ABSTRACT

ROBINSON, CHRISTINA ANN. Three Essays on Health Economics. (Under the direction of Robert Clark and Xiaoyong Zheng).

This essay examines topics in health economics. The first study uses data obtained from the Health and Retirement Study (HRS) and the Rand HRS files, to examine the relationship between access to retiree health insurance (RHI) and the decision to leave one's career job. This paper does not restrict attention to individual's who choose to take a full retirement, as recent data indicates that only 51.4% of individuals leave a career job and fully retire, while nearly 25% leave their career job, and pursue a partial retirement. In this paper a Cox Proportional Hazard Model with time varying covariates is utilized to estimate the probability that an individual disengages from their career job, given they have not yet done so. Results indicate that those with access to RHI are significantly more likely to leave their career employer in all time periods than identical individuals without RHI.

The second essay uses data obtained from the NLSY79 Child/Young Adult Survey, to examine the relationship between a household's Food Stamp Program (FSP) participation, and child overweight and obesity. This paper considers a dynamic process for weight gain—explicitly modeling the role last period's weight plays in determining this period's weight. To measure obesity, a child's BMI is compared to the ideal BMI for the child's age, height, and gender. Results suggest that FSP participation does not significantly affect the deviation of a child's current BMI from the ideal level, indicating that FSP participation does not contribute to childhood obesity. Further, I find that a child who becomes more overweight in one period, will become less overweight in the next, indicating that children tend toward their

medically ideal weight. Both results are robust across sample specification and hold for all children ages 5-18, regardless of age, gender, and household income.

The third essay considers a related issue. There is a wide body of literature that examines the effect of FSP participation on obesity outcomes for adults and a smaller body of work that examines the same relationship for children. The literature focusing on adults finds that FSP participation is positively related to obesity in women, while work focusing on children fails to find a similar effect. This creates an interesting economic puzzle as most children live in the same household as their mother, and as such, the foods they consume and the effect of that food on their weight are expected to be similar.

In this paper I directly address this puzzle, and examine the relationship between a mother's Food Stamp Program (FSP) participation, and obesity. To this end I perform three separate and distinct analyses. First I consider weight accumulation as an AR-1 process and explicitly model the role last period's weight plays in determining this period's weight. Results suggest that FSP participation does not significantly affect a mother's BMI but does affect a non-mother's. This indicates that FSP participation affects the two groups differently and further that women who are not mothers are driving the effect identified in previous literature. However, because this is the first paper to model weight as an AR-1 process there is no prior expectation of the effect of FSP participation in such a framework.

Thus, I further examine this finding using a Cox Proportional Hazard model to identify the effect of FSP participation on the probability that a mother becomes obese given she is not currently obese. Results from this estimation indicate that mothers do suffer an increased risk for obesity given FSP participation. However, there are several forms of bias

that plague this estimation, and so, I perform an additional estimation and directly examine the food purchasing behavior of FSP households.

For this part of the analysis I use data from the A.C. Nielsen HomeScan survey to examine the food purchasing decisions of FSP eligible households and compare the healthiness of foods purchased by households with and without children. Results from this estimation indicate that households with children purchase significantly healthier food than households without. Thus, it is not surprising that children who live in FSP households are not at an increased risk of obesity, and the puzzle is resolved.

Three Essays in Health Economics

by
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DEDICATION

To my mother and father who have always believed in me

To Joshua who never doubted me

BIOGRAPHY

Christina Ann Robinson was born to Daniel and Theresa Robinson on November 11th, 1981. While attending Maynard High School she played soccer and ran track. Christina graduated in 2000 and attended Bentley College in Waltham, MA where she received her Bachelors of Science in Economics with a minor in Mathematics in May 2004. The following fall she entered the Ph.D. program in Economics at North Carolina State University. As a graduate student Christina served as a teaching assistant, an independent instructor and a research assistant. Upon graduation from North Carolina State University, Christina will begin a faculty appointment in the Department of Economics at Missouri State University in Springfield Missouri.

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Retiree Health Insurance and Disengagement From a Career Job

I. Introduction

Over the past decade or so the face of retirement in America has begun to change. In the past it was common for older workers to leave full-time, year-round employment and enter a state of full retirement during which they did not work and lived off their savings, annuity payments, and social security benefits. The more recent trend (beginning in the mid-1990's) has been for workers to leave their career job and enter a state of partial retirement during which they work fewer hours and enjoy more time as leisure. Empirically, it has been found that nearly 60% of individuals who leave a career job after age 50 do so in a gradual manner (Cahill et al., 2006). As the face of retirement changes, so must the way in which we evaluate the effect of retirement benefits. Specifically, we must now consider how retirement benefits influence a worker's decision to separate from his/her career job, not from the labor force as a whole.

Having the ability to truly characterize the effect of RHI on the labor market transitions of older workers is of significant interest to a wide variety of groups including firms, human resource departments, and policy makers. Each of these groups is dealing with the fact that the current workforce is aging and being replaced by a smaller population of working individuals. The key to managing this transition is to fully understand the factors that affect an individual's decision to remain in the labor force or to curtail their labor market participation. A solid understanding of these factors will allow these groups to design benefit

packages that will attract and retain high quality workers and manage the departure of current workers in an efficient manner.

One retirement benefit that has received a considerable amount of attention in economic literature, and whose value may be underestimated when individuals who phase into retirement are excluded from empirical analysis, is Retiree Health Insurance (RHI). RHI is an employer-sponsored benefit that provides health insurance coverage to retired individuals who meet the eligibility criteria.[1] Plans typically include medical and prescription drug coverage and may or may not be available to retirees after they become Medicare eligible. Previous studies have focused their attention on identifying the effect of RHI on the decision to retire fully (i.e., transition directly from a state of full-time employment to full-time retirement).

The effect of RHI on the transition from full-time employment to full-time retirement has been examined closely in previous literature. Mermin, Johnson, and Murphy (2007) compare the labor force trends and retirement expectations of baby-boomers to a cohort of individuals 20 years their senior. They found that the baby-boomers are working later into life, are more likely to have a Defined Contribution (DC) than a Defined Benefit (DB) pension plan, and are less likely to have access to RHI than the previous generation. In both generations, those with RHI anticipate retiring earlier in life than those who do not have access to such benefits. Marton and Woodbury (2006) directly estimate the probability that

[1] The requirements for benefit receipt often include: a minimum duration of tenure with a company, enrollment in an employer sponsored retirement plan, and a minimum age at which an employee separates from the firm.

an individual retires in 1994 (1996) given a failure to do so in the previous period, 1992 (1994). They found that those who are offered RHI tend to retire at a younger age than those who are not.

This paper contributes to the literature in two main ways. First, this paper estimates a hazard function, with time varying covariates, to model the effect of RHI on the labor market transitions of older workers. Previous work, such as that of Marton and Woodbury (2006), was based on a conditional probit model and utilized only an individual's initial condition in the empirical analysis. The flexibility with which duration analysis can accommodate time-varying covariates allows me to include an individual's past and current characteristics into the empirical analysis. This is critical as individuals base their labor market choices on their past and present conditions. Thus, the hazard model estimated in this paper will be based on a more accurate picture of an individual, which increases the model's ability to estimate the effect of RHI benefits on the decision to leave a career job.

Second, this work accounts for the increased prevalence of phased retirement by estimating the probability that a worker leaves their career job which, for the purposes of this analysis, is defined as any job that an individual has worked at on a full-time basis for a minimum tenure of 10 years. This paper is not concerned with the behavior of an individual once they disengage from their career employer and does not distinguish between those who fully-retire and those who take a phased retirement. This will provide a more accurate estimate of the role RHI plays in the labor force participation decisions made by older workers. Additionally, this work employs more recent data from the Health and Retirement

Study (HRS), which will provide a fuller view of the labor-market transitions made by older workers. I expect that workers who have access to RHI will leave their career job at a younger age than those who do not, and that they will enjoy a significantly longer period of time away from a state of full-time employment.

Consistent with the findings from previous literature I find that workers with RHI are significantly more likely to disengage from a career job. Specifically, I find that individuals with access to RHI are 21.20% more likely to leave their career job in any given time period than a similar individual who does not have access to RHI.

The remainder of this paper is organized as follows: the next section provides an overview of literature related to RHI and retirement behavior. The third section presents a theoretical model of the labor-leisure choice and the empirical model used to derive the probability of disengaging from a career employer. The fourth section describes the data obtained from the HRS and Rand HRS data files. The fifth section presents empirical results and is followed by a section devoted to model diagnostics. The seventh section concludes.

II. Literature Review

There is a well-developed body of literature exploring the various factors that influence the decision to retire, a subsection of which is devoted to examining the effect of RHI benefits on the retirement decision. This work has not only explored how access to RHI affects the decision to retire, but has taken into consideration how various personal and plan characteristics are likely to interact with RHI. Some of the individual specific factors

considered in the research include an individual's current health status, age, and pension enrollment. Research on plan characteristics has focused on cost-sharing agreements, and the monetary cost of obtaining RHI. This paper expands the scope of the existing literature, and considers the effect of RHI on the decision to leave a career job (regardless of an individual's subsequent labor market activities).

Access to a RHI plan mitigates the financial risk of retiring early in life, as the benefits provide protection against the high costs associated with unforeseen health problems. Assuming that the majority of individuals are (at least to some degree) risk averse, access to RHI is likely to increase the probability and prevalence of early retirement. Headen, Clark, and Ghent (1995) used data from the 1988 August Supplement of the Current Population Survey to carefully identify individuals who had access to RHI. Empirically they estimate an ordered probit model and identify the effect access to RHI has on the probability that they separate from their career employer. They find that RHI increases the probability that a person is retired by 42 percentage points, and that access to RHI increases the probability an individual leaves the labor force at a young age (relative to those without access to RHI benefits).

Blau and Gilleskie (2001) used data from the 1992 and 1994 waves of the HRS to estimate the labor force participation patterns of men between 51 and 62 years old. They found that RHI increases the labor force exit rate by 2-6 percentage points depending on the cost sharing agreement between a worker and their employer but does not significantly affect the probability that a worker will change jobs. Their estimation, however, excludes certain

labor market transitions; within their framework individuals are only permitted to leave the labor force completely or to switch jobs. Thus, individuals who partially retire but do not switch employers are not considered to have experienced a labor market transition. Such an individual would be classified as remaining on the same job although they have transitioned from full-time to part-time employment. Thus, the number of individuals who have made a change in their employment status may be underestimated which may lead to an underestimate for the effect RHI has on the decision to retire.

Marton and Woodbury (2006) use HRS data from the 1992, 1994, and 1996 waves to further expose the impact RHI benefits have on the retirement decision. They estimate the correlation between RHI and the retirement behavior of older men through conditional probit estimation. Specifically, they model the probability that an individual retires in 1994 (1996) given they were working in 1992 (1994) and the probability that a person who was working in 1992 is retired by 1996. Their findings indicate that RHI benefits significantly increase the probability that a worker leaves the labor force. Further, they find that RHI has a greater effect on the probability of retiring in 1994 than in 1996, which serves as evidence that individuals are more likely to enroll in RHI at younger ages than they are as they approach Medicare eligibility. Their work is strictly concerned with the effect of RHI on retirement and does not consider the effect RHI has on the decision to obtain a new job or to reduce the number of hours of work per week; both of which, are important decisions likely to be affected by access to RHI.

This paper is also concerned with the effect of RHI on the labor market transitions of older workers and builds on the work of Blau and Gilleskie (2001) and Marton and Woodbury (2006). Unlike the work of Blau and Gilleskie (2001), the empirical analysis performed in this paper includes all individuals who leave their career job, regardless of what they do afterward. While Blau and Gilleskie only consider the effect of RHI on the probability of leaving a career job and taking either a full retirement or switching to a different employer, this paper is interested in all labor market transitions. This model is more inclusive and considers those who take a full retirement, who reduce their hours at their current job (i.e. cut back from full- to part-time), those who leave their career job and become a part or full-time employee elsewhere, and those who leave for a variety of other reasons.

The paper also builds on the work of Marton and Woodbury (2006) by estimating a full hazard model, which by nature of being a true duration model is better equipped to handle the dynamic nature of the labor force participation decisions that older workers are making. Additionally, Marton and Woodbury (2006) only estimate the effect of RHI on the probability of leaving a full-time job, and taking a full retirement. Like the work of Blau and Gilleskie (2001) the work of Marton and Woodbury (2006) excludes those who chose a phased/partial retirement.

Access to RHI is not the only measure of interest; the cost of the plan is also expected to play a large role in the retirement decision. In general, the cost sharing agreement between a firm and an active employee will differ from the agreement between a firm and a retiree. If

the premium paid by the retiree is greater than the premium paid by an active employee the real value of the benefit is reduced. Thus, while access to RHI is expected to significantly lower the age at which a person retires, high cost plans are expected to have a smaller effect on the retirement decision than low cost plans. Empirically it has been shown that a high premium cost (relative to the cost paid by an active employee) reduces the effect RHI has on the retirement decision (Johnson, Davidoff, and Perse 1999).

The characteristics of an individual, including their age, health, and wealth, are other factors that play an important role, in the retirement decision. These factors are expected to either enhance or detract from the effect of RHI. While RHI is an attractive benefit offered to an employee, a person who is in good health, with a long expected life span, may behave differently than a person in poor health who has a shorter expected life span. Since those who are likely to live-longer need to spread their consumption over a longer period of time, it is expected that, regardless of access to RHI, they will delay retirement longer than a similar person who is in poor-health. Thus, it is expected that RHI will have a greater influence on the behavior of the less healthy. Linsenmeier (2002), however, finds that the effect of RHI is not significantly different for a person in poor health than for a person in good health.

Age has an important influence on the retirement decision of individuals, as an additional year of work reduces the time until an individual becomes Medicare eligible. The closer an individual is to becoming Medicare eligible, the lower the value of RHI becomes. As such, people who are offered RHI are likely to retire at a relatively young age in order to extract as much value from the benefit as possible. As an individual approaches the age of

Medicare eligibility they become less likely to take an early retirement (regardless of RHI offerings), as each additional year of work reduces the probability that the benefits of early retirement outweigh the costs. Empirically, Marton and Woodbury (2006) found that RHI has a significantly greater effect on the retirement behavior of younger workers than on that of older workers.

III. Modeling The Retirement Decision

This paper strives to explain the connection between access to RHI benefits, and an individual's decision to leave their career job. To understand the decision to disengage from a career job I follow Heckman (1978 and 1981) and consider a simple dynamic model of discrete choice. In this framework individuals choose their labor market participation status in each observable time period. Agents are assumed to maximize their lifetime utility subject to their lifetime budget constraint.

In each consecutive time period individuals must decide whether it is utility maximizing to remain at their career job ($D = 0$), or leave their current state of employment and disengage from their career employer, ($D = 1$). $V = V(D,i,t)$ is the expected present discounted value of lifetime utility for individual i, given their labor market participation status, in time period t.

Thus, the expected lifetime utility for individual i, given they continue to work their career job at time t, is given by,

(1). $V_0 = V(0,i,t)$.

While the expected lifetime utility for individual i, given they disengage from their career job at time t, is given by

(2). $V_1 = V(1,i,t)$

When deciding to leave a career job, or to remain a career worker, individuals compare (1) to (2), and choose to leave their career job when $V_0(0,i,t) < V_1(1,i,t)$, which indicates that the expected lifetime utility from leaving a career job is greater than that from continued employment at a career job.

Empirical Model

The dynamic nature of labor market participation choices made by individuals, and the many changes that older workers face necessitates a model that captures the transitions individuals are going through. Duration analysis easily accommodates time varying covariates and as such, is ideal for this context where an individual's current situation plays a significant role in their decision to retire in each period. Within the realm of standard duration analysis lays three separate and distinct parameterization strategies.

The first, nonparametric analysis, does not require any assumption about the distribution of failure times (i.e., the baseline hazard), and does not include covariates. This modeling technique essentially lets the data speak for itself and models the time to occurrence based solely on the passage of time. The second modeling approach is to utilize semiparametric analysis, which does not require an assumption about the baseline hazard, but parameterizes the effect of covariates. Finally, the third modeling approach, parametric estimation, requires an assumption about the shape of the baseline hazard and includes

covariates in the analysis. In general, semiparametric models are more robust than parametric models, since they do not assume a distributional form for the baseline hazard and are preferred to nonparametric models as they permit covariates to enter the analysis.

Regardless of parameterization method employed, hazard function estimation (duration analysis) is preferred to conditional probit/logit estimation when a dynamic decision is being analyzed and the primary point under analysis is the length of time before an individual exits an initial state. Duration analysis is preferred to conditional probit/logit estimation for its flexibility and ability to analyze the probability of a failure occurring, given lack of a failure in any previous period. Logistic estimation would require estimation be based on the probability of failure in period t, given lack of failure in some previous period, for example, $t-1$. Hazard models, on the other hand, can easily accommodate the changing conditions which individuals must constantly adapt to, and consider in their decision making process. As such, they are able to capture the dynamics of decision making over a broader time period than conditional logit and probit estimation, and thus, truly estimate the probability of failure, given failure has not yet occurred.

To model the instantaneous probability of disengaging from a career job, given an individual has not done so in previous periods, I follow the approach laid out in Cleves, Gould, Guitierrez, and Marchenko (2007). First, consider the survivor function, $S(t)$, which represents the probability of remaining at a career job past time t, or alternatively, is the probability that an individual has not yet disengaged from their career employer. The survivor function is defined as,

(3). $S(t) = 1 - F(t) = \Pr(T > t)$,

where t, is the period in which an individual leaves their career job, or censoring occurs. By definition, $S(t)$ is simply one minus the cumulative distribution function of T, F(t), and thus, the density function, $f(t)$, can easily be obtained from $S(t)$, as

(4). $f(t) = \frac{dF(t)}{dt} = \frac{d}{dt}\{1 - S(t)\} = -S'(t)$.

Utilizing (3) and (4) the hazard function, $h(t)$, which represents the instantaneous rate of failure, can be shown to be,

(5). $h(t) = \lim_{\Delta t \to 0} \frac{P[t + \Delta t > T > t \mid T \geq t]}{\Delta t} = \frac{f(t)}{S(t)}$.

From (5) it is easy to see that when failure becomes more (less) likely, the hazard increases (decreases), while the survivor rate decreases (increases).

Due to the merits of semiparametric techniques, I employ the Cox proportional hazard model, which specifies the hazard function as,

(6). $h(t) = h_0(t)\exp\{\beta_0 + x_{it}\beta_x\}$,

where, $h_0(t)$ is the baseline hazard, for which no distributional assumption has been made, and x_{it} defines the path of all covariates (some of which are time-varying), for individual i from time t to time $t + \Delta t$.

The likelihood function is, given by,

(7). $L = \prod_{i=1}^{n} h(t) \times S(t)$,

from which, estimates for each β_x are obtained via maximum partial likelihood estimation. The cumulative hazard, $H(t)$, is the total risk of failure over the time period of analysis and can be calculated from the hazard as,

(8). $H(t \mid x) = \int_0^t h(u \mid x)du.$

IV. Data

I use data obtained from both the HRS and the Rand HRS files to estimate the effect RHI benefits have on the hazard of disengaging from career employment. The HRS is a biennial survey of older Americans (as least 50 years of age). The modern survey is the combination of two similar studies, the "original" HRS study and the "AHEAD" (Asset and Health Dynamic among the Oldest Old) study. The original study took place in 1992, 1994 and 1996, and interviewed individuals born between 1931 and 1941. The AHEAD study took place in 1993 and 1995, and employed a sample of those born prior to 1923. In 1998 the two studies were combined, and two additional cohorts (CODA and War Babies) were created. The first new cohort, the CODA group, included American's born between 1924-1930. The War Babies is a cohort that includes those born between 1942 and 1947. In 2004 a fifth wave, the Early Baby Boomers (those born between 1948 and 1953), was added.

The HRS is designed to provide information about the life experiences of aging Americans. To be eligible for survey participation an individual must be at least 50 years of age at the time the cohort enters the survey or be married to (and currently living with) an

eligible individual. Respondents are asked a broad series of questions about their past actions, their present condition, and their expectations about the future. Specifically they are questioned about their financial status, their physical and mental health, their retirement plans, their insurance status, and their employment status.

The RAND HRS data set is an easy to use version of the classic survey that combines data from previous survey waves with data collected from one's spouse to impute missing values and increase the data set's richness. The RAND data also contains additional variables, which are created by combining responses from several HRS questions. RAND constructed variables used in the empirical estimation are an individual's marital status, labor market status, assets (including pension wealth), and health. I also consider a spouse's health, and the number of hours worked per week.

A career job is defined as any job that an individual has worked on a full-time basis for at least 10 years. A person is considered a full-time employee if they spend 30 or more hours per week at work. Restricting tenure to at least 10 years is necessary, as workers generally need to meet a service requirement before becoming eligible for RHI benefits. An agent is considered to have disengaged from their career employer the first time they report a labor market status other than "working full-time"—this may indicate that an individual has: fully retired, partially retired, become unemployed, started working part time, or otherwise left the labor force.

In 1992 the HRS consisted of 12,652 individuals of which 46.38% were male, and the average age was 55.2 years. Within this group 81.24% of individuals were married or living

with a partner, 77.71% of individuals reported being in good health, and 80.30% of individuals had a spouse who reported good health. 52.87% had at most a high school diploma, while 20.30% had at least an associate degree. 52.56% of respondents were full-time workers, who worked an average of 40.25 hours per week, and had an average tenure of 16.08 years. 46.46% received health insurance from their current employer, of which 77.33% were able to extend this coverage after retiring from their job. 62.13% were enrolled in a DB pension plan, 34.67% were enrolled in a DC plan, and 3.20% were enrolled in both a DB and a DC plan. These summary statistics are presented in Table 1.1.

To estimate the effect RHI has on the decision to leave a career job, I restrict the sample to those who were between 50 and 60 years of age in 1992, which reduces the sample to 9,356. Eliminating anyone who is not classified as a full-time employee in 1992 reduces the sample to 5,660, and removing those with fewer than 10 years of tenure (in 1992), reduces the sample to 3,123. These large drops are the result of low response rates to the questions asking about labor market participation (specifically hours worked per week, and duration of tenure) and the demographic makeup of the overall sample. For example, women represent nearly 55% of the overall sample, of which only 44% were working full-time in 1992. I next, remove those who reported having more than 50 years of tenure and reduce the sample to 3,119. Then anyone who reported working more than 60 hours per week is removed, which results in a sample of 3,042. Finally, I eliminate anyone who did not respond to the question: "Does the organization have any health insurance plan available to retirees?" resulting in a final sample of 2,102 observations.

In the final sample used in estimation, 60.79% were male, and the average age was 54.68 years. Within this group 80.11% were white, and 17.51% were black. 76.50% were married or living with a partner, 88.73% reported being in good health, and 85.16% had a spouse in good health. 50.76% had at most a high school diploma, and 27.78% had an associate degree or higher. On average they worked 42.70 hours per week, and had 23.99 years of tenure. 99.76% of these full-time workers obtained health insurance from their current employer, while 76.93% were able to extend this coverage into their retirement. 58.80% were enrolled in a DB pension plan, 23.45% were enrolled in a DC pension plan, and 3.18% were enrolled in both. These summary statistics are presented in Table 1.2.

Comparing Tables 1.1 and 1.2 indicates that men constitute a larger portion of those working a career job than they do in the full sample. Otherwise, those working at a career job are demographically similar to the full sample. They are, however, in better health than the full sample and have healthier spouses. Professionally, the two groups are significantly different. Career workers have been at their job longer, work more hours per week, are more likely to have employer provided health insurance, and are more likely to be enrolled in a pension plan (both DB and DC). Additionally those working a career job are also more likely to be public sector employees.

Table 1.3 presents employment trends for individuals who were working full-time in 1992. Panel 1 shows the trend for the group as a whole, while panel 2 presents the employment patterns for those with RHI. Panel 3 displays the employment patterns of those without RHI. The first column of the first panel indicates that only 34.15% of individuals

working full-time in 1992 were still working full-time in 2006. The first column of panel 2 indicates that only 32.90% of individuals with access to RHI, who were working full-time in 1992, remained full-time workers in 2006. The first column of the third panel indicates that 39.16% of individuals without access to RHI, who were working full-time in 1992, were still working full-time in 2006. The information presented in Table 1.3 provides preliminary support to the hypothesis that access to RHI benefits increases the propensity for individual's to leave a full-time job. Table 1.4 presents the same information for individuals who were working a career job in 1992 and has the same implications.

V. Results

To estimate the probability of disengaging from a career job, and the effect RHI has on this decision, I first estimate the Kaplan-Meier cumulative empirical hazard. The Kaplan-Meier cumulative hazard function is a non-parametric tool that estimates the time-to-failure. The first panel of Table 1.5 provides Kaplan-Meier estimates for all individuals working a career job in 1992, the second panel provides Kaplan-Meier estimates for individuals with access to RHI, and the third panel provides Kaplan-Meier estimates for those without access to RHI. Table 1.5 indicates that the hazard grows with age. For example, in 1996 the average age of those in the sample is 58.5 years, and the cumulative hazard is 0.462. This should be interpreted as, the probability of disengaging from a career job in 1996, given continued employment until that point, is 46.2%. In 2004 the average age in the sample is

65.5 years and the cumulative hazard is 0.916, indicating that the probability of leaving a career job (given an individual has not yet done so) has risen to 91.6%.

