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11

Where Does the Wage Penalty Bite?

Christian A. Gregory and Christopher J. Ruhm

11.1 Introduction

How does BMI affect wages? At first blush, the answer seems obvious. Over the last fifteen years, a large literature has established the negative correlation between obesity—the condition of having a body mass index (BMI) greater than thirty—and wages, at least for women. On average, obese women make 2 to 8 percent less than their normal weight counterparts. Obese men do not make any less than men of normal weight, and heavy black men may earn slightly more.[1]

The question we ask is not about obesity, however, at least not obesity alone. We are interested in the more general relationship between BMI and wages. In particular, we examine two assumptions that characterize previous research. The first is that the BMI range above thirty is "where the action is." Although there are good reasons to focus on obese persons, the rest of BMI distribution has been treated as an afterthought in most of this literature. The second is that the conditional expectation of wages is linear in BMI, or characterized by some other relatively simple parametric relationship (such as a quadratic). While specifications based on these assumptions are valuable because they are tractable and easily interpretable, there are good reasons to assume they are not true *ex ante.* In the simplest case, if BMI really does reflect something meaningful about health, it could be that wages

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1. Throughout, we use the conventional definitions of "underweight," "healthy" (or normal) weight, "overweight," and "obese" for persons in the BMI ranges of: < 18.5, $18.5 - < 25.0$, $25.0 - < 30.0$, and ≥ 30.0 (National Heart, Lung and Blood Institute 1998).

are negatively associated with both overweight and underweight. Linear models capture only the average effect—which, in this example, might well be zero—and therefore miss important ways that BMI affects earnings.

Only recently have economists begun examine the shape of the conditional wage function. Wada and Tekin (2007) is the first study we are aware of that allowed a measure of body weight to enter into a wage regression as a quadratic. Even more recent has been the adoption of semiparametric methods. Shimokawa (2008) used data from China to estimate semiparametric models and finds that wages are lower for men and women in the tails of the BMI distribution. Kline and Tobias (2008), using data from the 1970 British Cohort study, found that marginal increases in BMI are most harmful for men who are overweight or obese and for women in the "healthy" weight range.

In addition to examining the shape of the conditional wage function, we address potential biases resulting from endogeneity of BMI and possible reverse causation, whereby wages determine body weight. We deal with endogeneity using an instrumental variables (IV) approach, where the respondent's BMI is instrumented with sibling BMI. To address the potential problem of reverse causality, we follow previous research in using lagged body weight to rule out the effect of current wages on weight. However, our analysis employs longer lags (at least thirteen years) and BMI from relatively early in the typical worklife. Both general approaches have been used before, but ours is the first application on data for U.S. subjects using semiparametric (SPM) methods.

We also examine potential mechanisms by which BMI affects wages and, in particular, are interested in understanding gender differences in these effects. Researchers have pursued several possibilities in this regard. One is that body weight affects health expenditures for women in a way that it does not for men, and that overweight and obese women pay for these expected expenditures in the form of lower wages (Bhattacharya and Bundorf 2005). Another is that health differences due to obesity have disparate effects on marginal productivity (Baum and Ford 2004). Still another is that women working in professions requiring public interaction are more penalized for obesity than corresponding men (Baum and Ford 2004; Pagan and Davila, 1997; Han, Norton, and Stearns 2009). Or, finally, employers might discriminate against overweight or obese women, but not men. Although direct evidence is only provided on the first of these possibilities, we interpret our findings in context of the growing literature examining how beauty is related to earnings.

Our analysis produces three main results. First, women's wages peak at thresholds far below the obesity cutoff, usually at a BMI of twenty-three or lower. This finding is robust to specifications correcting for endogeneity or reverse causation and suggests that BMI does not serve as an index of underlying health or medical costs in a wage-setting context. We test and confirm this intuition through a nonparametric analysis of relationship between BMI and medical expenditures. An alternative, which we believe to be more consistent with our findings, is that BMI is a proxy for physical attractiveness (or beauty), which is known to affect earnings.

Second, the estimates for men are more dependent on the choice of preferred models. Our primary specifications suggest that the conditional wage function is increasing in BMI through the beginning of the range of overweight and remains constant or declines modestly thereafter. Conversely, models using long-lags of BMI or instrumental variables indicate that male wages peak at very low BMI levels, suggesting that, as for women, the observed patterns are more likely to indicate physical attractiveness than underlying health status or medical costs.

Third, there are often substantial differences for blacks and whites, with the main specifications suggesting that the conditional wage function peaks at a considerably higher BMI for minorities and declines more slowly thereafter. Such findings might be consistent with a role for attractiveness, if there are racial differences in perceptions of ideal body weight. However, the IV estimates reveal smaller racial disparities, so that these interpretations require caution.

11.2 Data

We use data on twenty-five to fifty-five-year-olds from the 1986, 1999, 2001, 2003, and 2005 waves of the Panel Study of Income Dynamics (PSID), a longitudinal survey that began in 1968 with 4,802 families.[2] An additional 581 immigrant families were added in 1997 and 1999, and new families were created from the existing ones due to the formation of new households (e.g., due to divorce or to grown children leaving home).[3] As of 2005, the PSID contained 8,041 families.

Previous related studies involving U.S. subjects have used data from the National Longitudinal Survey of Youth 1979 (NLSY). We chose instead to utilize the PSID, primarily because it has characteristics of both longitudinal and cross-sectional data. Since the NLSY provides information for a single, fairly narrow birth cohort covering a somewhat limited age range, previous analyses using it have been largely restricted to relatively young workers. By contrast, the PSID is a self-replenishing panel that began in 1968 and so is more suitable to addressing differences in the effects across age groups. As we argue later, such differences point to possible mechanisms by which BMI affects earnings. That said, we show that our results are not

2. The original sample includes a nationally representative group of 2,930 families, with the complement from a low-income sample.

3. An earlier attempt to include Latino immigrants dates to 1990, at which time 2,043 immigrant families from the three most prevalent Latino groups in the United States were included. This sample was dropped after 1995.

driven by use of the PSID sample: similar patterns are obtained using comparable age ranges in the PSID and NLSY.

The PSID gathers information through an interview with one primary adult—usually the male head of household, referred to as the "head." On occasion, the spouse or cohabiting partner, the wife/"wife," as she is called, is the family respondent. In the waves used for this study, the PSID collects data on height and weight of the head and wife/"wife" only. The survey respondent gives height and weight information about themselves as well as their spouse or cohabiting partner. In an effort to minimize reporting error, we include only observations for which the head or wife reports his or her own height and weight.

Self-reported height and weight contain errors. We adjust for these using the regression correction suggested by Lee and Sepanski (1995) and commonly employed in the literature (Cawley 2004; Chou, Grossman, and Saffer 2004; Lakdawalla and Philipson 2007). Specifically, using data from the National Health and Nutrition Examination Survey (NHANES) III (1986 to 1994), NHANES 1999, NHANES 2001, and NHANES 2003, we regress measured height (weight) on self-reported height (weight), its square and its cube. The results, for models stratified by gender and race, are used to predict actual BMI (in the PSID) as a function of self-reported BMI.[4]

Hourly wages are constructed by dividing total earnings for the calendar year previous to the interview by total hours worked in that year.[5] For all but a handful of persons, total earnings and hours refer to the main job: very few people report second jobs or overtime earnings. The PSID imputes wages for people who report earnings but not hours or vice versa. We retain these observations (less than 2 percent of our sample) although our results are not sensitive to doing so. Our sample includes twenty-five to fifty-five-year-olds who worked at least twenty hours per week in their main job. These restrictions limit the sample to prime-age workers. We normalize wages to 2005 dollars using the Consumer Price Index (CPI), drop observations reporting wages less than half of the federal minimum, and trim the top 1/2 percent of wage observations.[6] Our final analysis sample contains 7,251 person-years for women and 5,775 person-years for men. Among women, we observe 1,433, 1,095, 516, and 520 persons in 1, 2, 3, and 4 years, respectively. Among

4. We use multiple waves of NHANES so that we can restrict the age range of the prediction samples to those relevant to our earnings study: namely, persons twenty-five to fifty-five years old.

5. Validity of the PSID income and hours data has been repeatedly evaluated. In two of the most cited evaluations (Bound et al. 1994; Duncan and Hill 1985) earnings were found to be relatively free from reporting error, but work hours were subject to significant mistakes. This induces errors into hourly earnings unlikely to abide by textbook assumptions about correlations between these variables and key regressors. However, there is no reason to believe that work hours in the PSID are subject to more reporting mistakes than similar measures in other data sets such as the Current Population Survey or NLSY (Bound, Brown, and Mathiowetz 2001; Hill 1992).

6. This procedure drops women with a wage above \$75.14 and men with a wage higher than \$152.57.

men, we observe 1,007, 666, 424, and 541 persons in 1, 2, 3, and 4 years, respectively.

11.3 Methods

The estimates were obtained using a semiparametric (SPM) local linear regression framework that can be usefully distinguished from both ordinary least squares (OLS) and a univariate kernel regression model. As is well known, ordinary least squares assumes that the conditional mean of the dependent variable is a linear function of the independent variables. This makes it easy to make predictions and to gauge statistical significance of the coefficients. However, the assumption of linearity is restrictive in ways that can only partially be overcome through standard transformations, such as including higher order polynomials of the explanatory variables of key interest. Kernel regression drops the linearity assumption and instead models the expectation of the dependent variable as a weighted mean at every point in the distribution of the independent variable. While this model can produce accurate univariate estimates with relatively small samples, in multivariate settings, it is not possible to maintain a meaningful level of accuracy without the sample size increasing exponentially. In this context, we use the specification

$$(1) \qquad Y_i = z_i \cdot \beta + f(\text{BMI}_i) + \varepsilon_i,$$

where Y_i is hourly wages of individual i, z_i is a vector individual characteristics and year effects, and f(BMI) is the nonparametric function transforming BMI into wages, which we refer to as the "conditional wage function."[7] The resulting models are semiparametric because they assume that the covariates included in z are linearly related to wages, whereas flexibility is maintained in transforming BMI into earnings.

