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The Effects of Food Stamps on Obesity

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Abstract

Poverty has historically been associated with a decrease in food consumption. This at least partially changed in 1964 when the Food Stamp Act began guaranteeing food for those in poverty. Since the Act's passage, the prevalence of obesity has increased dramatically, particularly among those with low incomes. This paper examines the effects of the Food Stamp Program on the prevalence of obesity using 1979 National Longitudinal Survey of Youth data. Results indicate food stamps have significant positive effects on obesity and the obesity gap for females, but these effects are relatively small and such benefits, consequently, are approximated to have played a minor role in increasing obesity at the aggregate level.

Key words: Food stamps; weight; obesity; BMI

JEL category: I18

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1. 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 (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 this dramatic, 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 because the medical literature finds that obesity increases morbidity and mortality (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 (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, estimates suggest 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).

Many societal changes do not initially appear to explain why the prevalence of obesity is increasing. For example, an increasing portion of Americans are exercising and dieting, and Americans are estimated to spend over 30 billion dollars on weight loss programs annually (Philipson and Posner 1999). Furthermore, Americans currently possess more knowledge of the consequences of obesity than ever before (Philipson and Posner 1999; Philipson 2001). Yet, Americans are more likely to be obese now than ever.

Economists have examined various causes of obesity. For example, Philipson (2001), Philipson and Posner (1999), and Lakdawalla and Philipson (2002, 2007) suggest that increased obesity is the result of jobs becoming more sedentary; Anderson, Butcher, and Levine (2003) 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; and 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.

I examine the effect of the Food Stamp Program 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. Various twentieth century government 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 (USDA 2003). In 2005, Food Stamp Program participants averaged $92.70 in monthly benefits at a cost of $31.0 billion to the government (USDA 2006a). 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 Food Stamp Program 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 Food Stamp Program served an estimated 25.7 million participants (USDA, 2006a), and the prevalence of obesity is currently over 30 %.

The Food Stamp Program potentially increases obesity by increasing food consumption, resulting in excessive caloric intake. Food stamps potentially increase food consumption by making the monetary cost of food zero for eligible individuals up to their food stamp allotment (though since Food Stamp Program 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, but this also appears to be true for the other 85 to 95 % of food stamp households that are unconstrained (Fraker 1990).

Although recipients could potentially use food stamps to buy healthier foods, recent evidence by Wilde, McNamara, and Ranney (1999) suggests food stamp recipients consume significantly more sugar and fat than eligible non-recipients. Additional evidence by Whitmore (2002) indicates that food stamp recipients in San Diego and Alabama in the 1990s consumed more soft drinks than peers who instead received cash benefits. If so, then it is possible that recipients not only consume more food, they consume more of the foods likely to lead to weight gain.

Food stamps might also exacerbate obesity by promoting binge eating. Townsend et al. (2001) suggest that abundant food at the beginning of each monthly food stamp cycle leads to over-eating, with food becoming scarce at the end of each cycle. They argue that the net effect of this cycle is weight gain. However, Townsend and colleagues also note that food insecurity and Food Stamp Program participation are related.[1] Food stamps could affect obesity by affecting (reducing) food insecurity; alternatively, those who are food insecure could be more likely to apply for and receive food stamp benefits, in which case food stamps and obesity would at least partially be correlated with each other through a third, potentially unmeasurable, factor (food insecurity).[2]

Only a couple of studies have examined the effects of Food Stamp Program participation on obesity. In the nutrition literature, seminal work by Gibson first examined this link.[3] Gibson (2003) finds that Food Stamp Program participation among low-income women (but not men) is significantly associated with increased obesity. In concurrence, economists Meyerhoefer and Pylypchuk (2008) find that contemporaneously-measured food stamp receipt has statistically significant positive effects on low-income women but not on low-income men.

In this project, I estimate the relationship between food stamp benefits and the probability of being obese and the obesity gap (which is the prevalence of obesity multiplied by the average amount by which BMI exceeds the obesity threshold) with National Longitudinal Survey of Youth (NLSY79) data. I focus the analysis on sub-samples of income-eligible males and females and control for possible omitted variable bias using an individual-specific fixed effects estimator. I attempt to build on Gibson's (2003) and Meyerhoefer and Pylypchuk's (2008) work by exploring 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 area for research 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. To do this, I estimate *(i)* models that explain weight changes over time with controls for initial weight status, *(ii)* models that identify the effects of current and past program receipt to explore whether food stamps have lagged effects, *(iii)* models that identify the effects of patterns of food stamp receipt, including short-term, medium-term, and long-term receipt, as well as the effects of receiving benefits in multiple spells, and *(iv)* models that explain the hazard rates for becoming obese at particular times during a 15-year period conditional on not yet being obese.

2. Data

I use 1979-cohort National Longitudinal Survey of Youth (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. 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.[4] After the 1994 survey, the NLSY79 began interviewing biennially, and these respondents have since been re-interviewed on that basis.

The NLSY79 identifies how much each respondent weighs in pounds at the time of the 1981, 1982, 1985, 1986, 1987, 1989, 1990, 1992, 1993, 1994, 1996, 1998, and 2000 surveys. The NLSY79 identifies height in inches at the time of the 1981, 1982, and 1985 surveys. I assume that height does not change after the 1985 survey because NLSY79 respondents are at least 20 years of age at that time. To measure obesity, I first calculate each individual's BMI. Obesity is then defined as a BMI of 30 or more (CDC 2006b). This results in a sample of 25,249 male and 24,328 female person-year observations that provide valid weight and height information and valid responses required to create the other covariates used throughout the analysis.

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, for example, low-income individuals who weigh more might be more likely to drop out, downward-biasing the sample average weight in later survey). However, I make one exception: 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. 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. This results in a balanced panel of 19,368 male person-year observations and 17,678 female person-year observations.

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.[5]

The NLSY79 also collects extensive information on each respondent's welfare experiences. For example, the NLSY79 identifies whether each respondent receives food stamp benefits in each month covered by the survey.[6] 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 person-year 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.

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. In addition, to be eligible, the household must have net monthly income less than a household size-specific amount. Because the NLSY79 collects the information needed to identify gross income, household size, and the ages of household members, I am able to select respondents to use in the analysis who are deemed to be income-eligible (according to the gross income test). This "income-eligible" sample contains 1,991 male person-year observations and 3,306 female person-year observations across the 11 surveys that collect weight information. Compared to the sample without eligibility restrictions, the income-eligible sample is significantly more likely to be obese and black or Hispanic and has significantly less education, larger families, and lower income.

Table 1 for eligible males and table 2 for eligible females give weighted sample means for key weight variables and key food stamp variables (whether the respondent received food stamps during the past calendar year and the amount of food stamps received during the past twelve months), as well as means of these variables separately for food stamp recipients and non-recipients (standard errors have been adjusted for sample stratification and clustering in these tables). Across all the surveys, 17.8 % of males (male person-year observations) and 23.6 % of females (female person-year observations) are obese. The portion of eligible females who receive food stamp benefits is substantially higher than that portion of eligible males: 46.6 % versus 20.6 %. Among males (females) who receive food stamps, benefits average $1,947 ($2,925) per year (all dollar amounts are adjusted for inflation to year-2005 dollars using the Consumer Price Index). This is almost identical 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). Tables 1 and 2 also show that food stamp recipients are significantly more likely to be obese than non-recipients. Specifically, 26.2 % (28.6 %) of eligible male (female) recipients are obese compared to 15.6 % (19.2 %) of non-recipients.

I next illustrate how BMI changes over time for these cohorts by plotting BMI for each year in which the NLSY79 collects weight information included in the analysis. Presented in figure 1 for income-eligible males and females combined, BMI increases over time from 23.8 in 1985 to 28.4 in 2000. When examining the genders separately, BMI is initially higher for males than females (in 1985), but this switches by 1993. For example, in 2000, eligible female BMI is a little over one index point higher than that for eligible males. Perhaps it is surprising that male BMI is ever higher than female BMI because NHANES data shows the opposite, but this appears to be a characteristic unique to the NLSY79 cohort also found by others (Cawley 2004).

Presented in figure 1 is also BMI for food stamp recipients and BMI for non-recipients. For males and females combined, BMI is higher for food stamp recipients than non-recipients. This differential also tends to grow over time. For example, recipients' BMI is initially 0.20 higher than non-recipients, but this differential grows to over 2.5 in 2000. When examined separately, this is also true for females but less so for males.

I next present a corresponding figure for the growth in the prevalence of obesity. Shown in figure 2 for eligible males and females combined, the prevalence of obesity increases over time. This increase is from 9.5 % in 1985 to 34.8 % in 2000. The prevalence of obesity is higher for females than males in every year except 1985. Figure 2 also presents the prevalence of obesity for food stamp recipients and non-recipients. As was the case with BMI, obesity is more prevalent for food stamp recipients. For example, recipients are about a percentage point more likely to be obese initially, and this gap grows to almost 20 percentage points by 2000. The recipient-non-recipient obesity differential is again typically larger for females when examined separately than males and grows over time for both genders.

The descriptive statistics and correlations presented thus far do not necessarily represent the causal effects of the Food Stamp Program on obesity. Next, I use multivariate regression analysis to estimate the relationship between food stamps and obesity holding various potentially confounding factors constant. First, I control for demographic characteristics such as race/ethnicity, age, education, marital status, household composition (number of biological children, household size), urban residence, household income, whether the respondent is employed, weeks worked during the past twelve months, occupation (with a set of occupation dummy variables), region of residence (with region dummy variables), and survey year of response (with a dummy variable for each year covered by the survey). I also control for local (county or SMSA) economic conditions because economic conditions may affect participation in public assistance programs. Specifically, I control for 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.[7]

Weighted descriptive statistics and definitions for these and other variables are presented in table 1 for eligible males and in table 2 for eligible females. For example, 27.1 % (33.1 %) of my sample of eligible males (females) is African-American and 8.7 % (7.3 %) is Hispanic. Descriptive statistics are also provided separately for food stamp recipients and non-recipients. Of note, both male and female recipients have significantly less education, significantly larger families (with more children), and are significantly less likely to be employed (and work fewer weeks). Eligible male recipients are more likely to be married but eligible female recipients are less likely to be married. Household income does not significantly differ, although this may not be surprising since everyone in the sample is income-eligible.