Consistent with theory, the second and third panels indicate that the cumulative hazard for those with and without RHI follows the same trend as the overall sample, and further, that the cumulative hazard is greater for those with access to RHI than for those without (for all periods except the 1994 to 1998 period, in which the hazard rates are identical to 2 decimal points). In 1996 the cumulative hazard for an individual with RHI was 0.474, while in 2004 it was 0.922. For individuals without access to RHI the cumulative hazards are 0.421 and 0.897, respectively. The Kaplan-Meier cumulative empirical hazard is shown in Figure 1.1, which indicates that those with RHI have a higher cumulative hazard in (nearly) all time periods relative to those without, the only exceptions being the 1992 to 1994 and 1998 to 2000 periods.[2] Figure 1.2, displays the smoothed non-parametric hazard, $h(t)$, and indicates that those with RHI have a higher instantaneous probability of disengaging from their career job, over the time period of interest. The parallel nature of the lines indicates that the proportional hazard assumption is valid for use in estimation.

Next, I test for equality of the cumulative hazard functions to determine if there is a difference in the hazard rate for those with and without access to RHI. To this end I perform

[2] In the 1992 to 1994 period this may be the result of individuals with access to RHI remaining on their career job in order to meet the service requirements for coverage. In the 1998 to 2000 period the average age of individuals remaining on their career job is 62. Since this corresponds to the age at which individuals become eligible for early retirement benefits from Social Security, it is expected that there will be a large group of individuals leaving the labor force at this time, regardless of access to RHI. In empirical estimation an alternative specification using binary age variables was considered, and the empirical results are not affected.

the Log-Rank and Wilcoxon tests. Both tests compare the survival experiences of r different groups and test the equality of these experiences. Both assume a null-hypothesis that the survival experiences (of all groups) are the same, and both employ a chi-square test statistic with $r-1$ degrees of freedom. The primary difference between the two tests lies in the weighting scheme utilized. The log-rank test applies a weight equal to 1 in all periods, while the Wilcoxon test applies larger weights to earlier periods, so that failures occurring when the number at risk is large receive more weight than failures that occur when the number at risk is small.

The results of these tests are presented in Tables 1.6 and 1.7 respectively. The "events observed" column displays the number of actual failures that are observed for each group, while the "events expected" column displays the number of failures that would be expected to occur if the survival experiences of the groups are the same. When the two columns are significantly different, the test statistics will be large, indicating that the groups have different hazards. The test statistics for the log-rank and Wilcoxon tests are 2.26 and 1.39 respectively, and the critical value for a chi-square with an alpha of 0.05 and one degree of freedom is 3.84. Thus, both tests fail to reject the null hypothesis that the two survival functions are equal. However, this is not cause for concern, as the model does not yet contain covariates, and thus RHI may still be found to significantly affect the instantaneous probability of disengaging from a career job.

Covariates are added to the model, and a semi-parametric Cox proportional hazard model is estimated. Table 1.8 displays both the parameter coefficients and the hazard ratio

for all covariates included in the model. The discussion that follows focuses on the hazard ratios for model 1, which is the preferred specification.[3] Hazard ratios are the exponentiated parameter coefficients and indicate whether a change in an important covariate makes failure more (or less) likely. A hazard ratio that is equal to 1.0 indicates that an increase in a covariate has no effect on the probability of failure, a hazard ratio greater than 1.0 indicates that an increase in a covariate makes failure more likely, and a value less than 1.0 indicates that an increase in a covariate makes failure less likely.

Depending on the nature of the covariate (i.e., dichotomous or continuous), hazard ratios either compare the hazard rate of one group to another group or compare the hazard after a change in a covariate to the hazard at its original value. For example, the hazard ratio for RHI is 1.212, which indicates that individuals with RHI are 21.20% more likely to disengage from a career job than an individual without RHI. The hazard ratio for good health is 0.647, which indicates that individuals who are in good health are 35.30% less likely to disengage from a career job in any period than individuals in poor health. The hazard ratio for continuous covariates is interpreted similarly to that for a dichotomous covariate. For example, the hazard ratio for age is 1.128, indicating that becoming a year older increases the probability of disengaging from a career job by 12.80%.

Consistent with theory and the hypothesis of this paper, empirical results indicate that access to RHI increases the probability of disengaging from a career employer by 21.20%.

[3] Model 1 is preferred over model 2 as both its Akaike's information criteria (AIC), and the Bayesian information criteria (BIC) values are lower than model 2's. AIC and BIC are competing model selection criteria under which, models with lower values are preferred over those with higher values.

Also of significance are: gender, age, race, own-health, disability status, marital status (at the 10% level), household assets (at the 10% level), and enrollment in a DB pension plan. Growing a year older increases the probability of disengaging from a career job by 12.80%, participation in a DB pension plan increases the hazard by 21.10%, and an increase in assets increases the hazard by 0.60%. Being male reduces the hazard by 16.30%, being in good health reduces the hazard by 35.30%, and being disabled reduces the hazard by 81.10%. The estimated Cox proportional hazard is shown in Figure 1.3. In Figure 1.3, the hazards for those with RHI and those without are approximately parallel, which further supports the proportional hazard assumption.

Table 1.9 displays the predicted disengagement trends (for individuals working at a career job in 1992) based on the estimated hazard function. The trends are consistent with those presented in Table 1.4 and indicate that individuals with access to RHI will disengage from their career employer at a faster rate than individuals without access to RHI. Comparing Tables 1.4 and 1.9 indicates that the model does a reasonably good job of predicting disengagement activities between 1992 and 2002; beyond which, the model over predicts disengagement activity. For example, in 2004 the data indicate that 384 (10.53% of) individuals who were working a career job in 1992 are still working at a career job. The model predicts that only 89 (2.44% of) individuals who were working a career job in 1992 will remain with their career employer.

A model including an interaction term between access to RHI and employment in the public sector[4] is presented as model 2 in Table 1.8. This term is intended to capture the fact that public sector employees are more likely to have RHI coverage than private sector employees. Specifically, of those working a career job in 1992, 88.67% of public sector employees had access to RHI, compared to only 76.02% of private sector employees. Empirical results indicate that this interaction term is insignificant and does not affect the estimation outlined above. This result, however, may be due to the difficulty associated with identifying public sector employees in the HRS data.[5] It is likely that public sector employees are under identified, and thus the effect of this interaction term may be understated.

VI. Model Diagnostics

To test the strength of the preferred model I estimate stratified Cox models and perform a link test and a direct test of the proportional hazard assumption. Recognizing that all individuals may not share the same baseline hazard, which would invalidate the pooled analysis, I test the model's robustness and estimate two stratified Cox models. These stratified models allow individuals to have different baseline hazards, depending on group membership—for example, it is possible that those who work in the public sector have a

[4] Public sector employees are all those who work for a (national, state, or local) government agency.

[5] From the HRS data it is not possible to identify all public sector employees as the majority are included in the public administration industry code, but teachers are not. Teachers are included in the professional and related services industry, which also includes doctors, lawyers, accountants, and thus, cannot be identified as public sector employees.

different baseline than those who work in the private sector. If the hazard ratios obtained from estimating the stratified Cox models differ greatly from those obtained from non-stratified estimation, this may indicate that the estimated effect of RHI on career job disengagement may not be robust. The first stratified model is based on employment in the public sector, and the second is based on gender. Estimates from the stratified models are presented in Table 1.10. Due to the similarity of the hazard ratio estimates between the stratified tests and estimates from the non-stratified Cox model, I conclude that the hazard functions are the same for all groups. This finding serves as evidence that the results of the non-stratified Cox proportional hazard model estimation are robust.

While the Cox proportional hazard model does not assign a specific distribution to the baseline hazard, the proportional hazard assumption requires that the baseline hazard is the same for all individuals in the sample. When performing duration analysis and, specifically, when estimating a proportional hazard model, it is critical that the proportional hazard assumption be satisfied. A violation of the proportional hazard assumption suggests that the model is incorrectly specified and that parameter estimates are likely biased. A model that is found to satisfy the proportional hazard assumption is assumed to be well parameterized and properly specified. To this end, I perform two tests; the first is the link test, and the second is a direct test.

The link test is a diagnostic tool used to detect specification error due to the presence of omitted variables. The test is performed in two stages. In the first stage $\hat{\beta}_x$ is obtained from estimating the Cox proportional hazard model. In the second stage the estimated value

is used in estimating, $x\beta_x = \beta_1(x\hat{\beta}_x) + \beta_2(x\hat{\beta}_x)^2$. If the squared linear predictor does not have significant explanatory power then, $\beta_1 = 1$ and $\beta_2 = 0$. Results from the link test are presented in Table 1.11. The estimate for β_2 is 0.095, and the standard error is 0.052, indicating that the squared linear predictor $(x\hat{\beta}_x)^2$ is insignificant at an alpha level of 0.05. This result indicates that the linear predictor contains the appropriate covariates and does not suffer from omitted variables bias.

Next, I directly test the proportional hazard assumption by interacting each covariate with analysis time and checking the significance of the new variable. If a variable is significant when interacted with time, this is seen as a violation of the Cox proportional hazard assumption. The Cox proportional hazard assumption requires a change in the level of a (non-time varying) covariate, to produce a multiplicative change in the baseline hazard function, independent of time. Since there are many covariates included in model 1, and each will be tested for time-interaction simultaneously, I utilize the Bonferroni adjustment. The Bonferroni adjustment is used to protect against type-1 errors when simultaneous statistical tests are being performed, and define the significance level to be, $\alpha = \frac{0.05}{j}$, where there are j covariates in the model (Weisstein). Thus, the statistical significance of each covariate-time interaction term is determined based on $\alpha = \frac{0.05}{20} = 0.0025$. Using this alpha level all variables are determined to satisfy the proportional hazard assumption with the

exception of an individual's own disability status. Results from these tests are presented in Table 1.12.

VII. Conclusion

This paper advances the current RHI literature by using true duration analysis techniques to identify the effect of RHI on career job disengagement for a cohort of individuals who were aged 50-60 in 1992. Empirical results indicate that RHI reduces the length of time that individual's spend working a career job. This paper makes two significant contributions to the already well-developed body of literature devoted to RHI. First and most significantly, this paper is the first to estimate a hazard model, which is the appropriate econometric method to use when analyzing the time until an event occurs. Second, this paper truly measures the effect RHI has on the decision to leave a career job, and does not concern itself with the type of labor market transition that is actually made. While this is a slightly less restrictive issue to concern oneself with, given the increased prevalence of phased and partial retirement this is now the relevant concern.

Consistent with theory, the empirical results indicate that individuals who are offered RHI benefits have a higher hazard of leaving a career employer than otherwise similar workers without access to RHI. These findings are consistent with the previous literature and indicate that RHI significantly increases the probability of leaving a career job. Unlike the previous work, however, this paper performs duration analysis and is able to quantify the overall effect of RHI. Conditional probit techniques, like those employed by Marton and

Woodbury (2006), are not capable of capturing the true dynamics and are only able to provide empirical estimates for the effect of RHI on the probability of retiring from a career job over two specific time periods. Hazard models estimate the probability of an event occurring given it has not occurred in any past period. The results from the hazard model estimation indicate that RHI increases the probability (instantaneous hazard) of disengaging from a career job by 21.20%. This result suggests that RHI benefits significantly increase the probability of leaving a career job prior to becoming Medicare eligible.

As the baby-boom generation ages the effect of RHI on labor market participation behavior is of significant interest to a growing number of individuals, firms, and human resource departments. Individuals are likely to prefer working for a firm that offers such a benefit, but are likely to leave a job that offers RHI earlier in life than they would a job without access to RHI. Despite the high cost of offering RHI, firms may find it a profitable endeavor for several reasons. First, offering RHI may create a form of "job-lock" and firms may have improved retention of middle age employees. Second, employees offered RHI are likely to work harder when they are young so as to maintain their employment. Finally, employees may find this benefit desirable enough that they will accept a reduced salary in lieu of such a valuable benefit. Further work is required to test the hypothesis that RHI may be mutually beneficial to firms and employees.

A second valuable extension of this work is to examine the effect of RHI on the labor market transitions of a younger cohort and compare the effect of RHI across generations. Such a comparison could have important policy implications as the Social Security fund

continues to deplete and individual's retirement preparations adjust. It may be that individuals who are not counting on as large a Social Security benefit place a lower value on RHI than their older counterparts, as they have been saving for their retirement for a larger portion of their life or have planned to work longer regardless of their Medicare eligibility.

While the results of this paper are a valuable contribution to the literature, care must be utilized in their interpretation for several reasons. First and foremost, the model does not include a measure for premium costs or the costs associated with care, both of which are expected to affect the value of the benefit to older workers. Second, the prevalence of RHI benefits is diminishing as more and more firms are finding the benefit too costly to offer. Third, as the sanctity of the Social Security system is changing, the attitudes of individuals who are currently approaching retirement may be different than those of individuals included in this analysis. Thus, there may be unobserved differences between generations that would affect the decision to disengage from a career job, which may either increase or decrease the workers perceived value of RHI. Finally individuals who prefer to leave their career job early in life are likely to self-select into a job that offers RHI introducing selection bias into the estimation. This bias is not controlled for in estimation and thus, the estimated hazard ratio may be an overestimate.

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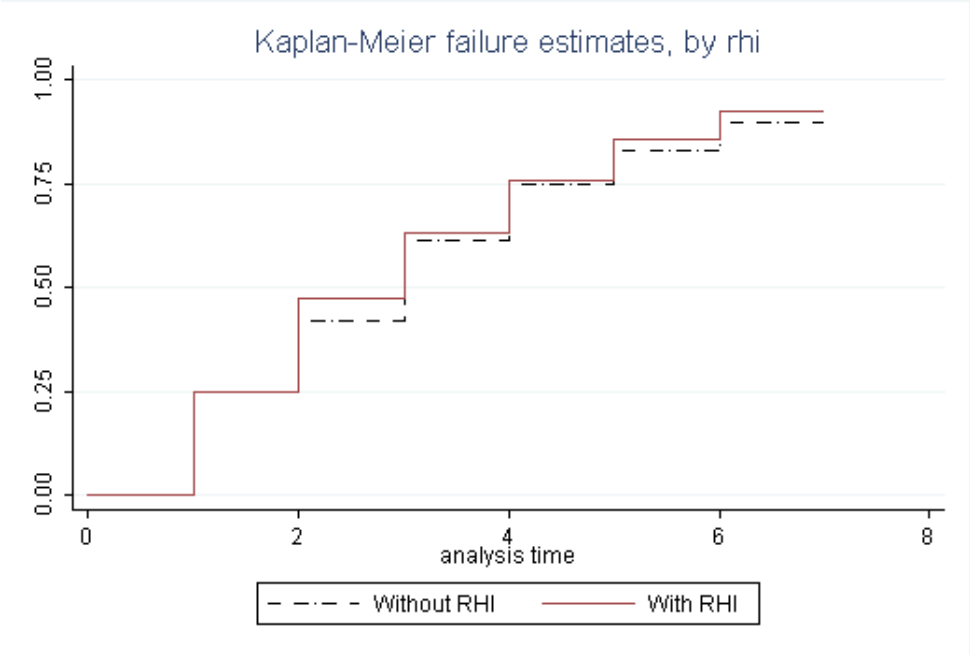

Figure 1.1: Kaplan-Meier Empirical Cumulative Hazard Function

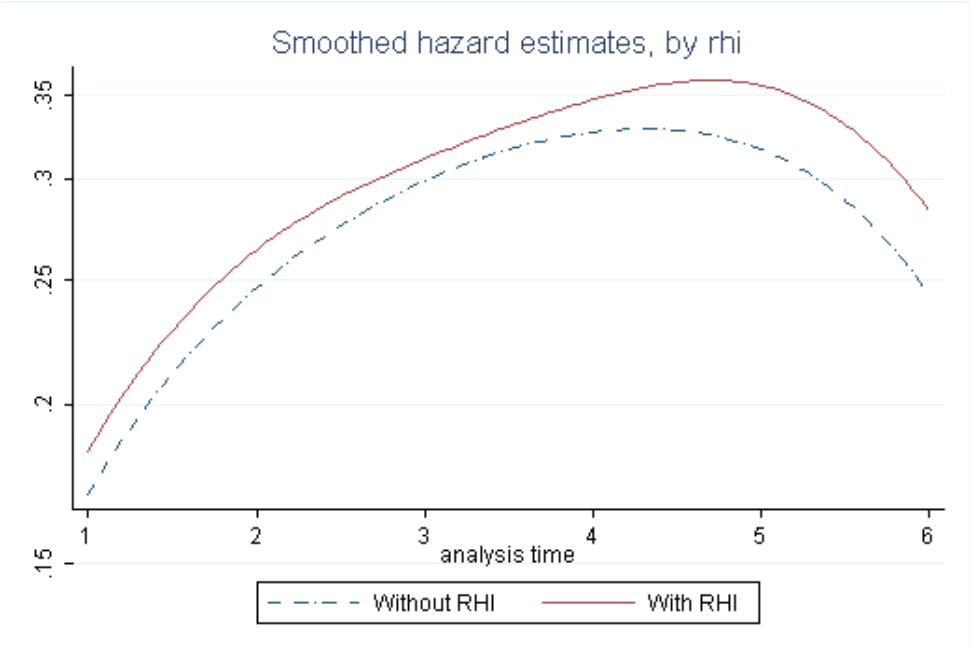

Figure 1.2: Smoothed Non-Parametric Hazard

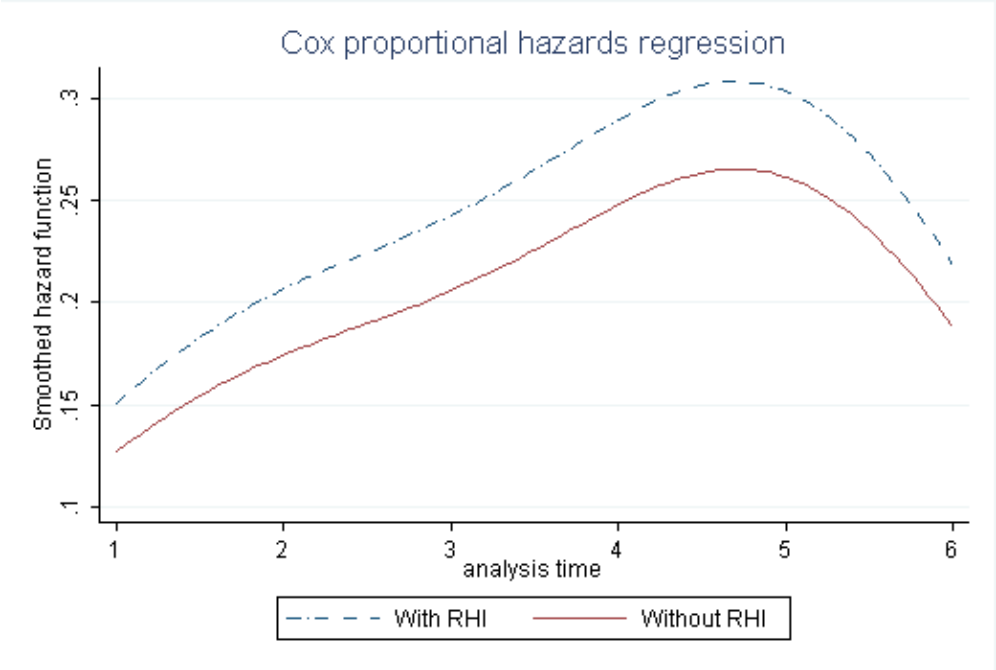

Figure 1.3: Cox Proportional Hazard

Table 1.1: Summary Statistics for Those Working Full-Time in 1992

	N	Mean	Standard Deviation	Minimum	Maximum
Gender (=1 if male)	12652	0.54	0.50	0	1
Age	12544	55.21	10.09	23.00	997.00
Marital Status (=1 if married)	12652	0.81	0.39	0	1
Self Reported Health Status (=1 if good health)	12651	0.78	0.42	0	1
Spouse's Self Reported Health Status (=1 if good health)	9899	0.80	0.40	0	1
White (=1 if white)	12652	0.79	0.40	0	1
Black (=1 if black)	12652	0.17	0.37	0	1
High School (=1 if highest level of education completed)	12652	0.48	0.50	0	1
College (=1 if highest level of education completed)	12652	0.20	0.40	0	1
Tenure	6794	16.08	12.12	-1.00	72.00
Hours Worked Per Week	8309	40.25	13.05	1	95
Employer Provided Health Insurance (=1 if insured)	12463	0.46	0.50	0	1
Retiree Health Insurance (=1 if insured)	5072	0.77	0.42	0	1
Public Sector Employee	12652	0.03	0.18	0	1
Total Household Assets (in $100,000)	10278	3.18	5.44	-2.28	$100.42
Defined Benefit Pension	12652	0.21	0.41	0	1
Defined Contribution Pension	12652	0.12	0.32	0	1

Table 1.2: Summary Statistics for Those Working A Career Job in 1992

	N	Mean	Standard Deviation	Minimum	Maximum
Gender (=1 if male)	2102	0.61	0.49	0	1
Age	2102	54.68	2.98	50	60
Marital Status (=1 if married)	2102	0.76	0.42	0	1
Self Reported Health Status (=1 if good health)	2102	0.89	0.32	0	1
Spouse's Self Reported Health Status (=1 if good health)	1537	0.85	0.36	0	1
White (=1 if white)	2102	0.80	0.40	0	1
Black (=1 if black)	2102	0.18	0.38	0	1
High School (=1 if highest level of education completed)	2102	0.51	0.50	0	1
College (=1 if highest level of education completed)	2102	0.28	0.45	0	1
Tenure	2102	23.99	8.55	10.00	48
Hours Worked Per Week	2102	42.70	6.19	30	60
Employer Provided Health Insurance (=1 if insured)	2102	0.99	0.05	0	1
Retiree Health Insurance (=1 if insured)	2102	0.77	0.42	0	1
Public Sector Employee	2102	0.07	0.26	0	1
Total Household Assets (in $100,000)	2102	2.78	3.74	-13.07	62.34
Defined Benefit Pension	2102	0.59	0.49	0	1
Defined Contribution Pension	2102	0.23	0.42	0	1

Table 1.3: Labor Market Participation Trends for All Individuals Working Full-Time[6] in 1992

	Percent Of Individuals Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	83.65	100						
1996	66.75	79.78	100					
1998	45.01	53.80	67.43	100				
2000	40.46	48.37	60.63	89.91	100			
2002	37.53	44.86	56.23	83.39	92.75	100		
2004	35.19	42.07	52.74	78.21	87.00	93.79	100	
2006	34.15	40.87	51.17	75.89	84.41	91.01	97.03	100

	Percent Of Individuals With RHI Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	82.37	100						
1996	64.84	78.72	100					
1998	43.29	52.56	66.77	100				
2000	38.93	47.26	60.03	89.91	100			
2002	36.01	43.72	55.54	83.18	92.52	100		
2004	33.85	41.10	52.21	78.19	86.97	94.00	100	
2006	32.90	39.94	50.74	75.99	84.52	91.35	97.18	100

	Percent Of Individuals Without RHI Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	88.76	100						
1996	74.30	83.71	100					
1998	51.81	58.37	69.73	100				
2000	46.59	52.49	62.70	89.92	100			
2002	43.57	49.10	58.65	84.11	93.53	100		
2004	40.56	45.70	54.59	78.29	87.07	93.09	100	
2006	39.16	44.12	52.70	75.58	84.05	89.86	96.63	100

[6] Full-time employment is defined as working 30 or more hours per week in an average workweek.

