Estimating the Effects of Wages on Obesity

DaeHwan Kim, PhD, and John Paul Leigh, PhD

Objectives: To estimate the effects of wages on obesity and body mass. **Methods:** Data on household heads, aged 20 to 65 years, with full-time jobs, were drawn from the Panel Study of Income Dynamics for 2003 to 2007. The Panel Study of Income Dynamics is a nationally representative sample. Instrumental variables (IV) for wages were created using knowledge of computer software and state legal minimum wages. Least squares (linear regression) with corrected standard errors were used to estimate the equations. **Results:** Statistical tests revealed both instruments were strong and tests for over-identifying restrictions were favorable. Wages were found to be predictive ($P < 0.05$) of obesity and body mass in regressions both before and after applying IVs. Coefficient estimates suggested stronger effects in the IV models. **Conclusion:** Results are consistent with the hypothesis that low wages increase obesity prevalence and body mass.

Learning Objectives

- Become familiar with previous findings on the link between the rising prevalence of obesity and falling or stagnant wages, including three proposed explanations for this association.
- Discuss the methods used by the authors to estimate the effects of wages on obesity, focusing on the role of the instrumental variables technique.
- Review the authors' conclusions regarding the nature of the association between body mass/obesity and wages.

Over the past 30 years, obesity prevalence has been increasing while real (inflation adjusted) wages have been stagnant or falling.[1,2] These trends are consistent with either: 1) low wages resulting in higher obesity prevalence; 2) higher prevalence resulting in lower wages; 3) some "third variable," correlated with both, changing over time; or 4) coincidence. Numerous public health researchers and some economists have suggested low income as a risk factor for obesity. From a public health perspective, Drewnowski and Specter[3] review some studies demonstrating strong positive correlations between poverty and obesity and suggest food prices may play a role. Economists Chou et al[4] and Rashad et al[5] use microlevel data from the National Health Interview Surveys and the National Health and Nutrition Examination Surveys to find strong negative correlations between family income and prevalence of obesity. In a similar vein, the economists Smith et al[6] use national longitudinal data to find that unemployment is associated with weight gain. These public health and economic obesity studies are consistent with the much broader literature in social epidemiology and health economics suggesting that low income, low socioeconomic status, and occupations with high job strain are risk factors for poor health.[7–10]

A burgeoning economics literature finds strong correlations between obesity and wages. The great majority of studies assume that this correlation reflects the effects of obesity on wages. For example, Baum and Ford[11] document a significant "wage penalty" among the obese in the National Longitudinal Survey of Youth during the 1990s. Baum and Ford also provide a useful review of the literature, which suggests that these penalties have been growing as the numbers of obese have been increasing.

The literature on "third variables" and "coincidence" is related. These studies essentially address whether there is evidence that, for example, changes in obesity cause changes in wages. Perhaps "time preference" or "ability to delay gratification" or luck is the true cause of the correlations.

Economists developed the instrumental variables (IV) technique to address issues of mutual or reciprocal causality as well as "third variables" and "coincidence."[12] Some economic studies, reviewed in Baum and Ford,[11] have used the IV technique, but these typically estimate the effects of obesity on wages, not vice versa. In fact, the authors are not aware of any IV economic studies of effects of individuals' wages on obesity for working age persons as opposed to effects on family income for only low-income people or income for only retirees. Our primary contribution, therefore, is to provide an IV analysis of the effects of wages on obesity and body mass for a public health and epidemiologic audience. An additional contribution is that we will use data from the Panel Study of Income Dynamics (PSID), a data set that is popular among social scientists but not frequently seen in public health or epidemiological journals.

DATA, METHOD, AND INSTRUMENTS

Data

The PSID, which began in 1968, is a longitudinal, representative US sample of men, women, and children and their families.[13] We use the three most recent waves: 2003, 2005, and 2007. The PSID fits our purpose because it contains information regarding respondents' height, weight, demographics, health insurance status, wages, smoking prevalence, and state-of-residence. We limited the sample to heads of households, currently working full time, and employed by someone else, between and including ages 20 to 65 years. We excluded full-time students, retirees, permanently disabled persons, self-employed, and nonheads of households. Finally, we excluded persons with missing data. These restrictions were imposed on all respondents for all years; we used a balanced design. Our sample size was 6312.

