NBER WORKING PAPER SERIES

BODY WEIGHT AND WOMEN'S LABOR MARKET OUTCOMES

John Cawley

Working Paper 7841
http://www.nber.org/papers/w7841

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2000

Body Weight and Women's Labor Market Outcomes
John Cawley
NBER Working Paper No. 7841
August 2000
JEL No. J3, I1

ABSTRACT

Several studies have found that, all else equal, heavier women earn less. Previous research has been unable to determine whether high weight is the cause of low wages, the result of low wages, or whether unobserved factors cause both higher weight and lower wages.

Applying the method of instrumental variables to data from the National Longitudinal Survey of Youth, this paper attempts to generate consistent estimates of the effect of weight on labor market outcomes for women. Three labor market outcomes are studied: hourly wages, employment, and sector of occupation.

This paper finds that weight lowers wages for white women; among this group, a difference in weight of two standard deviations (roughly sixty-five pounds) is associated with a difference in wages of 7%. In absolute value, this is equivalent to the wage effect of roughly one year of education, two years of job tenure, or three years of work experience. In contrast, this paper finds only weak evidence that weight lowers wages for hispanic women, and no evidence that weight lowers the wages of black women. This paper also concludes that there is no effect of weight on the probability of employment or sector of occupation.

John Cawley
109 S.Observatory, SPH-II,M2240
University of Michigan
Ann Arbor, MI 48109-2029
and NBER
jcawley@umich.edu

Introduction

Several previous studies have found, among women, a negative correlation between body weight and wages.[1] There exist three broad categories of explanations for this phenomenon. First, obesity may cause lower wages. Examples of such explanations are that obese women face discrimination in the labor market[2] and that obese women are less productive.

The second category of explanations is that low wages cause obesity. This may be true if, for example, poor labor market outcomes lead to depression and depression leads to weight gain.

The third category of explanations is that unobserved variables cause both obesity and low wages. One example of such a variable is rate of time discount. If someone assigns little value to future events, they may invest little in both their unobserved human capital (and thus have low wages) and their health (and may therefore be overweight).

This paper tests the first category of explanations, that high weight lowers wages, using the method of instrumental variables. Specifically, the weight of a child is used as an instrument for the weight of the child's mother. This method, which exploits the genetic variation in weight, is justified with reference to multidisciplinary research that suggests that the weight of children is uncorrelated with their mother's wage residual.

This paper focuses on women for two reasons. First, previous studies of this question (described in section 1 below) have consistently found a relationship between weight and wages for women, but generally not men. Second, the method of instru-

[1]See, e.g., Register and Williams (1990), Averett and Korenman (1996), and Pagan and Davila (1997).

[2]This is the conclusion of Averett and Korenman (1996).

mental variables used in this paper exploits an instrument that is available in the data only for women.

The question of whether there exists discrimination in the labor market against obese persons is likely to become more important with time. Recent studies have found dramatic increases in the prevalence of obesity in the United States during the 1980s[3] and 1990s.[4] This trend was similar across age, gender, and race-ethnic groups. The prevalence of obesity in the U. S. is expected to continue to rise.[5]

The outline of this paper is as follows. Section 1 is devoted to a brief review of related studies. The data used in this paper are described in section 2. The relationship between weight and wages using the methods of ordinary least squares and instrumental variables is estimated in section 3. Finally, in section 4, I test whether weight is correlated with market employment or sector of employment.

1 Previous Studies of Women's Weight and Wages

There have been several studies of women's weight and their wages or income[6], but this section is devoted to the two that acknowledged the possibility that weight is endogenous and have used techniques to generate consistent estimates of the effect of weight on wages. Both of these studies use data from the National Longitudinal Survey of Youth (NLSY), the data which is also used in this paper.

"The Economic Reality of *The Beauty Myth*" (1996), by Averett and Korenman,

[3]Flegal et al. (1998) find that the prevalence of obesity in the U. S. rose from 14.5% in 1976-80 to 22.5% in 1988-94. Their estimates are based on measured weight and height.

[4]Mokdad et al. (1999) find that the prevalence of obesity increased from 12.0% in 1991 to 17.9% in 1998. These estimates are based on self-reported height and weight.

[5]Flegal et al. (1998).

[6]See, e.g. Register and Williams (1990), Gortmaker et al. (1993), Loh (1993), Hamermesh and Biddle (1994), and Haskins and Ransford (1999).

was the first to address the endogeneity of weight in this context. They attempt to solve the problem by differencing between sisters, which will remove variance in weight attributable to a shared family environment.

When they difference among sisters, they eliminate the portions of variance in weight attributable to shared genes or a shared family environment. However, the behavioral genetics literature consistently finds no effect of shared family environment on weight.[7] Moreover, after differencing they are still left with the variance in weight attributable to environment unshared by sisters, which is endogenous. The strategy of Averett and Korenman is flawed; the potential source of variance in weight that they seek to remove (shared family environment) in fact explains a negligible proportion of the variance in weight, and some of the variance that remains (due to unshared environment) is endogenous.

Using the 1988 data of the NLSY, Averett and Korenman conclude that obese women have a lower family income-to-needs ratio than women whose weight is in the "recommended" range (based on actuarial tables). They find this to be true before and after taking sister differences. They also examine log wages as an outcome measure, and find that obesity is associated with lower wages in their cross-sectional regressions. Estimating separately by race, they conclude that the wage penalty associated with overweight is less for black than white women. However, when Averett and Korenman estimate their wage model using the sister-differencing procedure, the coefficients on obesity are not statistically significant, at least in part because the sample of paired sisters is small.

The second related study to address the issue of endogeneity of weight is Pagan and Davila (1997). This study finds that women who meet the clinical definition of obese earn less than their more slender counterparts in the 1989 NLSY data.

[7] See footnote 23.

Pagan and Davila acknowledge the possibility that weight is endogenous, and, using a Hausman specification test, fail to reject the hypothesis that weight is uncorrelated with the error term of the wage equation. However, their test is marred by the fact that their instruments (family poverty level in 1988, health limitations, and indicator variables about self-esteem) are also correlated with the error term in the wage equation. Poverty level in the previous year could be correlated with both this year's wage residual and body weight. Health limitations could affect unobservable aspects of productivity as well as weight. Self-esteem could be a reflection of workplace success. Given that their IV estimation suffers the same kind of bias as their OLS estimation, it is not surprising that, through their Hausman test, they fail to reject the hypothesis that OLS and IV coefficients are equal.

Pagan and Davila also test for differences in occupation by weight classification. They estimate models of occupation choice for a nonobese sample and multiply the vector of estimated coefficients with the vector of characteristics of each person in the obese sample to generate an estimate of the probability that the obese person would have a given occupation were they nonobese. They find that there are fewer overweight women in managerial and professional occupations than their model predicts.

