The Impact of Obesity on Wages

John Cawley

ABSTRACT

Previous studies of the relationship between body weight and wages have found mixed results. This paper uses a larger data set and several regression strategies in an attempt to generate more consistent estimates of the effect of weight on wages. Differences across gender, race, and ethnicity are explored.

This paper finds that weight lowers wages for white females; OLS estimates indicate that a difference in weight of two standard deviations (roughly 65 pounds) is associated with a difference in wages of 9 percent. In absolute value, this is equivalent to the wage effect of roughly one and a half years of education or three years of work experience. Negative correlations between weight and wages observed for other gender-ethnic groups appear to be due to unobserved heterogeneity.

I. Introduction

Several previous studies have found, among females, a negative correlation between body weight and wages.[1] There exist three broad categories of explanations for this finding. The first explanation is that obesity lowers wages; for example, by lowering productivity or because of workplace discrimination. The second is that low wages cause obesity. This would be true if poorer people consume

John Cawley is an assistant professor of policy analysis and management at Cornell University. *For their helpful comments, he thanks Susan Averett, Gary Becker, John Bound, Charlie Brown, Rachel Dunifon, Michael Grossman, James Heckman, Sanders Korenman, Darius Lakdawalla, Helen Levy, Will Manning, David Meltzer, Tomas Philipson, Chris Ruhm, seminar participants, and two anonymous referees. The author thanks Justine Lynge for editorial assistance. The data used in this article can be obtained beginning October 2004 through September 2007 from John Cawley, 134 MVR Hall, Department of Policy Analysis and Management, Ithaca, NY 14853-4401. Email: jhc38@cornell.edu.*
[Submitted September 2000; accepted January 2003]
ISSN 022-166X; E-ISSN 1548-8004

1. See, for example, Register and Williams (1990), Averett and Korenman (1996), and Pagan and Davila (1997).

cheaper, more fattening, foods. The third category of explanations is that unobserved variables cause both obesity and low wages. This paper uses several econometric methods in an effort to determine which of these three explanations is responsible for the correlation between weight and wages. Differences in the correlation between weight and wages across gender, race, and ethnicity are explored. The question of how obesity correlates with labor market outcomes, and why, is important in part because the prevalence of obesity in the United States has risen dramatically in recent years, from 15 percent during 1976–80 to 30.9 percent during 1999–2000.[2]

The outline of this paper is as follows. Section II presents a basic model of weight and wages. Section III discusses the methods and related literature in the context of the model. The data used in this paper are described in Section IV. Empirical results are presented in Section V.

II. A Model of Weight and Wages

Assume that wages W and Body Mass Index (or BMI)[3] B have the following relationship for individual i at time t :

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

In Equation 1, X is a vector of variables that affect wages (such as measures of human capital) and ε is the residual.

If BMI is strictly exogenous then an OLS estimate of β can be interpreted as a consistent estimate of the true effect of BMI on log wages. However, research in behavioral genetics suggests that roughly half of the variation in BMI is due to nongenetic factors such as individual choices and environment.[4] In addition, obesity may be influenced by wages, especially for adult females.[5] Each of these findings suggests that BMI may be endogenous.

To classify the sources of potential endogeneity in weight, the wage residual in Equation 1 can be decomposed as having a genetic component G^W, a nongenetic component NG^W, and a residual ν that is i.i.d. over individuals and time.

$$(2)\quad \varepsilon_{it} = G^W_{it} + NG^W_{it} + \nu_{it}$$

BMI may in turn be affected by wages and personal characteristics.

$$(3)\quad B_{it} = X_{it}\gamma + W_{it}\alpha + Z_{it}\phi + G^B_{it} + NG^B_{it} + \xi_{it}$$

2. Flegal et al. (2002).

3. BMI is calculated as weight in kilograms divided by height in meters squared. BMI is the standard measure of fatness in epidemiology and medicine (U. S. Department of Health and Human Services, 2001). For example, BMI is used to classify individuals as overweight and obese by the U. S. National Institutes of Health, the World Health Organization, and the International Obesity Task Force; see Flegal et al. (1998).

4. Genes explain roughly half of the cross-sectional and temporal variation in individual weight (see, for example, Comuzzie and Allison, 1998). Individual environment and choices appear to be responsible for the other half of variation.

5. Sobal and Stunkard (1989) survey 144 published studies on the subject of socioeconomic status (SES) and obesity and conclude that, in developed countries, the relationship between SES and obesity is negative for women and inconsistent for men and children.

In Equation 3, X is the same vector of variables that affect wages, W represents wages, Z is a vector of variables that affect BMI but do not directly affect wages, G^B represents the influence of genetics on BMI, NG^B represents the influence of nongenetic factors (such as an individual's choices, upbringing, and culture) on BMI. Residual BMI is represented by ξ. The variables on the right-hand side of Equation 3 indicate the potential pitfalls of an OLS estimation of Equation 1: current wages may affect BMI (if $\alpha \neq 0$), genetic factors that influence BMI (G^B) may be correlated with genetic factors that affect wages (G^W), and nongenetic factors that influence BMI (NG^B) may be correlated with nongenetic factors that affect wages (NG^W). Each of these scenarios implies that the OLS assumption that B is uncorrelated with ε in Equation 1 is violated and that an OLS estimate of β is biased.

III. Methods and Previous Studies

Several papers have studied the relationship between body weight and either wages or income,[6] but this section reviews only those that took steps to deal with the potential endogeneity of weight when estimating the effect of weight on wages.

In the previous literature, three strategies have been used to adjust for the likelihood that weight is endogenous. The first is to replace B with a lagged value of B. This strategy is based on the assumption that lagged weight is uncorrelated with the current wage residual: $B_{it-\tau} \perp \varepsilon_{it}$, which assumes no serial correlation in the wage residuals for the two periods: $\varepsilon_{it-\tau} \perp \varepsilon_{it}$. While this strategy will remove any contemporaneous effect of wages on weight, it does not deal with the problem that the genetic and nongenetic components of lagged weight ($G^B_{it-\tau}$ and $NG^B_{it-\tau}$) may be correlated with the genetic and nongenetic components of current wages (G^W_{it} and NG^W_{it}).

Gortmaker et al. (1993), Sargent and Blanchflower (1995), and Averett and Korenman (1996) regressed current income or wages on measures of body weight from seven years earlier. Each found that the income or wages of young females was lower if they had been overweight or obese in the past. Each study also found little if any evidence of a difference in income or wages for males based on weight status seven years earlier.

