Wages, BMI, and Age

Christian A. Gregory
University of North Carolina, Greensboro

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Abstract:

Previous research generally finds that obesity negatively affects wages for women and does not affect wages for men. But this literature has for the most part focused on young workers and has not examined whether the effect of obesity might change as people age. In this essay, I examine the effect of obesity–and body mass more generally–on wages across the age distribution, using conventional parametric and more flexible semiparametric approaches. My parametric results suggest that the literature may overstate the effect of BMI and obesity on earnings for women and almost certainly understates any negative association for men. For women, my results show that the negative effects of BMI and obesity are concentrated among women between 25 and 35 years old. While women in this age group experience an average 0.5 to 0.7 percent decrease in earnings for each point increase in body mass (roughly 7.5 pounds), women over 40 will suffer at most a 0.25 percent decrease in earnings for each extra point of body mass, and may not experience any wage penalty at all. Similarly, women who are 31-35 years old experience a 7.7 percent decrease in wages for being obese, while women over 40 experience only a 3.9 percent decrease. More flexible models largely confirm these results. For men, my parametric results indicate that, for those who are in their 20's or early 30's, BMI has no effect on earnings or is associated with a small increase; this is consonant with the rest of the literature. However, for men over 35, the effect of extra body mass is clearly negative: an extra BMI point brings with it a 0.3 percent decrease in earnings for men 36-40 years old, and for men over 40, an extra BMI point is associated with a 0.5 percent decrease in wages. More flexible semiparametric models suggest that the negative association of BMI and wages may be as much as three times more than these estimates in some ranges of BMI. For instance, these models suggest that men 36-40 years old who have a BMI between 27 and 37 experience a 0.9 - 1.2 percent decrease in wages for each extra BMI point, as opposed to a .3 percent decrease predicted by the linear model.

1 Introduction

Studies of the correlation between obesity and wages for subjects in the United States have fairly consistently found that obese women earn less than non-obese women; estimates of this negative association range from 1 to 12 percent. Work in this area has also found that obese men earn only slightly less–and may earn slightly more–than their non-obese counterparts (Register and Williams, 1990; Pagan and Davila, 1997; Harper, 2000; Averett and Korenmann, 1996; Sargent and Blanchflower, 1994; Gortmaker et al., 1993; Loh, 1993; Baum and Ford, 2004; Cawley, 2004; Norton and Han, 2008). However, most of this literature examines people who were relatively young when wage data were obtained. Sargent and Blanchflower (1994), for example, use wage data from subjects who were 23 years old; Harper (2000) looks at persons who were 33 at the time of survey; Loh (1993) and Register and Williams (1990) use data on those whose mean age was just over 22 years old; Pagan and Davila (1997) use data for respondents whose average age was 28; similarly, subjects examined by Averett and Korenmann (1996) and Gortmaker et al. (1993) were 27 years old on average. Norton and Han (2008) looked at data for persons who were younger than 27 years at the time of data collection. A few recent studies have included persons over 35 years old: Baum and Ford (2004) use the National Longitudinal Survey of Youth 1979 (NLSY79) through 1998, at which point the age range was 33-41 years, and Cawley (2004) uses data from the NLSY79 through 2000, which includes persons two years older. In addition, Gregory and Ruhm (2009) examine the effect of body mass index (BMI) on wages for persons between 25 and 55 years old.[1] Although these studies do include older workers, except for the last, none has examined how the association between wages and obesity (or BMI) changes as people age. And the last study is limited by sample size in its ability to model and examine this change fully.

[1]Body Mass Index (BMI) is defined as weight in kilograms divided by height in meters squared.