In summary, previous studies of wages and weight have found that heavy women tend to suffer a wage or income penalty. This paper seeks to improve on this literature in four ways, by: 1) using the entire panel, rather than just a single year, of the NLSY data; 2) correcting for reporting error in weight and height; 3) correcting for selection bias in the estimates of women's wages; and most importantly, 4) conducting valid tests of the exogeneity of weight and generating consistent estimates of the effect of body weight on women's wages.

2 Data: NLSY

This section introduces the data used throughout this paper. The National Longitudinal Survey of Youth (NLSY), designed to represent the entire population of American youth in 1979, consists of a randomly chosen sample of 6,111 U. S. civilian youths, a supplemental sample of 5,295 randomly chosen minority and economically disadvantaged civilian youths, and a sample of 1,280 youths on active duty in the military.[8] All youths were between fourteen and twenty-two years of age when the first of annual interviews was conducted in 1979. Since 1994, interviews have been conducted every two years. Retention rates for those NLSY respondents remaining eligible for interview have remained close to 90 percent during the sixteen years of interviews.

At the baseline of the NLSY, respondents were asked to report their race or ethnicity, which the NLSY simplifed into three groups: black, hispanic, and nonblack/nonhispanic. I refer to nonblack nonhispanics as whites throughout this paper, although it should be noted that this group is heterogeneous.

The NLSY recorded the self-reported weight of respondents in 1981, 1982, 1985, 1986, 1988, 1989, 1990, 1992, 1993, 1994, 1996, and 1998. Reported height was recorded in 1981, 1982, and 1985; given the age of the respondents, the height in 1985 was assumed to be the respondents' adult height.

These self reports of weight and height include some degree of reporting error, which may bias coefficient estimates. Specifically, when only one regressor is measured with error, there is attenuation bias in the OLS estimate of the coefficient associated

[8]Due to funding constraints, some members of the original sample are no longer being interviewed. After the 1984 surveys, interviewing ceased for 1,079 members of the military subsample; retained for continued interviewing were 201 respondents randomly selected from the entire military sample. Beginning with the 1991 survey, 1,643 economically disadvantaged white respondents from the supplemental sample are no longer being interviewed.

with that regressor. However, if there are multiple regressors measured with error, there is no consistent rule about the sign of the bias in the coefficients of the variables measured with error.[9] I correct the NLSY measures of weight and height for reporting error in the method of Lee and Sepanski (1995) and Bound et al. (1999); see Appendix A for details.[10]

This paper uses two measures of body weight: 1) weight in pounds (controlling for height in inches); and 2) body mass index (BMI). BMI, the standard measure of fatness and obesity in epidemiology and medicine, is defined as weight in kilograms divided by height in meters squared.[11]

Weight tends to rise with age. In order to distinguish the effects of weight from those of age and time, I include a linear measure of age and indicator variables for time as regressors in my log wage regressions.

Weight may also be affected by current pregnancy. For this reason, women who are pregnant at the time that they report their body weight are dropped from the sample.[12]

This paper uses three dependent variables: 1) log of current hourly wage at primary job; 2) an indicator variable for whether occupation is coded as white collar (as opposed to blue collar) using Census classifications; and 3) an indicator variable

[9] Judge et al. (1985).

[10] I have also estimated the models in this paper without correcting for reporting error in height and weight and I find very similar results.

[11] The U. S. National Institutes of Health classifies BMI as follows: below 18.5 is underweight, between 18.5 and 25 is healthy, between 25 and 30 is overweight and over 30 is obese. See U. S. National Institutes of Health (1998) and Epstein and Higgins (1992).

[12] I use two questions in the NLSY to eliminate women who are pregnant at the time that they report their weight. First, women were asked whether they were currently pregnant at the time of interview. Second, in some years they were also asked whether they had, in retrospect, been pregnant at the time of the last interview. I drop from the sample women who answered yes to either of these questions.

that equals one if the respondent is currently employed or currently active duty in the military, and equals zero if the respondent is unemployed or out of the labor force.

In each year, the NLSY calculates the hourly wage earned by the respondent at their primary job. I recode outliers; if the hourly wage is less than \$1 an hour, I recode it to \$1 and if the hourly wage exceeds \$500 an hour, I recode it to \$500.[13]

I classify all occupations as either white collar or blue collar, using Census codes for occupation. White collar workers are those working in sectors described by the U. S. Census as Professional, Technical, or Kindred Workers, Non-Farm Managers and Administrators, Sales Workers, and Clerical and Unskilled Workers. The only unskilled workers in the last group are those in white-collar positions, such as cashiers, file clerks, bill collectors, and messengers.

I include the following regressors in the log wage regressions: general intelligence (which is a measure of cognitive ability derived from the ten Armed Services Vocational Aptitude Battery tests)[14], highest grade completed, years of actual work experience (defined as weeks of reported actual work experience divided by fifty), job tenure, age, and indicator variables for year, local unemployment rate, current school enrollment[15], region of residence, and black and hispanic. I also include indicator variables for missing data associated with each regressor except the weight variables. Table 1 provides summary statistics for the sample of women used in the log wage regressions.

INSERT TABLE 1 HERE

The instrument used in the IV section of this paper is the BMI of a biological child

[13] After recoding, there are 109 women in the sample with bottom-coded wages and 7 women with top-coded wages.

[14] See Jensen (1987) for a full description of this measure of cognitive ability.

[15] I also experimented with dropping those currently enrolled from the sample and found very similar results.

aged six to nine.[16] A single observation of child BMI is used as an instrument for every (up to twelve) observations of mother's weight.[17] Although the instrument does not vary with time, the mother's weight does, so in each year a woman may have a unique value for instrumented BMI. The data on child weight and height comes from the Child Supplement to the NLSY, which consists of all children born to NLSY female respondents who were living in their mother's household at the time of a child assessment interview and who completed an interview. All of the children in the NLSY Child Sample are biological children, so they represent suitable instruments to gauge the genetic variation in BMI.

The use of children to instrument for mother's weight requires that the sample be limited to women that have borne children. It is possible that the empirical results found for this sample do not generalize to all women, but 82.65% of all women in the NLSY had given birth by 1998, so the sample of women with at least one birth may not differ significantly from the entire population of women.

NLSY sample weights are used in all estimations described in this paper. T statistics reported in the tables of this paper reflect robust standard errors are calculated with clustering by individual to account for correlations in the error terms of each

[16] Sorensen et al. (1992) find that the mother-child correlation in BMI has reached its adult level by the child's age 7.