The second strategy used to deal with the endogeneity of weight is to estimate Equation 1 after taking differences with another individual with highly correlated genes (either a same-sex sibling or twin). Based on Equation 3, the differenced regressor of interest is:

$$B_{1t} - B_{2t} = (X_{1t} - X_{2t})\gamma + (W_{1t} - W_{2t})\alpha + (Z_{1t} - Z_{2t})\phi + (G^B_{1t} - G^B_{2t}) + (NG^B_{1t} - NG^B_{2t}) + (\xi_{1t} - \xi_{2t})$$

The differencing strategy assumes that all unobservable heterogeneity is constant within pairs (that is, that $G_1 = G_2$ and $NG_1 = NG_2$) so that all relevant unobserved heterogeneity is differenced away. This strategy also assumes that wages do not

6. See, for example, Register and Williams (1990), Loh (1993), Hamermesh and Biddle (1994), and Haskins and Ransford (1999).

influence weight ($\alpha = 0$), so that the differenced weight variable is uncorrelated with the differenced wage residual $(B_{1t} - B_{2t}) \perp (\varepsilon_{1t} - \varepsilon_{2t})$.

Averett and Korenman (1996), in addition to using lagged values of weight, difference between siblings. In taking this difference, they eliminate the variance in weight attributable to shared genes or shared environment. However, after differencing they are still left with: a) the variance in weight attributable to genes unshared by siblings since $G_1 \neq G_2$ within sibling pairs, and b) the variance in weight attributable to nongenetic factors unshared by siblings since $NG_1 \neq NG_2$ within sibling pairs. The coefficients on weight estimated by the sibling-differencing procedure of Averett and Korenman are not statistically significant, which is attributable in part to their small sample of siblings (288 sister pairs and 570 brother pairs).

Behrman and Rosenzweig (2001) examine the relationship between BMI and wages among females in the Minnesota Twins Registry. The drawback of this data is its relatively small sample size; even the OLS coefficient on BMI is not statistically significant if they control for schooling and work experience (N = 1,518). The authors estimate a regression differencing within 808 monozygotic (MZ) twin pairs; the coefficient on weight is not statistically significant.

The third strategy used to deal with the endogeneity of weight is to use variables Z as instruments in IV estimation under the assumption that $Z_{it} \perp \varepsilon_{it}$. Pagan and Davila (1997) find using OLS that obese females earn less than their more slender counterparts and seek to determine whether their OLS estimate is biased. Using a Hausman specification test, they fail to reject the hypothesis that weight is uncorrelated with the error term of the wage equation. However, their test is called into question because their instruments (family poverty level, health limitations, and indicator variables about self-esteem) are likely correlated with the error term in the wage equation. Given that their IV estimation likely suffers the same kind of bias as OLS, it is not surprising that, through their Hausman test, they fail to reject the hypothesis that OLS and IV coefficients are equal.

Behrman and Rosenzweig (2001), after removing the variation common between MZ twins, seek to remove any remaining endogeneity through IV, using lagged weight as an instrument. Their IV coefficient on BMI is not statistically significant.

This paper will estimate the effect of weight on wages using OLS and each of the three strategies described above to deal with the potential endogeneity of weight. This paper uses a larger data set to produce more precise estimates and also seeks to use better instruments to generate a more consistent IV estimate. An additional innovation of this paper is to correct the self-reported measures of weight and height for reporting error.

IV. Data: National Longitudinal Survey of Youth

The data used in this study are from The National Longitudinal Survey of Youth (NLSY), which was designed to represent the entire population of American youth. All sample members were between 14 and 22 years of age when the first annual interview was conducted in 1979. Since 1994, interviews have been conducted every two years.

At the baseline of the NLSY, respondents were asked to report their race or ethnicity, which the NLSY simplified into three groups: black, Hispanic, and nonblack/nonHispanic. For the sake of brevity, the last group is referred to as white throughout this paper, although it is a heterogeneous group.

The NLSY recorded the self-reported weight of respondents in 1981, 1982, 1985, 1986, 1988, 1989, 1990, 1992, 1993, 1994, 1996, 1998, and 2000. Data from these 13 years were pooled to create the sample used in this paper. Reported height was recorded in 1981, 1982, and 1985; given that respondents were between the ages of 20 and 27 in 1985, 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.[7] In order to correct for this reporting error, true height and weight in the NLSY are predicted using information on the relationship between true and reported values in the Third National Health and Nutrition Examination Survey (NHANES III)[8] and using the method outlined in Lee and Sepanski (1995) and Bound et al. (2002). Separately by race and gender, actual weight was regressed on reported weight and its square. This process was repeated for 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 values of weight and height, corrected for reporting error, are used throughout the paper.[9]

This paper uses three measures of body weight: (1) body mass index (BMI); (2) weight in pounds (controlling for height in inches); and (3) indicator variables for the clinical classifications underweight, overweight, and obese, where the excluded category is healthy weight.[10]

Weight tends to rise with age. In order to distinguish the effects of weight from those of age and time, linear measures of age and time are included as regressors in the log wage regressions.

Weight also may be affected by current or recent pregnancy. For this reason, females who are pregnant at the time that they report their body weight are dropped from the sample.[11] To control for effects of recent pregnancy, the set of regressors includes the age of a woman's youngest child and the total number of children to whom she has given birth.

The following variables are included as regressors in order to control for differences in human capital: general intelligence (which is a measure of cognitive ability derived from the ten Armed Services Vocational Aptitude Battery tests administered

7. See Judge et al. (1985).

8. Third National Health and Nutrition Examination Survey (NHANES III) conducted in 1988–94, surveyed a nationally representative sample of 33,994 persons aged 2 months and older; 31,311 of those respondents also underwent physical examinations.

9. An appendix detailing this correction for reporting error is available from the author upon request.

10. 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).

11. Two questions are used 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. Women who answered yes to either of these questions are dropped from the sample for the year of their pregnancy.

in 1980),[12] highest grade completed, mother's highest grade completed, and father's highest grade completed. The following regressors are included to control for characteristics of employment: years of actual work experience (defined as weeks of reported actual work experience divided by 50), job tenure, and indicator variables for whether the respondent's occupation is white collar or blue collar,[13] current school enrollment, county unemployment rate, and whether the respondent's job is part-time (defined as less than 20 hours per week). The set of regressors also includes age, year, and indicator variables for marital status and region of residence. Indicator variables for missing data associated with each regressor, except the weight variables, are also included.

