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The Effects of Food Stamps on Obesity

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Abstract

This report uses 1985-2000 data from the 1979 cohort of the National Longitudinal Survey of Youth to examine the effects of the Food Stamp Program on obesity. The effects are found to differ by gender, level of benefits, and duration of participation. Results suggest that, for females, current program participation increases Body Mass Index (by 0.5 index point on average) as well as the probability of being obese (between 2 and 5 percentage points). Current program participation was not found to have significant effects for males. Long-term participation is found to increase obesity for females and males.

Food Assistance
& Nutrition
Research Program

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Executive Summary (3-pages)

An increasing number of Americans are obese. In fact, the latest estimates indicate that about 30 % of adult Americans are currently obese, which is roughly a 100 % increase from 25 years ago. As a result of the dramatic increase in obesity, adult Americans are now more likely to be obese than to smoke cigarettes.

Public health officials in the United States have become increasingly alarmed about the growing prevalence of obesity in part because recent research indicates that societal costs of obesity, which include medical expenses, exceed those of cigarette smoking and alcoholism. Further, the medical literature finds that obesity increases morbidity and mortality by increasing the prevalence of diabetes, cardiovascular disease, stroke, cancer, hypertension, dyslipidemia, gout, sleep apnea, and osteoarthritis. Some have asserted that obesity will soon overtake tobacco as the leading preventable cause of death. In response, Americans are estimated to spend over 30 billion dollars on weight loss programs annually (Philipson and Posner, 1999).

Many non-economic societal changes do not initially appear to explain why the prevalence of obesity is increasing. An increasing portion of Americans are exercising and dieting, and Americans currently possess more knowledge of the consequences of obesity than ever before. Yet, Americans are more likely to be obese now than ever. Perhaps obesity is an economic phenomenon where individuals select their optimal weight, which may not be medically optimal (the weight that minimizes mortality), by comparing the marginal benefit with the marginal cost of losing or gaining weight. If so, then economic factors may serve to explain at least a portion of the increasing prevalence of obesity.

I examine the effect of an economic factor -- the Food Stamp Program (FSP) -- on obesity. Prior to the Food Stamp Act of 1964 (and other food assistance programs passed during the twentieth century), poverty was assumed to be associated with a decrease in food consumption. However, various twentieth century government entitlement programs changed this by constructing a safety net that helps prevent those in poverty from starvation. The Food Stamp Act does this by guaranteeing an allotment of food for those below the poverty level. Perhaps as a result, the literature suggests Food Stamps increase food consumption by more than an equivalent amount of cash would, even for households that receive less in Food Stamp benefits than they spend on food. Further, some recent evidence suggests Food Stamp recipients consume significantly more sugar and meat than eligible non-recipients.

In this project, I estimate the relationship between Food Stamp benefits and BMI and the probability of being obese with National Longitudinal Survey of Youth (NLSY79) data. I first use ordinary least squares (OLS) regression models to estimate the effects of Food Stamp receipt on BMI and logits to estimate the effects of Food Stamp receipt on the probability of being obese. Next, in an attempt to control for potential unobserved heterogeneity bias, I re-estimate the models using predicted Food Stamp benefits derived from a two-step estimator that first predicts Food Stamp benefits using Instrumental Variables (IV). I also estimate individual-specific fixed effects models to control for potentially biasing effects of individual-specific unobserved heterogeneity. In addition, I estimate dynamic models that explain the change in BMI, the conditional probability of becoming obese (conditional on not being obese), the conditional probability of no longer being obese (conditional on being obese initially), and the hazard rate for becoming obese at a particular time conditional on not yet being obese. Finally, I re-estimate these models using alternative Food Stamp variable specifications including one that

identifies the effects of current and past program receipt to explore timing effects such as whether Food Stamps have contemporaneous or lagged effects. In another, I examine patterns of receipt over the preceding two years to identify the effects of receiving benefits in one spell either short-term (for less than 9 months), medium-term (between 9 and 23 months), or long-term (24 months) and the effects of received benefits during multiple spells. Each of these model specifications are estimated using two samples: a low-income sub-sample (defined as those with no more than a high school education) and a sub-sample of respondents approximated to be eligible for Food Stamp benefits. Models are estimated with these samples separately for males and females.

Descriptive statistics from the 1979 NLSY cohort show that FSP participation and obesity are correlated for females. For example, 27.8 % of low-income females on Food Stamps are obese compared to 19.0 % of low-income female non-recipients. Similarly, among females approximated to be eligible for benefits, those receiving Food Stamps are more likely to be obese: 28.3 % versus 17.7 %. This association is much weaker for males. OLS models controlling for a spate of observable characteristics essentially enable us to compare individuals who are alike in all observable ways (the same gender, race/ethnicity, education, income, etc.) except Food Stamp receipt. In these models, female Food Stamp recipients are significantly more likely to be obese (and to have higher BMI) than female non-recipients. For example, providing a low-income female non-recipient with Food Stamp benefits is predicted to increase the probability of being obese between roughly 2 and 5 percentage points (and to increase BMI by a majority of an index point). In corresponding models that examine males, Foods Stamps have statistically insignificant effects on BMI and obesity.

Of course, OLS estimates could be biased by unobserved characteristics correlated with both FSP participation and obesity (and BMI). However, alternative specifications used to control for these sources of bias fail to reject the null hypothesis that OLS results are not biased. Where instruments are deemed valid, the evidence suggests the OLS and IV estimates are not statistically different from one another. Fixed effects models also support conclusions with OLS results, with many instances of significant positive effects of Food Stamp benefits on BMI and the probability of being obese, specifically for females.

The dynamic models also show positive effects of Food Stamp benefits for females. Such benefits significantly increase the typical change in BMI between surveys and significantly increase the hazard of becoming obese (conditional on not yet being obese). Further, lagged Food Stamp benefits (from previous years) often significantly increase BMI and obesity. Again, these conclusions tend to be true primarily for females, with insignificant effects for males. These models also show that long-term Food Stamp receipt increases BMI and obesity, even in some instances for males, but receiving assistance from the FSP for a more limited period does not have this side-effect.

In some cases, dynamic effects are larger than those found in models identifying contemporaneous effects. For example, receiving Food Stamps continually during the two years preceding the interview date increases obesity by at least 10 percentage points. Over a 15-year period, the hazard models suggest Food Stamp benefits significantly decrease the probability of not yet being obese between 10 and 20 percentage points. Similarly, for eligible females, positive effects of Food Stamps become successively larger with the inclusion of additional lagged Food Stamp covariate terms.

These results can be used to approximate the amount to which Food Stamp benefits have contributed to the increase in obesity. During the 1976-1980 period covered by NHANES II, the prevalence of obesity was 15.0 %, with roughly 20.9 million obese adult American adults aged 20 through 74. In the 2003-2004 NHANES surveys, the prevalence of obesity was 32.2 %, with roughly 62.1 million obese American adults. Thus, as the prevalence of obesity doubled between these periods, the number of obese American adults increased by 41.2 million. However, between 1978 and 2003, the number of Food Stamp recipients increased from just 16.0 million to 21.3 million, which is an increase of 5.3 million (though more than that moved through the program). Using reputedly conservative OLS estimates, assume Food Stamps increase the probability of being obese by 4 percentage points. This suggests that 212,000 additional Americans became obese due to Food Stamps (4 % of 5.3 million = 212,000) between these periods. This would account for half of one % (0.5 %) of the 41.2 million increase in obese American adults (212,000/41.2 million = 0.005). Had this approximated contribution to obesity by the FSP not been made, the prevalence of obesity would be 32.1 % rather than 32.2 % (after subtracting 212,000 from 62.1 million obese American adults). Thus, while the effects of Food Stamps on obesity appear statistically significant at the individual-recipient level, the FSP has probably had virtually an immeasurably small impact on the growing prevalence of obesity.

There are reasons to believe that the estimated contribution of the FSP to the increasing prevalence of obesity is an underestimate: dynamic models indicate larger positive effects once cumulative effects of Food Stamps (or effects of Food Stamp receipt from past periods) are included in the analysis. However, this is likely to have a small impact on the prevalence of obesity because only a small minority of recipients receive benefits long-term. Further, though the increase in Food Stamp receipt has been 5.3 million, more than that have moved through the program during which time they were evidently more susceptible to becoming obese. However, this is likely to have a small impact on the prevalence of obesity because results show that receiving benefits short-term (and medium-term) does not have a significant effect on obesity.

Regardless, since the FSP appears inadvertently to increase obesity, policymakers should seek ways to provide food assistance without exacerbating obesity. One approach might be to redouble efforts to educate newly-certified Food Stamp recipients about healthy and nutritious eating habits and weight management (or weight reduction). Such action might change the FSP from being a contributor to obesity to a benefactor reducing this prevalence.

The Effects of Food Stamps on Obesity

I. Introduction

An increasing number of Americans are obese, where obese is defined as having a body mass index (BMI) of 30 or more and where BMI equals weight in kilograms divided by height in meters squared (CDC, 2006a). In fact, the latest estimates indicate that about 30 % of adult Americans are currently obese, which is roughly a 100 % increase from 25 years ago (Kuczmarski et al., 1994; VanItallie, 1996; Flegal et al., 1998; Flegal et al., 2002; Ogden et al., 2006). These increases are found for both males and females, as well as for various races. As a result of the dramatic increase in the prevalence of obesity, adult Americans are now more likely to be obese than to smoke cigarettes: only 22.5 % of adult Americans currently smoke (Campaign for Tobacco-Free Kids, 2004).

Public health officials in the United States have become increasingly alarmed about the growing prevalence of obesity in part because recent research indicates that societal costs of obesity exceed those of cigarette smoking and alcoholism (Sturm, 2002). One such cost is the medical expense that obesity imposes. Sturm (2002) and Finkelstein, Fiebelkorn, and Wang (2003) estimate that obesity increases inpatient and outpatient spending by about 36 %. In accord, Wolf and Colditz (1998) estimate that the year-1995 economic costs of obesity were almost 100 billion, about half of which were direct medical costs. The medical literature finds that obesity increases morbidity and mortality (Pi-Sunyer, 1994; Stevens et al., 1998; Calle et al., 1999) by increasing the prevalence of diabetes, cardiovascular disease, stroke, cancer, hypertension, dyslipidemia, gout, sleep apnea, and osteoarthritis (McGinnis and Foege, 1993; Pi-Sunyer, 1994; Wolf and Colditz, 1998; Must et al., 1999; Chow et al., 2000; Rauscher, 2000; Castro-Rodriguez et al., 2001; Field, 2001; Michaud et al., 2001; Kenchaiah et al., 2002). Some have asserted that obesity will soon overtake tobacco as the leading preventable cause of death (Mokdad et al., 2004). Currently, the medical literature estimates that obesity contributes to between 111,909 and 365,000 premature adult deaths in the U.S. each year compared to 435,000 premature deaths due to tobacco (Allison et al., 1999; Mokdad et al., 2004; Flegal et al., 2005; Mokdad 2005).

Since federal, state, and local governments pay roughly half the cost of health care in the United States, obesity will have a substantial impact on public programs such as Social Security and Medicare/Medicaid. Finkelstein et al. (2003) estimate that obese Medicare (Medicaid) recipients cost $1,486 ($864) more per year than such recipients of normal weight. Obese individuals are also shown to experience social penalties in their interpersonal activities and in the "marriage market" and to earn lower wages (Register and Williams, 1990; Gortmaker et al., 1993; Hamermesh and Biddle, 1994; Averett and Korenman, 1996; Pagan and Davila, 1997; Baum and Ford, 2004; Cawley, 2004). In response to the various costs of obesity, Americans are estimated to spend over 30 billion dollars on weight loss programs annually (National Institute of Diabetes and Digestive Kidney Diseases, 1996; Cawley, 1999; Philipson and Posner, 1999).

Many non-economic societal changes do not initially appear to explain why the prevalence of obesity is increasing. Consider the following: *(i)* an increasing portion of Americans are exercising and dieting, *(ii)* Americans currently possess more knowledge of the consequences of obesity than ever before via government and medical awareness campaigns, *(iii)* biological factors, though capable of explaining weight differences within a cohort, should not have changed enough to explain differences in obesity over the last half-century, and *(iv)* weight is no longer a status symbol indicating prosperity (Philipson and Posner, 1999; Philipson, 2001).

Yet, Americans are more likely to be obese now than ever. Perhaps obesity is an economic phenomenon where individuals select their optimal weight, which may not be medically optimal (the weight that minimizes mortality), by comparing the marginal benefit with the marginal cost of losing or gaining weight. If so, then economic factors may serve to explain at least a portion of the increasing prevalence of obesity.

Fortunately, researchers have recently begun to examine the economic causes of obesity. For example, Philipson (2001), Philipson and Posner (1999), and Lakdawalla and Philipson (2002) suggest that increased obesity is the result of jobs becoming more sedentary; Anderson, Butcher, and Levine (2003a, 2003b) find evidence that maternal employment increases childhood obesity because working mothers have less time to prepare healthy meals; Cutler, Glaeser, and Shapiro (2003) assert that technological advances in food preparation making food readily available have caused hyperbolic consumers (defined as those who lack self-control) to overeat; Chou, Grossman, and Safer (2004) find that BMI and obesity have significantly increased due to increases in the number of restaurants and decreases in food prices (prices in fast-food and full-service restaurants and the price of home food); and DeCicca (2004) and Gruber and Frakes (2005) examine the effects of cigarette taxes on BMI and obesity (finding conflicting results).

I seek to examine the effect of another economic factor -- the Food Stamp Program (FSP) -- on obesity. Prior to the Food Stamp Act of 1964 (and other food assistance programs passed during the twentieth century), poverty was assumed to be associated with a decrease in food consumption. However, various twentieth century government entitlement programs changed this by constructing a safety net that helps prevent those in poverty from starvation. The Food Stamp Act does this by guaranteeing an allotment of food for those below the poverty level. The program does this by providing participants with electronic benefits cards with credit redeemable for food (USDA, 2003a). In 2005, FSP participants averaged $92.70 in monthly benefits at a cost of $31.0 billion to the government (USDA, 2006a). Ironically, it is in the period since the Food Stamp Act's passage that the prevalence of obesity has increased so dramatically. Between 1971 and 1974, the FSP served between 9.3 and 12.8 million participants annually (USDA, 2006a), and the prevalence of obesity in the United States was 14.5 % (Flegal et al., 2002). These statistics have doubled. In 2005, the FSP served an estimated 25.7 million participants (USDA, 2006a), and the prevalence of obesity is currently over 30 % (Flegal et al., 2002).

The FSP potentially increases obesity by increasing food consumption. The FSP potentially increases food consumption by making the monetary cost of food zero for eligible individuals up to their Food Stamp allotment (though since FSP participation rates are well below 100 %, non-monetary costs such as stigma and the opportunity cost of applying and re-certifying for the benefits likely remain significant). A survey of the literature suggests a dollar of Food Stamps increases food consumption between $0.17 and $0.47, which is more than an equivalent amount of cash would (Fraker, 1990). It is not surprising that this would be true for constrained households (those who receive an amount of Food Stamp benefits that is greater than the amount they would otherwise spend on food), but this also appears to be true for the other 85 to 95 % of Food Stamp households that are unconstrained (households that receive an amount of Food Stamp benefits that is less than the amount they would otherwise spend on food) (Fraker, 1990). Further, recent evidence by Wilde, McNamara, and Ranney (1999) suggests Food Stamp recipients consume significantly more sugar and fat than eligible non-recipients.

Economic theory suggests that the quantity of a good demanded increases as the price decreases. If true, then the FSP may at least partially explain why income is not positively associated with obesity. Otherwise, the utility maximizing framework in economics suggests that the demand for “normal goods” is increasing in income. Assuming food is a normal good, food consumption should be increasing in income as well. Consequently, we might assume that obesity is more prevalent among those with greater income. The opposite is often true. Socioeconomic status (SES) in developed countries has been found to be negatively associated with weight and obesity for females, though this relationship is weaker for men (Sobal and Stunkard, 1989; Stunkard and Sorensen, 1993; Jeffery, French, Forster, and Spry, 1991; Lantz et al., 1998; Wardle, Walter, and Jarvis, 2002), with recent evidence even suggesting those in poverty have not experienced the largest increases in obesity (Chang and Lauderdale, 2005).

Only a couple of studies have examined the effects of FSP participation on obesity.[1] In the nutrition literature, seminal work by Gibson first examined this link. Separately examining men and women using a standard multivariate regression framework, Gibson (2003) finds that FSP participation among low-income women (but not men) is significantly associated with increased obesity.[2] Similarly, Chen, Yen, and Eastwood, using 1994-1996 Continuing Survey of Food Intakes by Individuals (CSFII) data, and Meyerhoefer and Pylyphuck (2006), using 2000-2003 Medical Expenditure Panel Survey (MEPS) data, find that contemporaneously-

[1] However, economic studies have found that food stamp receipt increases food expenditures (Fraker, Devaney, and Cavin, 1986; Devaney and Fraker, 1989; Fraker, 1990; Fraker, Martini, and Ohls, 1995) and nutrient intake (Devaney and Moffitt, 1991; Rose, Habicht, and Devaney, 1997; Basiotis, Kramer-LeBlanc, and Kennedy, 1998; Wilde, McNamara, and Ranney, 1999).

[2] Gibson also examines the effects of the FSP on overweight in children (Gibson, 2004, 2006).

measured Food Stamp receipt has statistically significant positive effects on low-income women but not on low-income men. All three studies make some attempt to control for systematic unobserved differences between Food Stamp recipients and non-recipients: Gibson uses individual-specific fixed effects models, Chen et al. use Heckman's (1978) simultaneous-equations framework to model the decision to participate in the FSP and obesity jointly, and Meyerhoefer and Pylypchuk essentially instrument Food Stamp receipt using state FSP outreach expenditures and state recertification length. However, none explore the dynamic relationship between Food Stamps and obesity where current weight is linked to past weight and past Food Stamp receipt. This seems like an important omission because contemporaneously-measured Food Stamp receipt would not be expected to have an instantaneous and substantial effect on weight. Instead, since current weight is not independent from past weight, the Food Stamp-weight relationship is likely much more complex.

In this project, I estimate the relationship between Food Stamp benefits and BMI and the probability of being obese with National Longitudinal Survey of Youth (NLSY79) data. I first use ordinary least squares (OLS) regression models to estimate the effects of Food Stamp receipt on BMI and logits to estimate the effects of Food Stamp receipt on the probability of being obese. Next, in an attempt to control for potential unobserved heterogeneity bias, I re-estimate the models using predicted Food Stamp benefits derived from a two-step Instrumental Variables (IV) estimator. I also estimate individual-specific fixed effects models to control for potentially biasing effects of individual-specific unobserved heterogeneity. In addition, I estimate dynamic models that explain the change in BMI, the conditional probability of becoming obese (conditional on not being obese), the conditional probability of no longer being obese (conditional on being obese initially), and the hazard rate for becoming obese at a particular time conditional on not yet being obese. Finally, I re-estimate these models using alternative Food Stamp variable specifications. One of these identifies the effects of current and past program receipt to explore timing effects such as whether Food Stamps have contemporaneous or lagged effects. Another estimates the effects of short-term, medium-term, and long-term Food Stamp receipt, as well as the effects of receiving benefits in multiple spells. Each of these model specifications are estimated using two samples: a low-income sub-sample (defined as those with no more than a high school education) and a sub-sample of respondents approximated to be eligible for Food Stamp benefits. Models are estimated with these samples separately for males and females.

OLS results suggest Food Stamp receipt significantly increases female BMI by less than one index point and significantly increases the female probability of being obese by a couple of percentage points (two to five). In corresponding models that examine males, Foods Stamps have statistically insignificant effects on BMI and obesity. The IV and fixed effects models provide virtually no evidence that OLS estimates are biased, and the dynamic models indicate, if anything, that the cumulative effects of Food Stamp receipt are somewhat larger than those indicated by OLS, specifically for females. Evidence also suggests that long-term Food Stamp receipt increases BMI and obesity, even for males, but receiving assistance from the FSP for a more limited period does not have this consequence. Regardless, even though Food Stamps have significant positive effects on BMI and obesity, these effects are small, and such benefits, consequently, are approximated to have played a very minor role in the increasing prevalence of obesity.

II. The Theoretical Model

Expanding on Philipson and Posner (1999) and Lakdawalla and Philipson's (2002) intuition for why consumers might rationally be at weights that are not medically optimal, I develop the following theoretical model to explain how Food Stamp Benefits potentially affect weight. I assume that utility is a function of current weight (W), where deviations from ideal weight (W_0) decrease utility,

$$\overline{W}(t) = |W_0 - W(t)|, \qquad (1)$$

with $U_{\overline{W}} < 0$, where subscripts indicate partial derivatives. Ideal weight is defined as the weight an individual would choose if such weight could be attained without cost. W_0 may or may not be one's optimal weight in a medical sense. I assume that utility is also a function of food (F) and other consumption (C),

$$U(t) = U(\overline{W}(t), F(t), C(t)), \qquad (2)$$

where U is an instantaneous utility function with $U_F>0$, $U_C>0$, $U_{FF}<0$, and $U_{CC}<0$. Thus, the utility function is assumed to be twice continuously differentiable and concave. I also assume that the marginal effect of ideal weight deviations is larger for those further from their ideal weight ($U_{\overline{W}\overline{W}} \leq 0$). In this model, current decisions affect future weight because weight is formed dynamically according to the following accumulation process,

$$W(t+1) = W(t) - \delta W(t) + F(t), \qquad (3)$$

where W(t+1) is future weight and δ is the rate of depreciation of the stock of weight over time. Perhaps δ represents the caloric expenditure required to live. Thus,

$$\partial W(t)/\partial t = F(t) - \delta W(t). \qquad (4)$$

For simplicity, I assume that the utility function is separable over time in C, F, and $\overline{W}$, that the rate of time preference is constant and given by σ, and that a lifetime is infinite. This generates a continuous-time lifetime utility function given by

$$U = \int_0^\infty e^{-\sigma t} U[\overline{W}(t), F(t), C(t)]dt. \qquad (5)$$

Consumers maximize this utility function subject to a continuous-time lifetime budget constraint,

$$\int_0^\infty e^{-rt}[C(t)+P(t)F(t)]dt \le I_0, \qquad (6)$$

where P(t) is the price of food at time t, r is the interest rate, and I_0 is the discounted value of lifetime income. In this setup, the price of other consumption is assumed to be the numeraire (normalized to be 1), and the capital market is assumed to be perfect. Maximizing the utility function (5) subject to the lifetime budget constraint (6) and the weight accumulation process (3 and 4) yields the following first-order conditions:

$$U_C = \lambda e^{-(r-\sigma)t} \qquad (7)$$

and

$$U_F = \lambda P(t)e^{-(r-\sigma)t} - \int_0^\infty e^{-\delta(t-\tau)}\, U_{\overline{W}}\, \overline{W}_W(\tau)\, d\tau, \qquad (8)$$

with $\overline{W}_W$ >0 for those overweight and $\overline{W}_W$ <0 for those underweight and where λ is the Lagrange multiplier, which is interpreted as the marginal utility of income. These first order conditions can be interpreted as follows. The marginal discounted lifetime utility of other consumption equals the marginal discounted lifetime cost (equation 7). Equation 8 shows that the total price of food consists of two parts. The first is the monetary price, P, which is discounted over time. The second is the discounted marginal utility of weight change. Since deviations from ideal weight decrease utility (and since food increases weight), the total cost of food is greater than the monetary cost for those overweight; however, the total cost of food is less than the monetary cost for those underweight. Combining the two first order conditions,

$$P(t)\, U_C = U_F + \int_0^{\infty} e^{-\delta(t-\tau)}\, U_{\overline{W}}\, \overline{W}_W\, (\tau)\, d\tau\,, \qquad (9)$$

shows that the marginal discounted lifetime utility of food plus the effect of food on the marginal discounted lifetime value of weight change must equal the marginal discounted lifetime utility of other consumption.

Solving for the endogenous variables (C, F, and $\overline{W}$), one can see that weight (W) is a function of prices (such as the price of food, P), lifetime income (I_0), the weight depreciation rate, and the rate of time preference. Increasing P unambiguously decreases food consumption for someone overweight, which decreases weight.

The model can be extended to show the effect of Food Stamp benefits. Many treat Food Stamp benefits as an increase in income (for example, see Fraker and Moffitt, 1988). However, assuming food from the FSP cannot be resold, then FSP receipt should not be treated as income when the utility maximizing quantity of food is less than the amount of food received through the FSP. To incorporate FSP receipt into the model, maximize

$$L = \int_0^{\infty} e^{-\sigma t} U[\overline{W}(t), F(t), C(t)]dt - \lambda \int_0^{\infty} e^{-rt}[C(t)+P(t)F_1(t)]dt \le I_0, \qquad (10)$$

where $$F(t) = F_1(t) + FSP(t), \qquad (11)$$

where $$\partial W(t)/\partial t = F_1(t) + FSP(t) - \delta W(t), \qquad (12)$$

and where F_1 is purchased food, FSP is food received through the FSP, and total food consumption is F. This setup assumes that a unit of food from either source (purchased and/or received from the FSP) yields the same utility. Referring to equation (9), increasing FSP prompts a decrease in purchased food consumption (and an increase in other consumption) by decreasing the marginal utility of food. In addition, for those over their ideal weight, increasing Food Stamp benefits increases the marginal utility of weight change, which reinforces the decrease in purchased food consumption. For those under their ideal weight, increasing FSP decreases the marginal utility of weight change, which augments the incentive to decrease purchased food consumption. Consequently, both those over and under their ideal weight will reduce purchased food consumption, though total food consumption (and weight) increases for both types because purchased food consumption falls by less than FSP food rises.