There are at least four mechanisms–all unobserved–that might explain a causal relationship between obesity and wages: labor market discrimination, preferences of consumers, marginal productivity differences, and health costs. Although the strength of each of these effects can be expected to change with age, it is unclear whether the total effect of aging would be to reduce or increase the measured effect of obesity on wages. Consider the case when the cause is labor market discrimination. Empirical work by Biddle and Hamermesh (1994) has shown that it is plausible that what we observe as an obesity effect is really an effect of personal appearance–at least insofar as being obese is considered a detriment to physical attractiveness. Although we do not know if the effect of looks on wage changes with age, it seems reasonable to think that the marginal effect of body weight on attractiveness would diminish with age, as the fraction of overweight or obese persons increases.[2] If that were true, then we would expect the obesity wage penalty to decrease with age. Similarly, if the cause were preferences of consumers or the public for persons with low BMI, one might expect that social norms about BMI would be relaxed as persons aged, and thus that the penalty to having a high body mass would decrease. On the other hand, if wages are affected by diminished marginal productivity due to the co-morbidities of obesity, then we should expect the effect of obesity to increase with age, as we know that age-specific prevalence of conditions such as diabetes and dyslipidemia is significantly higher for obese persons as they get older (Finkelstein et al., 2007). Similarly, we would expect the effect of obesity to increase if, as Bhattacharya and Bundorf (2005) argue, employers are able to trade off wages for expected health costs due to obesity, which we know increase with age (Finkelstein et al., 2007).

In this essay, I examine the effect of obesity–and body mass more generally–on wages across the age distribution, using conventional parametric and more flexible semiparametric approaches. My parametric results suggest that the literature may overstate the effect of BMI

[2]Results of a robustness check reported by Gregory and Ruhm (2009) are consistent with this thesis.

and obesity on earnings for women and almost certainly understates any negative association for men. For women, my results show that the negative effects of BMI and obesity are concentrated among women between 25 and 35 years old. While women in this age group experience an average 0.5 to 0.7 percent decrease in earnings for each point increase in body mass (roughly 7.5 pounds), women over 40 will suffer at most a 0.25 percent decrease in earnings for each extra point of body mass, and may not experience any wage penalty at all. Similarly, women who are 31-35 years old experience a 7.7 percent decrease in wages for being obese, while women over 40 experience only a 3.9 percent decrease. More flexible models largely confirm these results. For men, my parametric results indicate that, for those who are in their 20's or early 30's, BMI has no effect on earnings or is associated with a small increase; this is consonant with the rest of the literature. However, for men over 35, the effect of extra body mass is clearly negative: an extra BMI point brings with it a 0.3 percent decrease in earnings for men 36-40 years old, and for men over 40, an extra BMI point is associated with a 0.5 percent decrease in wages. More flexible semiparametric models suggest that the negative association of BMI and wages may be as much as three times more than these estimates in some ranges of BMI. For instance, these models suggest that men 36-40 years old who have a BMI between 27 and 37 experience a 0.9 - 1.2 percent decrease in wages for each extra BMI point.

2 Data

The data used for this analysis come from the NLSY79. The NLSY79 is a survey that was administered yearly from 1979 to 1994 and has been given biennially after 1994; it collects data on a rich set of labor market outcomes, demographics, and, in select years, height and weight for persons born between 1957 and 1965. In 1979, the NLSY was comprised of a sample of 12,686 persons.

Because it has collected information on a wide variety of family background, demographic, and labor market variables over almost three decades, the NLSY79 has been the primary resource for research into the effect of obesity on wages for subjects in the United States.[3] The limitation of the dataset is that it is restricted to a single cohort only now reaching middle age. This makes examining the effect of age on the wage-BMI relation over this cohort's entire worklives impossible. However, the NLSY79 has sample sizes between two and three times larger than, for example, the Panel Study of Income Dynamics (PSID), at least for the age cohort that it does represent. This lends statistical power to estimates and allows for a finer examination of the age distribution than the PSID. So, while I use the NLSY79 for this study, I compare my results to those obtained by Gregory and Ruhm (2009), who used the PSID, whenever possible.