In each year, the NLSY calculates the hourly wage earned by the respondent at his or her primary job. Outliers in wage are recoded; if the hourly wage is less than \$1 an hour, it is recoded to \$1 and if the hourly wage exceeds \$500 an hour, it is recoded to \$500.[14]

Gortmaker et al. (1993) studied 1988 earnings data from the NLSY and Pagan and Davila (1997) studied 1989 data from the same source. The primary sample used by Averett and Korenman (1996) is also a single year of data (1988) from the NLSY, and in an appendix they present results for three years of data (1988–90) pooled. This paper also studies the NLSY but pools all 13 years that contain weight data.

Appendix Tables A1 and A2 provide summary statistics for the samples of females and males.

NLSY sample weights are used in all estimations described in this paper. *T*-statistics reported for OLS and IV regressions reflect robust standard errors that are calculated with clustering by individual to account for correlations in the error terms of each individual over time.

V. Empirical Results

The hypotheses that all coefficients are equal across race/ethnic groups, and that the coefficients on BMI are equal across race/ethnic groups, were tested. For both males and females, each hypothesis was rejected at the 5 percent significance level, so regressions are estimated separately by race and gender. Results for women are presented in Table 1 and those for men are presented in Table 2.[15]

12. See Jensen (1987) for a full description of this measure of cognitive ability.

13. All occupations are classified 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, NonFarm Managers and Administrators, Sales Workers, and Clerical and Unskilled Workers.

14. As a result, 634 person-year observations are bottom-coded and 55 person-year observations are top-coded.

15. 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 (see Berndt, 1991, Chapter 11). In results not presented in this paper, the method of Heckman (1979) was used to correct for selection bias in the log wage regression results for women. Family income not attributable to the wages of the respondent served as an instrument for the propensity of women to engage in market employment. There was little evidence of selection bias (judging by the coefficient on the inverse Mill's ratio), perhaps because many women work at some point during the ages (17–44) represented in this

Columns 1, 4, and 7 of Table 1 indicate that, for each group of females, both BMI and weight in pounds have negative and statistically significant OLS coefficients. The point estimate is largest for white females and smallest for black females. An increase of two standard deviations (64 pounds) from the mean weight in pounds among white females is associated with a decrease in wages of 9 percent, which is roughly equal in magnitude to the difference associated with 1.5 years of education, or three years of work experience. In contrast, for black females, an increase in weight of two standard deviations (79 pounds) from the mean is associated with a decrease in wages of 4.7 percent, and the same two standard deviation increase for Hispanic females (62 pounds) is associated with a decrease in wages of 6.8 percent.

Columns 1, 4, and 7 of Table 2 indicate that the signs and magnitudes of the OLS coefficients on weight for males vary by ethnic group. For white males, the coefficients on BMI and weight in pounds are not significantly different from zero. For black males, higher body weight is associated with *higher* wages; an increase in weight of two standard deviations (70 pounds) from the mean weight in pounds is associated with a 4.2 percent increase in wages. The coefficients on weight for Hispanic males resemble those for females: negative and statistically significant. Among Hispanic males, an increase in weight of two standard deviations (73.5 pounds) from the mean weight in pounds is associated with a decrease in wages of 8.1 percent, which is similar in magnitude to the wage effect of 2.5 years of education or 4.5 years of work experience.

Equation 1 assumes that log wages are linear in BMI (or weight in pounds). Table 3, which contains the results of RESET tests for linearity,[16] indicates that at a 5 percent significance level, the hypothesis of linearity of wages in BMI is rejected for black females, Hispanic females, white males, and black males, but that it is impossible to reject the hypothesis of linearity for white females and Hispanic males. At the same significance level, the hypothesis of linearity of wages in weight in pounds is rejected for Hispanic females and white males but cannot be rejected for any other group. Given this evidence that wages may be nonlinear in weight for certain measures of weight and certain race-ethnic groups, models are also estimated using indicator variables for clinical weight classification.

Columns 1, 4, and 7 of Tables 1 and 2 also present the OLS coefficients on the indicator variables for clinical weight classification. Among white females, there is no detectable wage differential between those who are underweight relative to those of healthy weight, but those who are overweight earn 4.5 percent less than those of healthy weight, and those who are obese earn, on average, 11.9 percent less than those of healthy weight—this is roughly equal to the effect of 1.8 years of education or 3.8 years of work experience.

Among black and Hispanic females, the OLS coefficients indicate that those who are overweight earn no less than those of healthy weight, while those who are obese earn roughly 6–8 percent less. Black females are the only females for whom the underweight earn less than those of healthy weight.

The pattern of log wages over weight classification is an inverted U shape for white males. In Table 2, the point estimate of the coefficient on the indicator for

sample. The adjustment also had very little effect on the magnitude of the coefficients on weight, so only results without the Heckman selection correction are presented in this paper.

16. Thursby and Schmidt (1977).

Table 1
Coefficients and t-Statistics from Log Wage Regressions for Females

	White Females			Black Females			Hispanic Females		
	OLS	OLS with Lag Weight	Fixed Effects	OLS	OLS with Lag Weight	Fixed Effects	OLS	OLS with Lag Weight	Fixed Effects
Column Number	1	2	3	4	5	6	7	8	9
BMI	−0.008	−0.008	−0.007	−0.004	−0.005	−0.0001	−0.006	−0.006	−0.003
	(−7.01)	(−4.62)	(−5.73)	(−3.20)	(−3.09)	(−0.11)	(−3.31)	(−2.73)	(−1.19)
Weight in pounds	−0.0014	−0.0014	−0.0012	−0.0006	−0.0009	0.0001	−0.0011	−0.0012	−0.0005
	(−6.98)	(−4.73)	(−5.65)	(−3.16)	(−3.00)	(0.15)	(−3.35)	(−2.77)	(−1.26)
Underweight	−0.01	0.019	−0.011	−0.056	−0.021	−0.084	−0.042	−0.071	0.028
	(−0.53)	(0.81)	(−0.75)	(−2.18)	(−0.99)	(−3.61)	(−1.17)	(−1.62)	(0.79)
Overweight	−0.045	−0.080	−0.016	−0.011	−0.080	0.018	−0.015	−0.039	0.006
	(−3.52)	(−4.35)	(−1.63)	(−0.75)	(−4.35)	(1.48)	(−0.75)	(−1.50)	(0.39)
Obese	−0.119	−0.089	−0.087	−0.061	−0.077	0.002	−0.082	−0.098	−0.02
	(−6.76)	(−3.35)	(−5.88)	(−3.31)	(−2.99)	(0.12)	(−3.22)	(−2.82)	(−0.83)
Number of observations	25,843	9,972	25,843	11,742	9,972	11,742	7,533	3,092	7,533