We restricted attention to household heads for several reasons. First, the PSID, historically, collected more information on heads than partners of heads. Second, our focus on wages and our desire to include prevalence of medical insurance as a covariate created two problems for partners of heads. Typically, when modeling wages for partners, additional analyses of labor force participation for partners is required.[14] When modeling health insurance for partners, the presence or absence of insurance from the heads' jobs must be accounted for.[15] By limiting our sample to house

From the Korea Insurance Research Institutes (Dr Kim), Seoul, Korea; and Center for Healthcare Policy and Research and Department of Public Health Sciences (Dr Leigh), University of California-Davis, Davis, Calif.

DaeHwan Kim and J. Paul Leigh have no financial interest in this research.
The JOEM Board and planners have no financial interest related to this research.

Address correspondence to: John Paul Leigh, PhD, Department of Public Health Sciences, University of California-Davis, Davis, CA 95616-8638; E-mail: pleigh@ucdavis.edu.

DOI: 10.1097/JOM.0b013e3181dbc867

heads, we avoided biases introduced by not accounting for labor force participation decisions of partners or of partners' choices of health insurance. Finally, some recent studies using the PSID continue to focus on household heads and one (Meer et al[16]) finds evidence for associations between income and health.[16,17]

Table 1 provides separate means for the unweighted full sample for the obese and the nonobese. We defined obese as body mass index (BMI) ≥ 30. Roughly 27.2% were obese and earned an average of $2.66 (2007 dollars) less per hour than the nonobese. In our regressions, wages were logged to account for well-known skewness in the distribution of wages.[18]

A number of independent variables measured standard socioeconomic and family background characteristics. These included age, age squared, gender, race, education, marital status and region of residence. We also included a variable for whether the respondent had any health insurance reasoning from the literature suggesting that access to medical care improves health.[19]

Smoking prevalence was added for several reasons. First, smoking prevalence may indirectly reflect unobservable time and risk preferences. For example, smokers are alleged to discount the future more heavily than nonsmokers.[20] Second, smokers may invest less in productivity-enhancing human capital and experience more productivity-reducing illnesses than nonsmokers.[21] Our smoking variable equaled one if the respondent answered "yes" to: "Do you smoke cigarettes?" However, because smoking might be considered endogenous, we ran regressions with and without it. Indicator (dummy) variables were created for four geographic regions, and years as indicated in Table 1.

Method

Obesity is a binary variable. There is some concern that by restricting attention to a binary variable we are discarding useful variation in data. We therefore conduct tandem analyses with both obesity and body mass treated as separate dependent variables.

There are at least three explanations for statistical associations between wages and obesity. First, the obese may receive lower wages. It could be that obesity may lead to health problems that, in turn, lead to lower productivity and subsequently lower wages. Alternatively, employers might believe that the obese will add disproportionate costs to medical or workers' compensation insurance premiums. Finally, customers, coworkers, or employers themselves might simply harbor prejudices against the obese.

Second, wages may increase or decrease the propensity to be obese. The economic textbook "income effect" suggests increasing wages would lead to more food intake and perhaps more obesity. Nevertheless, higher wages might lead to more expensive food intake which might contain fewer calories than inexpensive food. Alternatively, the epidemiological literature suggests that poverty leads to obesity for a number of reasons including fewer safe parks and neighborhoods that invite exercise in poor areas as well as greater consumption of fat-dense fast-foods and calorie-rich soft drinks.[22–25]

Third, there may be some unobserved, difficult-to-measure "third variables" such as time or risk preferences that are responsible for both low wages and poor health as measured by obesity.[26] Nevertheless, if risk or time preferences are relatively fixed over time, the importance of "third variables" is problematic as an explanation because obesity has been increasing significantly over the past 20 years.

If obesity affects wages or if there are unobserved variables that affect both, then linear regression (Ordinary Least Squares) estimates will be biased due to simultaneity or endogeneity.[12] For ease of presentation, we will consider body mass as the dependent variable:

$$\mathrm{BMI}_{it} = \delta \ln W_{it} + X'_{it}\beta + \nu_{it} \tag{1}$$

TABLE 1. Descriptive Statistics of Variables: Definitions, Means, and (Standard Deviations)