Table 1.4: Labor Market Participation Trends for All Individuals Working a Career Job[7] in 1992

	Percent Of Individuals Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	74.71	100						
1996	53.14	71.13	100					
1998	38.08	50.97	71.66	100				
2000	26.36	35.29	49.61	69.24	100			
2002	16.71	22.37	31.44	43.88	63.37	100		
2004	10.53	14.10	19.82	27.67	39.96	63.05	100	
2006	6.64	8.89	12.49	17.44	25.18	39.74	63.02	100

	Percent Of Individuals With RHI Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	74.55	100						
1996	51.71	69.36	100					
1998	36.94	49.55	71.44	100				
2000	25.04	33.58	48.42	67.77	100			
2002	15.28	20.49	29.55	41.36	61.02	100		
2004	8.89	11.93	17.19	24.07	35.51	58.19	100	
2006	5.52	7.40	10.67	14.94	22.04	36.12	62.07	100

	Percent Of Individuals Without RHI Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	74.88	100						
1996	54.80	73.18	100					
1998	39.40	52.61	71.89	100				
2000	27.90	37.26	50.92	70.83	100			
2002	18.36	24.53	33.51	46.62	65.82	100		
2004	12.44	16.61	22.70	31.58	44.59	67.74	100	
2006	7.94	10.60	14.49	20.15	28.45	42.23	63.81	100

[7] A career job is any job that a person works full-time (30 or more hours per week) for a minimum tenure of 10 years

Table 1.5: Kaplan Meier-Empirical Cumulative Hazard

Individuals Working a Career Job in 1992		
Year	Cumulative Hazard	Standard Error
1992	0.000	0
1994	0.247	0.009
1996	0.462	0.011
1998	0.627	0.011
2000	0.755	0.009
2002	0.851	0.008
2004	0.916	0.006
2006	0.916	0.006

Individuals with RHI Working a Career Job in 1992		
Year	Cumulative Hazard	Standard Error
1992	0.000	0
1994	0.247	0.011
1996	0.474	0.012
1998	0.631	0.012
2000	0.757	0.011
2002	0.857	0.009
2004	0.922	0.007
2006	0.922	0.007

Individuals without RHI Working a Career Job in 1992		
Year	Cumulative Hazard	Standard Error
1992	0.000	0
1994	0.250	0.020
1996	0.421	0.022
1998	0.612	0.022
2000	0.746	0.020
2002	0.831	0.017
2004	0.897	0.014
2006	0.897	0.014

Table 1.6: Log-Rank Test for Equality of Survivor Functions

Retiree Health Insurance	Events Observed	Events Expected
Access to Retiree Health Insurance	1491	1467.6
No Access to Retiree Health Insurance	435	458.4
Total	1926	1926
Chi Squared	2.26	
P-Vale	0.133	

Table 1.7: Wilcoxon Test for Equality of Survivor Functions

Retiree Health Insurance	Events Observed	Events Expected	Sum of Ranks
Access to Retiree Health Insurance	1491	1467.6	27246
No Access to Retiree Health Insurance	435	458.4	-27246
Total	1926	1926	0
Chi Squared	1.39		
P-Vale	0.239		

Table 1.8: Results From Cox-Proportional Hazard Model Estimation

	Model 1		Model 2	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
Male	-0.178^{+++}	0.837^{++}	-0.178^{+++}	0.837^{+++}
	(0.059)	(0.050)	(0.059)	(0.050)
Retiree Health Insurance (RHI)	0.192^{++}	1.212^{++}	0.205^{+++}	1.227^{+++}
	(0.069)	(0.083)	(0.070)	(0.086)
Employer Sponsored Health Insurance	0.055	1.057	0.057	1.058
	(0.710)	(0.750)	(0.710)	(0.751)
Age	0.121^{+++}	1.128^{+++}	0.121^{+++}	1.113^{+++}
	(0.069)	(0.011)	(0.010)	(0.011)
Public Sector Employee	-0.071	0.932	0.201	1.223
	(0.106)	(0.099)	(0.297)	(0.363)
Public Employee with RHI	.	.	-0.307	0.736
	.	.	(0.317)	(0.233)
No High School Diploma	0.078	1.081	0.080	1.083
	(0.079)	(0.085)	(0.079)	(0.085)
College Degree	-0.098	0.907	-0.094	0.910
	(0.062)	(0.056)	(0.062)	(0.057)
White	0.392	1.480	0.389	1.475
	(0.219)	(0.324)	(0.219)	(0.323)
Black	0.478^{+}	1.612^{+}	0.475	1.608
	(0.228)	(0.368)	(0.228)	(0.367)
Defined Benefit (DB)	0.192^{++}	1.212^{++}	0.193^{++}	1.213^{++}
	(0.083)	(0.101)	(0.083)	(0.101)
Defined Contribution (DC)	0.046	1.048	0.046	1.048
	(0.092)	(0.096)	(0.092)	(0.096)
Both DB and DC	0.192	1.211	0.192	1.212
	(0.161)	(0.195)	(0.161)	(0.195)
Spouse's Work Hours Increased	-0.085	0.918	-0.085	0.918
	(0.086)	(0.079)	(0.086)	(0.079)
Spouse's Work Hours Decreased	0.042	1.043	0.043	1.044
	(0.071)	(0.074)	(0.071)	(0.074)
Tenure	0.005	1.005	0.005^{++}	1.005
	(0.003)	(0.003)	(0.003)	(0.003)
Health Status	-0.435^{+++}	0.647^{+++}	-0.434^{+++}	0.648^{+++}
	(0.069)	(0.045)	(0.069)	(0.045)
Marital Status	0.162^{+}	1.176^{+}	0.162^{+}	1.176^{+}
	(0.093)	(0.109)	(0.093)	(0.109)
Disability	-1.668^{+++}	0.189^{+++}	-1.663^{+++}	0.189^{+++}
	(0.174)	(0.033)	(0.174)	(0.033)
Household Assets	0.006^{+}	1.006^{++}	0.006^{+}	1.006^{+}
	(0.003)	(0.003)	(0.003)	(0.003)
Spouse's Health Status	-0.013	0.987	-0.015	0.985
	(0.079)	(0.078)	(0.079)	(0.078)
Log Likelihood	-9761.26	-9761.26	-9760.82	-9760.82
N	6065	6065	6065	6065

*Standard Errors are shown in parentheses
$^{+}$ indicates $p \leq 0.10$, $^{++}$ indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

Table 1.9: Predicted Labor Market Participation Trends for All Individuals Working a Career Job in 1992

	Percent Of Individuals Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	74.07	100						
1996	55.97	75.56	100					
1998	40.41	54.56	72.21	100				
2000	24.97	33.70	44.61	61.78	100			
2002	16.93	22.85	30.25	41.89	67.80	100		
2004	2.44	3.30	4.36	6.04	9.78	14.42	100	
2006	1.26	1.70	2.25	3.12	5.05	7.46	51.69	100

	Percent Of Individuals With RHI Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	74.50	100						
1996	54.22	72.77	100					
1998	38.22	51.30	70.50	100				
2000	22.43	30.11	41.38	58.69	100			
2002	14.41	19.34	26.58	37.70	64.24	100		
2004	1.38	1.85	2.54	3.61	6.15	9.57	100	
2006	0.56	0.75	1.04	1.47	2.51	3.90	40.74	100

	Percent Of Individuals Without RHI Working Full Time In							
Percent Still On Job	1992	1994	1996	1998	2000	2002	2004	2006
1992	100							
1994	73.58	100						
1996	58.00	78.82	100					
1998	42.94	58.37	74.06	100				
2000	27.90	37.92	48.11	64.97	100			
2002	19.85	26.97	34.22	46.21	71.13	100		
2004	3.67	4.99	6.33	8.55	13.16	18.51	100	
2006	2.07	2.82	3.58	4.83	7.43	10.45	56.45	100

Table 1.10: Stratified Hazard Model Estimation

	Model 1 Strata=Pub	Model 2 Strata=Male
	Hazard Ratio	Hazard Ratio
Male	0.837^{++}	1
	(0.050)	.
Retiree Health Insurance (RHI)	1.216^{++}	1.209^{+++}
	(0.083)	(0.083)
Employer Sponsored Health Insurance	1.054	1.058
	(0.748)	(0.751)
Age	1.129^{+++}	1.128^{+++}
	(0.011)	(0.011)
Public Sector Employee	1	0.935
	.	(0.099)
No High School Diploma	1.081	1.081
	(0.085)	(0.085)
College Degree	0.906	0.905
	(0.056)	(0.056)
White	1.482^{+}	1.478^{+}
	(0.325)	(0.324)
Black	1.614^{+}	1.611^{+}
	(0.368)	(0.368)
Defined Benefit (DB)	1.212^{++}	1.212^{++}
	(0.101)	(0.101)
Defined Contribution (DC)	1.048	1.046
	(0.096)	(0.096)
Both DB and DC	1.209	1.210
	(0.195)	(0.195)
Spouse's Work Hours Increased	0.918	0.919
	(0.079)	(0.079)
Spouse's Work Hours Decreased	1.045	1.041
	(0.074)	(0.074)
Tenure	1.005	1.005
	(0.003)	(0.003)
Health Status	0.648^{+++}	0.648^{+++}
	(0.045)	(0.045)
Marital Status	1.174^{+}	1.172^{+}
	(0.109)	(0.109)
Disability	0.189^{+++}	0.189^{+++}
	(0.033)	(0.033)
Household Assets	1.006^{++}	1.006^{++}
	(0.003)	(0.003)
Spouse's Health Status	0.983	0.990
	(0.078)	(0.078)
N	6065	6065

*Standard Errors are shown in parentheses
$^{+}$ indicates $p \leq 0.10$, $^{++}$ indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

Table 1.11: Link Test Results

	Coefficient
Variable of Prediction	-0.476
	(0.805)
Variable of Prediction Squared	0.095
	(0.052)
N	6065

*Standard Errors are shown in parentheses
$^{+}$ indicates $p \leq 0.10$, $^{++}$ indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

Table 1.12: Direct Test of Proportional Hazard Assumption

Covariate Interacted With Analysis Time	Hazard Ratio
Male	1.030
	(0.035)
Retiree Health Insurance (RHI)	0.969
	(0.040)
Employer Sponsored Health Insurance	1.935
	(1.541)
Age	0.990
	(0.006)
Public Sector Employee	0.909
	(0.061)
No High School Diploma	0.985
	(0.046)
College Degree	0.970
	(0.035)
White	1.079
	(0.047)
Black	0.943
	(0.042)
Defined Benefit (DB)	1.024
	(0.035)
Defined Contribution (DC)	1.040
	(0.040)
Both DB and DC	1.040
	(0.093)
Spouse's Work Hours Increased	1.012
	(0.053)
Spouse's Work Hours Decreased	0.992
	(0.041)
Tenure	0.995
	(0.002)
Health Status	1.134
	(0.048)
Marital Status	1.017
	(0.038)
Disability	0.245^{+}
	(0.026)
Household Assets	0.996
	(0.002)
Spouse's Health Status	1.018
	(0.034)
N	6065

*Standard Errors are shown in parentheses
$^{+}$ indicates $p \leq 0.0025$

Chapter 2
Household's Food Stamp Program Participation and Childhood Obesity

I. Introduction

The number of children classified as overweight (having a BMI that is in the 85th percentile for children of a similar age and height) has increased dramatically over the past several decades. It has been estimated that in 2005-2006 nearly 10.9% of children and adolescents aged 2 through 19 were at or above the 97th percentile of the 2000 BMI-for-age growth charts; 15.5 % were at or above the 95th percentile; and 30.1% were at or above the 85th (Ogden, Carroll, and Flegal 2008). It has also been found that the heaviest children today, are significantly heavier than the heaviest children of a decade ago. Although the rise in childhood obesity has tapered off over the past five years, the incidence of childhood obesity is an issue that demands attention.

The Center for Disease Control (CDC) estimates that nearly 70% of obese children become obese adults. This is cause for concern when one considers the large number of deaths that are attributable directly to obesity. In 2005 obesity was responsible for nearly 112,000 excess deaths (Flegal, Graubard, and Williamson 2005). Additionally individuals who are obese are at a higher risk for dangerous secondary diseases such as heart disease, stroke, diabetes, arthritis, and certain cancers. These diseases rank high on the list of preventable diseases, and can be very costly to manage.

Many sources of adult obesity have received attention in economic literature. Recently, the connection between the Food Stamp Program (FSP) and obesity has been

analyzed, and two main ways through which FSP participation is directly related to obesity have been identified. First, FSP participation has been shown to increase food consumption by an amount greater than intended, as the marginal propensity to consume food from a dollar of food stamp benefits (FSB) is greater than the marginal propensity to consume food from a dollar of money income. Empirically it has been shown that an additional dollar of food stamp income increases food expenditure by $0.17 to $0.47, while an additional dollar of cash income increases food consumption by only $0.03 to $0.17. These estimates indicate that the marginal propensity to consume food from a dollar of FSB is between 2 and 10 percent larger than the marginal propensity to consume food from cash income (Fraker, 1990).

Additionally, individuals who receive food stamps are more likely to be food insecure than those who do not.[1] When people who are worried about having enough food are given the ability to purchase food products, it is likely that they will focus on quantity over quality. An emphasis on quantity will likely lead a FSP participant to make poor choices and over consume low quality food. Fox and Cole (2004) found that FSP participants score lower on the Healthy Eating Index, than non-participants (regardless income). Further, they find that FSP participants are less likely to have a high-quality diet than non-participants.

Cawley (1999, 2000, 2001) found that calorie consumption is addictive in nature. Richards, Patterson, and Tegene (2007) further examined the addictive properties of food and

[1] Individuals are considered to be food insecure, if they have concerns about their ability to obtain enough food to sustain life.

found that complex carbohydrates, protein, and sodium are foods, which are highly addictive. Wilde, McNamara, and Ranney (2000) studied the effect FSP participation has on the quality of food individuals consume. They found that FSP participants have significantly higher consumption of meat, added sugars, and fats than their (low-income) non-participant counterparts. Taken together these findings indicate that FSP participants consume a highly addictive and unhealthy diet, which, if consumed over a long enough period of time, will lead to increased body-weight, and a higher likelihood of obesity.

The first piece of research to examine the relationship between FSP participation and obesity was Gibson (2003). She studied the trend in adult obesity, and found that FSP participation tends to cause an increase in women's BMI, and increased the probability that they are classified as obese. Hofferth and Curtin (2005) studied the effects of poverty and participation in government sponsored food programs on a child's weight. They examined how participation in the FSP, the school lunch program, the school breakfast program, and different combinations of these programs influence a child's BMI. Their estimations show that FSP participation is associated with a BMI increase for children with a BMI that is below normal, but not for those with a normal (or above normal) BMI. Further, they found that FSP participation does not increase the likelihood that a child is overweight.

While these early pieces of research are a valuable contribution to our understanding of the connection between FSP participation and obesity, they fail to acknowledge that weight is not a measure independently determined each period. It is unlikely that a person who weighs 200 pounds this year weighed only 100 pounds last year. As such, it is prudent

to measure obesity as a dynamic process that takes place over several periods, and study the effects of FSP participation within such a framework. Failure to do so, would lead to biased results on FSP participation, and yield incorrect policy implications.

A recent paper by Baum (2007) is the first to acknowledge the dynamic process through which a person's body mass index (BMI) increases. Baum uses data from the National Longitudinal Survey of Youth 1979 (NLSY79) to study obesity in adults who receive food stamps, and finds a positive relationship between FSP participation, BMI growth, and the probability of becoming obese. The estimated effects of FSP participation on BMI from his dynamic models are considerably larger than the effect found in previous literature. This indicates that additional work needs to be done to determine if obesity should be measured as a dynamic process.

This paper continues this line of research, by studying the effects of FSP participation on obesity in a framework that carefully models an individual's dynamic weight accumulation process. Unlike Baum (2007), the focus of this study is on children. More specifically, this study models the deviation of a child's current BMI from the ideal BMI, which can be regarded as a measure of obesity (Must, Dallal, and Dietz, 1991), as a dynamic process. It further considers how this process is affected by living in a household that participates in the FSP. If the deviation from ideal BMI is significantly higher for FSP participants, this indicates that FSB receipt is positively correlated with child over-weight and obesity. The approach employed in this study enjoys two main advantages. First, by carefully modeling the dynamic weight accumulation process, the estimated effects of FSP

participation on obesity are more reliable. Second, since a dynamic model is estimated, both the short and long run effects of FSP participation on obesity can be quantified.

I find no evidence to suggest that a household's FSP participation affects the deviation of a child's current BMI from their medically ideal BMI, indicating that FSP participation does not contribute to childhood obesity. This result is consistent with previous literature, which found that FSP participation does not increase the probability that a child is obese. Additionally, I find that there is a tendency for children to approach their ideal BMI, indicating that there is no positive momentum in the BMI growth path. Children, who become more overweight (or underweight) in one period, are likely to move closer to their ideal BMI in the next period.

The remainder of this paper is organized as follows: the next section provides an overview of literature related to FSP participation and obesity. The third section presents the theoretical model, used to derive the BMI growth path, the fourth presents comparative statics, and the fifth discusses the estimation strategy. The sixth section describes the data obtained from the NLSY79 and NLSY79 Child and Young Adult Survey. The seventh section presents the empirical results and discussion, and the eighth concludes.

II. Literature Review:

A sizable body of literature exists on the topic of childhood overweight and obesity. Several papers have examined the relationship between a child's BMI and their parents, suggesting that a child's behavior is influenced by the decisions that their parents make for

themselves. As such, there are several components of a child's home and social life that can provide insight into the rising number of obese and overweight children. Since children make very few choices for themselves (parents are assumed to determine what their children do), an examination of the household is likely to provide, at least, a partial explanation for (the increased prevalence of) child overweight.

Past generations lived in a patriarchal society, and the majority of mothers would stay home—their primary job being to care for the home and children. These mothers had a great deal of time they could devote to cooking homemade, nutritious meals. Further, they had more time to spend interacting with, playing with, and raising their children. As such, these children were likely to be physically active, to have learned healthy habits, and to have their activities and time use monitored. In today's society the majority of households have either two parents who both work, or are one-parent families where the adult must work to support the family. This has reduced the amount of parent-child interactions, as well as the quality of the interactions that do take place. Empirically, the reduction in quantity and quality of parental interactions has been shown to increase the probability that a child becomes obese (Davis and You 2007).

A child born to a low-income family, that is not receiving FSB, is likely to be undernourished and underweight. Should that household begin to receive FSB the household will have more food available for the child, which is expected to increase their BMI. Additionally, this food is likely to be low quality, leading the child to eat more fats and sugar than they did in previous periods. Overtime this may cause a child's BMI to increase to

unhealthy levels. The longer FSB are received the more likely this becomes. Empirically, it has been found that long-term FSP participation increases a child's BMI, and probability of being obese (Gibson 2004). These findings, however, are specific to girls between the ages of 5 and 11 and are based on previous characteristics of the child and the household.

Gibson's model did not consider a child's previous BMI, and thus, failed to properly identify the BMI growth path, and the process through which a child becomes obese. Failure to measure the BMI accumulation path is a failure to account for the dynamics that drive a child's growth process. As such, the estimated effect of FSP participation on BMI is likely to be confounded by the effect a child's previous BMI has on their current BMI level.

Recognizing that a person's BMI grows over time, and empirically estimating the dynamic effect of FSP participation on an individual's BMI is a key to understanding the rise in the number of obese individuals. Baum (2007) recognized the dynamics at work and estimated three models to observe how an adult's weight changed as a result of FSP participation. He found that women who receive FSB have BMIs that grow faster than non-recipients, and that FSP participants have a higher probability of becoming obese in any period (given that they were not obese in the previous period). Baum's results are specific to women, as he finds no significant effect for men, and his analysis does not include the children who are growing up in these households.

Baum (2007) does a better job of considering the dynamic effect that FSP participation has on a person's BMI. However, his models do not account for previous BMI,

and as such, remain ad-hoc in nature. Like Gibson (2004), Baum does not fully capture the dynamics of weight accumulation.

This paper contributes to the literature by directly modeling the dynamic process for the deviation of a child's BMI from their ideal BMI. In all periods, BMI is assumed to depend on last period's BMI, current caloric intake (which depends on this years FSB), and current caloric expenditure. As such, this paper, explicitly models the obesity evolution process. Having the ability to estimate how FSP participation influences the deviation between current and ideal BMI, and the BMI deviation growth path will provide a better understanding of the true effect FSP participation has on child obesity.

III. Theoretical Model

The goal of this research is two fold. First, this paper aims to explain the connection between FSP participation and the growth of a child's BMI, exploiting the connection between FSP participation and BMI^D, defined as the deviation of a child's BMI from the ideal BMI level (denoted as BMI^*), that is, $BMI^D = [BMI - BMI^*]$. Over time, BMI^D can increase, remain the same, or decrease. If the absolute difference between current and ideal BMI increases with FSP participation, this would indicate that the FSP has a perverse effect on a child's health.

Next, this paper recognizes that the number of children classified as overweight and obese grew considerably between 1986 and 2004. To examine the increased prevalence of overweight children, this paper estimates the probability of a child becoming obese as a

result of FSP participation. To account for the dynamic nature of obesity, and the fact that a family's composition and financial security change over time, I estimate a hazard function with time-varying covariates.

To model a child's behavior, I employ their parent's utility function and assume that parents obtain utility from their own choices, and from the choices they make for their children. It is anticipated that children who are either under or overweight are likely to have higher medical care costs than children of a healthy weight. Higher medical care bills will be utility decreasing for parents, indicating that parents obtain utility from having children who are at their medically ideal weight.

Since the focus of this paper is the child's weight accumulation process, I hold the parent's decisions for themselves constant and focus on the choices they make for their children. It is reasonable to believe that parents choose the amount of food their children consume and the non-food products they are allowed. The per-period utility function, where all components of utility not directly related to children have been suppressed, is specified as,

(1). $U_{it} = U(U_{it}^{C}, H_{it}^{C})$.

U_{it}^{C} is the child's current utility level, and H_{it}^{C} is the child's current health. Parents obtain utility from having a healthy child, indicating that $\frac{\partial U_{it}}{\partial H_{it}^{c}} > 0$. Further, the happier the child, the higher the parent's utility, that is, $\frac{\partial U_{it}}{\partial U_{it}^{C}} > 0$. Children are assumed to gain happiness

from consumption of food products, and consumption of all other goods. Thus, the vector of relevant consumption variables is given by,

(2). $U_{it}^{C} = U(F_{it}, C_{it})$,

where, F_{it} is consumption of food, and C_{it} is non-food consumption. Children are happier if they consume more food or non-food items, that is, $\frac{\partial U_{it}^{C}}{\partial F_{it}} > 0$, and $\frac{\partial U_{it}^{C}}{\partial C_{it}} > 0$.

Following Jacobson (2000) an extended version of the Grossman Model is used to define the health production process. Over time an individual's health, H_{it} is expected to decrease, but, through investment, the natural deterioration of health (from aging), can be offset. Thus, from the time of birth, the child's health, H_{it}^{C}, is expected to start deteriorating, at rate δ. The child's health evolution process is given by, $\frac{\partial H_{it}^{C}}{\partial t} = I_{it} - \delta_{it}^{C} H_{it}^{C}$, where I_{it} is the parent's investment in child health.

One factor that will enter the parent's health investment decision is the magnitude by which, a child's current weight deviates from the ideal weight. This measure is an indicator of a child's under/overweight status and is an important component of H_{it}^{C}. Since children who are either underweight or overweight are expected to be less healthy than children of ideal weight, any $BMI_{it}^{D} \neq 0$ is utility decreasing. If $BMI_{it}^{D} < 0$, meaning the child is currently underweight, then $\frac{\partial U}{\partial H_{it}^{C}} \frac{\partial H_{it}^{C}}{\partial BMI_{it}^{D}} > 0$, which means that reducing BMI^{D} is utility increasing. Similarly, if a child is currently overweight, that is, $BMI_{it}^{D} > 0$, then

$\frac{\partial U}{\partial H_{it}^{C}} \frac{\partial H_{it}^{C}}{\partial BMI_{it}^{D}} < 0$, which also implies that reducing their child's BMI^{D} is utility increasing for the parent.

The Budget Constraint

The child's per period budget constraint is a function of the portion of the parent's income that is allocated to the child, and the consumption choices. The per-period budget constraint is specified as,

(3). $S_{it} = P'_{Ct} C_{it} + P'_{Ft} F_{it}$

where, S_{it} is the amount of household income, allocated to the child. P'_{Ft} is the effective price of 1 unit of food, which is defined as $P'_{Ft} = P_{Ft} - \alpha FSB_{it}$, where P_{Ft} is the money price of 1 unit of food, α represents the proportion of FSB allocated to expenditure on food, and αFSB_{it} represents the reduction in the price of 1 unit of food due to FSP participation. $P'_{Ct} = P_{Ct} - \beta FSB_{it}$ is the true price of 1 unit of all non-food products, where P'_{ct} is the effective price of 1 unit of a non-food consumption good, β represents the portion of FSB allocated to expenditure on non-food products, and βFSB_{it} is the reduction in the price of 1 unit of consumption goods as a result of FSB receipt.

The Transition Equation

To complete the model, the transition equation for the state variable, BMI^{D} needs to be specified. BMI_{it}^{D} is assumed to be a function of the child's BMI^{D} at the beginning of period *t* (end of period *t*-1), and this period's food consumption, such that,

(4). $BMI_{it}^{D} = BMI(BMI_{it-1}^{D}, F_{it})$,

with the properties that $\frac{\partial BMI_{it}^{D}}{\partial BMI_{it-1}^{D}}$ is ambiguous, and $\frac{\partial BMI_{it}^{D}}{\partial F_{it}}$ is positive. $\frac{\partial BMI_{it}^{D}}{\partial BMI_{it-1}^{D}}$ is ambiguous as there is likely momentum in the weight accumulation process. A child who is overweight this period is expected to become more overweight in the next period, while a child who is underweight this period is expected to become more underweight in the next period. $\frac{\partial BMI_{it}^{D}}{\partial F_{it}} > 0$, as the more food someone eats, the more weight they are expected to gain, which increases a child's BMI_{it}^{D}.

Characterizing the Optimal Solution

Combining (1)-(4), the child's utility maximization problem is to,

$$\max_{F_{it}, C_{it}} \sum_{t=0}^{\infty} \beta_t U(U_{it}^{C}, H_{it}^{C}) \text{ subject to,}$$

(5). $S_{it} = P_{Ct}' C + P_{Ft}' F$

$BMI_{it}^{D} = BMI(BMI_{it-1}^{D}, F_{it})$

Using standard techniques, the Bellman equation can be written as,

(6). $V_{it}(BMI_{it-1}^{D} \mid Z_{it}) = U(BMI_{it-1}^{D}) + \beta[V_{it+1}(BMI_{it}^{D})]$

and the Lagrange expression is

(7). $L = U(U_{it}^{C}, H_{it}^{C}) + \beta[V_{it+1}(BMI_{it}^{D})] + \lambda_t \left[S_{it} - P_{Ct}' C_{it} - P_{Ft}{}' F_{it} \right]$.