Notes:
1) Data: NLSY females
2) One of three measures of weight is used: BMI, weight in pounds (controlling for height in inches) or the three indicator variables for clinical weight classification: underweight, overweight, and obese (where healthy weight is the excluded category).
3) For BMI and weight in pounds, coefficients and *t* statistics are listed. For indicators of clinical weight classification, the percent change in log wages associated with a change in the indicator variable from 0 to 1 and *t* statistics are listed.
4) Other regressors include: number of children ever born, age of youngest child, general intelligence, highest grade completed, mother's highest grade completed, father's highest grade completed, years of actual work experience, job tenure, age, year, and indicator variables for marital status, county unemployment rate, current school enrollment, part-time job, white collar job, and region of residence.

Table 2
Coefficients and t-Statistics from Log Wage Regressions for Males

	White Males			Black Males			Hispanic Males		
	OLS	OLS with Lag Weight	Fixed Effects	OLS	OLS with Lag Weight	Fixed Effects	OLS	OLS with Lag Weight	Fixed Effects
Column Number	1	2	3	4	5	6	7	8	9
BMI	−0.001	−0.003	−0.0001	0.004	0.005	0.003	−0.007	−0.009	−0.002
	(−0.83)	(−1.54)	(−0.21)	(2.19)	(2.04)	(1.96)	(−3.12)	(−3.15)	(−1.03)
Weight in pounds	−0.0002	0.0005	0.0001	0.0006	0.0007	0.0005	−0.0011	−0.001	−0.0003
	(−1.01)	(−1.68)	(0.07)	(2.21)	(2.06)	(1.96)	(−3.47)	(−3.18)	(−0.90)
Underweight	−0.14	0.005	−0.035	−0.099	−0.046	0.013	0.029	0.107	−0.005
	(−3.05)	(0.07)	(−1.12)	(−2.75)	(−0.70)	(0.28)	(0.44)	(1.13)	(−0.12)
Overweight	0.039	0.016	0.022	0.031	0.019	0.014	−0.025	−0.021	0.018
	(3.04)	(1.05)	(2.63)	(1.87)	(0.94)	(1.14)	(−1.13)	(−0.82)	(1.15)
Obese	−0.033	−0.075	0.013	0.043	0.042	0.031	−0.066	−0.100	0.023
	(−1.73)	(−3.05)	(0.89)	(1.80)	(1.29)	(1.64)	(−2.21)	(−2.41)	(0.91)
Number of observations	29,410	12,410	29,410	13,414	6,128	13,414	9,070	4,079	9,070

Notes:
1) Data: NLSY males.
2) One of three measures of weight is used: BMI, weight in pounds (controlling for height in inches) or the three indicator variables for clinical weight classification: underweight, overweight, and obese (where healthy weight is the excluded category).
3) For BMI and weight in pounds, coefficients and t statistics are listed. For indicators of clinical weight calssification, the percent change in log wages associated with a change in the indicator variable from 0 to 1 and t statistics are listed.
4) Other regressors include: number of children ever born, age of youngest child, general intelligence, highest grade completed, mother's highest grade completed, father's highest grade completed, years of actual work experience, job tenure, age, year, and indicator variables for marital status, county unemployment rate, current school enrollment, part-time job, white collar job, and region of residence.

Table 3
Test of Linearity

	F Statistics and *p* Values	
Group	BMC	Weight in Pounds
White females	1.21	0.54
	p=0.304	p=0.655
Black females	4.38	2.35
	p=0.004	p=0.071
Hispanic females	3.89	5.44
	p=0.009	p=0.001
White males	13.85	5.64
	p=0.000	p=0.001
Black males	4.8	0.06
	p=0.002	p=0.981
Hispanic males	1.04	0.24
	p=0.374	p=0.868

Notes:
1) Data: NLSY.
2) *F* statistics are associated with Thursby and Schmidt (1977) tests of linearity; specifically, with the hypothesis that the coefficients on the weight measure to the second, third, and fourth powers are jointly equal to zero.

underweight is negative, that for overweight is positive, and that for obese is negative. While the OLS coefficients on both BMI and weight in pounds were positive and significant for black males, the OLS coefficients on the indicator variables for weight classification indicate that this is due to underweight black men earning less than healthy weight black men, not due to overweight and obese black men earning more than healthy weight black men (though the point estimates of the coefficients on overweight and obese are positive).

The OLS results for Hispanic males resemble those for Hispanic females; the coefficient on underweight is not statistically significant, while that on obese is statistically significant and negative.

Averett and Korenman (1996) report a coefficient on obesity for white females that is strikingly similar: −0.12 compared with −0.119 found in this paper.[17] Their coefficient on obesity for black females is also virtually identical but is not statistically significant.

The OLS estimates suggest that, in general, heavier females of each ethnic group and heavier Hispanic males tend to earn less than members of the same group of

17. See Averett and Korenman (1996), Table 7, column 8.

healthy weight. However, as mentioned earlier, OLS estimates of the coefficient on weight in Equation 1 are questionable because there may exist reverse causality; that is, heavier people may tend to earn less because low wages result in weight gain. The previous literature tried to eliminate such effects by substituting a lagged value of weight for its contemporaneous value. Each of the three papers in the previous literature to use this strategy (Gortmaker et al., 1993; Sargent and Blanchflower, 1995; and Averett and Korenman, 1996) used a lag of seven years, so to facilitate comparisons this paper will follow that convention. Columns 2, 5, and 8 in Tables 1 and 2 present OLS results using a measure of weight lagged seven years. The point estimates of the lagged measures of BMI and weight in pounds are, in general, similar to those on current weight. The smaller sample sizes in the lagged regressions result in higher standard errors, so in some cases the coefficients are not statistically significant in a lagged regression while a similar point estimate is significant in the contemporaneous regression.