Variable	Definition	Full Sample (n = 6,312)	Obese (N = 1,718)	Nonobese (n = 4,594)
Obesity	1 if BMI ≥30	0.27 (0.45)	1.00 (0.00)	0.00 (0.00)
BMI	Weight in kilogram over height squared in meter	27.87 (4.96)	34.24 (3.99)	25.49 (2.66)
ln(Wagerate)	Log of hourly wage rate	2.96 (0.62)	2.89 (0.59)	2.98 (0.64)
Age	Age	41.91 (10.76)	42.09 (10.62)	41.84 (0.82)
Age squared	Age squared	1,872.3 (915.0)	1,884.5 (918.3)	1,867.7 (913.8)
Male	1 if male	0.85 (0.36)	0.85 (0.36)	0.85 (0.36)
White	1 if white, nonHispanic	0.90 (0.30)	0.87 (0.34)	0.91 (0.29)
Married	1 if married	0.70 (0.46)	0.72 (0.45)	0.69 (0.46)
Highschool	1 if has at least high school degree	0.90 (0.30)	0.88 (0.32)	0.90 (0.30)
Insurance	1 if has any health insurance	0.89 (0.31)	0.90 (0.30)	0.89 (0.31)
Smoking	1 if currently smoking	0.23 (0.42)	0.17 (0.37)	0.26 (0.44)
Computer skill	1 if does word processing and e-mail	0.17 (0.38)	0.16 (0.36)	0.18 (0.38)
Minimum wages	State minimum wages	5.08 (0.73)	5.02 (0.70)	5.10 (0.74)
Northeast	1 if live in Northeast	0.17 (0.37)	0.17 (0.37)	0.17 (0.37)
South	1 if live in South	0.32 (0.47)	0.37 (0.48)	0.31 (0.46)
North central	1 if live in North central	0.31 (0.46)	0.30 (0.46)	0.32 (0.47)
West	1 if live in West	0.20 (0.40)	0.17 (0.37)	0.21 (0.41)
Year 2003	1 if year is 2003	0.34 (0.47)	0.30 (0.46)	0.35 (0.48)
Year 2005	1 if year is 2005	0.33 (0.47)	0.34 (0.47)	0.33 (0.47)
Year 2007	1 if year is 2007	0.33 (0.47)	0.36 (0.48)	0.32 (0.46)

Differences in the obese and nonobese means for the following variables were statistically significant ($P < 0.05$): BMI, ln(wagerate), white, married, highschool, insurance, smoking, computer skills, minimum wages, South, North Central, West, year 2003, year 2007.

where ln$W$ is the natural logarithm of the real hourly wage rate, δ is the coefficient for ln-wage, X is a matrix of independent (exogenous) variables that might affect BMI, and β is a vector of parameters. The error term, ν_{it}, has two error components: α_i and υ_{it} and can be rewritten as $\nu_{it} = \alpha_i + \upsilon_{it}$.

The α_i is the individual fixed effect which is time invariant and υ_{it} is idiosyncratic error. Literature often suggests fixed effects models using panel data. Nevertheless, fixed effect models provide consistent estimates of the coefficients on ln-wage only under a limited form of endogeneity of the regressors (covariates): ln-wage may be correlated with the fixed effect α_i but not with υ_{it}. It could be, as Cawley[27] suggests, that the unobserved factors that influence both weight and wages may themselves vary over time. Following as Cawley,[27] we employ instruments (z) that are correlated with ln-wage and uncorrelated with υ_{it} in a random effects model.

We assume there are two exogenous variables excluded from the structural Equation 1: z_1 and z_2. We assume z_1 and z_2 are uncorrelated with the error υ_{it}. These two assumptions are known as exclusion restrictions. Given the data on the z_1 and z_2, we first compute ln$\hat{W}$ for each observation (data point) by estimating the following reduced form equation:

$$\ln\hat{W}_{it} = \hat{\pi}_1 z_1 + \hat{\pi}_2 z_2 + X_{it}'\hat{\beta} \qquad (2)$$

where $\hat{\pi}_1$ and $\hat{\pi}_2$ are estimated coefficients for the two instruments. The ln$\hat{W}_{it}$ are the fitted values for ln-wage. Second, after replacing lnW_{it} with ln$\hat{W}_{it}$, we generate a consistent estimator for δ:

$$\mathrm{BMI}_{it} = \delta \ln\hat{W}_{it} + X_{it}'\beta + \nu_{it} \qquad (3)$$

Formal and informal explanations of IV models are available.[12,28,29] Briefly, the IV technique can be explained as follows. First, "instruments" are identified. We selected one variable reflecting respondents' familiarity with computer software and another measuring the legal minimum wage in which the respondent resides. Second, ln-wages are then regressed on the instruments together with other independent (exogenous) variables in the "first stage" regression. This is written above as Equation 2. Predicted (fitted) values on ln-wages are then obtained from the first stage regression. Obesity (or BMI) is then regressed on the predicted (fitted) ln-wage variable together with other independent variables in the "second stage" regression. This is equivalent to Equation 3 above. The predicted (fitted) wage variable is the IV and, in theory, provides a better estimate of the effects of wages on obesity than the non-IV wage variable. By running the regression in 2 above, the fitted values for ln-wage are purged of the correlation with the error term. The fitted values are that portion of ln-wage that is not influenced by the effects of body mass on wages or by unobserved, "third variables."