I examine hourly wages in this study to be consistent with the rest of this literature, although other outcomes (such as probability of employment and total compensation) are certainly worth study. The hourly wage information that I use is constructed in the NLSY79 through a series of questions about the time unit and rate of pay for the respondent's current or most recent job. For any respondent who reports a time unit rate of pay other than hourly, an hourly rate is constructed by the Center for Human Resources Research (CHRR). The sample includes observations for respondents who were unemployed or out of the labor force at the time of interview, but have had a job since the last interview; in these cases, the wages reported are for the most recent job since the last interview. I exclude from analysis pregnant women, persons in the military, and self-employed persons. Hourly wages are deflated to 2006 basis using the CPI. For the estimates shown here, I have changed any wage value that is less than half of the minimum wage to the maximum of the mean value of non-missing wage values for that person

[3] Gregory and Ruhm (2009) is the first study of which I am aware to use another source, the Panel Study of Income Dynamics (PSID) to study the effect of BMI on wages for U.S. subjects.

and half the minimum wage; additionally, I have changed any wage value in the top one-tenth of one percent of the wage distribution to the minimum of the mean value of observed wages for that person and the 99.9^{th} percentile value.[4]

I construct BMI from self-reported height and weight measures. There are 16 survey years in which weight data are recorded: 1981, 1982, 1985, 1986, 1988, 1989, 1990, 1992, 1993, 1994, 1996, 1998, 2000, 2002, 2004, and 2006. Height data are collected in 1981, 1982, and 1985. Since all respondents have reached the age of 20 in 1985, this is assumed to be their adult stature.

Self-reported height and weight data are known to be subject to reporting error. I have used data from the National Health and Nutrition Survey (NHANES) 1988-94, 1999-2000, 2001-2002, and 2003-2004 to correct for self-reporting bias using a procedure similar to that suggested by Lee and Sepanski (1995), Cawley (2004) and Lakdawalla and Philipson (2007), among others. This procedure takes advantage of the fact that NHANES has both measured and self-reported BMI data; using this procedure, I regress measured height (weight) on self-reported height (weight), their squares, age and its square; I use the coefficients–stratified by gender and race–to predict actual from reported height and weight in the NLSY sample. I use these corrected measures throughout this study.

An emerging strand of the literature on weight and wages has been critical of using BMI as a measure of body fat, preferring other measures such as biolectrial impedence, skinfold thickness, or waist circumference. (Johannson et al., 2009; Wada and Tekin, 2007; Burkhauser

[4]In all cases, extreme wage values appear to be due to reporting errors. I am sensitive to the argument made by Bollinger and Chandra (2005), who recommend against winsorizing procedures like these. However, whereas the values chosen to replace outliers in Bollinger and Chandra (2005) are dependent on full sample distributions, I choose replacement values here based on the person-level distributions of wages. I have also estimated all of the models shown below using data in which I trimmed only a handful of wage observations–i.e. those above $30,000 per hour. The parametric results were the same; the semiparametric estimates were only marginally affected, mostly in the sense that this trimming exacerbated the well-known characteristic of linear smoothers to overfit (undersmooth) the data.

and Cawley, 2008). While it is true that BMI is an imperfect measure of body fat, it has yet to be demonstrated that it is inferior to these other measures by some standard measure, such as densitometry. As Deurenberg et al. (1991) have noted, the correlation between body fat measured by densitometry and BMI is fairly high–between .78 and .92 for men and women respectively in the age group relevant to this study. Most importantly, almost all of the literature that looks at the relationship between body composition and earnings uses BMI, and it is the only measure available in the NLSY79.

The sample design of the NLSY79 affords considerable latitude to researchers interested in labor market outcomes, as it is comprised of three subsamples: a representative cross sectional subsample (6,185 people in 1979), supplementary subsamples (5,295 people in 1979), and a military subsample (1,206 people in 1979). The supplementary subsamples include oversamples of black, Hispanic, and economically disadvantaged white respondents.[5] There are many applications in which one would prefer to use to use the "full" sample, which includes the representative and supplementary subsamples: for example, one might use this sample to get race-specific estimates for the effect of BMI or obesity, as has been done by Cawley (2004). For this application, I show results derived from the representative sample, although the results for the parametric models are the same for the full sample.[6] I show these results here to retain consistency with the semiparametric estimates, for which the smaller sample sizes are more conducive to more computationally intensive procedures.