Our estimates use the stepwise double residual method outlined in Robinson (1988). In the first step, we estimate $\hat{Y}_i$ and $\hat{z}_i$, as predicted values from a nonparametric regression of each of the independent and dependent variables on BMI. From these we derive $e\hat{p}s_i^Y = Y_i - \hat{Y}_i$ and $e\hat{p}s_i^z = z_i - \hat{z}_i$, representing the portions of the dependent and explanatory variables that are unrelated to BMI. In the second step, we regress $e\hat{p}s^Y$ on $e\hat{p}s^z$ to get $\hat{\beta}_{eps}$. Finally, we estimate the conditional wage function, $\hat{f}(\text{BMI}_i)$, by nonparametrically regressing the wage residual $Y_i - z_i \cdot \hat{\beta}_{eps}$ on BMI_i, using the techniques detailed in the appendix.[8] The intuition behind this procedure is to purge the dependent variable of the portion of the supplemental variables

7. We use levels instead of logarithms of wages to make our estimates easily interpretable in the figures and tables. Using log wages as the dependent variable yields quantitatively and qualitatively similar results.

8. We also estimated f(BMI) using the first differencing procedure outlined by Yatchew (2003), and obtained essentially the same results. However, we maintained the double residual method for our point estimates and confidence intervals to preserve efficiency.

that are unrelated to BMI and then provide a local linear regression estimate showing the relationship of this residual to BMI itself. We estimate confidence intervals using the "wild" bootstrap algorithm outlined by Yatchew (1998, 688) and Yatchew (2003, 160ff).[9]

For our instrumental variables estimates, we use the same stepwise procedure, but add to the first stage the residuals of a linear regression of BMI on the instruments. Just as with the other explanatory variables, we form a nonparametric prediction of the residual conditional on BMI ($iv\hat{e}ps$) and a residual ($e\hat{p}s^{iveps}$). We include that residual in the second stage residual regression and form our estimate of $\hat{f}$(BMI) as before. This procedure removes the variation in BMI *not* explained by the instruments from the second stage regression, so that what identifies $\hat{f}$(BMI) is what the instruments do explain (Shimokawa 2008; Yatchew 2003).

We employ two strategies to address the problems that hamper estimation of the causal effect of BMI on earnings. First, to deal with the issue of reverse causality, we estimate models in which the independent variable of interest is lagged BMI (see Seargent and Blanchflower 1994; Averett and Korenmann 1996; Baum and Ford 2004; Cawley 2004). The general argument subtending this strategy is that current wages might influence current BMI, but cannot affect BMI in previous years. However, a statistical association may exist if body weight or wages are correlated across time. We address this difficulty in two ways. First, where previous related studies have used BMI lags of up to seven years, we analyze wages in 1999 to 2005 as a function of BMI in 1986, or thirteen to nineteen years earlier. Second, we limit this portion of the analysis to individuals less than twenty-six years old in 1986, under the assumption that wages early in the person's work career are unlikely to determine BMI during middle adulthood.

To account for the potential endogeneity between BMI and wages, we follow an instrumental variables strategy similar to that developed by Behrman and Rosenzweig (2001), and more recently used by Cawley (2004), where sibling BMI is the instrument.[10] The validity of this strategy rests on the suppositions that sibling BMI is correlated with own BMI, and that it is uncorrelated with one's own earnings, except through BMI. The first assumption is uncontroversial and can be tested. The second is more problematic. In

9. This algorithm is often applied when heteroskedasticity is a concern. To form 95 percent confidence intervals, we resample 1,200 times from the residuals to form bootstrap data sets and perform the local linear regression procedure outlined in the appendix at between 200 and 300 points in the BMI distribution.

10. Kline and Tobias (2008) have similarly used parent BMI as an instrument; Shimokawa (2008) has used sibling BMI and lagged child weight as instruments. An alternative is to estimate fixed effects (FE) models (Baum and Ford 2004), which automatically account for all time-invariant sources of heterogeneity. However, FE methods may be problematic for this application because they assume that weight changes translate instantly (or very rapidly) into wage changes, whereas current earnings are likely to be affected by both contemporaneous and past body weight.

particular, sibling BMI could be independently related to wages if siblings share traits affecting both weight and wage outcomes due to environmental influences or genetics.

Until recently, much of the literature suggested that the environmental influences on body weight tend to be nonshared between siblings, and that their importance diminishes in adolescence (Maes, Neale, and Eaves 1997). However, recent developments suggest that environment may be more important than once thought.[11] Similarly, the emerging literature linking genetics to human behavior suggests caution. For example, certain polymorphisms of the D4 dopamine receptor gene are correlated with attention deficit hyperactivity disorder (ADHD) (Sunohara et al. 2000; El-Faddagh et al. 2004).[12] It is well known that the regulation of dopamine affects experiences of satiation and, therefore, eating behavior.[13] Research has also found that both childhood inattention and adult obesity are correlated with the dopamine D4 receptor gene in women with Seasonal Affective Disorder (SAD) (Levitan et al. 2004). These studies raise the possibility that child behaviors affecting learning and, subsequently, wages may be correlated with genetic factors also influencing body weight.[14] Therefore, care is needed in interpreting the results of IV models (like those following) identified by genetic variation in BMI.

11.4 Full Sample Results

We next summarize our semiparametric estimates of the relationship between BMI and wages. Throughout, we stratify by sex, since BMI could have quite different effects for men and women.[15] All models control for age, marital status, number of children, presence of a child less than two years old in the household, level of schooling, job tenure (in months), the survey

11. Most studies attribute the effect of genetics to the difference in the covariance between monozygotic (MZ) and dizygotic (DZ) twins' body weight, since DZ twins share only half their genetic material with the other twin. But in addition to having different genes, DZ twins may also have different dominant and recessive copies of shared genes. This "nonadditive" genotype variation might explain a significant amount of variation in traits such as body weight. One recent study (Segal and Allison 2002) identifying this variation through the use of "virtual twins"—same-aged siblings that don't share any genetic material—found that a 5 to 45 percent of the variation in BMI could be due to environmental influences.

12. Swanson et al. (2000) found no correlation between the presence of the genetic trait and neuropsychological abnormalities sometimes associated with ADHD; however, they did find a correlation between the genetic marker and extreme behavior.

13. However, at least one study failed to find a direct link between obesity and the D4 dopamine receptor gene (Poston et al. 1998).

14. Holtkamp et al. (2004) found that children with ADHD were also more likely to be obese, suggesting the plausibility of a genetic connection.

15. All estimates are unweighted, in part because the PSID assigns a zero weight to anyone entering the sample through cohabitation or marriage. To ensure that our results are not driven by this choice, we estimated models using only the nationally representative sample or limiting the analysis to observations with positive weights and using these weights in the second-stage regression (of $e\hat{p}s^Y$ on $e\hat{p}s^z$). In both cases, the results are essentially the same as those shown.

year, and region of residence.[16] Race/ethnicity are also held constant in the full sample estimates (but not when stratifying by race). Unless otherwise noted, the y-axis of the figures indicates the expected wage, calculated by adding $\hat{f}$(BMI) to the group-specific average predicted wage; results are displayed for BMI ranging from twenty to forty.[17]

11.4.1 Main Specifications

Figure 11.1 shows full sample estimates. The conditional wage function of women is characterized by a peak at a BMI of 22.8. Weight gains at lower BMI are associated with higher earnings, although the confidence intervals are sufficiently large that we can not generally reject the null hypothesis of no effect. By contrast, predicted wages decline rapidly at higher BMI levels, and monotonically, expect for a statistically insignificant upwards tick just below the obesity threshold.

These findings suggest that female wages begin to fall well before conventional cutoffs for obesity or overweight, and even well within the healthy weight range. Thus, there is little evidence of an obesity penalty per se. Instead, the data suggest that women whose weight rises above a relatively low threshold experience reduced earnings. Of course, BMI does not perfectly measure obesity and some women in the normal BMI range may actually be clinically obese.[18] However, even if there are classification errors, the very low BMI at which the wage function peaks makes it much more probable that we are observing the effects of appearance or beauty, rather than obesity or poor health. A growing literature suggests that attractive individuals earn more than their counterparts (Hamermesh and Biddle 1994; Biddle and Hamermesh 1998; Harper 2000; French 2002), although the mechanisms for this are not fully understood. A possible explanation for our results is that females are considered most attractive at low levels of BMI. Consistent with this, Maynard et al. (2006) provide evidence that the desired BMI of adult women is between 22 and 23, or almost exactly where the conditional wage function peaks.

The patterns for men differ substantially. Predicted wages are maximized at a BMI of 26.7—in the overweight range—with lower and higher body weight associated with substantial but imprecisely estimated decreases. Yet, these results also provide little evidence of a sizeable "obesity penalty," except perhaps at extremely high BMI. Instead, they raise

16. We excluded occupation from our primary estimates, since this is one mechanism through which BMI could affect earnings. Specifications adding controls for broad occupational categories resulted in similar estimates for women and flatter BMI-earnings profiles for men.

17. This range covers approximately the fifth through ninety-fifth percentiles of women and the first through ninety-eighth percentiles of men. We exclude from the analysis persons with BMI greater than forty-five, as these observations exert disproportionate influence on the semiparametric estimates. This trimming drops 34 men and 125 women.

18. Burkhauser and Cawley (2008) provide evidence that BMI is more likely to understate than to overstate obesity prevalence.