3. Empirical Methods

I use multivariate regression analysis to estimate the relationship between food stamps and the probability of being obese.[8] However, some (Jolliffe 2004) have argued that this measure places unnecessary importance on the BMI threshold of 30 or more. Perhaps moving from a BMI of 29 to 30 is not substantially worse than moving from a BMI of 30 to 31; however, 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. The dichotomous obesity indicator is also sensitive to measurement error around the obesity threshold. Therefore, I estimate an additional set of regressions modeling obesity using an "obesity gap" measure. In particular, the obesity gap, adopted from the poverty-measurement literature (Jolliffe 2004), is defined as the percentage by which BMI exceeds the obesity threshold:

$$\text{Obesity Gap} = I(BMI_i \geq 30)[(BMI_i - 30)/30],$$

where BMI_i is respondent i's BMI and I is an indicator variable that equals one if the respondent is obese and zero otherwise. Across the population, this is the probability of being obese multiplied by the average percentage by which those obese exceed the obesity threshold. The obesity gap measure is designed to identify the depth of the obesity problem by capturing changes in the distribution of the obese, which is potentially important because policymakers may not care if BMI increases from 23 to 24, but they may be concerned if it increases from 32 to 33. Shown in table 1, the obesity gap averages 2.815 for income-eligible males and 4.627 for income-eligible females, and the obesity gap is significantly higher for food stamp recipients regardless of gender.

I use OLS regressions to model the probability of being obese and the obesity gap. I use a linear probability specification to model the probability of being obese because corresponding coefficients are easier to interpret. Another advantage is that when estimating individual-specific fixed effects models (described later), the linear probability specification includes respondents with no variation in the outcome variable (obesity) across NLSY79 surveys, while fixed effects logit models would not include respondents who are either never obese or always obese during the survey period. The key variables are a measure of weight such as obesity or the obesity gap (W) and food stamp benefits (FSB). Formally, I estimate

$$W_{it} = \beta_0 + \beta_1\mathbf{X}_{it} + \beta_2 FSB_{it} + \beta_3 W_{it-1} + \boldsymbol{\beta_4 FSB_{it-1}} + \boldsymbol{\upsilon}_i + \varepsilon_{Wit}$$

for respondent i at time t, where $\mathbf{X}$ is a vector of covariates, $\boldsymbol{\upsilon}_i$ is a vector of unobserved individual-specific fixed effects, and ε_W is the error term. In this model (and in all others that use multiple person-year observations from the same respondent), I adjust my standard errors to account for respondent-specific correlation because respondents potentially provide multiple weight observations (across multiple NLSY79 surveys).

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 general, if food stamp benefits are correlated with any unobserved characteristic that is also correlated with obesity, then OLS regressions will not identify the causal effects of food stamp benefits on obesity, producing unobserved heterogeneity bias.

In an attempt to control for potential unobserved heterogeneity bias, I follow Gibson (2003) by estimating individual-specific fixed effects models that compare multiple person-year observations from the same respondent (i.e., I include the fixed effects, υ_i, in the model). If the 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. My fixed effects model specifications essentially compare respondent-specific variation in food stamp receipt over time with variation in the probability of being obese and the obesity gap. Of course, if the respondent's unobserved component is not constant over time, then the estimates may still be biased. Closely related, I also re-estimate the OLS models with a lagged measure of weight (BMI from a preceding interview, W_{it-1}) included. Estimating the change in weight is also designed to control for time-invariant individual-specific unobserved characteristics.

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.[9] Thus, I next examine the lagged effects of food stamp benefits (with a vector of covariates, $\mathbf{FSB}_{i,t-1}$, measuring food stamp benefits from prior years). Examining the effects of food stamps 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.

In a related set of models, I instead estimate the effects of patterns of past food stamp receipt using the classification system proposed by Murphy and Harrell (1992). In particular, I divide those who have received food stamps at some point over the 24 months preceding the interview into four mutually exclusive and exhaustive groups (the reference category is not receiving food stamps over the last two years). Those who receive benefits during only one spell are 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 receive benefits during multiple spells are assigned to a separate category. Of the male (female) food stamp recipients in my sample, about 35 % (16 %) receive benefits short-term, 25 % (17 %) medium-term, and 21 % (53 %) long-term, with 19 % (14 %) experiencing multiple spells.

In a final model specification, I estimate a hazard model for becoming obese (conditional on not yet being obese) to show the cumulative effects of food stamp benefits over time. Specifically, this model 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. In particular, I follow Meyer, who recommends a semi-parametric approach where time is represented by a vector of time-varying dummy variables. 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.

4. Results

Contemporaneous Results

First, I estimate the effects of whether the respondent received food stamp benefits (a dichotomous variable) during the 12 months preceding the survey date (referred to hereafter as contemporaneous receipt) on the probability of being obese and the obesity gap separately for income-eligible males and income-eligible females in unweighted OLS regressions.[10] Model 1 in table 3 presents the effect of receiving food stamps on obesity and model 4 presents that effect on the obesity gap. (A representative set of results for the other non-food stamp covariates is presented in appendix tables.) OLS results for income-eligible females suggest that receiving food stamps significantly increases obesity (model 1) and the obesity gap (model 4) at the 1 % level. For example, the point estimates predict that switching from not receiving food stamps to receiving these benefits will increase obesity by 8.2 percentage points and the obesity gap by 2.257 index points. However, food stamp benefits do not significantly affect male obesity or the male obesity gap.

Next, I re-estimate the models using the individual-specific fixed effects specification. Model 2 presents the effect of food stamps on obesity and model 5 presents that effect on the obesity gap. The effect of food stamps on the probability of being obese for income-eligible males remains statistically insignificant. Somewhat differently, food stamps now significantly increase the obesity gap for males at the 10 % level. For income-eligible females, positive effects of food stamps on obesity and the obesity gap are now 32.9 and 42.3 % the size of those in corresponding OLS specifications. Switching from not receiving food stamps to receiving these benefits increases obesity by roughly 2.7 probability points in model 2; the same change increases the obesity gap by 0.955 index points in model 5. In addition, the effects of food stamps on females continue to be statistically significant, now at the 10 % level in the obesity model and at the 5 % level in the obesity gap model. In sum, this suggests that OLS estimates for females are biased upward. Indeed, Hausman tests for females reject the null hypothesis that the results are not statistically different in the obesity (obesity gap) model with an F-statistic of 10.59 (5.35) and a p-value of 0.001 (0.020). This null hypothesis cannot be rejected for income-eligible males in either obesity model at conventional levels.

In another attempt to control for time-invariant unobserved individual-specific characteristics, I next re-estimate the obesity and obesity gap OLS models including a lagged measure of weight (BMI from the preceding interview) as a covariate.[11] Essentially, when including lagged weight, the regression attempts to explain the change in weight between NLSY79 surveys. Results, presented as obesity model 3 and obesity gap model 6 in table 3, also show that the positive effects of food stamps in the original OLS models are at least somewhat attenuated when controlling for time-invariant unobserved heterogeneity. In particular, the positive effects of food stamps on obesity and the obesity gap for income-eligible females with lagged weight included are between 40 and 50 % the size of those effects when lagged weight is excluded (with, for example, a food stamp coefficient of 0.040 instead of 0.082 in the female obesity model). Furthermore, Hausman tests for females indicate that the effects of food stamps with lagged weight included are statistically smaller than OLS effects with lagged weight excluded (rejecting the null hypothesis of no statistical difference at the 5 % level in both female obesity models). For males, food stamps continue to have a statistically insignificant effect on the prevalence of obesity, and the point estimate for food stamps in the obesity gap model is smaller when controlling for lagged weight, although it is statistically significant now at the 10 % level. Regardless, Hausman tests for males are unable to reject the null hypothesis that OLS food stamp results with and without lagged weight are not statistically different.

Initial results indicate that food stamps significantly increase both obesity measures for income-eligible females, with some evidence that food stamps have a marginally significant positive effect on the obesity gap (but not on the probability of being obese) for income-eligible males. Results in table 3 also indicate that, if anything, OLS results overestimate the positive effects of food stamps on the measures of weight. For brevity, and because controlling for time-invariant unobserved characteristics appreciably affects the food stamp estimates, I present results only from the fixed effects specification in successive models.

Additional Contemporaneous Specifications

To explore the extent to which sample selection criteria affect the results, I next present basic fixed effects model results using samples of *(i)* all NLSY79 respondents, *(ii)* respondents with income less than 200% of the poverty line, *(iii)* respondents who are approximated to be income and asset eligible, *(iv)* respondents who have ever been in poverty, *(v)* respondents whose average income is in the bottom average-income quartile, and *(iv)* respondents who have ever received food stamps.[12] In sum, the results do not change substantively in most cases with sample selection criteria. Hausman tests are only able to reject the null hypothesis that the food stamp results using the income-eligible sample and an alternative sample are not statistically different at the 5 % level in one instance. Perhaps this suggests the estimates are not biased due to sample selection. Conversely, since the food stamp estimates are similar across the samples, perhaps this instead simply indicates that significant food stamp effects are obtained from those with much lower incomes even when using larger, more inclusive samples.