Roughly three percent of observations that meet sample selection criteria have valid wage values but are missing height and weight and thus BMI. One way to deal with missing values would be to set the missing value to zero and create a variable indicating that the variable is missing and set it to one, as has been done by some others.(Baum and Ruhm, 2007; Cawley,

[5]The NLSY dropped the military and economically disadvantaged white subsamples in 1985 and 1991, but has revised the sample weights to reflect the new probabilities of sampling.

[6]See Appendix A for further discussion.

2004). In this study, however, it would be inappropriate to set BMI to zero in flexible specifications. For this reason, I have discarded these observations. I show in Appendix B that whether one imputes BMI or discards these observations does not affect the results.

Aside from BMI and age, other controls in the parametric and semiparametric models include race (in OLS models), education, total labor market experience, job tenure, weekly hours, Census region, indicator for SMSA, rural residence, number of children in the household, part-time status (under 20 hours a week), indicator for school enrollment, marital status, and indicators for years of survey. Among these variables, only race and age are not chosen by the subjects of the survey. The rest of the controls represent choices that are arguably related to both body mass and wages in complicated ways. I include them here to make the results of this study comparable to most of the previous literature, which, despite their endogeneity to weight and wages, has for the most part used these controls as a way to isolate the effect of body mass on earnings.[7] Means of dependent and explanatory variables with the exception of the year dummies are shown in Table 1.

3 Empirical Specifications

As mentioned above, this study addresses the change in the effect of BMI on wages over the age distribution. The general model that I employ to model earnings as a function of BMI is

$$w_{it} = X_{it}\beta + [(G_{it})|Age] * \delta + \varepsilon_{it}, \tag{1}$$

where G is the parameterization of BMI. In parametric models, $G = BMI_{it}$ or $G = W_{it}$, where W is a vector of indicator variables for BMI category: $W_{it} = [BMI_{it} < 18.5, 18.5 \leq BMI_{it} <$

[7] A notable exception is Han et al. (2009), which estimates the indirect effect of teen BMI on education and education on occupation choice and earnings.

$25, 25 \leq BMI_{it} < 30, 30 \leq BMI_{it}]$. In all specifications, the estimates of this marginal effect are interacted with age: I use age categories 21-25, 26-30, 31-35, 36-40, and 41 and older.[8]

As is well-known, the mechanisms through which body mass might have its effect on wages are not always observed on an individual level. For example, although body mass can be thought of as an index of underlying health, there is wide variation in the actual levels of health experienced by people with high and low body mass. In addition, overweight or obese persons might have higher preferences for immediate gratification (consumption) over investment (i.e. exercise, dieting), and so might not invest as much as they might otherwise in education or training, which clearly would affect wages. Finally, it is also known that persons with higher body mass are more likely to suffer from depression independent of observed health conditions (Dong et al., 2004). These factors, among others, which are correlated with BMI but not observed will tend to bias estimates of the marginal effect of BMI on wages in an ordinary least squares (OLS) econometric framework. With this in mind, we can restate the error term in (1) as

$$\varepsilon_{it} = \mu_i(X_i, BMI_i) + \kappa_{it}(X_{it}, BMI_{it}) + \upsilon_{it}, \tag{2}$$

where μ and κ are time-invariant and time-varying unobserved factors that are correlated with observed characteristics, and υ is a random error.

Although it would be ideal to model μ as well as κ, strategies to identify both of them have been in short supply. One of the ways proposed to model endogenous factors quite generally has been to instrument for own BMI with the BMI of a sibling (Cawley, 2004), parent (Kline and Tobias, 2008), or child (Shimokawa, 2008). Whatever the strengths or weaknesses of this approach, it poses a limiting practical problem for this application. Namely, using this strategy even as a robustness check would make the size of age-specific samples too small to draw

[8]These age groups are large enough to measure effects meaningfully, but not so large as to elide differences in effects at different moments in workers' careers.

meaningful inferences.