III. Data

I use 1979-cohort NLSY79 data to estimate the effects of Food Stamp benefits on obesity. In 1979, the NLSY79 began annually interviewing a cohort of 12,686 respondents (6,283 of whom were female) who were between the ages of 14 and 21. The cohort initially included oversamples of blacks, Hispanics, low-income whites, and military personnel. However, the military sample was dropped in 1984 and the low-income whites were dropped in 1990, and I do not include either in my analysis for that reason. Because I include the black and Hispanic oversamples, I use sampling weights throughout the analysis. After the 1994 survey, the NLSY79 began interviewing biennially, and these respondents have since been re-interviewed on that basis. In each survey, the NLSY79 collects information on each respondent’s individual characteristics. In addition, questions about weight were asked in the

1981, 1982, 1985, 1986, 1987, 1989, 1990, 1992, 1993, 1994, 1996, 1998, 2000, and 2002 surveys, and questions about height were asked in the 1981, 1982, and 1985 surveys (Center for Human Resource Research, 2004). I assume that height does not change after the 1985 survey because NLSY79 respondents are at least 20 years of age at that time, and I exclude pregnant females and new mothers (women who have given birth within a year) because their reported weight may not be representative of their non-pregnancy weight.

The NLSY79 measures of weight and height are self-reported. Unfortunately, self-reported weight (and, to a lesser extent, self-reported height) potentially is measured with error. Fortunately, the National Health and Nutrition Examination Survey (NHANES) – NHANESIII (1988-1994), in particular – contains both actual and reported weight. Cawley (2000) uses this data to determine the extent of measurement error in weight (and height) and finds that those overweight underestimate their weight and those underweight overestimate their weight. Though the NLSY79 only collects self-reported weight, Cawley, using NHANESIII data, is able to predict actual weight for NLSY79 respondents from their self-reported weight. He does this by regressing actual weight on self-reported weight (and its squared value) using NLSY79-aged NHANESIII respondents. Then, he uses gender- and race-specific NHANESIII results to adjust self-reported weight in NLSY79 data. I use his procedure to adjust my NLSY79 data, and my results (as well as results from alternative correction specifications) are available upon request.

The NLSY79 is not a simple random sample (where every observation has an equal probability of selection). Instead, it is a multi-stage, stratified sample with respondents who are geographically clustered (Center for Human Resource Research, 2004). As a result, respondents within clusters will tend to be similar, causing conventional standard errors (that assume a random sample design) to be too small. However, survey design commands in STATA allow researchers to adjust standard errors for stratification and clustering (STATA, 2001), and I adjust my standard errors using this procedure. Fortunately, the severity of understated standard errors due to sampling design will be abated in later surveys as respondents move, mixing more uniformly throughout the United States.

The NLSY79 surveys that collect information about weight identify how much each respondent weighs in pounds at the time of the survey. To measure obesity, I calculate each individual's body mass index (BMI). Obesity is defined as a BMI of 30 or more (CDC, 2006b). The Centers for Disease Control and Prevention (CDC) considers adults to be underweight if their BMI is less than 18.5 and to be overweight if their BMI is 25 to 30. The CDC's method for identifying obesity in those under age 21 is through age- and gender-specific BMI growth charts (rather than simply using greater than or equal to 30 as the cutoff). For consistency across respondents, I use a cutoff of 30 for all respondents.

To maintain a consistent sample across all survey years, I eliminate respondents who do not provide valid weight (and height) information in all surveys that collect weight information. Otherwise, changes in sample average weight over time might reflect attrition (where, perhaps, low-income individuals who weigh more might be more likely to drop out, downward-biasing the sample average weight in later survey years, for example). However, I make one exception: I do not entirely eliminate female respondents who have missing weight information due to giving birth; instead, these respondents' weight observation is ignored from survey years when pregnant (or recently after giving birth) as described above, but their prior and future non-pregnant weight observations (from other survey years) are included in the analysis.

The NLSY79 also collects extensive information on each respondent's welfare experiences. However, information on welfare program participation is not collected for

NLSY79 respondents under the age of 18 who are not married, not in college, and without children. I only include weight observations from the 1985 and successive NLSY79 surveys (when respondents are at least 20 years of age) so Food Stamp usage will not increase simply because youths cross the 18-year threshold. The NLSY79 identifies whether each respondent receives Food Stamp benefits in each month covered by the survey. The NLSY79 also identifies the amount of Food Stamp benefits received in each month. Thus, it is possible to determine not only whether respondents received Food Stamp benefits but also the amount received. I create two variables to measure Food Stamp benefits. The first Food Stamp benefits variable is discrete and equals one if the respondent receives such benefits (and zero otherwise). The other variable is continuous and equals the amount of Food Stamp benefits received (over the twelve months preceding the survey date).

It is also possible with NLSY79 data to approximate whether respondents are eligible for Food Stamp benefits. Determining potential Food Stamp benefits is a complex process that hinges on the government's eligibility criteria. To be eligible for Food Stamp benefits, a household must:

- Have gross monthly income less than a household size-specific amount, though the gross income test is disregarded if the household contains an elderly (aged 60 and over) or disabled member.
- Have net monthly income (gross income minus 20 % of earned monthly income, a standard deduction, child support payments, a dependent care deduction, an excess shelter cost deduction, and medical expenses for elderly and disabled household members) less than a household size-specific amount.
- Have assets whose value is less than a specified amount. This amount is not specific to household size, but the amount is higher if the household contains an elderly or a disabled member. Further, the full value of the family's vehicles is not counted – instead, only each vehicle's value above a year-specific threshold amount is counted as an asset.

Households that receive Aid to Families with Dependent Children (AFDC -- now Temporary Aid to Needy Families [TANF]) or Supplemental Security Income (SSI) are automatically eligible for benefits. However, if such households have sufficient income, then their Food Stamp allotment may be zero.

The NLSY79 collects the information needed to identify gross income, net income, household size, the ages of household members, the value of assets, and vehicle values in the 1985 through 2000 surveys. In particular, in these survey years, the NLSY79 collects information on: wages, salary, farms, businesses, and/or military service (each identified separately) for the respondent and the respondent's spouse (and for the respondent's partner in 1994 and successive surveys); the earned income (one component) of other household members; unemployment compensation, AFDC benefits, SSI benefits, veterans' benefits, disability payments, income from "other types" of welfare assistance, income from trusts and/or estates, childcare support, and alimony for the respondent and the respondent's spouse (and for the respondent's partner in 1994 and successive surveys); welfare income (one component) for all other household members; and the value of savings and checking accounts, money markets, credit union savings, U.S. savings bonds, IRAs and/or Keoghs, certificates of deposit, personal loans, common stock, preferred stock, stock options, corporate or government bonds, mutual funds, estates or trusts, and any item worth more than $500 such as furniture or jewelry. The NLSY79 also collects information on child support payments made by the respondent and the respondent's spouse or partner in 1994 and successive surveys.

Unfortunately, approximating Food Stamp eligibility using the NLSY79 has some limitations. First, as mentioned above, the NLSY79 does not collect "partner" income or child support payments prior to 1994. This is a shortcoming because measures of partner income are used to determine Food Stamp eligibility when the partner is considered part of the household. Child support payments are important because they are deducted from gross income to determine net income. Second, the NLSY79 does not collect information on shelter costs (such as utility payments), so each individual's excess shelter cost deduction is not identified. A third limitation is that NLSY79 respondents report annual measures of earned income, unearned income, and childcare payments. This is problematic because Food Stamp eligibility is determined monthly. A fourth limitation is that the NLSY79 does not identify whether households contain disabled members. This is important because for households with a disabled member the gross income limit is disregarded, the excess shelter cost deduction is not capped, medical expenses above a threshold amount per month ($35 in 2004) are deductible, and the asset limit is higher ($3,000 instead of $2,000 in 2004) (Dean and Rosenbaum, 2002). A final limitation is that, though the NLSY79 asks respondents for the total value of all vehicles, it does not identify the number of vehicles. This is important because only each vehicle's value above a threshold amount ($4,650 in 2004) is counted as an asset. Further, the NLSY79 does not collect any asset information prior to the 1985 survey or in the 2002 survey, which explains why observations from the 2002 survey wave, which does collect weight information, are not included in the analysis.

Descriptive Statistics

I first select respondents with no more than a high school education to use in the analysis because they should be more likely to be eligible for Food Stamps than a sample of all NLSY79 respondents (without education restrictions). After making the necessary exclusions, my sample contains 11,748 male and 10,558 female person-year observations across the 11 used surveys that collect weight information. In this sample when weighted, about 47 % are female, 13.6 % are African-American (referred to as black from henceforth for brevity), and 5.9 % are

Hispanic.[3] I also perform the analysis using a sub-sample of those approximated to be eligible for Food Stamps based on the program's gross and net income tests and asset test. The corresponding sub-sample of those approximated to be eligible for Food Stamp benefits contains 3,681 male and 4,799 female person-year observations.

Table 1 gives the sample means for the key dependent variables (BMI and the probability of being obese) and the key explanatory variables (Food Stamp receipt and the amount of Food Stamps received) for low-income males and females, as well as these mean statistics for corresponding low-income Food Stamp recipients and non-recipients. As shown in this table, 5 % of low-income males and 14.7 % of low-income females receive Food Stamp benefits. Among those who receive Food Stamps, household benefits average $2,090 for males and $2,738 for females per year. This is reasonably similar to that found in USDA administrative data: Food Stamp households receive an average of $212.90 in benefits per month (USDA, 2006a) and receive benefits for an average of 11 months per year (USDA, 2006b). Table 1 also shows that average BMI and the probability of being obesity are higher for low-income female Food Stamp recipients than low-income female non-recipients. Specifically, 27.8 % of low-income female recipients are obese compared to 19.0 % of low-income female non-recipients. Similarly, low-income female recipients have higher BMIs: 26.8 versus 25.3. However, the same is not true for low-income males, where, for example, low-income male recipient BMI is slightly lower than corresponding low-income male BMI for non-recipients.

[3] Even when weighted, descriptive statistics from the NLSY79 are not necessarily comparable to those from other data sets (such as NHANES) because the NLSY79 is a cohort of respondents no more than seven years apart in age (aged 35 to 42 in 2000, for example).

Table 2 presents these descriptive statistics for the sub-sample of observations approximated to be eligible for Food Stamp benefits. BMI and obesity are not universally higher in the eligible sub-sample than in the low-income sub-sample. However, both eligible male and eligible female Food Stamp recipients have higher BMIs and are more likely to be obese than corresponding eligible non-recipients. As we would expect, those in the eligible sub-samples are more likely to receive Food Stamp benefits.

I next illustrate how BMI changes over time for these cohorts by plotting BMI for each year in which the NLSY79 collects weight information. Presented in figure 1 for low-income males and in figure 2 for low-income females, BMI increases over time from, for example, 24.7 (23.3) in 1985 to 28.8 (28.3) in 2000 for low-income males (females). BMI is higher for low-income males than low-income females, ranging from about 1.5 index points higher in 1985 to 0.5 index points higher in 2000. This is surprising because NHANES data shows the opposite. This appears to be a characteristic unique to the NLSY79 cohort. Regardless, others have found male BMI to be larger than female BMI in NLSY79 data (Cawley, 2004).

BMI growth paths for the sub-sample approximated to be eligible are presented in figures 3 and 4. Compared to low-income females, BMI initially is lower in the low-income female sub-sample, but eligible female BMI becomes larger by 1989 and remains so through the year-2002 survey. Conversely, low-income male BMI is higher than eligible male BMI throughout. Further, while BMI is somewhat higher for low-income males than low-income females (with this gap narrowing over time), the opposite is true in some years for the eligible sub-samples.

Presented in these figures (figures 1 through 4) is also BMI for corresponding Food Stamp recipients and non-recipients. In the low-income sub-samples, BMI tends to be higher for Food Stamp recipients than non-recipients, specifically for females. This differential also tends to grow over time. For example, in the low-income female sub-sample, recipient BMI is initially 0.7 index points higher than that for low-income female non-recipients, but this differential grows to 3.3 index points by year-2000. The recipient-non-recipient BMI difference is perhaps a bit starker and more consistent in the eligible sub-samples than in the low-income sub-samples. For example, eligible male recipient BMI is higher than eligible male non-recipient BMI in most years.

I next present corresponding figures for the growth in the prevalence of obesity. Shown in figures 5 and 6 for low-income males and low-income females, respectively, the prevalence of obesity tends to increase over time. For example, for low-income males (females), this increase is from 11.57 (9.92) % in 1985 to 31.61 (33.95) % in 2000. Presented in figures 7 and 8, eligible males are initially more likely to be obese than eligible females, but this reverses by the early 1990s. Further, by year-2000, the prevalence of obesity is higher in the eligible female sub-sample than in any of the other sub-samples examined.

Obesity figures 5 through 8 also present the prevalence of obesity for corresponding Food Stamp recipients and non-recipients. As was the case with BMI, obesity tends to be more prevalent for Food Stamp recipients than their non-recipient counterparts. For example, in the low-income female sub-sample, recipients are roughly five percentage points more likely to be obese, and this gap grows to almost 20 percentage points by year-2000. Further, the recipient-non-recipient obesity differential is larger for females than males, both in the low-income sub-sample and in the sub-sample of those eligible for benefits.

Somewhat differently, Ver Ploeg, Mancino, and Lin (2006) find that in NHANES data the BMI gap between Food Stamp recipients and eligible non-participants increased between 1976-1980 and 1988-1994 but then decreased thereafter, with the BMI of eligible non-participants becoming larger by 1999-2002. Ver Ploeg et al. also find that the probability of being overweight increased less for Food Stamp participants than for eligible non-participants between 1972 and 2002 in NHANES data. Differences in trends between my NLSY79 sample and Ver Ploeg et al.'s NHANES sample may be due to following a particular cohort over time that, by definition, ages versus examining a cross-section of respondents with no aging. That is, obesity does not level off in my sample because the NLSY79 cohort continues to age. Regardless, I find that obesity increases faster after 1996 for Food Stamp recipients than for non-recipients. Some of this could be due to the decrease in the FSP caseload during this period. For example, the number of Food Stamp recipients in NLSY79 data between 1994 and 2000 declines by 50 %, with non-obese recipients being the ones more likely to leave the FSP.

The descriptive statistics and correlations presented thus far in tables and figures do not necessarily represent the causal effects of the FSP on obesity. To identify causal effects, I use multivariate regression analysis to hold constant potentially confounding factors. First, I control for individual characteristics with a standard set of demographic variables. The demographic covariates include controls for gender, race/ethnicity, age, education, marital status, household composition (number of children, household size), household income, urban residence, state of residence, and survey year of response. Descriptive statistics for these (and other) variables are presented in table 1 for the low-income sub-samples and in table 2 for the sub-samples approximated to be eligible for Food Stamp benefits.

I also control for local (county or SMSA) economic conditions (descriptive statistics presented in tables 3 and 4) because economic conditions may affect participation in public assistance programs. To do this, I include variables identifying the local unemployment rate, potential earnings (proxied by local per capita income), the % of the local labor force that is female, the % of the local population with a high school education and a college education, the % of the local population employed, and the % of the local labor force in manufacturing and wholesale/retail trade.

I also control for state political orientation (descriptive statistics presented in tables 3 and 4) because liberal states may have more generous FSP eligibility criteria and may also be less likely to stigmatize those who receive welfare (Figlio, Gundersen, and Ziliak, 2000; Ziliak, Gundersen, and Figlio, 2003). I control for state political orientation with variables indicating how often members of the state's congressional delegation (representatives and senators separately) cast liberal votes as measured by Americans for Democratic Action (ADA) as well as the political affiliation of the governor and state legislature (representatives and senators separately) (Americans for Democratic Action, 2005).

I also control for AFDC/TANF Program characteristics. The 1996 welfare reform act (the Personal Responsibility and Work Opportunity Reconciliation Act -- PRWORA) began allowing states to develop their own TANF eligibility standards, benefits, and time limits. Since that time, states have tailored unique TANF programs. I include a TANF dummy variable equal to one if PRWORA welfare reform is in force and (six) pre-PRWORA welfare waiver dummy variables equal to one if a pre-welfare reform state waiver is in force either terminating or reducing benefits due to time limits, changing work exemption policies, changing sanctions for violations, increasing earned income disregards, changing family cap rules, or implementing work requirements (see Crouse, 1999). In addition, I include controls for other state TANF program characteristics. States differed in their monthly maximum benefit levels (for example, state-specific household size-specific maximum AFDC/TANF benefits for a family of four) prior to PRWORA; after PRWORA, states began differing in their time limits in which recipients may receive TANF benefits (months of allowable lifetime receipt), whether household benefits are capped for births occurring during participation spells (family caps), child age (in months) for which caregivers are exempt from work requirements, their most severe sanctions for program violations (whether the most severe sanction is full or permanent instead of partial and temporary), their income/asset limits, and their earned income disregards (flat dollar amounts and percentages of earnings disregarded from benefits calculation for the first month with earnings). If PRWORA's TANF work requirements increase employment and, consequently, earnings, then they may affect Food Stamp benefits by making recipients ineligible for Food Stamps due to the program's income test. Furthermore, state TANF programs may affect Food Stamp benefits because those eligible for TANF benefits are automatically eligible for Food Stamps. Information required to create these variables is obtained from a report on state AFDC/TANF policies by Crouse (1999) and from the Urban Institute's online Welfare Rules Database (The Urban Institute, 2005).

IV. Estimation Methodology and Identification

My goal is to identify the causal effects of Food Stamp benefits on obesity. In this context, 'causal effect' is defined as it would be, for example, in the evaluation of a social program: a causal effect is the average effect on a nonrandom treated subpopulation, where covariates attempt to control for the nonrandom assignment of the treatment (Angrist and

Krueger, 1999). This differs from the causal effect of a medical treatment that is randomly assigned to a sub-sample.

Ordinary Least Squares (OLS) Models

To identify causal effects, I estimate the probability of being obese using multivariate regression analysis. However, modeling whether BMI is above or below the threshold that defines obesity is not necessarily a better approach than a continuous model of BMI (Jolliffe, 2004). This is because the obesity threshold is likely to be somewhat arbitrary. For example, moving from a BMI of 29 to 30 is probably not substantially worse than moving from a BMI of 28 to 29. Further, the dichotomous measure of obesity does not change when those obese gain weight (and starkly changes from 0 to 1 when those barely below the obesity threshold gain small amounts of weight). Therefore, I estimate an additional set of regressions modeling obesity with a continuous BMI measure in OLS regression framework.

The key variables in these models are a measure of weight (W) such as the probability of being obese or BMI and Food Stamp benefits (FSB). Formally, I estimate

$$W_{it} = \beta_0 + \beta_1\mathbf{X}_{it} + \beta_2 FSB_{it} + \varepsilon_{it} \qquad (13)$$

for observation i at time t, where $\mathbf{X}$ is a vector of covariates and ε is the error term. When the outcome is measured as a discrete variable such as the probability of being obese, the models take the logit specification. In this model and in all others that use multiple observations from the same respondent, I adjust my standard errors to account for respondent-specific correlation because respondents potentially provide multiple observations (from multiple survey years). Otherwise, standard errors will be understated and significance levels will be overstated.

Even within the context of multivariate regression analysis, estimates are susceptible to various sources of bias. One potential source of bias is due to unobserved heterogeneity, where obese respondents systematically differ from their non-obese counterparts in ways that are difficult for researchers to measure. In particular, unobserved characteristics, which may be time-variant, may be correlated with obesity and FSP participation. For example, suppose that those who are “food insecure” are more likely to apply for and receive Food Stamps. If these same food insecure individuals are more likely to be obese because they are prone to eating disorders such as binge-eating when food is available (the arguments of Gibson, 2003, and Townsend et al., 2001), then obesity and Food Stamp benefits will both be correlated with food insecurity. If food insecurity is unobserved to the researcher, then the Food Stamp benefit variable will pick of the effects of Food Stamps as well as the effects of food insecurity on obesity. If Food Stamp benefits increase obesity and food insecurity increases obesity and Food Stamp benefits, then the positive Food Stamp benefit coefficient would be biased upward. In general, if Food Stamp benefits are correlated with any unobserved characteristic that is also correlated with obesity, then OLS regression will not identify the causal effects of Food Stamp benefits on obesity, producing unobserved heterogeneity bias.

Another type of bias is reverse causality and/or simultaneity bias. Reverse causality bias would exist if obesity determines (or influences) FSP participation. Simultaneity bias would exist if obesity and FSP participation affect each other (or are determined concurrently). It would seem easy to argue that consumers decide (at least monthly) how much to eat and whether to apply for and, if eligible, use Food Stamps.

<u>Instrumental Variable Models</u>

I attempt to control for potential unobserved heterogeneity bias using three approaches. In my first approach, I use a two-step procedure that first predicts Food Stamp benefits with exogenous characteristics and then uses the predicted estimate of Food Stamp benefits to estimate the effects of Food Stamp benefits on obesity in a second-stage model. More formally, I estimate

$$FSB_{it} = \alpha_0 + \alpha_1\mathbf{X}_{it} + \alpha_2\mathbf{Z}_{it} + \varepsilon_{it} \qquad (14)$$

and

$$W_{it} = \beta_0 + \beta_1\mathbf{X}_{it} + \beta_2 \widehat{FSB}_{it} + \varepsilon_{it} \qquad (15)$$

for observation i at time t, where **X** and ε are as defined above, $\widehat{FSB}$ is the predicted value of Food Stamp benefits, and **Z** is a vector of instruments that predict Food Stamp benefits but have no effect on weight. (This procedure is often referred to as instrumental variable estimation. The goal is to generate unbiased estimates by finding instruments that are as highly correlated as possible with the endogenous regressor [Food Stamp benefits] but that are uncorrelated with the error, ε.)

As instruments, I use some of the household characteristics required to determine Food Stamp eligibility. Specifically, these characteristics include the value of vehicles and the presence of an elderly member. Eligibility criteria will serve as exogenous instruments identifying Food Stamp benefits if *(i)* Food Stamp eligibility criteria significantly explain Food Stamp receipt and *(ii)* Food Stamp eligibility criteria do not significantly affect obesity independently of Food Stamp benefits. Certainly the value of vehicles and the presence of an elderly member affect Food Stamp benefits because they directly determine eligibility (for example, the presence of a senior raises gross income and asset limits). However, these instruments will be invalid if they affect obesity (for example, if non-car owners burn more calories). Ultimately, F-tests will be used to determine whether household Food Stamp eligibility characteristics are indeed valid instruments for Food Stamp benefits. Comparisons (using Hausman tests) with OLS models containing the actual measure of the Food Stamp benefit variable will indicate whether OLS estimates are indeed biased.

My second approach is similar to my first approach except that I use another type of instrument. In this approach, I exploit state variation in Food Stamp eligibility laws (Kabbani and Wilde, 2003, use similar instruments). This is possible because the 1996 welfare reform act, PRWORA, began allowing states to develop their own Food Stamp eligibility standards (within a set of federal guidelines). In 2002, The Farm Security and Rural Investment Act (the Farm Bill) further expanded the options and waivers available to states. Since that time, states have utilized various options and waivers. My second approach predicts Food Stamp benefits with instruments that reflect variation in state Food Stamp eligibility laws. Therefore **Z** becomes a vector of state Food Stamp eligibility criteria. A sampling of these options and waivers are listed below roughly in chronological order:

- PRWORA gives states the option of extending Food Stamp benefits to able-bodied adults without dependents (ABAWDs) (defined as adults aged 18 through 50 not providing care to a dependent) whose benefits would otherwise have expired if they live in an economically depressed area with high unemployment (10 % or higher) or insufficient job opportunities (GAO, 1999; Rosenbaum, 2002).
- PRWORA gives states the option of making work and training requirement penalties more severe (Gabor and Botsko, 2001; USDA, 2003b, p. 18).
- PRWORA gives states the option of disqualifying Food Stamp recipients for failing to meet obligations specified by other means-tested assistance and benefit programs such as TANF (Gabor and Botsko, 1998, 2001; USDA, 2003b, p. 19).
- States have the option of requiring recipients to report changes in income either periodically (periodic reporting) or as circumstances change (incident reporting) (USDA, 2003b, p. 1).