[17] The single observation of child weight was chosen in the following manner. For each woman, the eldest child aged 6 to 9 was examined in the most recent year. If the child's height and weight were measured, those values were chosen. Otherwise, the next most recent year's observation on the eldest child was examined. If the eldest child had no measured values of height and weight, the next eldest child was examined, and so on. If no child of a given woman had measured weight and height in any year, a mother's report of the child's height and weight were used. Of all of the observations of child weight and height, 98.7% were measured and the remainder reported by the mother. In models run with an added indicator variable for mother report of weight and height, the coefficient on the indicator was not statistically significant.

individual over time.

3 Weight and Wages

The goal of this paper is to generate a consistent estimate of the causal effect of body weight on labor market outcomes. I assume that the relationship between wages w and BMI b has the following form for individual i at time t:

$$w_{it} = e^{b_{it}\beta + X_{it}\gamma + \tau_t + u_{it}}$$

or

$$\ln w_{it} = b_{it}\beta + X_{it}\gamma + \tau_t + u_{it} \quad (1)$$

where X is a vector of variables, τ is a time-specific effect and u is the residual, which is assumed to be uncorrelated with b, X, and τ. If BMI were strictly exogenous, we could interpret β as the true effect of BMI on log wages.

A Ramsey RESET test was used to test the assumption implicit in equation (1) that log wages are linear in BMI (or weight in pounds).[18] I cannot reject at the 5% significance level the hypothesis that log wages are linear in BMI or weight in pounds.[19]

Assume that BMI has the following projection or reduced form:

$$b_{it} = Z_{it}\pi + X_{it}\delta + \epsilon_{it} \quad (2)$$

where X is a set of variables that affect both BMI and log wages, Z is a set of variables that are correlated with BMI but not the error term in wages, and ϵ is the residual.

[18] Thursby and Schmidt (1977). While I use the Ramsey RESET to test for linearity of wages in the weight variables, I acknowledge that no test can discriminate between unknown omitted variables and an unknown functional form.

[19] In its use of linear measures of body weight instead of indicator variables for weight classification, this paper differs from many of the studies cited in section 1.

For now, I will assume that ϵ and u are uncorrelated, but I will relax that assumption later in this section.

OLS coefficients and t statistics of equation (1) appear in Table 2.

INSERT TABLE 2 HERE

Table 2 indicates that both BMI and weight in pounds have negative and statistically significant coefficients. The magnitude of the coefficient on weight in pounds implies that if two otherwise identical women differed in weight by ten pounds, we would expect the lighter one to enjoy 1% higher wages.

At the bottom of Table 2, I list the standard deviations of BMI and weight in pounds in the sample. If weight is normally distributed, the standard deviations and coefficients in Table 2 imply that if two otherwise identical women differed such that one was at the median and one was at the 95th percentile for weight, we would expect the lighter one to enjoy roughly 7% higher wages. For comparison, the coefficients on height suggest that each inch in height is associated with 1.1% higher wages.

There is a large literature on the extent to which studies of women's labor force participation are influenced by sample selection bias due to the fact that many women do not work for pay.[20] Despite the fact that studies examining the wages of women are likely to be affected by selection bias–since they attempt to make inferences about all women using data only on working women–none of the studies of weight and women's wages reviewed in section 1 attempted to determine the degree of selection bias in their estimates.

The method of Heckman (1979) is used to correct the log wage regression results for any selection bias. As instruments for the propensity to engage in market employment, i.e. variables that affect labor force participation but not wages, this

[20]For a review, see Chapter 11 of Berndt (1991).

paper follows the traditional literature on women's labor force participation, and uses marital status, number of children in the household, age of the youngest child in the household, and family income that is not attributable to the wages of the respondent.

Listed alongside the OLS estimates in Table 2 are estimates corrected for selection. At the bottom of the table are the t-statistics associated with the inverse Mills ratio, which represent a test for the presence of selection bias. For the sample of all women, the coefficient on the inverse Mills ratio is not statistically significant. However, I do find evidence of selection bias for some subsets of the sample, so for all the log wage regressions in this paper, results both uncorrected and corrected for selection are presented for the sake of comparison.

These OLS estimates suggest that, in general, heavier women tend to earn less. However, in the terminology of equations (1) and (2), OLS estimates of β are consistent if and only if u_{it} and ϵ_{it} are uncorrelated. As mentioned earlier, the errors terms might be correlated if there is reverse causality (e.g. labor market failure causes depression and subsequent weight gain) or if unobserved variables (e.g. relating to lifestyle) cause both heaviness and adverse labor market outcomes.

If the error terms are correlated, one can still generate a consistent estimate of β if one can identify a set of variables Z that are correlated with BMI but not the error term in wages. Given Z, one can calculate an instrumental variables estimate of β. In this paper, the instrument for a mother's weight is the BMI of one of her children. Specifically, the set of instruments consists of eight variables: the BMI of the child interacted with the child's gender and the child's age, which ranges from six to nine.

A series of articles has been published outlining the harms of weak instruments. Bound, Jaeger, and Baker (1993) point out two problems associated with weak instruments. First, a weak correlation between the instrument and the endogenous variable will exacerbate any problems associated with a correlation between the instrument and the wage residual. Second, the magnitude of finite sample bias in IV estimates approaches that of the OLS bias as the R^2 between the endogenous explanatory variable and the instruments approaches zero. They suggest that the R^2 and F statistics from the first stage of two-stage least squares be reported as approximate guides to the quality of the IV estimates. Staiger and Stock (1997) argue that 10 is an acceptable value of the F statistic associated with the hypothesis that the coefficients on the instruments in the first-stage regression of two-stage least squares are jointly equal to zero.

The set of instruments used in this paper appears to meet the standard of Staiger and Stock. The hypothesis that all coefficients on instruments are jointly equal to zero in the first stage of IV estimation is rejected; the F statistic is 10.47 when BMI is the endogenous regressor, and 10.23 when weight in pounds is the endogenous regressor.[21] The marginal R^2 associated with the instruments is .04 when BMI is the endogenous regressor, and .11 when weight in pounds is the endogenous regressor.

However, there are additional requirements of an instrument. In particular, it is imperative that the instrument be uncorrelated with the error term in the second stage of instrumental variables estimation; if it is correlated, the IV procedure has accomplished nothing (and may in fact have caused harm[22]) because the instrumented variable is still endogenous. The identifying assumption of this paper is that the BMI of a child is correlated with the weight of its mother and is uncorrelated with the mother's wage residual. The evidence in favor of this assumption is: 1) There is no

[21] It is not surprising that the correlation between mother and child BMI is high; heritability studies suggest that genetics account for as much as 70% of the variance in weight across people; see Yanovski and Yanovski (1999). Most estimates from U.S. data of the correlation between the adult BMI of a mother, and the childhood or adolescent BMI of her child are in the range .21-.36. The correlation does not differ by the gender of the child. See Maes et al. (1997), p. 334.

