Where Does the Wage Penalty Bite?

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Abstract:

The literature examining the relationship between body mass index (BMI) and wages has fairly consistently found that BMI has a negative impact on earnings for women, and less (if any) consequences for men. In this paper, we relax the assumption–largely unquestioned in this research–that the conditional mean of wages is linear or piecewise linear in body mass index (BMI). Using data from the 1986 and 1999-2005 Panel Study of Income Dynamics, we estimate semi-parametric wage models that allow earnings to vary with BMI in a highly flexible manner. For women, the results show that earnings peak at levels far below the clinical threshold of "obesity" or even "overweight". For men, our main estimates suggest a reasonably flat BMI-wage profile that peaks early in the "overweight" category. However, the results of instrumental variables (IV) models are more similar to those for women. The findings for females (and the IV estimates for males) suggest that it is not obesity but rather some other factor – such as physical attractiveness – that may be producing the observed relationship between BMI and wages. We also provide non-parametric estimates of the association between BMI and health expenditures, using data from the Medical Expenditure Panel Survey. These cast further doubt on the hypothesis that the wage penalties associated with increasing BMI occur because the latter serve as an index for underlying medical costs.

1 Introduction

How does BMI affect wages? At first blush, the answer seems obvious. Over the last 15 years, a large literature has established the negative correlation between obesity–the condition of having a body mass index (BMI) greater than 30–and wages, at least for women. On average, obese women make two to eight percent less than their normal weight counterparts. Obese men don't 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 30 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 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 semi-parametric methods. Shimokawa (2008) used data from China to estimate semi-parametric

[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).

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 13 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 semi-parametric (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). 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 23 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 non-parametric 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.

2 Data

We use data on 25-55 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

[2]The original sample includes a nationally representative group of 2930 families, with the complement from a low-income sample.

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 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/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 et al., 2004; Lakdawalla and Philipson, 2007). Specifically, using data from the National Health and Nutrition Examination Survey (NHANES) III (1986-94), NHANES 1999, NHANES 2001, and NHANES 2003, we regress measured height (weight) on self-reported

[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.

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 25 to 55 year olds who worked at least 20 hours per week in their main job. These restrictions limit the sample to prime-age workers. We normalize wages to 2005 dollars using the CPI, drop observations reporting wages less than half of the federal minimum, and trim the top $\frac{1}{2}\%$ percent of wage observations.[6] Our final analysis sample contains 7,251 women and 5,775 men.

3 Methods

The estimates were obtained using a semiparametric (SPM) local linear regression framework that can be usefully distinguished from both 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

[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 25-55 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 et al., 2001; Hill, 1992).

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

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 these contexts, we use the specification

$$Y_i = z_i * \beta + f(BMI_i) + \varepsilon_i, \tag{1}$$

where Y_i is hourly wages of individual i, z_i is a vector individual characteristics and year effects, and $f(BMI)$ is the non-parametric function transforming BMI into wages, which we refer to as the "conditional wage function."[7] The resulting models are semi-parametric because they assume that the covariates included in z are linearly related to wages, whereas flexibilty 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 non-parametric 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, $\hat{f}(BMI_i)$, by non-parametrically regressing the wage residual $Y_i - z_i * \hat{\beta}_{eps}$ on BMI_i, using the techniques detailed in the Appendix.[8] The intuition

[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.

behind this procedure is to purge the dependent variable of the portion of the supplemental variables 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, p. 688) and Yatchew (2003, pp. 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 non-parametric prediction of the residual conditional on BMI ($\hat{iveps}$) and a residual ($\hat{eps}^{iveps}$). We include that residual in the second stage residual regression and form our estimate of $\hat{f}(BMI)$ as above. 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 7 years, we analyze wages in 1999-2005 as a function of BMI in 1986, or 13-19 years earlier. Second, we limit this portion of the analysis to individuals less than 26 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 instrumen-

[9]This algorithm is often applied when heteroskedasticity is a concern. To form 95-percent confidence intervals, we resample 1200 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.

tal 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 own earnings, except through BMI. The first assumption is uncontroversial and can be tested. The second is more problematic. In 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 non-shared between siblings, and that their importance diminishes in adolescence (Maes et al., 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 (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 inat-

[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.

[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 "non-additive" 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 neuro-psychological 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 direct link between obesity and the D4 dopamine receptor gene (Poston et al., 1998).

tention and adult obesity are correlated with the Dopamine D4 receptor gene in women with Seasonal Affective Disorder (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 below) identified by genetic variation in BMI.

4 Full Sample Results

We next summarize our semi-parametric 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 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 20 to 40.[17]

[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 co-habitation 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.

[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 5th through 95th percentiles of women and the 1st through 98th percentiles of men. We exclude from the analysis persons with BMI greater than 45, as these observations exert disproportionate influence on the semi-parametric estmates. This trimming drops 34 men and 125 women.

4.1 Main Specifications

Figure 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 (Biddle and Hamermesh, 1994; Hamermesh and Biddle, 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 bodyweight associated with substantial

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

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 the possibility of wage reductions from being too light. For instance, the predicted hourly wage of a man with a BMI of 35 is just \$0.81 per hour below that of his peer with a BMI of 27, while a BMI of 20 is associated with hourly earnings that are \$3.19 less. Such results are consistent with the possibility, supported by previous evidence (DiGioachino et al., 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.

4.2 Are Semi-Parametric Estimates Worth the Effort?

Are the benefits from using the semi-parametric models are worth the added complexity (and computational time) need to estimate them? Our answer is a qualified "yes." To illustrate the potential gains from these estimates, Figure 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 occuring below a BMI of 23 (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 23, and decreasing nearly monotonically thereafter.