First order conditions of the maximization problem (assuming interior solutions) are

$$
(8).\quad \begin{aligned}
&F_{it}: \quad \frac{\partial U}{\partial U_{it}^{C}}\frac{\partial U_{it}^{C}}{\partial F_{it}} + \frac{\partial U}{\partial H_{it}^{C}}\frac{\partial H_{it}^{C}}{\partial BMI_{it}^{D}}\frac{\partial BMI_{it}^{D}}{\partial F_{it}} + \beta\left[\frac{\partial V_{it+1}}{\partial BMI_{it}^{D}}\frac{\partial BMI_{it}^{D}}{\partial F_{it}}\right] - \lambda_t P'_{Ft} = 0 \\
&C_{it}: \quad \frac{\partial U}{\partial U_{it}^{C}}\frac{\partial U_{it}^{C}}{\partial C_{it}} - \lambda_t P'_{Ct} = 0 \\
&\lambda_t: \quad S_{it} - P'_{Ct}C_{it} - P'_{Ft}F_{it=0}
\end{aligned}
$$

The optimal choices for F_{it} and C_{it} are characterized by the set of first order conditions above and they are functions of food price, income, and deviation from ideal BMI, such that,

$$
(9).\quad \begin{aligned}
F_{it}^{*} &= F_{it}(P'_{Ft}, P'_{Ct}, M_{it}, BMI_{it-1}^{d}) \\
C_{it}^{*} &= C_{it}(P'_{Ft}, P'_{Ct}, M_{it}, BMI_{it-1}^{d})
\end{aligned}.
$$

The model outlined above differs from that of Baum (2007) in three main ways. First and foremost, Baum considers a continuous-time lifetime utility maximization problem, while the dynamic model in this paper is a discrete time model. The discrete time setup is more appropriate as survey data is used in estimation, and thus observations are only available on a discrete basis.

Second, Baum's model considers an infinite time horizon, which is unreasonable as agents are expected to pass away at some future time period, T. The model in this paper considers a time interval over the ages of 5 to 18 years of age, but could be extended to accommodate adults, in which case the time horizon would be specified as 19 to T.

Third, my model employs a Grossman style health production function, to account for the fact that an individual's BMI is an integral part of their overall health, which directly affects an individual's utility. Baum's model does not include a measure of health, and only

includes deviation from ideal weight in the utility function. These differences yield a model that is more consistent with the data, and economic theory.

IV. Comparative Statics and Testable Implications

The primary goal of this research is to estimate the effect of FSB_{it} and BMI_{it-1}^{D} on BMI_{it}^{D}. (4) implies that the change in BMI_{it}^{D} resulting from a change in FSB_{it} is given by,

(10). $$\frac{\partial BMI_{it}^{D}}{\partial FSB_{it}} = \frac{\partial BMI_{it}^{D}}{\partial F_{it}} \frac{\partial F_{it}}{\partial P'_{Ft}} \frac{\partial P'_{Ft}}{\partial FSB_{it}}.$$

It is expected that $\frac{\partial BMI_{it}^{D}}{\partial FSB_{it}}$ will be positive due to the following facts. First, $\frac{\partial BMI_{it}^{D}}{\partial F_{it}}$ will be positive as discussed above. Second, $\frac{\partial F_{it}}{\partial P'_{Ft}}$ will be negative as the more expensive the real price of food becomes the less food households will purchase. Finally, $\frac{\partial P'_{Ft}}{\partial FSB_{it}}$ is also negative, as an increase in FSB received, reduces the real price of food. This prediction can be tested by the data.

The change in BMI_{it}^{D} resulting from a change in BMI_{it-1}^{D} is given by,

(11). $$\frac{dBMI_{it}^{D}}{dBMI_{it-1}^{D}} = \frac{\partial BMI_{it}^{D}}{\partial BMI_{it-1}^{D}} + \frac{\partial BMI_{it}^{D}}{\partial F_{it}} \frac{\partial F_{it}}{\partial BMI_{it-1}^{D}}.$$

As discussed above, $\frac{\partial BMI_{it}^{D}}{\partial BMI_{it-1}^{D}}$ is ambiguous and $\frac{\partial BMI_{it}^{D}}{\partial F_{it}}$ will be positive. It is clear that the ambiguous nature of $\frac{\partial BMI_{it}^{D}}{\partial BMI_{it-1}^{D}}$ leads (11) to be ambiguous as well. Additionally, the sign of $\frac{\partial F_{it}}{\partial BMI_{it-1}^{D}}$ cannot be determined, as can be determined form (9). Without imposing further specification assumptions for the utility function, the health production function, or the BMI evolution function, it is clear that F_{it} depends on BMI_{it-1}^{D} in a complex way. Intuitively, the sign can be either positive or negative.

On one hand, a child who has a positive BMI_{it-1}^{D} needs to consume less food in order for his BMI to fall, and his BMI_{it}^{D} to approach the medically ideal level. On the other hand, a higher BMI_{it-1}^{D} and hence a higher BMI_{it}^{D} makes the child unhappy, which can be offset by consuming more food. When BMI_{it-1}^{D} is negative, a higher BMI_{it-1}^{D} and hence a higher BMI_{it}^{D} increases the child's unhappiness and would result in the child consuming more food, leading $\frac{\partial F_{it}}{\partial BMI_{it-1}^{D}}$ to be positive. However, as the child's BMI approaches their medically ideal BMI they have an incentive to eat less, and thus, the sign of $\frac{\partial F_{it}}{\partial BMI_{it-1}^{D}}$ will be negative.

V. Estimation Strategy

To estimate the BMI^D accumulation process, based on the theoretical model presented above, I approximate a child's BMI^D to be a function of their: previous BMI^D, mother's BMI, family's FSP participation, and other control variables including gender, race, family size, mother's education attainment, and household income, such that

(12). $BMI_{it}^D = \beta_0 + \beta_1 BMI_{it-1}^D + \beta_2 MBMI_{it} + \beta_3 FS_{it} + \beta_4 Fam_{it} + \beta_5 Edu_{it} + \beta_6 \ln(Inc_{it}) + u_i + \varepsilon_{it}$,

where BMI_{it-1}^D is last period's BMI deviation from the ideal BMI, $MBMI_{it}$ is the mothers current BMI, FS_{it} is the current FSP participation, Fam_{it} is family size, Edu_{it} is the mothers educational attainment, $\ln(Inc_{it})$ is the log of household income, u_i is a child specific error term (fixed effects), and ε_{it} is the error term. This model truly captures the dynamic nature of BMI^D by including the child's previous BMI^D. Doing so reduces the potential for reverse causality bias and simultaneity bias discussed by Gibson (2003, 2004) and Baum (2007) that plagued previous studies of the effect of FSP on obesity.

Reverse causality bias arises if a child's previous BMI^D determines a family's enrollment in the FSP. This can happen especially when a child's previous BMI^D is negative. Simultaneity bias arises if a family's enrollment in the FSP influences a child's BMI^D, but at the same time, a child's BMI^D influences a family's decision to enroll in the FSP. With a dynamic model, it is clear, that it is possible for FS_{it} to be determined or influenced by BMI_{it-1}^D, but not by BMI_{it}^D, thus reducing the likelihood of both reverse causality and simultaneity problems.

Controlling for the fixed effects is important because it controls for selection bias, which is another bias that plagued previous studies. Failing to do so could make the FS variable endogenous, resulting in biased estimates. This is because it is possible that u_i, which we cannot observe, contains child (or family) specific information that may influence the decision to enroll in the FSP and a child's BMI^D at the same time. For example, heterogeneity may exist if there are systematic and unobserved differences in the behavior of children who have obese parents and those who do not. It is possible that obese parents are more likely to be poor and enroll in the FSP. At the same time, it is also possible that they are more likely to place lower value on their child's BMI and have a lower level of parental concern for their child's BMI, making it easier for a child to exercise less, eat more, and have a positive BMI^D.

However, controlling for the fixed effects does not eliminate the potential heterogeneity bias resulting from correlation between a family's FSP participation and the unobserved error, ε_{it} which, may cause FSP participation to be endogenous. To account for the potential endogeneity of FS_{it}, from the fixed effects, I first difference the BMI^D equation over time to eliminate the child and family specific fixed effects. Then, due to the potential endogeneity bias caused by the correlation between FS_{it} and ε_{it} I consider two specifications: the first under the assumption that the $\text{cov}(FS_{it}, \varepsilon_{it}) = 0$, and the second, under the assumption that the $\text{cov}(FS_{it}, \varepsilon_{it}) \neq 0$.

Under the assumption that $\text{cov}(FS_{it}, \varepsilon_{it}) = 0$, I base my estimation of the parameters in (12), on,

(13). $\Delta BMI_{it}^{D} = \beta_1 \Delta BMI_{it-1}^{D} + \beta_2 \Delta MBMI_{it} + \beta_3 \Delta FS_{it} + \beta_4 \Delta Fam_{it} + \beta_5 \Delta Edu_{it} + \beta_6 \Delta \ln(Inc_{it}) + \Delta \varepsilon_{it}$

where $\Delta BMI_{it}^{D} = BMI_{it}^{D} - BMI_{it-1}^{D}$ and the other terms are similarly defined. The main parameter of interest is β_3, which captures the effect a family's FSP participation has on a child's BMI^{D}. Also of interest is β_1 which captures the effect a child's BMI_{it-1}^{D} has on the current periods BMI^{D}.

Under the assumption that (13) remains biased, which will be the case if, $\text{cov}(FS_{it}, \varepsilon_{it}) \neq 0$, I consider a two-stage approach. In this specification, I use FSP participation, with a two-period lag (FS_{it-2}), as an instrument for current FSP participation. In this first stage I regress ΔFS_{it} on ΔFS_{it-2} and other covariates to obtain the predicted value of ΔFS_{it}, denoted, $\Delta \hat{FS}_{it}$. In the second stage I estimate the parameters in (12), based on,

(14). $\Delta BMI_{it}^{D} = \beta_1 \Delta BMI_{it-1}^{D} + \beta_2 \Delta MBMI_{it} + \beta_3 \Delta \hat{FS}_{it} + \beta_4 \Delta Fam_{it} + \beta_5 \Delta Edu_{it} + \beta_6 \Delta \ln(Inc_{it}) + \Delta \varepsilon_{it}$

(14) will generate unbiased estimates for the effect of FSP participation, provided ΔFS_{it-2}, is in fact a valid instrument for ΔFS_{it}. This is the case as long as, ΔFS_{it-2} significantly effects ΔFS_{it}, but does not have a significant effect on ΔBMI_{it}^{D}, independent of ΔFS_{it}. The strength of ΔFS_{it-2} as an instrument is determined using a t-test, while the Hausman test is used to identify bias in OLS estimates obtained from (13).

Additionally, a semiparametric Cox proportional hazard model is estimated to identify the effect of FSP participation on the probability that a child becomes obese. The

Cox model is preferred to conditional probit/logit estimation as it is a true duration model, and thus, is more flexible and better equipped to analyze the probability of a failure (becoming obese) occurring, given a lack of failure in any previous period. Moreover, the Cox model is able to incorporate time-varying covariates, which is critical when attempting to model a dynamic process. Please see the appendix for a detailed explanation of the hazard model.

VI. Data

I use data obtained from both the NLSY79 and the NLSY79 Child and Young Adult surveys to estimate the effect a change in a family's FSP participation has on a child's BMI. The NLSY79 is a longitudinal survey, initiated in 1979 that originally interviewed 12,686 individuals who were between the ages of 14 and 22. The respondents were surveyed annually from 1979 to 1994, and biennially thereafter.

The NLSY79 Child and Young Adult survey was started in 1986, and gathers detailed information about children born to the women of the NLSY79. The survey classifies anyone below the age of 15 as a child, and anyone over 15 as a young adult. Information about a child is collected from the mother, while young adults are surveyed directly and are asked a series of questions similar to those their mother's were asked in early waves of the NLSY79. Regardless of child/young adult classification the survey gathers information about a participant's health, growth, and development. An additional feature of the NLSY79 and NLSY79 Child and Young Adult survey is the ability to link a child's information to their

mother's information, so that household level analysis can be performed. I assume that each mother represents a distinct household, and allow each mother to have an unlimited number of children.

Currently, The NLYS79 Child and Young Adult Survey has completed 10 waves of interviews; due to the fact that we are interested in changes in variables, this provides 9 usable time periods. Specifically changes are calculated between: 1986 and 1988, 1988 and 1990, 1990 and 1992, 1992 and 1994, 1994 and 1996, 1996 and 1998, 1998 and 2000, 2000 and 2002, and finally from 2002 and 2004. The 1986-1988 period is not used in estimation, as it is not possible to calculate the previous change in a child's BMI^D.

I consider two distinct measures of a family's FSP participation. The first is the number of months in which a family reports receiving a positive amount of FSB and the second is the dollar amount of FSB reported. I also consider two measures for mother's education: the highest degree obtained, and the highest grade completed. Household income is taken to be the sum of the mother's and her spouse's (when available) pre-tax income earned from wages, salary, commissions or tips. All income is measured in 2004 dollars.

To measure how a child's BMI is affected by their families' FSP participation I utilize the variation in the deviation between a child's true and ideal BMI. This is preferred to simply measuring the change in a child's current and past BMI, as a child's BMI grows with age. Unfortunately, the CDC does not publish a measure of ideal BMI for children and young adults, which forces me to use an imperfect measure for a child's ideal BMI. I

approximate a child's ideal BMI to be the BMI that corresponds to the 50th percentile for age and gender (Must, Dallal, and Dietz, 1991).

The full sample consists of 9,682 children, which yields 77,456 child-year observations. Due to the distinct characteristics of children less than 5 years of age, and young adults over the age of 18, I restrict my sample to include only those children between 5 and 18 years of age. This reduces the sample to 46,996 observations. In this sample, 48.8% are females, and the average age is 11.4 years. The current change in BMI^D ranges from -33.87 to 26.46 with an average of 0.30 index points while the previous change in BMI^D ranges from -33.87 to 29.02, with an average of 0.28. On average, FSP participation changed by -0.48 months, and FSB receipt changed by -$96.76. The average household income, measured in 2004 dollars, was $66,767.45, with a minimum of $31.00, a maximum of $691,487.00. These summary statistics are presented in Table 2.1.

Due to the fact that 24 months is a reasonably short period of time, I place limits on the size of each change of interest. The change in both a child's current and past BMI^D is restricted to be no larger than 5 in absolute value. Removing those children for whom the change in BMI^D cannot be measured, is outside of reasonable limits, or is missing, leaves 20,575 observations. Family size is not permitted to change by more than 5 people per period. Observations with either missing or large values for change in their family size are removed, leaving 20,428 child-year observations. Finally, those individuals who have missing or invalid incomes (non-positive income) are removed from the sample, resulting in a final sample of 10,899 child-year observations.

In the sample used in estimation 48.8% are females, and the average age is 11.5 years. The change in the current period's BMI^D was, on average 0.25 index points, with a standard deviation of 1.94. The average change in a child's BMI^D from the previous period was 0.32 index points per period, with a standard deviation of 1.91 points. The average change in FSP participation was -0.48 months, while the average change in FSB receipt was -$115.00. The average income of individuals in the sample was $65,397.02, with a minimum of $79.60, and a maximum of $691,487.00. These summary statistics are presented in Table 2.2. Comparing Tables 2.1 and 2.2 shows little variation in the sample means between this and the full sample; as such the sample used in estimation is fairly representative of the full sample.

Complete analysis is also performed on a sub-sample of families with household income less than $25,000, hereafter referred to as the low-income sample. Removing families with income greater than $25,000 yields a sample of 8,265 child-year observations, of which 4,900 are between the ages of 5 and 18. In this sample, 48.4% are female, and the average age is 10.8 years. The current period's change in BMI^D is, on average 0.32 points with a standard deviation of 2.76 points. The previous period's change in BMI^D was, on average, 0.25 index points, with a standard deviation of 3.01. The average change in FSP participation was -0.53 months, while the change in FSB was -$149.29. Within this sample the average income is $13,414.86, with a minimum of $31.00 and a maximum of $25,000.00. These summary statistics are presented in Table 2.3.

The sample is further reduced to 2,973 after eliminating those with missing or outlying observations for the change in BMI^D. Removing those observations for which the previous change in BMI^D could not be observed, or had a value beyond a reasonable limit leaves 2,351 observations. Observations with either missing or large values for change in their family size are removed, leaving 2,334 child-year observations. Finally 1,094 observations are lost due to missing observations for the change in family income, reducing the final sample to 1,240 child-year observations.

In the low-income sample used in estimation, 47.4% are female, and the average age is 11.04 years. On average, the current change in a child's BMI^D was 0.27 BMI index points, with a standard deviation of 1.89 points. The average previous change in BMI^D was 0.39 points with a standard deviation of 1.87 points. The average change in months of food stamp participation was -0.66, while the average change in FSB receipt was -$189.00. In this sample the average family income was $13,699.18, with a minimum of $79.60 and a maximum of $25,000. These summary statistics are presented in Table 2.4.

Comparing Tables 2.3 and 2.4, it is clear that there is little variation in the sample means between the fill low-income sample and the low-income sample used in estimation, with the exception of the change in BMI^D_{it-1}; as such, the low-income sample used in estimation is fairly representative of the full low-income sample. Comparing Tables 2.2 and 2.4, there is little variation in the sample means between the full and low-income samples, with the exception of the two FSP measures, which are significantly greater in the low-

income sample than in the full sample. This indicates that the samples are demographically similar, the main distinction being the income level.

VII. Empirical Results and Discussion

To identify the effect of participation in the FSP on a child's BMI and probability of becoming obese I begin by using weighted OLS to estimate the change in a child's BMI^D that results from a change in their family's FSP participation. I also perform IV estimation to test for and remove bias caused by unobserved heterogeneity. Additionally hazard estimation is performed to test the hypothesis that participation in the FSP increases the probability that a child becomes obese. Separate OLS estimations are performed for the full and the low-income samples, as the two groups of children must be considered separately from a policy perspective. Additionally, due to the stark differences between boys and girls separate estimations are performed on the basis of gender.

Results from IV estimation are presented in Table 2.5 and indicate that ΔFS_{it-2} is a strong instrument for ΔFS_{it}, for the full and low-income samples. Further, results from Hausman tests reveal that the OLS estimates are not biased for either the full or low-income samples (with χ_5^2 of 2.30 and 1.09 respectively). Thus, it is the case that the $\text{cov}(FS_{it}, \varepsilon_{it}) = 0$, and results from OLS estimation are not biased. As such, the discussion that follows is based on results from OLS estimation.

Results from OLS estimation for the full sample of children are displayed in Table 2.6. The first column shows results for all children (boys and girls), the second column

displays results for girls, and the third for boys. Table 2.7 displays the same information for the low-income sample.[2] OLS results indicate that a change in a family's FSP participation (measured in months or FSB received) does not significantly affect a child's BMI^D. This is a somewhat surprising result given that the FSP is designed to provide families the ability to purchase more food, which is expected to increase the BMI of all individuals in the household. As such, I had anticipated that an increase in FSP participation would increase a child's BMI at an above average rate, which would increase BMI^D for overweight children and reduce BMI^D for underweight children.

In all samples and specifications, the change in BMI^D_{it-1} is statistically significant, and negative in sign. This indicates that children tend to approach their ideal BMI, regardless of their current BMI, and under/over weight classification. That is, a child who becomes less overweight (or more underweight) in one period will have a negative BMI^D_{it-1}, which will act to increase BMI^D_{it}. A child who became more overweight (or less underweight) in the previous period will have a positive BMI^D_{it-1}, which will act to reduce BMI^D_{it}. This suggests that there is neither positive nor negative momentum in the weight accumulation process of a child. Although this term is of significant interest, it is important to note that it may be an artifact of mean reversion, and, thus, must be interpreted with great caution.

This finding is of significant interest, as this is the first paper to include such a term in estimation. The only other paper to estimate a dynamic model is Baum (2007), which did not

[2] Tables 6 and 7 display the results for the preferred specification only. A model is preferred to others if it has a higher adjusted R^2. Full results are available by request.

include a term for previous BMI. Without this term the BMI evolution path was not properly estimated.

In the low-income girl sample the change in a mother's BMI is statistically significant and is always positive in sign. This suggests that children move further away from their ideal BMI as their mother's BMI increases, which is the expected effect for overweight children. Since parents make the majority of decisions for their children I had expected that a mother's BMI would move in the same direction as her child's. This finding, however, is at odds with the empirical findings for low-income girls, who become more underweight as their mother's gain weight.

When significant an increase in family size is found to reduce a child's BMI^D. This is the expected effect for overweight children who find themselves with less food, as an increase in family members is expected to result in less food per person. However, the same logic leads one to conclude that underweight children should find their BMI^D increasing. The empirical result indicates that underweight children tend to move closer to their ideal BMI as a result of family size increasing.

Results from the Cox proportional hazard estimation are presented in Table 2.8, and indicate that FSP participation does not significantly increase the probability that a child becomes obese, regardless of household income. The first column presents findings for the full sample, and indicates that being white reduces the probability of a child becoming obese by 39.3%, while having an obese mother increases the probability of a child becoming obese by 208.0%. The results from estimation based on the low-income sample indicate that being

white reduces the probability of becoming obese by 39.6%, having an increase in income reduces the probability of becoming obese by 0.7% and having an obese mother is found to increase the probability of a child becoming obese by 123.1%.

The results obtained from both OLS and hazard estimation are consistent with those of Bhattacharya and Currie (2002), and Hofferth and Curtin (2005). Bhattacharya and Currie (2002) found no significant relationship between the FSP participation of an adolescent's family and their probability of being overweight. Hofferth and Curtin (2005) found that household participation in the FSP does not have a significant effect on a low-income child's likelihood of being overweight; and is, in fact, associated with a child being of normal weight. However, this finding is at odds with Gibson (2004). Gibson (2004) finds that long-term FSP participation increases the BMI and probability of being overweight for low-income female children between the ages of 5 and 11.

VIII. Conclusion

This paper advances the literature on childhood obesity by exploring the relationship between a family's FSP participation and the deviation of a child's current BMI from their medically ideal BMI. This paper makes two significant contributions to the already rich body of literature. Most significantly this paper is the first to include a term for a child's previous BMI, which is important as weight is accumulated over time, and people rarely have large changes in weight from one year to another. Second, this paper is the first to apply

dynamic modeling techniques to children, and the second to apply dynamic techniques to the issue of obesity.

Consistent with previous literature this paper finds no statistically significant relationship between participation in the FSP and childhood obesity. However, this paper does provide important insight into the dynamics of a child's deviation from ideal BMI. This paper examined how a child's BMI fluctuates from the ideal level and finds that there is a tendency for any deviation from ideal to be counteracted in the next period. That is, a child who's $BMI^D > 0$ in one period had a tendency to have a lower BMI^D in the next period, while children with $BMI^D < 0$ experience the opposite.

This paper also finds a significant relationship between the BMI of a low-income mother and that of her daughters. The empirical findings of this paper indicate that there is a positive and direct relationship between the change in a woman's BMI and her child's BMI^D. This indicates that as mothers gain weight there is a negative impact on their child's health regardless of the child's initial BMI^D. Specifically, as a woman's BMI increases an overweight child becomes more overweight, and an underweight child becomes more underweight.

There are several possible explanations for this finding. It may be that mothers who are gaining weight find utility in knowing that their children are slim, and thus do not have an incentive to try and increase their child's BMI, permitting them to remain underweight. Mothers of overweight children do not have the same incentive. Another possible explanation may be that mothers who experience change in their life may reward (or

comfort) themselves with more food but are better able to monitor their children's food consumption. That is a mother who eats to feel better may be able to prevent her child from doing the same, although she cannot prevent herself. A solid understanding of the relationship between a mother's BMI growth and that of her child's would be of great benefit to medical professionals, educators, and policy makers. Further work should be done to examine this connection.

While the results of this paper are a valuable contribution to the literature, care must be utilized in their interpretation for several reasons. First and foremost, this paper does not control for a child's overall health, and does not account for any illnesses, eating disorders, or diseases the child may have, which would affect their BMI. Second, this paper does not control for the activities in which a child participates. It is likely that children who are highly active will have lower BMI's than those who do not. Third, this paper does not test for the effects of long-term and continuous enrollment in the FSP, which is expected to significantly affect a child's BMI. The longer a family is enrolled in the program the greater the effects of enrollment will be, thus, while this paper finds no relationship between FSP enrollment and a child's BMI^D, this may be only the short-term effect. It is possible that in the long-term, FSP participation is associated with overweight and obesity in children.