A common strategy for isolating μ, which I employ here and has been employed by others (Baum and Ford, 2004; Shimokawa, 2008), is a fixed effects (FE) strategy. In this model, we have

$$w_{it} = X_{it}\beta + [(G_{it})|Age] * \delta + \mu_i + \upsilon_{it}, \tag{3}$$

where μ represents time invariant components of personal attributes like health, preferences for consumption, and disposition for depression, among others. There are at least two concerns about this strategy: first, and obviously, it will not capture κ; second, it asserts the there is a contemporaneous effect of BMI on wages, which is implausible.

With respect to the first objection, the literature suggests that FE and sibling IV models will yield qualitatively similar results. For example, although Cawley (2004) and Baum and Ford (2004) prefer instrumental variable (IV) and fixed effect (FE) specifications respectively, both find that women's wages are negatively affected by being obese and that men's wages are less so. It might be objected that κ may be due to reverse causality, which could operate independently of any fixed effects. The literature has addressed this by using lagged BMI as a regressor of interest in OLS (Averett and Korenmann, 1996; Cawley, 2004) or FE models (Shimokawa, 2008). These studies rarely find robust differences between estimates using contemporary and lagged values of BMI. Indeed, I have estimated all of the parametric models using a lagged BMI as the regressor of interest with no change in the results.[9] With respect to the second objection, if one views current BMI as embodying the effect of health and capital investments since the end of the previous period, then current period BMI is actually a good regressor of interest; it will be correlated with both recent health investments and current health, independent of permanent health stock captured by μ. Finally, although I'm mindful of the limitations of

[9] I used the previous survey wave observation of BMI in these models to preserve sample size in the youngest age groups.

current period BMI, I use it here in order to make these estimates comparable to the rest of the literature, which has used it most frequently as the regressor of interest.

While linear models of the marginal effect of BMI on wages will be informative about variation around the mean value of BMI, recent work (Shimokawa, 2008; Kline and Tobias, 2008; Gregory and Ruhm, 2009) has suggested that more flexible models can highlight features of expected wages over the entire BMI distribution that are missed by linear models. In order to examine whether this holds in this application, in addition to the parametric specifications, I employ semiparametric models that allow all regressors other than BMI to vary linearly with the log of wages, but allow the form of the relationship between BMI and wages to be dictated by the entire BMI distribution, rather than the mean only. Model 3 in this context becomes

$$w_{it} = X_{it}\beta + [f(BMI_{it})|Age] + \mu_i + \upsilon_{it}. \tag{4}$$

Although this method is more resource intensive, it also can offer a more accurate sense of the complexity of the conditional earnings function. For example, Gregory and Ruhm (2009) have shown that the conditional wage distribution for women in the PSID is not particularly well approximated by linear models and that it peaks at a BMI level of about 22.5. Their results are important because they suggest that what has been called an obesity effect is almost certainly not one for women, which would imply that the health effects of body weight are not the cause of decreased wages, at least not alone.

For the flexible estimates, the method I employ is similar to that described by Gregory and Ruhm (2009), Shimokawa (2008), and Yatchew (2003), among others, and is generally based on the estimator proposed by Robinson (1988). In brief, it involves an extension of univariate kernel regression, in which one estimates a weighted regression for each data point in the sample, including in each regression only the observations that fall within a chosen window width (called the bandwidth) of the data point in question. At the extremes, a conventional regression is one in which all data points are included in the window for the regression, and a model that simply interpolates the data is one that includes only one data point in the window width. One chooses the appropriate bandwidth by estimating the local linear regression over many bandwidths and choosing the one that minimizes the mean squared error of the estimate. For applications like the current one, in addition to using this smoothing regression on the variable of interest, one also estimates the effect of other variables in a linear framework. Hence, the semiparametric estimates are also called "partially linear." This method includes purging the dependent variables of the correlation with BMI by use of such a non-parametric smoothing regression and using those purged variables in a linear regression that includes everything except BMI. One uses the residuals of that regression to form the estimate of $\hat{f}(.)$. Fixed effects are established in this context through taking differences in the smoothed variables and regression residuals for each person. I describe the estimation process for the fixed-effect partially linear model (4) in more detail in Appendix C.