For men, the gains to more flexible models are larger. In Figure 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 semi-parametric model. These differences are non-trivial 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, we would recommend these as time-efficient and relatively simple procedures for much future research. However, the preferred parametric specification may not be obvious *a priori*. The semi-parametric procedures employed here may help to guide that choice and provide a more complete understanding of the conditional earnings function.

4.3 PSID vs. NLSY

Previous related U.S. research has generally used data from the NLSY, rather than the PSID. Although we view the PSID to be preferable 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 33 to 47 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,

[19]For example, `Stata` has a pre-programmed routine (the `lpoly` command) that will estimate local polynomial fits with usable, although not asymptotically correct, confidence intervals.

[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

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 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 (2007) has recently shown that the negative correlation between BMI and wages strengthens as men age, consistent with our results.

Second, we ran semi-parametric models for the PSID and NLSY subsamples. These estimates, summarized in Figure 3, reveal generally similar patterns.[22] However, there is evidence of greater non-linearities 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 approcximately linear in the NLSY, there might be less gain from the flexible SPM estimates.

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 clubs. We examine this issue in Figure 4, which shows how lagged BMI is related to wages.

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.

Specifically, we measure BMI in 1986 and wages during 1999-2005. To reduce the possibility that lagged BMI itself is strongly influenced by (prior) earnings, we restrict this analysis to persons less than 26 years old in 1986, and so at the beginning of their worklives. Since BMI typically rises with age, the distribution of lagged BMI is to the left of the contemporaneous distribution. Therefore, Figure 4 displays BMI (in 1986) over the range 18 to 37, rather than 20 to 40.[23]

The results for long-lags of BMI and are fairly similar to those using contemporaneous 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 18) 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.

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 5.

[23] This corresponds to approximately the 5th to 96th percentile of the female BMI distribution in 1986.

[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 10 recommended by Staiger and Stock (1997) to avoid problems with weak

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 26, further suggesting that we are not observing the effects of obesity.

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 25 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 et al., 1998; Andreyeva et al., 2004; Arterburn et al., 2005), suggests that health costs are similar for "healthy" weight and "overweight" individuals but substantially higher for obese and, especially, severely obese persons.

5 Race

The wage functions of white and black females differ markedly (see Figure 6). As in the full sample, the earnings of white women are predicted 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" catgory. 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 higher medical costs or health problems. Were this the case, we would

instruments.

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 35.

The results for men are even more interesting. The wage function of white males reaches a maximum at a BMI of 26 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 6 and 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]

6 Simulations

Table 1 displays semi-parametric estimates of the difference in predicted wages at specified BMI levels, relative to a reference group of females with a BMI of 23 or males with a BMI of 27.[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 semi-parametric instrumental variables (SPM-IV) models. Standard errors are estimated from bootstrap replications, with p-values

[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 et al., 2001).

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

assigned using the percentile method. Coefficient estimates for the supplementary regressors are contained in Appendix Tables A-1 and A-2.

Table 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 bodyweight. Compared to women with a BMI of 23, BMIs of 25, 30 and 35 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 35. Conversely, the findings for black females are more dependent on the choice of estimation techniques. Using actual BMI, predicted earnings reach a maximum at a BMI slightly above 26 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 penalty is associated with high BMI, except perhaps for severe obesity. Thus, a BMI of 30 or 35 predicts hourly wages that are a statistically insignificant \$0.21 and and \$0.81 lower than expected at a BMI of 27, 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 20 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 20; those with a BMI of 35 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 20 and 25 for blacks, and then flattens temporarily, whereas the pattern is reversed for whites.

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 23 – 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 non-parametric 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

[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% of BMI observations. Using levels, rather than logs, of expenditures gives similar results.

women should begin to rise at low BMI, starting at around 23. 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 8 displays the non-parametric relationship between BMI and log medical costs.[30] For women, predicted health expenditures change little prior to the 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 fall-off in wages, we should therefore expect, *ceteris paribus*, a steeper BMI-wage gradient for older than younger persons. Instead, figure 9 shows that the conditional wage function declines from its peak much more rapidly for 35-44 than for 45-55 year old women. Similarly, wages are essentially unrelated to BMI for the oldest (45-55 year old) males, whereas the data suggest earnings penalties at high (and low) BMI for younger men (see figure 10). Finally, note that female wages are predicted to reach a maximum at a BMI of around 22 or 23 for all three age groups, well below the

[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% (29%) of women (men). Second, the distribution is extremely skewed. A more appropriate specification, in a semi-parametric 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.

"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]

8 Discussion

The preceding analysis used semi-parametric regression methods to examine how body weight is related to wages. Compared to previous research, 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 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 26 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.

[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.

[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.

The results for men are even more dependent on the estimation technique. In our main specifications, earnings increase through a BMI of around 27 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 (non-instrumented) 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. It would also be desirable to model medical expenditures simultaneously with earnings, using data from a single source, to get a better sense of 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), 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 non-linear and benefit from models that permit considerable flexibility. We obtain this using our semi-parametric 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 non-parametric 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.

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Table 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 Semi-Parametric (SPM) Models; Standard Errors in Parenthesis. ***p<.001, **p<.01, *p<.05 †p<.10

