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Women's Increasing Wage Penalties from Being Overweight and Obese

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Women's Increasing Wage Penalties from Being Overweight and Obese*

by

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Abstract

This paper first utilizes annual surveys between the 1981 and 2000 waves of the National Longitudinal Survey of Youth to estimate the effect of being overweight on hourly wages. Previous studies have shown that white women are the only race-gender group for which weight has a statistically significant effect on wages. This paper finds a statistically significant continual increase in the wage penalty for overweight and obese white women followed throughout two decades. A supporting analysis from a cross-sectional dataset, comprised of the 1987 National Medical Expenditure Survey and the 2000 and 2004 waves of the Medical Expenditure Panel Survey, also shows an increasing wage penalty. The bias against weight has increased, despite drastic increases in the rate of obesity in the United States. Alternatively, the increasing rarity of thinness has led to its rising premium.

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I. Introduction

Obesity has become a serious public health concern in the United States. Besides the obvious personal health consequences associated with being overweight, there are costs to society in terms of increased medical expenditures and loss of productivity. Like race and gender, weight is another factor that leads to discrimination. Rebecca Puhl of the Rudd Center for Food Policy and Obesity at Yale University states, "The stigma of obesity has actually worsened in the past 40 years with the increase in prevalence of obesity. The bias [has become] more socially acceptable.[1]" Although almost everyone has more contact with the stigmatized group, the stigma is growing along with the national waistline.

Obesity is a relevant issue in labor economics. A large body of economic literature explores how race and gender have impacted wages of women and minorities throughout the history of the United States. In a similar vein, our culture promotes and rewards thinness and beauty, providing consequences for being overweight. Since the rate of obesity has increased dramatically in the United States, researchers have studied the economic consequences of weight for at least 15 years. Studies have shown statistically significant penalties from weight on wages. This paper explores how the wage penalty from weight has changed between 1981 and 2004. We might expect a declining penalty due to the increase in the percentage of overweight individuals. On the other hand, increasing awareness of and bias against weight may have increased the penalty over time.

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[1] Personal Interview. Tatiana Andreyeva, Rudd Center for Food Policy and Obesity, Yale University, November 2006.

Body Mass Index (BMI) is a measure of a person's body weight, scaled according to height. Defined as weight (kg) divided by the square of height $(m)^2$, it has been criticized for its inability to distinguish between muscle and fat. Regardless, researchers use this measure of body mass to determine weight status. A BMI reading over 25 classifies the person as overweight, and a reading over 30 signifies obesity. A reading over 40 classifies the person as morbidly obese. More than 64 percent of American adults were overweight or obese in the 1999-2000 National Health and Nutrition Survey (NHANES) (Flegal, 2002). This represents a 36 percent increase from NHANES II (1976-1980), when the rate was 47 percent. Approximately 59 million adults, or 31 percent, were considered obese in 2000, having increased from 15 percent in the earlier NHANES sample.

The effect of obesity on wages is of specific interest to economists. Obesity is a discriminatory factor in hiring and promotions. The growing literature already shows a statistically significant penalty from higher weight on wages. Since the rate of obesity has increased in the United States, it is important to understand not only the level of the wage penalty, but also how the penalty has changed. While the population of "normal" weight people has declined, the awareness and stigma of weight seem to have increased. This paper utilizes econometric models to show how the wage penalty has changed throughout twenty years of data. Section II includes a review of economic literature. Section III discusses datasets. Section IV explains econometric models, analysis, and results. Section V concludes, with suggestions for further research on the changing mechanisms through which weight has affected wage levels.

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[2] Equivalently, it is calculated as 703*weight (lb) / height^2 (in).

II. Literature Review

The economics literature studying the economic effects of being overweight or obese has grown over the past 15 years. One primary issue is whether or not, and the extent to which, increasing weight affects wages. Register and Williams (1990) study the effect of obesity on wage rates with a sample of roughly 8000 men and women between the ages of 18 and 25, from the 1982 round of the National Longitudinal Survey of Youth (NLSY). Controlling for the link between physical appearance and occupational choice, their results show a significant 12 percent penalty for obese women, but no significant penalty for obese men. The authors note the need to repeat the analysis for an older sample, since many 18- to 25- year old individuals are in school, and therefore have highly variable wages.

Loh (1993) continues this research with analyses of wage levels of full-time workers in the 1982 NLSY and wage changes between 1982 and 1985. He finds no significant effects in 1982 for either males or females. However, wages grew roughly 5 percent less between the two rounds for obese men and women. Concerns remained regarding the endogeneity of weight. Weight may very well be correlated with unobserved factors in the error term of the wage equation, causing bias. For instance, wage model covariates do not include a measure of the rate of time discount. If obese individuals discount future outcomes more steeply, they are less likely to invest in health and human capital since the current value of future outcomes is smaller. If there is less investment in human capital, wages are lower (Burkhauser, 2004).

Averett and Korenman (1996) use a sample of respondents ages 23 to 31 (5090 women, 4951 men) from the 1988 wave of the NLSY to study the effects of BMI on income, marital status, and hourly pay differentials. To control for the endogeneity of weight, Averett and Korenman utilize 1981 BMI in their first model. They show a statistically significant 15 percent penalty on hourly wages for women with a BMI greater than or equal to 30. Using 1988 BMI, they find a 10 percent penalty on wages. For men, there is an 8 percent penalty using 1981 BMI, and a 3 percent penalty using 1988 BMI. The primary discrimination, however, results from the marriage market, as both the probability of being married and spouse's earnings account for a large portion of the difference in economic status. Further, the authors estimate models including an interaction between obesity in 1981 and 1988. Women who became obese between 1981 and 1988 seem to be no worse off than women of recommended weight, while those who were obese at younger ages face significant wage penalties.

Pagan and Davila (1997) estimate cross-sectional wage models similar to those of Averett and Korenman, using 1989 NLSY data. First, the authors run a multinominal logit model to compare the occupational distribution of the obese and the non-obese, separated by gender. They find that obese men choose jobs where they have a productivity advantage over the non-obese, or where they receive a premium for undertaking risks. Men face low barriers when moving across occupations, and are more likely to work in repair, transportation, and manufacturing industries. The authors then utilize an instrumental variables (IV) approach, first regressing BMI on exogenous variables (health limitations, "self esteem" dummy variables, family poverty level in 1988, education, experience, race, ethnic group, marital status, school enrollment, region, and occupation). They find that the net effect of obesity on the earnings of men is slightly positive. Larger women, confined to low-level service sector and clerical occupations, face wage penalties of at least 10 percent. The set of instruments are, however, directly related to the dependent variable. Furthermore, health limitations and "self esteem" variables could be related to the rate of time discount, found in the error term of the wage equation.

Since the literature up to this point shows significant wage penalties for larger women, questions appeared regarding the mechanisms through which weight affects wages. Discrimination could be based upon stereotypes of larger people, specifically that they lack self-discipline, and are lazy, less conscientious, and slower. Further, employers might be paying lower wages due to the higher costs of insuring obese and overweight individuals. A few papers, with conflicting results, address this possibility. Baum and Ford (2004) explore the mechanisms by which obese workers earn lower wages, proposing several possibilities, using data from the 12 years between 1981 through 1998 NLSY rounds in which weight and height were requested.

Individual models estimate a statistically significant 6 percent wage penalty from obesity for women, and a 3 percent penalty for men. Individual difference models estimate a 2.3 percent penalty for women, and a 0.7 percent penalty for men. By including a term interacting obesity and health insurance dummy variables, they show that there is actually less of a wage penalty when employers provide health insurance. In the individual difference models, obese men obtain a 4.7 percent increase in their pay, while women obtain a 2.7 percent increase. Finally, they show that workers in customer-oriented occupations earn less, but do not face a larger wage penalty for being obese.

Bhattacharya and Bundorf (2005) estimate a model in which they compare the wage penalty for obesity using two separate cohorts, those with health insurance and those without health insurance. Using 1989-1999 NLSY data, they provide evidence that the obese pay for higher expected medical expenditures through lower wages, contrary to the findings of Baum and Ford (2004). The authors show that obese people with health coverage were paid $1.70 per hour less than the insured non-obese throughout the entire period. The difference in wages between non-insured obese and non-obese people was only $0.40. Therefore, the insured obese indirectly pay for higher expected medical expenditures through lower wages. While the results contrast with those of Baum and Ford (2004), note that these authors did not take unobserved heterogeneity and endogeneity of weight into account when specifying their models. Further, neither Baum and Ford nor Bhattacharya and Bundorf explore the effect of being overweight, but not obese, on wages.