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Table 2.1: Summary Statistics for the Full Sample

	N	Mean	Standard Deviation	Minimum	Maximum
Gender	46996	0.488	0.499	0	1.00
Age	46996	11.391	3.845	5.00	18.00
Household Income	45823	66.77	57.85	0.31	691.49
Change in BMI^D	28337	0.295	2.827	-33.87	26.46
Previous Change in BMI^D_{t-1}	28508	0.284	3.08	-33.87	29.02
Change in Family Size	41212	-0.048	1.265	-14.00	13.00
Change in FSP Participation (in months)	46996	-0.482	5.169	-24.00	24.00
Change in FSB Received	46996	-0.097	2.361	-$93.20	$72.75
Change in log of Family Income	17105	0.124	0.62	-6.69	7.00

*Household Income and FSB receipt are reported in thousands of dollars

Table 2.2: Summary Statistics for the Final Full Sample

	N	Mean	Standard Deviation	Minimum	Maximum
Gender	10899	0.488	0.499	0	1.00
Age	10899	11.540	3.468	5.00	18.00
Household Income	10899	65.39	54.81	0.80	691.49
Change in BMI^D	10899	0.250	1.943	-4.97	4.99
Previous Change in BMI^D_{t-1}	10899	0.315	1.914	-4.99	4.99
Change in Family Size	10899	-0.010	0.865	-5.00	5.00
Change in FSP Participation (in months)	10899	-0.483	5.215	-24.00	24.00
Change in FSB Received	10899	-0.115	2.974	-$93.20	56.08
Change in log of Family Income	10899	0.135	0.709	-6.98	7.56

* Household Income and FSB receipt are reported in thousands of dollars

Table 2.3: Summary Statistics for the Low-Income Sub-sample

	N	Mean	Standard Deviation	Minimum	Maximum
Gender	4900	0.484	0.499	0	1
Age	4900	10.82	3.738	5.00	18.00
Household Income	4900	13.41	7.42	0.31	25.00
Change in BMI^D	3216	0.318	2.762	-15.700	26.464
Previous Change in BMI^D_{t-1}	3148	0.254	3.013	-32.781	17.162
Change in Family Size	4461	0.020	1.307	-10.00	12.00
Change in FSP Participation (in months)	4900	-0.527	5.712	-24.00	24.00
Change in FSB Received	4900	-0.149	3.771	-93.22	56.08
Change in log of Family Income	2582	0.131	1.133	-6.69	5.59

* Household Income and FSB receipt are reported in thousands of dollars

Table 2.4: Summary Statistics for the Final Low-Income Sub-sample

	N	Mean	Standard Deviation	Minimum	Maximum
Gender	1240	0.474	0.499	0	1.00
Age	1240	11.036	3.309	5.00	18.00
Household Income	1240	13.70	7.08	0.80	25.00
Change in BMI^D	1240	0.274	1.890	-4.91	4.91
Previous Change in BMI^D_{t-1}	1240	0.389	1.878	-4.87	4.94
Change in Family Size	1240	0.060	0.827	-4.00	4.00
Change in FSP Participation (in months)	1240	-0.660	5.690	-24.00	24.00
Change in FSB Received	1240	-0.189	4.180	-56.83	56.09
Change in log of Family Income	1240	0.134	1.057	-5.52	4.55

* Household Income and FSB receipt are reported in thousands of dollars

Table 2.5: Instrumental Variable Estimation Results for the Full and Low-Income Samples

	Full Sample	Low-Income Sample
Change in BMI^{D}_{it-1}	-0.213^{+++}	-0.423^{+++}
	(0.023)	(0.100)
Change in Mother's BMI	.	0.215^{+}
	.	(0.115)
Change in FSP Participation (instrumented)	-0.077^{+}	0.056
	(0.046)	(0.058)
Change in Family Size	-0.140^{++}	-0.403
	(0.050)	(0.276)
Change in Highest Grade Completed	.	-0.044
	.	(0.329)
Change in Highest Degree Earned	-0.848^{+}	.
	(0.443)	.
Change in log(Income)	0.050	-0.045
	(0.064)	(0.186)
Change in AFDC Participation	0.555^{+}	-0.048
	(0.315)	(1.031)
Hausman Test Statistic	2.30	1.09
N	1903	109

*Standard errors are shown in parentheses

$^{+}$indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$indicates $p \leq 0.01$

Table 2.6: Weighted OLS Results for the Full Sample

	All Children	Girls	Boys
Change in BMI^{D}_{it-1}	-0.212^{+++}	-0.187^{+++}	-0.266^{+++}
	(0.015)	(0.022)	(0.032)
Change in Mother's BMI	.	.	.
	.	.	.
Change in FSP Participation	-0.0003	0.008	.
	(0.006)	(0.009)	.
Change in FSB Receipt	.	.	0.068
	.	.	(0.050)
Change in Family Size	-0.120^{++}	-0.164^{++}	-0.026
	(0.034)	(0.046)	(0.082)
Change in Highest Grade Completed	.	.	0.113
	.	.	(0.108)
Change in Highest Degree Earned	-0.114	0.020	.
	(0.169)	(0.212)	.
Change in log(Income)	0.103^{++}	0.161^{++}	0.038
	(0.041)	(0.059)	(0.091)
Change in AFDC Participation	0.032	-0.068	.
	(0.126)	(0.181)	.
Adjusted R^2	0.048	0.044	0.067
N	4,012	2,018	944

*Standard errors are shown in parentheses

$^{+}$indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$indicates $p \leq 0.01$

Table 2.7: Weighted OLS Results for the Low-Income Sample

	All Children	Girls	Boys
Change in BMI^{D}_{it-1}	-0.311^{+++}	-0.202^{+}	-0.350^{++}
	(0.090)	(0.120)	(0.030)
Change in Mother's BMI	0.248^{++}	0.273^{++}	0.182
	(0.030)	(0.133)	(0.167)
Change in FSP Participation	0.020	.	0.052
	(0.032)	.	(0.049)
Change in FSB Receipt	.	-0.279	.
	.	(0.200)	.
Change in Family Size	-0.360	-0.288	-0.575
	(0.256)	(0.329)	(0.398)
Change in Highest Grade Completed	-0.324	-0.695	-0.047
	(0.290)	(0.452)	(0.381)
Change in Highest Degree Earned	.	.	.
	.	.	.
Change in log(Income)	0.197	0.298^{+}	-0.012
	(0.145)	(0.175)	(0.259)
Change in AFDC Participation	-0.012	2.214^{++}	-1.368
	(0.631)	(0.885)	(0.890)
Adjusted R^2	0.101	0.196	0.108
N	140	71	69

*Standard errors are shown in parentheses

$^{+}$indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$indicates $p \leq 0.01$

Table 2.8: Hazard Estimation Results for the Full and Low-Income Samples

	Full Sample (hazard ratios)	Low Income Sample (hazard ratios)
Male	1.139	0.940
	(0.172)	(0.230)
White	0.608^{+}	0.604^{++}
	(0.099)	(0.154)
Obese Mother (=1 if mother is obese)	3.080^{+++}	2.231^{+++}
	(0.549)	(0.730)
FSP Participation	0.985	1.094
	(0.199)	(0.315)
Family Size	0.987	1.085
	(0.041)	(0.076)
Highest Grade Completed by Mother	0.9994	.
	(0.036)	.
Log of Household Income	1.102	0.993^{++}
	(0.092)	(0.197)
Participation in AFDC	.	.
	.	.
N	6780	1542

[*]Standard errors are shown in parentheses

[+]indicates $p \leq 0.10$, [++]indicates $p \leq 0.05$, [+++]indicates $p \leq 0.01$

APPENDIX

The dynamic nature of weight accumulation, the process through which individuals become obese, and the many changes (physical and social) that children in the sample are experiencing, makes employment of a model that captures the transitions individuals are going through necessary. The NLSY79 and NLSY79 Child and Young Adult survey data employed by this paper are longitudinal data sets, which allow individuals to be tracked over time, and their current characteristics observed. Given the data sets richness, and the dynamic nature of weight accumulation, it is prudent to model such a decision using duration analysis, which easily accommodates time-varying covariates, and is naturally concerned with analyzing the time until an event occurs.

Within the realm of standard duration analysis lays three separate and distinct parameterization strategies. The first, nonparametric analysis, does not require any assumption about the distribution of failure times (i.e. the baseline hazard), and does not include covariates. This modeling technique essentially lets the data speak for itself, and models the time to occurrence based solely on the passage of time itself. The second modeling approach is to utilize, semiparametric analysis, which, does not require an assumption about the baseline hazard, but parameterizes the effect of covariates. Finally, the third modeling approach, parametric estimation, requires an assumption about the shape of the baseline hazard, and includes covariates in the analysis. In general, semiparametric models are more robust than parametric models, since they do not assume a distributional

form for the baseline hazard, and are preferred to nonparametric models as they permit covariates to enter the analysis.

Regardless of parameterization method employed, hazard function estimation (duration analysis) is preferred to conditional probit/logit estimation, when a dynamic decision is being analyzed, and the primary point under analysis is the length of time before an individual exits an initial state. Duration analysis is preferred to conditional logit estimation for its flexibility, and ability to analyze the probability of a failure occurring, given lack of a failure in any previous period. Logistic estimation would require estimation be based on the probability of failure in period t, given lack of failure in some previous period, for example, $t-1$. Hazard models, on the other hand, can easily accommodate the changing conditions which individuals must constantly adapt to, and consider in their decision making process. As such, they are able to capture the dynamics of decision making over a broader time period than conditional logit estimation, and thus, truly estimate the probability of failure, given failure has not yet occurred.

To model the instantaneous probability of a child becoming obese, given a child has not done so in previous periods, I follow the approach laid out in Cleves, Gould, Guitierrez and Marchenko (2007). First, consider the survivor function, $S(t)$, which represents the probability of remaining at healthy BMI past time t, or alternatively, is the probability that an individual has not yet become obese. The survivor function is specified as,

(3). $S(t) = 1 - F(t) = \Pr(T > t)$, where t, is the period in which a child becomes obese, or censoring occurs. Empirically, $S(t)$ is simply one minus cumulative distribution function of T, and thus, the density function, $f(t)$, can easily be obtained from $S(t)$, as

(4). $f(t) = \dfrac{dF(t)}{dt} = \dfrac{d}{dt}\{1 - S(t)\} = -S'(t)$.

Utilizing (3) and (4) the hazard function, $h(t)$, which represents the instantaneous rate of failure, can be shown to be,

(5). $h(t) = \lim_{\Delta t \to 0} \dfrac{P[t + \Delta t > T > t \mid T \geq t]}{\Delta t} = \dfrac{f(t)}{S(t)}$.

From (5) it is easy to see that when failure becomes more (less) likely, the hazard increases (decreases), while the survivor rate decreases (increases).

Due to the merits of semiparametric techniques, I employ the Cox proportional hazard model, which is specifies the hazard function as,

(6). $h(t) = h_0(t)\exp\{\beta_0 + x_{it}\beta_x\}$,

where, $h_0(t)$ is the baseline hazard, for which no distributional assumption has been made, and x_{it} defines the path of all covariates (some of which are time-varying), for individual i from time t to time $t + \Delta t$.

The likelihood function is, given by,

(7). $L = \prod_{i=1}^{n} h(t) \times S(t)$,

from which, estimates for each β_x are obtained via maximum partial likelihood estimation. The cumulative hazard, $H(t)$, is the total risk of failure over the time period of analysis and can be calculated from the hazard as,

(8). $H(t \mid x) = \int_0^t h(u \mid x)du$

Chapter 3

Bridging the Gap Between the Effects of Food Stamp Program Participation for Children and Adults

I. Introduction

Over the past several decades there has been an increased prevalence of both adult and childhood obesity in American society. This has received significant attention from researchers and governmental agencies, as there are both public health concerns and financial consequences associated with this condition. Obesity is associated with an increased risk for heart disease, stroke, type-2 diabetes, arthritis, and certain forms of cancer—all of which are serious (and costly) conditions. It has been estimated that medical expenditures associated with obesity account for 9% of all national medical expenditures in a given year. Nearly half of this bill is paid for by the government through Medicare and Medicaid expenditures, which translates to a higher tax bill for all tax-paying citizens. Moreover, it has been estimated that obese individuals who are Medicare (Medicaid) participants cost on average $1,486 ($864) more per year than their healthy weight counterparts (Finklestein et al. 2003).

Given the large financial burden (associated with obesity) that falls to the Federal Government, a sizable body of research has addressed the impact of social welfare programs on the obesity outcomes of participants. One program that has received significant attention is the Food Stamp Program (FSP), which is designed as a safety net to ensure that low-income families have an adequate amount of food for survival. This research has revealed a considerable amount of evidence linking the FSP to adult obesity. However, the research

that addresses the connection between FSP participation and childhood obesity has failed to identify a similar effect. In fact, this work has (with one notable exception) found that FSP participation does not increase (and may actually decrease) the prevalence of childhood obesity.[1]

These divergent findings create an interesting economic puzzle as they suggest that FSP participation affects women and children (who presumably live in the same household) differently. This is especially surprising when one considers that mothers are primarily responsible for food purchasing and preparation, and often times control their child's food consumption. As such their food and weight fluctuation experiences are expected to be similar. Additionally, mothers have a great deal of influence over their child's activity level (which is related to caloric expenditure). Mothers who are physically active are likely to have active children, while sedentary mothers are more likely to have sedentary children. The more active an individual is the more calories they expend and the less likely they are to become overweight/obese. Thus, it is clear that mothers are largely responsible for the obesity outcomes of their children.

Previous research (focusing on adults) has found that women who participate in the FSP are more likely (than non-participants) to be obese. However, this work has failed to consider the impact that motherhood has on weight and obesity outcomes. If mothers make healthy food related choices and do not have an increased probability of becoming obese

[1] Gibson (2004) found that FSP participation increases the probability that low-income girls between the ages of 5 and 11 become obese. She found no similar effect for girls over 11 or for boys of any age.

from FSP participation, then it is not surprising that children in FSP households do not have an increased risk of obesity. However, if the effect of FSP participation on obesity found by previous literature is found to hold for mothers and non-mothers alike, then the puzzle remains unsolved. This paper directly addresses this puzzle by considering the possibility that FSP participation affects mothers differently than non-mothers.

Empirically, this is done in three ways. First, I consider weight as an AR-1 process and identify the effect FSP participation has on weight accumulation. In this part of the analysis I find limited evidence that FSP participation increases the likelihood of obesity for non-mothers, but does not have a similar effect for mothers. However, because previous literature has not considered weight accumulation as an AR-1 process, I have no prior expectation about the effect of FSP participation on BMI growth in such a dynamic framework.

As such, I estimate a Cox proportional hazard model to measure the effect of FSP participation on the probability of becoming obese for mothers. This analysis indicates that mothers who participate in the FSP are more likely to become obese than non-mothers, which is counter to the hypothesis of this paper. However, there are multiple forms of bias that plague this analysis. Hence, this analysis is only able to identify a correlation between FSP participation and obesity and cannot identify a causal effect.

Due to the conflicting results obtained from the first two estimations, I perform a third estimation in which I employ data from the A.C. Nielsen HomeScan Survey and estimate the nutritional quality of foods purchased by Food Stamp Eligible (FSE)

households. In this part of the analysis the healthiness of food is measured by the Glycemic Index (GI), which measures how the carbohydrates contained in foods affect blood glucose levels. I then draw comparisons between households with and without children present.[2] If Food Stamp households with children are found to purchase healthier food bundles than households without children, this indicates that households with children contain healthier foods than those without. Consuming a diet rich in healthy food is less likely to be associated with obesity than a diet rich in fat and sugar. Empirical results from this third and final estimation indicate that households with children purchase healthier foods than households without children. Thus, it is not surprising that children living in FSP households are no more likely to become obese than children living in households that do not participate in the FSP.

The remainder of this paper is organized as follows: the next section provides an overview of literature related to FSP participation and obesity. The third section presents the theoretical model, while the fourth discusses the estimation strategies. The fifth section describes the data obtained from the National Longitudinal Survey of Youth 1979 (NLSY79) and the AC Nielsen HomeScan Survey. The sixth section presents the empirical results and discussion and the final section concludes.

[2] These households are approximated to be Food Stamp Eligible (FSE) based on the USDA's 2005 Gross Income Eligibility Criteria.

II. Literature Review

There is a sizable body of literature that examines the relationship between participation in the FSP, the food purchasing behaviors of FSP households, and obesity. This work has examined several avenues through which FSP participation may be positively related to obesity. Amongst these are, the propensity to consume food from a dollar of Food Stamp Benefits (FSB), the type of food that is consumed in FSP households, and the food purchasing patterns of FSP households. Other work has directly estimated the effect of FSP participation on BMI and the probability of becoming obese. Recent work has analyzed the effect of FSB receipt on obesity in a dynamic framework.

Given that obesity is generally caused by an imbalance of calories consumed and those expended the types and quantities of foods consumed by FSP participating households have been examined in a variety of ways. From theory it is expected that providing low-income households with additional income will lead to increased consumption of all goods, including food. An increase in food consumption means higher caloric intake, which if not combined with an increase in caloric expenditure, may (over a long enough period of time) lead to overweight and obesity. Empirically it has been shown that the marginal propensity to consume food from a dollar of FSB is between $0.17 and $0.47, while the marginal propensity to consume food from a dollar of money income is between $0.03 and $0.17. This indicates that the marginal propensity to consume food from a dollar of FSB is between 2 and 10 percent larger than the marginal propensity to consume food from cash income

(Fraker, 1990). This finding indicates that FSP participation encourages participants to consume more food than they would if they were given an equivalent cash benefit.

Although obesity is mainly caused by an imbalance between calories consumed and those expended there is also evidence that over consumption of food in one period followed by under consumption of food in the next period can lead to increased body weight (Dietz 1995).[3] Wilde and Ranney (1998) found this consumption pattern to be prevalent amongst FSP participants. They examined the purchasing and consumption patterns of FSP households over the course of a month and found that a large portion of FSP participants only buy food once per month. Moreover, they found that by the fourth week of each month adults report a large drop in food consumption, but that the food consumption of children remains fairly constant. This serves as an indication that parents exhibit protective behavior toward their children, which would lead parents to choose a healthy diet for their children, which in turn, would protect them from becoming overweight.

Beyond the quantity of food purchased and consumed by FSP households, is the nutritional content of the food being brought into the house. FSP households are, by definition, low-income households and as such are expected to stretch their food budget as far as possible (Darmon, Ferguson, and Briend 2002). Thus, they are likely to buy unhealthy, low-quality foods, which tend to cost less than healthy foods (such as fresh fruits and vegetables). Wilde, McNamara, and Ranney (2000) studied the foods commonly consumed

[3] Dietz focused on children but his results have been verified (for women), by a number of studies including Olson (1999) and Townsend et al (2001).

by FS households and found that they tend to consume a high calorie diet, rich in meat, sugars, and fats. Similarly, Fox and Cole (2004) used the Healthy Eating Index (HEI) and found that FSP participants score lower on the HEI, than non-participants (regardless income), and are less likely to have a high-quality diet than non-participants. These studies indicate that FSP participants are consuming a diet that is likely to lead to weight gain, and may eventually lead to obesity.

Given the link between FSP participation and poor diet, Gibson (2003) estimates the effect of FSP participation on an adult's BMI and their probability of being obese. Her findings indicated that FSB receipt leads to an increase in BMI and a high probability of obesity in women. She finds no similar effects for men. Similarly, Baum (2007) quantifies the effect of FSP participation on obesity, but unlike Gibson (2003), does so in a dynamic framework. He finds that women who receive FSB have BMIs that grow faster than non-recipients, and that FSP participants have a higher probability of becoming obese in any period. Like Gibson (2003), Baum's results are specific to women.

Hofferth and Curtin (2005) study the effects of poverty and participation in government sponsored food programs on a child's weight. They examine the effect of participation in the FSP, school lunch program, school breakfast program, and different combinations of these programs on a child's BMI. They find that living in a FSP household does not significantly increase a low-income child's likelihood of being overweight; and is, in fact, associated with a child being of normal weight. Jones et al. (2003) examine the prevalence of obesity in low-income children and find that FSP participation significantly

reduces the odds that a low-income girl (between the ages of 5 and 12) is overweight; however, they did not find an effect for an equivalent male.

Both of the aforementioned results are consistent with the findings of the preceding chapter of this dissertation; in which, I examine the effects of FSP participation on obesity in a framework that carefully models weight accumulation as a dynamic process. Specifically, the current period's weight is taken to be a function of the previous period's weight as well as other covariates. Two estimations were performed. In the first the weight accumulation process is examined, and no significant relationship between a household's FSP participation status and a child's BMI is identified. This result suggests that FSP participation does not influence the weight accumulation path for children, and thus does not play a causal role in childhood obesity. To further test this finding a Cox Proportional Hazard model is estimated, the results of which indicate that FSP participation does not affect the probability that a child becomes obese.

Thus far, the only work to explore the relationship between FSP participation and obesity in mothers is Gibson (2006), whose analysis is limited to mothers with daughters between the ages of 5 and 11. She considers the effect of FSP participation on the obesity outcome of a mother conditional on her child's obesity status and vice versa. Her findings indicate that FSP participation significantly increases the probability that a mother (with a young daughter) is obese, and the probability that the two are obese simultaneously. She finds no evidence that FSP participation affects the probability that a mother is obese given that her daughter is not (and vice versa). While Gibson does find evidence that FSP

participation is positively related to motherhood obesity her analysis is limited to a very specific group of mothers. Her findings may not extend to mothers of sons or mothers with very young and/or older girls. This paper builds on Gibson (2006) by considering the effect of FSP participation on mothers unconditional on her child's age, gender, and obesity status.

This paper also builds on the work of Gibson (2003, 2006) and Baum (2007) and makes two significant contributions to the existing literature. First and foremost, this paper bridges the gap in the literature focusing on women and children by directing its attention entirely on mothers. If results indicate that participation in the FSP is not related to obesity in mothers, but is for women who are not mothers, this will provide an important piece of the puzzle. Such a finding will indicate that women without children drive the effect found in previous work.

Second, this paper is the first to use the A.C. Nielsen HomeScan data to analyze the food purchasing behavior of FSE households and to draw comparisons between households with and without children. Use of this unique data set allows me to directly observe the foods purchased by FSE households. Additionally, this paper is the first to use the GI to objectively identify the "healthiness" of foods brought into a household. This analysis is pivotal to understanding the food related purchases and consumption choices being made by FSE households. Knowledge of the foods that are brought into FSE households is of great interest to policy makers as they evaluate the amount of FSB families should be allocated, and the distribution method that should be employed.

III. Modeling BMI outcomes

This paper strives to measure the effect of FSP participation on BMI outcomes of mothers (as a sub-group of women), and to identify any differences in the effect of FSP participation on obesity outcomes for mothers and non-mothers. An individual's BMI is an accumulation of their past and present condition. If an individual consumes more calories in a period than they are able to expend they are expected to gain weight. If this happens over a long enough period of time individuals will find that they have become overweight, and may eventually become obese. This paper aims to explain the connection between FSP participation and the growth of a woman's BMI, exploiting the connection between FSP participation and BMI^d which is defined as the deviation of a woman's BMI from the ideal BMI level (denoted as $BMI*$), that is, $BMI^d = [BMI - BMI*]$. Over time, BMI^d can increase, remain the same, or decrease. If the absolute difference between current and ideal BMI increases with FSP participation, this would indicate that the FSP has a perverse effect on a woman's health.

Due to the complex relationship between food consumption and utility, individuals may rationally prefer to be at a weight that is not medically optimal. This occurs because people gain utility directly from food (especially that, which tastes good), but simultaneously gain disutility from weight gain (if they are already at or above their ideal weight). Depending on the strength of these effects individuals may find that their utility maximizing weight is different than their medically ideal weight (Philipson and Posner 1999 and Lakdawalla and Philipson 2002).

To model the BMI growth and obesity processes I construct a discrete time dynamic model of utility maximization, which incorporates the findings of Philipson and Posner (1999) and Lakdawalla and Philipson (2002). The utility function includes the individual's health, food consumption, and consumption of other goods, and is given by,

(1). $U = U(F_{it}, C_{it}, H_{it})$

where, F_{it} is the food consumption of individual i in time period t, C_{it} is individual i's non-food consumption in time period t, and H_{it} is the health of individual i in time period t. H_{it} is defined to be a function of BMI^d and other health related measures such that,

(2). $H_{it} = H(BMI_{it}^d, X_{it})$,

where X_{it} is a vector of other health related covariates. BMI_{it}^d, is a function of past weight, depreciation of past weight stock (the calories required to sustain life), and food consumed, such that,

(3). $BMI_{it}^d = BMI(BMI_{it-1}^d, F_{it})$.

The Grossman Model is used to define the health production process. Over time an individual's health, H_{it} is expected to decrease, but, through investment, I_{it}, the natural deterioration of health (from aging), can be offset. Thus, from the time of birth, an individual's health, H_{it}, is expected to start deteriorating, at rate δ. The health evolution process is given by, $\frac{\partial H_{it}}{\partial t} = I_{it} - \delta_{it} H_{it}$.

The per-period budget constraint is specified as,

(4). $M_{it} = P'_{ct} C_{it} + P'_{Ft} F_{it}$

where M_{it} is total household income. P'_{Ft} is the effective price of 1 unit of food, which is defined as $P'_{Ft} = P_{Ft} - \alpha FSB_{it}$, where P_{Ft} is the money price of 1 unit of food, α represents the proportion of FSB allocated to expenditure on food, and αFSB_{it} represents the reduction in the price of 1 unit of food due to FSP participation. $P'_{Ct} = P_{Ct} - (1-\alpha)FSB_{it}$ is the true price of 1 unit of all non-food products, where P_{ct} is the effective price of 1 unit of a non-food consumption good, $(1-\alpha)$ is the portion of FSB allocated to expenditure on non-food products, and $(1-\alpha)FSB_{it}$ is the reduction in the price of 1 unit of consumption goods as a result of FSB receipt.