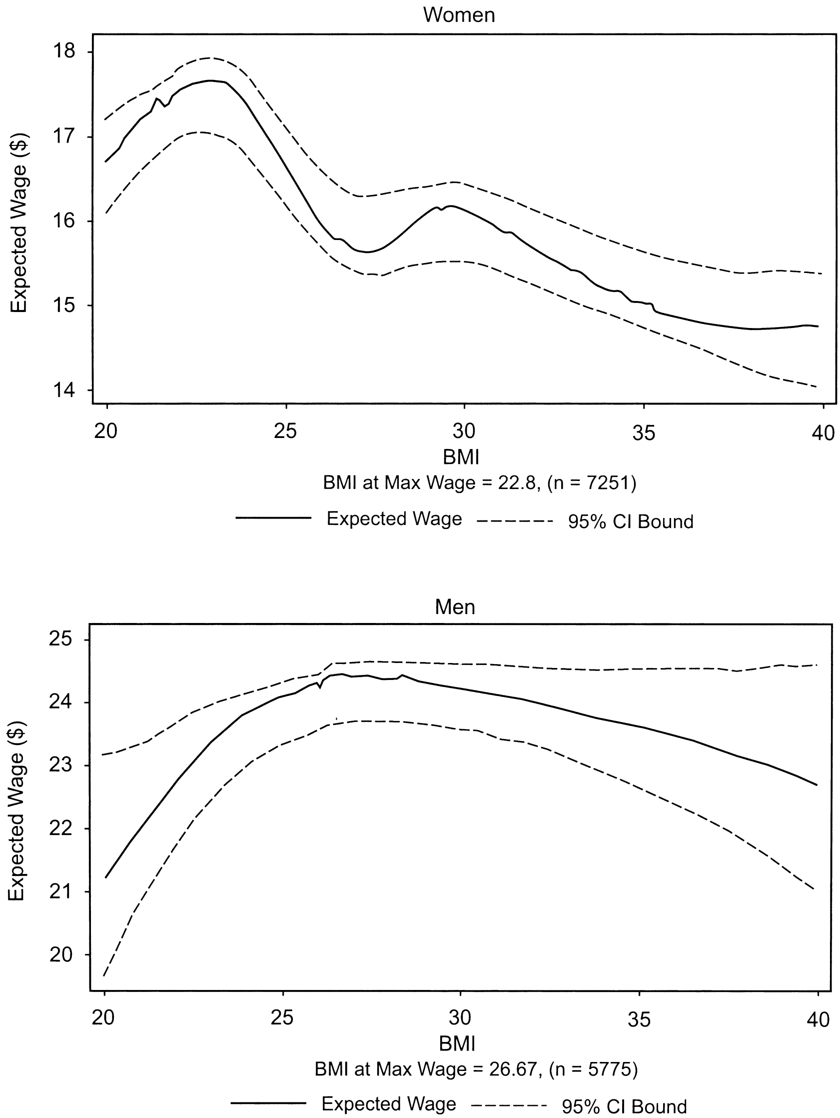


Fig. 11.1 BMI and expected wages, full sample

the possibility of wage reductions from being too light. For instance, the predicted hourly wage of a man with a BMI of thirty-five is just $0.81 per hour below that of his peer with a BMI of twenty-seven, while a BMI of twenty is associated with hourly earnings that are $3.19 less. Such results are consistent with the possibility, supported by previous evidence (DiGioachino, Sargent, and Topping 2001; Maynard et al. 2006), that males are held to a different appearance standard than females, with thin women viewed as attractive while corresponding men are considered scrawny. However, as discussed below, we obtain considerably different estimates for men (but not women) when using instrumental variables techniques, so these results should be interpreted with some caution.

11.4.2 Are Semiparametric Estimates Worth the Effort?

Are the benefits from using the semiparametric models worth the added complexity (and computational time) needed to estimate them? Our answer is a qualified yes. To illustrate the potential gains from these estimates, figure 11.2 plots the results from modeling wages as linear or quadratic in BMI, alongside the SPM estimates that are novel to this analysis. The conditional wage function of women is monotonically decreasing in BMI for the linear and quadratic specifications, which provide essentially identical estimates. While generally reasonable, the parametric models miss the increase in the wages occurring below a BMI of twenty-three (although the differences are small and often not significant), and understate the drop in earnings predicted immediately thereafter. At the very least, the SPM estimates suggest that the conditional wage function is flat until a BMI of twenty-three, and decreasing nearly monotonically thereafter.

For men, the gains to more flexible models are larger. In figure 11.2, it is clear that the linear specification fares the worst. The quadratic model does better in approximating the conditional wage function, and is sensible if we think that health effects or costs of obesity drive the BMI-wage relationship and begin to bind the wage function at *some* point in the BMI distribution. However, even the quadratic model is restrictive—overestimating wages at low BMI and in the overweight range, and indicating that the conditional wage function is maximized at a considerably higher BMI than the semiparametric model. These differences are nontrivial since the quadratic specification suggests an obesity penalty, while the more flexible estimates indicate that wages begin to decline much earlier, indicating that other factors may be at work.

Potentially useful, and computationally cheaper, alternatives to our SPM procedure might involve estimating models with higher order polynomials in BMI or linear splines.[19] Indeed, these could be time-efficient and relatively simple procedures for much future research. However, the preferred parametric specification may not be obvious a priori. The semiparametric procedures employed here may help to guide that choice and provide a more complete understanding of the conditional earnings function.

19. For example, `Stata` has a preprogrammed routine (the `lpoly` command) that will estimate local polynomial fits with usable, although not asymptotically correct, confidence intervals. This procedure does not address the issue of bandwidth selection, by which flexible models minimize mean squared error. For more on this procedure, see the appendix.

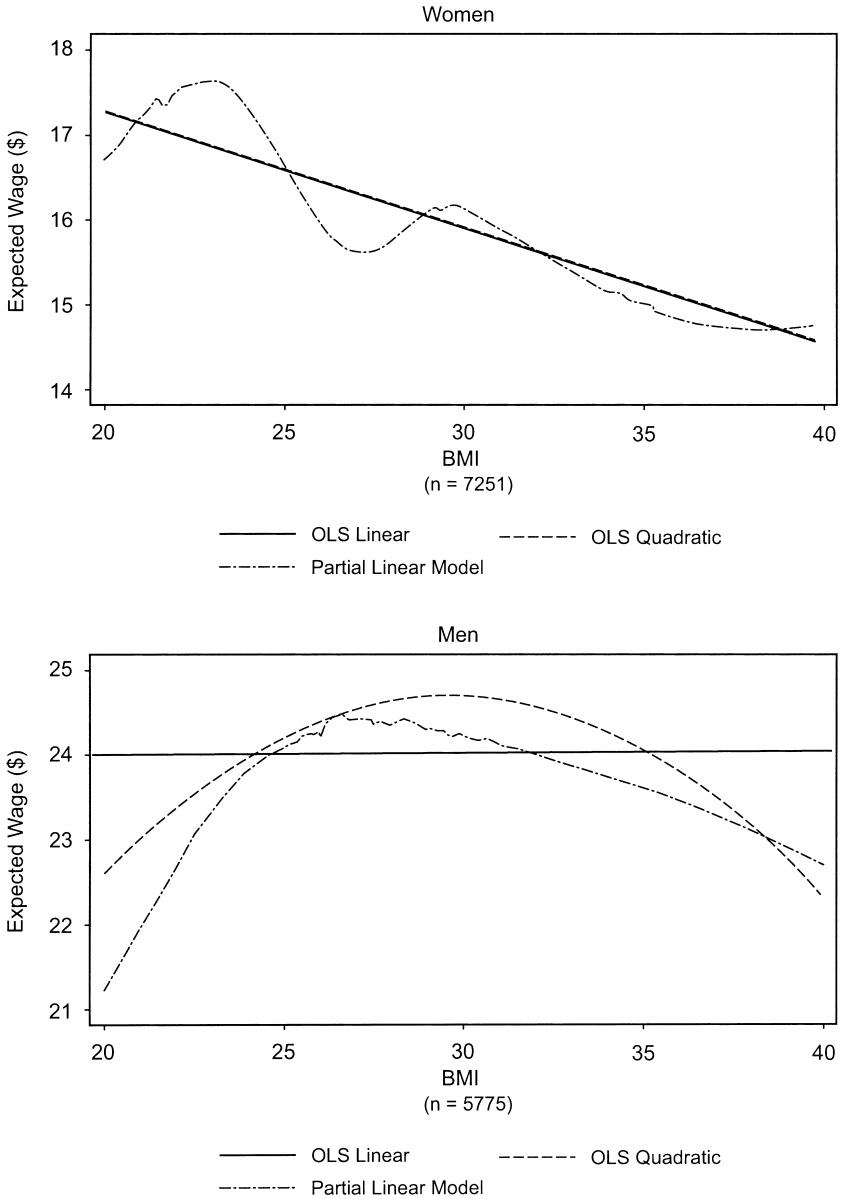


Fig. 11.2 Comparison of three estimation models

11.4.3 PSID versus NLSY

Previous related U.S. research has generally used data from the NLSY, rather than the PSID. Although the PSID is more comprehensive in several respects, most importantly because it is not limited to a single cohort or narrow age range, we checked whether the results were sensitive to its use. To do so, we obtained NSLY data for 1998 through 2004 (approximating the years of our main PSID analysis), during which time NLSY respondents were thirty-three to forty-seven years old. We constructed a sample of correspondingly aged individuals from the PSID and performed two analyses. First, we estimated simple OLS models for the two data sets.[20] For women, the estimates turned out to be quite similar. For instance, the coefficient (standard error) on BMI was –0.122 (0.017) in the PSID and –.168 (.024) in the NLSY.[21] For men, the results were somewhat different: using the PSID, we obtained a coefficient (standard error) of 0.017 (0.044), while the estimates were –.192 (.043) for the NLSY. The PSID findings are consistent with those shown in figure 11.2. Although the NLSY estimates for males run counter to some prior research (which does not uncover an obesity effect on wages), this is likely due to the young age range of the men previously examined. Gregory (2010) and Han, Norton, and Stearns (2009) have recently shown that the negative correlation between BMI and wages strengthens as men age, consistent with our results.

Second, we ran semiparametric models for the PSID and NLSY subsamples. These estimates, summarized in figure 11.3, reveal generally similar patterns.[22] However, there is evidence of greater nonlinearities for women in the PSID than the NLSY, while the male wage function reaches a maximum at a lower BMI in the NLSY. Overall, it seems likely that we would find even less evidence of a pure obesity effect in the NLSY, since the conditional wage function is maximized at a lower BMI. However, since the female wage function is approximately linear in the NLSY, there might be less gain from the flexible SPM estimates.

11.4.4 Reverse Causation

The preceeding findings could be biased due to reverse causation, where higher wages lead to lower BMI. For example, this could occur because high earners can more easily afford expensive foods, such as fruits and produce, that are healthy and low in calories. Alternatively, they may have greater flexibility in their jobs to find time to exercise and could more often join health

20. The NLSY data include only persons in the representative sample, and we use similar sample restrictions as in the PSID. The regressions are not weighted. Since we cannot easily identify pregnant women in the PSID, we run specifications for the NLSY data with pregnant women included. Separate NLSY models that exclude pregnant women yield similar results.