The high degree of similarity between the point estimates on linear measures of weight in the lagged and contemporaneous OLS regressions is consistent with either of two hypotheses: either (a) current wages have little impact on current weight; or (b) current wages do affect current weight, but there is such high serial correlation in both wages and weight that when even distant BMI is used as a regressor, the effect of wages on weight is measured just as strongly.

Differences in coefficients on lagged and contemporaneous values of weight are greater in the regressions using indicator variables for weight classification; for example, the indicator for lagged underweight status has a considerably smaller point estimate than that for contemporary underweight status for white and black men. Furthermore, lagged (but not contemporaneous) obesity is statistically significant and negative for white males. With the exception of white females, the coefficients on lagged obesity tend to be larger in absolute than those on contemporaneous obesity; this is consistent with the results of Averett and Korenman (1996).[18]

The strategy of using lagged weight does not address the issue of time-invariant heterogeneity on both weight and wages. It is impossible to test for the presence of unobserved heterogeneity, but a comparison across weight groups of important observed variables that are known to affect wages can be suggestive. Table 4 lists the average intelligence test score and education of those who according to clinical classifications are underweight or healthy weight compared to those who are overweight or obese, within each gender-ethnic group. *T*-statistics associated with the hypothesis that the difference between the group means is zero appear in parentheses.

Table 4 indicates that for each group of females, those in the lighter group have on average more years of education and higher test scores than those who are in the heavier group. The results for males are again very different from those for females; of four comparisons for white males and Hispanic males, only for the education of white males is the difference statistically significant, with lighter individuals having on average a higher value of the human capital measure. In contrast, among black males, the difference is statistically significant and negative for both education and intelligence test scores—that is, black males who are overweight or obese tend to have on average *higher* education and intelligence scores than black males who are

18. See Averett and Korenman (1996), Table 7, column 7.

Table 4
Difference in Unconditional Means between (Underweight and Healthy Weight) and (Overweight and Obese)

Group	Highest Grade Completed	General Intelligence
White females	0.548	0.127
	(5.85)	(3.19)
	N = 1787, 1048	N = 1733, 1017
Black females	0.378	0.093
	(3.36)	(1.69)
	N = 592, 741	N = 584, 727
Hispanic females	0.538	0.197
	(2.94)	(2.89)
	N = 393, 449	N = 384, 435
White males	0.282	0.034
	(2.75)	(0.84)
	N = 1077, 1641	N = 1024, 1572
Black males	−0.291	−0.16
	(−2.69)	(−2.88)
	N = 588, 775	N = 567, 752
Hispanic males	0.082	−0.06
	(0.45)	(−0.83)
	N = 326, 523	N = 302, 493

Notes:
1) Data: NLSY.
2) Includes one observation of each individual, observed between the ages of 28 and 32.
3) Listed is the difference in means between the lighter group and the heavier group, the *t* statistic associated with the hypothesis that the two means are equal, and the number of observations in the two groups. A positive difference in the means indicates that the lighter group has a higher mean than the heavier group.

lighter. This correlation suggests that unobserved heterogeneity is the reason that black males were the only group with a positive correlation between wages and either BMI or weight in pounds. If unobserved variables that affect wages are correlated with weight in the same way education and intelligence test scores are correlated with weight, then omitted variable bias in OLS estimates of β will generate spurious results that imply that weight lowers wages for females and weight raises wages for black men.

These findings for females are consistent with those of Sargent and Blanchflower (1994), who find that girls (but not boys) obese at age 16 performed worse than those not obese at age 16 on math and reading tests in later years. They also found that both men and women who had been obese at age 16 ended up with fewer years of schooling than those not obese at age 16. Similarly, Gortmaker et al. (1993) find that women, but not men, who were overweight in 1981 had less education in 1988 compared to those who had not been overweight in 1981.

A fixed-effects model is used to eliminate time-invariant heterogeneity. While the previous literature took differences between siblings or twins, this paper exploits the longitudinal nature of the NLSY data to eliminate individual-specific fixed effects. Assuming that the influence of genes and nongenetic factors is constant over time, the individual fixed-effects method eliminates more variation due to unobserved nongenetic factors than does differencing between either siblings or twins, and will eliminate just as much of the variation due to genes as differencing between MZ twins (which is more than is eliminated by differencing between nontwin siblings).

Columns 3, 6, and 9 of Tables 1 and 2 report estimates from fixed-effects regressions. The most dramatic difference is that the negative coefficients on BMI and weight in pounds are much smaller and no longer statistically significant for black females, Hispanic females, and Hispanic males. This suggests that the OLS results for these groups are driven largely by unobserved time-invariant heterogeneity.

The coefficients on BMI and weight in pounds are virtually unchanged for white females. The fixed-effects coefficients for black males are smaller than those from OLS and are just barely statistically significant at a 5 percent level. So far, the finding that heavier white females earn less and heavier black males earn more is robust.

Linearity of wages in weight was rejected for black and Hispanic females, as well as for white males. For these three groups, the small fixed-effects point estimates could be due to differencing across a nonlinear function. Columns 3, 6, and 9 of Tables 1 and 2 also list the fixed-effects estimates of coefficients on indicator variables for weight classification. Each of the coefficients on clinical weight classification is not statistically significant for Hispanic females. However, the coefficient on the indicator variable on underweight is statistically significant and negative for black females, and the indicator for overweight is statistically significant and positive for white males.[19] No fixed-effects coefficient on weight classification is statistically significant for black men. It is also noteworthy that the fixed-effects coefficient on obesity is statistically significant and negative for white females, which is consistent with the results from both the OLS with current weight and the OLS with lagged weight regressions. These results suggest that the negative correlations between weight and wages observed for black females, Hispanic females, and Hispanic males are due to unobserved time-invariant heterogeneity; once time-invariant heterogeneity is eliminated, negative correlations between weight and wages disappear. In contrast, the negative correlation between weight and wages persists for white females.

Behrman and Rosenzweig (2001) find no statistically significant relationship between BMI and wages once they difference within female MZ twins. However, the small size of their sample (N = 808) may partly explain their failure to reject the hypothesis of no effect of weight on wages. For both males and females (with blacks, whites, and Hispanics pooled), Averett and Korenman (1996) find negative but not statistically significant coefficients on indicator variables for weight status in their within-sibling regressions.[20] However, their failure to reject the hypothesis of no

19. The finding that the coefficient on the indicator for overweight is statistically significant for white males in the OLS with current weight and fixed-effects regressions is consistent with McLean and Moon (1980), which finds in 1973 data from the National Longitudinal Survey of Mature Men that overweight middle-aged men earn more than lighter men of the same age; they attribute this to a “portly banker” effect; that in certain groups girth is a signal of power or strength that commands respect.