In results below, we first applied the Stata program "xtreg" to regressions of obesity and BMI on ln-wage, demographic variables, insurance, regions, and year dummies. The "xt" refers to running panel data for random effects. This first set of regressions did not use the IV method. In the next set, we applied the IV method. First, we ran "first stage" regressions analogous to Equation 2. Second, we ran "second stage" regressions analogous to Equation 3. These regressions were again run with random effects and were linear. Stata did not have a command for random effects, IV, for either logit or probit. However, Angrist[30] argues that neither probit nor logit are necessary for testing hypotheses in large data sets even though the dependent variable is binary. Robust standard errors allowed for household clustering and clustering within states.

Instruments

We used familiarity with computer software packages as our first instrument for wages. We reasoned that computer skills would lift productivity and wages but, theoretically, not be related to obesity. In fact, we are not familiar with any study that includes computer skills a determinant of obesity, or for that matter, a determinant of any measure of health or health behavior. Krueger,[31] on the other hand, documents substantial wage benefits associated with strong computer skills. The PSID provides various measures of respondents' computer use. We created a computer skills binary variable that equaled one if the respondent used e-mail and did word processing on popular software such as Microsoft Word and zero otherwise. We selected the legal minimum wage in the respondent's state-of-residence as our second instrument. The minimum wage is known to raise the level of wages in communities and states.[18] Minimum wage levels tend to have their greatest effects at or near the bottom of the wage distribution.[18] On the other hand, there does not appear to be any logical reason why obesity or BMI of individuals would influence minimum wage legislation. This is important, because it is one of the requirements for "good" instruments. Data on state minimum wages were drawn from the United States Department of Labor.[32]

RESULTS

Table 1 presents descriptive statistics. Roughly 27% of the sample was obese. In the full sample, mean age was roughly 42 years, roughly 10% did not graduate from high school, and roughly 85% were men (reflecting our household head sample), 90% white non-Hispanic, and 70% married. The variable with perhaps the greatest difference in mean values between the obese and nonobese was smoking: roughly 17% of the obese smoked whereas 26% of the nonobese reported that they were current smokers. The mean for computer skills was approximately 17%, which might appear low. The PSID, however, oversamples the poor.

Without IV

Table 2 present results ignoring endogeneity, that is, not using the IV technique. The first dependent variable in Table 2 is BMI and the second is obesity. The left side presents the names of variables and the middle and right columns, the results for coefficients and standard errors. In the BMI regression, the coefficient on ln-wage was statistically significant ($P < 0.0001$) and its value was -0.38. Standard errors appear in parentheses. This coefficient suggests that a 10% increase in wages from the average wage of \$19.3 to \$21.2 was associated with a 0.036 decline in BMI. This effect is small. However, wages are skewed with many people earning much more than the minimum wage. A 100% increase in wages would be associated with a 0.26 decrease in BMI. In the obesity equation, the coefficient on ln-wages was -0.03. This coefficient suggests that a 10% increase in wages is associated with a 0.003 decline in the chances of being obese. A 100% increase in wages would be associated with a 0.02 decrease in the chances of obesity.

We also ran similar regression that omitted smoking, the potentially endogenous variable. Both coefficients remained statistically significant ($P < 0.0001$ and $P = 0.017$, respectively for BMI and obesity) but the sizes of the coefficients dropped roughly 10%. Results on exogenous control variables were also of interest. Statistically significant variables suggested that both BMI and obesity: increased with age, but at a decreasing rate and were higher for married people and southerners. The insurance variable was not statistically significant in either regression.

IV Models: First Stage Regressions

Table 3 presents the results of a regression of ln-wages on the two instruments, computer skills ($P < 0.01$) and minimum wages ($P < 0.01$), as well as the other exogenous (independent) variables. The +0.15 coefficient on computer skills suggests that respondents with computer skills earned roughly 15% more than respondents without those skills. A \$1 increase in the minimum