21. Our results are also similar to those obtained by Cawley (2004), when we estimate models using the log (rather than level) of earnings, as he did.

22. The smoothing estimates were normed to address some differences in scaling between the two data sets.

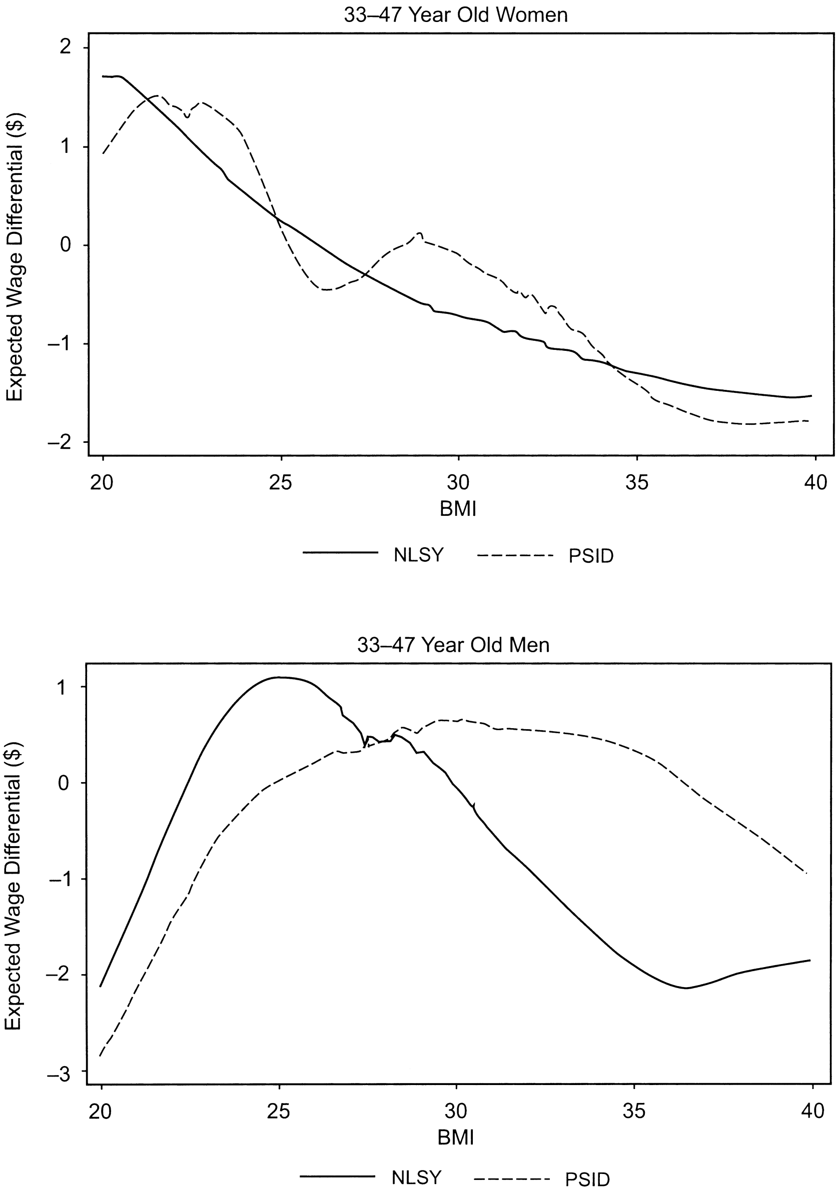


Fig. 11.3 BMI and estimated wage differentials, PSID-NLSY comparisons

clubs. We examine this issue in figure 11.4, which shows how lagged BMI is related to wages. Specifically, we measure BMI in 1986 and wages during 1999 to 2005. To reduce the possibility that lagged BMI itself is strongly influenced by (prior) earnings, we restrict this analysis to persons less than twenty-six years old in 1986, and so at the beginning of their work lives. Since

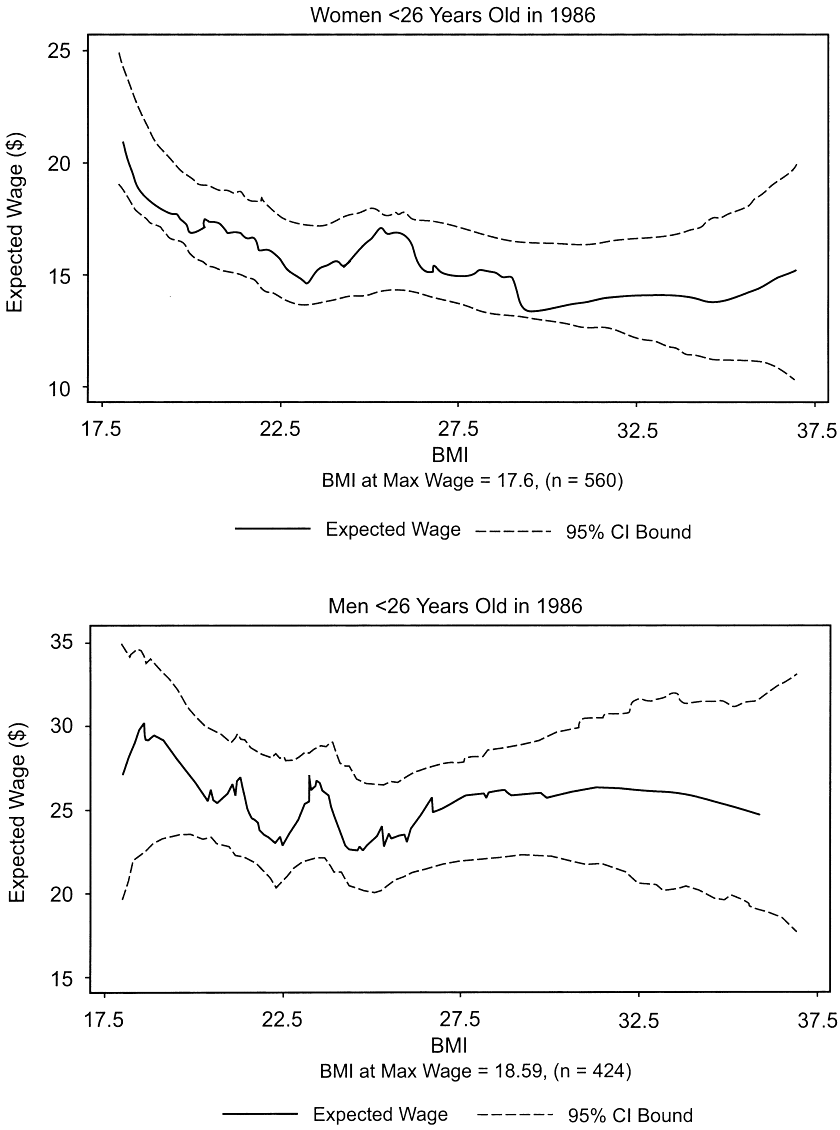


Fig. 11.4 Lagged BMI and expected wages

BMI typically rises with age, the distribution of lagged BMI is to the left of the contemporaneous distribution. Therefore, figure 11.4 displays BMI (in 1986) over the range eighteen to thirty-seven, rather than twenty to forty.[23]

The results for long-lags of BMI are fairly similar to those using con-

23. This corresponds to approximately the fifth to ninety-sixth percentile of the female BMI distribution in 1986.

temporaneous weight (and the full sample), once we account for the lower average BMI of young adults, and they again provide scant evidence of an obesity penalty. Specifically, the female wage function peaks at a very low BMI level (below eighteen) that is actually in the underweight category, although the earnings penalties thereafter are not always monotonic or statistically significant. For men, lagged BMI is essentially unrelated to contemporaneous wages, but with the peak predicted at a very low (18.6) BMI. These patterns are similar to those of women and suggest that being thinner is (almost always) better for males as well as females. We return to this result when examining our instrumental variables estimates.

11.4.5 Instrumental Variables

BMI could be correlated with unobserved factors also affecting wages. For example, persons earning high wages because they are motivated at work might similarly be motivated to exercise and consume healthy diets. The same might be true for individuals with low discount rates. In both of these cases, BMI will be correlated with the error term in our wage specification. We address this possibility by estimating instrumental variables estimates, using sibling BMI as the instrument.[24] These results are shown in figure 11.5.

For women, the IV estimates are similar to those obtained in the main models. Specifically, the conditional wage function is maximized at an even lower level of BMI (21.4), with a rapid decline in earnings predicted from the middle of the healthy weight range to just beyond the threshold for overweight. However, the wage function is flat after a BMI of twenty-six, further suggesting that we are not observing the effects of obesity.

The IV estimation makes a much larger difference for men. Where the main specifications indicated that the wage function increased into the overweight range, and then declined relatively slowly, the IV models suggest essentially no effect through a BMI of twenty-five or so, but with wages predicted to fall rapidly thereafter. Such results could indicate a role of poor health or medical costs but only if the effects begin to bind at the beginning of the overweight category. This seems unlikely, since most available research (Quesenberry, Caan, and Jacobson 1998; Andreyeva, Sturm, and Ringel 2004; Arterburn, Maciejewski, and Tsevat 2005) suggests that health costs are similar for healthy weight and overweight individuals but substantially higher for obese and, especially, severely obese persons.

11.5 Race

The wage functions of white and black females differ markedly (see figure 11.6). As in the full sample, the earnings of white women are predicted

24. In a standard linear model, first-stage *F*-statistics on the instruments are 29.5 for women and 16.2 for men, well in excess of the level of ten recommended by Staiger and Stock (1997) to avoid problems with weak instruments.