4 Descriptive Results

4.1 Obesity Wage Differentials

Although I intend to treat BMI more flexibly than has generally been done in the literature, it is useful to begin with a conventional treatment of body mass–particularly, obesity–as related to wages. As a simple graphical illustration of the differences in the relationship between obesity and wages across the age distribution, Figures 1 and 2 show the differences in expected log wages between obese and non-obese persons stratified by age category (21-25, 26-30, 31-35, 36-40, and over 40 years old) for women and men, respectively. The figures also show 95% confidence intervals for these differences. As mentioned above, most studies of the effect of obesity on wages have looked at only the youngest three of these age groups, but the figures both suggest changes in the effect of BMI as people get older.

The results for women, in general, show a “U-shaped” pattern of differences; while obese women earn roughly 14 percent less per hour than the non-obese in the sample when they are 21-25 years old, this unconditional difference increases to 20 percent for women 26-30 or 31-35 years old, and then decreases in magnitude to roughly 14 percent for women over 40. The 95% confidence intervals for these estimates suggest that the differences in all age groups alone are statistically different from zero. (They are different at $p < .01$ as well.) However, differences between age groups (i.e. if we compare differences in one age group to another) are not significant at conventional levels.

Certainly, we should be cautious about generalizing from these results about the effect of body mass on earnings. However, it is worth noting that the estimates are consistent with those of Baum and Ford (2004), who also found that the wage penalty for obese women increased for the NLSY79 sample until 1994, when they were between 29 and 36 years old, and then decreased in 1996 and 1998. Moreover, the average penalty for workers up to 35 years old in my estimates here (18 percent) is roughly the same as that estimated by Baum and Ford (2004) (about 21 percent). However, these figures also highlight that the decrease in the wage penalty has been sustained as women aged. This result is important because it suggests that, to the degree that our current understanding of the wage penalty is based on samples that are heavily weighted toward younger workers, it will offer an incomplete picture of the wage-BMI relationship.[10]

The results for men suggest that the wage penalty increases with age. The difference in wages for obese and non-obese men is a statistically insignificant 2 percent when they are 21-25

[10] I use Baum and Ford (2004) as a comparison because it is the only study which looks at simple mean differences between obese and non-obese persons as they change over time.

years old. However, for men 26-30 and 31-35 years old, the difference in wages increases to 9 percent and is statistically different from zero at $p < .05$. By the time men are over 35 years old, the unconditional obesity penalty is roughly 13 percent and is statistically different from zero at this level. (All of the wage differences within the age groups are also significant at $p < .01$ with the exception of the difference for those 21-25 years old.) The 95% confidence intervals plotted in the figure show that, if we compare the wage difference for men 21-25 years old with those for men 36-40 and over 40 years old, these difference-in-differences are significant at $p < .05$. If we were to plot 90% confidence intervals, we would see that, in addition, the wage difference for men 31-35 years old is significantly different from that for men 21-25 years old.

This result suggests that the penalty to being obese increases for men as they get older. These results are stronger in terms of magnitude and significance than those for women. They show that the obesity penalty is more than 50 percent greater for men over 40 than for men in their late 20's, and differences between those in their early 20's and men over 35 are statistically significant. While these results for those up to their early 30's are larger than more fully specified regression estimates in the literature–which find little or no penalty for extra body mass–they suggest that for older men being obese may indeed be a detriment to wages.