Cawley (2004) utilizes 1981-2000 NLSY data from the years in which weight and height are included. He obtains estimates of true weight and height in the NLSY data by utilizing coefficients reported in NHANES III, which includes self-reported numbers and actual values taken from physical examinations. Separately by race-gender groups, actual weight is regressed on reported weight and its square. Judging by the high R-squared of .995, reported weight and its square are strong predictors of actual weight. The same process was repeated for height, leading to similarly significant results. In NHANES III, self reported height and weight of NLSY-aged white females result in underestimated BMI by an average of 1.58 percent, while male calculated BMI is underestimated by an average of 1.0 percent. Finally, self-reports of both weight and height in the NLSY are multiplied by the coefficients reported in NHANES III according to race-gender group. In his wage models, Cawley finds statistically significant results for women, though substantially less for black and Hispanic women. For white women, the coefficient on BMI is -0.008, and the coefficient on weight in pounds is -0.0014. For a two standard deviation increase in weight (64 lbs.), white women are paid 9 percent less. Black men seem to receive higher wages with higher weight, and Hispanic men incur a wage penalty.

Due to the endogeneity of weight, Cawley turns to IV, attempting to find a set of instruments that are correlated with BMI, but uncorrelated with the error term in the wage equation. The first instrument discussed is sibling BMI, which is highly correlated with respondent BMI. Further, he assumes that sibling BMI is uncorrelated with the respondent's wage residual. To control for the age and gender of the sibling, the author also includes these variables in the set of instruments. The instruments are good predictors of a woman's weight. For white females, the first stage regression shows a t-statistic of 23.47. However, it is impossible to prove that sibling BMI is uncorrelated with the residual in the wage equation. The respondent's rate of time discount is included in the residual. If this rate of discount is influenced by the family, then the sibling's BMI is also correlated with it. This paper will focus on associations between BMI and wages, rather than causal effects, due to the difficulty involved in determining an appropriate instrument.

Results show that BMI and weight in pounds have statistically significant effects on wages at the 5 percent level for white females only. The coefficient on BMI is -0.0017, and the coefficient on weight in pounds is -0.0028. These coefficients are, in absolute value, twice as large as those found in the earlier OLS models. Here, a two standard deviation increase in weight is associated with an 18 percent decline in wages. White and

Hispanic males' BMI has an effect on wages significant at the 9 percent level. Results for all other race-gender groups are insignificant, including black and Hispanic females. Averett and Korenman (1999) explain that increased weight has a stronger negative impact on the self-esteem of white females.

Although researchers have reported the negative effect of weight on wages, few have examined how the effect changes over time. As a continually increasing proportion of the population becomes classified as overweight, the question arises. Since significant effects are found mostly for white females, this paper's focus is on the changing penalty from weight on wages for that group. Surveys do not have sufficient observations on non-whites to find such differences. Our conclusions will be specific to white female observations in our datasets.

III. Data

This paper utilizes two datasets, one panel and one cross-sectional, to explore the changing penalty from weight on wages. The panel dataset allows year-by-year comparisons among a cohort of women who are in their youth at the beginning of the sample. The cross-sectional dataset captures a broader representation of society, since each year of data contains a much wider age range than the panel. Further, this dataset is uncomplicated by group composition effects. In the panel, the cohort of women who grow older could have characteristics specific to their group that affect wages.

III.I National Longitudinal Survey of Youth

The first dataset utilized in this paper is taken from the National Longitudinal Survey of Youth (NLSY), as cleaned and specified by Cawley (2004). This panel survey, conducted by the U.S. Department of Labor, Bureau of Labor Statistics, began with annual interviews of 12,686 young males and females in 1979. Since 1994, interviews have been conducted every other year. The NLSY simplifies race categories into three groups, black, Hispanic, and non-black/non-Hispanic (referred to as white in the literature). The NLSY includes self-reported weight in 13 years included in our sample, 1981, 1982, 1985, 1986, 1988, 1989, 1990, 1992, 1993, 1994, 1996, 1998, and 2000. Height was reported in 1981, 1982, and 1985; height in 1985 is used in our models. The dataset includes pooled data from these 13 years, spanning two decades.

As described above in Literature Review, self-reports of weight and height are adjusted according to race-gender specific coefficients determined by regression in the NHANES III. Females who are pregnant when they report weight are dropped from the sample. Wages for all years are adjusted to 1990 dollars according to the CPI – All Urban Consumers series. Outliers in the wage variable are recoded such that the wage range is $1 to $500, since the dependent variable is the natural log wage.

OLS models with white females rely on 25,843 observations ranging from ages 16 to 43. Models are estimated on the sample of working women. Figure 1 shows the dramatic increases in rates of being overweight and obese in white females from 1981 to 2000. See Table 1 for summary statistics.

III.II National Medical Expenditure Survey / Medical Expenditure Panel Survey

The second dataset utilized in this paper is a pooled cross-sectional dataset made of the 1987 National Medical Expenditure Survey (NMES) and the 2000 and 2004 waves of the Medical Expenditure Panel Survey (MEPS). The NMES, conducted by the United States Department of Health and Human Services (Agency for Health Care Policy and Research), is a three-part national survey of the U.S. population. It includes questions on health care services utilized, demographic variables, and personal health characteristics. Data is made available for member institutions of the Interuniversity Consortium for Political and Social Research (ICPSR) at the University of Michigan. The Household Survey includes 38,846 individuals; 30,038 of these individuals are also included in the Health Status Questionnaire and Access to Care Supplement. The Household Survey contains all variables utilized in analysis here, with the exception of body height and weight, found in the health supplement.

Efforts to publish data on medical expenditures were continued with the Medical Expenditure Panel Survey (MEPS), which began in 1996. The MEPS, conducted by the United States Department of Health & Human Services (Agency for Healthcare Research and Quality), is a set of large-scale surveys of families and individuals, their medical providers, and employers. There are two major components, the Household Component and the Insurance Component. The MEPS has demographic and body characteristics data similar to the NMES. The survey is called a panel because questions are asked of respondents in numerous rounds. However, there is a new set of respondents every two years. This paper utilizes data from the 2000 and 2004 MEPS since the previous MEPS samples do not include measures of weight and height.

Again, self-reports of weight and height are adjusted according to race-gender coefficients determined by regression in the NHANES III, as described above in Literature Review. Wages for all years are adjusted to 2004 dollars according to the CPI – All Urban Consumers series. Outliers in the wage variable are recoded such that the wage range is $1 to $65.63[3]. OLS models with employed white females rely on 11,899

[3] The maximum wage reported in NLSY is $500, whereas the maximum wage reported in MEPS is $65.63.

observations, ranging from ages 16 to 64. See Table 2 for summary statistics of white females in the OLS dataset. Average BMI increases from 24.33 in 1987 to 26.97 in 2000. It further increases to 27.33 in 2004. Similarly, average BMI increases 23.53 in 1998 to 26.80 in 2000 in the NLSY sample.

IV. Econometric Methods and Analysis

IV.I Econometric Model

Based on previous studies of the effects of obesity on wages, this paper focuses on white women. Cawley's results present a convincing case that BMI has statistically significant effects on wages, but for white women only. Studies propose that larger white women have self-esteem problems not experienced by other race-gender groups, which could influence their ability to advocate for higher wages. As seen in Figure 1, the cohort becomes increasingly overweight and obese throughout two decades. Studies have described the effects of race and gender on wages, and how the effects have changed over time. This paper introduces analysis exploring how the effect of weight on wages has changed for white women.

All models utilizing NLSY data have robust standard errors, clustered to account for the fact that the individuals are in the sample more than once. Wages are bottom coded at $1.00 since our dependent variable is the natural log. Further, all models are limited to the sample of working white women who report positive wages. Previous literature has provided evidence that BMI has a negative effect on wages. The probability of being employed could decline with increased BMI because of the disincentive to work that is associated with the lower wages. If this is the case, then we will underestimate the effect of weight on wages; overweight women who are discouraged to work are excluded from our models. The effective wage of these discouraged workers is zero. The goal is to explore how the weight penalty has changed over time. If the effect of BMI on participation has increased or decreased, the disincentive to work could also affect the time trend we seek to capture.