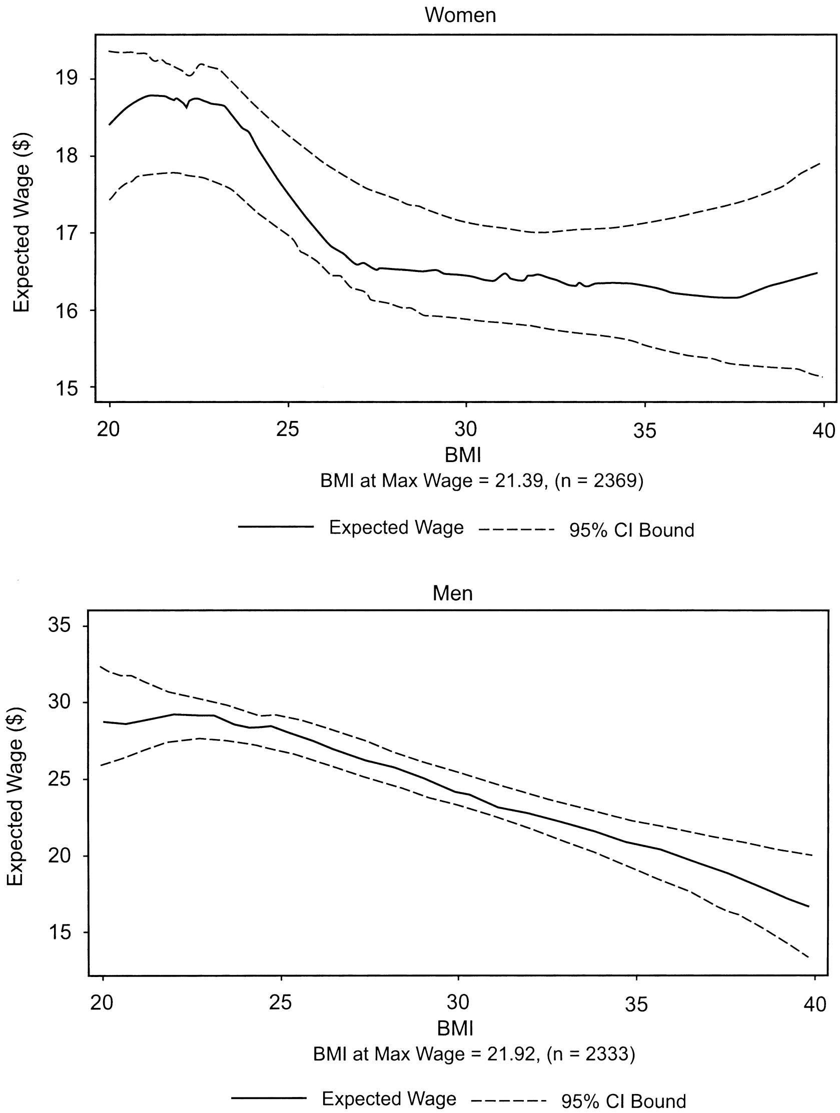
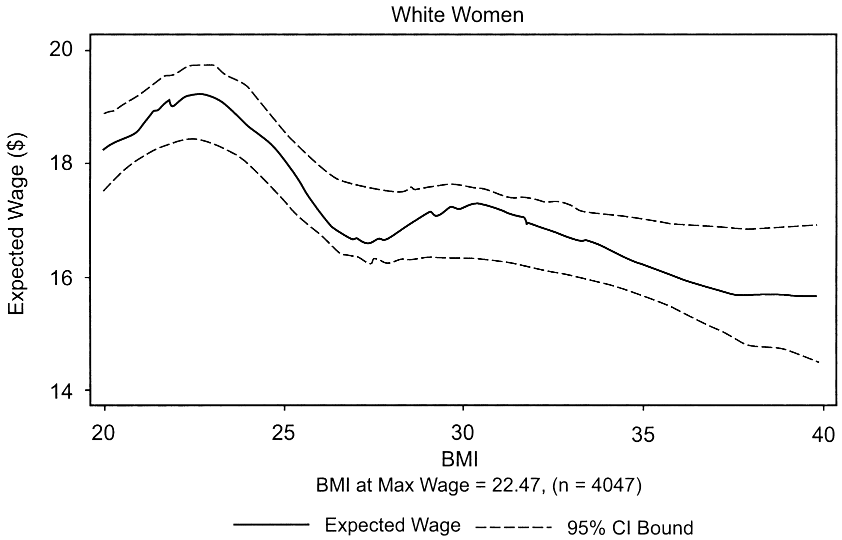


Fig. 11.5 Instrumental variables estimates

to peak well below the overweight threshold (at a BMI of 22.5), to decline markedly immediately thereafter, but then to be relatively flat beyond the middle of the overweight category. By contrast, the pattern for black women is consistent with a true obesity penalty, since the maximum predicted wage occurs at a BMI of 26.1, and nearly all of the economically or statistically significant reduction takes place at or beyond the obesity threshold. However, these results probably do not indicate that the obesity effect is due to



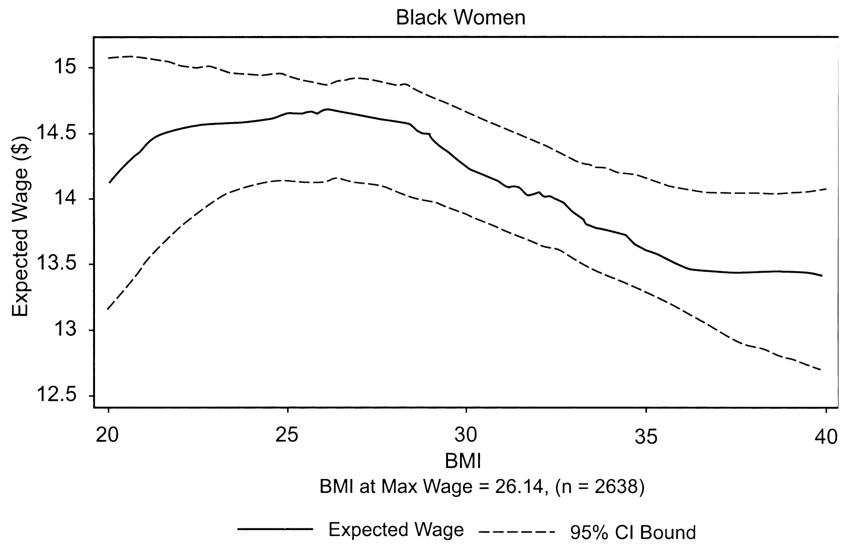


Fig. 11.6 BMI and expected wages of women, by race

higher medical costs or health problems. Were this the case, we would expect the wages of severely obese individuals to be substantially below those of their mildly obese counterparts (since severe obesity has by far the most deleterious health consequences). Instead, there is no evidence that the wage function continues to decline beyond a BMI of thirty-five.

The results for men are even more interesting. The wage function of white males reaches a maximum at a BMI of twenty-six, but remains relatively flat subsequently, with even severely obese men predicted to earn only modestly less. Conversely, the expected earnings of black males rise well past the obesity threshold (to a BMI of 32.1) and then remain flat or decline modestly.

These findings suggest substantial race differences in the BMI-wage profile, with greater and more binding weight penalties for whites than blacks that, except for black men, begin well before the obesity threshold.[25] Assuming that the relationship between BMI and health or medical costs is similar for blacks and whites, the racial disparities make it unlikely that the results in figures 11.6 and 11.7 reflect underlying effects of BMI on health conditions or medical costs. Instead, we think it more probable that these reflect appearance effects, combined with different standards of desired weight being applied to blacks and whites (and males and females).[26]

11.6 Simulations

Table 11.1 displays semiparametric estimates of the difference in predicted wages at specified BMI levels, relative to a reference group of females with a BMI of twenty-three or males with a BMI of twenty-seven.[27] The results are presented for subsamples, stratified by race and sex, for both our main SPM specifications (using actual BMI) as well as from semiparametric instrumental variables (SPM-IV) models. Standard errors are estimated from bootstrap replications, with *p*-values assigned using the percentile method. Coefficient estimates for the supplementary regressors are contained in appendix tables 11A.1 and 11A.2.

Table 11.1 highlights several points made previously, as well as some new ones. First, the wage function for females begins to decline at a relatively low body weight. Compared to women with a BMI of twenty-three, BMIs of twenty-five, thirty, and thirty-five predict statistically significant penalties of \$0.96, \$1.51, and \$2.62 per hour. This pattern is driven by white females, where the conditional wage function indicates even larger (although less precisely estimated) gaps of \$1.02, \$1.93, and \$3.51 per hour. The IV models reveal a similar pattern for white women, although with somewhat weaker predicted wage declines and standard errors that "blow up" at BMIs above thirty-five. Conversely, the findings for black females are more dependent on the choice of estimation techniques. Using actual BMI, predicted earn-

25. Instrumental variables suggest that this may also be the case for black males, as discussed below.

26. For example, college students report higher desired BMI for African American than white females, and for females than males (DiGioachino, Sargent, and Topping 2001).

27. The reference category is chosen to approximate the BMI level maximizing the conditional wage function in the main full sample specifications.