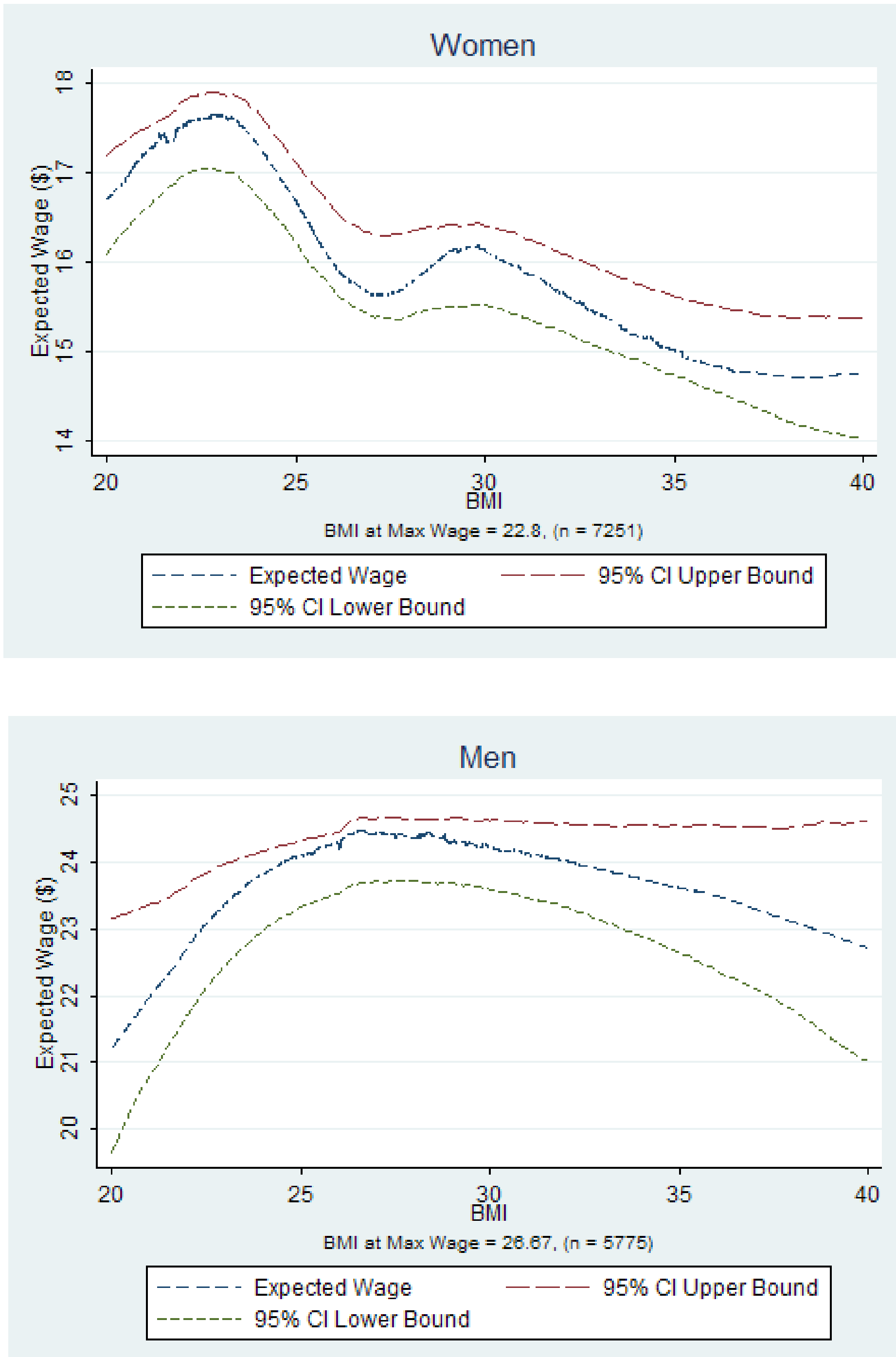


Figure 1: BMI and Expected Wages, Full Sample

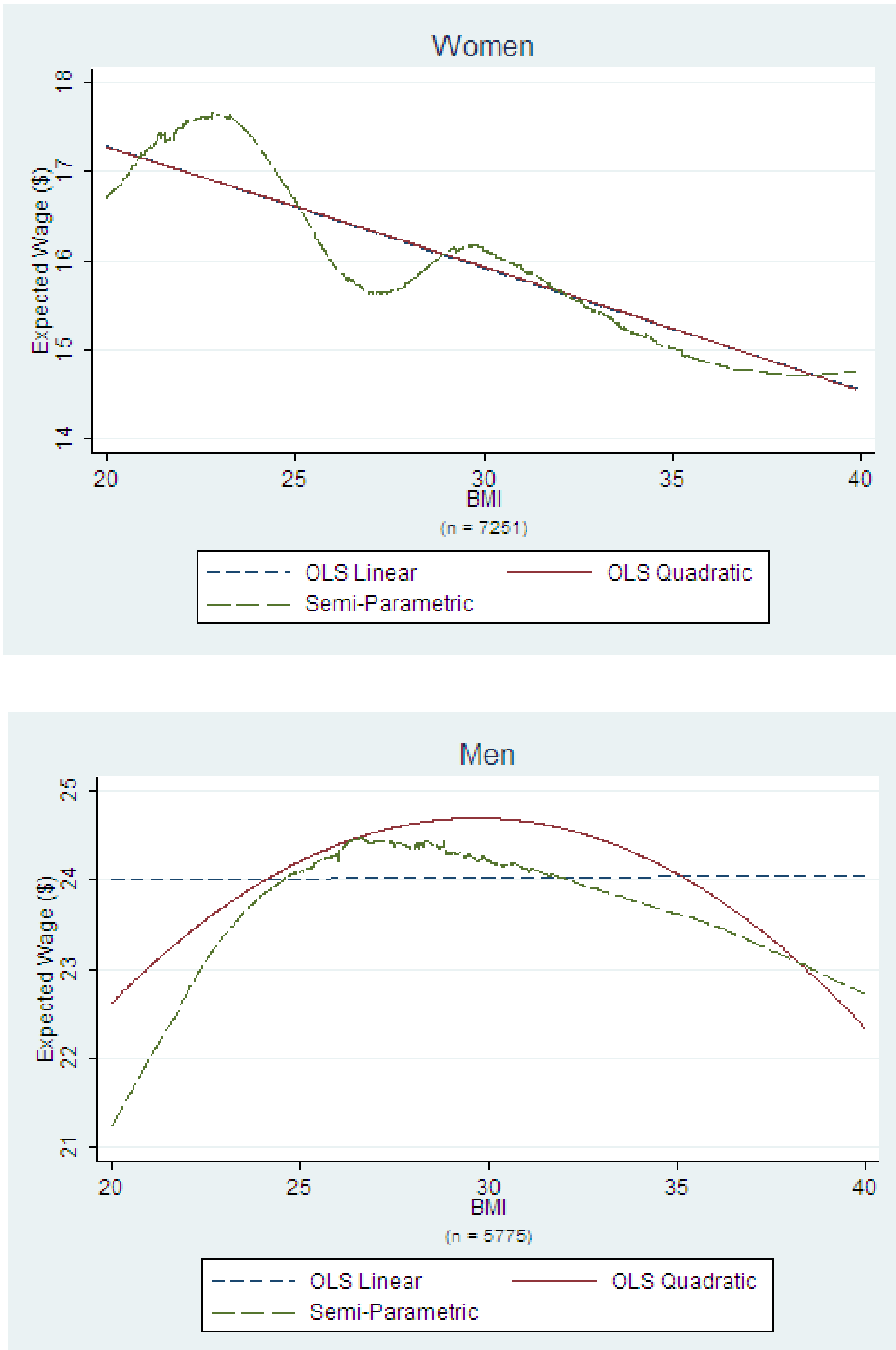
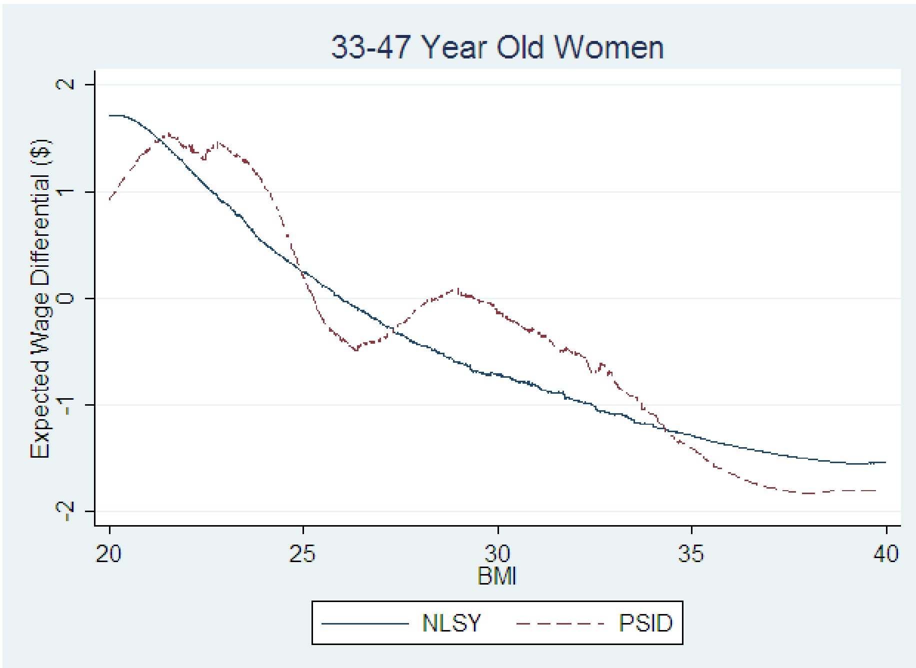