Starting with the baseline model, variations are added to explore the year-by-year changing effect of BMI on the log wage.

$$(1)\ \ln W_{it} = BMI_{it}\,\beta + X_{it}\,\gamma + \varepsilon_{it}$$

The dependent variable is the natural log of the hourly wage. BMI is the body weight status measurement. The set of control variables includes linear measures of age and time. The NLSY includes the age of the woman's youngest child, and the total number of children to whom she has given birth. Additional control variables include general intelligence (derived from ten Armed Services Vocational Aptitude Battery tests), highest grade completed, mother's highest grade completed, father's highest grade completed, years of actual work experience, job tenure, an indicator variable for white collar or blue collar work, current school enrollment, county unemployment rate, a part-time work dummy variable, marital status indicators, region of residence, and finally, dummy variables for missing data associated with each regressor (except weight). The NMES/MEPS includes the total number of children living in the household. Additional control variables include highest grade completed, marital status indicators, and geographic region of residence.

The model described in equation (1) assumes a constant BMI effect over time. In order to capture potential changes in the BMI effect, the following model is estimated.

$$(2)\ \ln W_{it} = BMI_{it}\beta + YRN_t\delta + YRN_t{*}BMI_{it}\lambda + X_{it}\,\gamma + \varepsilon_{it}$$

The variable YRN is defined as Year less 1981 (NLSY) or 1987 (NMES/MEPS). The variable YRN*BMI captures the changing effect of BMI on wages.

Prior to estimating the restrictive model for the NLSY, a more general dummy variable model was attempted. Instead of having the YRN_t*BMI_{it} variable, there was a set of dummy variables for the each of the years (excluding 1981), and a set of terms interacting the year dummy variables with BMI. This model is more general than the restrictive model, since it allows the effect of BMI on the wage to vary completely over time. None of the Year*BMI interaction variables had a statistically significant effect on log wage (results not shown). Additionally, the coefficient on BMI was not significant. Therefore, we return to the results from the more parsimonious model.

IV.II Results from the National Longitudinal Survey of Youth

The coefficient on YRN_t*BMI_{it} is an estimate of the linear trend of the effect of BMI on wages since 1981. Results are in Table 3. The coefficient on BMI is -0.00577, and is significant at the 1 percent level. The coefficient on YRN_t*BMI_{it} is -0.00023, and it is significant at the 10 percent level. This suggests that when holding all other factors constant, the penalty from higher BMI grows throughout two decades of data. First by multiplying the coefficient on YRN_t*B_{it} by the values of YRN_t, we obtain the year-by-year differing penalty from BMI on wage. We add these values to the initial effect, the coefficient on BMI, to obtain the year-by-year penalties from a one-point increase in BMI on log wage.

Comparisons in this paper will be made between the 25th and 75th percentiles for BMI of white women, or roughly one standard deviation. Keeping all other variables constant at their mean values, we will simulate the percentage wage penalty incurred by going from the lower quartile to the upper quartile. Shen (2006) lists the 25th and 75th percentiles for BMI at 21.0 and 28.4, a difference of 7.4 points. For a 5'4" woman (64 in.), these BMI values correspond to weights of 122.36 lbs. and 165.47 lbs. The penalty for being at the 75th percentile, rather than the 25th percentile, grows from 4.29 percent in 1981 to 7.47 percent in 2000 (Figure 2). This analysis shows that the weight penalty almost doubles over a period during which weight stigma increased.

IV.III Results from the National Medical Expenditure Survey / Medical Expenditure Panel Survey

IV.III.I Baseline Model

Section IV.II includes models run on a panel dataset. Results would lead us to think that the wage penalty for being overweight has increased over time due to increased weight stigmatization. However, the first set of analyses involved the same women being followed for twenty years. While the coefficient under examination is that on Year*BMI, and we find significant results, it could be that these effects result from a group composition effect. That is, the panel of women could show an increasing wage penalty due at least partially to the effects of increasing age within the group, and cumulative discrimination over many years. Supporting analyses from a cross-sectional dataset will help determine whether the negative, significant coefficient on BMI*Year is strictly from a group composition effect, or if it is indicative of what has happened in society at large. Therefore, it provides a clearer indication of the average penalty from weight on wage. While 2000 data from the NLSY includes women roughly 40 years of age, the 2000 MEPS data captures the entire age spectrum. Our next step is to utilize the NMES/MEPS data, and see how results compare to the NLSY results. As stated above, this second analysis uses data from 1987, 2000 and 2004.

The coefficient on BMI is -0.00489, and is significant at the 1 percent level (Table 4). The coefficient on YRN_t*BMI_{it} is not significant, suggesting that the effect of BMI on the wage has not changed over time. Averett and Korenman (1996) found that women who became obese between 1981 and 1988 were no worse off than women of recommended weight, while those who were obese at younger ages face significant wage penalties. Unlike that study, we find in the cross-sectional data that all white women face some wage penalty from weight.

IV.III.II Synthetic Cohort Models

The NLSY dataset specified by Cawley begins with respondents between the ages of 16 and 24 in 1981. The NLSY models in this paper study white women's changing wage penalties from being overweight between 1981 and 2000. It is found that penalties increase over time, presumably due to an increase in weight stigmatization. The initial NMES/MEPS results do not show the same significant time trend. However, this dataset, unlike the NLSY, is a cross-section, so it better represents the average population. For instance, the 2000 data includes the entire age spectrum, whereas in NLSY, the youngest respondents in 2000 are 35 (since they were 16 in 1981).

For a further comparison, we can construct a "synthetic cohort," pretending that the NMES/MEPS dataset is a panel. For instance, since 1981 data in NLSY includes ages 16-24, 2000 data includes ages 35-43. In NMES/MEPS, we can use ages 22-30 in 1987 (since this pretend cohort was 16-24 in 1981), and therefore, ages 35-43 in 2000, and 39-47 in 2004. This synthetic cohort will allow us to make comparisons to the results from the NLSY panel data; we can follow the "same" women throughout a seventeen-year period. Besides using the same ages as those in NLSY data, we can also utilize a broader age range. For instance, we can study women under the age of 60 in 2004. Therefore, we use ages 16-42 in 1987, ages 29-55 in 2000, and then ages 33-59 in 2004. By using these synthetic cohorts, we can study the changing effects of being overweight on wages. Further, we can compare our results with NLSY models, and see if they support the idea that the wage penalty has increased for women, or declined as the rate of obesity has increased.

Using the aforementioned equation (1), the first synthetic cohort model follows the NLSY ages. Therefore, 1987 data is restricted to ages 22-30, 2000 data is restricted to ages 35-43, and 2004 data is restricted to ages 39-47. The coefficient on YRN_t*BMI_{it} is insignificant (Table 5). An alternative is to restrict 1987 data to ages 16-24, and therefore, 2000 data is restricted to ages 29-37, and 2004 data is restricted to ages 33-41 (Table 6). The coefficient on BMI is insignificant. The coefficient on YRN_t*BMI_{it} is -0.00055, and it is significant at the 5 percent level. Holding all other factors constant, the penalty from BMI grows throughout two decades of data. By multiplying the coefficient on YRN_t*BMI_{it} by the values of YRN_t, we obtain the year-by-year increase in wage penalty from a one-point increase in BMI. Using the one standard deviation increase in BMI of 7.4 points, the interpretation shows that by 2004, compared to 1987, there is a 7.25 percent larger penalty (Figure 3).

The last synthetic cohort model uses a much wider age range. Although 65 is the typical retirement age in the United States, 2004 observations are restricted to ages less than 60, since ages 60-65 can be considered a pre-retirement period. Therefore, 1987 data contains ages 16-42, 2000 data contains ages 29-55, and 2004 data contains ages 33-59. The coefficient on BMI is -0.00376, and is significant at the 5 percent level (Table

7). The coefficient on YRN_t*B_{it} is -0.00028, and is also significant at the 5 percent level. Holding all other factors constant, the penalty from BMI grows throughout two decades of data. First by multiplying the coefficient on YRN_t*BMI_{it} by the values of YRN_t, we obtain the year-by-year differing penalty from BMI on wage. We add these values to the initial effect, the coefficient on BMI. Our final results are the year-by-year wage penalties from a one standard deviation increase in BMI of 7.4 points (Figure 4). The penalty grows from 2.81 percent in 1987 to 6.29 percent in 2004. This analysis shows that the weight penalty more than doubles as weight stigma increases.

