	16 oz. whole kernel, lowest price
	Canned Peaches	0.386760	29 oz. can, halves or slices
	Fresh Orange Juice	0.445992	64 oz. (1.89 liters) Tropicana or Florida Natural brand
	Canned Sweet peas	0.083624	15-17 oz. can, Del Monte or Green Giant
PR_Meat	T-bone steak	0.237067	Price per pound
	Ground Beef/ Hamburger	0.237067	Price per pound, lowest price
	Sausage	0.221322	Price per pound, 100% pork
	Frying Chicken	0.166892	Price per pound, whole fryer
	Chunk Light Tuna	0.137652	6.0 oz. can, Starkist or Chicken of the Sea
PR_Dairy	Whole Milk	0.369760	Half-gallon carton
	Eggs	0.067366	One dozen, Grade A, Large
	Margarine	0.281437	One pound, cubes, Blue Bonnet or Parkay
	Grated parmesan cheese	0.281437	8 oz. canister, Kraft brand
PR_Alco	Beer	0.498462	Heineken's, 6-pack, 12-oz. containers, excluding the deposit
	Wine	0.501538	Livingston Cellars or Gallo Chablis or Chenin Blanc, 1.5-liter bottle
PR_Nalco	Coffee, vacuum-packed	0.571906	11.5 oz. can, Maxwell House, Hills Brothers, or Folgers
	Coca Cola	0.428094	2 liter, excluding any deposit
PR_FF	Hamburger sandwich	0.333334	McDonald's Quarter-Pounder with cheese, where available
	Pizza	0.333333	11"-12" thin crust cheese pizza; Pizza Hut or Pizza Inn where available
	Fried chicken	0.333333	Thigh and drumstick, with or without extras, whichever is less expensive, Kentucky Fried Chicken or Church's where available

PR_HC	Office visit, doctor	0.425333	American Medical Association procedure 99213 (general)
	Office visit, dentist	0.425333	American Dental Association procedure 1110 (adult teeth cleaning)
	Ibuprofen	0.149334	200 mg, 51 tablets, Advil brand

2. Example: Relative Price of Meat and Fish (*PR_Meat*) in San Francisco

	T-bone Steak	Ground Beef or Hamburger	Sausage	Frying Chicken	Chunk Light Tuna
Local Price	9.32	3.14	4.78	1.55	0.99
Mean Price	8.91	2.30	3.38	1.10	0.69
Weight	0.237067	0.237067	0.221322	0.166892	0.137652

Then *PR_Meat* for San Francisco, CA is calculated as:

$$PR\_Meat = \frac{9.32}{8.91}*0.237067 + \frac{3.14}{2.30}*0.237067 + \frac{4.78}{3.38}*0.221322 + \frac{1.55}{1.10}*0.166892 + \frac{0.99}{0.69}*0.137652$$
$$= 1.316$$

which is 31.6% percent higher than the national average price.

Appendix II: Non-cognitive Abilities

1. Rotter Internal-External Locus of Control Scale

Respondents were asked to select one of each of the paired statements and decide if the selected statement was much closer or slightly closer to their opinion of themselves.

Pair One:
A. (1) What happens to me is my own doing…………………………………………………...…..1
Or
(2) Sometimes I feel that I don't have enough control over the direction my life is taking……...…...…2
B. Is this statement much closer of slightly closer to your opinion?
much closer……………………...…………………………………………………………….1
slightly closer…………………...…………………………………………………………...2

Pair Two:
A. (1) When I make plans, I am almost certain that I can make them work…………………….……….....1
Or
(2) It is not always wise to plan too far ahead, because many things turn out to be a matter of good or bad fortune anyhow……….……………………………………………………….......…...…2
B. Is this statement much closer of slightly closer to your opinion?
much closer…………………………...……………………………………………………….1
slightly closer…………………...…………………………………………………………...2