- States that use incident reporting have the option of first adjusting food stamp benefits when the certification period expires (USDA, 2003b, p. 2).
- States that use incident reporting may be granted waivers reducing the types of changes that must be reported (USDA, 2003b, p. 3).
- The 2001 Agriculture Appropriations Act gives states the option of replacing the FSP's vehicle rule with a more liberal vehicle rule from a TANF assistance or non-cash benefit program (Super and Dean, 2001; Center on Budget and Policy Priorities, 2003; and USDA, 2003b, p. 6).
- Effective November 2000, states have the option of making households that receive means-tested cash assistance or means-tested non-cash benefits funded by a TANF or TANF Maintenance of Effort (MOE) assistance program automatically eligible for Food Stamp benefits (Super and Dean, 2001; USDA, 2003b, p. 8).
- States have the option of using a standard utility allowance (rather than a household's actual utility costs) in calculating a household's excess shelter cost deduction (Posey, 2002; USDA, 2003b, p. 10; Dean and Rosenbaum, 2002).
- The Farm Bill gives states the option of disregarding changes in deductions used to calculate net income during the certification period (Dean and Rosenbaum, 2002; Rosenbaum, 2002; Posey, 2002; USDA, 2003b, p. 2).
- The Farm Bill allows states to continue providing Food Stamp benefits to households formerly receiving TANF benefits for up to five months after cessation of TANF assistance (Hayes, 2002; Dean and Rosenbaum, 2002; GAO, 2002; Posey, 2002; USDA, 2003b, p. 4).
- The Farm Bill gives states the option of reducing the sources of income and types of assets used to determine eligibility (Posey, 2002; Rosenbaum, 2002; USDA, 2003b, p. 5). However, some limitations apply.
- The Farm Bill gives states the option of excluding child support payments from income (USDA, 2003b, p. 12).

Because Food Stamp eligibility criteria vary between states and over time within states, I identify the effects of Food Stamp benefits using variation in Food Stamp eligibility policies. Certainly state Food Stamp eligibility criteria should affect Food Stamp benefits. Further, it seems reasonable to assume that state Food Stamp eligibility criteria are unrelated to obesity when controlling for Food Stamp benefits. For example, state legislatures probably do not alter Food Stamp eligibility criteria based on a state's prevalence of obesity. Again, F-tests are used to determine whether state Food Stamp eligibility criteria are indeed valid instruments.

However, comparing the effects of various Food Stamp eligibility options and waivers across states will produce misleading results if such differences are due to state-specific effects that are not the result of the options and waivers. To control for such effects, I include state-specific dummy variables in the regression models. Thus, the models identify the effects of state Food Stamp eligibility criteria on Food Stamp benefits by examining the effects of state Food Stamp eligibility changes on changes in Food Stamp benefits. Similarly, estimates will also be biased if the usage of the options and waivers is correlated with but not due to year-specific effects. To control for year-specific effects, I include a dummy variable for each year covered by the model (one for each survey year). The year dummy variables pick up national trends while variation in state Food Stamp eligibility criteria across states within a particular year identify the effects of state Food Stamp eligibility criteria. Thus, the effects of state eligibility criteria are identified from variation over time and across states.

To estimate the effects of state Food Stamp eligibility criteria on Food Stamp benefits, I use data on each state's use of FSP options and waivers as well as when these options and waivers went in force and when they were changed, if applicable. I gather this information from Gabor and Botsko (1998), Super and Dean (2001), and Knaus (2003), and the Urban Institute (see Finegold, Margrabe, and Ratcliffe, 2006). The NLSY79 identifies each respondent's state of residence, enabling me to link measures of state Food Stamp eligibility criteria with each respondent.

The proposed IV procedure has some shortcomings. First, instruments that are weakly correlated with the endogenous covariate in the first stage model often generate large second stage standard errors. Even more troubling, the IV literature shows that IV estimates may still be biased when the identification variables are weakly associated with the endogenous covariate (and when there is a relationship, even if only a weak one, between the instruments and the second stage error). With weak instruments, Nelson and Startz (1990a,b), Bound, Jaeger, and Baker (1995), and Staiger and Stock (1997) argue that IV estimates may be biased in the direction of OLS. Again, for IV to produce unbiased estimates, the instruments must significantly explain the endogenous covariate. However, Bound et al. (1995) show that in large samples, instruments may appear to have statistically significant effects when, in fact, their relationship to the endogenous covariate is weak. That is, in large samples, testing the null hypothesis that the instruments have no effect may produce statistically significant p-values with relatively small F-statistics. Thus, Bound et al. (1995) conclude that finding appropriate instruments is more difficult than previously thought. To help determine instrument quality, the IV literature recommends reporting the F-statistic for the instruments (Bound et al., 1995; Staiger and Stock, 1997).

Fixed Effects Models

In my third approach to control for potential unobserved heterogeneity bias, I use NLSY79 data to estimate individual-specific fixed effects models that compare multiple observations from the same respondent. I assume that the effects of Food Stamp benefits on BMI and obesity can be estimated from the following model:

$$W_{ist} = \beta_0 + \beta_1\mathbf{X}_{it} + \beta_2 FSB_{it} + \nu_i + \varepsilon_{ist} \qquad (16)$$

where ν_i is an individual-specific factor representing respondent i’s unobserved characteristics, and ε is the error term for respondent i at time t. In this context, if correlation between FSB and ν_i exists and if the heterogeneity component (ν_i) is unobserved to the researcher, then estimates will be biased. That is, because ν_i is unobserved, it cannot explicitly be included, subjecting the estimates to potential unobserved heterogeneity bias. However, if this individual-specific unobserved component is the same across observations from the same respondent (time invariant for each respondent), then it can be identified and controlled for with respondent-specific dummy variables. In practice, the individual-specific fixed effects model essentially compares observations over time from the same respondent. Just as continuous-outcome fixed effects models are estimated with respondent-specific dummy variables, discrete-outcome fixed effects models take the logit functional form and include respondent dummy variables (fixed effects logit models can be estimated in STATA, 2001). Unfortunately, the fixed effects model has some limitations. First, if the respondent's unobserved component is not constant over time, then the estimates may still be biased. Another limitation of the fixed effects model is that it does nothing to control for reverse causality (or simultaneity), where obesity determines FSP participation. I also estimate a corresponding fixed effects linear probability model for the probability of being obese. The advantage of using the logit model fixed effects specification is that the outcome variable is constrained to be between zero and one. Conversely, predicted outcomes using the linear probability model specification may be negative or larger than 100 %. The advantage of using the linear probability model specification is that respondents with no variation in the outcome variable are included. Conversely, the logit model specification does not include respondents who are either never obese or always obese across NLSY79 survey years.

Dynamic Models: Change in BMI and Transition Equations

The third part of my analysis examines dynamic effects of Food Stamp benefits on BMI and obesity. Because current weight is not independent from past weight, contemporaneously-measured covariates probably affect weight *change*. Thus, I first estimate another model specification using change in BMI as the dependent variable,

$$\Delta W_{it} = \beta_0 + \beta_1 \mathbf{X}_{it} + \beta_2 FSB_{it} + \varepsilon_{it}, \qquad (17)$$

where Δ indicates change. A variant on this specification is to estimate conditional transition equations. Such equations estimate the probability of becoming obese from a non-obese sub-sample and the probability of no longer being obese from an obese sub-sample. Formally,

$$\text{Prob } (\text{Obese}_t = 1 \mid \text{Obese}_{t-1} \neq 1) = \Phi(\{ W_{it} - \mathbf{X_{it}}\beta_{it}\} / \sigma), \qquad (18)$$

where Φ is the normal cumulative distribution function, σ is the standard deviation of the error (where the error is assumed to be normally distributed), and $\mathbf{X}_i$ is a vector of covariates redefined to include $\mathbf{FSB}_{it}$. For consistency, I measure these changes (the change in BMI and the conditional changes in obesity) over a two-year time interval. Specifically, I examine changes between the 1985 and 1987 surveys, the 1987 and 1989 surveys, 1990 and 1992, 1992 and 1994, 1994 and 1996, 1996 and 1998, 1998 and 2000, and 2000 and 2002 (with weight observations from 1986, 1989, and 1993 disregarded because they cannot be matched with corresponding two-year-later weight measurements).

Dynamic Models: Hazard Models

Since less than 10 % of NLSY79 youths were obese in 1985 but almost 30 % were by 2000, obesity could be estimated using a survivor function ("surviving" is defined in this context as not yet being obese). This specification uses hazard rates to estimate the effects of Food Stamp benefits on the probability of becoming obese between NLSY79 surveys (ten between-survey transitions from the 1985 through 2000 surveys that collect weight information). I follow the approach taken by Prentice and Gloeckler (1978) and Meyer (1990, 1995) and use a hazard specification that does not impose parametric restrictions on the underlying baseline hazard function. If the baseline hazard function were estimated by assuming a parametric form (such as a Weibull form) and that parametric form were incorrect, then estimates would be inconsistent. This hazard model also gives consistent estimates when there is censored data. Here, the data is censored after the year-2000 NLSY79 survey.

Let $\lambda_i(t)$ be the hazard rate for observation i in year t, where the hazard rate is defined as the probability of becoming obese in year t given that the respondent is not yet obese. Formally, if T_i is the year in which a respondent becomes obese, then the hazard rate is defined as

$$\lim_{h \longrightarrow 0^+} \frac{prob[t+h > T_i \geq t \mid T_i \geq t]}{h} = \lambda_i(t). \qquad (19)$$

Empirically, the hazard rate is

$$\lambda_i(t) = \lambda_0(t)\exp(\mathbf{X}_i'\beta) \qquad (20)$$

where $\lambda_0(t)$ is the baseline hazard rate for year t and $\mathbf{X}_i$ is a vector of covariates (including $\mathbf{FSB}_{it}$). Following Meyer (1990, 1995), given that a respondent is not yet obese by year t, the probability that the respondent does not become obese in year t+1 is

$$prob[T_i \geq t+1 \mid T_i \geq t] = \exp[-\int_t^{t+1} \lambda_i(u)du] = \exp[-\exp(\mathbf{X}_i'\beta)\int_t^{t+1} \lambda_0(u)du], \quad (21)$$

which gives

$$prob[T_i \geq t+1 \mid T_i \geq t] = \exp(-\exp(\mathbf{X}_i'\beta + \gamma(t))) \qquad (22)$$

with

$$\gamma(t) = \ln\{\int_{t}^{t+1} \lambda_0(u)du\} \qquad (23)$$

because $\mathbf{X}_i$ is constant between t and t+1. Thus, the likelihood function is

$$l(\gamma,\beta) = \prod_{i=1}^{N} \{[1-\exp(-\exp(\gamma(k_i)+\mathbf{X}_i'\beta))]^{\delta_i} \prod_{t=0}^{k_i-1} \exp(-\exp(\gamma(t)+\mathbf{X}_i'\beta))\} \quad (24)$$

where N is the number of respondents, k_i is the minimum of T_i and ten and δ_i equals one if t equals T_i and zero otherwise. The first term equals one unless a respondent becomes obese between years t and t+1. The second term is the probability that a respondent is not yet obese by year t.

Models with Lagged Food Stamp Benefits

As specified, FSB_{it} identifies the effects of contemporaneous FSP receipt (at time t); however, past Food Stamp benefits may affect past weight which affects current weight. In the final portion of models, the Food Stamp variable identifies the effects of program receipt from past periods. In the first of these models, FSB_{it} is specified as a vector such that

$$\mathbf{FSB}_{it} = (FSB_{it}, FSB_{it-1}, FSB_{it-2}, \ldots FSB_{it-n}) \qquad (25)$$

where n is the number of past periods examined (with results presented for n equal to one, three, and seven). This shows whether Food Stamp receipt affects weight contemporaneously or with a lag. In another set of models, I estimate the effects of patterns of past Food Stamp receipt (using the classification system proposed by Murphy and Harrell, 1992). Specifically, I estimate the effects of receiving Food Stamp benefits over the preceding two years in one spell either short-term (for less than 9 months), medium-term (between 9 and 23 months), or long-term (24 months). These models also estimate the effects of receiving benefits during multiple spells.

V. Results

OLS Results

First, I estimate the effects of Food Stamp benefits on BMI and the probability of being obese in OLS (and logit) regressions separately using sub-samples of low-income males and females. Table 5 reports the effects of the Food Stamp benefit covariates. Model 1 (for both sub-samples) examines the effect of receiving Food Stamps (a dichotomous variable) on BMI, model 2 examines the effect of the amount of Food Stamps received (a continuous variable) on BMI, and model 3 includes both the dichotomous and the continuous Food Stamp benefits variables (from models 1 and 2). Correspondingly, models 4, 5, and 6 re-estimate models 1, 2, and 3 using the probability of being obese as the outcome variable instead of BMI. For each model, I also report the predicted value of the outcome variable for not receiving and for receiving Food Stamp benefits (or for receiving $2,400 in Food Stamp benefits during the year, which is roughly the annual average for recipients). Appendix tables A1 through A4 present the effects of the other covariates for the low-income sub-samples (appendix tables A1 and A2) and the eligible sub-samples (appendix tables A3 and A4).

Initial results for low-income females suggest that Food Stamps significantly increase BMI and obesity. This is true for females for both the FSP participation variable in models 1 and 4 and, at the 10 % level, for the amount of Food Stamp benefits received in models 2 and 5. However, the amount of Food Stamp benefits received never has a statistically significant effect when both are included in the same model. The coefficient point estimates suggest switching from not receiving Food Stamp benefits to receiving them (or from not receiving Food Stamp benefits to receiving $2,400 in Food Stamp benefits per year) increases BMI by an average of about 0.5 index points across models 1, 2, and 3. The same change increases the probability of being obese between roughly 2 and 5 percentage points. However, Food Stamp benefits do not significantly affect males in any of the models.

Though the models in table 5 use low-income NLSY79 respondents, corresponding results may mask the effects of Food Stamp benefits because a portion of included observations are ineligible for benefits. Therefore, I next re-estimate the models (in table 5) including only observations approximated to be eligible for Food Stamp benefits based on state- and year-specific eligibility criteria and household characteristics. Results using eligible respondents, which are presented in table 6, suggest that Food Stamp benefits significantly increase BMI and the probability of being obese for females but not for males. The magnitudes of the Food Stamp variable coefficients are comparable, if not somewhat larger, to those in table 5 for the low-income sub-samples. For example, receiving Food Stamps is projected to increase low-income female obesity by 5.1 % but to increase obesity among eligible respondents by 6.3 %. Further, the Food Stamp covariates typically have larger t-statistics in table 6. For example, Food Stamp receipt significantly affects obesity at the 5 % level among low-income females but at the 1 % level among eligible respondents.

Instrumental Variables Results

The OLS results thus far establish correlation between Food Stamp benefits and BMI and the prevalence of obesity holding multiple observable factors constant. However, these models do not necessarily establish whether Food Stamps *cause* recipients to gain weight. This is because Food Stamp benefits and BMI/obesity could be correlated with other unobserved characteristics. In an effort to identify the causal effects of Food Stamp benefits, I next re-estimate the models in tables 5 and 6 using a measure of *predicted* Food Stamp benefits rather than actual Food Stamp benefits (however, I do not present corresponding results from the model specification that includes both Food Stamp receipt and the amount of Food Stamps received because in this model only the dichotomous measure tends to be statistically significant -- see tables 5 and 6).

I use two sets of instruments: first, I use household characteristics that determine program eligibility, and, second, I use state eligibility criteria. Sample first-stage IV Food Stamp receipt model results using the first set of instruments for the low-income sub-samples are presented in appendix table A5 and sample model results using the second set of instruments for the low-income samples are presented in appendix table A6. Corresponding first-stage results for the eligible sub-samples are in appendix tables A7 and A8. These first-stage results show that household vehicle values significantly decrease Food Stamp receipt, but, surprisingly, the presence of a senior significantly decreases Food Stamp receipt (see appendix tables A5 and A7). First-stage results in appendix tables A6 and A8 show that USDA-approved state outreach plans significantly increase Food Stamp receipt.

Second-stage BMI and obesity results for the low-income sub-samples are presented in table 7 and results for the eligible sub-samples are presented in table 8. All of these tables (presenting second-stage results) report F-statistics (and indicators of statistical significance) for *(i)* the significance of the instruments in the first-stage models, *(ii)* the validity of the exclusion restrictions (excluding the instruments from the second-stage models), and *(iii)* Hausman tests of the null hypothesis that the OLS results and IV results are not statistically different.

Reported in table 7 for the low-income sub-samples of males and females, household characteristics (household vehicle values and the presence of a senior) significantly explain Food Stamp benefits in first-stage models at the 1% level. Considering the low-income sub-sample of males, second-stage exclusion restrictions appear valid, and results show that Food Stamp benefits continue to have statistically insignificant effects on BMI and obesity (as with OLS results), with Hausman tests being unable to reject the null hypothesis of no difference between OLS and IV estimates. Unfortunately, second-stage Food Stamp benefit results for the low-income sub-sample of females are not valid because F-tests suggest the instruments should not be excluded from second-stage BMI and obesity models. Perhaps females without vehicles face a higher time cost of food consumption due to lack of transportation to grocery stores or a higher monetary cost of food consumption when cheaper supermarkets are not within walking distance. Furthermore, those without vehicles may travel more by foot, consequently burning more calories.

Results in table 8 considering the eligible sub-samples are similar to those in table 7 for the low-income sub-samples. For example, the instruments continue to explain Food Stamp benefits significantly at the 1 % level. Hausman tests continue to fail to reject the null hypothesis that the OLS and IV estimates are not statistically different for the sub-sample of eligible males. Further, the instruments are again invalid for the sub-sample of eligible females because F-tests indicate they should be included in the second-stage BMI and obesity models.

I next re-estimate the models presented in tables 7 and 8 using state eligibility laws as instruments. Corresponding low-income sub-sample results are presented in table 9 and results for the sub-samples of eligible respondents are presented in table 10. State eligibility laws tend to have statistically significant effects on Food Stamp benefits in first-stage models for low-income males, but for low-income females they only have significant effects on the amount of Food Stamps received at the 10 % level. Further, F-tests suggest the instruments are properly excluded from second-stage BMI and obesity models for both low-income males and females. Where the instruments are valid, Hausman tests do not reject the null hypothesis that the OLS and second-stage IV Food Stamp estimates are not statistically different. Continuing, presented in table 10, corresponding results for the sub-sample of respondents approximated to be eligible for benefits show that the instruments do not significantly affect Food Stamp benefits for males. In models 1 and 3, the instruments affect eligible females at the 10 % level, but Hausman tests fail to reject the null hypothesis that the OLS and IV estimates are statistically different.

In sum, where valid, the IV models provide no evidence that positive OLS effects of Food Stamp benefits are inconsistently large: in none of the models where the instruments are deemed valid do Hausman tests indicate OLS bias away from zero. However, OLS and IV estimates may appear to be the same because second-stage IV results are estimated imprecisely.

Fixed Effects Results

IV estimates are only as strong as their instruments. When instruments are weak, IV estimates often are as well with large standard errors. Another approach to control for potential unobserved heterogeneity bias is to estimate individual-specific fixed effects models. Controlling for time-invariant unobserved heterogeneity, my fixed effects specifications essentially compare changes in Food Stamp receipt over time with changes in BMI and the probability of being obese over time. Table 11 presents individual-specific fixed effects model results for the low-income sub-sample and table 12 presents corresponding results for those approximated to be eligible. For each sample, I use two fixed effects specifications to model obesity: a fixed effects logit model and a fixed effects linear probability model. The advantage of using the logit model specification is that the outcome (the probability of being obese) is constrained to be between zero and 100 % (predicted outcomes using the linear probability model specification may be negative or larger than 100 %). The advantage of using the linear probability model specification is that respondents with no variation in the outcome variable (obesity) across survey years are included (the logit model specification does not include respondents who are either never obese or always obese across NLSY79 survey years).

Fixed effects models using the low-income sub-sample provide some evidence that Food Stamp benefits increase BMI and obesity. Presented in table 11, the amount of Food Stamps received significantly increases BMI for low-income males at the 10 % level. For low-income females, receiving Food Stamps significantly increases BMI and the probability of being obese (in both the logit and linear probability fixed effects specifications). Much in agreement, results in table 12 using the eligible sub-samples show that receiving Food Stamps significantly increases BMI at the 5% level for males and females. Thus, there is at least some evidence that when controlling for time-invariant individual-specific characteristics, Food Stamps increase BMI and obesity. In none of the models is Food Stamp receipt found to decrease these measures.

Dynamic Results: Change in BMI and Transition Equations

Weight is not independently determined each period; instead, as defined in the theoretical model, contemporaneous weight is weight stock net of contemporaneous weight change. To begin to account for this, I next model the effects of Food Stamp benefits on the change in BMI and on transition equations for the conditional probability of becoming obese (conditional on not being obese) and the conditional probability of no longer being obese (conditional on being obese) between surveys. Table 13 presents Food Stamp covariate results from these models for the low-income sub-samples and table 14 presents corresponding results for the eligible sub-samples.

Shown in table 13, results indicate that Food Stamp benefits significantly increase the change in BMI between surveys for the low-income female sub-sample in model 1 (and at the 10

% level for males in model 2). For example, in model 1, with no Food Stamps, low-income female BMI is predicted to change by 0.57 index points between surveys; however, with such benefits, BMI is predicted to increase by almost 0.8 index points, which is an increase of over 0.2 index points. To put this effect in perspective, consider the following. Weighted means indicate the NLSY79 low-income female sub-sample prevalence of obesity in 1998 was 0.298 (with average BMI of 27.4). By year-2000, the sample prevalence of obesity increased to 0.330, with BMI increasing by 0.6 index points (from 1998) to 28.0. Had BMI instead increased by 0.8 index points, as model 1 in table 13 suggests with Food Stamp receipt, the year-2000 low-income female prevalence of obesity would have been 0.334, which is .4 percentage points higher. However, Food Stamp benefits do not significantly affect the conditional probability of becoming obese and the conditional probability of no longer being obese for the low-income sub-sample of females. Also of note, for males at the 10 % level, Food Stamps decrease the probability of transitioning from obese to no longer obese, decreasing this transition rate from 13.9 % to 8.2 % (model 5).

Results are different when using the eligible sub-sample. In table 14, Food Stamp benefits have statistically insignificant effects on eligible females, but, interestingly, for eligible males, significantly decrease the probability of transitioning from obese to not obese. Food Stamps continue to increase the change in BMI at the 10 % level for eligible males (model 2).

Dynamic Models: Hazard Rate Results

I next estimate a hazard model for becoming obese (conditional on not yet being obese) to show the cumulative effect of Food Stamp benefits over time. I explore two hazard specifications for both the dichotomous Food Stamp covariate and the continuous Food Stamp covariate. The first includes the Food Stamp covariate but does not interact it with duration variables, resulting in a proportional effect of Food Stamps over time (model 1 for Food Stamp receipt and model 2 for the amount of Food Stamps). The second hazard specification interacts the Food Stamp covariate with duration dummy variables, allowing such benefits to have different effects in each period (model 3 for Food Stamp receipt and model 4 for the amount of Food Stamps received). I do not present corresponding Food Stamp covariate results in tables (though coefficient results are available upon request) because in non-linear hazard specifications it is difficult to interpret the magnitudes of the effects. Instead, I first discuss whether Food Stamps have statistically significant effects, and then I illustrate the magnitudes of these effects in figures, described below.

Referring to the F-statistic for tests of the joint significance of the set of Food Stamp benefit covariates, Food Stamp benefits have statistically insignificant effects for low-income males. Results are mixed for low-income females. The dichotomous Food Stamp covariate specification has significant, positive effects on females in models 1 and 3, but the amount of Food Stamps received has insignificant effects in models 2 and 4. Much the same is true for the eligible sub-samples, where receiving Food Stamps has significant, positive effects for eligible females (in models 1 and 3) but insignificant effects for eligible males (except for model 4, where effects are significant and positive).

To illustrate the magnitudes of the Food Stamp effects on the obesity hazard, I next plot the predicted survivor rates for the annual probability of not yet being obese without Food Stamp receipt and with Food Stamp receipt using model 3 estimates. Then, I do the same using model 4 estimates, predicting the annual survivor rates with no Food Stamp benefits and with $2,400 in annual Food Stamp benefits in each year. I do not present corresponding figures for hazard models 1 and 2 because they are more restrictive, constraining Food Stamp benefits to have a proportional effect in each period. The two sets of simulations are presented in figures 9 and 10 for low-income males and in figures 11 and 12 for low-income females. Corresponding eligible sub-sample simulations are presented in figures 13 through 16.

Figure 11 for low-income females suggests that receiving Food Stamp benefits decreases the survivor rate by over 12 percentage points by year-2000. The effect of receiving $2,400 annually in Food Stamp benefits is even larger, decreasing the probability of not yet being obese by year-2000 by about 20 percentage points in figure 12. The magnitudes of these effects are somewhat smaller for corresponding males in figures 9 and 10, though low-income male point estimates have been noted to be statistically insignificant. These effects are about the same size for the eligible female sub-sample, where, for example, receiving Food Stamp benefits decreases the probability of not yet being obese roughly 20 percentage points by year-2000.