Thus far, the NLSY and NMES/MEPS synthetic cohort models generally show an increasing penalty from BMI on the wage. In the last synthetic cohort model, observations were restricted such that the maximum age in 2004 is 59. As such, we do not obtain the explanatory benefits of a non-restricted dataset. The final model uses an unrestricted dataset, however, dummy variables are created to represent those individuals not in the synthetic cohort. Therefore, the baseline group in this model is the synthetic cohort. By having an unrestricted dataset, but still delineating the differential effects of weight on wages between those in the cohort and those not in the cohort, there is an acknowledgement that the cohort could have unique group composition effects. While the cohort shows an increasing penalty, it could be that those outside of this group have either a declining penalty or no clear penalty at all.

$$(1)\ \ln W_{it} = BMI_{it}\beta + YRN_t\delta + YRN_t*BMI_{it}\lambda + YNG\chi + OLD\varphi + YNG*BMI_{it}\phi + OLD*BMI_{it}\eta + X_{it}\gamma + \varepsilon_{it}$$

The dummy variables YNG and OLD specify whether the individual is younger or older than the synthetic cohort in the year of the observation. The variables $YNG*BMI_{it}$ and $OLD*BMI_{it}$ are interactions between the YNG and OLD dummy variables and BMI.

The coefficient on BMI is -0.00439, and is significant at the 1 percent level (Table 8). The coefficient on YRN_t*B_{it} is -0.00021, and is significant at the 10 percent level. Holding all other factors constant, the penalty from BMI grows throughout two decades of data. Our final results are the year-by-year penalties from a one standard deviation increase in BMI on log wage for those in the synthetic cohort (Figure 5). The penalty grows from 3.26 percent in 1987 to 5.99 percent in 2004. However, careful interpretation also shows an increasing penalty for those individuals who are older and younger than the cohort. This analysis shows an increasing wage penalty beyond a composition effect. This seems to suggest that the average wage penalty in society has increased. Put another way, thinness has an increasing premium.

Simulated hourly wages for the nine series can be found in Figure 6. Average values are used for the control variables. There are three groups, young, cohort, and thin, combined with two body types, a BMI of 21, and a BMI of 28.4. For a height of 5'4", these BMI values correspond to body weights of 122.36 and 165.47, respectively. There are no values for the young group in 1987, since it does not exist in that year (the synthetic cohort includes the youngest age, 16). For each group, there are increasing wage penalties. For the younger group in 2000, a BMI of 28.4 is associated with a slightly higher wage than a BMI of 21. However, in 2004, there is a $0.04 penalty associated with the BMI of 28.4. For the synthetic cohort, the penalty grows from $0.36 in 1987 to $0.64 in 2000, and then to $0.75 in 2004. For the older group, the penalty grows from $0.08 in 1987 to $0.31 in 2000, and then to $0.40 in 2004. In line with NLSY results, the NMES/MEPS models show that weight is associated with an increasing wage penalty over time. Again, this paper does not explore the underlying reasons for the increasing penalty, but rather, proves and acknowledges its significance.

V. Conclusion

The purpose of this paper is to estimate the changing wage penalties for being overweight and obese in the United States since the early 1980s, a period which has seen a dramatic increase in the rate of obesity. Coincidentally, the stigma placed on larger people may have increased. Previous literature has studied the effects of weight on the wage level for either single-year datasets, or data pooled from many years. It is generally found that white women face significant wage penalties from weight, while other race-gender groups face smaller or no effects. Therefore, this paper focuses on white women. After verifying the negative impact of weight on wages, this paper steps forward by studying how the wage penalty from weight has changed.

We might expect that the penalty has declined, because as the population of "normal" weight individuals has declined, there would be less room for discrimination. However, the bias against weight appears to have increased. By utilizing two datasets, with multiple econometric specifications, this paper helps us understand that weight has had consistently increasing penalties on wages. The samples are limited to employed women who report positive wages. Therefore, the estimates do not include the effects of larger women who might have been discouraged from working by the lower wages they would have received.

First, thirteen years of data from the National Longitudinal Survey of Youth are pooled together for an analysis. This dataset follows the same panel of respondents. An OLS model shows that the total penalty from a one standard deviation increase in BMI

(7.4 points) increases from 4.29 percent in 1981 to 7.47 percent in 2000. The wage penalty almost doubles as weight stigma increases.

It is important to remember that the panel data follows the same women for many years. A cross-sectional dataset better captures the societal averages, since each survey year includes a new group of people. The second dataset utilized in this paper is culled from the 1987 National Medical Expenditure Survey, and the 2000 and 2004 waves of the Medical Expenditure Panel Survey. The cross-sectional data captures the average effect over a wider age range. Initial attempts suggest that the weight penalty on wages has not changed over time.

A synthetic cohort model is attempted with data restricted to ages 16-24 in 1987, ages 29-37 in 2000, and ages 33-41 in 2004. This model shows that by 2004, compared to 1987, each one standard deviation increase in BMI is associated with a 7.25 percent larger penalty on the wage. In the last synthetic cohort model, we utilize a wider age range such that the maximum age in 2004 is the pre-early retirement age of 59. Data from 1987 includes ages 16-42, 2000 includes 29-55, and 2004 includes 33-59. Using the OLS model, we find an increasing penalty as we found in NLSY. The wage penalty from a one standard deviation in BMI increases from 2.81 percent in 1987 to 6.29 percent in 2004.

Finally, we utilize a model that has no restrictions on observations, but rather, uses dummy variables to signify observations that are younger and older than the synthetic cohort in the given year. These dummy variables are interacted with BMI. Both the dummy variables and interaction variables are included in the baseline OLS model. Therefore, the synthetic cohort becomes the baseline part of the model. The penalty for a one standard deviation in BMI grows from 3.26 percent in 1987 to 5.99 percent in 2004. Alternatively, the dollar value wage penalty for an observation with a BMI of 28.4, compared to the same observation with a BMI of 21, grows from $0.36 in 1987 to $0.64 in 2000, and then to $0.75 in 2004. Further, the wage penalty grows for individuals who are older and younger than those in the synthetic cohort. We might have explained the NLSY results by saying that they could be partially affected by the composition effect of the group. However, increasing penalties for younger and older observations suggest that the increasing penalty is not simply a composition effect.

The increasing wage penalty corresponds to current psychological research that demonstrates increased weight stigmatization in the United States. Further, as larger women age, their wages incur the effects of years of cumulative discrimination. With other factors controlled, their starting wages are lower. Throughout their working careers, these women receive less frequent raises and promotions. Therefore, we see increasing penalties in both NLSY data and the synthetic cohort constructed from NMES/MEPS data. This paper has shown that an obese 43 year-old woman received a larger wage penalty in 2004 than she received at 20 in 1981. This paper also provides some evidence that an obese 20 year-old woman receives a larger wage penalty today than she would have in 1981 at age 20. Future literature should further explore this aspect of the story, as well as the mechanisms by which the wage disparities occur. It can be concluded that increased body weight has drastic economic consequences that have grown over time. Alternatively, the increasing rarity of thinness has created its growing wage premium.

References

Averett, Susan, and Sanders Korenman. 1996. “The Economic Reality of the Beauty Myth.” *Journal of Human Resources* 31(2):304-30.

Averett, Susan, and Sanders Korenman. 1999. “Black-White Differences in Social and Economic Consequences of Obesity.” *International Journal of Obesity* 23:166-73.

Baum, Charles L. II and William F. Ford. 2004. “The wage effects of obesity: a Longitudinal study.” *Health Economics* 13: 885-89.

Behrman, Jere R., and Mark R. Rosenzweig. 2001. “The Returns to Increasing Body Weight.” Unpublished.

Bhattacharya, Jay and M. Kate Bundorf. April 2005. “The Incidence of the Healthcare Costs of Obesity.” NBER Working Paper No. 11303.

Burkhauser, Richard and John Cawley. 2002. “Obesity, Disability, and Movement onto The Disability Insurance Rolls.” University of Michigan Retirement Research Center Working Paper No. 089.

Cawley, John. 2000. “Body Weight and Women’s Labor Market Outcomes.” NBER Working Paper No. 7841.

Cawley, John. 2004. “The Impact of Obesity of Wages.” *Journal of Human Resources*, 39(2):451-74.

Flegal, KM, et. al. 2002. “Prevalence and trends in obesity among US adults, 1999-2000.” *The Journal of the American Medical Association*, 288(14) (October):1772-3.

Loh, Eng Seng. 1993. “The Economic Effects of Physical Appearance.” *Social Science Quarterly* 74(2):420-38.

Pagan, Jose, and Alberto Davila. 1997. “Obesity, Occupational Attainment, and Earnings.” *Social Science Quarterly* 78:3 (September), 756-70.