Examining each alternative sample in turn, the positive effect of food stamps on all NLSY79 females is unchanged in obesity model 1 and is smaller in obesity gap model 7, and these effects are now statistically significant at the 1 % level. Receiving food stamps continues to increase female obesity by 2.7 percentage points, and the effect of food stamps on the obesity gap is a bit over half the size when using all females. The effects of food stamps on obesity and the obesity gap for males, however, continue to be statistically insignificant. Regardless, Hausman tests are unable to reject the null hypothesis that the food stamp effects using all NLSY79 respondents are not statistically different from the effects using the income-eligible respondents.

In obesity model 2 and obesity gap model 8, I use a sample of respondents with income less than 200 % of the poverty line. For females, the effects of food stamps are largely unchanged, with, for example, receipt increasing the prevalence of obesity by 2.9 percentage points compared to 2.7 percentage points when income less than 130 % of the poverty line is used as a selection criterion. The food stamp coefficient in the obesity gap model for females (0.799) is 83 % the size of that coefficient when using the income-eligible sample. While the effects of food stamps in both obesity models for females are statistically significant at the 1 % level, the effects of food stamps for males remain statistically insignificant. Not surprisingly, results using the broader income-selection criteria are not statistically different than corresponding results using only those who are income-eligible for food stamps.

I next re-estimate the models including only income- and asset-eligible respondents.[13] In model 9, food stamps significantly increase the obesity gap by 1.387 index points at the 1 % level for females, which is about 45 % larger than the positive effect of food stamps on the female obesity gap using the income-eligible sample. Food stamps also now significantly increase the obesity gap for income- and asset-eligible males at the 10 % level. However, the food stamp coefficient in obesity model 3 for income- and asset-eligible females is somewhat smaller than that with the income-eligible sample (0.018 versus 0.027), and the effect with the further-restricted eligibility sample is not statistically significant at conventional levels. Hausman tests indicate that the point estimate on the food stamp covariate in the male obesity gap model (model 9) is significantly larger than that when using income-eligible males, but the food stamp point estimate in the obesity model for males (model 3) is not. In neither of the cross-model comparisons using females are the food stamp effects statistically different.

I next examine respondents who have ever been in poverty. Food stamps increase the prevalence of obesity for these females by 2.5 percentage points (model 4), which is 95 % the size of that effect when using the income-eligible sample, and food stamps increase the female obesity gap (model 10) by 0.533 index points, which is an effect about 55 % as large. As with the income- and asset-eligible sample, food stamps now significantly increase the male obesity gap at the 10 % level, but effects on the male obesity prevalence remain statistically insignificant. Hausman tests cannot reject the null hypothesis that the food stamp results are not statistically different at the 5 % level between models using the ever-in-poverty sample and the income-eligible sample.

Obesity model 5 and obesity gap model 11 examine the effects of food stamps using those with average income in the bottom average-income quartile. Food stamps continue to increase the prevalence of obesity and the obesity gap for females, with point estimates 22 % larger and 22 % smaller, respectively, than those in models using income-eligible females. Both effects are statistically significant at the 5 % level. Food stamp effects are not statistically different from zero for males with average income in the bottom quartile. None of the food stamp effects using this sample are statistically different than those using the income-eligible sample.

Results are largely unchanged when instead expanding the sample to include respondents who have ever received food stamps. Considering this sample, such benefits increase obesity for females by 0.028 percentage points, which is almost exactly the same size as the corresponding effect for income-eligible females. The effect of food stamps on the obesity gap is about 71 % the size for females ever on food stamps as for income-eligible females. Furthermore, food stamps do not have statistically significant effects on obesity or the obesity gap for males who have ever received food stamps, and none of the food stamp effects are statistically different between the income-eligible sample and the sample that has ever received food stamp benefits.

The effects of food stamps remain statistically insignificant for males across most of these models using alternative sample selection criteria. Though the food stamp coefficients for females are smaller when using some alternative samples and larger when using others, they are never statistically different from corresponding coefficients using the original income-eligible. Since changing the sample inclusion criteria does not appreciably change the results, I use the balanced panel of income-eligible respondents in successive models.

Lagged Stamp Benefits Results

To examine the effects of food stamp receipt from prior periods, I estimate three lagged fixed effects specifications. In the first, I include only one-year lagged food stamp benefits (model 1 for obesity and model 4 for the obesity gap in table 5). In the second, I include contemporaneous food stamp benefits and one-year lagged food stamp benefits to see which has a larger effect (model 2 for obesity and model 5 for the obesity gap). Specification 3 adds lagged food stamp benefits from the preceding second and third years (model 3 for obesity and model 6 for the obesity gap).[14]

In lagged specification 1, one-year lagged food stamp receipt significantly increases obesity for income-eligible females at the 10 % level and significantly increases the obesity gap for females at the 5 % level. The effect of one-year lagged food stamps on the obesity gap for males is also positive and is statistically significant at the 1 % level, but this effect on the male prevalence of obesity is not. In specification 2, one-year lagged food stamp receipt continues to increase the obesity gap for income-eligible males, but contemporaneous food stamp receipt does not. Neither affect the probability of being obese for income-eligible males. This remains true of contemporaneous and one-year lagged food stamp receipt for males when two- and three-year lagged benefits are included in specification 3. However, results are less conclusive for income-eligible females. In particular, none of the food stamp covariates have statistically significant effects in specifications 2 or 3.

In some cases, the effects of lagged food stamp receipt are larger than contemporaneous effects. As a specific example, switching from no food stamp receipt to receiving food stamp benefits lagged by one year for income-eligible males increases the obesity gap by 1.419 index points (model 2 in table 5), but the effect of contemporaneously-measured food stamps in that model is considerably smaller, with a coefficient of 0.260. Furthermore, the cumulative effect of food stamp receipt may increase when additional lags are included. For example, for income-eligible females, the effect of one-year lagged food stamp receipt is a 0.916 point increase (with a t-statistic of 2.13) in the obesity gap (model 4 in table 5), the effect of contemporaneous and one-year lagged food stamp receipt combined is a 1.271 point increase (with a t-statistic of 3.25 for the statistical significance of the joint effect) in the obesity gap (model 5 in table 5), and the effect of contemporaneous, one-year lagged, and two-and three-year lagged food stamp receipt combined is a 1.680 point increase (with a t-statistic of 2.71 for the statistical significance of the cumulative effect) in the obesity gap (model 6 in table 5).

Patterns of Food Stamp Receipt

I next examine the effects of patterns of past food stamp receipt. Presented in table 6, results using the fixed effects model specification indicate that long-term food stamp receipt significantly increases obesity and the obesity gap for income-eligible females at the 5 % level. For example, long-term female recipients are predicted to be 4.8 percentage points more likely to be obese than their non-recipient counterparts. In addition, long-term receipt is predicted to increase the obesity gap by 2.000 index points. Long-term food stamp receipt does not have a statistically significant effect on the prevalence of obesity for income-eligible males, but it does significantly increase the male obesity gap. Short-term and medium-term food stamp receipt do not tend to have statistically significant effects on obesity and the obesity gap for income-eligible males or females, as is true for receiving food stamps during multiple spells at the 5 % level. In sum, these results suggests that long-term food stamp receipt has detrimental effects on obesity and the obesity gap and that receiving such benefits short-term and intermittently may not adversely affect these measures of weight.

Hazard Rate Results

In a final set of dynamic model specifications, I estimate hazard rates that separately use contemporaneous food stamp receipt, lagged food stamp receipt, and the various patterns of food stamp receipt (long-term receipt, medium-term, etc.). In addition, I explore the effects of interacting these food stamp covariates with duration dummy variables, allowing such benefits to have a different effect in each period (year), as opposed to constraining food stamps to have a proportional effect across all years. I ultimately choose only to present results that interact food stamp receipt with the duration variables because these specifications are the most flexible and they are broadly similar to specifications without the duration-food stamp interaction terms. Also for brevity, I only present results from models that include contemporaneous food stamp receipt or the patterns of food stamp receipt described above.

F-statistics for tests of the joint significance of the food stamp benefit covariates tend to indicate that food stamps significantly increase the hazard for becoming obese for income-eligible females but not for males.[15] Rather than present coefficient point estimates, to illustrate the magnitudes of the food stamp effects, I plot predicted survivor rates for the probability of not yet being obese first without food stamp receipt and then with food stamp receipt in each year (though a full set of coefficient estimates is available upon request). These two sets of simulations are presented in figures 3 (using contemporaneous food stamp receipt) and 4 (for patterns of food stamp receipt – long-term receipt, in particular) for income-eligible males and in figures 5 (using contemporaneous food stamp receipt) and 6 (for long-term food stamp receipt) for income-eligible females.

Figure 3 for income-eligible males suggests that receiving food stamp benefits contemporaneously over the 15-year period has little effect on the survivor rate until perhaps the last couple of years when, if anything, food stamp receipt increases the probability of not yet being obese. The effect of receiving food stamp benefits long-term in figure 4 is negative, ultimately decreasing the probability of not yet being obese by year-2000 by about 10 percentage points. For income-eligible females, contemporaneous food stamp receipt over the 15-year period decreases the probability of not yet being obese by about 18 percentage points (figure 5), and long-term food stamp receipt decreases this probability by around 22 percentage points (figure 6). These figures indicate that the cumulative effects of food stamps received over a 15-year period are potentially relatively large.