Lagged Food Stamp Benefits Results

Food Stamp benefits received today would not instantaneously be expected to substantially change weight; instead, because today’s weight is much the same as yesterday’s weight, Food Stamp receipt would be expected to affect weight somewhat slowly, perhaps being measurable only over a significant amount of time. Thus, I next examine the lagged effects of Food Stamp benefits on BMI and obesity (the effects of Food Stamp benefits from prior periods). Examining the effects of Food Stamp benefits from prior periods on current weight may also address concerns about reverse causality: sequentially, weight today does not affect Food Stamp receipt from prior periods.

To examine the effects of prior periods’ Food Stamp receipt, I estimate three lagged specifications. In the first, I include contemporaneous Food Stamp benefits and one-year lagged Food Stamp benefits. In the second, I include contemporaneous Food Stamp benefits and one-, two-, and three-year lagged Food Stamp benefits. The third specification adds lagged Food Stamp benefits from the previous fourth, fifth, sixth, and seventh years.[4] I do this separately for both the dichotomous Food Stamp receipt covariate specification and the continuous amount of Food Stamps received covariate specification for both BMI and the probability of being obese. This results in twelve models for each sample. Results for the low-income sub-sample are presented in table 15 for males and in table 16 for females and for the eligible sub-sample in tables 17 for males and in table 18 for females. All of the tables contain the predicted value of BMI and the predicted probability of being obese for no Food Stamp benefits in the considered periods and for receiving Food Stamp benefits (or receiving $2,400 in benefits) in each period considered.

For low-income males, Food Stamp benefits tend to have statistically insignificant effects however specified (see table 15). However, when examining low-income females (table 16), results show that dichotomously-measured one-year lagged Food Stamp receipt (models 1 and 4) significantly affects BMI and obesity, but contemporaneous Food Stamp receipt does not. This remains true when additional lags are included, suggesting one-year lagged Food Stamp receipt affects weight, not contemporaneous receipt. However, the results are less conclusive when Food Stamp benefits are measured continuously. Significant effects for other lags occasionally appear but not systematically.

[4] I do not include additional lags (from earlier years) because they are unavailable for a portion of the observations. For example, while Food Stamp benefits from 1979 are collected seven years prior to first weight observation used in the analysis from 1985, benefits in 1978 are not, resulting in missing values for eight-year lags for weight observations from 1985.

Much the same is true for the eligible sub-samples. For example, Food Stamps generally have statistically insignificant effects on males, and one-year lagged Food Stamp receipt significantly affects female BMI and obesity at the 5 % level, with contemporaneous Food Stamp benefits having insignificant effects. However, when measured continuously as the amount of benefits received, neither contemporaneous nor one-year lagged effects are significant. Other lagged Food Stamp covariates sporadically have significant effects, but it is difficult to discern a consistent pattern.

In sum, results are mixed but provide some evidence that one-year lagged Food Stamp benefits significantly affect BMI and obesity for females when measured dichotomously. Simulated effects of receiving Food Stamp benefits with lags are somewhat larger. For example, switching from no Food Stamp receipt to receiving Food Stamp benefits for low-income females with one-year lags (model 1, table 16) increases BMI from 26.1 to 26.9, which is about a 0.8 point increase. This in the initial OLS specification without lags results in a 0.7-point increase (from 26.0 to 26.7 in model 1, table 5). This change for eligible females is 1.2 BMI index points (model 1, table 18) with one-year lags and 0.9 BMI index points without (model 1, table 6). Further, there is some evidence that such simulated effects continue to grow larger as additional lags are added. For eligible females, adding two- and three-year lags increases the simulated effect of receiving Food Stamps to a 1.5-point increase in BMI (model 2, table 18), and adding four additional lags (model 3, table 18) results in a 2-point increase in BMI.

In a related set of models, I estimate the effects of patterns of FSP participation on BMI and obesity. In particular, I divide those who have received Food Stamps at some point over the 24 months preceding the interview date into four mutually exclusive and exhaustive groups (the reference category is not receiving Food Stamps over the last two years). Those who received benefits during only one spell were classified as receiving benefits either short-term (for less than 9 months), medium-term (between 9 and 23 months), or long-term (24 months). Those who received benefits during multiple spells were assigned to a separate category. This classification was based on reports suggesting recipients could be accurately classified in one of these four ways (Murphy and Harrell, 1992). Of the Food Stamp recipients in my sample, about 31 % receive benefits short-term, 19 % medium-term, and 34 % for a long-term, with 16 % experiencing multiple spells.

Presented in table 19 for the low-income sub-sample, results indicate long-term Food Stamp receipt significantly increases low-income male obesity and low-income female BMI and obesity. For example, long-term low-income female recipients are predicted to be almost 10 percentage points more likely to be obese than their non-recipient counterparts. Further, they are predicted to be over 5 percentage points more likely to be obese than their short-term and medium-term recipient counterparts, and short-term and medium-term Food Stamp receipt do not have statistically significant effects on BMI and obesity.

Long-term Food Stamp receipt significantly increases BMI and obesity in table 20 for both eligible males and eligible females. For example, long-term Food Stamp receipt again increases female obesity by about 10 percentage points; furthermore, long-term receipt increases eligible male obesity by about 15 percentage points. There is also some evidence that multiple spells of Food Stamp receipt increase BMI and obesity for eligible females. However, short-term and medium-term Food Stamp receipt again do not appear to increase BMI or obesity. This suggests that extensive use of Food Stamps increases BMI and obesity, but receiving assistance from the FSP for more limited periods does not have this consequence.

Results are largely the same in alternative specifications that examine, for example, the preceding 48 months (instead of the preceding 24 months) and that separately categorize multiple spell recipients by duration (short-term, multiple spells; medium-term, multiple spells; and long-term, multiple spells). However, by definition, none are in the long-term, multiple spell category because all long-term recipients experience (by construction) one long spell, suggesting Murphy and Harrell's (1992) categories are sufficiently exhaustive.

VI. Conclusions

Medical researchers generally agree that obesity results from sustained caloric intake sufficiently in excess of caloric expenditures from physical activity. Because food and activity choices are subject to time and budget constraints, economic factors that affect these constraints potentially influence obesity as well. This study examines one such factor, the FSP, which is hypothesized potentially to increase obesity by effectively supplying food to eligible recipients at no (or reduced) cost, consequently increasing caloric intake, particularly for those in low-income households. Indeed, research typically suggests food expenditures increase between \$0.17 and \$0.47 per dollar of Food Stamp benefits (Fraker, 1990), and that this increase is larger than that generated by an equivalent amount of cash, even for households that receive less in Food Stamp benefits than they spend on food. Some recent evidence even suggests Food Stamp recipients consume significantly more sugar and meat than eligible non-recipients (Wilde et al., 1999).

Descriptive statistics from the 1979 NLSY cohort show that FSP participation and obesity are often correlated for females. For example, 27.8 % of low-income females on Food Stamps are obese compared to 19.0 % of low-income female non-recipients. Similarly, among females approximated to be eligible for benefits, those receiving Food Stamps are more likely to be obese: 28.3 % versus 17.7 %. This association is much weaker for males. OLS models controlling for a spate of observable characteristics essentially enable us to compare individuals who are alike in all observable ways (the same gender, race/ethnicity, education, income, etc.) except Food Stamp receipt. In these models, female Food Stamp recipients are significantly more likely to be obese (and to have higher BMI) than female non-recipients. For example, providing a low-income female non-recipient with Food Stamp benefits is predicted to increase the probability of being obese between roughly 2 and 5 percentage points (and to increase BMI by a majority of an index point). However, the effects of Food Stamps on low-income males are typically statistically insignificant. These results are largely the same for the sample of respondents approximated to be eligible for benefits.

Of course, OLS estimates could be biased by unobserved characteristics correlated with both FSP participation and obesity (and BMI). However, alternative specifications used to control for these sources of bias fail to reject the null hypothesis that OLS results are not biased. Where instruments are deemed valid, the evidence suggests the OLS and IV estimates are not statistically different from one another. Fixed effects models also support conclusions with OLS results, with many instances of significant positive effects of Food Stamp benefits on BMI and the probability of being obese, specifically for females.

The dynamic models also show positive effects of Food Stamp benefits for females. Such benefits significantly increase the typical change in BMI between surveys and significantly increase the hazard of becoming obese (conditional on not yet being obese). Further, lagged Food Stamp benefits (from previous years) often significantly increase BMI and obesity. Again, these conclusions tend to be true primarily for females, with insignificant effects on males. These models also show that long-term Food Stamp receipt increases BMI and obesity, even in some instances for males, but receiving assistance from the FSP for a more limited period does not have this side-effect.

In some cases, dynamic effects are larger than those found in models identifying contemporaneous effects. For example, receiving Food Stamps continually during the two years preceding the interview date increases obesity by at least 10 percentage points. Over a 15-year period, the hazard models suggest Food Stamp benefits significantly decrease the probability of not yet being obese between 10 and 20 percentage points. Similarly, for eligible females, positive effects of Food Stamps become successively larger with the inclusion of additional lagged Food Stamp covariate terms.

The size of my contemporaneously-measured effect of Food Stamp receipt on obesity (for example, a 4 percentage-point increase would change a 20 % prevalence of obesity by 20 %) is larger than that found by Gibson (2003) and Meyerhoefer and Pylypchuk (2006), who predict that Food Stamp receipt increases the prevalence of obesity by 9.1 % and 6.7 %, respectively, but smaller than that found by Chen et al. (2005), who predict a 40 % increase. However, my dynamic models also reveal that Food Stamp receipt potentially has larger effects. For example, receiving Food Stamps long-term increases the probability that females are obese by 10 percentage points, which is a 50 % change in obesity. These dynamic models also show that *(i)* short-term (and medium-term) Food Stamp receipt does not significantly increase obesity and *(ii)* long-term Food Stamp receipt significantly increases obesity for males. Gibson, Chen et al., and Meyerhoefer and Pylypchuk’s contemporaneously-measured effects were statistically insignificant for males.

These results can be used to approximate the amount to which Food Stamp benefits have contributed to the increase in obesity. During the 1976-1980 period covered by NHANES

II, the prevalence of obesity was 15.0 %, with roughly 20.9 million obese American adults aged 20 through 74 (Flegal et al., 1998, 2002). In the 2003-2004 NHANES surveys examined by Ogden et al. (2006), the prevalence of obesity was 32.2 %, with roughly 62.1 million obese American adults. Thus, as the prevalence of obesity doubled between these periods, the number of obese American adults increased by 41.2 million. However, between 1978 and 2003, the number of Food Stamp recipients increased from just 16.0 million to 21.3 million, which is an increase of 5.3 million (USDA, 2006a). Using reputedly conservative OLS estimates, assume Food Stamps increase the probability of being obese by 4 percentage points. This suggests that 212,000 additional Americans became obese due to Food Stamps (4 % of 5.3 million = 212,000) between these periods. This would account for half of one % (0.5 %) of the 41.2 million increase in obese American adults (212,000/41.2 million = 0.005). Had this approximated contribution to obesity by the FSP not been made, the prevalence of obesity would be 32.1 % rather than 32.2 % (after subtracting 212,000 from 62.1 million obese American adults). Thus, while the effects of Food Stamps on obesity appear statistically significant at the individual-recipient level, the FSP has probably had virtually an immeasurably small impact on the growing prevalence of obesity.

Of course, there are reasons to believe that the estimated contribution of the FSP to the increasing prevalence of obesity is an underestimate: dynamic models indicate larger positive effects once cumulative effects of Food Stamps (or effects of Food Stamp receipt from past periods) are included in the analysis. However, this is likely to have a small impact on the prevalence of obesity because only a minority of recipients receive benefits long-term (for at least two years). Further, though the increase in Food Stamp receipt has been 5.3 million, more than that have moved through the program during which time they were evidently more susceptible to becoming obese. For example, Rank and Hirschl (2005) project that about half of all Americans will receive Food Stamps at some point during their lifetimes. However, this is likely to have a small impact on the prevalence of obesity because results show that receiving benefits short-term (and medium-term) does not have an effect on obesity.

Regardless, even in the absurd case where we assume Food Stamps cause all recipients to become obese, the FSP would play only a minor role in the increasing prevalence of obesity. For example, assume that all the additional 5.3 million Food Stamp recipients (between 1976-1980 and 2003-2004) became obese (and were not obese to begin with). This would indicate only 12.8 % of the increase in the number of obese American adults is due to Food Stamps (5.3 million/41.2 million = 0.128). Were this assumed contribution to obesity by the FSP not made, then the prevalence of obesity would be 29.5 % rather than 32.2 % (after subtracting 5.3 million obese American adults due to the FSP from 62.1 million obese American adults). Even in this admittedly-outrageous example, the contribution of the FSP to obesity would be minor.

Regardless, since the FSP appears inadvertently to increase obesity, policymakers should seek ways to provide food assistance without exacerbating obesity. One approach might be to redouble efforts to educate newly-certified Food Stamp recipients about healthy and nutritious eating habits and weight management (or weight reduction). Such action might change the FSP from being a contributor to obesity to a benefactor reducing this prevalence.

Many consider the increasing incidence of obesity to be reaching epic proportions. Since medically recommended diets and exercise appear to be doing little to abate the ever-increasing prevalence of obesity, identifying economic factors that potentially contribute to this epidemic has become more important. Ultimately, successfully identifying this and/or other such factors enables public officials to better direct policy designed to control the incidence of obesity, particularly among those with low incomes where obesity is more prevalent.

VII. References

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Table 1: Descriptive Statistics: The Low-Income Sub-Sample

	Low-Income Males				Low-Income Females			
Dependant Variables	Full Sample		Recipients	Non-recipients	Full Sample		Recipients	Non-recipients
Body Mass Index	26.620	(0.160)	26.596	26.621	25.597	(0.175)	26.852	25.380
Prevalence of Obesity	0.201	(0.012)	0.213	0.201	0.203	(0.011)	0.278	0.190
Food Stamp Variables								
Received Food Stamps	0.050	(0.004)	-	-	0.147	(0.011)	-	-
Amount of Food Stamps[a]	2.090	(0.176)	-	-	2.738	(0.085)	-	-
Demographic Characteristics								
Black (=1 if black)	0.129	(0.017)	0.220	0.124	0.143	(0.019)	0.388	0.101
Hispanic (=1 if Hispanic)	0.062	(0.010)	0.100	0.060	0.056	(0.009)	0.087	0.050
Age	30.536	(0.094)	29.746	30.578	30.724	(0.094)	30.267	30.803
Education	11.602	(0.038)	10.850	11.641	11.617	(0.033)	11.085	11.708
Marital Status (=1 if married)	0.577	(0.014)	0.552	0.579	0.568	(0.015)	0.254	0.622
Children	1.012	(0.032)	1.444	0.989	1.461	(0.037)	2.113	1.348
Family Size	3.296	(0.035)	3.801	3.270	3.499	(0.038)	3.916	3.427
Household Income ($1,000s)[b]	51.099	(1.226)	26.095	52.418	45.888	(1.069)	22.647	49.902
Urban (=1 if urban residence)	0.705	(0.030)	0.660	0.707	0.694	(0.032)	0.691	0.694

Sample means with standard errors in parentheses. There are 11,748 low-income males and 10,558 low-income females. [a] zero values are excluded. [b] Annual household income in year-2005 dollars.

Table 2: Descriptive Statistics: The Eligible Sub-Sample

	Eligible Males				Eligible Females			
Dependant Variables	Full	Sample	Recipients	Non-recipients	Full	Sample	Recipients	Non-recipients
Body Mass Index	25.688	(0.179)	26.432	25.546	25.771	(0.233)	27.074	24.944
Prevalence of Obesity	0.155	(0.012)	0.218	0.144	0.218	(0.012)	0.283	0.177
Food Stamp Variables								
Received Food Stamps	0.159	(0.012)	-	-	0.388	(0.017)	-	-
Amount of Food Stamps[a]	2.223	(0.202)	-	-	2.904	(0.085)	-	-
Demographic Characteristics								
Black	0.247	(0.030)	0.248	0.247	0.291	(0.031)	0.424	0.207
Hispanic	0.072	(0.012)	0.082	0.070	0.071	(0.010)	0.083	0.064
Age	28.482	(0.169)	29.997	28.194	29.302	(0.120)	30.201	28.732
Education	12.154	(0.091)	11.260	12.324	12.204	(0.079)	11.422	12.699
Marital Status	0.267	(0.016)	0.492	0.224	0.244	(0.014)	0.188	0.280
Children	0.567	(0.038)	1.283	0.431	1.431	(0.043)	2.101	1.006
Family Size	3.466	(0.051)	3.706	3.420	3.699	(0.050)	3.877	3.586
Household Income ($1,000s)[b]	37.084	(1.295)	24.479	39.474	33.321	(0.995)	23.020	39.856
Urban	0.775	(0.026)	0.708	0.787	0.752	(0.026)	0.726	0.768

Sample means with standard errors in parentheses. There are 3,681 eligible males and 4,799 eligible females. [a] zero values are excluded. [b] Annual household income in year-2005 dollars.

Table 3: Descriptive Statistics for the Low-Income Sub-Sample

	Low-Income Males		Low-Income Females	
Economic Conditions Variables				
Local Unemployment Rate	0.067	(0.002)	0.068	(0.002)
Local Per Capita Income	22.668	(0.312)	22.630	(0.324)
Portion of Local Labor Force Female	0.409	(0.003)	0.411	(0.003)
Local Population High-School Educated	0.670	(0.009)	0.667	(0.009)
Local Population College-Educated	0.152	(0.004)	0.153	(0.004)
Local Population Employed	0.433	(0.004)	0.433	(0.004)
Local Labor Force in Manufacturing	0.212	(0.009)	0.210	(0.009)
Local Labor Force in Wholesale/Retail Trade	0.185	(0.002)	0.185	(0.002)
Political Variables				
Representative's ADA Ranking	0.414	(0.010)	0.418	(0.011)
Senator's ADA Ranking	0.519	(0.019)	0.511	(0.020)
Democrat Governor	0.478	(0.021)	0.470	(0.020)
Portion of State House Democrat	0.576	(0.009)	0.589	(0.009)
Portion of State Senate Democrat	0.565	(0.012)	0.584	(0.013)
Welfare Characteristics Variables				
Post-TANF (=1 if TANF in force)	0.178	(0.002)	0.181	(0.003)
Pre-Welfare Reform Waiver #1	0.029	(0.004)	0.029	(0.004)
Pre-Welfare Reform Waiver #2	0.048	(0.005)	0.042	(0.005)
Pre-Welfare Reform Waiver #3	0.062	(0.005)	0.057	(0.005)
Pre-Welfare Reform Waiver #4	0.073	(0.009)	0.067	(0.008)
Pre-Welfare Reform Waiver #5	0.046	(0.006)	0.046	(0.007)
Pre-Welfare Reform Waiver #6	0.013	(0.002)	0.016	(0.003)
State Maximum Benefits	749.245	(23.436)	742.919	(25.414)
No Time Limit[a]	0.075	(0.029)	0.050	(0.020)
Time Limit[a,b]	55.981	(0.792)	55.454	(1.053)
Family Caps[a]	0.500	(0.044)	0.510	(0.044)
Child Age[a]	10.068	(0.700)	10.629	(0.848)
Severe Sanctions[a]	0.707	(0.038)	0.677	(0.038)
Earned Income Disregards[a]	104.224	(8.952)	101.086	(10.252)
Earned Income Disregards[a]	51.056	(2.482)	52.516	(2.386)
Asset Limit[a,c]	2337.411	(95.034)	2356.376	(99.054)
No Asset Limit[a]	0.076	(0.028)	0.078	(0.030)
TANF Vehicle Exemption[a,d]	6607.612	(285.549)	6384.336	(281.977)
Vehicles Included in TANF Asset Test[a]	0.552	(0.042)	0.549	(0.042)
Household Eligibility Characteristics				

Vehicle Value	7.027	(0.268)	6.195	(0.258)
Senior Present	0.087	(0.007)	0.056	(0.006)
State Eligibility Characteristics				
FSP Vehicle Asset Limit[a]	0.069	(0.033)	0.068	(0.027)
EBT[a]	0.484	(0.034)	0.510	(0.035)
Non-Parental Adults Caregivers[a,e]	0.669	(0.038)	0.645	(0.041)
Simplified Periodic Reporting[a,f]	0.734	(0.041)	0.761	(0.041)
Categorical Eligibility[a]	0.783	(0.032)	0.781	(0.031)
Severe Sanctions[a,g]	0.494	(0.043)	0.450	(0.043)
Outreach Plan[a]	0.489	(0.045)	0.447	(0.045)

Sample means with standard errors in parentheses. There are 11,748 low-income males and 10,558 low-income females. [a] Only post-welfare reform observations are used for the descriptive statistic. [b] Only observations in states with time limits are used in the descriptive statistics. [c] Only observations in states with asset limits are used in the descriptive statistics. [d] Only observations in states without vehicle exclusions are used in the descriptive statistics. [e] The excluded category is only parents are allowed to be considered the caregiver. [f] The excluded category is incident reporting. [g] Sanctions for E&T offenses are either extended beyond that normally required by the Food Stamp Program, permanent (instead of temporary), or applied to the entire household (instead of only the offending member).

Table 4: Descriptive Statistics for the Eligible Sub-Sample

	Eligible Males		**Eligible Females**	
Economic Conditions Variables				
Local Unemployment Rate	0.072	(0.002)	0.071	(0.002)
Local Per Capita Income	22.739	(0.306)	22.544	(0.290)
Portion of Local Labor Force Female	0.410	(0.003)	0.412	(0.003)
Local Population High-School Educated	0.666	(0.007)	0.662	(0.007)
Local Population College-Educated	0.158	(0.004)	0.156	(0.003)
Local Population Employed	0.428	(0.004)	0.425	(0.004)
Local Labor Force in Manufacturing	0.201	(0.007)	0.197	(0.007)
Local Labor Force in Wholesale/Retail Trade	0.184	(0.002)	0.184	(0.002)
Political Variables				
Representative's ADA Ranking	0.404	(0.010)	0.411	(0.011)
Senator's ADA Ranking	0.527	(0.020)	0.519	(0.020)
Democrat Governor	0.533	(0.020)	0.502	(0.021)
Portion of State House Democrat	0.589	(0.009)	0.602	(0.009)
Portion of State Senate Democrat	0.576	(0.012)	0.593	(0.012)
Welfare Characteristics Variables				
Post-TANF (=1 if TANF in force)	0.106	(0.007)	0.123	(0.006)
Pre-Welfare Reform Waiver #1	0.014	(0.003)	0.019	(0.003)
Pre-Welfare Reform Waiver #2	0.030	(0.005)	0.030	(0.004)
Pre-Welfare Reform Waiver #3	0.035	(0.005)	0.040	(0.004)
Pre-Welfare Reform Waiver #4	0.061	(0.009)	0.066	(0.009)
Pre-Welfare Reform Waiver #5	0.027	(0.005)	0.028	(0.004)
Pre-Welfare Reform Waiver #6	0.010	(0.003)	0.011	(0.002)
State Maximum Benefits	750.899	(21.019)	740.061	(25.093)
No Time Limit[a]	0.070	(0.029)	0.068	(0.028)
Time Limit[a,b]	56.933	(0.669)	55.771	(0.769)
Family Caps[a]	0.464	(0.052)	0.471	(0.045)
Child Age[a]	11.384	(1.317)	10.834	(0.887)
Severe Sanctions[a]	0.627	(0.051)	0.631	(0.043)
Earned Income Disregards[a]	106.345	(9.193)	127.742	(17.088)
Earned Income Disregards[a]	49.891	(2.587)	49.770	(2.165)
Asset Limit[a,c]	2225.738	(82.006)	2357.200	(97.718)
No Asset Limit[a]	0.032	(0.017)	0.076	(0.024)
TANF Vehicle Exemption[a,d]	6057.164	(250.667)	6144.415	(242.010)
Vehicles Included in TANF Asset Test[a]	0.582	(0.048)	0.554	(0.045)
Household Eligibility Characteristics				

Vehicle Value	2.852	(0.189)	2.445	(0.153)
Senior Present	0.223	(0.016)	0.116	(0.009)
State Eligibility Characteristics				
FSP Vehicle Asset Limit[a]	0.000	(0.000)	0.073	(0.041)
EBT[a]	0.526	(0.048)	0.482	(0.038)
Non-Parental Adults Caregivers[a,e]	0.614	(0.050)	0.624	(0.048)
Simplified Periodic Reporting[a,f]	0.784	(0.043)	0.785	(0.038)
Categorical Eligibility[a]	0.732	(0.046)	0.764	(0.038)
Severe Sanctions[a,g]	0.524	(0.052)	0.525	(0.045)
Outreach Plan[a]	0.495	(0.053)	0.472	(0.044)

Sample means with standard errors in parentheses. There are 3,681 eligible males and 4,799 eligible females. [a] Only post-welfare reform observations are used for the descriptive statistic. [b] Only observations in states with time limits are used in the descriptive statistics. [c] Only observations in states with asset limits are used in the descriptive statistics. [d] Only observations in states without vehicle exclusions are used in the descriptive statistics. [e] The excluded category is only parents are allowed to be considered the caregiver. [f] The excluded category is incident reporting. [g] Sanctions for E&T offenses are either extended beyond that normally required by the Food Stamp Program, permanent (instead of temporary), or applied to the entire household (instead of only the offending member).