Register, Charles A. and Donald R. Williams. 1990. “Wage Effects of Obesity Among Young Workers.” *Social Science Quarterly* 71(1):130-41.

Shen, Wei, et. al. 2006. “Waist Circumference Correlates with Metabolic Syndrome Indicators Better Than Percentage Fat.” *Obesity* 14(4):727-36.

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Log Wage	25845	1.98	0.60	0	6.16
Corrected BMI	25845	24.08	5.37	6.73	88.07
Year*BMI	25845	214.39	162.67	0	1673.28
Year	25845	8.54	5.63	0	19
Corrected Weight	25845	143.32	33.61	42.60	572.13
Year*Weight	25845	1276.57	975.86	0	10870.44
Corrected Height	25845	64.65	2.27	51.03	80.74
Year*Height	25845	552.28	365.03	0	1370.54
Ever born	25845	0.99	1.16	0	10
Young kid	25845	2.58	4.12	0	27
No. Children in Household	25845	0.50	0.50	0	1
White Collar	25845	0.59	0.49	0	1
Missing White Collar	25845	0.09	0.29	0	1
Mother's HGC	25845	11.37	3.31	0	20
Missing Mother's HGC	25845	0.04	0.19	0	1
Father's HGC	25845	11.19	4.47	0	20
Missing Father's HGC	25845	0.07	0.26	0	1
Married, Spouse Present	25845	0.53	0.50	0	1
Married, Other	25845	0.15	0.36	0	1
GCPS1 (Intelligence)	25845	0.09	0.93	-3.88	2.40
Missing GCPS1	25845	0.03	0.17	0	1
HGC	25845	13.14	2.40	0	20
Missing HGC	25845	0.00	0.06	0	1
Enrolled in School	25845	0.13	0.34	0	1
Years of Work Experience	25845	7.24	5.33	0	23.7
Missing Years of Work	25845	0.07	0.25	0	1
Years at Current Job	25845	3.05	3.66	0	23.12
Missing Years at Current Job	25845	0.01	0.10	0	1
Part-time Work Indicator	25845	0.85	0.36	0	1
Missing Part-Time Work	25845	0.04	0.20	0	1
Age	25845	28.54	6.09	16	43
Low Unemployment in County	25845	0.43	0.49	0	1
High Unemployment in County	25845	0.20	0.40	0	1
Missing Unemployment	25845	0.02	0.15	0	1
Northeast	25845	0.19	0.39	0	1
North-Central	25845	0.30	0.46	0	1
South	25845	0.33	0.47	0	1

Table 1: Descriptive Statistics of Variables Used in NLSY Analysis (Pooled Sample)

Definitions: Log Wage: natural log of wage, recoded to $1 to $500. Corrected BMI: BMI adjusted with NHANES III coefficient. Year*BMI: (year-1981)*Corrected BMI interaction variable. Year: (year-1981). Corrected Weight: weight adjusted with NHANES III coefficient. Year*Weight: (year-1981)*Corrected Weight interaction variable. Corrected Height: height adjusted with NHANES III coefficients. Year*Height: (year-1981)*Corrected Height interaction variable. Ever born: number of children ever born. Young kid: age of youngest child. Children Indicator: Dummy variable indicating whether or not there are children. White Collar: Dummy variable indicating job status (white collar, blue collar). Missing White Collar: Dummy variable for observations with missing White Collar value. Mother's HGC: Mother's highest grade completed. Missing Mother's HGC: Dummy variable for observations with missing Mother's HGC value. Father's HGC: Father's highest grade completed. Missing Father's HGC: Dummy variable for observations with missing Father's HGC value. Married, Spouse Present: Indicator – married, spouse present. Married, Other: Indicator for been married, but not with spouse. GPCS1 (Intelligence): General Intelligence. Missing GCPS1: Dummy variable for observations with missing GPCS1. HGC: highest grade completed. Missing HGC: Dummy variable for observations with missing HGC value. Enrolled in School: Dummy variable for school enrollment value. Years of Work Experience: Years of actual work experience. Missing

Years of Work Experience: Dummy variable for observations with missing Years of Work Experience value. Tenure: Years at current job. Missing Tenure: Dummy variable for observations with missing tenure value. Part-Time Work Indicator: Indicator for part-time work (continued on next page).
Missing Part-Time Work Indicator: Dummy variable for observations with missing Part-Time Work Indicator value. Age: Age in years (16-43). Low unemployment in county: Indicator for unemployment under 6% in county. High unemployment in county: Indicator for unemployment greater than or equal to 9% in county. Missing Unemployment: Dummy variable for observations with missing unemployment data. Northeast: Indicator for Northeast region. North-Central: Indicator for North Central region. South: Indicator for South Region. Year Dummy: dummy variables for years 1982-2000. Year Dummy * BMI: Interaction variables for Year Dummy * Corrected BMI.

Table 2: Descriptive Statistics of Variables Used in NMES/MEPS Analysis (Pooled Sample)					
Variable	N	Mean	Std. Dev.	Minimum	Maximum
Log Wage	11899	2.45	0.60	0	4.18
Corrected BMI	11899	26.21	6.38	12.17	195.95
Year*Corrected BMI	11899	270.01	220.60	0	2547.39
Year	11899	9.92	7.51	0	17
Test	11899	0.21	0.41	0	1
Test 2	11899	0.25	0.44	0	1
Test 5	11899	0.66	0.47	0	1
Test 5 Young	11899	0.19	0.39	0	1
Test 5 Old	11899	0.15	0.36	0	1
Test5Young*Corrected BMI	11899	4.89	10.57	0	195.95
Test 5 Old * Corrected BMI	11899	3.99	9.79	0	150.79
Age	11899	38.22	12.26	16	64
HGC	11899	12.96	2.70	0	17
Married, Spouse Present	11899	0.56	0.50	0	1
Married, Other	11899	0.19	0.39	0	1
Midwest	11899	0.24	0.43	0	1
South	11899	0.35	0.48	0	1
West	11899	0.23	0.42	0	1
No. of Children in HH	11899	0.72	1.10	0	11

Definitions: Log Wage: natural log of wage, recoded to $1 to $65.63. Corrected BMI: BMI adjusted with NHANES III coefficient. Year: (Year-1987)*Corrected BMI interaction variable. Year: (Year-1987). Test=dummy for those in cohort ages 16-24 in 1987. Test2: dummy for those in cohort ages 22-30 in 1987. Test5: dummy for those in cohort ages 16-42 in 1987. Test 5 Young: dummy for those younger than those in test cohort. Test 5 Old: dummy for those older than those in test cohort. Test5Young*Corrected BMI: interaction between test5yng and Corrected BMI. Test 5 Old * Corrected BMI: interaction between Test 5 Old and BMI. Age: age from 5/3 rounds. HGC=highest grade completed (0-17). Married, Spouse Present.. Married, Other: been married, spouse no longer present. Midwest: Dummy for those in Midwest. South: Dummy for those in South. West: dummy for those in West. No. of Children in HH: number of children in household.

Table 3: NLSY Results

Variable	Coefficient	Std. Err.
Corrected BMI	-0.00577**	0.00190
Year	0.00940*	0.00446
Year*Corrected BMI	-0.00023****	0.00014
Ever born	-0.0357***	0.00924
Young Kid	-0.00557**	0.00176
Children Indicator	-0.00298	0.01926
White Collar	0.17435***	0.01200
Missing White Collar	0.11728***	0.01470
Mother's HGC	-0.00066	0.00338
Missing Mother's HGC	0.00829	0.05043
Father's HGC	0.00579*	0.00248
Missing Father's HGC	0.08362*	0.03976
Married, Spouse Present	0.03345*	0.01440
Married, Other	0.06894***	0.01824
GCPS1 (Intelligence)	0.05670***	0.00871
Missing GCPS1	-0.07590*	0.03576
HGC	0.05920***	0.00399
Missing HGC	0.81294***	0.10592
Enrolled in School	-0.12323***	0.01332
Years of Work Experience	0.02527***	0.00255
Missing Years of Work	0.29621***	0.03532
Tenure	0.02608***	0.00182
Missing Tenure	0.07869	0.06505
Part-Time Work Indicator	0.02653	0.01805
Missing Part-Time Work	-0.12348***	0.02394
Age	-0.00154	0.00371
Low Unemployment	0.06828***	0.00976
High Unemployment	-0.00726	0.01122
Missing Unemployment	-0.00129	0.03107
Northeast	-0.00507	0.02157
North Central	-0.13047***	0.01914
South	-0.11282***	0.01906
Constant	0.96621***	0.09783