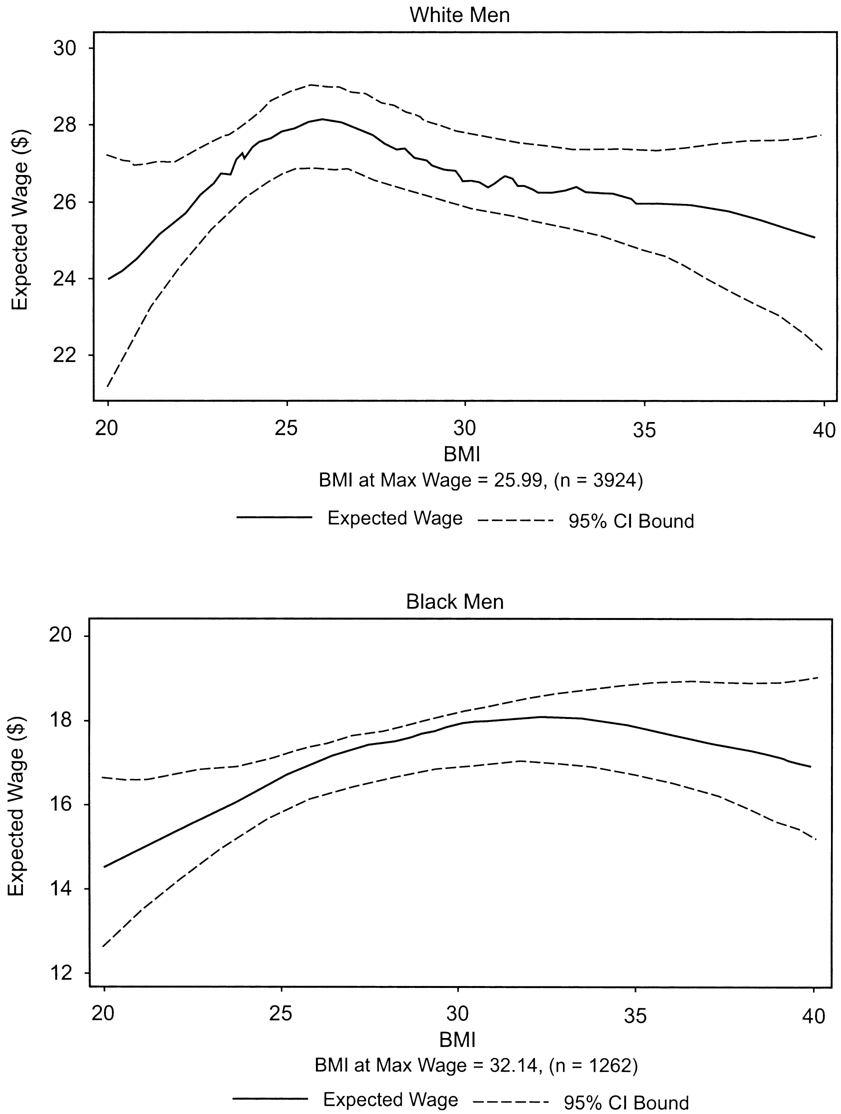


Fig. 11.7 BMI and expected wages of men, by race

ings reach a maximum at a BMI slightly above twenty-six and then decline relatively slowly. However, the IV estimates suggest a flatter conditional wage function prior to the peak, which occurs earlier (at a BMI of 21.6), and with a more rapid decline thereafter. Thus, the IV estimates for black females look relatively similar to the patterns seen for white women.

For men, the primary SPM estimates suggest that only a small wage pen-

Table 11.1 **Wage difference ($) relative to predicted earnings at reference BMI**

	Women (reference BMI = 23)					Men (reference BMI = 27)				
BMI	20	25	30	35	40	20	25	30	35	40
					Full Sample					
SPM	–.93*	–.96**	–1.51***	–2.62***	–2.89***	–3.19**	–.33	–.21	–.81	–1.72
	(.351)	(.277)	(.317)	(.311)	(.407)	(.928)	(.172)	(.195)	(.524)	(.993)
SPM–IV	–.24	–1.13*	–2.19***	–2.17**	–2.17**	2.28	1.84	–2.34***	–5.70***	–10.05***
	(.548)	(.319)	(.477)	(.658)	(.790)	(1.755)	(.574)	(.631)	(1.025)	(1.82)
					Whites					
SPM	–.90†	–1.02*	–1.93***	–3.51***	–3.50***	–3.87*	.01	–1.31*	–1.89*	–2.94†
	(.481)	(.419)	(.464)	(.717)	(.718)	(1.572)	(.668)	(.652)	(1.525)	(1.52)
SPM–IV	–.84	–1.45†	–1.79*	–1.17	.000	2.07	2.14**	–2.82***	–6.81***	–11.17**
	(.841)	(.686)	(.791)	(.852)	(1.274)	(2.101)	(.550)	(.565)	(1.29)	(2.660)
					Blacks					
SPM	–.49	.05	–.315	–1.16*	–1.17*	–2.82**	–.68**	.60*	.507	–.43
	(.355)	(.140)	(.316)	(.437)	(.437)	(1.02)	(.18)	(.210)	(.599)	(1.06)
SPM–IV	.02	–.27	–1.33**	–2.15**	–2.63**	3.61	–.18	–.25	–5.09**	–8.63**
	(.498)	(.223)	(.446)	(.619)	(.777)	(2.324)	(.559)	(.847)	(1.101)	(1.76)

Note: Results from Semiparametric (SPM) Models. Standard errors in parentheses.
***$p < .001$
**$p < .01$
*$p < .05$
†$p < .10$

alty is associated with high BMI, except perhaps for severe obesity. Thus, a BMI of thirty or thirty-five predicts hourly wages that are a statistically insignificant \$0.21 and \$0.81 lower than expected at a BMI of twenty-seven, with larger gaps for white males but positive predicted effects for blacks. On the other hand, hourly earnings are anticipated to be two to four dollars lower at a BMI of twenty than for the reference group.

The IV results for males are quite different: the wage function is monotonomically downward sloping beginning at low levels of BMI, with very large penalties associated with excess weight. Thus, men at the obesity threshold (BMI = 30) are anticipated to earn over four dollars per hour less than their counterparts with a BMI of twenty; those with a BMI of thirty-five are predicted to receive about eight dollars less. These differences are of similar size for white and black men, with the most important disparity being that the conditional wage function declines substantially between a BMI of twenty and twenty-five for blacks, and then flattens temporarily, whereas the pattern is reversed for whites.

11.7 BMI and Medical Expenses

Obese individuals might suffer a wage penalty because they have high medical costs that are partially paid by employers, through the health insurance system. Bhattacharya and Bundorf (2005) offer a version of this argument, providing evidence from the Medical Expenditure Panel Survey (MEPS) that the wage effects of obesity, for women, are borne entirely by those with employer-provided health insurance and, further, that the expected health costs of obesity are significantly higher for women than men.[28] Based on this, they claim that the effect of obesity on female wages is due to employers who offer insurance trading off wages against expected health expenditures, rather than because of any "beauty premium" or "appearance penalty."

We are doubtful of such a mechanism for the simple reason that the conditional wage function for women turns downwards so early—at a BMI of under twenty-three—far below either the obesity threshold or the level at which health costs might be expected to increase. Nevertheless, we directly test the possibility that health expenditures explain our results in two ways. First, we use MEPS data to produce a univariate nonparametric estimate of the log of total health expenditures (in 2005 dollars) as a function of BMI.[29] If our previous results are explained by employers using body weight to risk-rate employees, we would expect the pattern of medical expenditures to approximately track that for earnings. In particular, the medical costs of women should begin to rise at low BMI, starting at around twenty-three.

28. However, somewhat contradictory findings are obtained by Baum and Ford (2004).

29. We used data from the MEPS 1999, 2001, 2003, and 2005 samples and trimmed the top 1 percent of BMI observations. Using levels, rather than logs, of expenditures gives similar results.

The health expenditures for men should either not increase much prior to the obesity threshold (if we believe the results based on actual BMI), or show a similar pattern as for women, although starting to rise slightly later (if we place greater trust in the IV estimates).

Figure 11.8 displays the nonparametric relationship between BMI and log medical costs.[30] For women, predicted health expenditures change little prior to the obesity threshold but increase rapidly thereafter. This pattern is quite plausible, but almost certainly indicates that medical costs do *not* explain the observed conditional wage function, since earnings begin to fall much earlier—in a region where body weight is essentially unrelated to health costs. By contrast, we observe a monotonically increasing BMI-medical cost gradient for men, which has some potential for explaining the wage function obtained from the IV estimates (but less so when using actual BMI).

Second, we examine how the conditional wage function varies with BMI for subgroups stratified by age and gender. The medical costs of obesity are likely to increase with age (Finkelstein et al. 2007). If such expenditures are the source of the falloff in wages, we should therefore expect, ceteris paribus, a steeper BMI-wage gradient for older than younger persons. Instead, figure 11.9 shows that the conditional wage function declines from its peak much more rapidly for thirty-five to forty-four than for forty-five to fifty-five-year-old women. Similarly, wages are essentially unrelated to BMI for the oldest (forty-five to fifty-five-year-old) males, whereas the data suggest earnings penalties at high (and low) BMI for younger men (see figure 11.10). Finally, note that female wages are predicted to reach a maximum at a BMI of around twenty-two or twenty-three for all three age groups, well below the obesity or overweight thresholds. This seems inconsistent with the possibility that health expenditures are the primary determinant of the relationship between earnings and BMI.[31]

11.8 Discussion

The preceding analysis used semiparametric regression methods to examine how body weight is related to wages. Compared to previous research,

30. Our analysis does not account for two important characteristics of the expenditure data. First, there are a lot of zeros: in our sample, accounting for roughly 12 percent (29 percent) of women (men). Second, the distribution is extremely skewed. A more appropriate specification, in a semiparametric context, would be a partial general linear model using a gamma distribution and a log link (e.g., see Müller [2001]). However, such models are computationally expensive, even for parsimonious specifications, and we leave it to future research to explore the benefits of using them to examine the relationship between health expenditures and BMI.

31. It is less clear what age-pattern is expected if beauty play, a key role. If BMI becomes less closely tied to perceptions of beauty at higher ages, or if appearance itself becomes a less important determinant of wages, we would expect a steeper wage function for younger than older women. Conversely, appearance at young ages could have long-lasting consequences by directly influencing future productivity through, for example, its effects on self-esteem (Mobius and Rosenblat 2006; Mocan and Tekin 2006), or if initial labor market opportunities establish a path for future outcomes.