4.2 BMI-Wage Relationships by Age

As mentioned above, recent work has shown that treating body mass in a more flexible manner can improve our understanding of the relationship between body mass and earnings. To augment the intuition offered by Figures 1 and 2, I have also produced univariate non-parametric estimates of log wages as a function of BMI for each age group in Figures 3 and 4.[11] The figures also use vertical lines to show the first and third quartile of BMI observations. I include these

[11] The figures show the predicted values for the middle 95% of BMI values in the sample.

for two reasons. First, they give us a easy way to gauge how BMI–as opposed to obesity–affects earnings on average in these samples. Second, they give us a sense of how changes in the distribution of body mass as people age may alter its effect on earnings.[12]

There are a few characteristics of the panels of Figure 3 worth highlighting. First, it is not obvious from casual inspection that the marginal effect of BMI decreases all that much as women get older, as is suggested by the results in Figure 1. For example, if we compare persons with BMIs of 20 and 30 in the 31-35 and 41 and over age groups, the respective differences in expected log wages are roughly -.16 and -.15. But, second, as is shown by the lines marking the first and third quartiles of the distribution, the middle of the distribution has grown wider and shifted decidedly right for women over 41 years old. The result is that the difference between women in the right tail of the distribution and those more or less in the center has decreased as women on the whole have gotten heavier and as extreme values of BMI have become more common. Although this rightward shift in the distribution of weight for women has been highlighted before (Ruhm, 2007), it has not been remarked in examinations of the effect of BMI or obesity on wages. Finally, the negative effect of BMI on wages for women is not an obesity effect. For all age cohorts, the peak of the earnings function is nowhere close to a BMI of 30; rather it lies around a BMI of 22. Although these are unconditional regressions, they nonetheless suggest that we should proceed with caution when using or interpreting models that assume that the wage penalty is only experienced by the obese.

As for the men's results, shown in Figure 4, it is not obvious that the effect of BMI on wages is increasing as men get beyond 35 years old. If we just examine the portion of the earnings curve that slopes downward (i.e. past the peak) in each of the panels, there is not much change in that part of the wage distribution. In fact, for men 36-40 the downward sloping

[12]For these estimates, I use the k nearest neighbors in a centered interval around each observation, where $k = (2 * (N)^{-1/5} + .05) * N$.

portion of the distribution appears flatter than for men 31-35 years old. However, the first and third quartiles also move rightward over the age distribution, such that the peak of the earnings curve is more or less in the middle of the interquartile range for men under 35, but for men over 35 the interquartile range captures more of the downward sloping portion of the distribution–to the right of the earnings peak. To get a clearer sense of this, one can imagine a straight line drawn through the first and third quartile values of predicted wages: as men get older, the slope of this line gets more negative. For men 31-35, 36-40, and 41 and up, the marginal effect of an extra BMI point is to reduce wages by about .8 percent, 1 percent, and 1.8 percent, respectively.

Both of these estimates confirm the intuition conveyed by Figures 1 and 2, and our sense that our current understanding of the effect of body mass on earnings may be incomplete. For women, the effect of BMI diminishes as they they grow older. For men, the effect of BMI increases as they get older. These figures also point to different age-related changes in the distribution of BMI that subtend these results. For women, the effect of BMI diminishes not simply because everyone is getting heavier, but also because as they get older, the distribution is more right-skewed. Extreme values become more prevalent and less penalized, relatively speaking. For men, on the other hand, the change in the effect of body mass on earnings is largely due to the shift to the right in the BMI distribution. In addition, the univariate nonparametric models for men indicate that we should use caution in using or interpreting linear specifications of wages.

5 Main Regression Results

5.1 Women

The top panel of Table 2 shows the results of specifications of (1) and (3) for women.[13] This table shows the results from OLS and FE models using obesity indicators (with normal weight being the reference group) interacted with age dummy variables in the left panel. In the right panel are OLS and FE models using current period BMI interacted with age dummy variables as the variables of interest.[14]

The marginal effects of both obesity (shown in the left panel) and BMI (shown in the right panel) in both OLS and FE models have a similar pattern over the age distribution. The effect of body weight increases as women get into their early 30's and declines thereafter.[15] The magnitudes of the effects are larger in the OLS than the FE models, as might be expected from a specification in which unobserved personal characteristics play a part in measuring the effect of body mass on wages.[16] Moreover, it is interesting to note that although the literature in general has found negative effects of obesity and BMI on earnings for women, Norton and Han (2008) found no measurable effect of lagged BMI on earnings when they used an instrumental variables approach on a sample of women who were between 21-26 years old. The results shown in Table 2 for women 21-25 using both obesity indicators and linear specifications of BMI are consistent with that result.