Legend: * p<0.05; ** p<0.01; *** p<0.001; **** p<0.10

Table 4: NMES/MEPS Results, Baseline Model

Variable	Coefficient	Std. Err.
Corrected BMI	-0.00489**	0.00150
Year * Corrected BMI	0.00005	0.00011
Year	0.00425	0.00292
Age	0.00811***	0.00047
HGC	0.09324***	0.00179
Married, Spouse Present	0.14882***	0.01315
Married, Other	0.10046***	0.01638
Midwest	-0.10175***	0.01476
South	-0.12187***	0.01386
West	-0.04664**	0.01500
No. of Children in HH	-0.01528***	0.00458
Constant	0.98478***	0.04753

Legend: * p<0.05; ** p<0.01; *** p<0.001

Table 5: NMES/MEPS Results, Synthetic Cohort, Ages 22-30 in 1987

Variable	Coefficient	Std. Err.
Corrected BMI	-0.00516	0.00307
Year * Corrected BMI	-0.00023	0.00023
Year	0.00568	0.00683
Age	0.01822***	0.00368
HGC	0.09084***	0.00363
Married, Spouse Present	0.05534*	0.02536
Married, Other	-0.01813	0.03215
Midwest	-0.09373**	0.02905
South	-0.10691***	0.02739
West	-0.06401*	0.02935
No. of Children in HH	-0.00602	0.00901
Constant	0.84782***	0.13075

Legend: * p<0.05; ** p<0.01; *** p<0.001

Table 6: NMES/MEPS Results, Synthetic Cohort, Ages 16-24 in 1987

Variable	Coefficient	Std. Err.
Corrected BMI	-0.00178	0.00401
Year * Corrected BMI	-0.00057*	0.00028
Year	0.03129***	0.00777
Age	0.00637	0.00412
HGC	0.10105***	0.00404
Married, Spouse Present	0.11838***	0.02527
Married, Other	0.09030*	0.03517
Midwest	-.015436***	0.03077
South	-0.17810***	0.02893
West	-0.06592*	0.03071
No. of Children in HH	-0.02806**	0.00862
Constant	0.84596***	0.13707

Legend: * p<0.05; ** p<0.01; *** p<0.001

Table 7: NMES/MEPS Results, Synthetic Cohort, Ages 16-42 in 1987

Variable	Coefficient	Std. Err.
Corrected BMI	-0.00376*	0.00188
Year * Corrected BMI	-0.00028*	0.00014
Year	0.01606***	0.00376
Age	0.00708***	0.00087
HGC	0.09388***	0.00220
Married, Spouse Present	0.08514***	0.01682
Married, Other	0.05006*	0.02039
Midwest	-0.09647***	0.01794
South	-0.12574***	0.01691
West	-0.05954**	0.01825
No. of Children in HH	-0.01735**	0.00549
Constant	1.04471***	0.05923

Legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 8: NMES/MEPS Results, Synthetic Cohort Base, Ages 16-42 in 1987		
Variable	Coefficient	Std. Err.
Corrected BMI	-0.00439**	0.00169
Year * Corrected BMI	-0.00021****	0.00012
Year	0.012887***	0.00331
Test 5 Young	-0.31515***	0.05335
Test 5 Old	-0.15621*	0.06350
Test 5 Young * BMI	0.00740***	0.00188
Test 5 Old * BMI	0.00347	0.00225
Age	0.00735***	0.00077
HGC	0.09170***	0.00179
Married, Spouse Present	0.12641***	0.01331
Married, Other	0.08121***	0.01644
Midwest	-0.09841***	0.01471
South	-0.11657***	0.01382
West	-0.04384**	0.01495
No. of Children in HH	-0.01774***	0.00456
Constant	1.05418***	0.05242

Legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$; **** $p<0.10$

Figure 1: White Females, Overweight/Obese 1981-2000			
Year	Overweight	Obese	Overweight + Obese
1981	8.6%	4.1%	12.6%
1982	10.5%	4.7%	15.2%
1985	14.3%	6.8%	21.1%
1986	16.5%	8.0%	24.5%
1988	18.8%	9.3%	28.1%
1989	19.0%	10.8%	29.7%
1990	19.5%	11.7%	31.3%
1992	22.4%	13.7%	36.1%
1993	22.9%	14.4%	37.2%
1994	22.2%	17.3%	39.5%
1996	24.2%	18.6%	42.7%
1998	24.2%	22.5%	46.8%
2000	24.8%	25.6%	50.4%