Table 5: The Effects of Food Stamp Benefits on BMI and Obesity: Low-Income OLS Results

	Body Mass Index			Probability of Being Obese		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Low-Income Males						
Received Food Stamps	0.073	-	0.010	0.098	-	0.070
	(0.420)	-	(0.406)	(0.201)	-	(0.196)
Amount of Food Stamps	-	0.014	0.013	-	0.024	0.014
	-	(0.082)	(0.062)	-	(0.041)	(0.036)
Predicted Values						
With No Food Stamps	26.737	26.737	26.737	0.209	0.209	0.209
With Food Stamps (=2,400)	26.774	26.772	26.779	0.224	0.218	0.225
Low-Income Females						
Received Food Stamps	0.617*	-	0.394	0.304**	-	0.264*
	(0.345)	-	(0.359)	(0.126)	-	(0.137)
Amount of Food Stamps	-	0.153*	0.090	-	0.056*	0.015
	-	(0.080)	(0.075)	-	(0.032)	(0.026)
Predicted Values						
With No Food Stamps	26.098	26.135	26.089	0.221	0.226	0.221
With Food Stamps (=2,400)	26.716	26.502	26.700	0.272	0.249	0.272

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 11,748 low-income males and 10,558 low-income females. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 6: The Effects of Food Stamp Benefits on BMI and Obesity: Eligible OLS Results

	Body Mass Index			Probability of Being Obese		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Eligible Males						
Received Food Stamps	0.196	-	0.292	0.289	-	0.307
	(0.395)	-	(0.411)	(0.200)	-	(0.213)
Amount of Food Stamps	-	-0.013	-0.046	-	0.031	-0.009
	-	(0.061)	(0.057)	-	(0.033)	(0.046)
Predicted Values						
With No Food Stamps	25.804	25.842	25.805	0.154	0.159	0.154
With Food Stamps (=2,400)	26.000	25.809	25.986	0.190	0.168	0.189
Eligible Females						
Received Food Stamps	0.906**	-	0.878**	0.381***	-	0.389***
	(0.370)	-	(0.407)	(0.129)	-	(0.139)
Amount of Food Stamps	-	0.121*	0.011	-	0.040	-0.003
	-	(0.071)	(0.071)	-	(0.030)	(0.024)
Predicted Values						
With No Food Stamps	26.078	26.327	26.075	0.220	0.241	0.220
With Food Stamps (=2,400)	26.984	26.618	26.981	0.283	0.257	0.284

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 3,681 eligible males and 4,799 eligible females. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 7: The Effects of Predicted Food Stamp Benefits on BMI and Obesity: Low-Income OLS Results

	Body Mass Index		**Probability of Being Obese**	
Low-Income Males	Model 1	Model 2	Model 3	Model 4
Received Food Stamps	0.810	-	0.862	-
	(1.498)	-	(0.582)	-
Amount of Food Stamps	-	-1.916	-	-0.162
	-	(1.605)	-	(0.889)
Predicted Values				
With No Food Stamps	26.716	27.052	0.204	0.219
With Food Stamps (=2,400)	27.526	22.452	0.361	0.163
F-Statistic for Instruments	52.16***	21.49***	52.16***	21.49***
F-Statistic for Restrictions	1.360	1.360	0.320	0.320
F-Statistic for Hausman Test	0.130	1.570	1.610	0.040
Low-Income Females				
Received Food Stamps	1.149	-	0.209	-
	(0.995)	-	(0.354)	-
Amount of Food Stamps	-	3.224**	-	2.025**
	-	(1.371)	-	(0.827)
Predicted Values				
With No Food Stamps	26.002	24.164	0.225	0.136
With Food Stamps (=2,400)	27.151	31.586	0.260	0.818
F-Statistic for Instruments	75.55***	13.52***	75.55***	13.52***
F-Statistic for Restrictions	4.08**	4.08**	8.91**	8.91**
F-Statistic for Hausman Test	0.060	5.05**	0.260	5.68**

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 11,748 low-income males and 10,558 low-income females. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables. The instruments are household vehicle values and the present of a senior adult.

Table 8: The Effects of Predicted Food Stamp Benefits on BMI and Obesity: Eligible OLS Results

	Body Mass Index		Probability of Being Obese	
Eligible Males	Model 1	Model 2	Model 3	Model 4
Received Food Stamps	0.364	-	0.994	-
	(1.513)	-	(0.624)	-
Amount of Food Stamps	-	-0.720	-	0.513
	-	(0.938)	-	(0.582)
Predicted Values				
With No Food Stamps	25.819	26.150	0.142	0.144
With Food Stamps (=2,400)	26.183	24.422	0.287	0.335
F-Statistic for Instruments	29.78***	14.33***	29.78***	14.33***
F-Statistic for Restrictions	0.82	0.82	1.08	1.08
F-Statistic for Hausman Test	0.03	0.62	1.66	0.72
Eligible Females				
Received Food Stamps	1.600	-	0.425	-
	(1.252)	-	(0.453)	-
Amount of Food Stamps	-	2.444***	-	1.289***
	-	(0.899)	-	(0.482)
Predicted Values				
With No Food Stamps	25.837	23.063	0.223	0.096
With Food Stamps (=2,400)	27.438	28.928	0.295	0.502
F-Statistic for Instruments	53.73***	9.73***	53.73***	9.73***
F-Statistic for Restrictions	3.39**	3.39**	6.11**	6.11**
F-Statistic for Hausman Test	0.13	6.77**	0.01	6.77**

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 3,681 eligible males and 4,799 eligible females. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables. The instruments are household vehicle values and the present of a senior adult.

Table 9: The Effects of Predicted Food Stamp Benefits on BMI and Obesity: Low-Income OLS Results

	Body Mass Index		Probability of Being Obese	
Low-Income Males	Model 1	Model 2	Model 3	Model 4
Received Food Stamps	0.969	-	0.737	-
	(1.670)	-	(0.640)	-
Amount of Food Stamps	-	-0.235	-	-0.309
	-	(1.582)	-	(0.744)
Predicted Values				
With No Food Stamps	26.708	26.814	0.206	0.223
With Food Stamps (=2,400)	27.677	26.248	0.337	0.125
F-Statistic for Instruments	16.97***	1.83*	16.97***	1.83*
F-Statistic for Restrictions	0.60	0.60	6.36	6.36
F-Statistic for Hausman Test	0.19	0.04	0.86	0.20
Low-Income Females				
Received Food Stamps	0.196	-	-0.511	-
	(1.221)	-	(0.449)	-
Amount of Food Stamps	-	-0.575	-	0.313
	-	(1.166)	-	(0.463)
Predicted Values				
With No Food Stamps	26.208	26.624	0.254	0.200
With Food Stamps (=2,400)	26.404	25.243	0.177	0.331
F-Statistic for Instruments	5.68	1.94*	5.68	1.94*
F-Statistic for Restrictions	0.48	0.48	4.25	4.25
F-Statistic for Hausman Test	0.46	0.39	4.42**	0.31

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 11,748 low-income males and 10,558 low-income females. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables. The instruments are state eligibility characteristics.

Table 10: The Effects of Predicted Food Stamp Benefits on BMI and Obesity: Eligible OLS Results

Eligible Sample	**Body Mass Index**		**Probability of Being Obese**	
Eligible Males	Model 1	Model 2	Model 3	Model 4
Received Food Stamps	-0.412	-	0.313	-
	(1.901)	-	(0.885)	-
Amount of Food Stamps	-	-0.583	-	0.188
	-	(1.070)	-	(0.798)
Predicted Values				
With No Food Stamps	25.956	26.101	0.158	0.159
With Food Stamps (=2,400)	25.543	24.701	0.199	0.221
F-Statistic for Instruments	8.09	1.44	8.09	1.44
F-Statistic for Restrictions	0.22	0.22	3.68	3.68
F-Statistic for Hausman Test	0.07	0.08	0.01	0.05
Eligible Females				
Received Food Stamps	-0.344	-	-0.470	-
	(1.936)	-	(0.643)	-
Amount of Food Stamps	-	-0.181	-	0.208
	-	(1.185)	-	(0.352)
Predicted Values				
With No Food Stamps	26.752	26.862	0.301	0.206
With Food Stamps (=2,400)	26.408	26.427	0.222	0.288
F-Statistic for Instruments	11.86*	1.71	11.86*	1.71
F-Statistic for Restrictions	1.51	1.51	4.72	4.72
F-Statistic for Hausman Test	0.63	0.06	2.03	0.24

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 3,681 eligible males and 4,799 eligible females. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables. The instruments are state eligibility characteristics.

Table 11: The Effects of Food Stamp Benefits on BMI and Obesity: Fixed Effects Models with the Low-Income Sub-Sample

	Body Mass Index		**Probability of Being Obese**		**Probability of Being Obese**	
Model Specification	OLS	OLS	Logit	Logit	OLS	OLS
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Low-Income Males						
Received Food Stamps	0.037	-	-0.207	-	-0.008	-
	(0.091)	-	(0.255)	-	(0.011)	-
Amount of Food Stamps	-	0.081*	-	-0.049	-	-0.002
	-	(0.044)	-	(0.151)	-	(0.005)
Low-Income Females						
Received Food Stamps	0.221**	-	0.427**	-	0.027***	-
	(0.092)	-	(0.200)	-	(0.009)	-
Amount of Food Stamps	-	0.041	-	0.076	-	0.005
	-	(0.038)	-	(0.060)	-	(0.004)

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 11,748 low-income males (7,430 of which were dropped from the logit model due to all positive or all negative outcomes values) and 10,558 low-income females (6,757 of which were dropped from the logit model due to all positive or all negative outcomes values). The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 12: The Effects of Food Stamp Benefits on BMI and Obesity: Fixed Effects Models with the Eligible Sub-Sample

	Body Mass Index		Probability of Being Obese		Probability of Being Obese	
Model Specification	OLS	OLS	Logit	Logit	OLS	OLS
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Eligible Males						
Received Food Stamps	0.271**	-	-0.082	-	0.001	-
	(0.137)	-	(0.457)	-	(0.015)	-
Amount of Food Stamps	-	0.113*	-	0.079	-	0.001
	-	(0.058)	-	(0.197)	-	(0.006)
Eligible Females						
Received Food Stamps	0.335**	-	0.368	-	0.025*	-
	(0.134)	-	(0.261)	-	(0.013)	-
Amount of Food Stamps	-	0.008	-	0.030	-	0.003
	-	(0.048)	-	(0.071)	-	(0.004)

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 3,681 eligible males (1,940 of which were dropped from the logit model due to all positive or all negative outcomes values) and 4,799 eligible females (2,609 of which were dropped from the logit model due to all positive or all negative outcomes values). The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 13: The Effects of Food Stamp Benefits on the Change in BMI, Becoming Obese, and No Longer Being Obese: Change Models with the Low-Income Sub-Sample

	BMI Change		Becoming Obese		No Longer Obese	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Low-Income Males						
Received Food Stamps	0.173	-	0.049	-	-0.640*	-
	(0.115)	-	(0.266)	-	(0.389)	-
Amount of Food Stamps	-	0.053*	-	-0.036	-	-0.188
	-	(0.030)	-	(0.091)	-	(0.186)
Predicted Values						
With No Food Stamps	0.482	0.486	0.071	0.071	0.139	0.137
With Food Stamps (=2,400)	0.655	0.616	0.074	0.066	0.082	0.095
Low-Income Females						
Received Food Stamps	0.225**	-	0.072	-	0.159	-
	(0.109)	-	(0.184)	-	(0.257)	-
Amount of Food Stamps	-	0.042	-	0.006	-	0.007
	-	(0.030)	-	(0.050)	-	(0.067)
Predicted Values						
With No Food Stamps	0.567	0.589	0.079	0.080	0.121	0.125
With Food Stamps (=2,400)	0.792	0.691	0.084	0.081	0.138	0.127

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. To maintain a consistent time interval for measured changes, included observations are those with valid weight observations from the 1985 and 1987 surveys, the 1987 and 1989 surveys, 1990 and 1992, 1992 and 1994, 1994 and 1996, 1996 and 1998, 1998 and 2000, and 2000 and 2002. There are 8,489 low-income males (1,953 of whom are obese and 6,536 of whom are not) and 6,944 low-income females (1,785 of whom are obese and 5,159 of whom are not). The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 14: The Effects of Food Stamp Benefits on the Change in BMI, Becoming Obese, and No Longer Being Obese: Change Models with the Eligible Sub-Sample

	BMI Change		Becoming Obese		No Longer Obese	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Eligible Males						
Received Food Stamps	0.085	-	0.194	-	-2.49***	-
	(0.164)	-	(0.344)	-	(0.708)	-
Amount of Food Stamps	-	0.071*	-	-0.155	-	-0.766*
	-	(0.036)	-	(0.130)	-	(0.442)
Predicted Values						
With No Food Stamps	0.578	0.568	0.068	0.073	0.214	0.192
With Food Stamps (=2,400)	0.663	0.740	0.080	0.053	0.052	0.068
Eligible Females						
Received Food Stamps	0.021	-	-0.049	-	0.209	-
	(0.140)	-	(0.211)	-	(0.377)	-
Amount of Food Stamps	-	0.013	-	-0.044	-	0.001
	-	(0.037)	-	(0.062)	-	(0.080)
Predicted Values						
With No Food Stamps	0.813	0.805	0.094	0.097	0.110	0.121
With Food Stamps (=2,400)	0.835	0.838	0.090	0.089	0.127	0.121

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. To maintain a consistent time interval for measured changes, included observations are those with valid weight observations from the 1985 and 1987 surveys, the 1987 and 1989 surveys, 1990 and 1992, 1992 and 1994, 1994 and 1996, 1996 and 1998, 1998 and 2000, and 2000 and 2002. There are 2,446 eligible males (425 of whom are obese and 2,021 of whom are not) and 2,981 eligible females (826 of whom are obese and 2,155 of whom are not). The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 15: The Effects of Lagged Food Stamp Benefits on BMI and Obesity: OLS Results, Low-Income Male Sub-Sample

	Body Mass Index						Probability of Being Obese					
Low-Income Males	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Received Food Stamps	-0.180	(0.320)	-0.246	(0.295)	-0.252	(0.287)	0.030	(0.165)	-0.020	(0.155)	-0.033	(0.153)
1 Year Lag	0.391	(0.366)	0.210	(0.304)	0.204	(0.296)	0.119	(0.167)	-0.012	(0.151)	-0.021	(0.149)
2 Year Lag	-	-	0.113	(0.279)	0.099	(0.261)	-	-	0.096	(0.126)	0.085	(0.121)
3 Year Lag	-	-	0.416	(0.299)	0.466*	(0.266)	-	-	0.258*	(0.144)	0.249*	(0.137)
4 Year Lag	-	-	-	-	-0.210	(0.251)	-	-	-	-	-0.069	(0.116)
5 Year Lag	-	-	-	-	-0.055	(0.243)	-	-	-	-	0.075	(0.115)
6 Year Lag	-	-	-	-	0.086	(0.242)	-	-	-	-	0.026	(0.119)
7 Year Lag	-	-	-	-	0.352	(0.282)	-	-	-	-	0.139	(0.118)
Predicted Values												
With No Food Stamps	26.729		26.712		26.704		0.209		0.207		0.206	
With Food Stamps	26.940		27.203		27.394		0.232		0.259		0.281	
Amount of Food Stamps	0.016	(0.078)	0.007	(0.067)	0.013	(0.062)	0.024	(0.039)	0.019	(0.036)	0.017	(0.035)
1 Year Lag	-0.007	(0.040)	-0.011	(0.033)	-0.013	(0.032)	0.005	(0.020)	0.002	(0.018)	0.000	(0.019)
2 Year Lag	-	-	0.027	(0.050)	0.027	(0.049)	-	-	0.011	(0.017)	0.011	(0.017)
3 Year Lag	-	-	0.059	(0.128)	0.058	(0.107)	-	-	0.036	(0.054)	0.027	(0.048)
4 Year Lag	-	-	-	-	-.228***	(0.083)	-	-	-	-	-0.047	(0.053)
5 Year Lag	-	-	-	-	-0.030	(0.024)	-	-	-	-	0.000	(0.015)
6 Year Lag	-	-	-	-	0.350*	(0.184)	-	-	-	-	0.125*	(0.067)
7 Year Lag	-	-	-	-	0.096	(0.090)	-	-	-	-	0.036	(0.042)
Predicted Values												
With No Food Stamps	26.738		26.733		26.725		0.210		0.209		0.208	
Food Stamps =2,400	26.760		26.930		27.381		0.220		0.235		0.275	

Standard errors are in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. There are 11,748 observations in the male low-income sub-sample. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 16: The Effects of Lagged Food Stamp Benefits on BMI and Obesity: OLS Results, Low-Income Female Sub-Sample

	Body Mass Index						**Probability of Being Obese**					
Low-Income Females	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Received Food Stamps	0.161	(0.299)	0.075	(0.280)	0.065	(0.274)	0.084	(0.124)	0.059	(0.120)	0.061	(0.118)
1 Year Lag	0.659**	(0.265)	0.418*	(0.254)	0.418*	(0.253)	0.314**	(0.126)	0.286**	(0.125)	0.287**	(0.124)
2 Year Lag	-	-	0.276	(0.231)	0.266	(0.227)	-	-	-0.079	(0.109)	-0.077	(0.108)
3 Year Lag	-	-	0.249	(0.224)	0.240	(0.192)	-	-	0.197*	(0.105)	0.196*	(0.101)
4 Year Lag	-	-	-	-	-0.036	(0.200)	-	-	-	-	0.059	(0.095)
5 Year Lag	-	-	-	-	-0.066	(0.205)	-	-	-	-	-0.108	(0.097)
6 Year Lag	-	-	-	-	0.265	(0.209)	-	-	-	-	0.055	(0.099)
7 Year Lag	-	-	-	-	-0.091	(0.258)	-	-	-	-	-0.024	(0.100)
Predicted Values												
With No Food Stamps	26.056		26.009		26.000		0.218		0.215		0.216	
With Food Stamps	26.877		27.027		27.061		0.286		0.295		0.293	
Amount of Food Stamps	0.111	(0.069)	0.073	(0.059)	0.069	(0.058)	0.034	(0.028)	0.026	(0.025)	0.025	(0.024)
1 Year Lag	0.135	(0.100)	0.075	(0.086)	0.072	(0.083)	0.069	(0.048)	0.058	(0.045)	0.059	(0.044)
2 Year Lag	-	-	0.095	(0.086)	0.082	(0.083)	-	-	-0.011	(0.034)	-0.013	(0.036)
3 Year Lag	-	-	0.165**	(0.077)	0.148**	(0.065)	-	-	0.068**	(0.028)	0.067**	(0.026)
4 Year Lag	-	-	-	-	0.057	(0.062)	-	-	-	-	-0.005	(0.021)
5 Year Lag	-	-	-	-	-0.035	(0.043)	-	-	-	-	-0.016	(0.020)
6 Year Lag	-	-	-	-	0.012	(0.060)	-	-	-	-	0.007	(0.030)
7 Year Lag	-	-	-	-	0.049	(0.056)	-	-	-	-	0.035	(0.026)
Predicted Values												
With No Food Stamps	26.113		26.065		26.052		0.225		0.222		0.222	
Food Stamps =2,400	26.705		27.046		27.142		0.266		0.280		0.287	

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 10,558 observations in the female low-income sub-sample. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 17: The Effects of Lagged Food Stamp Benefits on BMI and Obesity: OLS Results, Eligible Male Sub-Sample

	Body Mass Index						Probability of Being Obese					
Eligible Males	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Received Food Stamps	0.191	(0.313)	0.141	(0.298)	0.170	(0.304)	0.274	(0.176)	0.210	(0.176)	0.204	(0.181)
1 Year Lag	0.009	(0.397)	-0.095	(0.374)	-0.108	(0.374)	0.024	(0.183)	-0.211	(0.185)	-0.214	(0.185)
2 Year Lag	-	-	-0.161	(0.372)	-0.120	(0.364)	-	-	0.309	(0.197)	0.317	(0.195)
3 Year Lag	-	-	0.653	(0.428)	0.830**	(0.416)	-	-	0.247	(0.216)	0.231	(0.224)
4 Year Lag	-	-	-	-	-0.542	(0.360)	-	-	-	-	-0.108	(0.177)
5 Year Lag	-	-	-	-	0.419	(0.364)	-	-	-	-	0.264	(0.164)
6 Year Lag	-	-	-	-	-0.048	(0.369)	-	-	-	-	-0.050	(0.164)
7 Year Lag	-	-	-	-	-0.383	(0.402)	-	-	-	-	-0.092	(0.186)
Predicted Values												
With No Food Stamps	25.804		25.766		25.791		0.154		0.149		0.149	
With Food Stamps	26.004		26.305		26.011		0.191		0.222		0.222	
Amount of Food Stamps	-0.010	(0.060)	-0.004	(0.053)	0.002	(0.051)	0.032	(0.032)	0.032	(0.031)	0.032	(0.031)
1 Year Lag	-0.027	(0.033)	-0.025	(0.030)	-0.024	(0.029)	0.001	(0.017)	0.000	(0.016)	0.000	(0.016)
2 Year Lag	-	-	0.006	(0.036)	0.004	(0.036)	-	-	0.008	(0.017)	0.008	(0.017)
3 Year Lag	-	-	-0.087	(0.153)	-0.016	(0.130)	-	-	-0.013	(0.072)	-0.010	(0.075)
4 Year Lag	-	-	-	-	-0.166	(0.145)	-	-	-	-	0.006	(0.074)
5 Year Lag	-	-	-	-	-0.036**	(0.015)	-	-	-	-	-0.013	(0.015)
6 Year Lag	-	-	-	-	0.032	(0.193)	-	-	-	-	0.011	(0.087)
7 Year Lag	-	-	-	-	0.046	(0.103)	-	-	-	-	-0.029	(0.060)
Predicted Values												
With No Food Stamps	25.847		25.857		25.863		0.159		0.159		0.160	
Food Stamps =2,400	25.757		25.592		25.484		0.169		0.167		0.161	

Standard errors are in parentheses. *p < 0.10, **p < 0.05, and ***p < 0.01. There are 3,681 observations in the male eligible sub-sample. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 18: The Effects of Lagged Food Stamp Benefits on BMI and Obesity: OLS Results, Eligible Female Sub-Sample

	Body Mass Index						Probability of Being Obese					
Eligible Females	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Received Food Stamps	0.261	(0.332)	0.186	(0.318)	0.144	(0.316)	0.172	(0.124)	0.158	(0.121)	0.161	(0.120)
1 Year Lag	1.012***	(0.334)	0.809**	(0.346)	0.807**	(0.346)	0.328**	(0.138)	0.333**	(0.151)	0.336**	(0.151)
2 Year Lag	-	-	-0.017	(0.337)	-0.093	(0.340)	-	-	-0.167	(0.133)	-0.181	(0.134)
3 Year Lag	-	-	0.611**	(0.304)	0.313	(0.290)	-	-	0.240**	(0.121)	0.195	(0.123)
4 Year Lag	-	-	-	-	0.035	(0.320)	-	-	-	-	0.000	(0.127)
5 Year Lag	-	-	-	-	0.313	(0.309)	-	-	-	-	0.189	(0.128)
6 Year Lag	-	-	-	-	0.498	(0.318)	-	-	-	-	-0.059	(0.128)
7 Year Lag	-	-	-	-	0.007	(0.389)	-	-	-	-	-0.060	(0.140)
Predicted Values												
With No Food Stamps	25.900		25.774		25.634		0.211		0.213		0.206	
With Food Stamps	27.173		27.363		27.658		0.294		0.301		0.302	
Amount of Food Stamps	0.098	(0.065)	0.059	(0.057)	0.054	(0.057)	0.030	(0.027)	0.022	(0.025)	0.021	(0.025)
1 Year Lag	0.096	(0.103)	0.025	(0.091)	0.010	(0.088)	0.045	(0.043)	0.037	(0.042)	0.034	(0.039)
2 Year Lag	-	-	0.104	(0.079)	0.065	(0.078)	-	-	-0.022	(0.039)	-0.033	(0.041)
3 Year Lag	-	-	0.264***	(0.082)	0.227***	(0.071)	-	-	0.091***	(0.033)	0.084***	(0.030)
4 Year Lag	-	-	-	-	0.059	(0.066)	-	-	-	-	0.001	(0.022)
5 Year Lag	-	-	-	-	0.045	(0.048)	-	-	-	-	0.010	(0.020)
6 Year Lag	-	-	-	-	0.067	(0.080)	-	-	-	-	0.018	(0.027)
7 Year Lag	-	-	-	-	0.061	(0.067)	-	-	-	-	0.027	(0.027)
Predicted Values												
With No Food Stamps	26.283		26.116		26.041		0.238		0.231		0.228	
Food Stamps =2,400	26.749		27.201		27.451		0.267		0.283		0.294	

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 4,799 observations in the female eligible sub-sample. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 19: The Effects of Lagged Food Stamp Benefits on BMI and Obesity: Low-Income OLS Results

	Low-Income Males		Low-Income Females	
	Body Mass Index	**Probability of Being Obese**	**Body Mass Index**	**Probability of Being Obese**
	Model 1	Model 2	Model 1	Model 2
Short-Term	-0.403	-0.144	0.317	0.183
	(0.342)	(0.098)	(0.314)	(0.148)
Medium-Term	0.222	0.097	0.064	0.202
	(0.548)	(0.260)	(0.417)	(0.177)
Long-Term	1.413	0.675**	1.502***	0.530***
	(1.022)	(0.291)	(0.513)	(0.165)
Multiple Spells	0.489	0.218	0.493	0.303
	(0.670)	(0.315)	(0.483)	(0.211)
Predicted Values				
With No Food Stamps	26.726	0.208	26.012	0.216
Food Stamps, Short-Term	26.323	0.187	26.328	0.246
Food Stamps, Medium-Term	26.930	0.222	26.090	0.251
Food Stamps, Long-Term	28.125	0.325	27.532	0.312
Food Stamps, Multiple Spells	27.222	0.244	26.698	0.283

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 11,713 low-income males and 10,512 low-income females. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Table 20: The Effects of Lagged Food Stamp Benefits on BMI and Obesity: Eligible OLS Results

	Eligible Males		Eligible Females	
	Body Mass Index	**Probability of Being Obese**	**Body Mass Index**	**Probability of Being Obese**
	Model 1	Model 2	Model 1	Model 2
Short-Term	-0.495	-0.160	0.455	0.073
	(0.368)	(0.246)	(0.566)	(0.194)
Medium-Term	0.149	0.254	0.714	0.320*
	(0.551)	(0.273)	(0.456)	(0.184)
Long-Term	1.599*	0.985***	1.796***	0.565***
	(0.894)	(0.284)	(0.528)	(0.169)
Multiple Spells	-0.535	-0.029	0.928*	0.568***
	(0.604)	(0.332)	(0.549)	(0.217)
Predicted Values				
With No Food Stamps	25.823	0.153	25.821	0.211
Food Stamps, Short-Term	25.329	0.135	26.276	0.222
Food Stamps, Medium-Term	25.927	0.182	26.572	0.263
Food Stamps, Long-Term	27.385	0.298	27.730	0.313
Food Stamps, Multiple Spells	25.320	0.157	27.346	0.345

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 3,651 eligible males and 4,758 eligible females. The models include individual characteristics variables, economic variables, political variables, state AFDC/TANF program characteristic variables, state dummy variables, and year dummy variables.