TABLE 2. Effect of Wages on BMI and Obesity Before Instrumental Variables

Independent Variable	BMI Equation Dependent Variable: BMI; Coefficient (Standard Error)	Obesity Equation Dependent Variable: Obesity; Coefficient (Standard Error)
ln(Wagerate)	−0.38 (0.09)*	−0.03 (0.01)*
Age	0.28 (0.05)*	0.01 (0.00)*
Age squared	−0.00 (0.00)*	−0.00 (0.00)*
Male	0.52 (0.22)†	−0.01 (0.02)
White	−0.22 (0.20)	−0.02 (0.02)
Married	0.55 (0.15)*	0.01 (0.02)
Highschool	−0.60 (0.25)†	−0.03 (0.02)
Insurance	−0.16 (0.15)	−0.01 (0.02)
Smoking	−0.88 (0.13)*	−0.09 (0.01)*
Northeast	0.23 (0.24)	0.00 (0.02)
South	0.63 (0.19)*	0.05 (0.02)*
West	−0.08 (0.21)	−0.02 (0.02)
Year 2005	0.36 (0.07)*	0.03 (0.01)*
Year 2007	0.56 (0.07)*	0.05 (0.01)*

Standard errors are in parentheses. Intercepts are not shown. Wald $\chi^2(16)$ = 262.42 (*P*-value: 0.000) for BMI equation and 111.68 (*P*-value: 0.000) for Obesity equation. Reference Groups for region and year are North central and Year 2003, respectively.

*Significant at 1%, two-tailed test.

†Significant at 5%, two-tailed test.

wage was associated with a 5% increase in wages earned by respondents. Table 3, bottom panel, also provides results on the strength of the instruments.

The signs and statistically significant coefficients on other independent variables in Table 3 lend credibility to our data and models. For example, compared to nonhigh school graduates, high school graduates received higher wages; married persons received more than nonmarried; and whites received more than all other racial groups combined.

TABLE 3. First Stage Regression

Independent Variables	Dependent Variable: ln(Wagerate); Coefficient (Standard Error)
Computer skills	0.15 (0.02)*
Minimum wages	0.05 (0.02)*
Age	0.05 (0.01)*
Age squared	−0.00 (0.00)*
Male	0.15 (0.03)*
White	0.10 (0.03)*
Married	0.14 (0.02)*
Highschool	0.24 (0.03)*
Insurance	0.15 (0.02)*
Smoking	−0.13 (0.02)*
Northeast	0.13 (0.03)*
South	0.00 (0.02)
West	0.06 (0.03)†
Year 2005	0.02 (0.01)*
Year 2007	0.04 (0.01)*
F-statistics for computer skills and minimum wages: 45.39	

Standard errors are in parentheses. Intercepts are not shown. R^2 = 0.23, Wald $\chi^2(17)$ = 1,204.36 (*P*-value: 0.000). Reference Groups for region and year are North central and Year 2003, respectively.

*Significant at 1%, two-tailed test.

†Significant at 5%, two-tailed test.

TABLE 4. Effect of Wages on BMI and Obesity With Instrumental Variables

Independent Variable Dependent Variable: BMI Coefficient (Standard Error)	BMI Equation	Obesity Equation Dependent Variable: Obesity Coefficient (Standard Error)
ln(Wagerate)	−3.30 (1.21)*	−0.25 (0.12)†
Age	0.38 (0.08)*	0.02 (0.01)*
Age squared	−0.00 (0.00)*	−0.00 (0.00)*
Male	0.90 (0.28)*	0.02 (0.03)
White	−0.25 (0.26)	−0.01 (0.02)
Married	1.08 (0.25)*	0.05 (0.02)†
Highschool	0.07 (0.38)	0.02 (0.04)
Insurance	0.38 (0.27)	0.03 (0.03)
Smoking	−1.49 (0.23)*	−0.13 (0.02)*
Northeast	0.63 (0.29)†	0.04 (0.03)
South	0.69 (0.18)*	0.05 (0.02)*
West	0.14 (0.25)	0.00 (0.02)
Year 2005	0.38 (0.09)*	0.03 (0.01)*
Year 2007	0.63 (0.10)*	0.05 (0.01)*

Standard errors are in parentheses. Intercepts are not shown. Wald $\chi^2(16)$ = 219.00 (*P*-value: 0.000) for BMI equation and 108.26 (*P*-value: 0.000) for obesity equation. Reference Groups for region and year are North central and Year 2003, respectively.

*Significant at 1%, two-tailed test.

†Significant at 5%, two-tailed test.