Figure 2: Comparison of Three Estimation Models



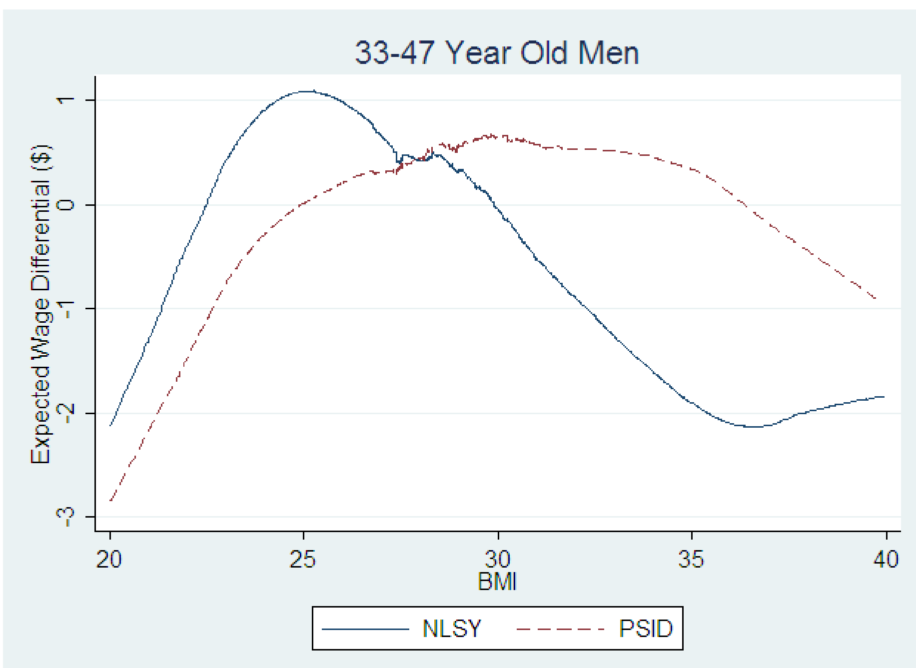
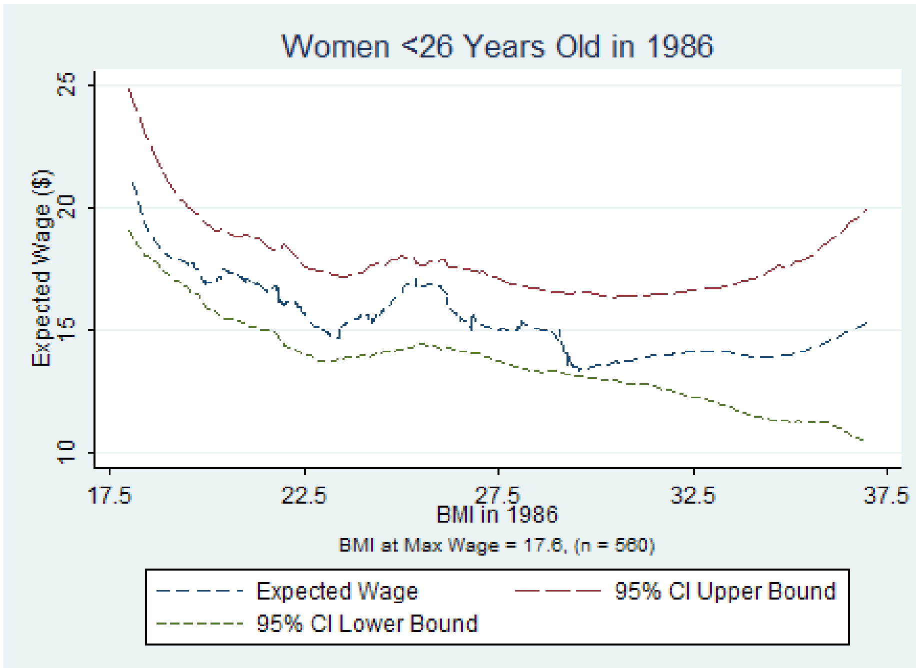