5. Conclusions

The Food Stamp Program effectively supplies food to eligible recipients at no (or reduced) cost, potentially increasing caloric intake. 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. Perhaps as a consequence, descriptive statistics from the eligible NLSY79 cohort show that Food Stamp Program participation and obesity are correlated: 28.1 % of those (eligible males and females combined) on food stamps are obese compared to 17.5 % of non-recipients. Regression models controlling for a spate of observable characteristics essentially enable me to compare individuals who are alike in observable ways (the same gender, race/ethnicity, education, income, etc.) except food stamp receipt. In these models for income-eligible females, significant positive effects on both the probability of being obese and the obesity gap suggest that food stamps increase weight both for females around the BMI-30 threshold and for females who are already obese (Jolliffe 2004). However, controlling for potential unobserved heterogeneity bias reduces the sizes of these positive effects, with, for example, switching from no food stamp receipt to receiving food stamps contemporaneously increasing the probability of being obese for income-eligible females by 2.7 percentage points. This result is obtained using an individual-specific fixed effects model to control for time-invariant unobserved heterogeneity, and results are largely robust to sample selection criteria.

The dynamic models show positive effects of food stamp benefits that are larger than those found in models identifying contemporaneous effects for females. In some cases, cumulative positive effects of food stamps become successively larger with the inclusion of additional lagged food stamp covariate terms. Similarly, receiving food stamps long-term increases obesity by almost 5.0 percentage points for income-eligible females, but receiving assistance from the Food Stamp Program for a more limited period does not. This indicates that temporary food stamp assistance does not adversely affect weight, but chronic food stamp receipt may promote lifestyle changes that lead to weight gain. Indeed, over a 15-year period, the hazard models suggest that long-term food stamp receipt significantly decreases the probability of not yet being obese roughly 20 percentage points for females.

Positive food stamp effects on the probability of being obese for income-eligible females but not for income-eligible males may be due to biological factors (for example, women give birth, men and women tend to store fat differently, and men typically consume more calories and therefore are less likely to receive more food stamps than they need) or to non-biological factors (e.g., society's perceptions of overweight for men and women may differ). Another explanation is that female food stamp recipients have individual characteristics that are systematically different than male recipients. For example, female recipients are more likely to be black and to have more children. However, perhaps more importantly, females are substantially more likely to be long-term recipients than males, with over 50 % of income-eligible female recipients receiving food stamps long-term. Just the opposite, income-eligible males are more likely to be short-term recipients than to receive benefits medium-term or long-term. Therefore, gender-specific food stamp receipt may partially proxy for duration of receipt.

The size of my contemporaneously-measured effect of food stamp receipt on obesity with the fixed effects specification (for example, a 2.7 percentage-point increase would change a 20 % prevalence of obesity by 13.5 %) is somewhat larger than that found by Gibson (2003) and Meyerhoefer and Pylypchuk (2008), who predict that food stamp receipt increases the prevalence of obesity by 9.1 % and 6.7 %. My dynamic models also reveal that food stamp receipt potentially has larger effects. For example, if receiving food stamps long-term increases the probability of being obese by 5 percentage points, then this increases the prevalence of obesity by 25 %. These dynamic models also show that *(i)* short-term and medium-term food stamp receipt do not significantly increase obesity and *(ii)* long-term food stamp receipt does not significantly increase the probability of being obese for males. Gibson's effects were also 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 contemporaneous fixed effects estimates, assume food stamps increase the probability of being obese by 2.7 %. This suggests that 143,000 additional Americans became obese due to food stamps (2.7 % of 5.3 million = 143,000) between these periods. This would account for less than half of one % (0.35 %) of the 41.2 million increase in obese American adults (143,000/41.2 million = 0.0035). Had this approximated contribution to obesity by the Food Stamp Program not been made, the prevalence of obesity would be roughly 32.1 % rather than 32.2 % (after subtracting 143,000 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 Food Stamp Program 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 Food Stamp Program 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, only a minority of recipients receive benefits long-term (for at least two years, much less for 15 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.

Even in the absurd case where food stamps cause all current recipients to become obese, the Food Stamp Program 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 by the Food Stamp Program 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 Food Stamp Program from 62.1 million obese American adults). Even in this admittedly-outrageous example, the contribution of the Food Stamp Program to obesity would be minor. Certainly other factors appear to have played a substantially larger role increasing obesity: Chou et al. (2004) suggest that the increase in the number of restaurants per capita explains roughly two-thirds of the increase in obesity; alternatively, Lakdawalla and Philipson (2002) suggest that the declining strenuousness of work explains about that amount (about 60 %) of the increase in obesity.

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Endnotes

[1] For example, Wilde and Nord (2005) find that food stamps have a positive impact on food insecurity, even when controlling for individual-specific fixed effects. However, Yen, Andrews, Chen, and Eastwood (2008) find that food stamps reduce food insecurity, Gundersen and Oliveira (2001) find no significant relationship when controlling for adverse selection into the Food Stamp Program, and Gundersen and Kreider (2008) conclude that it is not clear food stamps and food insecurity are positively associated in the presence of reporting errors.

[2] While food insecurity is often found to be positively associated with weight and obesity for adults (Townsend et al., 2001; Gibson, 2003), a couple of recent studies examining children and adolescents have found either no relationship (Bhargava, Jolliffe, and Howard 2008; Gundersen et al. 2008) or an inverse relationship (Rose and Bodor 2006).

[3] Other 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 et al. 1999).

[4] Following NLSY79 recommendations (Center for Human Resource Research 1999), I do not use sampling weights in successive models. Instead, I include covariates to control for characteristics of the over-samples (e.g., dummy variables for race/ethnicity).

[5] However, results using uncorrected measures of weight and height are similar.

[6] Food Stamp Program participation also may be misreported, with empirical evidence indicating that errors of omission are substantially more prevalent than errors of commission (Bollinger and David 1997; Bitler, Currie, and Scholz 2003). While I do not address misreporting empirically, others (Bollinger and David 1997, 2001, 2005) have shown that survey respondents seem to be

predisposed to provide either accurate or inaccurate food stamp information and that reporting errors are less likely to be due to difficulty recalling whether participation occurred in a specific month.

[7] Ziliak, Gundersen, and Figlio (2003) show that the portion of people eligible for food stamps who participate in the program is influenced by economic conditions.

[8] I also estimate the models for underweight and overweight (instead of obesity). Underweight is defined by the CDC as a BMI less than 18.5 and overweight is a BMI of 25 to 30 (CDC 2006b). Food stamps never have statistically significant effects on the probability of being underweight for eligible males or eligible females. The effects of food stamps on the probability of being overweight are statistically insignificant in most instances for eligible males. However, results for overweight are quite different for eligible females. The effects of food stamps on the probability of being overweight but not obese are marginally significant and negative in some cases, but the effects of such benefits on the probability of being overweight inclusive of obesity are often significant and positive.

[9] However, contemporaneously-measured food stamp covariate can have an impact in the regression analysis because it measures food stamp participation over the year preceding the survey date.

[10] Results using other specifications for food stamp benefits (for example, using a continuous measure of the amount of food stamp benefits received during the past year and including both the dummy variable for receiving food stamp benefits and the continuous dollar amount received) produce substantively similar results.

[11] When including a lagged measure of weight as a covariate, I control for the length of time in weeks between interview observations.

[12] This follows Gundersen and Ziliak's (2003, 2008) approach to explore the effects of sample selection criteria.

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[13] To be eligible for food stamp benefits, a household must 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. The NLSY79 collects the information needed to identify the value of assets and vehicle values in the 1985 through 2000 surveys. In particular, in these survey years, the NLSY79 collects information on 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. Unfortunately, the NLSY79 does not collect any asset information prior to the 1985 survey or in the 2002 survey, which explains why person-year observations from the 2002 survey wave, which does collect weight information, are not included in the analysis.

[14] I explore the effects of including additional lags (from earlier years), but the results are similar to those reported.

[15] Specifically, F-tests for the significance of contemporaneous food stamp receipt and long-term food stamp receipt cannot reject the null hypothesis of no effect for eligible males, with F-statistics (p-values) of 1.43 (0.154) and 1.42 (0.157), respectively. However, for eligible females, corresponding F-statistics (p-values) are 1.73 (0.069) and 2.14 (0.015), respectively.

Table 1: Descriptive Statistics for Eligible Males

Dependent Variables	**Eligible Males**		**Recipients**	**Non-Recipients**
Body Mass Index (BMI=Weight/(Height^2))	25.952	(0.274)	26.972	25.687*
Prevalence of Obesity (BMI = 30+)	0.178	(0.019)	0.262	0.156**
Obesity Gap (I(BMI$_i$ ≥ 30)[(BMI$_i$ – 30)/30])	2.815	(0.389)	4.847	2.287**
Key Explanatory Variables				
Received Food Stamps (=1 if received benefits)	0.206	(0.016)	-	-
Food Stamp Amount (1000s in 2005 dollars)[a]	1.947	(0.125)	-	-
Demographic Characteristics				
Black (=1 if black)	0.271	(0.034)	0.275	0.270
Hispanic (=1 if Hispanic)	0.087	(0.016)	0.106	0.082
Age (in years)	29.915	(0.211)	30.576	29.743
Education (in years)	12.050	(0.135)	11.176	12.278***
Marital Status (=1 if married)	0.310	(0.024)	0.518	0.256***
Children (number of biological children)	1.187	(0.068)	1.676	1.060***
Family Size (number in household)	3.260	(0.088)	3.693	3.147***
Urban (=1 if residence in urban area)	0.717	(0.032)	0.660	0.731
Household Income ($10,000s in 2005 dollars)	1.605	(0.043)	1.673	1.587
Employed (=1 if employed during year)	0.737	(0.016)	0.658	0.757**
Weeks Worked (=weeks worked during year/52)	0.515	(0.018)	0.430	0.537**
Health (=1 if health limits ability to work)	0.090	(0.011)	0.105	0.086
Manager (=1 if occupation is in management)	0.064	(0.008)	0.027	0.074***
Sales (=1 if occupation is in sales)	0.096	(0.009)	0.037	0.111***
Service (=1 if occupation is in service)	0.122	(0.011)	0.139	0.117
Farming (=1 if occupation is farming)	0.062	(0.009)	0.061	0.063
Mechanic (=1 if occupation is in mechanics)	0.149	(0.012)	0.136	0.152
Labor (=1 if occupation is a laborer)	0.215	(0.016)	0.208	0.216
Economic Conditions Variables				
Local Unemployment Rate (%)	0.070	(0.002)	0.078	0.068***
Local Per Capita Income ($1000s in 2005 dollars)	22.335	(0.332)	21.408	22.577*
Portion of Local Labor Force Female (%)	0.414	(0.003)	0.405	0.416
Local Population High-School Educated (%)	0.661	(0.010)	0.630	0.669**
Local Population College-Educated (%)	0.156	(0.004)	0.140	0.160**
Local Population Employed (%)	0.424	(0.005)	0.408	0.428**
Local Labor Force in Manufacturing (%)	0.190	(0.007)	0.196	0.189
Local Labor Force in Wholesale/Retail Trade (%)	0.187	(0.002)	0.181	0.188*

Sample means with standard errors in parentheses. There are 1,991 income-eligible male person-year observations. [a] Excludes zero values (non-recipients). * indicates whether the recipient and non-recipient sample means are statistically different at the 10 % level, ** at the 5 % level, and *** at the 1 % level.