IV Models: Tests for Strength of IVs and Validity of IVs

We conducted two tests on each instrument. We first tested for the strength of the instruments with regressions of ln-wage on the indicator for computer skills, state minimum wages and other exogenous variables. F-statistics on the instruments (F = 45.39) exceeded 10, suggesting that the instruments were, indeed, strong (Table 2).[12] We second tested for validity of IVs with the *J*-statistic (Sargan-Hansen statistic; Cameron and Trivedi,[12]) for over-identifying restrictions. Chi-square results indicated that we could not reject the null hypothesis that the instruments were exogenous. The Hansen-*J* statistic for validity of the IV was 0.231 (P = 0.631) in the BMI equation and 0.014 (P = 0.901) in the obesity equation.

IV Models: Second Stage Regressions

The IV results for the effect of ln-wages on BMI and obesity are presented in Table 4. Results for BMI appear on the left and for obesity on the right. In the BMI regression, the coefficient on ln-wage was statistically significant ($P < 0.01$) and its value was −3.3. Standard errors appear in parentheses. This coefficient suggests that a 10% increase in wages is associated with 0.32 decline in BMI. A 100% increase in wages would be associated with a 2.29 decline in BMI. These values are considerably larger than those observed in regressions without the IV.

In the obesity equation, the coefficient on ln-wages was −0.25 ($P < 0.029$). This coefficient suggests that a 10% increase in wages is associated with 0.024 decline in the chances of being obese. A 100% increase in wages would be associated with 0.17 decrease in the chances of obesity. Again, these effects were considerably larger than the ones observed in regressions above that did not use the IV method.

We also ran similar regressions that omitted smoking, the potentially endogenous variable. Both coefficients remained statistically significant ($P < 0.01$ and $P \leq 0.1$, respectively for BMI and obesity) but the sizes of the coefficients dropped roughly 22% and 24%, respectively.

Male workers had higher BMI than female workers, both before and after applying the IV technique (Tables 2 and 4). This is contrary to findings showing greater prevalence among women than men.[4] This contrary result might be due to our sample restrictions that included only household heads with fulltime jobs, age 20 to 65 years; obese women may be less likely than nonobese women to hold fulltime jobs.

DISCUSSION

Public health and medical researchers frequently grapple with how to statistically model relations between two variables that might be mutually dependent.[33,34] For example, does stroke cause depression or vice versa or both? [34] The IV technique offers one approach to model statistical interdependence.[12] There are a number of limitations, noted below, but the technique has been popular for more than 40 years in economics and other social sciences. The IV technique is enjoying increasing interest within public health, occupational medicine, and epidemiology in recent years.[28]

We applied IV techniques to investigate whether wages might be risk factors for body mass or obesity. By using longitudinal data from a large national sample of employees, we first estimated associations between body mass and obesity on the one hand and wages on the other without the IV technique and second, with the IV technique. In all cases, we found strong negative correlations. Although statistical significance was generally about the same, the estimated coefficients were larger in the IV than in the non-IV results. Combining our results with the much larger literature on the "obesity wage penalty," we conclude that body mass and obesity on the one hand and wages on the other are mutually interdependent: low wages increase the chances of obesity and obesity decreases wages.[11,27]

The larger sizes for coefficients after IV than before IV have precedent in the literature. For example, in a related literature, a similar increase in the estimated effect of education on health is observed when comparing studies and results that did and did not use the IV technique. Grossman[35] suggests three possible reasons for the larger IV estimate: variation in who is most affected by the instrument; spillover effects; and measurement error. First, in our context, it could be that our IV disproportionately measured those among the low income obese that were especially likely to be affected by minimum wages or knowledge of computer skills. Second, in our context, spillover effects might have resulted if obese workers tended to cluster together within the same businesses that paid lower wages. Third, it is well known that systematic measurement error afflicts self-reported weight. It is likely that random measurement error was also present in our data and therefore imparted a downward bias to non-IV estimates. Finally, our findings for smaller obesity effects on wages before IV and larger ones for after IV is consistent with the smoking penalty literature. Auld,[21] for example, investigates smoking and wage correlations and finds that the before IV estimates yield an 8% smoking penalty but the after IV estimates yield a 24% penalty for smoking.

Our results are consistent with numerous epidemiologic, public health, and least two economic studies suggesting that poverty or low income is a partial cause of obesity.[4,5,36,37] The results are, in addition, consistent with literature indicating that poverty or low income is causally related to various measures of health and behavior such as mortality,[9] self-assessed health status,[8] smoking,[38] and poor health, in general.[7,39] Our results are consistent with 30-year tends in falling real wages for Americans with low levels of education and rising obesity prevalence among the poor. Finally, our results are also consistent with the job strain and obesity literature[40] because occupations with job strain are also likely to pay low wages.[41]