Figure 1

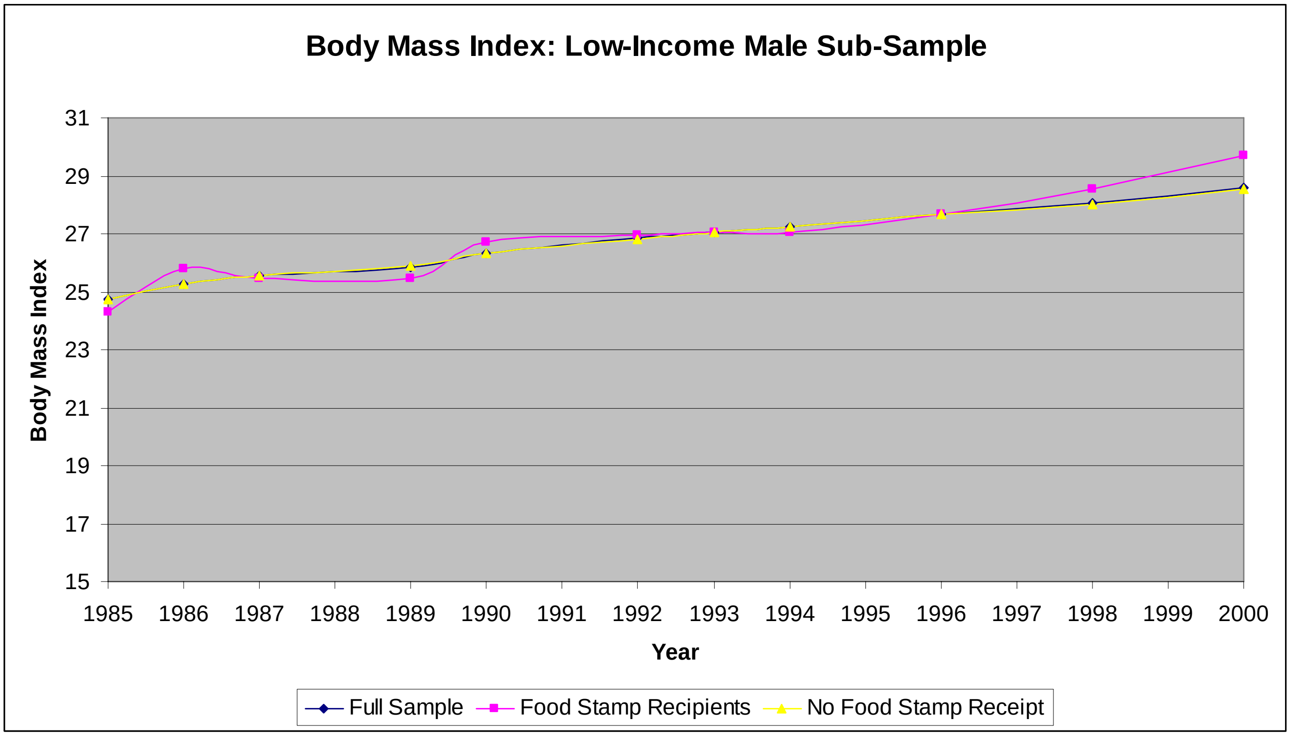


Figure 2

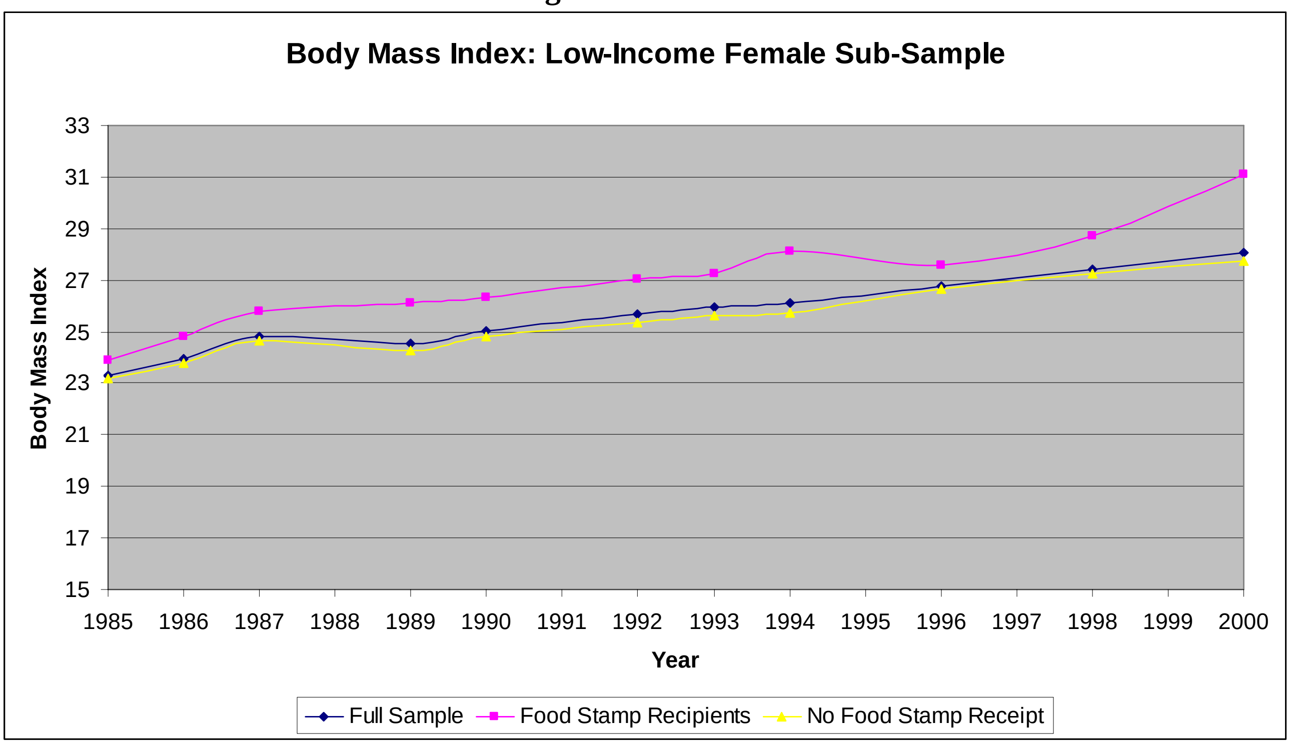
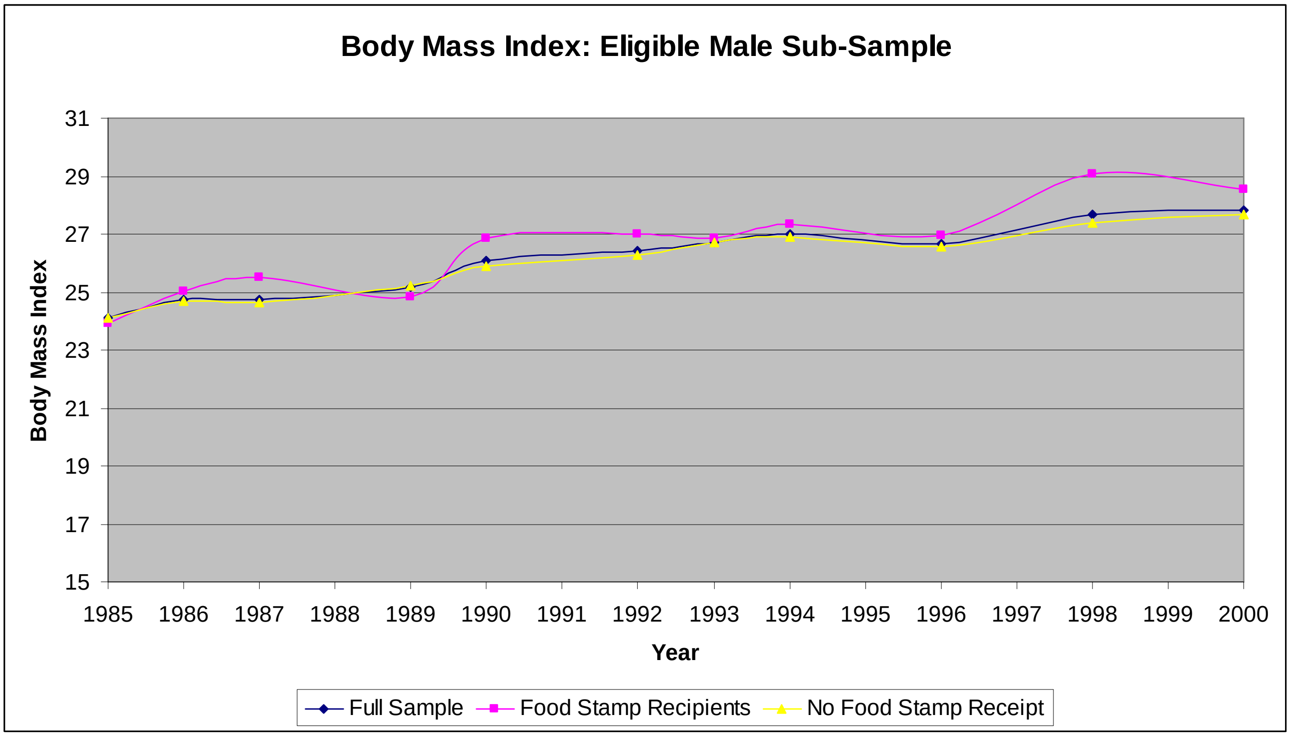


Figure 3



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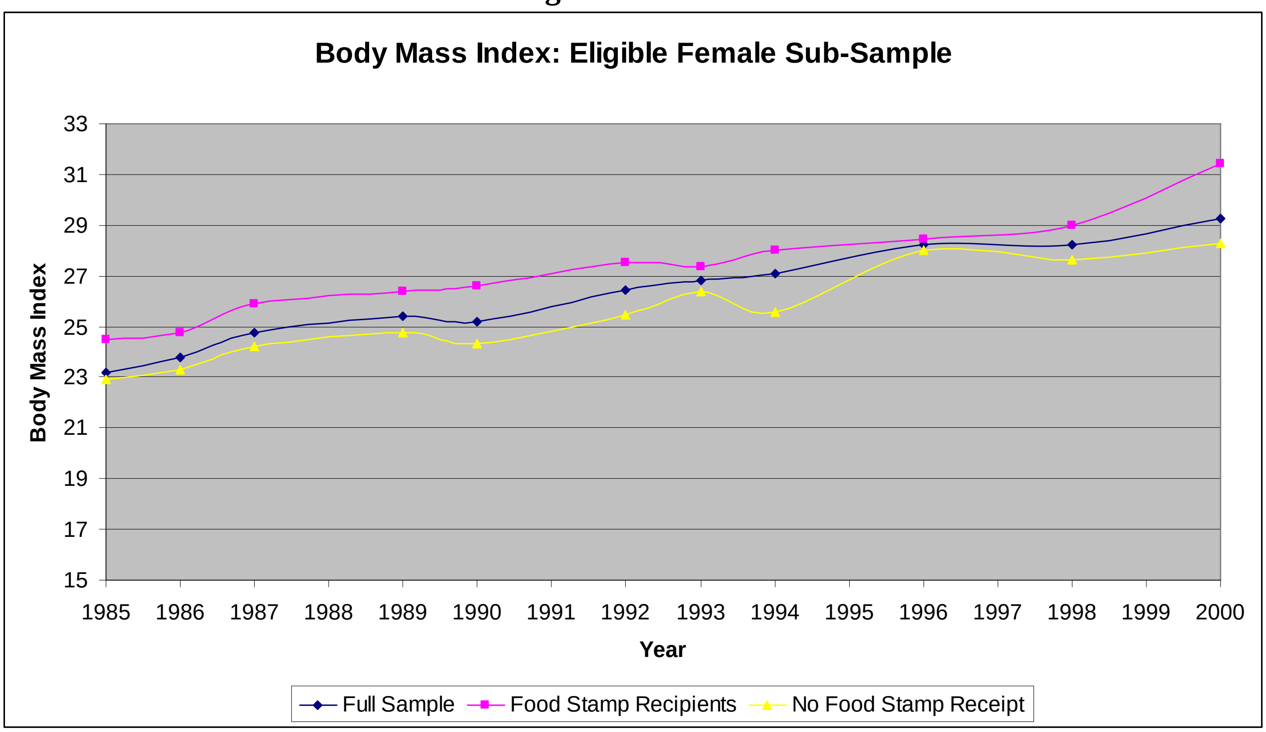
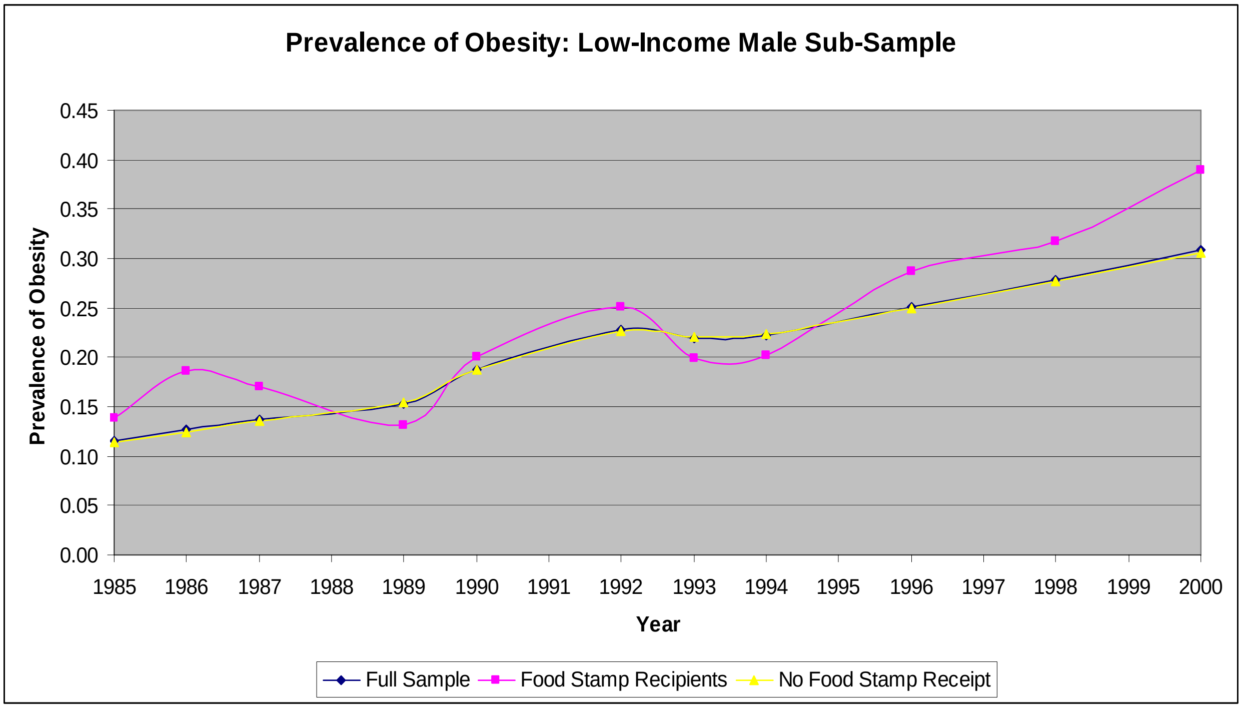


Figure 5



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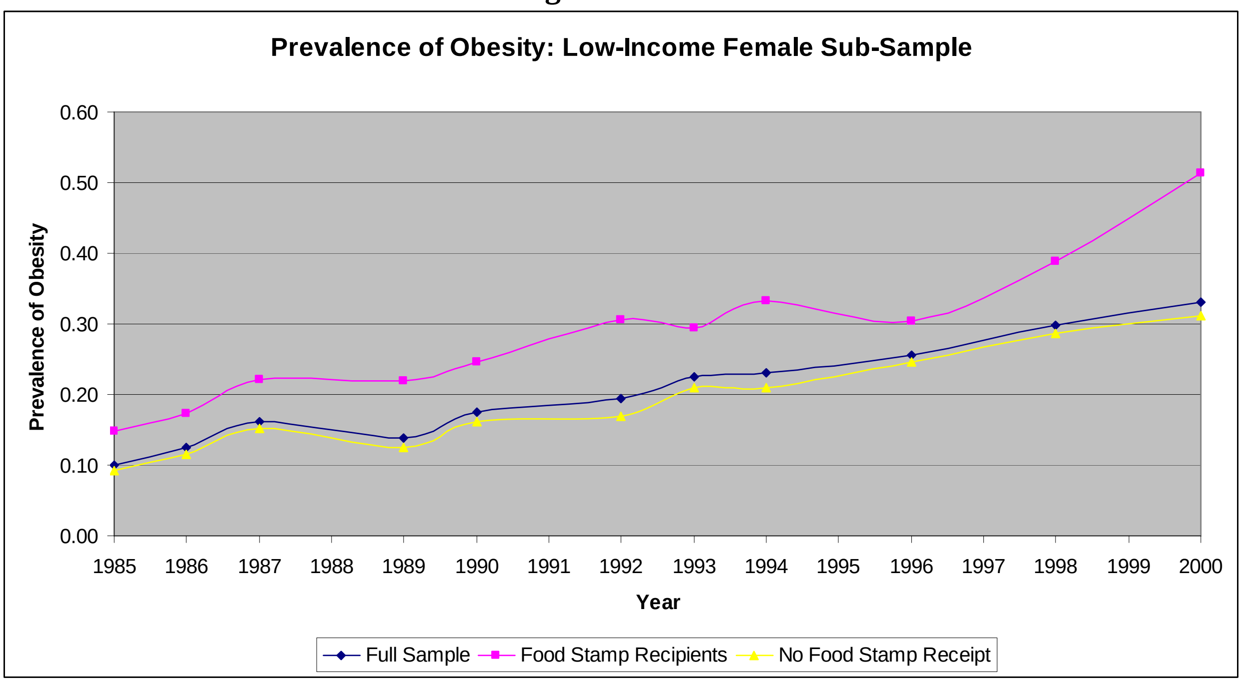