Table 2: Descriptive Statistics for Eligible Females

Dependent Variables	**Eligible Females**		**Recipients**	**Non-Recipients**
Body Mass Index (BMI=Weight/(Height^2))	26.116	(0.257)	27.022	25.324***
Prevalence of Obesity (BMI = 30+)	0.236	(0.014)	0.286	0.192***
Obesity Gap (I(BMI$_i$ ≥ 30)[(BMI$_i$ – 30)/30])	4.627	(0.453)	5.964	3.459***
Key Explanatory Variables				
Received Food Stamps (=1 if received benefits)	0.466	(0.018)		
Food Stamp Amount (1000s in 2005 dollars)[a]	2.925	(0.076)		
Demographic Characteristics				
Black (=1 if black)	0.331	(0.036)	0.435	0.241***
Hispanic (=1 if Hispanic)	0.073	(0.012)	0.089	0.059
Age (in years)	30.661	(0.140)	30.712	30.616
Education (in years)	11.853	(0.091)	11.365	12.280***
Marital Status (=1 if married)	0.199	(0.016)	0.173	0.222*
Children (number of biological children)	1.962	(0.054)	2.427	1.556***
Family Size (number in household)	3.604	(0.052)	3.804	3.430***
Urban (=1 if residence in urban area)	0.718	(0.027)	0.699	0.736
Household Income ($10,000s in 2005 dollars)	1.616	(0.031)	1.622	1.611
Employed (=1 if employed during year)	0.620	(0.015)	0.466	0.755***
Weeks Worked (=weeks worked during year/52)	0.403	(0.012)	0.266	0.522***
Health (=1 if health limits ability to work)	0.070	(0.007)	0.084	0.057**
Manager (=1 if occupation is in management)	0.067	(0.007)	0.017	0.110***
Sales (=1 if occupation is in sales)	0.187	(0.011)	0.128	0.238***
Service (=1 if occupation is in service)	0.220	(0.013)	0.185	0.250***
Farming (=1 if occupation is farming)	0.014	(0.003)	0.016	0.012
Mechanic (=1 if occupation is in mechanics)	0.026	(0.005)	0.020	0.030
Labor (=1 if occupation is a laborer)	0.074	(0.007)	0.063	0.084
Economic Conditions Variables				
Local Unemployment Rate (%)	0.070	(0.002)	0.073	0.067**
Local Per Capita Income ($1000s in 2005 dollars)	22.350	(0.323)	21.746	22.878**
Portion of Local Labor Force Female (%)	0.414	(0.003)	0.412	0.415
Local Population High-School Educated (%)	0.661	(0.008)	0.644	0.675**
Local Population College-Educated (%)	0.154	(0.004)	0.146	0.161***
Local Population Employed (%)	0.421	(0.004)	0.411	0.429***
Local Labor Force in Manufacturing (%)	0.188	(0.007)	0.192	0.185
Local Labor Force in Wholesale/Retail Trade (%)	0.187	(0.002)	0.184	0.188

Sample means with standard errors in parentheses. There are 3,306 income-eligible female person-year observations. [a] Excludes zero values (non-recipients). * indicates whether the recipient and non-recipient sample means are statistically different at the 10 % level, ** at the 5 % level, and *** at the 1 % level.

Table 3: The Effects of Food Stamp Benefits on the Probability of being Obese and the Obesity Gap: OLS and Fixed Effects Models

Income-Eligible Males		**Probability of Being Obese**	
	Model 1	Model 2	Model 3
Food Stamps	0.030	-0.006	-0.010
	(0.030)	(0.020)	(0.018)
		Obesity Gap	
	Model 4	Model 5	Model 6
Food Stamps	1.404	0.783*	1.078*
	(1.111)	(0.480)	(0.640)
Person-Year Observations	1,991	1,991	1,987
Income-Eligible Females		**Probability of Being Obese**	
	Model 1	Model 2	Model 3
Food Stamps	0.082***	0.027*	0.040**
	(0.023)	(0.016)	(0.016)
		Obesity Gap	
	Model 4	Model 5	Model 6
Food Stamps	2.257***	0.955**	0.971***
	(0.705)	(0.426)	(0.454)
Person-Year Observations	3,306	3,306	2,837
Specification	OLS	Fixed Effects	OLS
Lagged Weight	No	No	Yes

Coefficient estimates with standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. The models include individual demographic, economic, region dummy, and year dummy variables.

Table 4: The Effects of Food Stamp Benefits on the Probability of being Obese and the Obesity Gap: Alternative Samples

Males				**Probability of Being Obese**		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Food Stamps	-0.001	-0.010	-0.014	0.001	0.003	-0.003
	(0.011)	(0.013)	(0.021)	(0.011)	(0.016)	(0.012)
				Obesity Gap		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Food Stamps	0.242	0.321	1.060*	0.328*	0.414	0.331
	(0.195)	(0.271)	(0.491)	(0.224)	(0.376)	(0.266)
Person-Year Observations	19,367	5,273	1,838	9,074	2,589	3,429
Females				**Probability of Being Obese**		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Food Stamps	0.027***	0.029***	0.018	0.025***	0.033***	0.028***
	(0.008)	(0.011)	(0.018)	(0.009)	(0.012)	(0.010)
				Obesity Gap		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Food Stamps	0.520***	0.799***	1.387***	0.533**	0.745**	0.687***
	(0.192)	(0.263)	(0.506)	(0.216)	(0.325)	(0.253)
Person-Year Observations	17,678	6,643	2,704	10,149	4,303	5,946
Sample	All Respondents	Income 200% of Poverty	Income and Asset Eligible	Ever in Poverty	Bottom Income Quartile	Ever Received Food Stamps

Coefficient estimates with standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. The models are individual-specific fixed effects specifications that include individual demographic, economic, region dummy, and year dummy variables. Model 1 includes all NLSY79 respondents from the balanced panel. Model 2 includes those whose income is less than 200 % of the poverty line.

Model 3 includes those who are approximated to be income and asset eligible. Model 4 includes those ever in poverty. Model 5 includes those whose average income is in the bottom income quartile. Model 6 includes those who have ever received food stamps.

Table 5: The Effects of Lagged Food Stamp Benefits on the Probability of being Obese and the Obesity Gap

Income-Eligible Males		**Probability of Being Obese**	
	Model 1	Model 2	Model 3
Contemporaneous	-	-0.001	-0.001
	-	(0.021)	(0.021)
One-Year Lag	-0.015	-0.014	-0.015
	(0.021)	(0.022)	(0.023)
Two/Three-Year Lags	-	-	0.003
	-	-	(0.020)
		Obesity Gap	
	Model 4	Model 5	Model 6
Contemporaneous	-	0.260	0.266
	-	(0.519)	(0.519)
One-Year Lag	1.525***	1.419***	1.341**
	(0.502)	(0.545)	(0.554)
Two/Three-Year Lags	-	-	0.367
	-	-	(0.477)
Income-Eligible Females		**Probability of Being Obese**	
	Model 1	Model 2	Model 3
Contemporaneous	-	0.018	0.018
	-	(0.018)	(0.018)
One-Year Lag	0.026*	0.017	0.014
	(0.016)	(0.018)	(0.019)
Two/Three-Year Lags	-	-	0.008
			(0.017)
		Obesity Gap	
	Model 4	Model 5	Model 6
Contemporaneous	-	0.678	0.669
	-	(0.483)	(0.483)
One-Year Lag	0.916**	0.593	0.427
	(0.430)	(0.488)	(0.505)
Two/Three-Year Lags	-	-	0.584
	-	-	(0.459)

Coefficient estimates with standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. The models are individual-specific fixed effects specifications that include individual demographic, economic, region dummy, and year dummy variables. The models include 1,991 income-eligible male person-year observations and 3,306 income-eligible female person-year observations. All model specifications are linear probability models.

Table 6: The Effects of Food Stamp Benefit Patterns of Receipt on the Probability of being Obese and the Obesity Gap

	Income-Eligible Males		Income-Eligible Females	
	Probability of Being Obese	**Obesity Gap**	**Probability of Being Obese**	**Obesity Gap**
Food Stamps	Model 1	Model 2	Model 1	Model 2
Short-Term	-0.022	-0.031	-0.001	0.271
	(0.025)	(0.600)	(0.022)	(0.596)
Medium-Term	-0.006	1.164*	0.019	0.413
	(0.029)	(0.695)	(0.023)	(0.614)
Long-Term	-0.017	3.253***	0.048**	2.000***
	(0.035)	(0.830)	(0.021)	(0.570)
Multiple Spells	-0.062*	-0.654	0.026	0.538
	(0.033)	(0.796)	(0.025)	(0.672)

Coefficient estimates with standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. The models are individual-specific fixed effects specifications that include individual demographic, economic, region dummy, and year dummy variables. The models include 1,991 income-eligible male person-year observations and 3,306 income-eligible female person-year observations. All model specifications are linear probability models.