Then, the consumer's problem is to,

$$\max_{F_{it},C_{it}} \sum_{t=0}^{\infty} \beta_t U(F_{it}, C_{it}, H_{it})$$

$$\text{(4).} \quad s.t. \quad M_{it} = P'_{ct} C_{it} + P'_{Ft} F_{it}$$

$$BMI^d_{it} = W(BMI^d_{it-1}, F_{it})$$

$$H_{it} = H(BMI^d_{it}, X_{it})$$

Using standard techniques, the Bellman equation can be written as,

$$\text{(6).} \quad V_{it}(BMI^d_{it-1} \mid Z_{it}) = U(BMI^d_{it-1}) + \beta[V_{it+1}(BMI^d_{it})]$$

and the Lagrange expression is

$$\text{(7).} \quad L = U(F_{it}, C_{it}, H_{it}) + \beta[V_{it+1}(BMI^d_{it})] + \lambda_t[M_{it} - P'_{Ct}C + P'_{Ft}F]$$

First order conditions of the maximization problem (assuming interior solutions) are

$$F_{it}: \quad \frac{\partial U}{\partial F_{it}} + \frac{\partial U}{\partial H_{it}} \frac{\partial H_{it}}{\partial BMI_{it}^{d}} \frac{\partial BMI_{it}^{d}}{\partial F_{it}} + \beta \left[\frac{\partial V_{it+1}}{\partial BMI_{it}^{d}} \frac{\partial BMI_{it}^{d}}{\partial F_{it}} \right] - \lambda_t P'_{Ft} = 0$$

(8). $$C_{it}: \quad \frac{\partial U}{\partial U_{it}} \frac{\partial U_{it}}{\partial C_{it}} - \lambda_t P'_{Ct} = 0$$

$$\lambda_t: \quad M_{it} - P'_{Ct} C_{it} - P'_{Ft} F_{it} = 0.$$

The optimal choices for F_{it} and C_{it} are characterized by the set of first order conditions above and are functions of food price, income, and deviation from ideal BMI, such that,

(9). $$\begin{aligned} F_{it}^{*} &= F_{it}(P'_{Ft}, P'_{Ct}, M_{it}, BMI_{it-1}^{d}) \\ C_{it}^{*} &= C_{it}(P'_{Ft}, P'_{Ct}, M_{it}, BMI_{it-1}^{d}) \end{aligned}.$$

The main effect of interest is the effect of FSP participation on BMI^{d} which is given by,

(10). $\frac{\partial BMI_{it}^{d}}{\partial FSB_{it}} = \frac{\partial BMI_{it}^{d}}{\partial F_{it}} \frac{\partial F_{it}}{\partial P'_{Ft}} \frac{\partial P'_{Ft}}{\partial FSB_{it}}$, and is positive in sign.[4]

Of secondary interest is the effect of BMI_{it-1}^{d} on BMI_{it}^{d} which is given by,

(11). $\frac{\partial BMI_{it}^{d}}{\partial BMI_{it-1}^{d}} = \frac{\partial BMI_{it}^{d}}{\partial BMI_{it-1}^{d}} + \frac{\partial BMI_{it}^{d}}{\partial F_{it}} \frac{\partial F_{it}}{\partial FMI_{it-1}^{d}}$, and is ambiguous in nature.[5]

IV. Estimation Strategies

Estimation Strategy 1: Modeling BMI growth as an AR-1 Process

Due to the fact that obesity is not a disease individuals fall prey to in a single time period, but is the result of choices made over a long period of time, it is appropriate to model

[4] The derivation of this effect can be found in Chapter 2 of this dissertation.
[5] The derivation of this effect can be found in Chapter 2 of this dissertation.

obesity as a dynamic process. To estimate the BMI^d growth path, based on the theoretical model presented above, I approximate a woman's BMI^d to be a function of her: previous BMI^d, FSP participation, and other control variables including race, family size, educational attainment, and household income, such that

(12). $BMI_{it}^d = \beta_0 + \beta_1 BMI_{it-1}^d + \beta_2 FS_{it} + \beta_3 Fam_{it} + \beta_4 Edu_{it} + \beta_5 \ln(Inc_{it}) + u_i + \varepsilon_{it}$,

where BMI_{it-1}^d is last period's BMI deviation from the ideal BMI, FS_{it} is the current FSP participation, Fam_{it} is family size, Edu_{it} is a woman's educational attainment, $\ln(inc_{it})$, is the log of household income, u_i is an individual specific error term (fixed effects), and ε_{it} is the error term. This model truly captures the dynamic nature of BMI^d by including a woman's previous BMI^d. Doing so reduces the potential for both the reverse causality bias and simultaneity bias (discussed by Gibson 2003, 2004 and Baum 2007) that plagued previous studies of the effect of FSP participation on obesity.

Reverse causality bias arises if a woman's previous BMI^d determines her enrollment in the FSP. This can happen especially when a woman's previous BMI^d is negative. Simultaneity bias arises if a woman's enrollment in the FSP influences her BMI^d, but at the same time, her BMI^d influences her decision to enroll in the FSP. With a dynamic model, it is clear, that it is possible for FS_{it} to be determined or influenced by BMI_{it-1}^d, but not by BMI_{it}^d, thus reducing the likelihood of reverse causality and simultaneity problems.

Controlling for the fixed effects is important because it controls for selection bias, which is another bias that plagued previous studies. Failing to do so could make the FS

variable endogenous, resulting in biased estimates. This is because it is possible that u_i, which we cannot observe, contains individual specific information that may influence the decision to enroll in the FSP and a woman's BMI^d at the same time.

However, controlling for the fixed effects does not eliminate the potential heterogeneity bias resulting from correlation between a woman's FSP participation and the unobserved error, ε_{it} which, may cause FSP participation to be endogenous. To account for the potential endogeneity of FS_{it}, from the fixed effects, I first difference the BMI^d equation over time to eliminate the fixed effects. Then, due to the potential endogeneity bias caused by the correlation between FS_{it} and ε_{it} I consider two specifications: the first under the assumption that the $\text{cov}(FS_{it}, \varepsilon_{it}) = 0$, and the second, under the assumption that the $\text{cov}(FS_{it}, \varepsilon_{it}) \neq 0$.

Under the assumption that $\text{cov}(FS_{it}, \varepsilon_{it}) = 0$, I base my estimation of the parameters in (12), on,

(13). $\Delta BMI_{it}^d = \beta_1 \Delta BMI_{it-1}^d + \beta_2 \Delta FS_{it} + \beta_3 \Delta Fam_{it} + \beta_4 \Delta Edu_{it} + \beta_5 \Delta \ln(Inc_{it}) + \Delta\varepsilon_{it}$

where $\Delta BMI_{it}^d = BMI_{it}^d - BMI_{it-1}^d$ and the other terms are similarly defined. The main parameter of interest is β_2, which captures the effect a woman's FSP participation has on her BMI^d. Also of interest is β_1 which captures the effect a woman's BMI_{it-1}^d has on her BMI_{it}^d.

Under the assumption that (13) remains biased, which will be the case if, $\text{cov}(FS_{it}, \varepsilon_{it}) \neq 0$, I consider a two-stage approach. In this specification, I use FSP

participation, with a two-period lag, (FS_{it-2}), as an instrument for current FSP participation. In this first stage I regress ΔFS_{it} on ΔFS_{it-2} and other covariates to obtain the predicted value of ΔFS_{it}, denoted, $\Delta \hat{FS}_{it}$. In the second stage I estimate the parameters in (12), based on,

(14). $\Delta BMI_{it}^{d} = \beta_1 \Delta BMI_{it-1}^{d} + \beta_2 \Delta \hat{FS}_{it} + \beta_3 \Delta Fam_{it} + \beta_4 \Delta Edu_{it} + \beta_5 \Delta \ln(Inc_{it}) + \Delta\varepsilon_{it}$.

(14) will generate unbiased estimates for the effect of FSP participation, provided ΔFS_{it-2}, is in fact a valid instrument for ΔFS_{it}. This is the case as long as, ΔFS_{it-2} significantly effects ΔFS_{it}, but does not have a significant effect on ΔBMI_{it}^{d}, independent of ΔFS_{it}. The strength of ΔFS_{it-2} as an instrument is determined using a t-test, while the Hausman test is used to identify bias in OLS estimates obtained from (13).

Estimation Strategy 2: Modeling the Probability of Becoming Obese

To identify the effect of FSP participation on the probability that a mother becomes obese a semiparametric Cox proportional hazard model of the form,

(15). $h(t) = h_0(t)\exp\{\beta_0 + x_{it}\beta_x\}$

is estimated. Hazard function estimation is preferred to conditional probit/logit estimation when a dynamic decision is being analyzed and the primary point under analysis is the length of time before an individual exits an initial state. Duration analysis is preferred to conditional probit/logit estimation for its flexibility and ability to analyze the probability of a failure occurring, given lack of a failure in any previous period. Moreover, the Cox model is

able to incorporate time-varying covariates, which is critical when attempting to model a dynamic process. [6]

Estimation Strategy 3: Modeling the Nutritional Quality of Food Purchases

To estimate the quality of food purchased, and thus consumed, by FS households the healthiness of foods purchased by a household is estimated to be a function of observable household and individual characteristics, such that

(16). $F_{it}^{N} = \beta_0 + \beta_1 Mom_{it} + \beta_2 X_{it} + \varepsilon_{it}$,

where, F_{it}^{N} is a measure of the "healthiness" of food purchased by household i in period t, Mom_{it} is a binary variable indicating the presence of children in a household (regardless of biological relationship). X_{it} is a vector of other covariates including a woman's labor market participation, marital status, age, race, educational attainment, region of residence, and ε_{it} is the unobserved error. The main parameter of interest is β_1, which captures the effect of children on the food purchasing behavior of households and allows me to compare the behavior of households with children to those without.

V. Data

For the first two parts of this analysis I use data from the 1986-2004 waves of the NLSY79 to identify the relationship between FSP participation and the obesity status of

[6] For a complete description of duration analysis, and in particular hazard model estimation please see Appendix 1.

mothers.[7] The NLSY79 is a longitudinal survey that began in 1979 and originally interviewed 12,686 individuals who were between the ages of 14 and 22. The respondents were surveyed annually from 1979 to 1994, and biennially thereafter. The NLSY79 is designed to gather detailed information about the life-changes experienced by this cohort of young people. Specifically data is collected about their: schooling, labor market participation, training investments, military experience, income and assets, health, alcohol and substance use, attitudes and aspirations, geographic residence, family background, household composition, martial history, and child care.

A woman's BMI is calculated based on her self-reported height and weight. A woman is classified as obese if her BMI is greater than 30, which is the threshold level (for obesity) defined by the Center for Disease Control (CDC). The only exceptions to this rule are women who are currently or have (within the last year) been pregnant, as the CDC table cannot be used for pregnant or nursing women. Following Baum (2007) and Gibson (2003) females are determined to be low-income if they have not earned more than a high school diploma. Individuals are determined to be FSP participants if they reported enrollment in the program or report receiving a positive amount of FSB.

[7] The 1987, 1989, 1991, 1993 waves are excluded from analysis to maintain a consistent time interval between observation periods.

Data for Estimation of BMI Growth in an AR-1 Framework

To identify the effect of FSP participation on the weight accumulation process I calculate changes between: 1986 and 1988, 1988 and 1990, 1990 and 1992, 1992 and 1994, 1994 and 1996, 1996 and 1998, 1998 and 2000, 2000 and 2002, 2002 and 2004. The 1986-1988 period is not used in estimation, as it is not possible to calculate BMI_{it-1}^{d}. To measure the effect of FSP participation on a woman's BMI growth path I utilize the deviation between a woman's actual BMI, and her medically ideal BMI (as defined by the CDC).

Estimation is based on a panel of women who were still considered active respondents to NLSY79 in 2004, and the unit of measurement is a woman-year observation. As of the 2004 wave of the NLSY79 there are 4,671 women yielding 42,039 woman-year observations. Due to the fact that NLSY79 is conducted on a biennial basis and 24 months is a reasonably short period of time, I place limits on the magnitude of each change of interest. Specifically, the change in BMI_{it}^{d}, BMI_{it-1}^{d}, and family size are restricted to be no larger than five (in absolute value).

Of the 42,039 observations 7,650 were removed from the study for invalid (negative or missing) entries for education level, resulting in a sample of 34,389 observations. Of these 5,890 are eliminated due to missing or invalid measures for the current periods change in BMI_{it}^{d}, and another 2,419 are removed due to missing or invalid measures for the change in BMI_{it-1}^{d}. Next I eliminated 10 observations for which I could not observe the change in their number of children, and another 2,966 observations for whom I am unable to observe the change in family size or for whom I observed an outlying value. Finally, 11,501

observations were removed because they had missing values for the change in their income, resulting in a final sample of 11,693 woman-year observations.

Summary statistics for the full sample of women are presented in the first column of Table 3.1. Of these women 76.95% (8,998) were mothers. The average change in BMI_{it}^{d} was 0.42 index points, and the average change in BMI_{it-1}^{d} was 0.45 index points. The average change in FSP participation was -0.26 months. Summary statistics for the 8,998 mothers are presented in the third column of Table 3.1. Within the sample of mothers the average change in BMI_{it}^{d} was 0.41 index points, and the average change in BMI_{it-1}^{d} was 0.46 index points. The average change in FSP participation was -0.32 months.

There are 8,555 observations considered low-income.[8] Sample means for this group are reported in the second column of Table 3.1. The average change in their BMI_{it}^{d} was 0.41 index points, while the average change in their BMI_{it-1}^{d} was 0.43 index points. On average the change in their FSP participation was -0.34 months. Of the low-income observations 6,834 are considered mothers. Sample means for this group are presented in the fourth column of Table 3.1. The average change in their BMI_{it}^{d} was 0.40 index points, while the average change in their BMI_{it-1}^{d} was 0.44 index points. Comparison of the aforementioned columns indicates that there is little variation between mothers and non-mothers, and between the full and low-income subsamples.

[8] In the full NLSY79 sample, nearly 60% of women, for whom education is observable, are considered low-income. In this study, 73.2% of women are considered low-income. This is somewhat higher than expected and is the result of the decision to drop observations with incomplete income information.

Data for Cox Proportional Hazard Model Estimation

To identify the effect of FSP participation on the probability that a mother becomes obese I use data from the 1986-2004 waves of the NLSY79 to construct two samples—the first is a sample of all mothers and the second a sample of low-income mothers. A woman enters the sample the first time she reports living with a child, regardless of their biological relationship, and remains in the sample until failure or censoring occurs. In 1986 there were 6,298 women, of whom 1,377 were eliminated because they had missing or invalid BMI observations. Next women whose education level is not observable were eliminated from the sample, leaving 4,396 women. In 1986 the average age of women in this sample was 25.6 years and 50.2% of women were already mothers. Nearly 40% of women were participating in the FSP, and of those participating in the FSP nearly 64.0% were mothers. On average, these women had completed 12.8 grades of school. Summary statistics for the full sample are presented in the first column of Table 3.2.

Of the 4,396 women in the sample 2,325 are considered low-income. In 1986 the average age of the low-income women was 25.6 years. 56.4% of women were already mothers. 45.6% of low-income women were participating in the FSP, and of those FSP participants 62.5% were mothers. On average, these women had completed 11.9 grades of school. Summary statistics for the low-income sample are presented in the second column of Table 3.2. Comparing the first two columns of Table 3.2 it seems that the full and low-income women are similar with the exception of their educational attainment.

Summary statistics for the 2,205 women who were already considered mothers in 1986 are presented in the third column of Table 3.2. The average age of these women was 26.1 years and nearly 51% participated in the FSP. Of these mothers 58.8% were married, 6.6% were separated from their spouse, 7.7% were divorced, 0.4% were widowed, and 26.5% had never been married. The average educational attainment in the mother sample (in 1986) was 12.3 grades.

Of the 2,205 women who are considered mothers (in 1986), 1,979 are considered low-income. The average age of these low-income mothers was 26.0 years of age, and 53.7% were FSP participants. 57.3% of the low-income mothers were married, 6.8% were separated from their spouse, 7.9% were divorced, 0.5% were widowed, and 27.6% had never been married. The average educational attainment was 11.9 grades. Summary statistics for the low-income mothers are presented in the fourth column of Table 3.2. Comparing the third and fourth columns of Table 3.2 it is clear that there is little variation in the sample means between the full sample of mothers and the low-income sample used in estimation.

Data for Estimation of Food Purchasing Behavior

For the third part of the analysis I employ data from the 2005 Nielsen HomeScan panel data set, which is available through an agreement between North Carolina State University and the United States Department of Agriculture (USDA). The panel is not randomly selected, but is the result of a stratified probability sampling based on demographic and geographic targets, chosen to create a sample that is demographically a "mini USA"

(Harris 2005). The HomeScan survey began in 1989 with an initial sample of 15,000 participants, and has grown ever since. In 2005 the panel included 61,500 households.

Each household selected into the panel is asked to track the products they purchase, which they do by scanning the UPC code of the item they bought via use of an electronic scanner that is provided by Nielsen. The scanner automatically records the specific item purchased, the UPC code, the type of food (i.e. snack food, fruit, prepared meal, etc.), the quantity purchased, the expenditure per item, and value of coupons used. Each week households are responsible for uploading the data to Nielsen. Some foods, such as fresh fruit, do not have barcodes, which makes collecting data on these foods very costly. As such, Nielsen asks a sub-set of participating households to participate in the Fresh Food Panel.

Upon entry into the survey respondents are asked a series of questions about their demographics, and their economic status. The information they provide at this time allows me to create a sample of FSE households, and to further sub-set those households based on the presence of children. Households are identified as FSE based on their household income and the USDA's gross income test criteria from 2005. Unfortunately the HomeScan survey does not record a household's actual income, which would be the ideal measure to use when determining a household's FSE. Instead the Nielsen survey employs 16 income brackets, which households are categorized into. Thus, identifying households as Food Stamp Eligible (FSE) is not straightforward to do, as the eligibility cut-off points often lie within one of the income brackets. As such, two samples are created.

In the first a household is deemed FSE if they report being in an income bracket which contains an eligibility cut-off point. This approach overestimates the number of FSE households. In the second a household is not counted as FSE unless the entire income bracket they report belonging too is at or below the cut-off point, which underestimates the number of FSE households. For example, in 2005 the gross monthly income limit for a family of three was $1,744 per month, which is equivalent to $20,928 annually. The income brackets that were used to determine FSE for a family of three were the brackets $15,999-$19,999 and $20,000-$24,999. Under the first scheme members of both brackets were deemed FSE; under the second scheme members of the first bracket were considered FSE, and members of the second were not.

The nutritional quality of food is measured using the GI, in the following manner.[9] First, foods found in the GI database were matched as closely as possible to those found in the HomeScan data. When a direct match could be made the GI value from the GI database was used. When a direct match could not be made one of two inference methods was employed, depending on how good a match could be made.

Some products, such as bread, are recorded with great detail in the Homescan data and in the GI, but a good match cannot be made. This happens when the classifications in the GI database do not match the descriptions found in the HomeScan data. In this case the average GI for the category is calculated, and the food is considered in an aggregate sense.

[9] Values for GI were obtained from www.glycemicindex.com during the months of October and November 2008.

For example, there are many varieties of bread reported in both the GI and the HomeScan data; however, the categories and product descriptions do not match well. Thus, in my analysis I used the average GI value for "bread" as the GI value for all varieties of "bread" in the HomeScan data.

Additionally, some foods, such as canned fruits are recorded in detail in both the GI and the HomeScan data and although the details do not match exactly, it is possible to make a direct match for some varieties and to infer values for the remainder. For example, in the GI database canned pears are classified as: pear halves in natural juice; pear halves, Bartlett, canned in pear juice; Pear halves, canned in reduced-sugar syrup (SPC Lite). With GI values of: 43, 44, and 25 respectively. In the HomeScan data canned pears are classified as pears in: heavy syrup; juice pack; light syrup; not applicable; syrup; water pack; extra light syrup; not stated.

The GI of canned pears was determined as follows: pear halves in natural juice was taken to represent pears in juice pack and was also used to approximate the not stated and not applicable categories; pear halves, canned in reduced sugar syrup was taken to approximate the light syrup, the water pack, and the extra light syrup categories; the pears in syrup classification in the HomeScan data was approximated to have a slightly higher GI than pears in juice pack and so the GI was specified at 46, while pears in heavy syrup was taken to be higher than all and was approximated to have a GI of 56. In any case where a direct match was not available and neither approximation method could be employed, GI was recorded as missing.

Next, the GI of each food purchased is summed (for each household) and then average GI per household was calculated. Finally, the average GI value was indexed by the number of people living in the household, resulting in a value referred to as the Glycemic Index Per Person (GIPP). The GIPP is constructed in order to compare the nutritional content of food purchased across households of various sizes. Due to the fact that low GI foods are considered healthier than high GI foods, GIPP is inversely related to a foods nutritional value, and hence an individual's health.

An additional measure, the percent of foods purchased by a household for which GI cannot be measured is constructed. This value is used to control for the fact that some households may purchase more foods for which GI values can be identified than other households. If this happened systematically across all households either with or without children, then GIPP for that group would be distorted and may appear higher or lower than it truly is. Additionally, (for estimation purposes only) household income is approximated to be the midpoint of the income bracket a household reported membership in. For example, if a household selected into the $10,000-$11,999 bracket then their household income is approximated to be $10,999.50.

Since this analysis is primarily concerned with the behavior of mothers all households without an identifiable female head of house were eliminated, resulting in a sample of 35,438 households. All households who reported (their purchases to Nielsen) fewer than 12 times were removed from the sample, and those without a valid entry for GIPP were also eliminated resulting in a final sample of 34,481. Summary statistics for the full sample are

presented in the first column of Table 3.3, summary statistics for the full sample of households without children are presented in the second column of Table 3.3, and summary statistics for households with children are presented in the third column of Table 3.3. Of these households, 25.4% (8,754) had at least one child present. The average GIPP of all households was 5,673 with a standard deviation of 3,115. The 25,727 households without children had an average GIPP of 6,127 and a standard deviation of 3,251. Households with at least one child present had an average GIPP of 4,340 with a standard deviation of 2,187.

Of the 34,481 households in the full sample, 3,676 were considered FSE under the first identification scheme. 32.6% of these households had at least one child present. Summary statistics for these households are presented in Table 3.4. The average GIPP for this group was 6,121 with a standard deviation of 3,571. Households with no children present had a GIPP of 6,977 with a standard deviation of 3,752. The households with children had an average GIPP of 4,349 with a standard deviation of 2,314.

Of the 34,481 households in the full sample, 2,655 were considered FSE under the second identification scheme and 31.9% had at least one child present. Summary statistics for these households are presented in Table 3.5. The average GIPP for this sample was 5,845 with a standard deviation of 3,581. In households where there were no children present the average GIPP was 6,633 with a standard deviation of 3,789. Households with at least one child present had an average GIPP of 4,163 with a standard deviation of 2,326.

VI. Results and Discussion

Results: Effect of FSP Participation on Weight in an AR-1 Framework

To identify the effect of motherhood on the obesity outcomes of women participating in the FSP I first estimate the weight accumulation process in an AR-1 framework that carefully controls for previous weight, and FSP participation. I consider 4 distinct samples in this estimation: the full sample of mothers, the full sample of non-mothers, low-income mothers, and low-income non-mothers. Results from these estimations are presented in Table 3.6.

Due to concerns of bias that will exist if $\text{cov}(FS_{it}, \varepsilon_{it}) \neq 0$ I estimate a two-stage model. Results from this estimation are presented in Table 3.7 and indicate that ΔFS_{it-2} is a strong instrument for ΔFS_{it}, for both the full and low-income samples. Further, results from Hausman tests reveal that the OLS estimates are not biased for either the full or low-income samples. Thus, it is the case that the $\text{cov}(FS_{it}, \varepsilon_{it}) = 0$, and results from OLS estimation are not biased. As such, the discussion that follows is based on results from OLS estimation.

The first column of Table 3.6 shows results for all mothers the second column displays results for all non-mothers, the third and fourth columns present the same information for low-income women. In estimations based on the full and low-income samples the change in FSP participation does not have a significant effect on the BMI^d of mothers, but significantly increases the BMI^d for non-mothers. Specifically, an increase in FSP participation increases the BMI^d of non-mothers as a whole by 0.053 points, and of low-income non-mothers by 0.093 points. As expected, the magnitude of the effect is

significantly larger for the low-income women (who are more likely to be FSP participants) than for the full sample of non-mothers. This result suggests that FSP participation affects the experiences of mothers and non-mothers differently. However, because this is the first paper to consider the relationship between weight and FSP participation in an AR-1 framework, this result should be examined further.

Also of interest is the effect of BMI_{it-1}^{d} on BMI_{it}^{d}. In nearly all estimations the change in BMI_{it-1}^{d} is statistically significant, and negative in sign. This indicates that women (regardless of motherhood status) tend to approach their ideal BMI, regardless of their current BMI. That is, a woman who becomes less overweight (or more underweight) in one period will have a negative BMI_{it-1}^{d}, which will act to increase BMI_{it}^{d}. A woman who became more overweight (or less underweight) in the previous period will have a positive BMI_{it-1}^{d}, which will act to reduce BMI_{it}^{d}. This suggests that there is neither positive nor negative momentum in the weight accumulation process. Although this term is of significant interest, it is important to note that it may be an artifact of mean reversion, and, thus, must be interpreted with great caution.