[22] Bound, Jaeger, and Baker (1993).

consistent pattern between *childhood* obesity and socioeconomic status; see the review in Sobal and Stunkard (1989). 2) There is no measurable effect of common household environment on body weight; see Stunkard et al. (1986), Price and Gottesman (1991), Sorensen et al. (1992, 1993), Vogler et al. (1995), and Maes et al. (1997).[23] These studies indicate that all of the similarity in weight between parents and children is genetic in origin.

While it is impossible to confirm the null hypothesis that child BMI is uncorrelated with the mother's wage residual, it can be illustrative to test whether instruments are correlated with observables that are believed to be correlated with the unobservables that affect the second-stage residual. To this end, mother's education and general intelligence were regressed on the set of instruments and the other regressors in the log wage regressions. The set of instruments was not statistically significant at the 10% level, which is suggestive evidence in favor of the identifying assumption.

The use of child's BMI as an instrument has an added advantage. Instrumental variables analysis only measures the effect of the endogenous regressor on the dependent variable for the population "treated" by the natural experiment. In many natural experiments, the treated population differs in important ways from the population, and the IV estimate for the treated population may differ dramatically from the treatment effect on the entire population.[24] Using the BMI of a child as an instrument for the weight of the child's mother largely avoids this problem, because genetics affects the body weight of every person and over 80% of the women in the

[23]Grilo and Pogue-Geile (1991), a comprehensive review of studies of the genetic and environmental influences on weight and obesity, conclude that "...only environmental experiences that are not shared among family members appear to be important. In contrast, experiences that are shared among family members appear largely irrelevant in determining individual differences in weight and obesity." (p. 520).

[24]Angrist, Imbens, and Rubin (1996).

NLSY have had children.

In first stage of 2SLS, I regress a measure of mother's weight (corrected for reporting error)[25] on eight interaction terms: the child's BMI times indicator variables for child gender and age. I interact the child's BMI with the child's age and gender because I want to measure the extent to which the child is heavy for their age and gender. The regressors from the second stage of 2SLS are also included in the first stage. Coefficients from the first stage of two stage least squares are listed in Table 3.

INSERT TABLE 3 HERE

In Table 3, all the coefficients on the instruments are of the expected sign; a high BMI child (relative to other children of the same age and gender) is associated with higher weight mother, whether measured in BMI or pounds. Every child BMI-age-gender interaction is significant at the 1% level in each regression. At the bottom of each table are listed the F statistics and partial R^2 of the instruments.

INSERT TABLE 4 HERE

Table 4 contains the two-stage least squares estimates of the effect of weight on log wages for women. Although the standard errors are larger due to the IV method, the point estimates of the coefficients generated by IV are similar to those generated

[25]Instrumental variables estimation is often proposed as a method of generating consistent estimates of coefficients of variables measured with error. (See, e.g., Fuller (1987) or Greene (1993).) However, such an approach requires one to find an instrument that is correlated with the true value of the variable measured with error and yet is independent of the reporting error. Since, as shown in Appendix A, reporting error in BMI is a function of level in BMI, it is not reasonable to assume that an instrument correlated with true BMI is uncorrelated with the reporting error in BMI. For this reason, I must still correct self-reported height and weight for reporting error before instrumental variables estimation.

by OLS. In fact, a Hausman test indicates that the hypothesis that the OLS and IV coefficients are equal cannot be rejected. In other words, any endogeneity of weight does not appreciably affect the OLS estimates and these should be preferred to the IV estimates.

I next test for differences in these results by race. I test and reject at the 5% significance level the hypothesis that the coefficients of equation (1) are equal for black, white, and hispanic women.[26] OLS and IV results are presented in Tables 5 and 6 for white females, Tables 7 and 8 for black females, and Tables 9 and 10 for hispanic females.[27]

INSERT TABLES 5 THROUGH 10 HERE

These tables reveal considerable differences by race. Only for white females are the OLS coefficients on weight variables statistically significant at the 5% level. The OLS coefficients on weight for hispanics are statistically significant at the 10%, but not the 5%, level. The OLS coefficients on weight for blacks are not statistically significant at any reasonable significance level.

As for the entire sample, Hausman tests conducted separately by race indicate that the hypothesis that the OLS and IV coefficients are equal cannot be rejected. Collectively, the results presented in Tables 5 through 10 indicate that the evidence is relatively strong that weight lowers the wages of women who are white, the evidence is relatively weak that weight lowers the wages of women who are hispanic, and there is no evidence that weight lowers the wages of women who are black. This is consistent with the finding of Averett and Korenman (1996), who find in OLS regressions that the wage "penalty" for overweight is smaller for black women than white women.

[26] I cannot reject at the 5% significance level the hypothesis that coefficients are equal across occupation sector (white or blue collar) within race groups.

[27] Results by race of the first-stage regressions for IV are available upon request.

It is reasonable to ask, how "large" is the wage penalty for body weight among white women? If weight is normally distributed, the standard deviations and coefficients in Table 5 imply that if two otherwise identical women differed such that one was at the median and one was at the 95th percentile for weight (a difference of roughly sixty-five pounds), the lighter one is expected to enjoy roughly 7% higher wages. Judging by the estimated coefficients of other variables in the model, this is equivalent in absolute value to the wage effect of roughly one year of education, two years of job tenure, or three years of work experience.

4 Employment and Occupation

So far in this paper I have taken as given employment and sector of employment. However, it is conceivable that while there may be no wage discrimination conditional on employment, discrimination may exist at the hiring stage. This section is devoted to estimating the correlation between weight and employment and sector of occupation.

4.1 Weight and Employment

The dependent variable in this section is an indicator variable that equals one if the woman is employed or on active duty in the military, and equals zero if the woman is unemployed or out of the labor force. I estimate both probit and probit with IV models using the same set of regressors as for the log wage regressions, minus job tenure and the indicator for white collar job.[28] In contrast to the log wage regressions, I could not reject the hypothesis that coefficients in are equal across race in the employment probit regressions. Table 11 reports the marginal probabilities

[28]The probit with instrumental variables estimation follows the strategy of Newey (1987).

associated with the probit coefficients and z scores.[29]

INSERT TABLE 11 HERE

The coefficients on BMI and weight in pounds are not statistically significant in the employment probit regression. However, it may be that weight is correlated with the error term in the probit regression for occupation choice. Just as in a linear regression, a correlation between a regressor and the error term violates the assumptions behind the nonlinear regression model.[30] I use the same instruments in the probit with IV regression as in the two-stage least squares regressions.