20. See Averett and Korenman (1996), Table 4, column 8.

effect of weight on wages may also be partly due to their small samples of siblings: 288 sisters and 570 brothers.

A fixed-effects strategy improves on OLS but is not ideal because unobserved factors influencing both weight and wages may vary over time. To deal with this problem, this paper turns to the method of instrumental variables. If one can identify a set of instruments Z that are correlated with BMI but not with ε, the error term in wages, then one can calculate an instrumental variables estimate of β. This paper uses an instrument correlated with the genetic variation in weight (G^B): the BMI of a sibling, controlling for the age and gender of the sibling. The BMI of a sibling (B_S) is assumed to be correlated with the sibling's personal characteristics, wages, and genes:

$$B_{st} = X_{st}\gamma + W_{st}\alpha + G^B_{st} + NG^B_{st} + \xi_{st}$$

The identifying assumption has two parts. The first is that the BMI of a sibling is strongly correlated with the BMI of the respondent. Siblings with the same parents are expected to share half of their genes, ensuring a high correlation between the siblings' genetic variation in weight G^B_S and G^B_i. Given that about half of the variation in weight is genetic in origin,[21] this ensures a strong correlation between sibling weights B_S and B_i.

The second part of the identifying assumption is that the weight of a sibling is uncorrelated with the respondent's wage residual. One might be concerned that the nongenetic variation in sibling weight NG^B_S is correlated with the respondent's wage residual through the nongenetic variation in the respondent's wage NG^W if both are, in part, determined by habits learned in the parents' household. However, studies have been unable to detect any effect of common household environment on body weight. Adoption studies have consistently found that the correlation in BMI between a child and its biological parents is the same for adoptees and natural children; that is, all of the correlation in weight can be attributed to shared genes and there is no effect attributable to shared family environment. This has been found for BMI,[22] weight class,[23] and even body silhouette.[24] Consistent with these findings, studies have been unable to reject the hypotheses that the correlations in weight, weight for height, and skinfold measures between unrelated adopted siblings are equal to zero.[25] Studies of twins reared apart also find no effect of a shared family environment on BMI; there is no significant difference between the correlation in weight of twins reared together and twins reared apart, nor is the correlation affected by age at separation or the similarity of separate rearing environments.[26] 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."[27] It is not possible to prove the null hypothesis of no effect of household

21. Comuzzie and Allison (1998).
22. Vogler et al. (1995).
23. Stunkard et al. (1986).
24. Sorensen and Stunkard (1993).
25. Grilo and Pogue-Geile (1991).
26. Price and Gottesman (1991), Maes et al. (1997).
27. Grilo and Pogue-Geile (1991), p. 520.

environment on body weight; the repeated failure to reject the null hypothesis is the strongest evidence that will ever be available. In addition, decades may have passed since the NLSY siblings lived in the same household, presumably weakening any household environment effect that ever did exist.

Alternately, one might be concerned that the genetic variation in sibling weight G_S^B is correlated with the respondent's wage residual through genetic variation in respondent's wage G^W. For this to be true, the genes that determine weight and any genes that determine wages would have to be either the same or bundled in transmission.

While it is impossible to prove the null hypothesis that sibling BMI is uncorrelated with the residual in the respondent's wage equation, it can be informative to examine whether sibling weight is correlated with observables that are believed to be related to unobserved factors that affect the wage residual. To this end, years of education and the intelligence test score of the respondent were regressed on the set of instruments (sibling weight, sibling age, and sibling gender) and the other regressors (except weight) from the wage regressions. While this is not a definitive test, if the instruments are correlated with these observables it would suggest that either G_S^B or NG_S^B is correlated with the respondent's wage residual and would cast doubt on the instruments' validity. However, the suggestive evidence from this test is consistent with the identifying assumption; in only one of 12 regressions (two outcomes by six race-gender groups) was the set of instruments significant at the 10 percent level—roughly what one would expect by chance.

A different observation of BMI from the same sibling is used as an instrument for each observation of respondent weight. Results from the first-stage regression confirm that sibling weight is a powerful instrument for respondent weight. The F statistic associated with the hypothesis that the first-stage coefficients on the instruments are jointly equal to zero was over 30 for white males and females, over 20 for black males and females, and was roughly 8 for Hispanic females and roughly 20 for Hispanic males; for five of the six groups this F statistic far exceeds the minimum F statistic of 10 suggested by Staiger and Stock (1997). For each race-gender group, the partial R-squared contributed by the instruments in the first stage is greater than 0.04.

IV coefficients on BMI and weight in pounds are presented in Columns 2, 4, and 6 of Tables 5 and 6. (Columns 1, 3, and 5 in those tables present, for the sake of comparison, OLS coefficients estimated using the IV sample.) IV has not been used to estimate coefficients on the indicator variables for clinical weight classification because there are three indicators for weight classifications in a single regression but only one instrument.

Tables 5 and 6 indicate that only for white females is the IV coefficient on weight statistically significant at a 5 percent level; the point estimate of that IV coefficient is roughly 70 percent higher than the OLS coefficient estimated using the same sample. The magnitude of the IV coefficient for white females is such that an increase of two standard deviations (64 pounds) from the mean weight in pounds is associated with a decrease in wages of 18 percent, which is roughly equal in magnitude to the difference associated with three years of education, or six years of work experience. A Hausman test indicates that the hypothesis that OLS and IV coefficients are equal cannot be rejected for any of the six race-gender groups. In other words, any endoge-

Table 5
IV Coefficients and t-Statistics from Log Wage Regressions for Females

	White Females		Black Females		Hispanic Females	
	OLS Using IV Sample	IV	OLS Using IV Sample	IV	OLS Using IV Sample	IV
Column Number	1	2	3	4	5	6
BMI	−0.010	−0.017	−0.003	−0.002	−0.006	−0.012
	(−6.10)	(−3.38)	(−2.13)	(−0.32)	(−2.35)	(−0.99)
		$F = 32.77$		$F = 20.36$		$F = 8.29$
Weight in pounds	−0.0016	−0.0028	−0.0006	−0.0003	−0.0012	−0.0023
	(−5.97)	(−3.40)	(−2.05)	(−0.31)	(−2.44)	(−1.02)
		$F = 32.79$		$F = 20.08$		$F = 8.48$
Number of observations	10,800	10,800	5,651	5,651	3,035	3,035

Notes:
1) Data: NLSY females.
2) One of two measures of weight is used: BMI or weight in pounds (controlling for height in inches).
3) Coefficients and *t*-statistics are listed.
4) Other regressors include: Number of children ever born, age of youngest child, general intelligence, highest grade completed, mother's highest grade completed, father's highest grade completed, years of actual work experience, job tenure, age, year, and indicator variables for marital status, county unemployment rate, current school enrollment, part-time job, white collar job, and region of residence.
5) Columns 2, 4, and 6 also list the *F*-statistic associated with the test of the hypothesis that the coefficients on the instruments are jointly equal to zero.