Pair Three:
A. (1) In my case, getting what I want has little or nothing to do with luck…………………….…….....1
Or
(2) Many time I might just as well decide what to do by flipping a coin………...……………...………2
B. Is this statement much closer of slightly closer to your opinion?
much closer…………………………...……………………………………………………….1
slightly closer…………………...…………………………………………………………...2

Pair Four:
A. (1) Many times I feel that I have little influence over the things that happen to me……………...……..1
Or
(2) It is impossible for me to believe that chance or luck plays an important role in my life……....…...2
B. Is this statement much closer of slightly closer to your opinion?
much closer…………………………...……………………………………………………….1
slightly closer…………………...…………………………………………………………...2

The following shows how the scale is constructed:

Internal Control Item		**External Control Item**	
Much closer	Slightly closer	Slightly closer	Much closer
1	2	3	4

Each of the four paired items is constructed in this manner. The values for each item are then summed. The maximum possible score is 16, indicating high external control, while the minimum possible score is 4, indicating high internal control.

2. Rosenberg Self-Esteem Scale

The questionnaire contains 10 statements of self-approval and disapproval with which respondents are asked to strongly agree (1), agree (2), disagree (3), or strongly disagree (4).

A. I feel that I am a person of worth, at least on an equal basis with others.

B. I feel that I have a number of good qualities.

C. All in all, I am inclined to feel that I am a failure.

D. I am able to do things as well as most others.

E. I feel I do not have much to be proud of.

F. I take a positive attitude toward myself.

G. On the whole, I am satisfied with myself.

H. I wish I could have more respect for myself.

I. I certainly feel useless at times.

J. At times I think I am no good at all.

The scale for each statement ranges from 1 to 4, and is scored in the self-approval direction: the higher the score is, the higher self-esteem. Note that Items A, B, D, F, and G need to be reversed prior to scoring in order for a higher score to designate higher self-esteem.

Appendix III: Regressions for Household Real Non-Labor Income

Variable	***Male Sample***	***Female Sample***
Age	-0.2638* (-2.73)	0.0220 (0.19)
Black	-1.0020* (-1.75)	-6.4156*** (-9.24)
RaceOth	-0.7923 (-1.00)	-0.8383 (-0.98)
Edu	0.3808*** (7.55)	0.5624*** (8.97)
Internal Scale	0.3366** (2.41)	0.3885** (2.17)
Rosenberg Scale	0.0454 (0.81)	0.2528 (3.76)
Married	14.6712*** (28.04)	28.2972*** (50.88)
Kids	-1.5396*** (-7.22)	1.7402*** (7.56)
Ed_Moth	0.4252*** (4.57)	0.8060*** (7.12)
NoEdM	4.3620*** (3.27)	5.4787** (3.15)
Ed_Fath	0.3648*** (4.86)	0.8350*** (9.15)
NoEdF	2.4740** (2.47)	7.3267*** (6.04)
Urban	1.3250** (2.37)	1.8291* (2.68)
MSA	0.9750* (1.94)	3.0919*** (5.05)
NE	3.1375*** (4.18)	2.7400** (2.94)
NC	-1.1559* (-1.74)	-3.6869*** (-4.50)
South	0.3808 (0.47)	-0.5583 (-0.56)
South_14	-0.8150 (-1.11)	-1.7893** (-1.99)
Time Trend	3.9880*** (9.88)	5.2818*** (10.81)
Constant	-15.8179*** (-5.80)	-49.6669*** (-14.60)
Number of Observations	16,687	16,866
R^2	0.1122	0.2736

Notes: (1) Dependent variable is the reported household real non-labor income.
(2) t-statistics in parentheses.
(3) *** represents statistical significant level in 1%, ** represents statistical significant level in 5%, and * represents statistical significant level in 10%.