Results: Effect of FSP Participation on the Hazard of Obesity

To further examine the initial evidence that FSP participation affects low-income mothers and non-mothers differently I estimate a semi-parametric Cox proportional hazard model. The results from this estimation are presented in Table 3.8, and the results from

Model 1, the preferred model, are discussed below.[10] Table 3.8 displays both the parameter coefficients and the hazard ratio for all covariates included in the model. The discussion that follows focuses on the hazard ratios, which are simply the exponentiated parameter coefficients. The hazard ratios indicate whether a change in an important covariate makes failure more (or less) likely. A hazard ratio that is equal to 1.0 indicates that an increase in a covariate has no effect on the probability of failure, while a hazard ratio greater than 1.0 indicates that an increase in a covariate makes failure more likely, and a value less than 1.0 indicates that an increase in a covariate makes failure less likely.

Depending on the nature of the covariate (i.e. dichotomous or continuous), hazard ratios either, compare the hazard rate of one group to another group, or compare the hazard after a change in a covariate to the hazard at its original value. For example, the hazard ratio for FSP participation is 1.204 indicating that FSP participants have a 20.4% higher probability of becoming obese than mothers who are not enrolled in the FSP. The hazard ratio for continuous covariates is interpreted similarly to that for a dichotomous covariate. For example, the hazard ratio for age is 1.013, indicating that becoming a year older increases the probability of becoming obese by 1.3%.

In this analysis the main covariate of interest, FSP participation is significant, and greater than 1.0 indicating that FSP participation is positively correlated to obesity in low-income mothers. Other statistically significant covariates are dichotomous variables for

[10] Model 1 is preferred over model 2 as both its Akaike's information criteria (AIC), and the Bayesian information criteria (BIC) values are lower than model 2's. AIC and BIC are competing model selection criteria under which, models with lower values are preferred over those with higher values.

married, separated, and divorced. The hazard ratios are 0.760, 0.513, and 0.505 indicating that married mothers are 24% less likely to become obese than never married mothers, separated mothers are 49.5% less likely to become obese than never married mothers, and divorced women are 48.7% less likely to become obese than never married mothers. The Cox proportional hazard is displayed in Figure 3.1.

Alternative model specifications, which include dichotomous measures for age and the number of children in the household, are also considered and do not alter the finding that FSP is positively correlated with obesity in low-income mothers. Thus, it seems to be the case that FSP participation is positively associated with obesity in mothers.

Although this finding is counter to the hypothesis of this paper, there are several reasons why this result cannot be interpreted to mean that there is no maternal effect protecting children whose families participate in the FSP. This result may simply be an artifact of bias due to the presence of omitted variables or other forms of bias that have plagued similar studies; and, as such, can not be interpreted to mean that FSP participation has a causal effect on obesity in mothers. Thus, I perform an additional analysis in which I examine the nutritional content of food brought into FSE households.

Results: Effect of Motherhood on Food Purchasing Behavior

I next examine the food brought into households approximated to be FSE and compare the nutritional value of food bundles purchased by households with children to those without. To perform this analysis I employ Ordinary Least Squares techniques and

carefully control for the presence of children in a household. Results from this analysis are presented in Table 3.9.

Under both definitions of FSE, empirical results indicate that households with children purchase food bundles with a lower GIPP than similar households without children. When FSE is overestimated households with at lest one child present were found to purchase a food bundle with a GIPP that is 1,737.13 points less than households without children. Under the second scheme where FSE is underestimated households with children present were found to purchase food bundles with a GIPP that is 1,791.59 points less than similar households without children.

Other covariates found to significantly impact a household's GIPP are marital status, region of residence, educational attainment of female head of house, labor force participation status of female head of house, and the percent of foods purchased for which GI was not observable. Educational level and marital status behave as expected. An increase in educational attainment is negatively associated with a households GIPP indicating that more educated women tend to purchase healthier foods than their less educated counterparts. Similarly married women purchase healthier foods than women who have never been married and those who are either separated or divorced which provides further evidence that women display protective behavior toward their loved ones. The more a woman works the healthier the food she buys, which is consistent with the idea that an increase in income leads to healthier food purchases. The percent of foods for which GI cannot be observed is significant at all alpha levels and is negative in sign.

The finding that FSE households with children purchase healthier foods than those without is a significant contribution to the existing body of literature that has examined the effect of FSP participation on obesity outcomes. This is the first study that directly observes the foods purchased by FSE households and through use of the GI objectively measures the "healthiness" of these foods. Previous studies that have measured the healthiness of foods bought and consumed by individuals have used subjective measures, which are less precise.

This result also sheds light into the divergent results of work studying the relationship between FSP participation in adults and children. Given that households with children are purchasing healthy foods it is reasonable to assume that children whose families participate in the FSP are eating a fairly nutritious diet. Thus, they are likely consuming few of the high fat, high sugar foods that are commonly associated with obesity. In this case, it is not surprising that children who live in FS households do not have an increased risk of obesity due to their family's participation in the FSP.

IX. Conclusion

This paper makes a valuable contribution to the current body of literature devoted to identifying the effect of FSP participation on obesity in the United States. Mainly, this paper recognizes and addresses the divergent findings of the work that focuses on adults and that which focuses on children. The previous work that focuses on adults has found strong evidence that FSP participation leads to both, a higher BMI and a higher probability of being obese for women. However, the work, which focuses on the children of FSP families, has

found significantly different results. The majority of this work finds that FSP participation has no effect on a child's BMI, while some find that FSP participation reduces the likelihood of obesity in children (Jones et al. 2003, Hofferth and Curtin 2005). Gibson (2003) is the only study to find that FSP participation is positively related to obesity and overweight in children, and even then this result is only valid for young girls (between the ages of 5-11).

This paper is the first to directly address this issue. Specifically this paper breaks down the average effect (the effect for all women) studied in previous literature by considering the possibility that FSP participation affects mothers and non-mothers differently. To this end I perform three separate and distinct analyses, all of which carefully control for motherhood status. First, I estimate the weight accumulation path of women (both mothers and non-mothers) as an AR-1 process. Results from this estimation indicate that FSP participation is related to weight gain in women who are not mothers, but does not have a similar effect on mothers. However, since this is the first paper to estimate weight gain in such a process there is no prior evidence of a relationship between FSP participation and weight accumulation when this modeling technique is employed.

I next consider a hazard model with time-varying covariates and estimate the probability that a mother becomes obese given she has not already done so. The results of this estimation indicate that FSP participation is positively related to obesity in both mothers and non-mothers, which is counter to the hypothesis of this paper. However, there are multiple forms of bias associated with this estimation that I am unable to control for. As

such these results are not sufficient to reject the notion that FSP participation affects mothers and non-mothers differently.

Thus, I perform a third and final estimation in which I explore the types and nutritional quality of foods purchased by FSE households. Empirical results indicate that FSE women with children purchase healthier food bundles than women without children. Given that obesity is a disease commonly attributed to eating large quantities of food and with consumption of unhealthy food, this result suggests that FSP participants who have children are less likely to become obese than their counterparts who are not mothers. Since the children are not being exposed to foods commonly associated with obesity it is not surprising that FSP participation does not impact the weight/obesity outcomes of children.

The first and third estimations serve as a step toward bridging the gap in the literature, which focuses on women and that which focuses on children. Results from the first estimation suggest that FSP participation doesn't affect the BMI^d of mothers but does affect the BMI^d of non-mothers. Results from the third estimation suggest that low-income households with children choose healthier food bundles than similar households without children. Given that FSP participation does not affect a mother's BMI^d and that FSE households with children contain healthier foods than those without it is not surprising that FSP participation is not associated with obesity in children. It is also not surprising that FSP participation is positively related to obesity in women. These results suggest that non-mothers are driving the effect identified in previous literature.

Although results from the first and third estimation seem at odds with the findings from the hazard model estimation there are several reasons why these results do not necessarily contradict one another. First and foremost neither analysis is able to observe the mental health nor behavior of the women included in these studies, which has been found to affect a woman's weight and by extension her obesity status. Thus, it is possible that while mothers may live in households that contain healthier food than non-mothers their emotional state may increase their likelihood of becoming obese.[11] Another possibility is that mothers are over consuming healthy food, which if not accompanied by an increase in activity will lead to weight gain and (eventually) to obesity. While obesity is commonly associated with consumption of unhealthy foods, it is not restricted to consumption of unhealthy food. Even the healthiest of foods will, if over consumed, lead to weight gain.

While the results of these estimations are a significant contribution to the literature care must be utilized in their interpretation for several reasons. First, there are many characteristics of a woman that I am unable to control for—mainly her physical and emotional well being which will both play a large role in her food behaviors and weight outcomes. Additionally, I am not able to control for the physical activities that she participates in, nor am I able to control for how physically demanding her work is. Third, this paper does not test for the effects of long-term and continuous enrollment in the FSP, which is expected to significantly affect a woman's BMI.

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[11] Simon et al (2008) found that the prevalence of obesity in depressed women is 22.4% higher than it is for non-depressed women. They also found that depression is associated with a higher calorie diet and with a lower level of physical activity.

III. References

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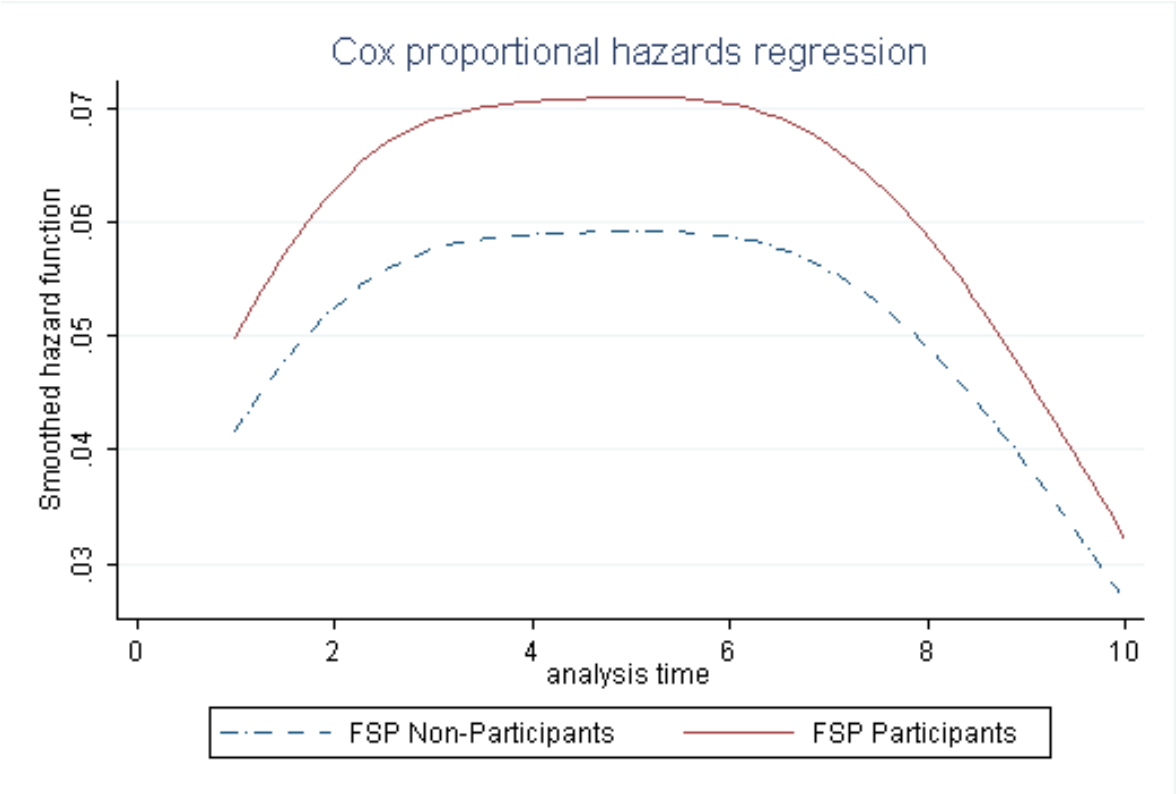

Figure 3.1: Cox Proportional Hazard

Table 3.1: Summary Statistics for All Women

	All Women	Low-Income Women	Mothers	Low-Income Mothers
Mother	0.77	0.80	1.00	1.00
Change in BMI_{it}^{d}	0.42	0.41	0.41	0.40
Change in BMI_{it-1}^{d}	0.45	0.43	0.46	0.44
Change in Family Size	-0.01	-0.03	0.06	0.03
Change in FSP Participation (in months)	-0.26	-0.34	-0.32	-0.39
Change in log of Family Income	0.14	0.14	0.14	0.14
Sample Size	11693	8555	8998	6834

Table 3.2: Summary Statistics for All Women in 1986

	All Women	Low-Income Women	Mothers	Low-Income Mothers
Age	25.63	25.64	26.1	26.03
White (=1 if white)	0.62	0.57	0.55	0.54
Black (=1 if black)	0.31	0.35	0.37	0.38
Married (=1 if married)	0.42	0.43	0.59	0.57
Separated (=1 if separated)	0.04	0.05	0.07	0.07
Divorced (=1 if divorced)	0.06	0.07	0.08	0.08
Widowed (=1 if widowed)	0.003	0.004	0.004	0.004
Never Married (=1 if never married)	0.43	0.39	0.27	0.28
Weeks Unemployed	3.00	3.21	3.86	3.93
Food Stamp Program Participation (=1 if participant)	0.40	0.46	0.51	0.54
Mothers (=1 if mother)	0.50	0.56	1.00	1.00
Highest Grade Completed	12.83	11.93	12.29	11.89
Sample Size	4396	3506	2205	1979

Table 3.3: Summary Statistics for AC Nielsen Households

	All Households	Households With Children	Households Without Children
Age of Female Head of House is Less than 25 years	0.002	0.004	0.002
Age of Female Head of House is 25-30 years	0.018	0.039	0.012
Age of Female Head of House is 30-34 years	0.045	0.116	0.021
Age of Female Head of House is 35-39 years	0.073	0.204	0.028
Age of Female Head of House is 40-44 years	0.108	0.254	0.058
Age of Female Head of House is 45-49 years	0.128	0.193	0.106
Age of Female Head of House is 50-54 years	0.133	0.097	0.145
Age of Female Head of House is 55-64 years	0.232	0.055	0.292
Age of Female Head of House is Over 65 years	0.242	0.019	0.318
Age of Male Head of House is Less than 25 years	0.001	0.002	0.001
Age of Male Head of House is 25-30 years	0.010	0.022	0.006
Age of Male Head of House is 30-34 years	0.031	0.080	0.014
Age of Male Head of House is 35-39 years	0.054	0.156	0.020
Age of Male Head of House is 40-44 years	0.077	0.210	0.032
Age of Male Head of House is 45-49 years	0.094	0.191	0.061
Age of Male Head of House is 50-54 years	0.095	0.112	0.089
Age of Male Head of House is 55-64 years	0.164	0.070	0.196
Age of Male Head of House is Over 65 years	0.181	0.021	0.236
White	0.845	0.760	0.859
Black	0.091	0.115	0.082
Oriental	0.022	0.035	0.018
Resides in Eastern United States	0.159	0.157	0.159
Resides in Central United States	0.239	0.242	0.238
Resides in Southern United States	0.392	0.397	0.391
Resides in Western United States	0.210	0.204	0.213
Respondent Married	0.651	0.812	0.596
Respondent Separated or Divorced	0.135	0.107	0.145
Respondent Widowed	0.099	0.025	0.124
Child in Household	0.254	1	0
Female Head of House Did not Graduate High School	0.036	0.024	0.040
Female Head of House is High School Graduate	0.590	0.520	0.614
Female Head of House is College Graduate	0.255	0.336	0.228
Female Head of House is Graduate School Graduate	0.100	0.100	0.100
Male Head of House Did not Graduate High School	0.052	0.049	0.053
Male Head of House is High School Graduate	0.401	0.462	0.380
Male Head of House is College Graduate	0.173	0.248	0.147
Male Head of House is Graduate School Graduate	0.082	0.103	0.074
Female Head of House Doesn't Work	0.419	0.303	0.458
Female Head of House Works Part-Time	0.113	0.168	0.095
Female Head of House Works Full-Time	0.449	0.510	0.428
Male Head of House Doesn't Work	0.230	0.077	0.282
Male Head of House Works Part-Time	0.030	0.020	0.034
Male Head of House Works Full-Time	0.447	0.765	0.339
Glycemic Index Per Person	5,673	4,340	6,127
Sample Size	34481	8754	25727

Table 3.4: Summary Statistics for the AC Nielsen Houses Estimated To Be Food Stamp Eligible (Overestimate Sample)

	All Households	Households With Children	Households Without Children
Age of Female Head of House is Less than 25 years	0.007	0.016	0.002
Age of Female Head of House is 25-30 years	0.026	0.066	0.007
Age of Female Head of House is 30-34 years	0.053	0.139	0.012
Age of Female Head of House is 35-39 years	0.072	0.179	0.021
Age of Female Head of House is 40-44 years	0.098	0.208	0.045
Age of Female Head of House is 45-49 years	0.109	0.159	0.085
Age of Female Head of House is 50-54 years	0.099	0.096	0.101
Age of Female Head of House is 55-64 years	0.196	0.079	0.252
Age of Female Head of House is Over 65 years	0.324	0.038	0.463
Age of Male Head of House is Less than 25 years	0.003	0.008	0.001
Age of Male Head of House is 25-30 years	0.016	0.038	0.005
Age of Male Head of House is 30-34 years	0.028	0.077	0.005
Age of Male Head of House is 35-39 years	0.050	0.129	0.012
Age of Male Head of House is 40-44 years	0.053	0.123	0.019
Age of Male Head of House is 45-49 years	0.068	0.119	0.043
Age of Male Head of House is 50-54 years	0.056	0.082	0.044
Age of Male Head of House is 55-64 years	0.092	0.057	0.110
Age of Male Head of House is Over 65 years	0.158	0.032	0.220
White	0.822	0.730	0.867
Black	0.103	0.146	0.082
Oriental	0.007	0.012	0.005
Resides in Eastern United States	0.151	0.145	0.153
Resides in Central United States	0.234	0.217	0.242
Resides in Southern United States	0.431	0.462	0.416
Resides in Western United States	0.198	0.182	0.205
Respondent Married	0.467	0.603	0.401
Respondent Separated or Divorced	0.218	0.215	0.220
Respondent Widowed	0.186	0.054	0.250
Child in Household	0.326	1	0
Female Head of House did not Graduate High School	0.096	0.077	0.106
Female Head of House is High School Graduate	0.727	0.689	0.746
Female Head of House is College Graduate	0.142	0.193	0.117
Female Head of House is Graduate School Graduate	0.019	0.021	0.019
Male Head of House did not Graduate High School	0.104	0.114	0.099
Male Head of House is High School Graduate	0.343	0.434	0.299
Male Head of House is College Graduate	0.061	0.094	0.047
Male Head of House is Graduate School Graduate	0.016	0.022	0.014
Female Head of House Doesn't Work	0.662	0.484	0.747
Female Head of House Works Part-Time	0.122	0.180	0.094
Female Head of House Works Full-Time	0.201	0.316	0.146
Male Head of House Doesn't Work	0.274	0.173	0.323
Male Head of House Works Part-Time	0.032	0.044	0.026
Male Head of House Works Full-Time	0.218	0.447	0.108
Glycemic Index Per Person	6,121	4,349	6,977
Sample Size	3676	1198	2478

Table 3.5: Summary Statistics for AC Nielsen Households Estimated To Be Food Stamp Eligible (Underestimate Sample)

	All Households	Households With Children	Households Without Children
Age of Female Head of House is Less than 25 years	0.006	0.015	0.002
Age of Female Head of House is 25-30 years	0.029	0.070	0.010
Age of Female Head of House is 30-34 years	0.050	0.130	0.013
Age of Female Head of House is 35-39 years	0.072	0.187	0.018
Age of Female Head of House is 40-44 years	0.099	0.202	0.050
Age of Female Head of House is 45-49 years	0.113	0.161	0.090
Age of Female Head of House is 50-54 years	0.099	0.079	0.109
Age of Female Head of House is 55-64 years	0.211	0.090	0.268
Age of Female Head of House is Over 65 years	0.304	0.046	0.425
Age of Male Head of House is Less than 25 years	0.004	0.008	0.002
Age of Male Head of House is 25-30 years	0.017	0.044	0.004
Age of Male Head of House is 30-34 years	0.026	0.068	0.006
Age of Male Head of House is 35-39 years	0.046	0.126	0.009
Age of Male Head of House is 40-44 years	0.055	0.125	0.023
Age of Male Head of House is 45-49 years	0.064	0.106	0.045
Age of Male Head of House is 50-54 years	0.053	0.079	0.041
Age of Male Head of House is 55-64 years	0.079	0.050	0.092
Age of Male Head of House is Over 65 years	0.127	0.041	0.167
White	0.794	0.706	0.834
Black	0.113	0.148	0.097
Oriental	0.014	0.018	0.012
Resides in Eastern United States	0.154	0.146	0.158
Resides in Central United States	0.223	0.200	0.233
Resides in Southern United States	0.424	0.470	0.402
Resides in Western United States	0.198	0.182	0.205
Respondent Married	0.413	0.584	0.332
Respondent Separated or Divorced	0.243	0.223	0.252
Respondent Widowed	0.192	0.059	0.254
Child in Household	0.319	1	0
Female Head of House did not Graduate High School	0.111	0.092	0.119
Female Head of House is High School Graduate	0.711	0.697	0.717
Female Head of House is College Graduate	0.140	0.176	0.123
Female Head of House is Graduate School Graduate	0.023	0.014	0.027
Male Head of House did not Graduate High School	0.099	0.126	0.086
Male Head of House is High School Graduate	0.293	0.403	0.242
Male Head of House is College Graduate	0.060	0.099	0.042
Male Head of House is Graduate School Graduate	0.019	0.020	0.018
Female Head of House Doesn't Work	0.698	0.536	0.774
Female Head of House Works Part-Time	0.122	0.181	0.095
Female Head of House Works Full-Time	0.163	0.262	0.117
Male Head of House Doesn't Work	0.253	0.197	0.280
Male Head of House Works Part-Time	0.028	0.046	0.020
Male Head of House Works Full-Time	0.189	0.405	0.088
Glycemic Index Per Person	5,845	4,163	6,633
Sample Size	2655	847	1808

Table 3.6: Results from OLS Estimation of AR-1 Model For All Samples[12]

	Full-Sample Mothers	Full Sample Non-Mothers	Low-Income Mothers	Low-Income Non-Mothers
Change in BMI^{d}_{it-1}	-0.213^{+++}	-0.053	-0.242^{+++}	-0.297^{+++}
	(0.023)	(0.042)	(0.034)	(0.071)
Change in FSP participation	0.001	0.057^{++}	-0.007	0.093^{++}
	(0.012)	(0.030)	(0.014)	(0.038)
Change in number of kids	0.122	.	0.198^{+}	.
	(0.076)	.	(0.109)	.
Change in highest grade of education	0.239^{++}	0.436^{++}	0.027	-0.869
	(0.104)	(0.152)	(0.323)	(0.701)
Change in the log of family income	0.077	0.211^{+++}	0.227^{++}	0.382^{+}
	(0.061)	(0.067)	(0.099)	(0.210)
Change in marital status	0.224	0.768^{++}	-0.002	1.140^{++}
	(0.150)	(0.212)	(0.197)	(0.363)
Adjusted R^2	0.047	0.052	0.061	0.166
N	1,745	571	812	177

*Standard Errors are shown in parentheses
$^{+}$Indicates p≤0.10, $^{++}$indicates p≤0.05, $^{+++}$ indicates p≤0.01

Table 3.7: Results from IV Estimation of AR-1 Model For All Samples

	Full-Sample Mothers	Full Sample Non-Mothers	Low-Income Mothers	Low-Income Non-Mothers
Change in BMI^{d}_{it-1}	-0.215^{++}	-0.480	-0.276^{+++}	-0.232^{++}
	(0.024)	(0.055)	(0.060)	(0.106)
Change in FSP participation	0.030	-0.529	0.026	-0.282
	(0.081)	(0.612)	(0.017)	(0.353)
Change in number of kids	0.112	.	0.261^{++}	.
	(0.077)	.	(0.123)	.
Change in highest grade of education	0.247^{++}	0.443^{++}	0.407	-2.651
	(0.106)	(0.196)	(0.841)	(1.917)
Change in the log of family income	0.076	0.151	0.218^{+}	0.085
	(0.061)	(0.107)	(0.117)	(0.400)
Change in marital status	0.259	0.491	-0.051	0.819
	(0.178)	(0.398)	(0.365)	(0.588)
Chi-Square	0.14	0.92	0.003	1.14
N	1,745	571	607	134

*Standard Errors are shown in parentheses
$^{+}$Indicates p≤0.10, $^{++}$indicates p≤0.05, $^{+++}$ indicates p≤0.01

[12] The preferred model for each sample is displayed above. Full Results are available from the author upon request.