Table 6
IV Coefficients and t-Statistics from Log Wage Regressions for Males

	White Males		Black Males		Hispanic Males	
	OLS Using IV Sample	IV	OLS Using IV Sample	IV	OLS Using IV Sample	IV
Column Number	1	2	3	4	5	6
BMI	−0.001	−0.013	0.006	−0.003	−0.006	−0.009
	(−0.45)	(−1.57)	(2.22)	(−0.38)	(−2.5)	(−1.25)
		$F = 31.32$		$F = 26.16$		$F = 21.21$
Weight in pounds	−0.0002	−0.0021	0.0009	−0.0004	−0.0010	−0.0018
	(−0.54)	(−1.72)	(2.34)	(−0.37)	(−2.67)	(−1.62)
		$F = 29.84$		$F = 26.34$		$F = 20.07$
Number of observations	13,355	13,355	6,811	6,811	4,374	4,374

Notes:
1) Data: NLSY males.
2) One of two measures of weight is used: BMI or weight in pounds (controlling for height in inches).
3) Coefficients and t-statistics are listed.
4) Other regressors include: Number of children ever born, age of youngest child, general intelligence, highest grade completed, mother's highest grade completed, father's highest grade completed, years of actual work experience, job tenure, age, year, and indicator variables for marital status, county unemployment rate, current school enrollment, part-time job, white collar job, and region of residence.
5) Columns 2, 4, and 6 also list the F-statistic associated with the test of the hypothesis that the coefficients on the instruments are jointly equal to zero.

neity of weight does not appreciably affect the OLS estimates and OLS should be preferred to IV since OLS results in lower standard errors.

VI. Summary

This paper measures and disentangles the correlation between weight and wages. Ordinary least squares results indicate that heavier white females, black females, Hispanic females, and Hispanic males tend to earn less, and heavier black males tend to earn more, than their lighter counterparts. Models are estimated using lagged body weight, in order to avoid the influence of wages on contemporaneous weight; results from these regressions are consistent with wages having little effect on contemporaneous weight. Individual fixed effects are removed to eliminate the influence of time-invariant unobserved heterogeneity on weight and wages; this procedure has a dramatic effect and eliminates the negative correlation between weight and wages for all but white females. Finally, the method of instrumental variables is used to determine if weight lowers wages. IV results indicate that the hypothesis that weight does not lower wages can be rejected only for white females.

One curious finding of this paper is that results for black males differ from those for all other groups. Heavier black males tend to earn more, although this appears to be due to underweight black men earning less than healthy weight black men, and not due to overweight or obese black men earning more than healthy-weight black men. Moreover, among black men, weight is positively correlated with education and intelligence test scores, a pattern opposite to that for most other groups.

In summary, unobserved heterogeneity seems to result in heavier black females, Hispanic females, and Hispanic males earning less than lighter members of those groups. In contrast, a result of striking consistency is that weight appears to lower the wages of white females; this finding is consistent across OLS with current weight, OLS with lagged weight, fixed effects, and IV. For white females, OLS estimates indicate that a difference in weight of two standard deviations (roughly 64 pounds) is associated with a difference in wages of 9 percent. This difference in wages is equivalent in absolute value to the wage effect of roughly 1.5 years of education or three years of work experience.

The sociological literature yields one possible explanation for the difference in results between white females and black and Hispanic females: that obesity has a more adverse impact on the self-esteem of white females than on that of black and Hispanic females, who report perceiving higher weight as a signal of power and stability.[28] Averett and Korenman (1999) study 1990 data from the NLSY and find that obesity is associated with lower self-esteem among white females, but not among black females. However, they also found that controlling for differences in self-esteem did not explain differences across race in the relationship between obesity and wages. Future research should further pursue explanations for such dramatic differences across gender and race in the correlation between weight and wages.

28. See, for example, Stearns (1997).

Table A1
Summary Statistics for Females

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Log Wage	45,120	1.96	.58	0	6.21
Body Mass Index	45,120	25.13	5.9	6.73	88.07
Weight in pounds	45,120	147.7	36.18	42.6	572.13
Height in inches	45,120	64.26	2.37	48.79	80.74
7-year lag BMI	18,078	23.65	5.09	11.77	56.12
7-year lag weight in pounds	18,085	13.9	31.46	71.48	342.35
7-year lag height in inches	20,031	64.22	2.37	49.87	74
Number children ever born	45,070	1.17	1.25	0	10
Age of youngest child	44,954	3.1	4.48	0	27
Black	45,120	.26	.44	0	1
Hispanic	45,120	.17	.37	0	1
White-collar job	40,700	.63	.48	0	1
General intelligence	43,835	.11	.96	−3.88	3.44
Highest grade completed	44,911	13	2.24	0	20
Mother’s highest grade completed	42,910	10.97	3.09	0	20
Father’s highest grade completed	39,206	11.08	3.86	0	20

Table A1 (*continued*)

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Enrolled in school	45,120	.13	.33	0	1
Years actual work experience	41,521	7.57	5.13	0	23.78
Years at current job	44,632	3.13	3.73	.02	30.54
Work more than 20 hours per week	43,052	.9	.3	0	1
Age	45,120	28.93	6.11	16	44
County UE rate <6 percent	44,092	.44	.5	0	1
County UE rate >= 9 percent	44,092	.21	.38	0	1
Northeast Region	44,827	.17	.38	0	1
North Central Region	44,827	.23	.42	0	1
West Region	44,827	.19	.39	0	1
Year	45,120	1,989.99	5.65	1981	2000
Married, spouse present	42,908	.46	.5	0	1
Married, spouse not present	42,908	.17	.38	0	1
Sibling BMI	19,488	25.45	5.36	7.80	68.92
Sibling is female	19,488	.50	.50	0	1
Sibling age	19,488	28.34	6.17	16	43

Data: NLSY.