The probit with IV coefficient on each weight variable is statistically significant at the 10%, but not the 5%, level. The magnitude of these coefficients implies that a gain in weight of ten pounds is associated with a 1% higher probability of employment. As a check of robustness, I re-estimated these models dropping from the sample women who were out of the labor force and found no evidence that weight affected the probability of employment.[31]

4.2 A Random Utility Model of Occupation Choice

This subsection is devoted to testing whether obesity is correlated with the probability of employment in a white collar as opposed to a blue collar job. I assume that each person derives utility based on their sector of occupation. People enjoy utility U_w if they work in the white-collar sector or utility U_b if they work in the blue-collar sector.

[29] The z scores reflect standard errors for probit with IV corrected for estimation in the first stage; see Murphy and Topel (1985).

[30] In nonlinear regression, if a regressor is correlated with the error term, it is expected that the transformed regressor is also correlated with the error term; see Greene (1993).

[31] Tables of the results of the employment probit regression excluding from the sample those who are out of the labor force are available upon request.

The utility that they enjoy in each sector is a function of their characteristics X:

$$\begin{aligned} U_w &= X\beta_w + \epsilon_w \\ U_b &= X\beta_b + \epsilon_b \end{aligned}$$

Let $Y = 1$ indicate that a NLSY respondent has a white-collar job and $Y = 0$ indicate that they have a blue-collar job. The probability that a person has a white-collar job is equal to the probability that their utility in the white-collar job is greater than the utility that they would enjoy in a blue-collar job:

$$\begin{aligned} \Pr[Y = 1|X] &= \Pr[U_W > U_B] \\ &= \Pr[X\beta_w + \epsilon_w > X\beta_b + \epsilon_b] \\ &= \Pr[X(\beta_w - \beta_b) + \epsilon_w - \epsilon_b > 0] \\ &= \Pr[X\beta + \epsilon > 0] \\ &= \Pr[\epsilon > -X\beta] \end{aligned}$$

Assuming that ϵ follows a normal distribution, the probability of white-collar employment as a function of characteristics X can be estimated with with a probit model. Marginal probabilities and z scores for the probit regressions appear in Table 12. The probit and probit with IV results in Table 12 provide no evidence that weight affects the probability of employment in a white-collar, as opposed to a blue-collar, job.

INSERT TABLE 12 HERE

5 Summary

This paper seeks to improve on previous literature on the relationship between weight and women's wages in four ways: 1) by using a much larger dataset; 2) correcting for reporting error in weight and height; 3) correcting for selection bias in the estimates of women's wages; and most importantly, 4) conducting valid tests of the endogeneity of weight and generating consistent estimates of the effect of body weight on women's wages.

This paper finds evidence that weight lowers wages for white women; among this group, a difference in weight of two standard deviations (roughly sixty-five pounds) is associated with a difference in wages of 7%. This difference in wages is equivalent in absolute value to the wage effect of roughly one year of education, two years of job tenure, or three years of work experience. The fact that weight lowers certain women's wages may become increasingly important over time, as the percentages of Americans meeting the clinical definitions of overweight and obese are predicted to continue to rise.[32]

It should be stressed that the finding that weight lowers wages is not conclusive evidence of workplace discrimination. Another hypothesis also consistent with these findings is that heavier workers are less productive at work. It has repeatedly been found, for example, that obese workers are more likely to miss work due to illness.[33] However, this explanation is complicated by the fact that this paper finds no evidence that weight lowers wages for black women.

This paper also finds evidence of a wage premium for height among white women; a difference of 3 inches in height is associated with a difference in wages of 4%. This paper finds no effect of weight or height on the probability of employment or sector of occupation.

---

[32]Flegal et al. (1998).

[33]Narbro et al. (1996) studied a sample of Swedish women and found that obese workers, relative to healthy-weight workers, had 1.5 to 1.9 times more work days lost to illness. Wolf and Colditz (1998) estimate that, in the U. S. in 1994, obesity-related illness resulted in 39.2 million missed work days.

Appendix A: Reporting Error in Weight and Height

Weight and height are self-reported in the NLSY; reporting error in these variables has the potential to bias coefficient estimates. In this appendix, I assess the extent of reporting error in weight and height in the NLSY, and correct for it, using the Third National Health and Nutrition Examination Survey (NHANES III).[34] NHANES III, conducted in 1988-1994, was designed to obtain information on the health and nutritional status of the U. S. population through interviews and direct physical examinations. NHANES III surveyed a nationally representative sample of 33,994 persons aged 2 months and older; 31,311 of those respondents also underwent physical examinations. NHANES III is useful for the purposes of this paper because it both asked respondents to report their weight and height and then, within four weeks, measured their weight and height. In order to assess the extent of reporting error in the NLSY, I examined the reported and actual weight and height of NHANES III respondents of the same age as the NLSY sample when they reported their weight and height (aged 17-40). There were 3,854 female NHANES III respondents in the NLSY age range.

In NHANES III, height and weight are reported such that NLSY-aged women tend to underreport their BMI by 1.5%. Underreporting of weight varies positively with actual weight; underweight women overreport, whereas overweight women underreport, their weight. There is no clear pattern of misreporting of height by actual height.

In order to correct for this reporting error, I predict true height and weight in the NLSY using information on the relationship between true and reported values in the NHANES III. This strategy is outlined in Lee and Sepanski (1995) and Bound et al. (1999). If one has validation data, which in this case contains measures of true and

[34] U. S. Dept. of Health and Human Services, 1996.

reported weight and height (and, therefore, BMI), one can regress the true value of the variable on its noisy reported value. The OLS coefficient on the reported value is then used in the primary dataset; specifically, it is multiplied by the reported value to create an estimate of the true value. (This assumes "transportability," i.e. that the relationship between true and reported values are the same in both datasets.) I then regress log wages on a set of regressors that includes transformed BMI, which is constructed using the transformed values of reported height and weight.

Measured weight was regressed on actual weight for a sample of NLSY-aged (i.e. 17-40) respondents to NHANES III. I estimate the regression separately by race; actual weight is regressed on reported weight and its square (in deviations about race group-specific means); the intercept is suppressed.[35] Reported weight and its square are strong predictors of actual weight; judging by the extremely high R^2 (each over .995), this model fits the data very well.

This process was repeated for height. Regressions of actual on measured height and its square (in deviations arbout race-specific means) were estimated separately by race.[36] Again, the extremely high R^2 (equal to 1 to the third decimal place) suggest that reported height and its square are outstanding predictors of actual height.