Table 3.8: Results From Cox Proportional Hazard Model Estimation

	Model 1		Model 2	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
White	-0.064	0.938	-0.039	0.962
	(0.183)	(0.172)	(0.162)	(0.811)
Black	0.190	1.209	0.241	1.272
	(0.200)	(0.242)	(0.179)	(0.178)
Married	-0.274^{++}	0.760^{++}	-0.302^{++}	0.739^{++}
	(0.123)	(0.093)	(0.109)	(0.081)
Separated	-0.683^{+++}	0.505^{+++}	-0.462^{+++}	0.630^{+++}
	(0.207)	(0.105)	(0.165)	(0.104)
Divorced	-0.667^{+++}	0.513^{+++}	-0.697^{+++}	0.498^{+++}
	(0.164)	(0.084)	(0.144)	(0.072)
Widow	-0.213	0.808	-0.408	0.665
	(0.369)	(0.298)	(0.346)	(0.230)
Household Income	0.021	1.021	.	.
	(0.046)	(0.047)	.	.
Weeks of Unemployment	.	.	-0.001	1.000
	.	.	(0.003)	(0.003)
Residence in North Central States	-0.161	0.851	-0.149	0.861
	(0.149)	(0.127)	(0.135)	(0.116)
Residence in Western States	0.005	1.005	0.066	1.069
	(0.160)	(0.161)	(0.142)	(0.152)
Residence in Southern States	-0.078	0.925	-0.048	0.953
	(0.139)	(0.129)	(0.126)	(0.120)
Age	0.013	1.013	0.011	1.011
	(0.015)	(0.015)	(0.013)	(0.014)
Food Stamp Program Participation	0.186^{+}	1.204^{+}	0.167^{++}	1.182^{++}
	(0.105)	(0.127)	(0.084)	(0.010)
Log Likelihood	-3550.95	-3550.95	-4732.43	-4732.43
N	1490	1490	1581	1581

*Standard Errors are shown in parentheses
$^{+}$Indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

Table 3.9: OLS Results For the Estimation of the Nutritional Quality of Food Purchases

	Food Stamp Eligibility Over Estimated	Food Stamp Eligibility Under Estimated
Constant	8672.50^{+++}	10433.00^{+++}
	(580.48)	(768.13)
Mom	-1737.13^{+++}	-1791.59^{+++}
	(146.05)	(185.32)
Household Income	-0.06^{+++}	-0.08^{+++}
	(0.01)	(0.01)
Female Head of House Works Part Time	-379.86^{++}	-438.64^{++}
	(153.27)	(201.70)
Female Head of House Works Full Time	-587.70^{+++}	-616.28^{+++}
	(139.88)	(185.99)
Respondent is Married	-1026.89^{++}	-1096.96^{++}
	(164.22)	(205.56)
Respondent is Separated or Divorced	-255.78^{++}	-173.13
	(171.59)	(214.86)
Respondent is Widowed	-109.99	18.33
	(186.19)	(240.33)
White	630.14^{++}	662.31^{++}
	(200.12)	(241.59)
Black	-181.67	-324.82
	(246.07)	(299.44)
Oriental	-555.31	-652.64
	(516.76)	(593.99)
East	1078.28^{+++}	743.15^{+++}
	(164.20)	(216.42)
Central	507.83^{+++}	6.71
	(149.36)	(198.09)
South	517.79^{+++}	287.02^{+}
	(134.65)	(176.52)
Female Head of House is Less than 25 years old	-395.40	123.02
	(641.54)	(816.67)
Female Head of House is 25-30 years	183.06	645.66^{+}
	(345.20)	(420.27)
Female Head of House is 30-34 years	551.18^{+}	895.02^{++}
	(270.37)	(345.70)
Female Head of House is 35-39 years	324.53	328.15
	(242.50)	(309.32)
Female Head of House is 40-44 years	200.33	275.29
	(215.39)	(270.57)
Female Head of House is 45-49 years	120.74	167.43
	(192.54)	(247.50)
Female Head of House is 50-54 years	316.27^{+}	312.68
	(188.88)	(246.65)
Female Head of House is 55-64 years	18.11	152.41
	(140.88)	(186.17)
Female Head of House Has Less than High School Diploma	709.89^{++}	539.78^{+}
	(294.55)	(381.09)
Female Head of House Has High School Diploma	690.25^{++}	500.39
	(255.40)	(337.98)
Female Head of House Has College Diploma	374.62	276.73
	(278.44)	(369.98)
Percent of Foods for which GI is not observable	-2543.87^{+++}	-4105.90
	(473.95)	(638.44)
Adjusted R^2	0.153	0.173
N	4499	2655

*Standard Errors are shown in parentheses
$^{+}$Indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

APPENDIX

This appendix provides a detailed discussion of the Cox Proportional hazard model and displays the non-parametric and semiparametric results of hazard model estimation for the following: the full sample of women, the full sample of mothers, the full sample of non-mothers, the low-income sample of women, and the low-income sample of non-mothers.

Duration analysis easily accommodates time varying covariates, and so is ideal for this context where an individual's current BMI plays a significant role in determining their BMI (and their obesity status) in the next period. Within the realm of standard duration analysis lays three separate and distinct parameterization strategies. The first, nonparametric analysis, does not require any assumption about the distribution of failure times (i.e. the baseline hazard), and does not include covariates. This modeling technique essentially lets the data speak for itself, and models the time to occurrence based solely on the passage of time. The second modeling approach is to utilize, semiparametric analysis, which, does not require an assumption about the baseline hazard, but parameterizes the effect of covariates. Finally, the third modeling approach, parametric estimation, requires an assumption about the shape of the baseline hazard, and includes covariates in the analysis. In general, semiparametric models are more robust than parametric models, since they do not assume a distributional form for the baseline hazard, and are preferred to nonparametric models as they permit covariates to enter the analysis.

Regardless of parameterization method employed, hazard function estimation (duration analysis) is preferred to conditional probit/logit estimation, when a dynamic decision is being analyzed, and the primary point under analysis is the length of time before an individual exits an initial state. Duration analysis is preferred to conditional probit/logit

estimation for its flexibility, and ability to analyze the probability of a failure occurring, given lack of a failure in any previous period. Logistic estimation would require estimation be based on the probability of failure in period t, given lack of failure in some previous period, for example, $t-1$. Hazard models, on the other hand, can easily accommodate the changing conditions which individuals must constantly adapt to, and consider in their decision making process. As such, they are able to capture the dynamics of decision making over a broader time period than conditional logit estimation, and thus, truly estimate the probability of failure, given failure has not yet occurred.

To model the instantaneous probability of becoming obese, given an individual has previously been of a healthy weight, I follow the approach laid out in Cleves, Gould, Guitierrez and Marchenko (2007). First, consider the survivor function, $S(t)$, which represents the probability of maintaining a healthy BMI beyond time t, or alternatively, is the probability that an individual has not yet become obese. The survivor function is defined as,

(3). $S(t) = 1 - F(t) = \Pr(T > t)$,

where t, is the period in which an individual becomes obese, or censoring occurs. By definition, $S(t)$ is simply one minus the cumulative distribution function of F(t), and thus, the density function, $f(t)$, can easily be obtained from $S(t)$, as

(4). $f(t) = \frac{dF(t)}{dt} = \frac{d}{dt}\{1 - S(t)\} = -S'(t)$.

Utilizing (3) and (4) the hazard function, $h(t)$, which represents the instantaneous rate of failure, can be shown to be,

(5). $h(t) = \lim_{\Delta t \to 0} \frac{P[t + \Delta t > T > t \mid T \geq t]}{\Delta t} = \frac{f(t)}{S(t)}$.

From (5) it is easy to see that when failure becomes more (less) likely, the hazard increases (decreases), while the survivor rate decreases (increases).

Due to the merits of semiparametric techniques, I employ the Cox proportional hazard model, which specifies the hazard function as,

(6). $h(t) = h_0(t)\exp\{\beta_0 + x_{it}\beta_x\}$,

where, $h_0(t)$ is the baseline hazard, for which no distributional assumption has been made, and x_{it} defines the path of all covariates (some of which are time-varying), for individual i from time t to time $t + \Delta t$.

The likelihood function is, given by,

(7). $L = \prod_{i=1}^{n} h(t) \times S(t)$,

from which, estimates for each β_x are obtained via maximum partial likelihood estimation. The cumulative hazard, $H(t)$, is the total risk of failure over the time period of analysis and can be calculated from the hazard as,

(8). $H(t \mid x) = \int_0^t h(u \mid x)du$.

Non-Parametric Techniques:

To estimate the relationship between FSP participation and the probability of becoming obese I first estimate the Kaplan-Meier cumulative empirical hazard. The Kaplan-Meier cumulative hazard function is a non-parametric tool that estimates the time-to-failure.

The first panel provides Kaplan-Meier estimates for respective sample regardless of their FSP participation status, the second panel provides Kaplan-Meier estimates for FSP participants, and the third panel provides Kaplan-Meier estimates for non-participants.

I then test for equality of the cumulative hazard functions, to determine if there is a difference in the hazard rate for those with FSB and those without. To this end I perform the Log-Rank and Wilcoxon tests. Both tests are interested in comparing the survival experiences of r different groups, and testing the equality of these experiences. Both assume a null-hypothesis that the survival experiences (of all groups) are the same, and both employ a chi-square test statistic, with $r-1$ degrees of freedom. The primary difference between the two tests lies in the weighting scheme utilized. The log-rank test applies a weight equal to 1 in all periods, while the Wilcoxon test applies larger weights to earlier periods, so that failures occurring when the number at risk is large receive more weight than failures that occur when the number at risk is small. These tests compare the "events observed" (the number of actual failures that are observed for each group), to the "events expected" (the number of failures that would be expected to occur if the survival experiences of the groups are the same). When the two columns are significantly different, the test statistics will be large, indicating that the groups have different hazards.

Semi-Parametric Techniques:

To identify the effect of FSP participation on the probability that a mother becomes obese in an environment that allows covariates to enter the analysis I estimate a semiparametric Cox proportional hazard model, of the form,

(15). $h(t) = h_0(t)\exp\{\beta_0 + x_{it}\beta_x\}$.

The Cox model is preferred to conditional probit/logit estimation as it is a true duration model, and thus, is more flexible and better equipped to analyze the probability of a failure (becoming obese) occurring, given lack of a failure in any previous period. Moreover, the Cox model is able to incorporate time-varying covariates, which is critical when attempting to model a dynamic process.

Results for the Full Sample of Women

Table 3.A1: Kaplan Meier-Empirical Cumulative Hazard

All Women		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.097	0.005
1990	0.165	0.006
1992	0.230	0.007
1994	0.294	0.008
1996	0.357	0.008
1998	0.418	0.008
2000	0.475	0.008
2002	0.525	0.008
2004	0.556	0.008
2006	0.582	0.008

Women Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.104	0.007
1990	0.184	0.009
1992	0.249	0.010
1994	0.308	0.011
1996	0.371	0.012
1998	0.422	0.012
2000	0.484	0.012
2002	0.535	0.013
2004	0.569	0.013
2006	0.618	0.018

Women Not Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.087	0.007
1990	0.148	0.008
1992	0.211	0.010
1994	0.279	0.010
1996	0.342	0.011
1998	0.409	0.011
2000	0.461	0.011
2002	0.512	0.011
2004	0.540	0.011
2006	0.566	0.011

Table 3.A2: Log-Rank Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected
Food Stamp Program Participants	985	937.08
Food Stamp Program Non-Participants	1169	1216.92
Total	2154	2154
Chi Squared	5.09	
P-Vale	0.024	

Table 3A.3: Wilcoxon Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected	Sum of Ranks
Food Stamp Program Participants	985	937.08	141823
Food Stamp Program Non-Participants	1169	1216.92	-141823
Total	2154	2154	0
Chi Squared	5.44		
P-Vale	0.020		

Table 3.A4: Results From Cox Proportional Hazard Model Estimation

	Model 1 Hazard Ratio	Model2 Hazard Ratio	Model 3 Hazard Ratio
White	0.835	0.938	0.758^{++}
	(0.099)	(0.172)	(0.111)
Black	1.607	1.209	1.307
	(0.203)	(0.242)	(0.205)
Married	1.053	0.760^{++}	1.036
	(0.076)	(0.093)	(0.096)
Separated	0.982	0.505^{+++}	0.764^{+}
	(0.121)	(0.105)	(0.125)
Divorced	0.721	0.513^{+++}	0.766^{++}
	(0.075)	(0.084)	(0.098)
Widow	1.061	0.808	1.112
	(0.302)	(0.298)	(0.363)
Household Income	.	1.021	1.016
	.	(0.047)	(0.038)
Weeks of Unemployment	1.001	.	.
	(0.003)	.	.
Residence in North Central States	0.920	0.851	0.897
	(0.089)	(0.127)	(0.113)
Residence in Western States	1.168	1.005	1.045
	(0.115)	(0.161)	(0.138)
Residence in Southern States	0.974	0.925	0.950
	(0.086)	(0.129)	(0.109)
Age	1.005	1.013	1.012
	(0.012)	(0.015)	(0.016)
Food Stamp Program Participation	1.108	1.204^{+}	1.138
	(0.063)	(0.127)	(0.093)
High School Graduate	.	.	1.066
	.	.	(0.087)
College Graduate	.	.	1.081
	.	.	(0.197)
Graduate School Graduate	.	.	0.790
	.	.	(0.399)
Log Likelihood	-10262.09	-3550.95	-5923.83
N	3490	1490	2825

*Standard Errors are shown in parentheses
$^{+}$ Indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

Results for the Full Sample of Mothers

Table 3.A5: Kaplan Meier-Empirical Cumulative Hazard

All Mothers		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.096	0.006
1990	0.160	0.007
1992	0.225	0.008
1994	0.289	0.009
1996	0.347	0.009
1998	0.401	0.010
2000	0.454	0.010
2002	0.496	0.010
2004	0.525	0.010
2006	0.546	0.010

All Mothers Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.103	0.008
1990	0.182	0.010
1992	0.256	0.012
1994	0.306	0.013
1996	0.366	0.013
1998	0.422	0.014
2000	0.476	0.014
2002	0.514	0.015
2004	0.548	0.015
2006	0.592	0.021

All Mothers Not Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.087	0.008
1990	0.138	0.010
1992	0.192	0.011
1994	0.268	0.012
1996	0.322	0.013
1998	0.376	0.013
2000	0.429	0.014
2002	0.475	0.014
2004	0.498	0.014
2006	0.517	0.014

Table 3.A6: Log-Rank Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected
Food Stamp Program Participants	671	723.19
Food Stamp Program Non-Participants	700	647.81
Total	1371	1371
Chi Squared	9.01	
P-Vale	0.003	

Table 3A.7: Wilcoxon Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected	Sum of Ranks
Food Stamp Program Participants	671	723.19	109757
Food Stamp Program Non-Participants	700	647.81	-109757
Total	1371	1371	0
Chi Squared	9.22		
P-Vale	0.002		

Table 3.A8: Results From Cox Proportional Hazard Model Estimation

	Model 1 Hazard Ratio	Model2 Hazard Ratio	Model 3 Hazard Ratio
White	0.873	0.856	0.871
	(0.113)	(0.137)	(0.140)
Black	1.215	1.127	1.113
	(0.170)	(0.195)	(0.193)
Married	0.637^{+++}	0.709^{+++}	0.712^{++}
	(0.056)	(0.077)	(0.077)
Separated	0.613^{+++}	0.535^{++}	0.534^{++}
	(0.084)	(0.097)	(0.097)
Divorced	0.472^{+++}	0.524^{+++}	0.524^{+++}
	(0.055)	(0.076)	(0.075)
Widow	0.783	1.003	1.005
	(0.217)	(0.304)	(0.305)
Household Income	.	0.991	0.990
	.	(0.039)	(0.039)
Weeks of Unemployment	1.001	.	.
	(0.003)	.	.
Residence in North Central States	0.865	0.831	0.830
	(0.092)	(0.108)	(0.107)
Residence in Western States	1.059	0.991	0.876
	(0.118)	(0.126)	(0.125)
Residence in Southern States	0.965	0.863	0.854
	(0.096)	(0.104)	(0.108)
Age	0.999	0.995	0.996
	(0.010)	(0.013)	(0.013)
Food Stamp Program Participation	1.048	1.134	1.135
	(0.068)	(0.099)	(0.099)
High School Graduate	.	.	1.091
	.	.	(0.094)
College Graduate	.	.	0.938
	.	.	(0.194)
Graduate School Graduate	.	.	1.486
	.	.	(0.619)
Log Likelihood	-8004.01	-4888.47	-4887.47
N	2586	2302	2302

*Standard Errors are shown in parentheses
$^{+}$Indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

Results for the Full Sample of Non-Mothers

Table 3.A9: Kaplan Meier-Empirical Cumulative Hazard

All Non-Mothers		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.272	0.011
1990	0.443	0.012
1992	0.569	0.012
1994	0.672	0.011
1996	0.738	0.011
1998	0.794	0.010
2000	0.825	0.009
2002	0.847	0.009
2004	0.868	0.008
2006	0.873	0.008

All Non-Mothers Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.325	0.017
1990	0.499	0.020
1992	0.606	0.019
1994	0.687	0.019
1996	0.743	0.017
1998	0.803	0.017
2000	0.840	0.015
2002	0.866	0.015
2004	0.887	0.013
2006	0.903	0.019

All Non-Mothers Not Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.229	0.014
1990	0.403	0.015
1992	0.544	0.016
1994	0.658	0.014
1996	0.731	0.014
1998	0.787	0.012
2000	0.815	0.012
2002	0.836	0.011
2004	0.857	0.011
2006	0.862	0.010

Table 3.A10: Log-Rank Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected
Food Stamp Program Participants	593	547.94
Food Stamp Program Non-Participants	938	983.06
Total	1531	1531
Chi Squared	13.74	
P-Vale	0.000	

Table 3.A11: Wilcoxon Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected	Sum of Ranks
Food Stamp Program Participants	593	547.94	74527
Food Stamp Program Non-Participants	938	983.06	-74527
Total	1531	1531	0
Chi Squared	13.74		
P-Vale	0.000		

Table 3.A12: Results From Cox Proportional Hazard Model Estimation

	Model 1 Hazard Ratio	Model2 Hazard Ratio	Model 3 Hazard Ratio
White	0.938	0.843	0.843
	(0.134)	(0.156)	(0.158)
Black	1.404^{++}	1.222	1.226
	(0.214)	(0.248)	(0.249)
Married	3.205^{+++}	2.963^{+++}	2.967^{+++}
	(0.235)	(0.290)	(0.291)
Separated	1.824^{++}	1.729^{++}	1.739^{++}
	(0.406)	(0.443)	(0.446)
Divorced	0.904	1.069	1.071
	(0.134)	(0.191)	(0.191)
Widow	1.601	1.818	1.837
	(0.724)	(0.924)	(0.934)
Household Income	.	1.009	1.009
	.	(0.040)	(0.040)
Weeks of Unemployment	0.998	.	.
	(0.004)	.	.
Residence in North Central States	1.175^{+}	1.285	1.286^{+}
	(0.115)	(0.181)	(0.181)
Residence in Western States	1.171	1.280	1.280^{++}
	(0.118)	(0.186)	(0.193)
Residence in Southern States	1.026	1.136	1.131
	(0.094)	(0.151)	(0.153)
Age	1.005	1.011	1.011
	(0.014)	(0.019)	(0.019)
Food Stamp Program Participation	1.119^{+}	1.199^{++}	1.203^{++}
	(0.068)	(0.123)	(0.103)
High School Graduate	.	.	1.007
	.	.	(0.094)
College Graduate	.	.	1.015
	.	.	(0.215)
Graduate School Graduate	.	.	1.331
	.	.	(0.432)
Log Likelihood	-7935.49	-4025.30	-4024.81
N	1573	1174	1174

*Standard Errors are shown in parentheses
$^{+}$Indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

Results for Low-Income Women

Table 3.A13: Kaplan Meier-Empirical Cumulative Hazard

All Low-Income Women		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.108	0.006
1990	0.182	0.007
1992	0.250	0.008
1994	0.320	0.009
1996	0.386	0.009
1998	0.450	0.009
2000	0.510	0.009
2002	0.564	0.009
2004	0.597	0.009
2006	0.625	0.009

Low-Income Women Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.113	0.007
1990	0.196	0.010
1992	0.263	0.011
1994	0.323	0.012
1996	0.389	0.012
1998	0.441	0.013
2000	0.506	0.013
2002	0.559	0.013
2004	0.595	0.013
2006	0.640	0.018

Low-Income Women Not Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.100	0.009
1990	0.166	0.011
1992	0.237	0.013
1994	0.315	0.013
1996	0.381	0.014
1998	0.452	0.014
2000	0.507	0.014
2002	0.562	0.013
2004	0.593	0.013
2006	0.620	0.013

Table 3.A14: Log-Rank Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected
Food Stamp Program Participants	917	907.66
Food Stamp Program Non-Participants	889	898.34
Total	1806	1806
Chi Squared	0.23	
P-Vale	0.630	

Table 3.A15: Wilcoxon Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected	Sum of Ranks
Food Stamp Program Participants	917	907.66	27222
Food Stamp Program Non-Participants	889	898.34	-27222
Total	1806	1806	0
Chi Squared	0.42		
P-Vale	0.520		

Table 3.A16: Results From Cox Proportional Hazard Model Estimation

	Model 1 Hazard Ratio	Model 2 Hazard Ratio	Model 3 Hazard Ratio
White	0.839	0.783^{+}	0.780^{+}
	(0.103)	(0.114)	(0.115)
Black	1.464 $^{++}$	1.282	1.300
	(0.192)	(0.201)	(0.208)
Married	1.000	1.006	1.047
	(0.079)	(0.097)	(0.104)
Separated	0.893	0.709^{++}	0.751^{+}
	(0.116)	(0.120)	(0.130)
Divorced	0.662^{+++}	0.725^{++}	0.769^{++}
	(0.073)	(0.095)	(0.103)
Widow	1.147	1.366	1.461
	(0.306)	(0.396)	(0.425)
Household Income	.	1.014	1.021
	.	(0.039)	(0.042)
Weeks of Unemployment	1.000	.	0.999
	(0.003)	.	(0.004)
Residence in North Central States	0.868	0.845	0.823
	(0.093)	(0.109)	(0.108)
Residence in Western States	1.084	1.035	1.022
	(0.117)	(0.137)	(0.136)
Residence in Southern States	0.920	0.889	0.854
	(0.089)	(0.105)	(0.102)
Age	1.010	1.012	1.015
	(0.014)	(0.016)	(0.017)
Food Stamp Program Participation	1.128^{+}	1.172^{+}	1.154^{+}
	(0.071)	(0.102)	(0.102)
Log Likelihood	-8366.09	-5435.06	-4969.65
N	2711	2427	2284

*Standard Errors are shown in parentheses
$^{+}$Indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$

Results for the Low-Income Non-Mothers

Table 3.A17: Kaplan Meier-Empirical Cumulative Hazard

All Low-Income Non-Mothers		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.311	0.014
1990	0.491	0.015
1992	0.613	0.014
1994	0.706	0.013
1996	0.766	0.013
1998	0.818	0.011
2000	0.852	0.011
2002	0.879	0.010
2004	0.898	0.009
2006	0.904	0.009

Low-Income Non-Mothers Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.357	0.019
1990	0.531	0.023
1992	0.632	0.021
1994	0.716	0.020
1996	0.770	0.019
1998	0.824	0.017
2000	0.860	0.015
2002	0.887	0.015
2004	0.905	0.013
2006	0.918	0.017

Low-Income Non-Mothers Not Participating in the FSP		
Year	Cumulative Hazard	Standard Error
1986	0.000	0
1988	0.257	0.019
1990	0.447	0.020
1992	0.595	0.021
1994	0.695	0.019
1996	0.762	0.018
1998	0.813	0.016
2000	0.844	0.015
2002	0.872	0.013
2004	0.893	0.013
2006	0.898	0.012

Table 3.A18: Log-Rank Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected
Food Stamp Program Participants	495	471.78
Food Stamp Program Non-Participants	546	569.22
Total	1041	1041
Chi Squared	2.94	
P-Vale	0.086	

Table 3.A19: Wilcoxon Test for Equality of Survivor Functions

Food Stamp Program Participation	Events Observed	Events Expected	Sum of Ranks
Food Stamp Program Participants	495	471.78	29772
Food Stamp Program Non-Participants	546	569.22	-29772
Total	1041	1041	0
Chi Squared	7.47		
P-Vale	0.006		

Table 3.A20: Results From Cox Proportional Hazard Model Estimation

	Model 1 Hazard Ratio	Model 2 Hazard Ratio	Model 3 Hazard Ratio
White	0.889	0.891	0.880
	(0.140)	(0.176)	(0.179)
Black	1.154	1.116	1.115
	(0.196)	(0.241)	(0.248)
Married	2.509^{+++}	2.439^{+++}	2.546^{+++}
	(0.213)	(0.263)	(0.284)
Separated	1.639^{++}	1.485	1.473
	(0.394)	(0.406)	(0.431)
Divorced	0.816	0.923	0.924
	(0.136)	(0.178)	(0.184)
Widow	1.456	1.697	1.778
	(0.660)	(0.865)	(0.907)
Household Income	.	1.010	1.009
	.	(0.046)	(0.047)
Weeks of Unemployment	0.996	.	0.997
	(0.005)	.	(0.007)
Residence in North Central States	1.220	1.249	1.239
	(0.160)	(0.217)	(0.218)
Residence in Western States	1.246	1.328^{+}	1.301
	(0.162)	(0.228)	(0.227)
Residence in Southern States	1.097	1.173	1.128
	(0.133)	(0.189)	(0.185)
Age	0.995	0.996	1.253
	(0.017)	(0.021)	(0.131)
Food Stamp Program Participation	1.125^{+}	1.261^{++}	1.253^{++}
	(0.083)	(0.129)	(0.131)
Log Likelihood	-4880.53	-2868.54	-2719.93
N	1019	789	767

*Standard Errors are shown in parentheses
$^{+}$ Indicates $p \leq 0.10$, $^{++}$indicates $p \leq 0.05$, $^{+++}$ indicates $p \leq 0.01$