Figure 7

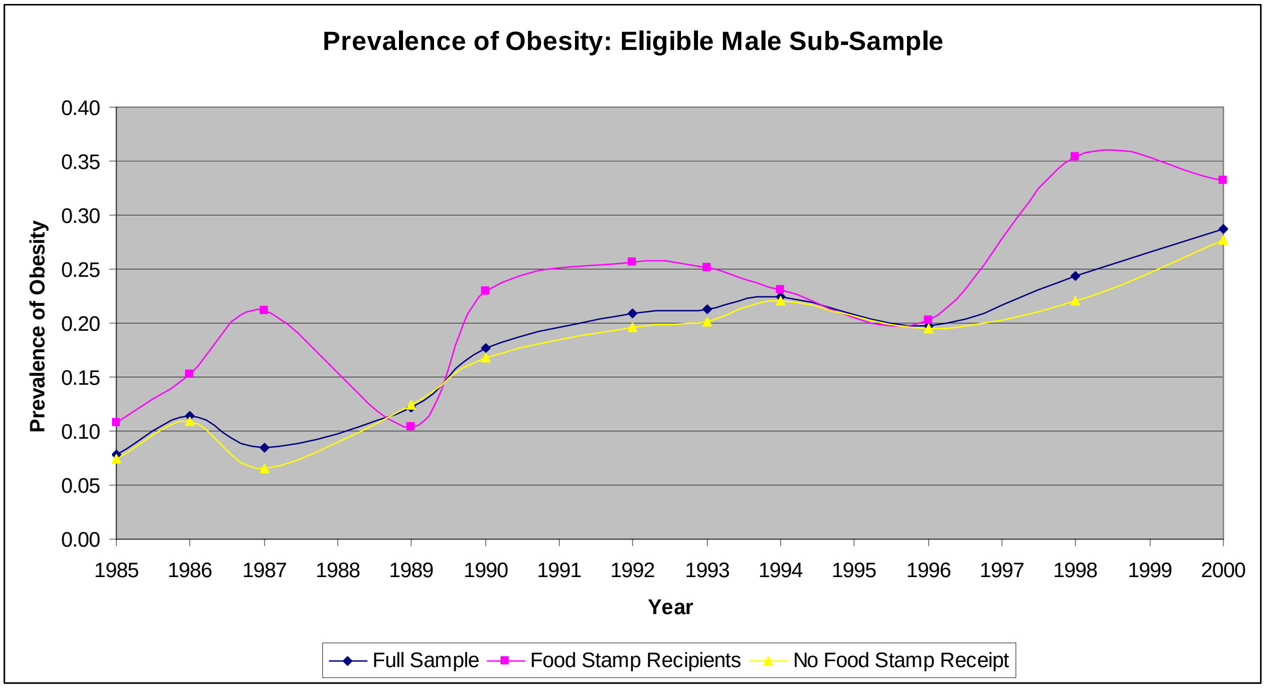


Figure 8

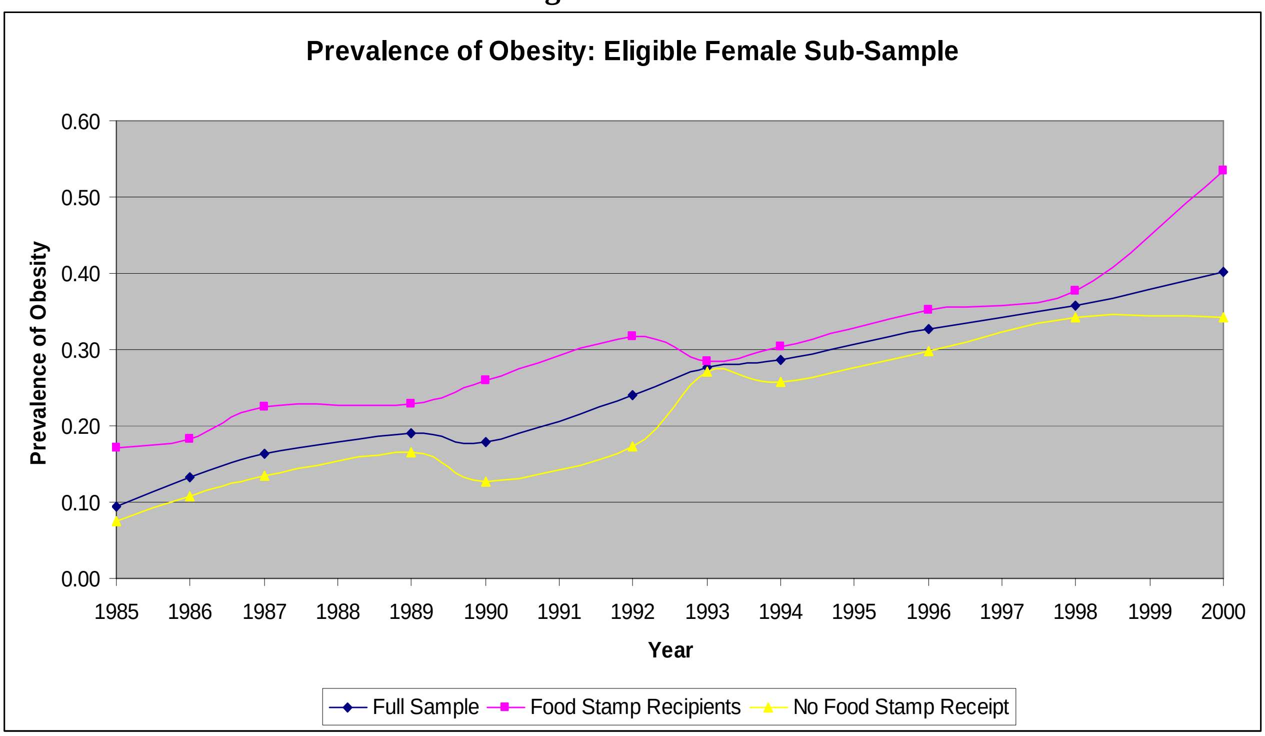


Figure 9

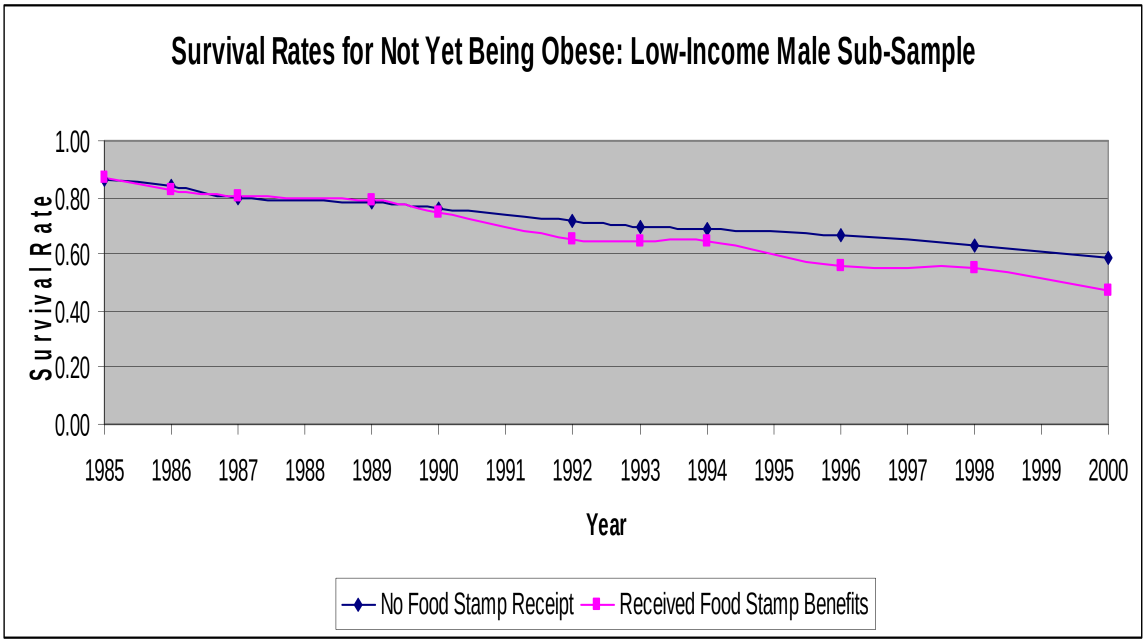


Figure 10

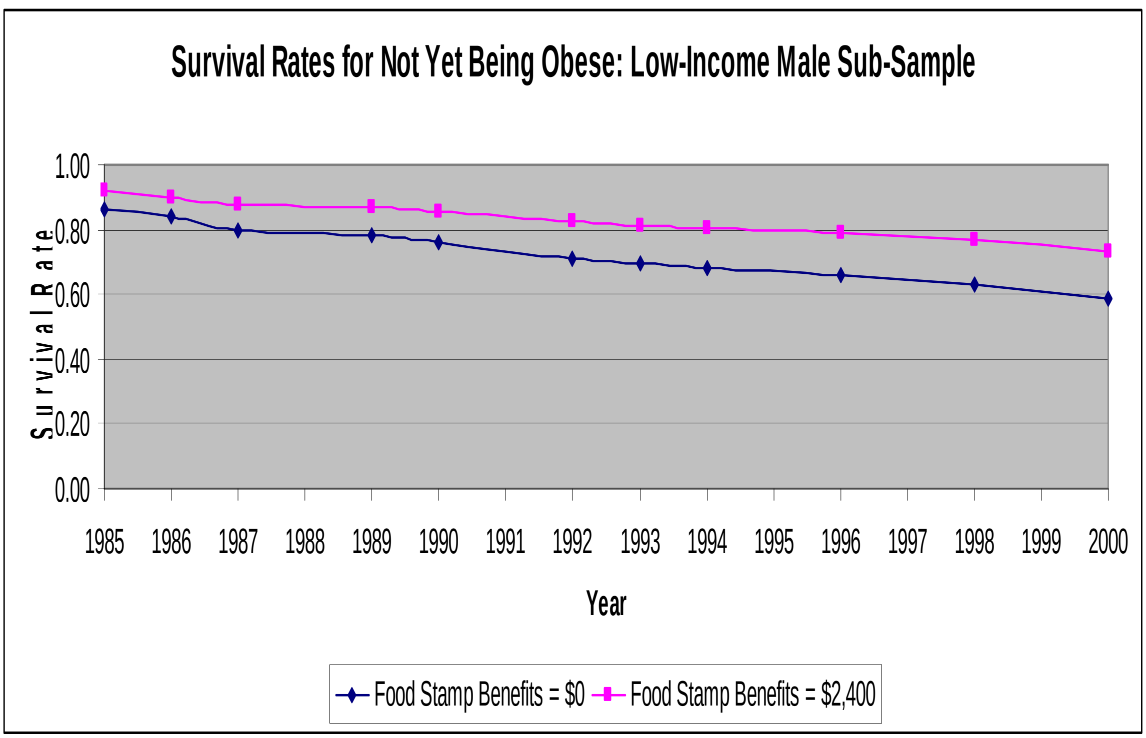


Figure 11

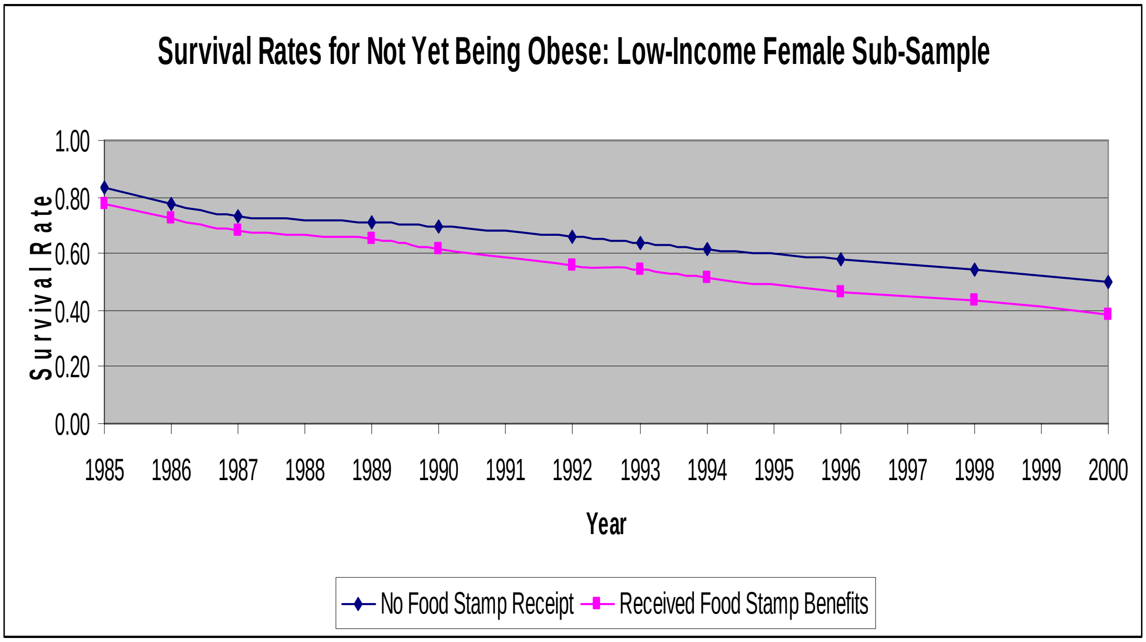


Figure 12

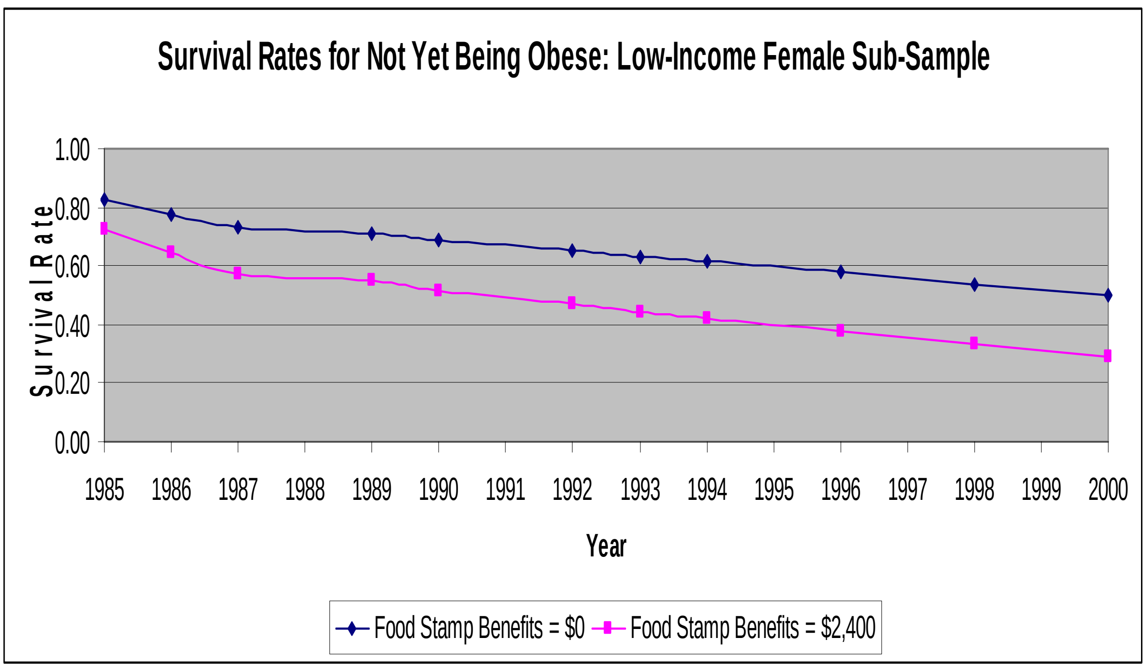


Figure 13

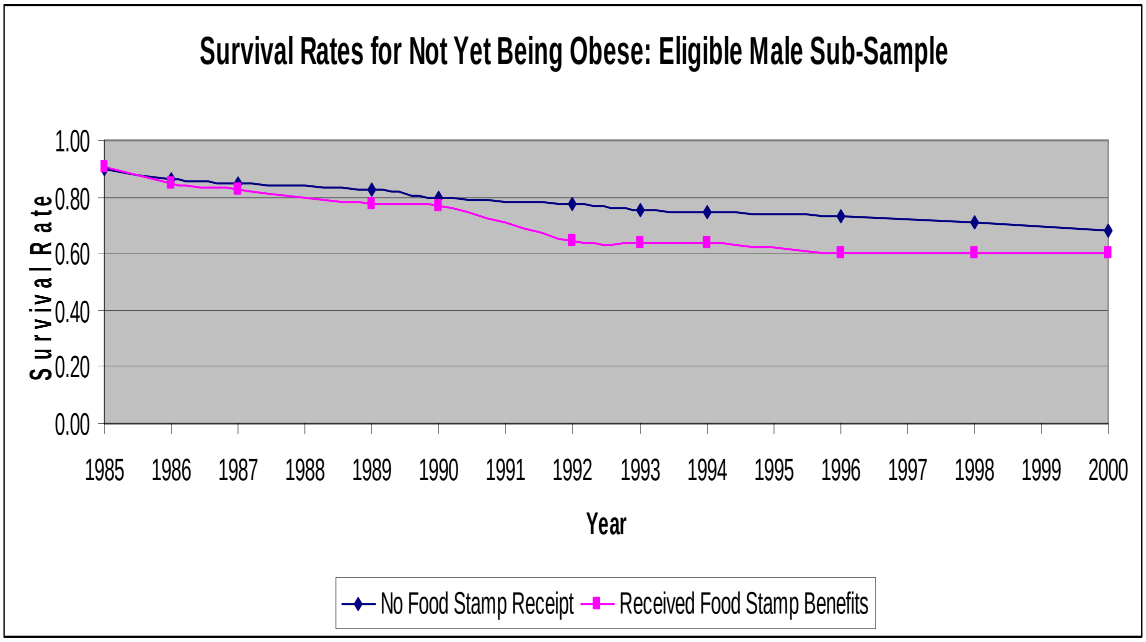


Figure 14

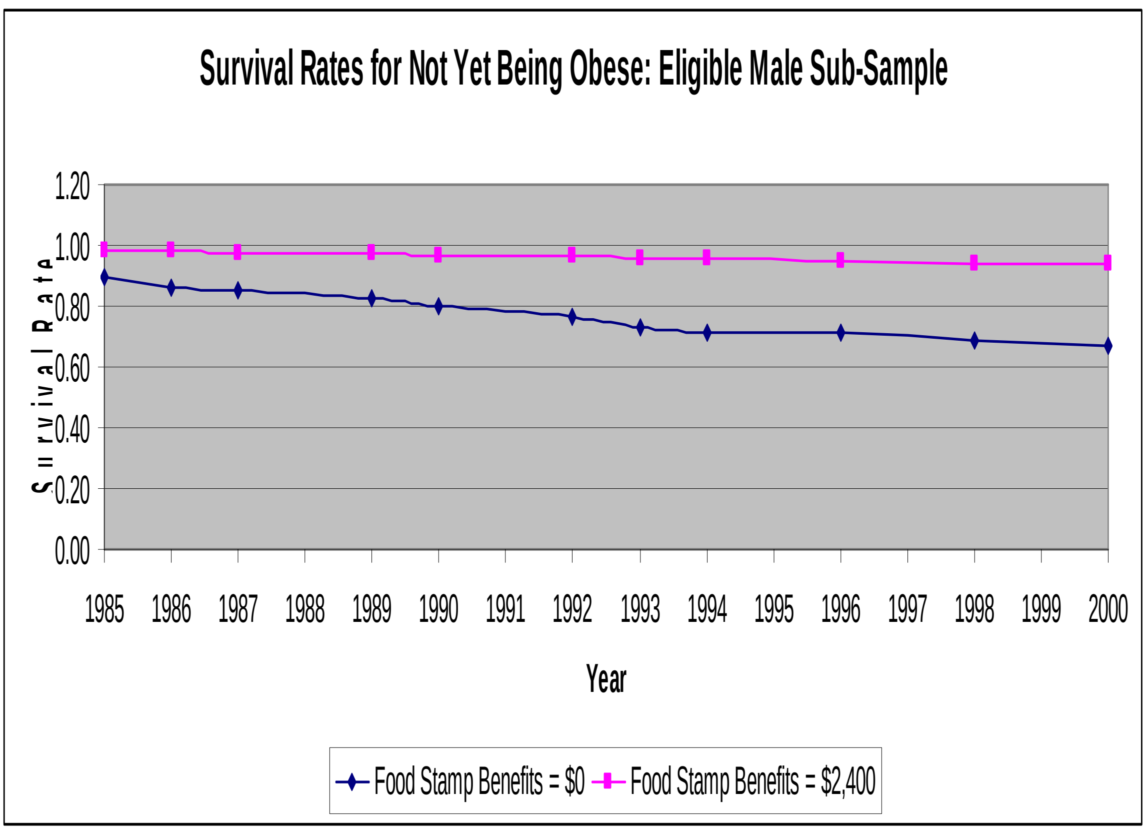


Figure 15

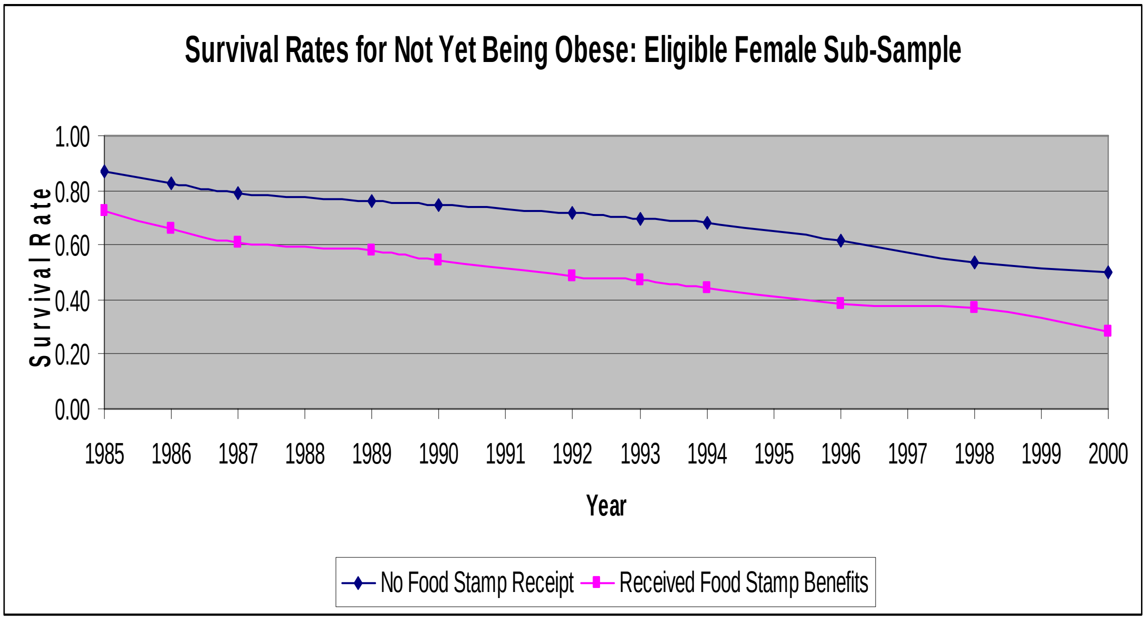
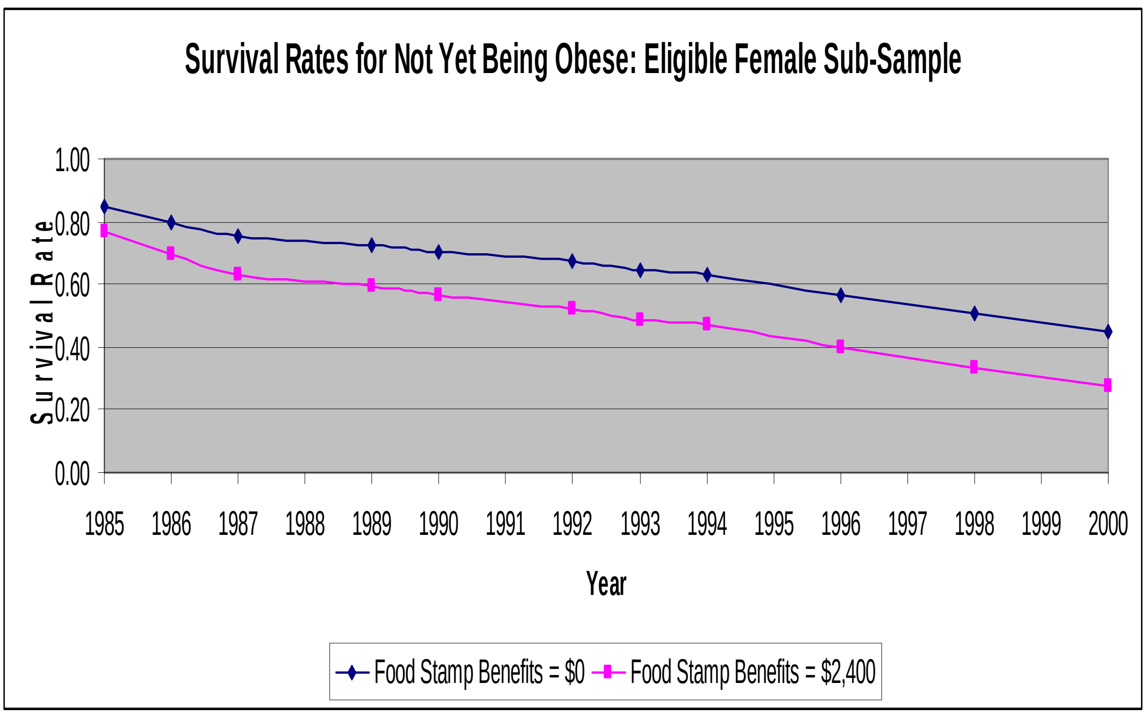


Figure 16



Appendix Table A1: The Effects of Other Covariates: OLS Results, Low-Income Male Sub-Sample

	Body Mass Index		Probability of Being Obese	
Household Income	0.001	(0.002)	-0.002*	(0.001)
Black	-0.505	(0.329)	-0.135	(0.178)
Hispanic	1.628***	(0.478)	0.559***	(0.202)
Age	0.096	(0.061)	0.038	(0.030)
Education Level	0.144	(0.119)	0.060	(0.061)
Marital Status	0.721***	(0.216)	0.315**	(0.124)
Children	0.146	(0.121)	0.004	(0.057)
Household Size	0.015	(0.060)	0.030	(0.034)
Urban	-0.465*	(0.282)	-0.228*	(0.135)
Local Unemployment Rate	0.350	(6.047)	-0.118	(2.723)
Local Per Capita Income	-0.039	(0.043)	-0.040*	(0.022)
Portion of Local Labor Force Female	-0.601	(4.510)	2.225	(2.394)
Local Population High-School Educated	2.841	(2.503)	2.191*	(1.315)
Local Population College-Educated	3.025	(4.758)	0.538	(2.469)
Local Population Employed	-11.136**	(4.544)	-2.341	(2.256)
Local Labor Force in Manufacturing	0.746	(2.449)	-0.113	(1.283)
Local Labor Force in Wholesale/Retail Trade	1.463	(6.276)	-3.588	(3.293)
Representative’s ADA Ranking	-0.398	(0.436)	0.095	(0.310)
Senator’s ADA Ranking	-0.589***	(0.213)	-0.237	(0.152)
Democrat Governor	0.002	(0.104)	0.038	(0.072)
Portion of State House Democrat	-1.941**	(0.852)	-1.164**	(0.538)
Portion of State Senate Democrat	-0.665	(0.789)	-0.362	(0.537)
Post-TANF	-0.939	(1.478)	-1.108	(1.399)
Pre-Welfare Reform Waiver #1	-0.019	(0.283)	-0.174	(0.177)
Pre-Welfare Reform Waiver #2	-0.315	(0.330)	-0.276	(0.192)
Pre-Welfare Reform Waiver #3	0.032	(0.352)	-0.004	(0.214)
Pre-Welfare Reform Waiver #4	-0.059	(0.251)	-0.052	(0.121)
Pre-Welfare Reform Waiver #5	-0.155	(0.383)	0.103	(0.161)
Pre-Welfare Reform Waiver #6	-0.068	(0.372)	-0.017	(0.207)
State Maximum Benefits	-0.001	(0.001)	-0.001	(0.001)
Time Limit	0.486	(1.385)	0.829	(0.679)
No Time Limit	0.006	(0.020)	0.012	(0.010)
Family Caps	-0.260	(0.317)	-0.195	(0.182)
Child Age	-0.033**	(0.013)	-0.020***	(0.007)
Severe Sanctions	-0.988***	(0.378)	-0.350*	(0.197)
Earned Income Disregards	0.001	(0.002)	0.001	(0.001)
Earned Income Disregards	0.004	(0.006)	0.001	(0.003)
Asset Limit	0.001	(0.001)	0.001	(0.001)
No Asset Limit	0.897	(1.709)	1.262	(1.007)

Vehicles Included in TANF Asset Test	0.001	(0.001)	0.002**	(0.001)
TANF Vehicle Exemption	-0.154	(0.394)	-0.196	(0.227)
Intercept	27.069***	(4.261)	-15.569***	(6.241)

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 11,748 low-income males.