Figure 1

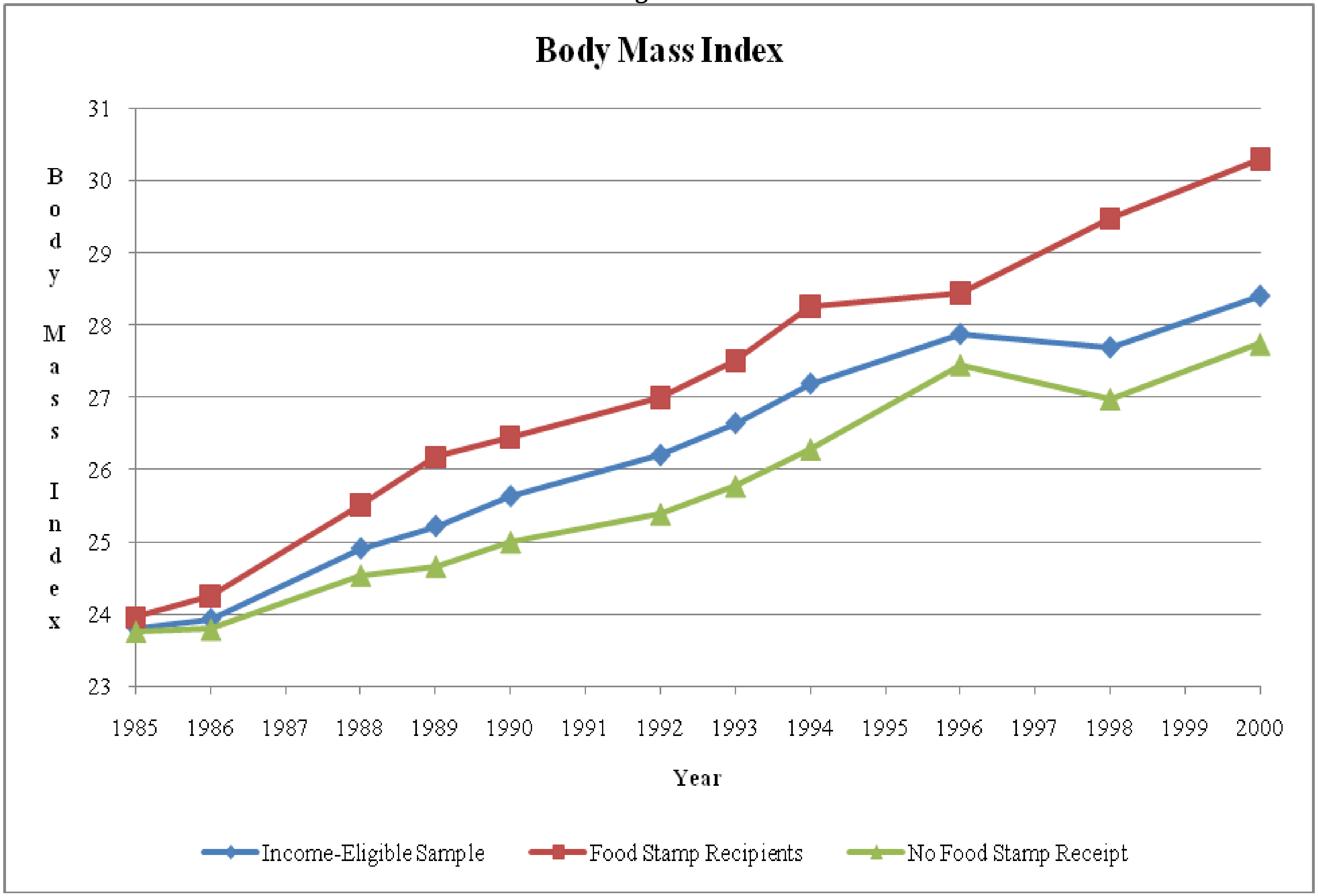
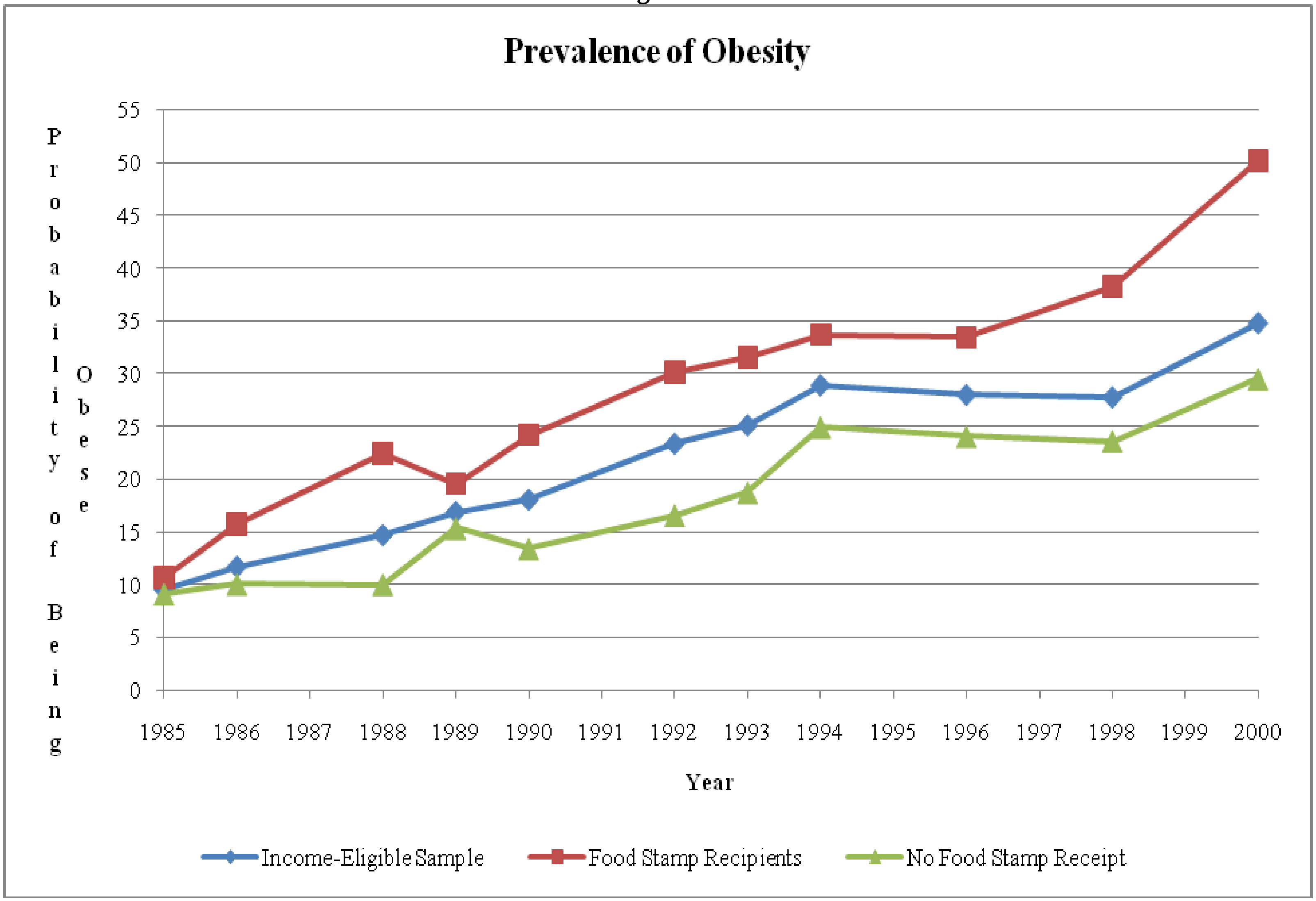

Body Mass Index
Body Mass Index
31
30
29
28
27
26
25
24
23
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
Year
Income-Eligible Sample
Food Stamp Recipients
No Food Stamp Receipt

Figure 2



Prevalence of Obesity
Probability of Being Obese
55
50
45
40
35
30
25
20
15
10
5
0
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
Year
Income-Eligible Sample
Food Stamp Recipients
No Food Stamp Receipt