Figure 2: NLSY Results

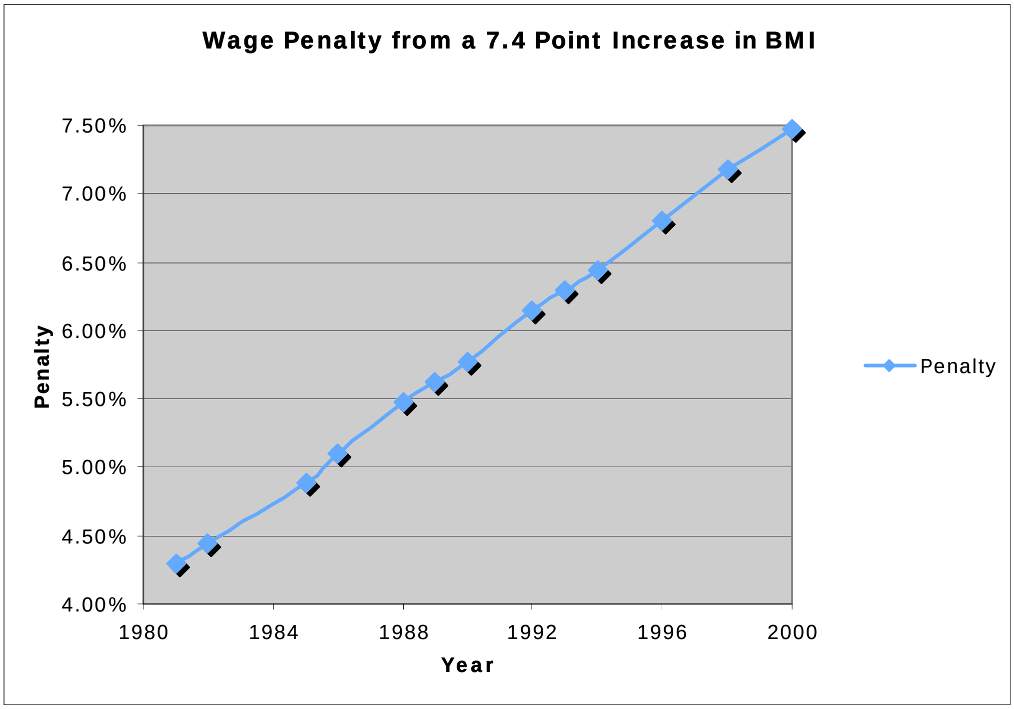


Figure 3: NMES/MEPS Results, Synthetic Cohort, Ages 16-24 in 1987

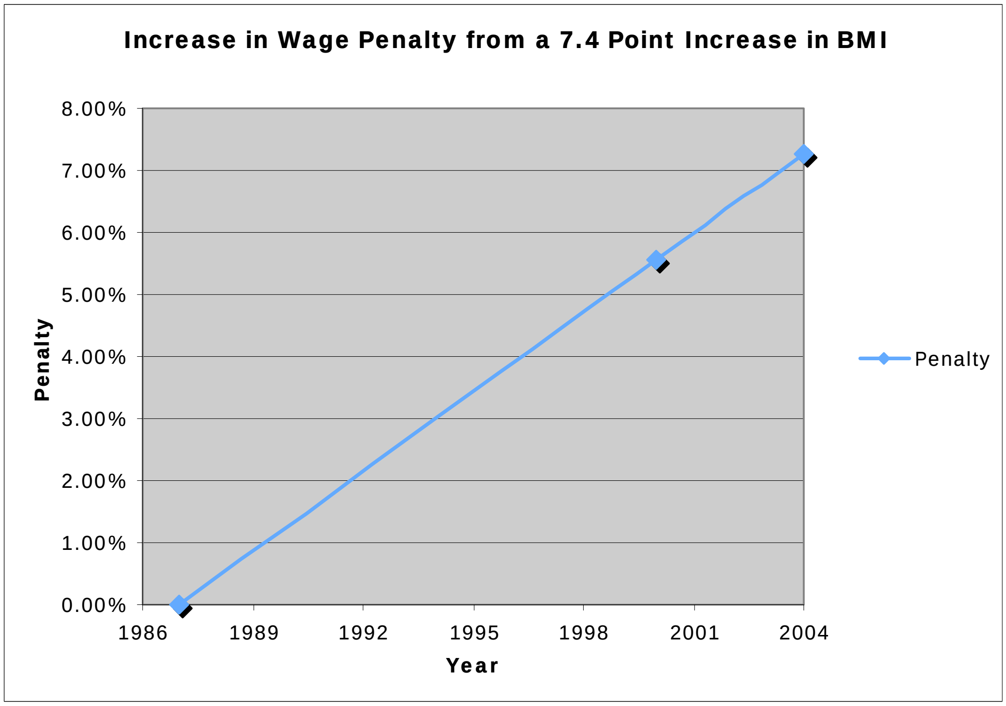


Figure 4: NMES/MEPS Results, Synthetic Cohort, Ages 16-42 in 1987

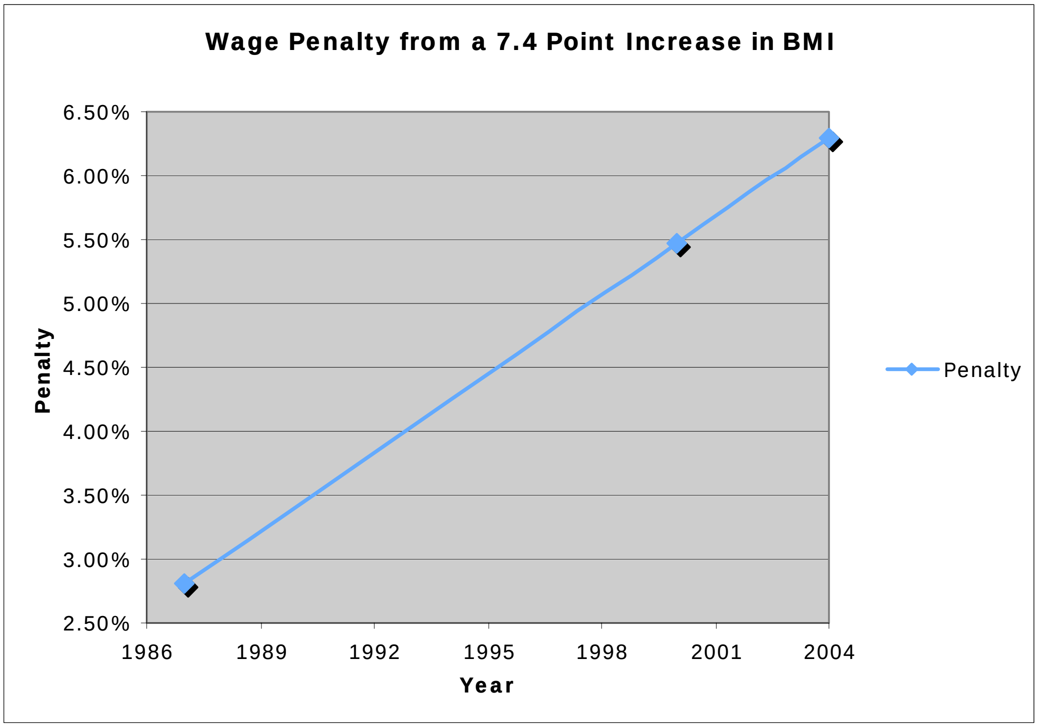


Figure 5: NMES/MEPS Results, Synthetic Cohort Base, Ages 16-42 in 1987

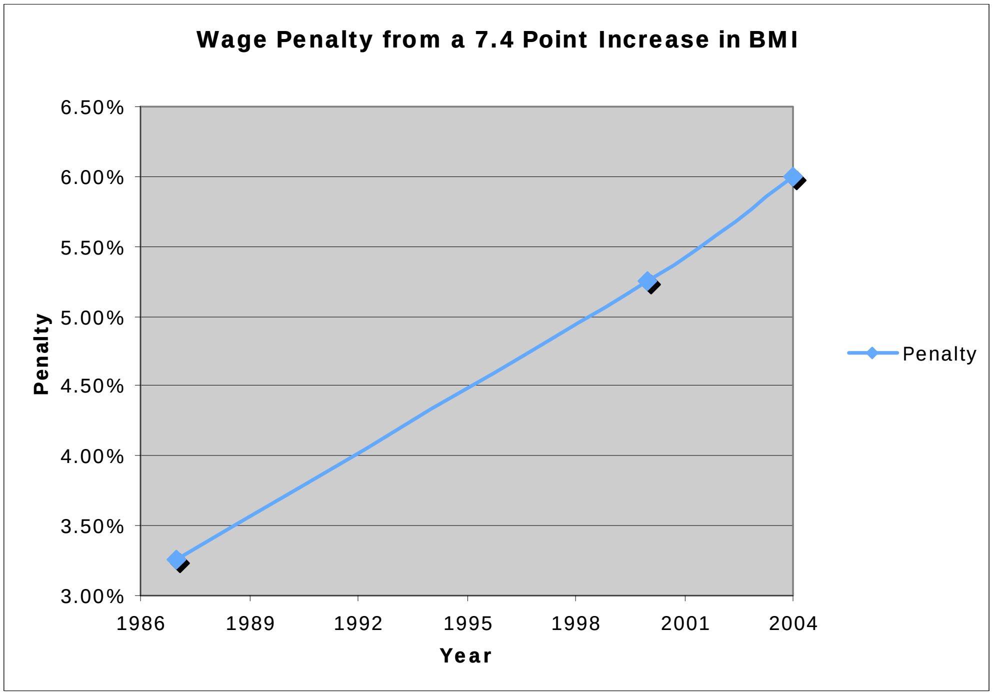
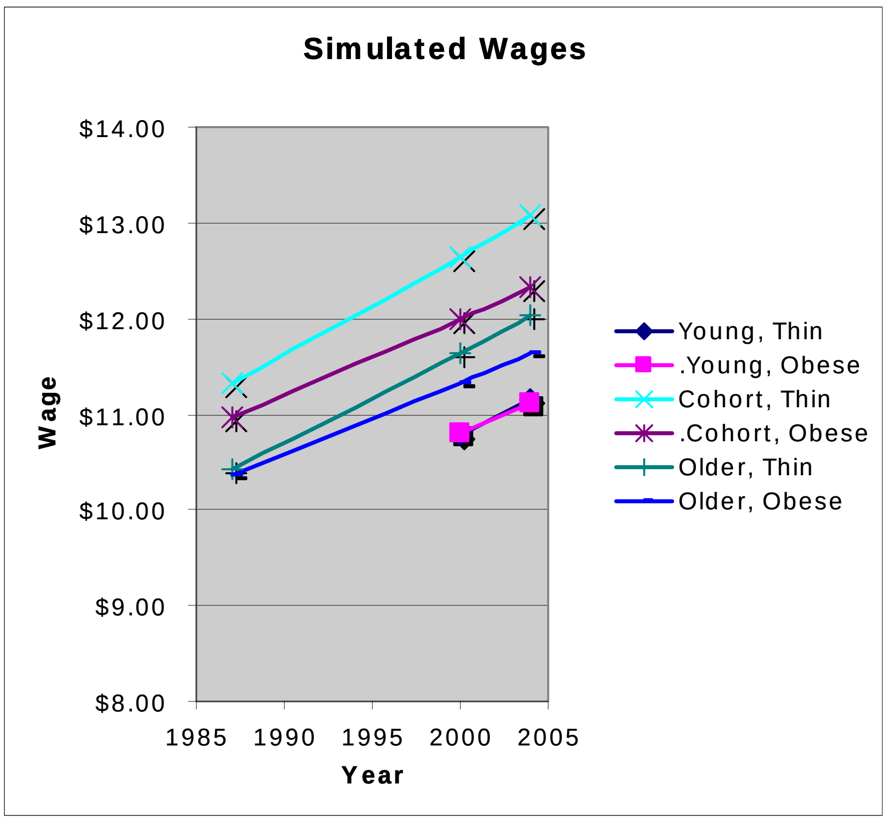
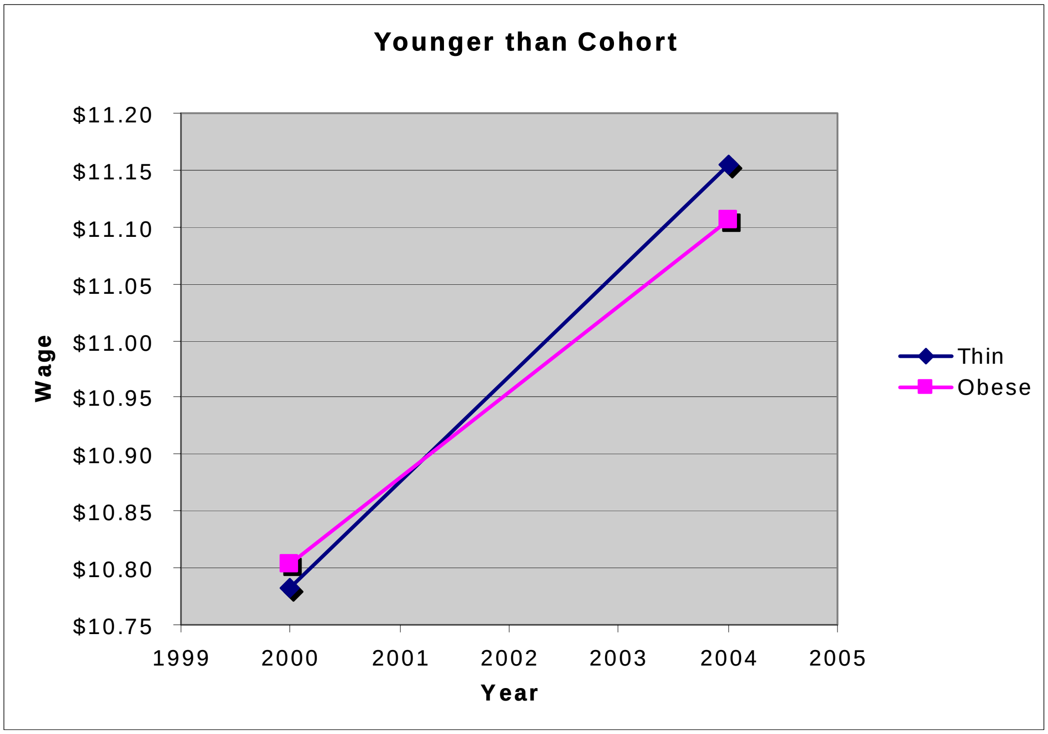
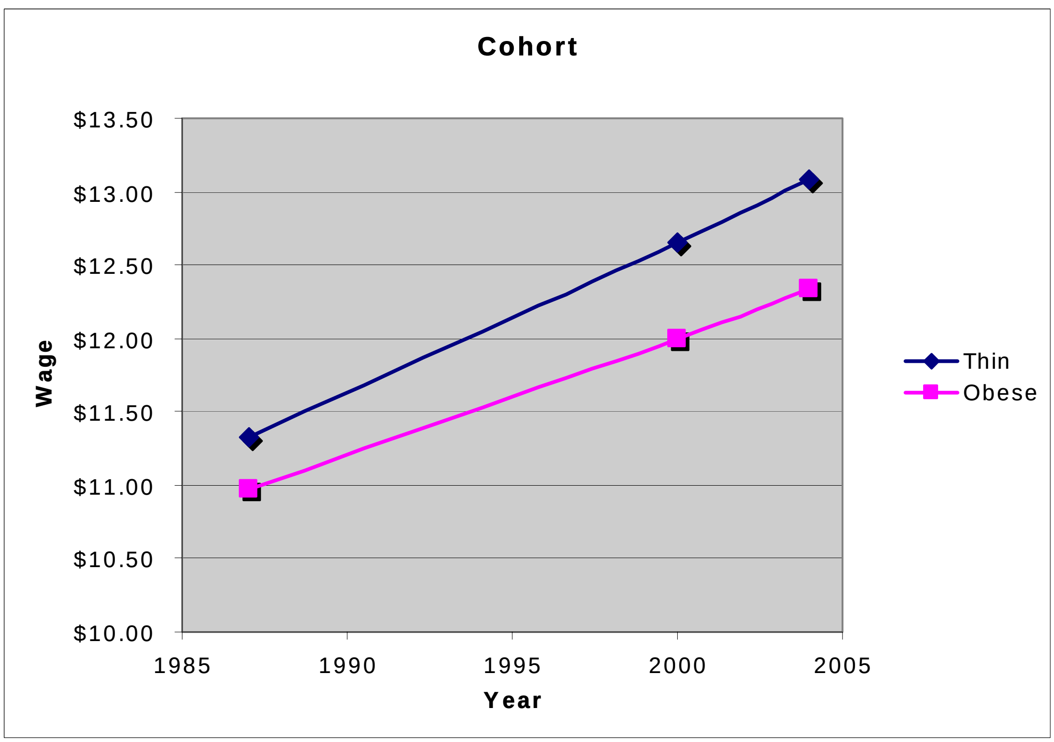