Self-reported height and weight in the NLSY are then multiplied by the coefficients on the reported values associated with the correct race-gender group in the NHANES III. The fitted value of BMI, corrected for reporting error, is used throughout the

[35] The hypothesis that the coefficients are equal across race was rejected. The hypothesis that these coefficients are equal across age groups could not be rejected. The hypothesis that the coefficient on the squared term is equal to zero was rejected, but the hypothesis that the coefficient on a cubic term is zero could not be rejected.

[36] The hypothesis that the coefficients are equal across race was rejected. The hypothesis that these coefficients are equal across age groups could not be rejected. The hypothesis that the coefficient on the squared term is equal to zero was rejected, but the hypothesis that the coefficient on a cubic term is zero could not be rejected.

paper. All of the models in this paper have also been estimated using reported BMI, with very similar results.

References

[1] Allison, D. B., J. Kaprio, M. Korkeila, M. Koskenvuo, M. C. Neale, and K. Hayakawa. "The Heritability of Body Mass Index Among an International Sample of Monozygotic Twins Reared Apart." *International Journal of Obesity*, 20, (1996): 501-506.

[2] Averett, Susan and Sanders Korenman, "The Economic Reality of the Beauty Myth." *Journal of Human Resources*, 31, 2 (1996): 304-330.

[3] Berndt, Ernst. *The Practice of Econometrics* New York: Addison-Wesley, 1991.

[4] Bound, John, Charles Brown, and Nancy Mathiowetz. "Measurement Error in Survey Data." in *Handbook of Econometrics volume 4*, ed. James Heckman and Ed Leamer. New York: Springer-Verlag, forthcoming 1999.

[5] Bound, John, David A. Jaeger, and Regina Baker. "The Cure Can Be Worse Than The Disease: A Cautionary Tale Regarding Instrumental Variables." *National Bureau of Economic Research Technical Paper #137*, Cambridge, MA 1993.

[6] Bound, John, David A. Jaeger, and Regina M. Baker. "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable Is Weak." *Journal of the American Statistical Association*, 90, 430 (1995): 443-450.

[7] Epstein, Frederick H. and Millicent Higgins. "Epidemiology of Obesity." in *Obesity*, ed. Per Bjorntorp and Bernard N. Brodoff. New York: J. B. Lippincott Company, 1992.

[8] Flegal, K. M., M. D. Carroll, R. J. Kuczmarski, and C. L. Johnson. "Overweight and obesity in the United States: prevalence and trends, 1960-1994" *International Journal of Obesity*, 22, (1998): 39-47.

[9] Fuller, Wayne A. *Measurement Error Models* New York: John Wiley & Sons, 1987.

[10] Gortmaker, Steven L., Aviva Must, James M. Perrin, Arthur M. Sobol, and William H. Dietz. "Social and Economic Consequences of Overweight in Adolescence and Young Adulthood." *New England Journal of Medicine*, 329, 14 (1993): 1008-1012.

[11] Greene, William H. *Econometric Analysis* 2nd edition. New York: Macmillan, 1993.

[12] Grilo, Carlos M. and Michael F. Pogue-Geile. "The Nature of Environmental Influences on Weight and Obesity: A Behavioral Genetic Analysis." *Psychological Bulletin*, 110, 3 (1991): 520-537.

[13] Hamermesh, Daniel S. and Jeff E. Biddle. "Beauty and the Labor Market." *American Economic Review*, 84, 5 (1994): 1174-1194.

[14] Haskins, Katherine M. and H. Edward Ransford. "The Relationship Between Weight and Career Payoffs Among Women." *Sociological Forum*, 14, 2 (1999): 295-318.

[15] Hausman, J. A. "Specification Tests in Econometrics." *Econometrica*, 46, 6 (1978): 1251-1271.

[16] Heckman, James J. "Sample Selection Bias as a Specification Error." *Econometrica*, 47, 1 (1979): 153-161.

[17] Jensen, A. R. "The *g* Behind Factor Analysis." in *The Influence of Cognitive Psychology on Testing and Measurement*, ed. R. R. Ronning, J. A. Glover, J. C. Conoley, and J. C. Dewitt. Hillsdale, NJ: Lawrence Erlbaum Publishing, 1987.

[18] Judge, George G., W. E. Griffiths, R. Carter Hill, Helmut Lutkepohl, and Tsoung-Chao Lee. *The Theory and Practice of Econometrics*, 2nd edition, New York: John Wiley and Sons, 1985.

[19] Lee, Lung-fei and Jungsywan H. Sepanski. "Estimation of Linear and Nonlinear Errors-in-Variables Models Using Validation Data." *Journal of the American Statistical Association*, 90, 429 (1995): 130-40.

[20] Loh, Eng Seng. "The Economic Effects of Physical Appearance." *Social Science Quarterly*, 74, 2 (1993): 420-438.

[21] Maes, Hermine H. M., Michael C. Neale, and Lindon J. Eaves. "Genetic and Environmental Factors in Relative Body Weight and Human Adiposity" *Behavior Genetics*, 27, 4 (1997): 325-351.

[22] Mokdad, Ali H., Mary K. Serdula, William H. Dietz, Barbara A. Bowman, James S. Marks, and Jeffrey P. Koplan. "The Spread of the Obesity Epidemic in the United States, 1991-1998." *Journal of the American Medical Association*, 282, 16 (1999): 1519-1522.

[23] Murphy, Kevin M. and Robert H. Topel. "Estimation and Inference in Two-Step Econometric Models." *Journal of Business and Economic Statistics*, 3, 4 (1985): 370-379.

[24] Narbro, K., E. Jonsson, B. Larsson, H. Waaler, H. Wedel, and L. Sjostrom. "Economic Consequences of Sick-Leave and Early Retirement in Obese Swedish

Women." *International Journal of Obesity and Related Metabolic Disorders*, 20, 10 (1996): 895-903

[25] Naslund, I. and G. Agren. "Social and Economic Effects of Bariatric Surgery." *Obesity Surgery*, 1, (1991): 137-140.

[26] Newey, Whitney K. "Efficient Estimation of Limited Dependent Variable Models with Endogenous Explanatory Variables." *Journal of Econometrics*, 36, 3 (1987): 231-250.

[27] Pagan, Jose A., and Alberto Davlia. "Obesity, Occupational Attainment, and Earnings." *Social Science Quarterly*, 78, 3 (1997): 756-770.

[28] Price, R. Arlen, and Irving I. Gottesman. "Body Fat in Identical Twins Reared Apart: Roles for Genes and Environment." *Behavior Genetics*, 21, 1 (1991): 1-7.

[29] Register, Charles A. and Donald R. Williams. "Wage Effects of Obesity among Young Workers." *Social Science Quarterly*, 71, 1 (1990): 130-141.