Figure 3

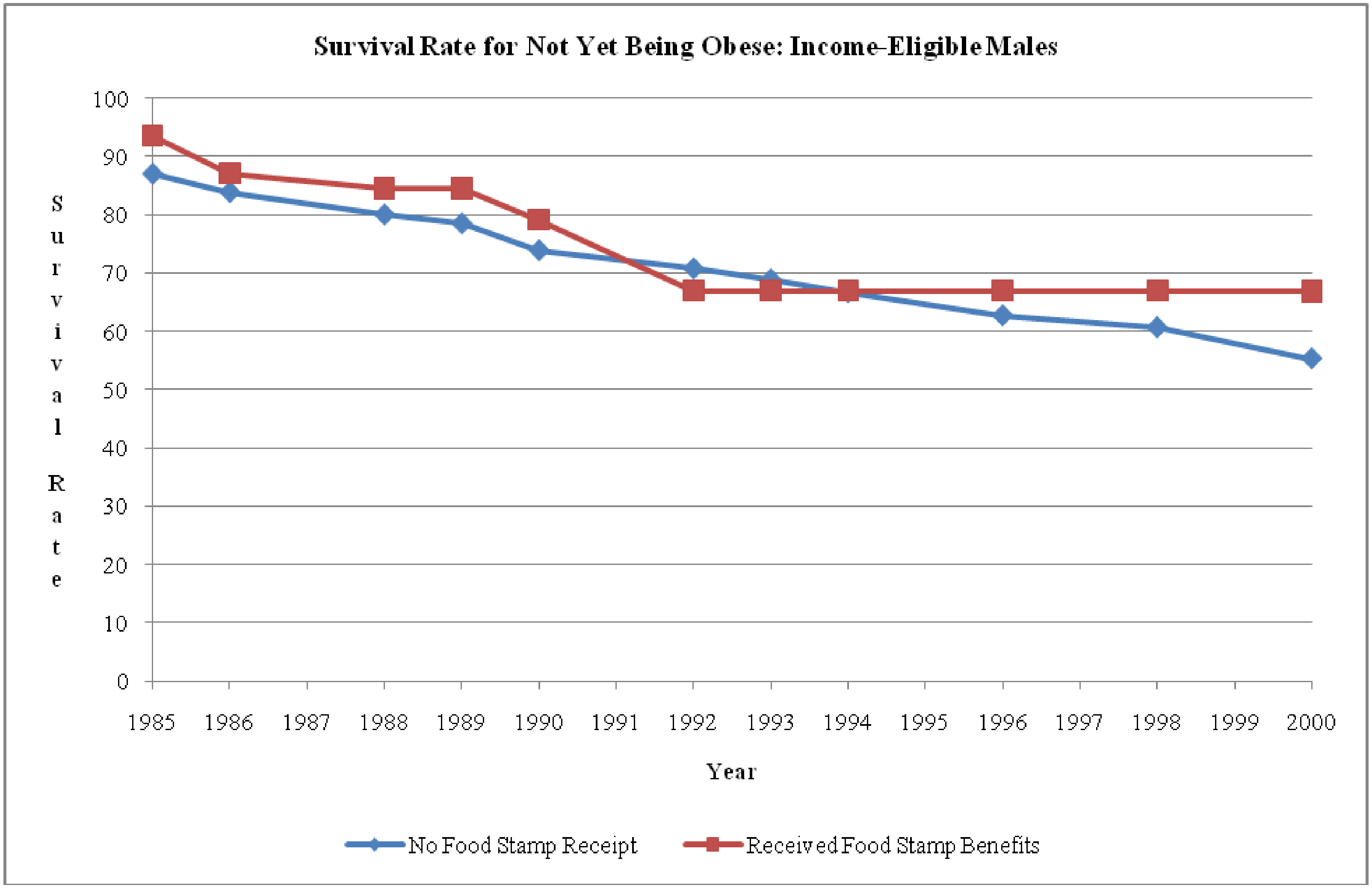

Survival Rate for Not Yet Being Obese: Income-Eligible Males
100
90
80
70
60
50
40
30
20
10
0
Survival Rate
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
Year
No Food Stamp Receipt
Received Food Stamp Benefits

Figure 4

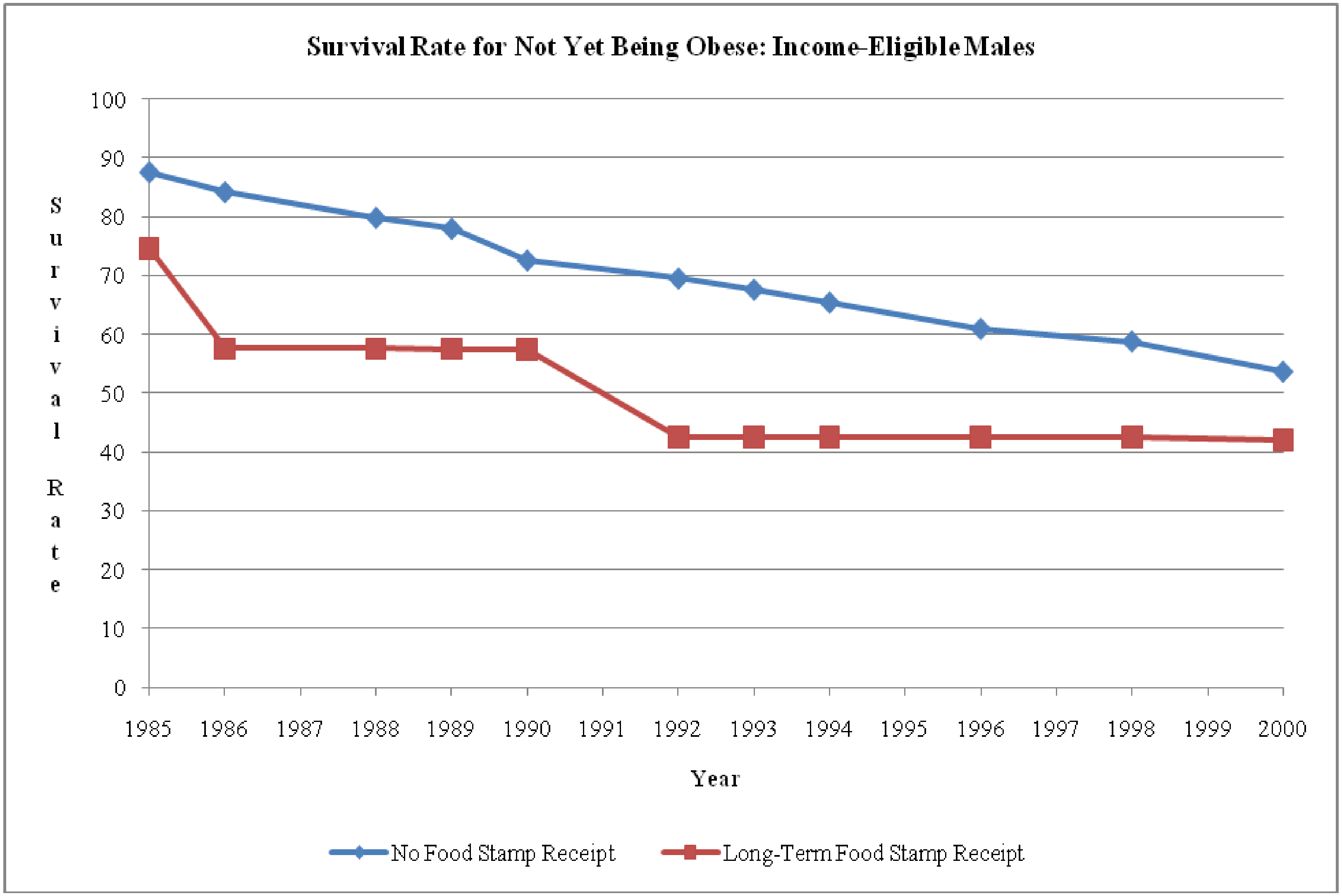

Survival Rate for Not Yet Being Obese: Income-Eligible Males
100
90
80
70
60
50
40
30
20
10
0
Survival Rate
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
Year
No Food Stamp Receipt
Long-Term Food Stamp Receipt