Appendix Table A2: The Effects of Other Covariates: OLS Results, Low-Income Female Sub-Sample

	Body Mass Index		Probability of Being Obese	
Household Income	-0.008**	(0.003)	-0.003*	(0.002)
Black	2.211***	(0.451)	0.554***	(0.165)
Hispanic	1.261**	(0.526)	0.293	(0.224)
Age	0.250***	(0.072)	0.096***	(0.031)
Education Level	-0.291**	(0.151)	-0.104*	(0.057)
Marital Status	0.159	(0.283)	0.035	(0.130)
Children	-0.250	(0.156)	-0.073	(0.058)
Household Size	0.138	(0.100)	0.056	(0.038)
Urban	-0.445	(0.353)	-0.173	(0.149)
Local Unemployment Rate	10.125*	(5.737)	6.543**	(2.664)
Local Per Capita Income	0.058	(0.061)	0.020	(0.025)
Portion of Local Labor Force Female	5.882	(4.977)	3.445	(2.212)
Local Population High-School Educated	2.102	(3.232)	1.253	(1.249)
Local Population College-Educated	-6.003	(5.907)	-3.020	(2.697)
Local Population Employed	1.414	(4.958)	1.630	(2.028)
Local Labor Force in Manufacturing	-1.204	(2.778)	-0.721	(1.227)
Local Labor Force in Wholesale/Retail Trade	-10.167	(8.083)	-4.146	(3.754)
Representative's ADA Ranking	0.326	(0.562)	0.200	(0.382)
Senator's ADA Ranking	-0.112	(0.283)	0.239	(0.157)
Democrat Governor	-0.063	(0.136)	0.041	(0.073)
Portion of State House Democrat	-2.169**	(1.057)	-1.122**	(0.468)
Portion of State Senate Democrat	-0.743	(1.065)	0.130	(0.557)
Post-TANF	-4.585*	(2.735)	-16.617***	(5.377))
Pre-Welfare Reform Waiver #1	-0.030	(0.404)	0.030	(0.191)
Pre-Welfare Reform Waiver #2	0.053	(0.436)	-0.098	(0.213)
Pre-Welfare Reform Waiver #3	0.133	(0.453)	0.121	(0.218)
Pre-Welfare Reform Waiver #4	0.058	(0.324)	-0.283*	(0.158)
Pre-Welfare Reform Waiver #5	-0.046	(0.352)	0.133	(0.169)
Pre-Welfare Reform Waiver #6	-0.379	(0.488)	-0.241	(0.230)
State Maximum Benefits	0.002	(0.001)	0.001	(0.001)
Time Limit	0.716	(1.479)	0.613	(0.756)
No Time Limit	0.010	(0.020)	0.006	(0.010)
Family Caps	0.624*	(0.376)	0.006	(0.202)
Child Age	0.030**	(0.015)	0.001	(0.007)
Severe Sanctions	-0.224	(0.422)	-0.040	(0.223)
Earned Income Disregards	0.002	(0.001)	0.001	(0.001)
Earned Income Disregards	-0.009	(0.007)	-0.007**	(0.003)
Asset Limit	0.001	(0.001)	0.001	(0.001)
No Asset Limit	-0.071	(2.097)	0.872	(1.197)

Vehicles Included in TANF Asset Test	0.001	(0.001)	0.001	(0.001)
TANF Vehicle Exemption	-0.217	(0.481)	-0.133	(0.244)
Intercept	19.449***	(5.563)	-6.761	(6..633)

Standard errors are in parentheses. *p < 0.10, **p < 0.05, and ***p < 0.01. There are 10,558 low-income females.

Appendix Table A3: The Effects of Other Covariates: OLS Results, Eligible Male Sub-Sample

	Body Mass Index		Probability of Being Obese	
Household Income	0.007**	(0.003)	0.001	(0.002)
Black	-0.072	(0.327)	0.087	(0.202)
Hispanic	2.043***	(0.592)	0.678**	(0.269)
Age	0.224***	(0.069)	0.145***	(0.038)
Education Level	0.039	(0.065)	0.002	(0.038)
Marital Status	0.398	(0.332)	0.163	(0.189)
Children	0.155	(0.153)	0.014	(0.070)
Household Size	0.023	(0.064)	0.018	(0.039)
Urban	-0.262	(0.427)	-0.300	(0.253)
Local Unemployment Rate	-1.291	(6.044)	2.397	(3.652)
Local Per Capita Income	-0.032	(0.049)	-0.041	(0.033)
Portion of Local Labor Force Female	-8.066	(5.306)	0.344	(3.335)
Local Population High-School Educated	1.862	(3.594)	3.067*	(1.898)
Local Population College-Educated	-3.254	(5.512)	-5.365*	(3.266)
Local Population Employed	-0.835	(5.278)	3.827	(2.991)
Local Labor Force in Manufacturing	-0.417	(2.828)	-1.509	(1.636)
Local Labor Force in Wholesale/Retail Trade	3.276	(8.199)	-2.821	(5.090)
Representative’s ADA Ranking	-2.484***	(0.948)	-0.207	(0.657)
Senator’s ADA Ranking	-0.639	(0.536)	-0.403	(0.381)
Democrat Governor	-0.064	(0.245)	0.047	(0.156)
Portion of State House Democrat	-0.109	(1.755)	-1.544	(1.171)
Portion of State Senate Democrat	-0.874	(1.860)	-0.301	(1.249)
Post-TANF	-5.078	(3.348)	-19.281***	(3.144)
Pre-Welfare Reform Waiver #1	2.125*	(1.088)	0.972	(0.596)
Pre-Welfare Reform Waiver #2	-0.374	(0.940)	-0.555	(0.719)
Pre-Welfare Reform Waiver #3	-0.715	(1.092)	-0.105	(0.861)
Pre-Welfare Reform Waiver #4	0.501	(0.632)	-0.039	(0.343)
Pre-Welfare Reform Waiver #5	0.078	(0.856)	0.104	(0.494)
Pre-Welfare Reform Waiver #6	-0.038	(1.128)	0.126	(0.607)
State Maximum Benefits	-0.004*	(0.002)	-0.003*	(0.002)
Time Limit	-1.632	(3.512)	-1.876	(1.506)
No Time Limit	-0.015	(0.054)	-0.016	(0.021)
Family Caps	1.363*	(0.736)	0.378	(0.362)
Child Age	0.055*	(0.032)	0.009	(0.015)
Severe Sanctions	0.044	(0.865)	0.151	(0.457)
Earned Income Disregards	0.002	(0.004)	0.001	(0.002)
Earned Income Disregards	0.003	(0.014)	-0.004	(0.007)
Asset Limit	0.001	(0.001)	0.001	(0.001)
No Asset Limit	-5.826	(5.637)	-2.004	(2.590)

Vehicles Included in TANF Asset Test	0.001	(0.001)	0.001	(0.001)
TANF Vehicle Exemption	-1.201	(0.931)	-0.523	(0.511)
Intercept	28.140***	(6.683)	-2.567	(3.558)

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 3,681 eligible males.

Appendix Table A4: The Effects of Other Covariates: OLS Results, Eligible Female Sub-Sample

	Body Mass Index		Probability of Being Obese	
Household Income	-0.003	(0.003)	0.001	(0.001)
Black	2.015***	(0.544)	0.551***	(0.187)
Hispanic	1.022*	(0.628)	0.018	(0.266)
Age	0.190**	(0.082)	0.100***	(0.029)
Education Level	-0.254**	(0.106)	-0.117***	(0.042)
Marital Status	0.093	(0.363)	0.133	(0.157)
Children	-0.239	(0.175)	-0.114*	(0.060)
Household Size	0.139	(0.096)	0.074**	(0.036)
Urban	-0.062	(0.490)	0.263	(0.207)
Local Unemployment Rate	-0.524	(7.292)	1.506	(3.212)
Local Per Capita Income	0.003	(0.076)	0.003	(0.033)
Portion of Local Labor Force Female	-2.380	(6.235)	-2.573	(2.442)
Local Population High-School Educated	-4.695	(4.035)	-1.404	(1.517)
Local Population College-Educated	-2.020	(6.757)	-2.524	(2.813)
Local Population Employed	9.977	(6.542)	5.042**	(2.378)
Local Labor Force in Manufacturing	-1.320	(4.101)	-1.087	(1.490)
Local Labor Force in Wholesale/Retail Trade	-0.465	(10.130)	-1.295	(3.670)
Representative’s ADA Ranking	1.178	(0.995)	0.485	(0.476)
Senator’s ADA Ranking	-0.793	(0.591)	-0.093	(0.256)
Democrat Governor	-0.289	(0.271)	0.059	(0.120)
Portion of State House Democrat	-2.883	(2.022)	-1.480*	(0.837)
Portion of State Senate Democrat	-2.434	(2.105)	-0.569	(0.929)
Post-TANF	-6.433**	(3.031)	-12.867***	(2.729)
Pre-Welfare Reform Waiver #1	2.925**	(1.283)	1.182***	(0.387)
Pre-Welfare Reform Waiver #2	-0.968	(1.205)	-0.092	(0.380)
Pre-Welfare Reform Waiver #3	-0.489	(1.235)	-0.875**	(0.430)
Pre-Welfare Reform Waiver #4	0.672	(0.615)	0.208	(0.251)
Pre-Welfare Reform Waiver #5	-0.571	(0.957)	0.173	(0.312)
Pre-Welfare Reform Waiver #6	-0.278	(1.014)	-0.838*	(0.446)
State Maximum Benefits	0.007***	(0.003)	0.002**	(0.001)
Time Limit	1.637	(3.213)	0.707	(1.323)
No Time Limit	0.029	(0.045)	0.019	(0.021)
Family Caps	1.532	(0.989)	0.052	(0.364)
Child Age	0.014	(0.036)	-0.001	(0.013)
Severe Sanctions	-2.350**	(0.993)	-0.332	(0.369)
Earned Income Disregards	0.005**	(0.002)	0.001	(0.001)
Earned Income Disregards	0.012	(0.015)	0.001	(0.006)
Asset Limit	0.001	(0.001)	0.001	(0.001)
No Asset Limit	2.657	(5.021)	0.280	(1.918)

Vehicles Included in TANF Asset Test	0.001	(0.001)	0.001	(0.001)
TANF Vehicle Exemption	-2.945**	(1.254)	-1.022**	(0.480)
Intercept	22.096***	(6.201)	7.041***	(2.066)

Standard errors are in parentheses. *p < 0.10, **p < 0.05, and ***p < 0.01. There are 4,799 eligible females.

Appendix Table A5: Food Stamp Receipt: OLS Results, Low-Income Sub-Sample Sample

	Low-Income Males		Low-Income Females	
Household Income	-0.033***	(0.006)	-0.016***	(0.002)
Black	0.062	(0.202)	1.077***	(0.130)
Hispanic	-0.134	(0.204)	0.207	(0.178)
Age	-0.028	(0.030)	-0.054**	(0.024)
Education Level	-0.163***	(0.044)	-0.225***	(0.039)
Marital Status	0.666***	(0.160)	-1.173***	(0.115)
Children	0.200***	(0.054)	0.605***	(0.051)
Household Size	0.080***	(0.031)	-0.011	(0.032)
Urban	0.072	(0.184)	-0.105	(0.139)
Vehicle Value	-0.149***	(0.0210	-0.172***	(0.020)
Senior Present	-0.189	(0.158)	-0.279**	(0.135)
Local Unemployment Rate	4.502*	(2.643)	0.072	(2.187)
Local Per Capita Income	-0.014	(0.023)	0.009	(0.019)
Portion of Local Labor Force Female	-1.018	(2.142)	-0.624	(1.852)
Local Population High-School Educated	-1.658	(1.381)	-2.864**	(1.120)
Local Population College-Educated	4.451*	(2.561)	4.248**	(2.158)
Local Population Employed	-5.058**	(2.359)	-6.561***	(1.761)
Local Labor Force in Manufacturing	2.258*	(1.199)	-0.318	(0.997)
Local Labor Force in Wholesale/Retail Trade	5.812	(3.642)	3.238	(3.059)
Representative's ADA Ranking	-0.395	(0.424)	0.061	(0.355)
Senator's ADA Ranking	-0.358	(0.243)	-0.557***	(0.183)
Democrat Governor	-0.015	(0.109)	0.088	(0.087)
Portion of State House Democrat	-0.267	(1.200)	-1.076*	(0.654)
Portion of State Senate Democrat	0.225	(0.918)	-0.814	(0.724)
Post-TANF	-12.735***	(2.438)	-20.342***	(2.521)
Pre-Welfare Reform Waiver #1	-0.321	(0.362)	-0.091	(0.284)
Pre-Welfare Reform Waiver #2	0.665*	(0.389)	-0.119	(0.264)
Pre-Welfare Reform Waiver #3	-0.445	(0.412)	0.144	(0.281)
Pre-Welfare Reform Waiver #4	-0.231	(0.230)	0.033	(0.173)
Pre-Welfare Reform Waiver #5	0.022	(0.373)	-0.105	(0.232)
Pre-Welfare Reform Waiver #6	-0.132	(0.399)	0.548*	(0.310)
State Maximum Benefits	0.001	(0.001)	-0.001	(0.001)
Time Limit	-0.505	(1.453)	-0.560	(1.336)
No Time Limit	-0.029	(0.018)	0.011	(0.020)
Family Caps	0.337	(0.487)	0.483*	(0.277)
Child Age	0.006	(0.012)	-0.011	(0.011)
Severe Sanctions	-0.877**	(0.416)	-0.105	(0.302)
Earned Income Disregards	-0.002	(0.002)	0.002*	(0.001)
Earned Income Disregards	0.004	(0.008)	0.004	(0.005)

Asset Limit	0.001	(0.001)	0.001	(0.001)
No Asset Limit	-0.363	(2.367)	0.001	(1.392)
Vehicles Included in TANF Asset Test	0.001	(0.001)	0.001	(0.001)
TANF Vehicle Exemption	-0.157	(0.478)	-0.077	(0.351)
Intercept	24.332***	(0.253)	8.147***	(2.055)

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 11,748 low-income males and 10,558 low-income females.

Appendix Table A6: Food Stamp Receipt: OLS Results, Low-Income Sub-Sample

	Low-Income Males		Low-Income Females	
Household Income	-0.040***	(0.006)	-0.019***	(0.003)
Black	0.237	(0.208)	1.235***	(0.134)
Hispanic	-0.086	(0.210)	0.215	(0.181)
Age	-0.042	(0.031)	-0.073***	(0.025)
Education Level	-0.194***	(0.046)	-0.254***	(0.040)
Marital Status	0.540***	(0.166)	-1.461***	(0.119)
Children	0.216***	(0.055)	0.652***	(0.052)
Household Size	0.079**	(0.031)	-0.021	(0.031)
Urban	0.142	(0.183)	-0.054	(0.140)
FSP Vehicle Asset Limit	0.089	(0.081)	-0.022	(0.136)
EBT	0.424	(0.314)	0.186	(0.224)
Non-Parental Adult Caregivers	-0.611	(0.538)	-0.073	(0.302)
Simplified Periodic Reporting	0.182	(0.426)	-0.307	(0.313)
Categorical Eligibility	-0.611	(0.481)	-0.404	(0.317)
Severe Sanctions	-0.188	(0.410)	-0.170	(0.286)
Outreach Plan	1.457***	(0.445)	0.434	(0.311)
Local Unemployment Rate	3.293	(2.653)	0.087	(2.213)
Local Per Capita Income	-0.015	(0.024)	0.013	(0.019)
Portion of Local Labor Force Female	-0.815	(2.131)	-0.291	(1.884)
Local Population High-School Educated	-1.532	(1.383)	-3.222***	(1.152)
Local Population College-Educated	3.870	(2.552)	4.467**	(2.243)
Local Population Employed	-5.140**	(2.377)	-6.777***	(1.750)
Local Labor Force in Manufacturing	2.197*	(1.219)	-0.174	(1.007)
Local Labor Force in Wholesale/Retail Trade	4.982	(3.688)	2.752	(3.102)
Representative’s ADA Ranking	-0.209	(0.437)	0.066	(0.353)
Senator’s ADA Ranking	-0.345	(0.239)	-0.546***	(0.180)
Democrat Governor	-0.040	(0.108)	0.097	(0.086)
Portion of State House Democrat	0.149	(1.228)	-0.981	(0.664)
Portion of State Senate Democrat	-0.064	(0.900)	-0.733	(0.710)
Post-TANF	-12.217***	(2.548)	-18.804***	(2.988)
Pre-Welfare Reform Waiver #1	-0.378	(0.374)	-0.192	(0.285)
Pre-Welfare Reform Waiver #2	0.520	(0.368)	-0.053	(0.251)
Pre-Welfare Reform Waiver #3	-0.479	(0.380)	0.083	(0.273)
Pre-Welfare Reform Waiver #4	-0.114	(0.234)	0.080	(0.179)
Pre-Welfare Reform Waiver #5	0.094	(0.332)	-0.100	(0.228)
Pre-Welfare Reform Waiver #6	-0.033	(0.369)	0.378	(0.300)
State Maximum Benefits	0.002	(0.001)	0.001	(0.001)
Time Limit	1.292	(1.896)	-0.557	(1.604)
No Time Limit	-0.004	(0.024)	0.010	(0.024)

Family Caps	0.703	(0.512)	0.288	(0.304)
Child Age	-0.004	(0.015)	-0.012	(0.013)
Severe Sanctions	-1.421***	(0.523)	0.008	(0.363)
Earned Income Disregards	-0.005	(0.003)	0.002**	(0.001)
Earned Income Disregards	0.008	(0.008)	0.006	(0.006)
Asset Limit	0.001	(0.001)	0.001	(0.001)
No Asset Limit	0.254	(2.347)	-1.149	(1.518)
Vehicles Included in TANF Asset Test	0.001	(0.001)	0.001	(0.001)
TANF Vehicle Exemption	-0.260	(0.458)	0.075	(0.345)
Intercept	10.023***	(2.014)	1.424***	(0.183)

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 11,748 low-income males and 10,558 low-income females.

Appendix Table A7: Food Stamp Receipt: OLS Results, Eligible Sub-Sample Sample

	Eligible Males		**Eligible Females**	
Household Income	-0.009***	(0.003)	-0.005***	(0.001)
Black	-0.083	(0.214)	0.789***	(0.129)
Hispanic	-0.163	(0.240)	0.025	(0.185)
Age	0.038	(0.031)	-0.002	(0.024)
Education Level	-0.102***	(0.035)	-0.209***	(0.029)
Marital Status	1.355***	(0.156)	-0.497***	(0.125)
Children	0.138**	(0.057)	0.695***	(0.055)
Household Size	-0.031	(0.032)	-0.175***	(0.036)
Urban	0.307	(0.208)	-0.094	(0.157)
Vehicle Value	-0.149***	(0.028)	-0.145***	(0.020)
Senior Present	-0.399***	(0.165)	-0.227*	(0.141)
Local Unemployment Rate	6.982**	(2.916)	4.438*	(2.483)
Local Per Capita Income	-0.001	(0.024)	0.008	(0.018)
Portion of Local Labor Force Female	-5.373**	(2.562)	0.466	(2.017)
Local Population High-School Educated	-3.833**	(1.615)	-2.216*	(1.179)
Local Population College-Educated	3.275	(2.957)	2.428	(2.137)
Local Population Employed	-1.118	(2.821)	-4.717**	(1.916)
Local Labor Force in Manufacturing	2.186*	(1.308)	-0.025	(1.030)
Local Labor Force in Wholesale/Retail Trade	14.002***	(4.327)	1.807	(3.170)
Representative’s ADA Ranking	0.360	(0.586)	-0.096	(0.421)
Senator’s ADA Ranking	-0.338	(0.318)	-0.305	(0.235)
Democrat Governor	-0.092	(0.131)	0.212**	(0.105)
Portion of State House Democrat	0.545	(1.470)	-0.353	(0.887)
Portion of State Senate Democrat	-0.210	(1.307)	-0.183	(0.873)
Post-TANF	-16.595***	(1.431)	-19.107***	(2.631)
Pre-Welfare Reform Waiver #1	-0.174	(0.597)	-0.412	(0.457)
Pre-Welfare Reform Waiver #2	0.714	(0.566)	-0.693*	(0.399)
Pre-Welfare Reform Waiver #3	-1.287**	(0.568)	0.983*	(0.548)
Pre-Welfare Reform Waiver #4	-0.198	(0.306)	0.053	(0.249)
Pre-Welfare Reform Waiver #5	0.352	(0.498)	-0.149	(0.359)
Pre-Welfare Reform Waiver #6	0.501	(0.574)	0.999**	(0.472)
State Maximum Benefits	0.001	(0.001)	-0.001	(0.001)
Time Limit	-1.056	(1.834)	-2.487*	(1.363)
No Time Limit	-0.014	(0.025)	-0.029	(0.021)
Family Caps	0.435	(0.514)	0.750**	(0.365)
Child Age	0.017	(0.013)	-0.003	(0.014)
Severe Sanctions	-1.119**	(0.524)	-0.330	(0.424)
Earned Income Disregards	0.001	(0.002)	0.002	(0.001)
Earned Income Disregards	0.011	(0.009)	0.004	(0.007)

Asset Limit	0.001	(0.001)	0.001	(0.001)
No Asset Limit	2.633	(3.079)	-0.626	(2.033)
Vehicles Included in TANF Asset Test	0.001	(0.001)	0.001	(0.001)
TANF Vehicle Exemption	-0.695	(0.664)	-0.188	(0.518)
Intercept	24.332***	(0.253)	6.673***	(2.041)

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 3,681 eligible males and 4,799 eligible females.

Appendix Table A8: Food Stamp Receipt: OLS Results, Eligible Sub-Sample Sample

	Eligible Males		Eligible Females	
Household Income	-0.012***	(0.003)	-0.008***	(0.002)
Black	0.046	(0.221)	0.904***	(0.129)
Hispanic	-0.124	(0.242)	0.091	(0.184)
Age	0.024	(0.031)	-0.017	(0.024)
Education Level	-0.120***	(0.037)	-0.231***	(0.030)
Marital Status	1.262***	(0.151)	-0.703***	(0.121)
Children	0.174***	(0.057)	0.727***	(0.054)
Household Size	-0.045	(0.032)	-0.188***	(0.034)
Urban	0.355	(0.203)	-0.028	(0.158)
FSP Vehicle Asset Limit	0.089	(0.081)	0.209*	(0.112)
EBT	0.209	(0.426)	0.220	(0.311)
Non-Parental Adult Caregivers	-0.277	(0.507)	-0.495	(0.376)
Simplified Periodic Reporting	0.337	(0.530)	-0.302	(0.401)
Categorical Eligibility	-0.397	(0.570)	-0.261	(0.4190
Severe Sanctions	0.370	(0.506)	-0.537	(0.385)
Outreach Plan	1.378***	(0.613)	0.890**	(0.407)
Local Unemployment Rate	6.445**	(2.915)	3.696	(2.464)
Local Per Capita Income	-0.007	(0.026)	0.005	(0.019)
Portion of Local Labor Force Female	-4.523*	(2.481)	0.153	(2.004)
Local Population High-School Educated	-3.521**	(1.577)	-2.536**	(1.200)
Local Population College-Educated	2.456	(2.879)	3.016	(2.173)
Local Population Employed	-0.385	(2.706)	-4.809**	(1.934)
Local Labor Force in Manufacturing	1.795	(1.287)	0.090	(1.032)
Local Labor Force in Wholesale/Retail Trade	12.085***	(4.290)	1.616	(3.184)
Representative’s ADA Ranking	0.376	(0.578)	-0.140	(0.415)
Senator’s ADA Ranking	-0.290	(0.311)	-0.189	(0.229)
Democrat Governor	-0.130	(0.129)	0.189*	(0.106)
Portion of State House Democrat	0.236	(1.423)	-0.267	(0.853)
Portion of State Senate Democrat	-0.206	(1.294)	-0.054	(0.852)
Post-TANF	-18.642***	(1.851)	-18.434***	(2.501)
Pre-Welfare Reform Waiver #1	-0.260	(0.576)	-0.463	(0.444)
Pre-Welfare Reform Waiver #2	0.582	(0.549)	-0.785**	(0.385)
Pre-Welfare Reform Waiver #3	-1.169***	(0.562)	1.020*	(0.522)
Pre-Welfare Reform Waiver #4	-0.208	(0.312)	0.100	(0.246)
Pre-Welfare Reform Waiver #5	0.391	(0.468)	-0.131	(0.355)
Pre-Welfare Reform Waiver #6	0.559	(0.559)	0.901**	(0.455)
State Maximum Benefits	0.002	(0.001)	-0.001	(0.001)
Time Limit	-0.366	(2.403)	-2.321	(1.700)

No Time Limit	0.004	(0.034)	-0.016	(0.023)
Family Caps	0.931	(0.624)	0.396	(0.453)
Child Age	0.001	(0.018)	-0.002	(0.016)
Severe Sanctions	-1.610**	(0.660)	-0.082	(0.535)
Earned Income Disregards	0.001	(0.002)	0.003*	(0.001)
Earned Income Disregards	0.018*	(0.010)	0.009	(0.008)
Asset Limit	0.001	(0.001)	0.001	(0.001)
No Asset Limit	1.929	(3.350)	-2.394	(2.572)
Vehicles Included in TANF Asset Test	0.001	(0.001)	0.001	(0.001)
TANF Vehicle Exemption	-0.957	(0.659)	0.155	(0.576)
Intercept	10.023***	(2.014)	1.424***	(0.183)

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. There are 3,681 eligible males and 4,799 eligible females.