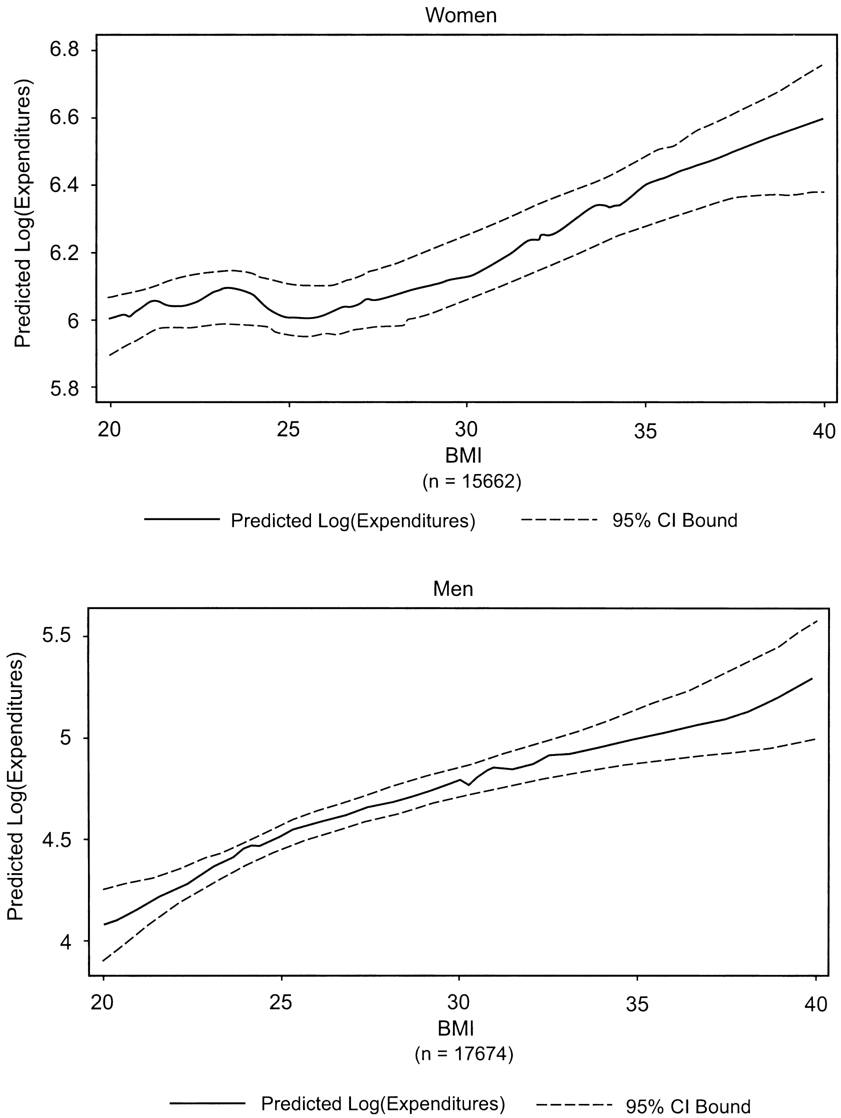


Fig. 11.8 BMI and expected medical care expenditures

these specifications allow great flexibility on the role of BMI, while imposing standard parametric restrictions on the other included controls.

A particularly striking finding is that increased BMI is associated with wage reductions for white females, beginning at low levels of weight—considerably below conventional thresholds for obesity or overweight. These results are robust to accounting for reverse causation or endogeneity and indicate that the conditional wage function is probably not being driven

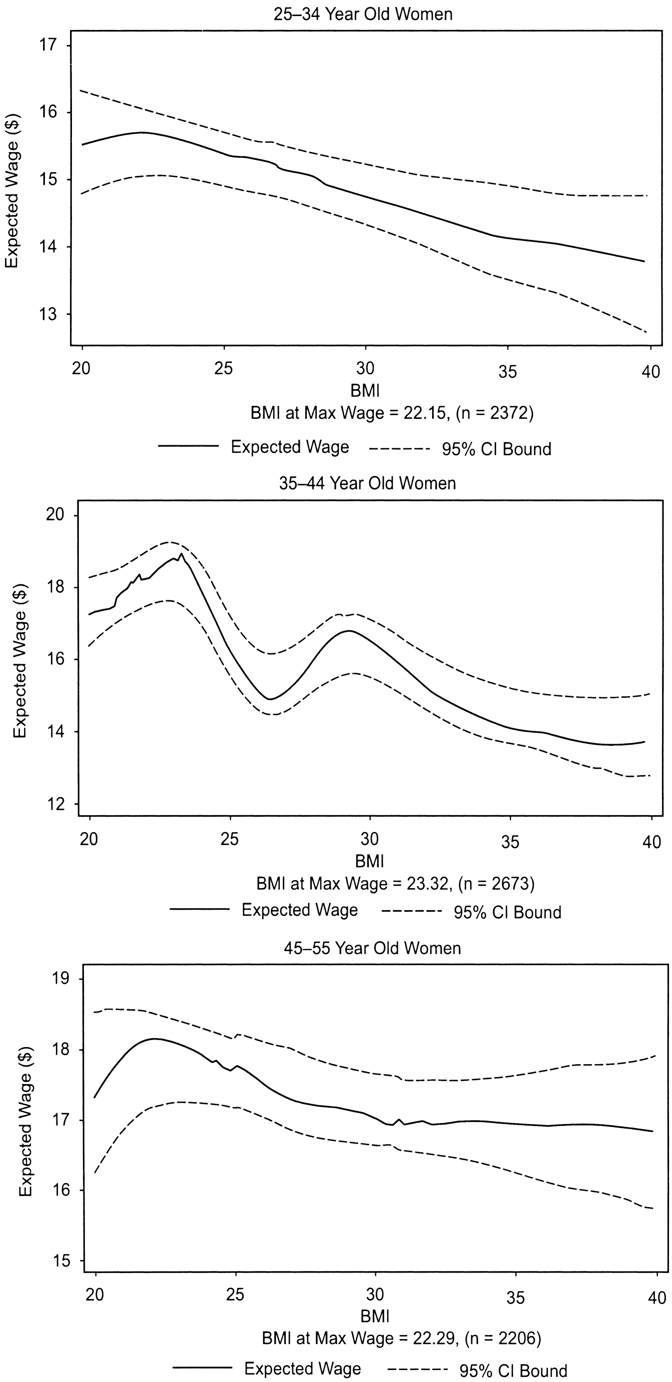


Fig. 11.9 BMI and expected wages, females by age

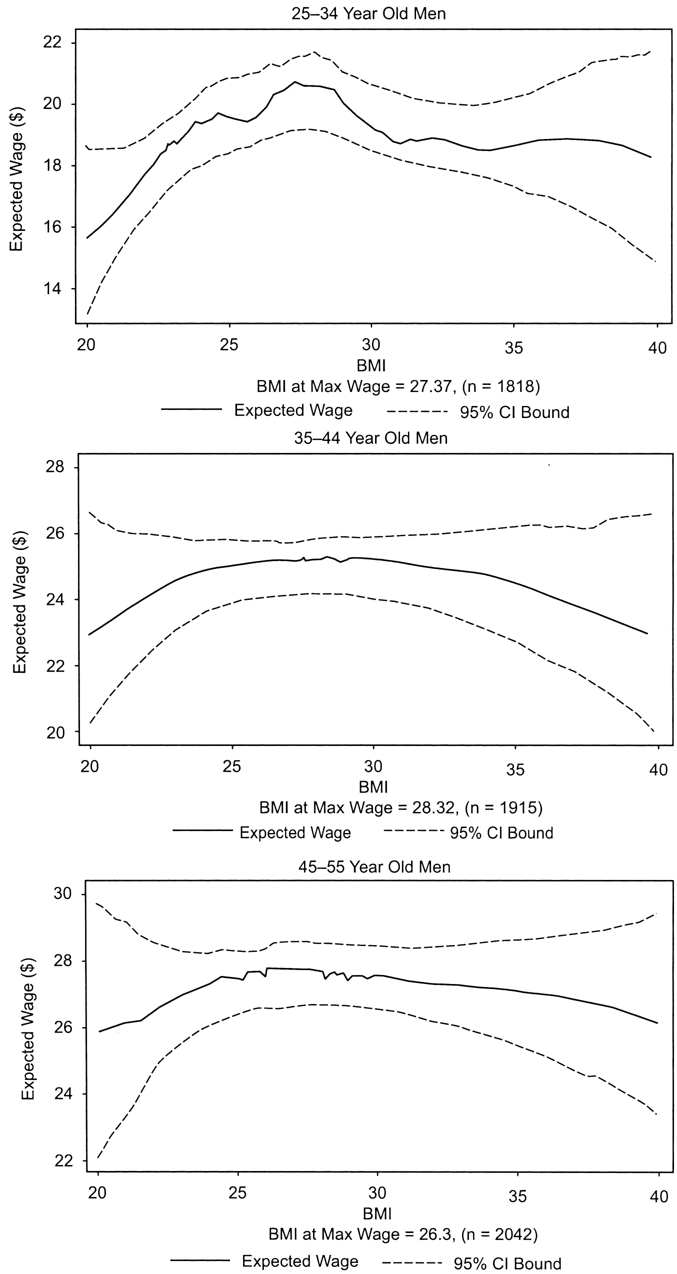


Fig. 11.10 BMI and expected wages, males by age

by the health effects of BMI or by obesity per se. Instead, they suggest that, over most of the BMI distribution, being "thinner is better" for white women, possibly due to social perceptions of beauty or desired appearance. The evidence for black females is more ambiguous. Our main specifications, conditioning on actual BMI, indicate that the earnings profile is flat prior to a BMI of around twenty-six, but then begins to decline fairly rapidly. This might reflect a different appearance standard for nonwhites, but also raises the possibility of an obesity penalty for this group.[32] However, instrumental variables estimates show a pattern more similar to that for white females, with earnings predicted to be maximized at a low BMI (21.8) and to decline rapidly thereafter.

The results for men are even more dependent on the estimation technique. In our main specifications, earnings increase through a BMI of around twenty-seven and then fall modestly. Conversely, the IV findings look similar to those for women, in predicting that wages decrease with BMI throughout virtually the entire range of the latter. Controlling for reverse causation (by including long-lags of BMI) also yields a conditional wage function that is maximized at a low BMI level and is fairly flat thereafter. The findings for black males differ from corresponding whites in that the main (noninstrumented) specifications show an increase in the conditional wage function until well into the obesity range, but with a more or less monotonic negative relationship between BMI and earnings predicted from the IV estimates.

Much can be done to clarify the interpretation of our results. Although health expenditures do not appear to drive the patterns, it is unclear whether the findings for women reflect labor market discrimination or some other cause. For example, females working in occupations requiring physical interaction might be subject to particular physical scrutiny. Adding controls for broad occupational categories slightly reduces the gradient of the wage function for females, consistent with occupational sorting; however, definitive answers to this question require controlling for occupational categories measuring the level of public interaction. Some results, particularly for males, are sensitive to the choice of specifications and we poorly understand why the results differ so starkly for whites and blacks. Modeling medical expenditures simultaneously with earnings, using data from a single source, could clarify the extent to which employers trade off wages for health expenditures.