Figure 3: BMI and Estimated Wage Differentials, PSID - NLSY Comparisons



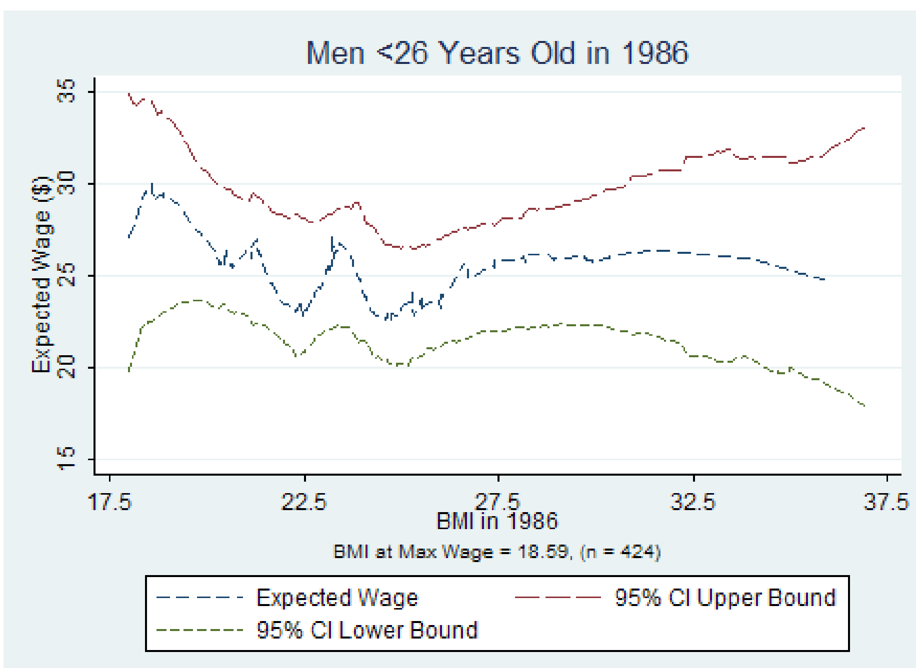


Figure 4: Lagged BMI and Expected Wages

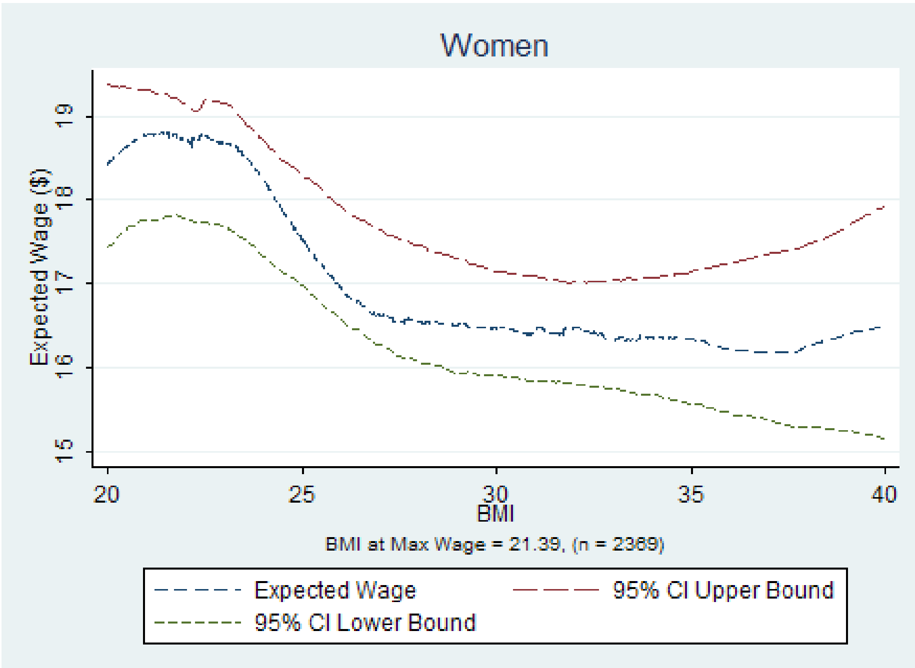


Figure 5: Instrumental Variables Estimates

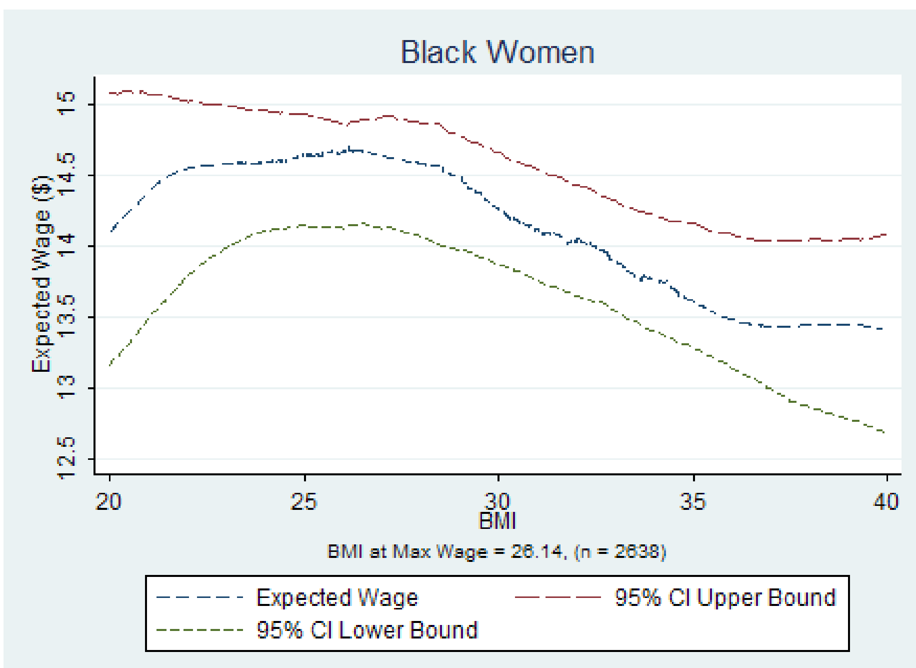


Figure 6: BMI and Expected Wages of Women, by Race

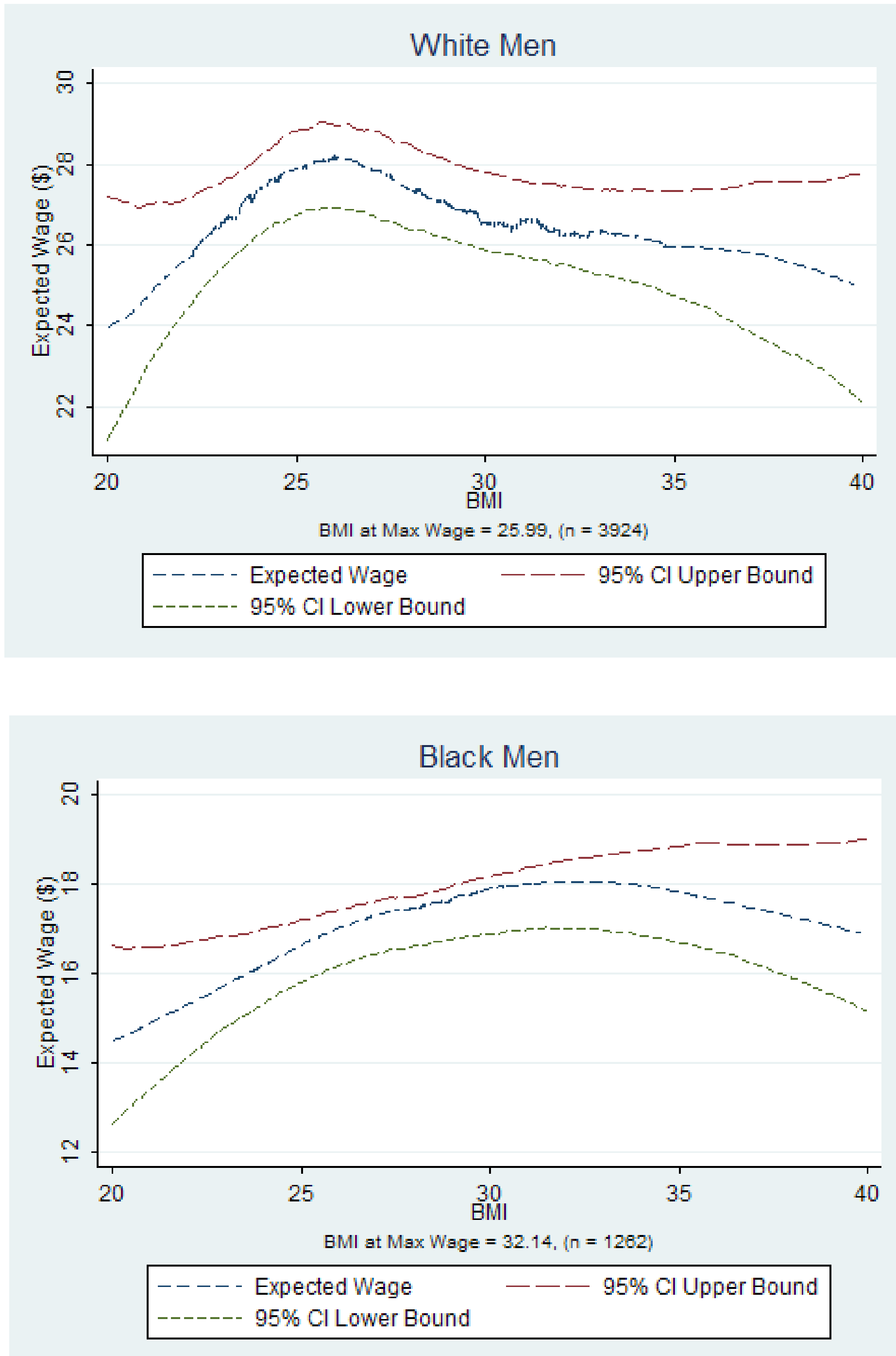


Figure 7: BMI and Expected Wages of Men, by Race

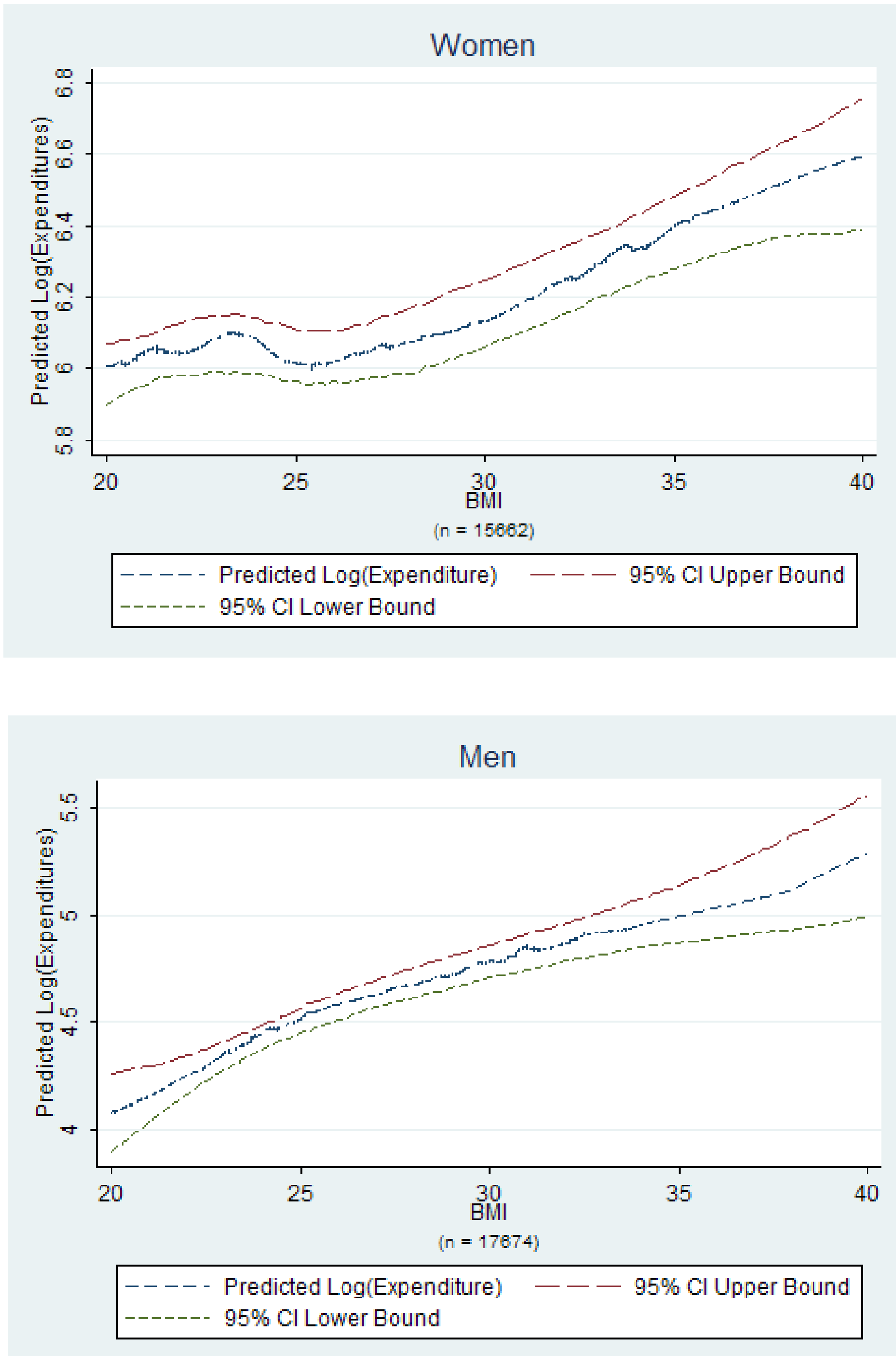


Figure 8: BMI and Expected Medical Care Expenditures

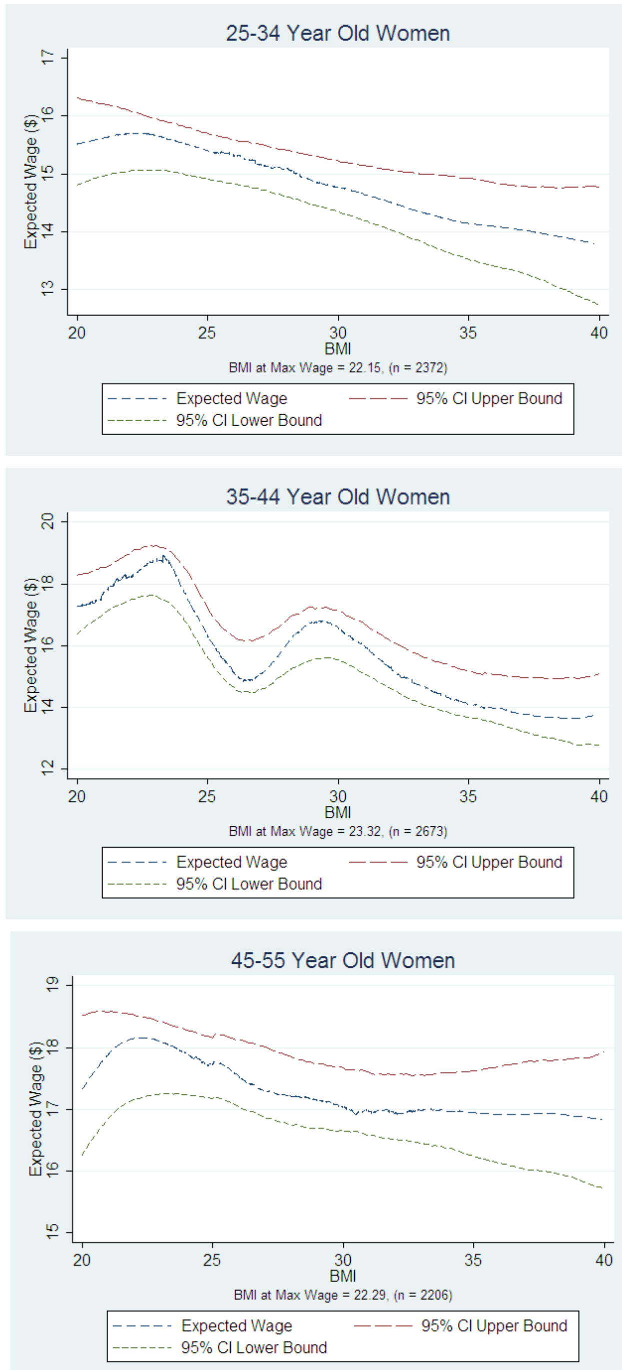


Figure 9: BMI and Expected Wages, Females by Age

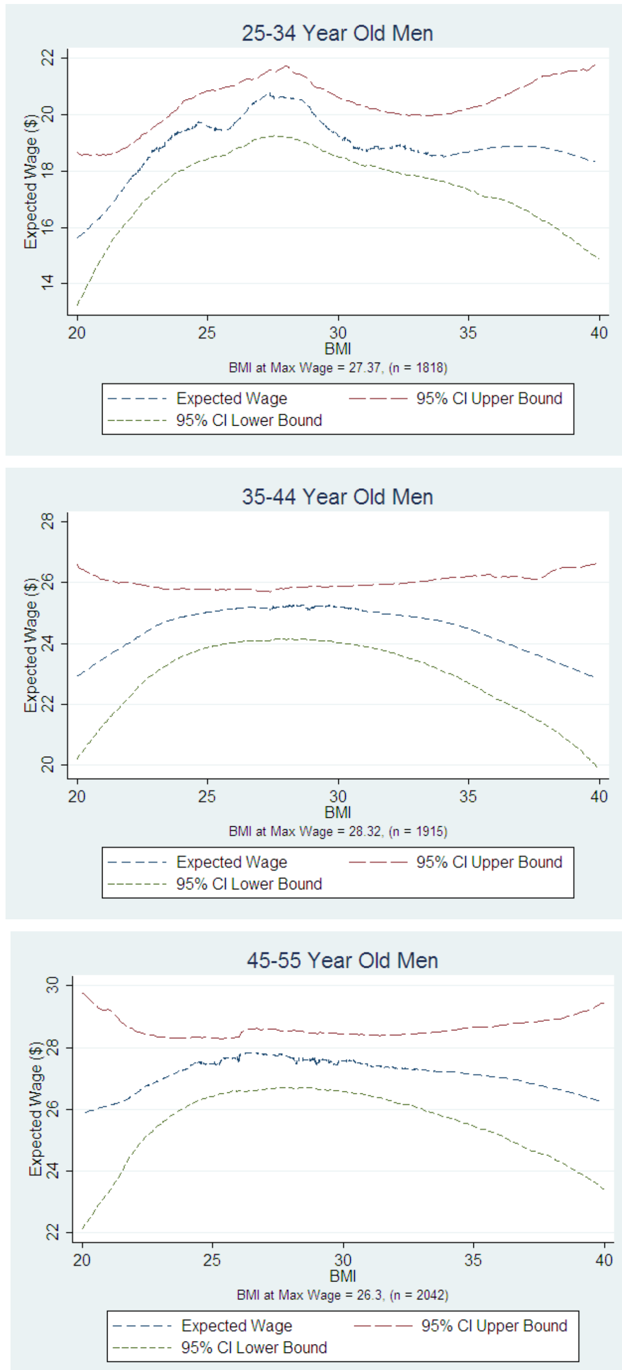