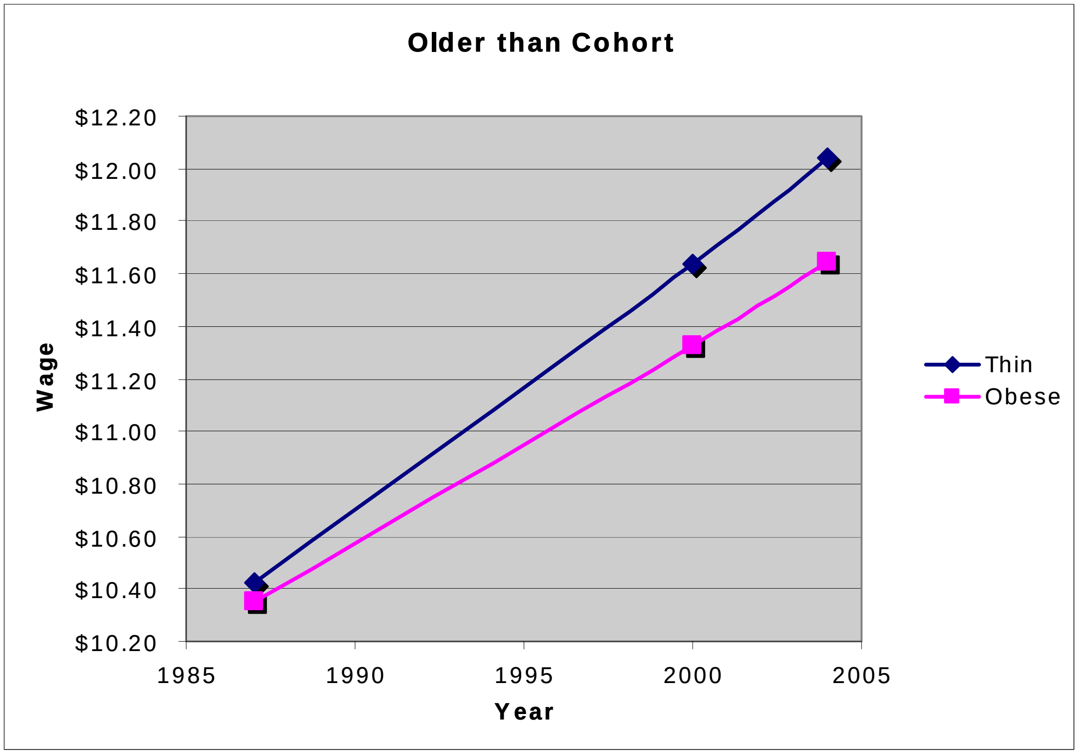
Figure 6: NMES/MEPS Results, Synthetic Cohort Base, Ages 16-42 in 1987 – Simulated Wages

	1987	2000	2004
Young, Thin	(n/a)	$10.78	$11.15
Young, Avg.	(n/a)	$10.80	$11.11
Cohort, Thin	$11.33	$12.64	$13.09
Cohort, Avg.	$10.97	$12.00	$12.34
Older, Thin	$10.43	$11.64	$12.04
Older, Avg.	$10.35	$11.33	$11.64




Younger than Cohort
Wage
$11.20
$11.15
$11.10
$11.05
$11.00
$10.95
$10.90
$10.85
$10.80
$10.75
1999
2000
2001
2002
2003
2004
2005
Year
Thin
Obese


Cohort
Wage
$13.50
$13.00
$12.50
$12.00
$11.50
$11.00
$10.50
$10.00
1985
1990
1995
2000
2005
Year
Thin
Obese


Older than Cohort
Wage
$12.20
$12.00
$11.80
$11.60
$11.40
$11.20
$11.00
$10.80
$10.60
$10.40
$10.20
1985
1990
1995
2000
2005
Year
Thin
Obese