These caveats notwithstanding, our analysis provides useful guidance for interpreting prior studies and conducting future research. First, when examining how BMI is related to earnings (and probably other outcomes),

32. For example, Stearns (1997) and Averett and Korenmann (1996) provide evidence that obesity has more deleterious effects on the self-esteem of white than black or Hispanic females.

it is important to allow for a variety of possible patterns rather than initially assuming that obesity is "where the action is." Indeed, we find little evidence of an obesity penalty per se, but instead often show that the conditional wage function is maximized at low levels of BMI, where excess weight is almost certainly not a key factor. Although we suspect that our results provide evidence of beauty or appearance effects, additional examination of these possibilities is needed. Second, the relationships are often highly nonlinear and benefit from models that permit considerable flexibility. We obtain this using our semiparametric specifications, but at the cost of considerable computational complexity. Simpler, although somewhat less flexible, modeling techniques might involve the use of higher order polynomials or linear splines. One possibility is to employ univariate nonparametric methods (without controls other than body weight) to establish the basic pattern, which then guide the choice of parametric models containing the full set of covariates.

Appendix

Nonparametric Smoothing Methods and Additional Econometric Estimates

Kernel regression drops the assumption of linearity and models the expectation of the dependent variable as a weighted mean at every point in the distribution of the independent variable. For example, the oft-used Nadarya-Watson kernel estimator can be defined as

(A1) $$\hat{r}_n(x) = \sum_{i=1}^{n} \ell_i(x) Y_i,$$

where $\hat{r}_n(x)$ is the predicted value of y at a given value x, and the weights are defined by the kernel function:

(A2) $$K(x) = \frac{70}{81}(1 - |x|^3)^3\, I(x),$$

where

$$I = \begin{cases} 1 & \text{if } |x| \le 0 \\ 0 & \text{otherwise.} \end{cases}$$

The choice of the kernel function—Gaussian, uniform, Epanechnikov—generally does not affect the result. The weighting function, $\ell(x)$ is defined as

(A3) $$\ell_i(x) = \frac{K[(x - x_i) / h]}{\sum_{j=1}^{n} K[(x - x_i) / h]}$$

where h is the bandwidth or smoothing parameter. This kind of estimator has the advantage of allowing for highly nonlinear relationships that are frequently missed even with linear estimators that include quadratic, cubic, and higher order terms.

In our analysis, we use local linear regression, which is similar in spirit to kernel regression, but instead of modeling the data with a locally weighted average, it uses a locally weighted linear regression. Local linear regression relaxes the linearity assumption of OLS and minimizes both boundary bias and design bias introduced by the kernel framework.[33] In general, we define the estimator and kernel as in equation (A1), but define $\ell(x)$, X_x, and W_x as follows:

(A4)
$$\ell(x) = e_1^T (X_x^T W_x X_x)^{-1} X_x^T W_x,$$
$$e_1 = (1,0,0,\ldots)^T,$$
$$X_x = \begin{bmatrix} 1 & x_1 - x \\ 1 & x_2 - x \\ 1 & x_3 - x \\ \vdots & \vdots \\ 1 & x_n - x \end{bmatrix},$$
$$W_x = \begin{bmatrix} w_1(x) & 0 & \cdots & 0 \\ 0 & w_2(x) & & \vdots \\ \vdots & \cdots & \ddots & \\ 0 & \cdots & \cdots & w_n(x) \end{bmatrix},$$
$$w_i(x) = K\left(\frac{x - x_i}{h}\right).$$

This formulation implies that the predicted value for a given value of x is the inner product of the first row of $\ell(x)$ with Y.

The choice of smoothing parameter, h, involves the tradeoff between bias and variance, as h defines the window of observations that will be used in local regression. For nonlinear functions, small windows of observations give high variance and low bias, whereas large windows offer the converse. We choose the bandwidth by selecting the span, k, the fraction of the data to include in the linear estimate, to minimize mean squared error ($bias^2 + variance$) for the estimator. This implies that for each realization of x the bandwidth changes according to the distance to the observation $(k \cdot N) / 2$ observations away. In particular, we minimize the leave-one-out cross-validation score over the range of the span. The cross validation score is defined as

33. On this point, see Wasserman (2006, 73ff.), Fan and Gijbels, (17–18, 60ff).

$$CV(k) = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{r}_{(-i)}(x_i))^2 \quad \text{(A5)}$$

where $\hat{r}_{(-i)}$ is the estimator derived from leaving out the ith observation.[34]

Table 11A.1 Semiparametric regression results for women

	Full sample	Whites	Blacks	Age < 26 in 1986	IV
Black	–1.149***			–1.597	–1.986**
	(0.269)			(0.978)	(0.766)
Hispanic	–2.865***				3.532*
	(0.537)				(1.588)
Age	0.054***	0.106***	–0.005	–0.404*	0.032
	(0.014)	(0.020)	(0.021)	(0.190)	(0.031)
Year 2001	0.214	0.298	0.151	0.989	–0.059
	(0.340)	(0.474)	(0.498)	(1.168)	(0.696)
Year 2003	1.184***	1.323**	0.988*	3.173*	0.318
	(0.332)	(0.462)	(0.497)	(1.352)	(0.673)
Year 2005	0.585*	0.660	0.104	2.866*	0.518
	(0.271)	(0.409)	(0.352)	(1.414)	(0.527)
Number of kids	–0.055	0.317*	–0.269*	–0.540	–0.025
	(0.099)	(0.151)	(0.130)	(0.368)	(0.193)
Married	0.638*	0.174	0.708*	–0.156	0.534
	(0.261)	(0.397)	(0.349)	(0.905)	(0.489)
Child under 2	2.253***	3.472***	0.661	2.429	2.263**
	(0.381)	(0.570)	(0.502)	(1.389)	(0.734)
Northeast	3.284***	2.313***	4.768***	5.040***	3.506***
	(0.343)	(0.462)	(0.570)	(1.329)	(0.651)
Midwest	0.382	–0.108	0.795	–0.154	1.320*
	(0.283)	(0.391)	(0.411)	(1.089)	(0.552)
West	2.372***	1.817***	3.893***	1.246	3.361***
	(0.338)	(0.455)	(0.679)	(1.166)	(0.667)
HS dropout	–3.008***	–3.482***	–1.786***	–2.624*	–3.597***
	(0.364)	(0.621)	(0.447)	(1.158)	(0.784)
Some college	1.386***	1.367***	1.520***	3.430***	0.350
	(0.269)	(0.395)	(0.352)	(0.942)	(0.531)
College graduate	7.677***	7.235***	8.140***	11.803***	7.266***
	(0.297)	(0.396)	(0.477)	(1.517)	(0.594)
Job tenure (mos)	0.024***	0.025***	0.025***	0.034***	0.027***
	(0.001)	(0.002)	(0.002)	(0.006)	(0.003)
IV residual					–0.015
					(0.162)
Constant	0.010	0.069	0.043	–0.111	0.014
	(0.107)	(0.155)	(0.147)	(0.354)	(0.206)
N	7,251	4,047	2,638	544	2,369

Note: Regression coefficients for supplementary covariates. Standard errors in parentheses.
***$p < .001$
**$p < .01$
*$p < .05$

34. When smoothing the dependent variables, we execute least-squares cross validation at the roughly 500 points .2 percentile points apart in the middle 95 percent of the distribution of BMI.

Table 11A.2 **Semiparametric regression results for men**

	Full sample	Whites	Blacks	Age < 26 in 1986	IV
Black	–5.310***			–3.833*	–5.171***
	(0.580)			(1.824)	(1.143)
Hispanic	–7.346***				–1.536
	(0.968)				(3.082)
Age	0.240***	0.303***	0.085*	–0.102	0.375***
	(0.028)	(0.037)	(0.041)	(0.379)	(0.051)
Year 2001	0.570	0.756	–0.258	0.814	1.602
	(0.635)	(0.825)	(0.936)	(2.124)	(1.140)
Year 2003	0.662	0.846	–0.470	–1.708	1.320
	(0.625)	(0.822)	(0.902)	(2.538)	(1.141)
Year 2005	0.541	0.844	–0.896	0.559	0.618
	(0.550)	(0.745)	(0.718)	(2.919)	(0.919)
Number of kids	1.142***	1.945***	–0.317	–0.719	1.783***
	(0.206)	(0.289)	(0.282)	(0.691)	(0.368)
Married	2.641***	3.222***	2.613***	4.011*	3.501***
	(0.561)	(0.788)	(0.699)	(1.768)	(0.973)
Child under 2	0.482	0.330	–0.466	8.792***	–0.075
	(0.762)	(1.051)	(1.063)	(2.646)	(1.296)
Northeast	4.951***	5.772***	2.360*	5.169	5.590***
	(0.660)	(0.838)	(1.122)	(2.648)	(1.135)
Midwest	0.776	0.769	1.534	1.495	0.698
	(0.561)	(0.734)	(0.791)	(1.794)	(1.028)
West	1.335*	1.795*	2.325*	–1.126	1.254
	(0.614)	(0.820)	(1.045)	(2.216)	(1.120)
HS dropout	–3.942***	–4.056***	–2.050*	–6.972**	–5.171***
	(0.739)	(1.147)	(0.875)	(2.686)	(1.357)
Some college	3.286***	3.380***	3.498***	4.101*	3.371***
	(0.568)	(0.761)	(0.726)	(1.920)	(0.962)
College graduate	11.720***	12.349***	7.031***	26.354***	11.987***
	(0.549)	(0.703)	(0.872)	(2.325)	(1.132)
Job tenure (mos)	0.013***	0.009**	0.021***	0.020*	0.001
	(0.002)	(0.003)	(0.003)	(0.009)	(0.004)
IV residual					0.735
					(0.434)
Constant	0.322	0.037	0.341	–0.259	–0.004
	(0.212)	(0.282)	(0.291)	(0.676)	(0.360)
N	5,775	3,924	1,262	427	2,333

Note: Table shows regression coefficients for supplementary covariates. Standard errors in parentheses.
***$p < .001$
**$p < .01$
*$p < .05$

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