Table A2
Summary Statistics for Males

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Log wage	51,899	2.16	.6	0	6.21
Body mass index	51,899	25.83	4.65	8.79	68.92
Weight in pounds	51,899	178.06	35.44	58.49	471.21
Height in inches	51,899	69.55	2.46	55.59	81.83
7-year lag BMI	22,620	24.86	4.13	10.02	56.49
7-year lag weight in pounds	22,626	171.3	32.05	71.88	415.16
7-year lag height in inches	23,141	69.52	2.49	54.66	81.85
Number children ever born	51,797	.98	1.23	0	9
Age of youngest child	51,772	1.55	3.25	0	32
Black	51,899	.26	.44	0	1
Hispanic	51,899	.17	.38	0	1
White-collar job	46,533	.35	.48	0	1
General intelligence	49,704	.05	.99	−3.96	3.42
Highest grade completed	51,729	12.61	2.39	0	20
Mother's highest grade completed	48,352	10.93	3.25	0	20
Father's highest grade completed	44,838	11.04	3.98	0	20

Table A2 (*continued*)

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Enrolled in school	51,899	.11	.31	0	1
Years actual work experience	45,589	8.11	5.34	0	23.94
Years at current job	51,221	3.32	3.9	.02	24.92
Work more than 20 hours per week	49,460	.95	.21	0	1
Age	51,899	28.66	6.04	16	43
County UE rate <6 percent	50,526	.44	.5	0	1
County UE rate >= 9 percent	50,526	.21	.41	0	1
Northeast Region	51,549	.18	.38	0	1
North Central Region	51,549	.24	.43	0	1
West Region	51,549	.2	.4	0	1
Year	51,899	1,989.82	5.6	1981	2000
Married, spouse present	48,348	.43	.5	0	1
Married, spouse not present	48,348	.12	.32	0	1
Sibling BMI	24,542	25.47	5.39	7.56	88.07
Sibling is female	24,542	.44	.50	0	1
Sibling age	24,542	28.17	6.07	16	43

Data: NLSY.

References

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

———. 1999. "Black-White Differences in Social and Economic Consequences of Obesity." *International Journal of Obesity* 23:166–73.

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

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

Bound, John, Charles Brown, and Nancy Mathiowetz. 2002. "Measurement Error in Survey Data." In *Handbook of Econometrics,* volume 5, ed. James Heckman and Ed Leamer, 3705–3843. New York: Springer-Verlag.

Comuzzie, A. G., and D. B. Allison. 1998. "The Search for Human Obesity Genes." *Science* 280:1374–77.

Epstein, Frederick H. and Millicent Higgins. 1992. "Epidemiology of Obesity." In *Obesity,* ed. Per Bjorntorp and Bernard N. Brodoff, 230–342. New York: J. B. Lippincott Company.

Flegal, K. M., M. D. Carroll, R. J. Kuczmarski, and C. L. Johnson. 1998. "Overweight and Obesity in the United States: Prevalence and Trends, 1960–1994" *International Journal of Obesity* 22:39–47.

Flegal, Katherine M., Margaret D. Carroll, Cynthia L. Ogden, and Clifford L. Johnson. 2002. "Prevalence and Trends in Obesity among U.S. Adults, 1999–2000." *JAMA.* 288(14):1723–27.

Gortmaker, Steven L., Aviva Must, James M. Perrin, Arthur M. Sobol, and William H. Dietz. 1993. "Social and Economic Consequences of Overweight in Adolescence and Young Adulthood." *New England Journal of Medicine* 329(14):1008–12.

Grilo, Carlos M., and Michael F. Pogue-Geile. 1991. "The Nature of Environmental Influences on Weight and Obesity: A Behavioral Genetic Analysis." *Psychological Bulletin* 110(3):520–37.

Hamermesh, Daniel S., and Jeff E. Biddle. 1994. "Beauty and the Labor Market." *American Economic Review* 84(5):1174–94.

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

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1):153–61.

Jensen, A. R. 1987. "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, 87–142. Hillsdale, N.J.: Lawrence Erlbaum Publishing.

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

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

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

Maes, Hermine H. M., M. C. Neale, and L. J. Eaves. 1997. "Genetic and Environmental Factors in Relative Body Weight and Human Adiposity." *Behavior Genetics* 27(4):325–51.

McLean, Robert A., and Marilyn Moon. 1980. "Health, Obesity, and Earnings." *American Journal of Public Health* 70(9):1006–1009.

Pagan, Jose A., and Alberto Davlia. 1997. "Obesity, Occupational Attainment, and Earnings." *Social Science Quarterly* 8(3):756–70.

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

Register, Charles A. and Donald R. Williams. 1980. "Wage Effects of Obesity among Young Workers." *Social Science Quarterly* 71(1):130–41.

Sargent, J. D., and D. G. Blanchflower. 1994. "Obesity and Stature in Adolescence and Earnings in Young Adulthood. Analysis of a British Birth Cohort." *Archives of Pediatrics and Adolescent Medicine* 148(7):681–87.

Sobal, Jeffery, and Albert J. Stunkard. 1989. "Socioeconomic Status and Obesity: A Review of the Literature." *Psychological Bulletin* 105(2):260–75.

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

Staiger, Douglas, and James H. Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica* 65(3):557–86.

Stearns, Peter N. 1997. *Fat History: Bodies and Beauty in the Modern West.* New York: New York University Press.

Stunkard, A. J., T. I. A. Sorensen, C. Hanis, T. W. Teasdale, R. Chakraborty, W. J. Schull, and F. Schulsinger. 1986. "An Adoption Study of Human Obesity." *New England Journal of Medicine* 314(4):193–98.

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

U.S. Department of Health and Human Services. 2001. *The Surgeon General's Call to Action to Prevent and Decrease Overweight and Obesity.* Washington, D.C.: GPO.

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

Vogler, G. P., T. I. A. Sorensen, A. J. Stunkard, M. R. Srinivasan, and D. C. Rao. 1995. "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* 19:40–45.