Figure 10: BMI and Expected Wages, Males by Age

Appendix: Non-parametric 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

$$\hat{r}_n(x) = \sum_{i=1}^{n} \ell_i(x) Y_i \tag{A-1}$$

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:

$$K(x) = \frac{70}{81}(1 - |x|^3)^3 I(x) \tag{A-2}$$

where

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

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

$$\ell_i(x) = \frac{K(\frac{x - x_i}{h})}{\sum_{j=1}^{n} K(\frac{x - x_i}{h})} \tag{A-3}$$

where h is the bandwidth or smoothing parameter. This kind of estimator has the advantage of allowing for highly non-linear 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 A-1, but define $\ell(x)$, X_x, and W_x as follows.

$$\ell(x) = e_1^T (X_x^T W_x X_x)^{-1} X_x^T W_x$$

$$e_1 = (1, 0, 0, ...)^T$$

$$X_x = \begin{bmatrix} 1 & x_1 - x \\ 1 & x_2 - x \\ 1 & x_3 - x \\ \vdots & \vdots \\ 1 & x_n - x \end{bmatrix}$$

[33] On this point, see Wasserman (2006), 73ff., Fan and Gijbels, pp.17-18, 60ff.

$$W_x = \begin{bmatrix} w_1(x) & 0 & \cdots & 0 \\ 0 & w_2(x) & & \vdots \\ \vdots & \cdots & \ddots & \\ 0 & \cdots & \cdots & w_n(x) \end{bmatrix}$$

$$w_i(x) = K(\frac{x - x_i}{h}) \tag{A-4}$$

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 non-linear 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 $(k * N)/2$ 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

$$CV(k) = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{r}_{(-i)}(x_i))^2 \tag{A-5}$$

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

[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 A-1: Semi-Parametric 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	7251	4047	2638	544	2369

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

Table A-2: Semi-Parametric 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	5775	3924	1262	427	2333

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