[30] Sobal, Jeffery and Albert J. Stunkard. "Socioeconomic Status and Obesity: A Review of the Literature." *Psychological Bulletin*, 105, 2 (1989): 260-275.

[31] Sorensen, Thorkild I. A. and Albert J. Stunkard. "Does Obesity Run in Families Because of Genes? An Adoption Study Using Silhouettes as a Measure of Obesity." *Acta Psychiatrica Scandanavia*, 370, supplement (1993): 67-72.

[32] Sorensen, Thorkild I. A., Claus Holst, and Albert J. Stunkard. "Childhood Body Mass Index–Genetic and Familial Environmental Influences Assessed in a Longitudinal Adoption Study." *International Journal of Obesity*, 16, (1992): 705-714.

[33] Sorensen, Thorkild I. A., Claus Holst, Albert J. Stunkard, and Lene Theil. "Correlations of Body Mass Index of Adult Adoptees and Their Biological and Adoptive Relatives." *International Journal of Obesity*, 16, (1992): 227-236.

[34] Staiger, Douglas, and James H. Stock. "Instrumental Variables Regression With Weak Instruments." *Econometrica* 65, 3 (1997): 557-586.

[35] Stunkard, Albert J., Thorkild I.A. Sorensen, Craig Hanis, Thomas W. Teasdale, Ranajit Chakraborty, William J. Schull, and Fini Schulsinger. "An Adoption Study of Human Obesity." *New England Journal of Medicine*, 314, 4 (1986): 193-198.

[36] Thursby, Jerry G. and Peter Schmidt. "Some Properties of Tests for Specification Error in a Linear Regression Model." *Journal of the American Statistical Association*, 72, 359 (1977): 635-41.

[37] U. S. Department of Health and Human Services, National Center for Health Statistics. *National Health and Nutrition Examination Survey III, 1988-1994* [Computer file]. ICPSR version. Washington, DC: U. S. Department of Health and Human Services, National Center for Health Statistics [producer], 1996. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 1998.

[38] U. S. National Institutes of Health, National Heart, Lung, and Blood Institute. *Clinical Guidelines on the Identification, Evaluation, and Treatment of Overweight and Obesity in Adults* Washington, DC: National Institutes of Health, National Heart, Lung, and Blood Institute, 1998.

[39] Vogler, George P., Thorkild I.A. Sorensen, Albert J. Stunkard, M.R. Srinivasan, and D.C. Rao. "Influences of Genes and Shared Family Environment on Adult

Body Mass Index Assessed in an Adoption Study by a Comprehensive Path Model." *International Journal of Obesity*, 19, (1995): 40-45.

[40] Wolf, A. M. and G. A. Colditz. "Current Estimates of the Economic Cost of Obesity in the United States." *Obesity Research*, 6, 2 (1998): 97-106.

[41] Yanovski, Jack A., and Susan Z. Yanovski. "Recent Advances in Obesity Research." *Journal of the American Medical Association*, 282, 16 (1999): 1504-1506.

TABLE 1
National Longitudinal Survey of Youth Females
Summary Statistics

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Log Wage	21391	1.87	.57	0	6.21
Body Mass Index (Corrected)	21391	25.42	5.81	7.71	65.66
Weight in Pounds (Corrected)	21391	148.63	35.52	48.82	415.82
Height in Inches (Corrected)	21391	64.09	2.33	50.76	72.76
Indicator: Black	21391	.3	.46	0	1
Indicator: Hispanic	21391	.19	.39	0	1
Indicator: White Collar Job	19786	.58	.49	0	1
General Intelligence	20767	0	.92	-3.62	2.97
Highest Grade Completed	21299	12.54	2.02	0	20
Enrolled in School	21391	.1	.3	0	1
Years of Actual Work Experience	20016	7.12	4.87	0	22.66
Years at Current Job	21148	2.9	3.48	.02	28.4
Age	21391	28.82	5.67	16	41
Indicator: Local UE Rate < 6%	20941	.4	.49	0	1
Indicator: Local UE Rate >= 9%	20941	.22	.42	0	1
Indicator: Northeast Region	21265	.14	.35	0	1
Indicator: North Central Region	21265	.25	.43	0	1
Indicator: West Region	21265	.18	.39	0	1
Year	21391	89.77	5.14	81	98
Indicator: Married, Spouse Present	21390	.55	.5	0	1
Indicator: Been Married, But Not M-SP	21390	.2	.4	0	1
Number of Children in Household	21389	1.64	1.16	0	9
Indicator: No Children in HH	21389	.19	.39	0	1
Age of Youngest Child	17100	5.1	4.13	0	23
Other Family Income	17867	23187.49	53354.21	0	1113846.4
BMI of Selected Child	21391	17.27	3.74	7.51	64.54
Age of Selected Child	21391	7.96	1.03	6	9

Table 2
Ordinary Least Squares
Relationship Between BMI and Log Wages
NLSY Females
Coefficients and (T Statistics)

	OLS		OLS Selection Corrected	
BMI	-.006 (-4.1)		-.005 (-4.08)	
Weight in Pounds		-.001 (-4.1)		-.001 (-4.07)
Height in Inches		.011 (3.34)		.011 (3.34)
N	21391	21391	29332	29332
R^2	.27	.27		
S.D. of Weight Variable	5.81	35.52		
T Statistic of Inverse Mills Ratio			-1.47	-1.47

The other regressors in the log wage regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, currently enrolled in school, year, local unemployment rates, region of residence, and black and hispanic. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample.

Table 3
First Stage of 2SLS
NLSY Females
Coefficients and (T Statistics)

	Dependent Variable BMI	Weight in Lbs.
BMI of Daughter Aged 6	.39	2.29
	(7.82)	(7.75)
BMI of Son Aged 6	.39	2.3
	(7.06)	(6.84)
BMI of Daughter Aged 7	.35	2.08
	(7.63)	(7.59)
BMI of Son Aged 7	.34	2.04
	(8.2)	(8.14)
BMI of Daughter Aged 8	.34	2.05
	(8.26)	(8.23)
BMI of Son Aged 8	.33	1.98
	(8.37)	(8.34)
BMI of Daughter Aged 9	.33	1.92
	(8.34)	(8.14)
BMI of Son Aged 9	.35	2.08
	(8.93)	(8.79)
R^2	.18	.24
ΔR^2 of instruments	.04	.11
F Statistic of Instruments	10.47	10.23
Number of Observations	21391	21391

Aside from the variables reported here, the other regressors in the regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, year local unemployment rates, region of residence, and black and hispanic. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample. Instruments are interactions of child BMI with child age and gender.