Appendix IV: Ordinary Least Squares Estimations for Female Sample

Variable	*lnBMI*	*D(Obese)*	*lnBMI*	*D(Obese)*
D(FSP)	0.008* (1.682)	0.028** (2.416)	0.006* (1.742)	0.017** (2.089)
lnWage	-0.004** (-2.480)	-0.013*** (-3.683)		
PR_FFruVeg	0.032* (1.754)	0.061 (1.338)	0.019 (1.123)	0.044 (1.083)
PR_PFruVeg	0.117*** (3.703)	0.265*** (3.362)	0.101*** (3.568)	0.247*** (3.560)
PR_Meat	-0.046 (-1.534)	-0.149** (-2.019)	-0.023 (-0.866)	-0.120* (-1.842)
PR_Dairy	-0.037 (-1.462)	-0.0769 (-1.228)	-0.067*** (-2.999)	-0.153*** (-2.805)
PR_Alco	0.055*** (2.970)	0.092** (2.013)	0.060*** (3.606)	0.084** (2.062)
PR_NAlco	0.063*** (2.744)	0.087 (1.523)	0.082*** (3.979)	0.131*** (2.594)
PR_FF	0.071*** (2.860)	0.064 (1.036)	0.083*** (3.733)	0.104* (1.896)
PR_HC	-0.002 (-0.118)	0.035 (0.808)	-0.007 (-0.449)	-0.002 (-0.054)
Inc	0.0002 (0.923)	0.0003 (0.626)	-0.0002 (-0.839)	-0.0005 (-0.949)
Age	0.0119*** (7.383)	0.0115*** (2.861)	0.0112*** (7.868)	0.0102*** (2.902)
Age^2	-0.0001*** (-5.597)	-0.0001*** (-1.924)	-0.0001*** (-5.732)	-0.0001* (-1.651)
Black	0.056*** (16.74)	0.074*** (8.794)	0.052*** (17.24)	0.059*** (7.998)
RaceOth	0.036*** (10.22)	0.038** (4.383)	0.034*** (10.97)	0.027*** (3.482)
Edu	0.0002 (0.784)	0.0006 (0.844)	0.0003 (1.145)	0.008 (1.133)
NonCog Scale	0.0004 (0.587)	-0.0018 (-0.984)	0.0001 (0.213)	-0.0027* (-1.719)
BMI20	0.0963*** (36.90)	0.0178*** (2.741)	0.0959*** (41.32)	0.0192*** (3.367)
$BMI20^2$	-0.0013*** (-23.43)	0.0008*** (6.091)	-0.0013*** (-26.50)	0.0008*** (6.527)
Married	0.011 (1.547)	0.006 (0.355)	0.020*** (3.226)	0.030** (1.992)
Kids	0.002* (1.894)	-0.001 (-0.193)	0.003*** (3.788)	0.005** (2.107)

Appendix IV: (Continued)

Variable	*lnBMI*	*D(Obese)*	*D(FSP)*	*lnWage*
Urban	-0.004 (-1.453)	0.001 (0.207)	-0.002 (-0.920)	0.005 (0.827)
MSA	0.0002 (0.071)	-0.0025 (-0.379)	0.0002 (0.069)	0.0005 (0.082)
NC	0.015*** (4.373)	0.030*** (2.002)	0.012*** (3.745)	0.020*** (2.650)
South	0.020*** (6.454)	0.035*** (4.405)	0.018*** (6.294)	0.033*** (4.694)
Preg	0.064*** (12.46)	0.038*** (2.959)	0.064*** (14.14)	0.045*** (3.970)
Constant	1.210*** (26.91)	-1.186*** (-10.61)	1.234*** (30.97)	-1.162*** (-11.84)
Number of Observations	15,834	15,834	20,944	20,944
R^2	0.545	0.309	0.525	0.299

Notes: (1) *D(FSP)* and *lnWage* are actual values instead of predicted values.
(2) t-statistics in parentheses.
(3) *** represents statistical significant level in 1%, ** represents statistical significant level in 5%, and * represents statistical significant level in 10%.

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