Smoking is generally associated with lower body weight and in our results generated among the lowest P-values of all independent variables in Tables 2 and 4. There are several explanations. Smoking affects body metabolism and burns calories. Nicotine included in cigarettes is an appetite suppressant and individuals who quit smoking look for food as a replacement.[42]

There are limitations to our study. The first among them is choice of instruments. For example, it could be that persons with computer skills may have more sedentary jobs than those without. Nevertheless, we ran additional regressions with an indicator for white-collar job and our main results were unchanged. Alternatively, it could be that persons with these skills are more inclined to exercise than those without. If these effects are canceling, then computer skills are a valid instrument. Again, all Hansen J tests were favorable for our instruments. Finally, the logic and evidence connecting computer skills and minimum wages to respondents' wages are compelling.[18,31,43]

The major strengths of the article are the IV approach and the large longitudinal data set. The IV approach directly addresses the possibility of mutual causality, a possibility that most prior studies of, for example, the effects of income on obesity have merely listed as a limitation.[4,37] An additional strength is the inclusion of an important health habit—smoking. Inclusion of prevalence of this habit helps minimize the influence of "third variables" that simultaneously affect obesity and wages. Finally, the fact that so many of our findings on control variables were consistent with the literature augers well for our findings on wages, body mass, and obesity. For example, for wages as the dependent variable we found wages increased with age but at a decreasing rate; men were paid more than women; whites more than all other categories combined; married people more than nonmarried people; high school graduates more than nongraduates; and smokers had a "wage penalty."[18,21] For body mass, we found body mass increased with age but at a decreasing rate; married persons were heavier than nonmarried persons; smokers were lighter than nonsmokers; and southern were heavier than nonsoutherners.[3,4,7,24,36,37]

Future research might consider whether these findings can be replicated with part-time workers. Because the definition of wages involves hours, future research may also address correlations between work hours and obesity.[44] But most importantly, we believe that IV models will prove useful in addressing the mutual interdependence between obesity and wages.

ACKNOWLEDGMENT

This study was supported in part by the National Institute for Occupational Safety and Health (OH008248-01) (to J.P.L.).

REFERENCES

1. Ogden CL, Carroll MD, Curtin LR, McDowell MA, Tabak CJ, Flegal KM. Prevalence of overweight and obesity in the United States, 1999–2004. *JAMA*. 2006;295:1549–1555.
2. Emanuel EJ, Fuchs VR. Who really pays for health care? The myth of "shared responsibility." *JAMA*. 2008;299:1057–1059.
3. Drewnowski A, Specter SE. Poverty and obesity: the role of energy density and energy costs. *Am J Clin Nutr*. 2004;7:6–16.
4. Chou SY, Grossman M, Saffer H. An economic analysis of adult obesity: results from the Behavioral Risk Factor Surveillance System. *J Health Econ*. 2004;23:565–587.
5. Rashad I, Grossman M, Chou SY. The super size of America: an economic estimation of body mass index and obesity in adults. *East Econ J*. 2006;32: 133–148.