Table 4
Second Stage of 2SLS
Relationship Between BMI and Log Wages
NLSY Females
Coefficients and (T Statistics)

	2SLS		2SLS Selection Corrected	
BMI	-.004 (-.62)		-.004 (-.62)	
Weight in Pounds		-.001 (-.68)		-.001 (-.68)
Height in Inches		.01 (1.81)		.01 (1.79)
N	21391	21391	29332	29332
T Statistic of Inverse Mills Ratio			-1.68	-1.68

The other regressors in the log wage regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, currently enrolled in school, year local unemployment rates, region of residence, and black and hispanic. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample.

Table 5
Ordinary Least Squares
Relationship Between BMI and Log Wages
NLSY White Females
Coefficients and (T Statistics)

	OLS		OLS Selection Corrected	
BMI	-.007 (-3.82)		-.007 (-3.8)	
Weight in Pounds		-.001 (-3.82)		-.001 (-3.8)
Height in Inches		.013 (3.17)		.013 (3.16)
N	10900	10900	14326	14326
R^2	.27	.27		
S.D. of Weight Variable	5.24	32.8		
T Statistic of Inverse Mills Ratio			-1.54	-1.51

The other regressors in the log wage regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, currently enrolled in school, year, local unemployment rates, and region of residence. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample.

Table 6
Second Stage of 2SLS
Relationship Between BMI and Log Wages
NLSY White Females
Coefficients and (T Statistics)

	2SLS		2SLS Selection Corrected	
BMI	-.007 (-.84)		-.007 (-.84)	
Weight in Pounds		-.001 (-.94)		-.001 (-.95)
Height in Inches		.014 (1.88)		.014 (1.86)
N	10900	10900	14326	14326
T Statistic of Inverse Mills Ratio			-1.76	-1.72

The other regressors in the log wage regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, currently enrolled in school, year local unemployment rates, and region of residence. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample.

Table 7
Ordinary Least Squares
Relationship Between BMI and Log Wages
NLSY Black Females
Coefficients and (T Statistics)

	OLS		OLS Selection Corrected	
BMI	-.002		-.002	
	(-1.49)		(-1.5)	
Weight in Pounds		0		0
		(-1.46)		(-1.47)
Height in Inches		.004		.004
		(.87)		(.9)
N	6400	6400	9209	9209
R^2	.32	.32		
S.D. of Weight Variable	6.48	39.72		
T Statistic of Inverse Mills Ratio			-.83	-.87

The other regressors in the log wage regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, currently enrolled in school, year, local unemployment rates, and region of residence. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample.

Table 8
Second Stage of 2SLS
Relationship Between BMI and Log Wages
NLSY Black Females
Coefficients and (T Statistics)

	2SLS		2SLS Selection Corrected	
BMI	.001 (.2)		.001 (.19)	
Weight in Pounds		0 (.27)		0 (.27)
Height in Inches		.001 (.14)		.001 (.17)
N	6400	6400	9209	9209
T Statistic of Inverse Mills Ratio			-.83	-.87

The other regressors in the log wage regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, currently enrolled in school, year local unemployment rates, and region of residence. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample.

Table 9
Ordinary Least Squares
Relationship Between BMI and Log Wages
NLSY Hispanic Females
Coefficients and (T Statistics)

	OLS		OLS Selection Corrected	
BMI	-.004 (-1.71)		-.004 (-1.71)	
Weight in Pounds		-.001 (-1.75)		-.001 (-1.76)
Height in Inches		.001 (.19)		.001 (.19)
N	4091	4091	5797	5797
R^2	.29	.29		
S.D. of Weight Variable	5.38	31.15		
T Statistic of Inverse Mills Ratio			-.11	-.08

The other regressors in the log wage regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, currently enrolled in school, year, local unemployment rates, and region of residence. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample.

Table 10
Second Stage of 2SLS
Relationship Between BMI and Log Wages
NLSY Hispanic Females
Coefficients and (T Statistics)

	2SLS		2SLS Selection Corrected	
BMI	.003 (.41)		.003 (.41)	
Weight in Pounds		.001 (.38)		.001 (.38)
Height in Inches		-.004 (-.47)		-.004 (-.47)
N	4091	4091	5797	5797
T Statistic of Inverse Mills Ratio			-.22	-.2

The other regressors in the log wage regression are: general intelligence (derived from the ten ASVAB tests), highest grade completed, actual work experience, job tenure, age, and indicator variables for white collar job, currently enrolled in school, year local unemployment rates, and region of residence. NLSY sample weights are used. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample.

Table 11
Probits and Probits with Instrumental Variables
Dependent Variable = 1 if Employed
NLSY Females
Marginal Probabilities and (Z Scores)

	Probit		Probit IV	
BMI	-.0008 (-.82)		.0057 (1.79)	
Weight in Lbs.		-.0008 (-.64)		.001 (1.79)
Height in Inches		.0012 (.48)		-.0036 (-1.08)
Number of Observations	29332	29332	29332	29332
Log Likelihood	-16109.43	-16109.69	-16105.19	-16105.65

Other regressors include: general intelligence, highest grade completed, weeks of work experience, age, and indicator variables for black, hispanic, local unemployment rate, currently enrolled in school, reg > ion, and year. NLSY sample weights are used in all regressions. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample. Probit results reported are the marginal probabilities associated with probit coefficients; z scores appear in parentheses. Probit with IV uses the method of Newey (1987). Probit IV standard errors are corrected according to Murphy and Topel (1985). Instruments are interactions of child BMI with child age and gender.

Table 12
Probits and Probits with Instrumental Variables
Dependent Variable = 1 if White Collar Worker
NLSY Females
Marginal Probabilities and (Z Scores)

	Probit		Probit IV	
BMI	-.0018 (-1.21)		-.0049 (-.51)	
Weight in Lbs.		-.0018 (-1.26)		-.0008 (-.49)
Height in Inches		-.0007 (-.19)		.0015 (.17)
Number of Observations	20467	20467	20467	20467
Log Likelihood	-12189.41	-12188.17	-12188.85	-12187.67

Other regressors include: general intelligence, highest grade completed, weeks of work experience, age, and indicator variables for black, hispanic, local unemployment rate, currently enrolled in school, reg > ion, and year. NLSY sample weights are used in all regressions. Robust standard errors are calculated with clustering by individual. Pregnant women are dropped from the sample. Probit results reported are the marginal probabilities associated with probit coefficients; z scores appear in parentheses. Probit with IV uses the method of Newey (1987). Probit IV standard errors are corrected according to Murphy and Topel (1985). Instruments are interactions of child BMI with child age and gender.