Figure 5

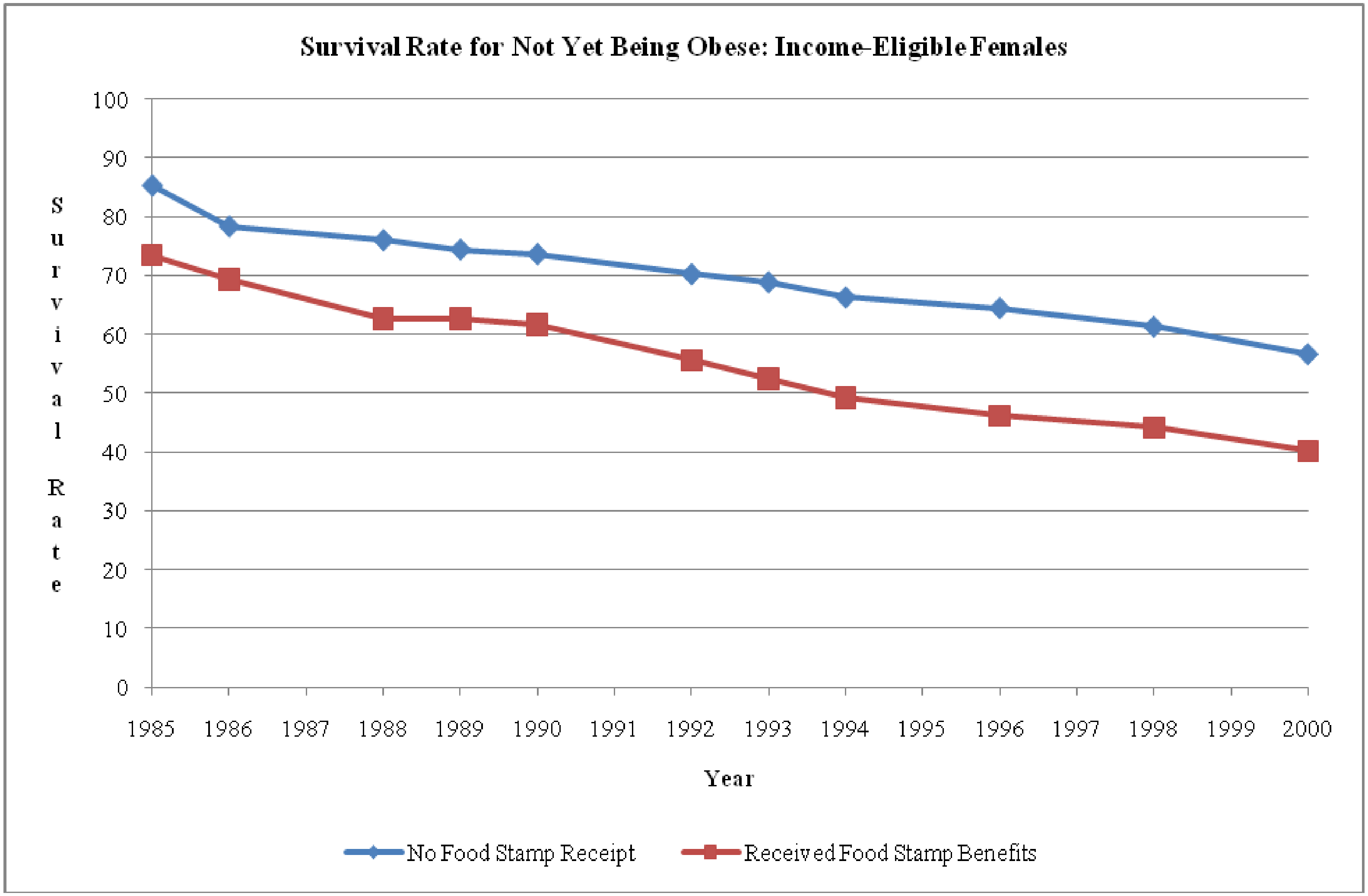
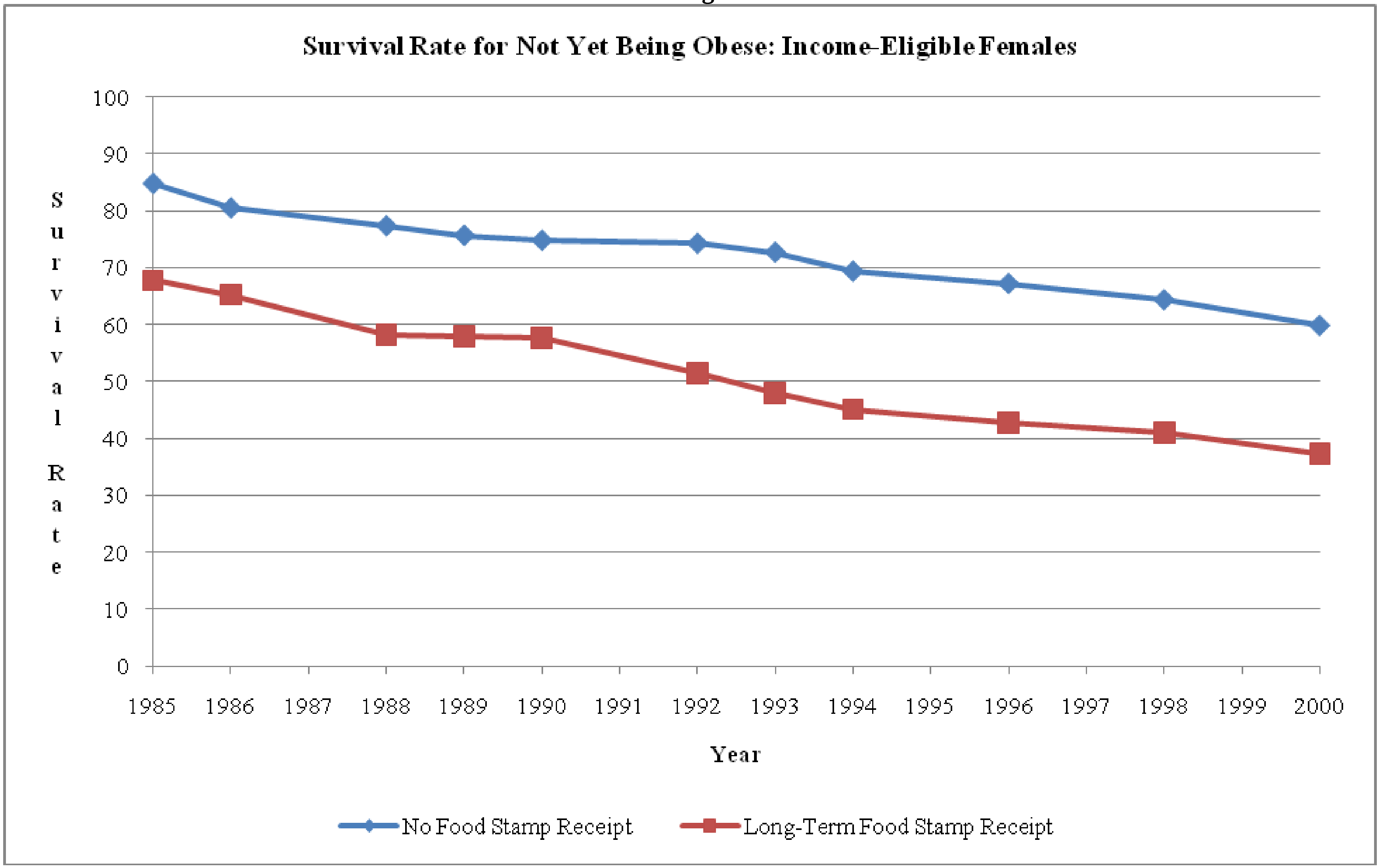

Survival Rate for Not Yet Being Obese: Income-Eligible Females
Survival Rate
100
90
80
70
60
50
40
30
20
10
0
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
Year
No Food Stamp Receipt
Received Food Stamp Benefits

Figure 6


Survival Rate for Not Yet Being Obese: Income-Eligible Females
Survival Rate
100
90
80
70
60
50
40
30
20
10
0
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
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1997
1998
1999
2000
Year
No Food Stamp Receipt
Long-Term Food Stamp Receipt

Appendix Table A1: The Effects of Selected Other Covariates on the Probability of being Obese and the Obesity Gap: Income-Eligible Males

Covariates	Probability of Being Obese		Obesity Gap	
Black	-0.036	(0.036)	-0.366	(0.789)
Hispanic	0.131**	(0.052)	5.831***	(2.186)
Age	0.012***	(0.003)	0.197	(0.139)
Education	0.011*	(0.007)	0.287	(0.233)
Marital Status	0.068*	(0.035)	1.798*	(1.031)
Children	0.019	(0.012)	0.779*	(0.426)
Family Size	0.009	(0.006)	0.250*	(0.149)
Urban	0.014	(0.034)	0.346	(1.006)
Household Income	0.000	(0.001)	0.000	(0.028)
Employed	-0.061	(0.049)	-1.946*	(1.101)
Weeks Worked	-0.003	(0.038)	-1.503	(1.100)
Health	-0.036	(0.033)	1.057	(1.176)
Manager	-0.045	(0.064)	0.717	(1.532)
Sales	0.012	(0.057)	1.873	(1.407)
Service	0.001	(0.053)	1.042	(1.095)
Farming	-0.011	(0.063)	0.390	(1.613)
Mechanic	-0.034	(0.053)	0.480	(1.121)
Labor	-0.014	(0.051)	0.050	(0.840)
Local Unemployment Rate	-0.437	(0.538)	-32.573*	(19.465)
Local Per Capita Income	0.005	(0.004)	0.224*	(0.137)
Portion of Local Labor Force Female	-0.972***	(0.370)	-22.076***	(7.959)
Local Population High-School Educated	-0.178	(0.258)	-2.339	(9.273)
Local Population College-Educated	-0.044	(0.454)	-4.860	(15.276)
Local Population Employed	-0.084	(0.382)	-14.788	(12.485)
Local Labor Force in Manufacturing	0.062	(0.206)	6.924	(4.864)
Local Labor Force in Wholesale/Retail Trade	0.124	(0.584)	10.102	(14.934)

Coefficient estimates with standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. Results are from obesity model 1 and obesity gap model 4 in table 3. The models also include region dummy and year dummy variables. All model specifications are linear probability models. There are 1,991 income-eligible male person-year observations.

Appendix Table A2: The Effects of Selected Other Covariates on the Probability of being Obese and the Obesity Gap: Income-Eligible Females

Covariates	Probability of Being Obese		Obesity Gap	
Black	0.098***	(0.035)	2.354***	(1.280)
Hispanic	0.044	(0.045)	1.006	(1.544)
Age	0.018***	(0.003)	0.462***	(0.108)
Education	-0.009	(0.008)	-0.131	(0.265)
Marital Status	-0.003	(0.032)	-0.625	(0.898)
Children	-0.016	(0.012)	-0.787	(0.500)
Family Size	0.011	(0.008)	0.200	(0.255)
Urban	-0.041	(0.036)	-2.077*	(1.261)
Household Income	0.000	(0.001)	0.020	(0.025)
Employed	-0.029	(0.044)	-0.167	(1.626)
Weeks Worked	-0.021	(0.036)	-1.622	(1.227)
Health	0.081**	(0.037)	2.505**	(1.168)
Manager	0.026	(0.056)	1.341	(1.858)
Sales	-0.016	(0.047)	-0.989	(1.642)
Service	0.028	(0.045)	0.303	(1.636)
Farming	-0.125*	(0.067)	-3.867**	(1.647)
Mechanic	0.084	(0.076)	-0.780	(1.986)
Labor	-0.001	(0.054)	0.200	(2.160)
Local Unemployment Rate	-0.501	(0.537)	-11.301	(20.293)
Local Per Capita Income	-0.003	(0.004)	-0.152	(0.174)
Portion of Local Labor Force Female	-0.574	(0.436)	-8.902	(18.472)
Local Population High-School Educated	-0.233	(0.265)	-11.348	(9.893)
Local Population College-Educated	0.449	(0.479)	21.910	(18.894)
Local Population Employed	0.182	(0.404)	8.326	(15.108)
Local Labor Force in Manufacturing	0.034	(0.232)	-0.666	(10.870)
Local Labor Force in Wholesale/Retail Trade	0.407	(0.692)	19.470	(23.495)

Coefficient estimates with standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. Results are from obesity model 1 and obesity gap model 4 in table 3. The models also include region dummy and year dummy variables. All model specifications are linear probability models. There are 3,306 income-eligible female person-year observations.