6. Smith TG, Stoddard C, Barnes MG. Why the poor get fat: weight gain and economic insecurity. *Forum Health Econ Policy.* 2009;12:article 5.
7. Marmot M. *The Status Syndrome*. New York, NY: Owl Books, Henry Holt and Company; 2004.
8. Ettner SL. New evidence on the relationship between income and health. *J Health Econ*. 1996;15:67–85.
9. Duleep HO. Measuring the effect of income on adult mortality using longitudinal administrative record data. *J Hum Resour*. 1986;21:238–251.
10. Schnall PL, Schwartz JE, Landsbergis PA, Warren K, Pickering TG. A longitudinal study of job strain and ambulatory blood pressure: results from a three-year follow-up. *Psychosom Med*. 1998;60:697–706.
11. Baum CL II, Ford WF. The wage effects of obesity: a longitudinal study. *Health Econ*. 2004;13:885–899.
12. Cameron AC, Trivedi PK. *Microeconometrics: Methods and Applications.* New York, NY: Cambridge University Press; 2005.
13. Panel Study of Income Dynamics. *An Overview of the Panel Study of Income Dynamics.* Ann Arbor, MI. Available at: http://psidonline.isr.umich.edu/Guide/Overview.html. Accessed September 14, 2009.
14. Heckman J. Shadow prices, market wages, and labor supply. *Econometrica.* 1974;42:679–694.
15. Meyer MH, Pavalko EK. Family, work, and access to health insurance among mature women. *J Health Soc Behav*. 1996;37:311–325.
16. Meer J, Miller DL, Rosen HS. Exploring the health-wealth nexus. *J Health Econ*. 2003;22:713–730.
17. Hajivassiliou VA, Ioannides YM. Unemployment and liquidity constraints. *J Appl Econom*. 2007;22:479–510.
18. Kaufman BE. *The Economics of Labor Markets*. 4th ed. New York, NY: The Dryden Press; 1994.
19. Ayanian JZ, Weissman JS, Schneider EC, Ginsburg JA, Zaslavsky AM. Unmet needs of uninsured adults in the United States. *JAMA*. 2000;284:2061–2069.
20. Farrell P, Fuchs VR. Schooling and health: the cigarette connection. *J Health Econ*. 1982;1:217–230.
21. Auld MC. Smoking, drinking, and income. *J Hum Resour*. 2005;40:5005–5018.
22. Jetter KM, Cassady DL. The availability and cost of healthier food alternatives. *Am J Prev Med*. 2006;30:38–44.
23. Drewnowski A, Darmon N. The economics of obesity: dietary energy density and energy cost. *Am J Clin Nutr*. 2005;82:265S–273S.
24. Hill JO, Wyatt HR, Reed GW, Peters JC. Obesity and the environment: where do we go from here? *Science*. 2003;299:853–855.
25. Jeffery RW, Baxter J, McGuire M, Linde J. Are fast food restaurants an environmental risk factor for obesity? *Int J Behav Nutr Phys Act*. 2006;3:2.
26. Berger MC, Leigh JP. Schooling, self-selection, and health. *J Hum Resour.* 1989;24:433–455.
27. Cawley J. The impact of obesity on wages. *J Hum Resour*. 2004;2:451–474.
28. Martens EP, Pestman WR, de Boer A, Belitser SV, Klungel OH. Instrumental variables: application and limitations. *Epidemiology*. 2006;17:260–267.
29. Leigh JP, Schembri M. Instrumental variables technique: cigarette price provided better estimate of effects of smoking on SF-12. *J Clin Epidemiol*. 2004;57:284–293.
30. Angrist JD. Estimation of limited dependent variable models with dummy endogenous regressors: simple strategies for empirical practice. *J Bus Econ Stat*. 2001;19:2–17.
31. Krueger AB. How computers have changed the wage structure: evidence from microdata, 1984–1989. *Q J Econ*. 1993;108:33–60.
32. United States Department of Labor. Available at: http://www.dol.gov/whd/minwage/america.htm. Accessed October 12, 2009.
33. Susser M. What is a cause and how do we know one? A grammar for pragmatic epidemiology. *Am J Epidemiol*. 1991;133:635–648.
34. Lyketsos CG, Treisman GJ, Lipsey JR, Morris LP, Robinson RG. Does stroke cause depression? *J Neuropsychiatry Clin Neurosci*. 1998;10:103–107.
35. Grossman M. The demand for health, 30 years later: a very personal retrospective and prospective reflection. *J Health Econ.* 2004;23:629–636.
36. Martikainen PT, Marmot MG. Socioeconomic differences in weight gain and determinants and consequences of coronary risk factors. *Am J Clin Nutr*. 1999;69:719–726.
37. Sundquist J, Johansson SE. The influence of socioeconomic status, ethnicity and lifestyle on body mass index in a longitudinal study. *Int J Epidemiol*. 1998;27:57–63.
38. Townsend J, Roderick P, Cooper J. Cigarette-smoking by socioeconomic group, sex, and age: effects of price, income and health publicity. *BMJ*. 1994;309:923–927.
39. Subramanian SV, Belli P, Kawachi I. The macroeconomic determinants of health. *Annu Rev Public Health*. 2002;23:287–302.
40. Brunner EJ, Chandola T, Marmot MG. Prospective effect of job strain on general and central obesity in the Whitehall II Study. *Am J Epidemiol*. 2007;165:828–837.
41. Warren JR, Hoonakker P, Carayon P, Brand J. Job characteristics as mediators in SES-health relationships. *Soc Sci Med*. 2004;59:1367–1378.
42. The Surgeon General's 1990 Report on the Health Benefits of Smoking Cessation Executive Summary—Introduction, Overview, and Conclusions. Available at: http://www.cdc.gov/mmwr/preview/mmwrhtml/00001801.htm. Accessed August 4, 2009.
43. Choi BC, Noseworthy AL. Classification, direction, and prevention of bias in epidemiologic research. *J Occup Med*. 1992;34:265–271.
44. Courtemanche C. Longer hours and larger waistlines? The relationship between hours and obesity. *Forum Health Econ Policy.* 2009;12:article 2.