[13] All of these results are for partially interacted models–that is, models that interact age only with BMI, rather than with all variables in the model. I focus on these methods because estimation of fully interacted semiparametric models is impractical in a semiparametric context. Parametric results from fully interacted models yield qualitatively similar results.

[14] I have also estimated a FE model using a one-period lag of BMI (and age interactions with it) as the primary regressor of interest. The results of these models are essentially identical to the FE models shown here.

[15] This result is similar to that of Gregory and Ruhm (2009), who found that women 35-45 showed the greatest negative effects of BMI on earnings, while those older and younger showed less effects.

[16] A Hausman test indicates that the unobserved time-invariant factors are correlated with the $X's$ and rejects a random effects specification for a fixed effects specification at $p < .001$.

The results from these specifications suggest that women in their early 30's can expect to see their wages drop by about 0.5 percent for each extra BMI point (again, about 7.5 pounds for most people), and that obese women this age can expect to earn 7.7 percent less than their normal weight counterparts at this age. Women who are over 40 would see at most only about a 0.25 percent drop for this same increase in body mass and they may see none at all. Similarly, obese women over 40 would see their wages drop by only about 3.9 percent. Moreover, all of these estimates–those using BMI and those using obesity indicators–suggest that the difference in the effect of BMI on those who are 31-35 and those over 40 is signficantly different at $p <.10$.

Once again, this result implies an important revision of our understanding of the effect of body mass on earnings for women. For the most part, researchers have assumed that BMI and obesity negatively affect wages for women in a uniform way. But these results suggest not only that the effect of BMI and obesity may diminish as women age, but that as they reach their 40's there may be no penalty to additional body mass at all.

5.2 Men

The results for the linear models for men are shown in the bottom panel of Table 2. All of the estimates suggest that as men get older the marginal effect of extra body mass goes from being near zero or slightly positive for those under 35 to being strong and negative for those over 40. For example, according to the results of FE models, for men who are 26-30 and 31-35, the effect of obesity on earnings is relatively small and statistically insignificant: point estimates suggest that being obese increases wages by about 1.6 percent for men 26-30, while it decreases wages by about 0.7 percent for men 31-35. However, obese men 36-40 years old see a reduction in wages by 4.9 percent; obese men at least 40 years old experience a decrease in earnings of about 5.7 percent. These estimates are both significant at $p < .05$.

Similarly, the models using BMI suggest increasing negative effects of BMI as men age. In

FE models, the effect of an extra BMI point is positive for men 21-25 and 26-30, but for men over age 40, the effect of extra body mass is to reduce wages by about 0.5 percent per BMI point. (This last effect is statistically significant at $p < .05$.) OLS models using both BMI and obesity show similar patterns of effects, with significant effects emerging for men as they reach their 40's.[17]

Although these patterns in estimated effects are consistent across models, it's important to know whether any of these age group predictions are statistically different from one another. Tests show that in the FE model all the estimates of the effect of obesity for men over 25 years of age are different from the effect for 21-25 year olds at $p < .01$. Marginal effects for men 26-30 and 31-35 are different from those for men over 40 at $p < .01$ and $p < .05$, respectively. In addition, estimates for these age groups are different from those for 36-40 year olds at $p < .01$ and $p < .05$, respectively, as well. In general, all of these FE results suggest that the process determining the effect of sobesity on earnings changes significantly as men age.

One could say much the same thing about the OLS and FE models using BMI. The estimates of the effects of BMI for age groups over 25 are statistically different from estimates for those 21-25 at $p < .01$. Moreover, the estimates for those 26-30 and 31-35 are statistically different from the estimates for those over 40 years of age. In the FE model, the point estimates for those 26-30 and 31-35 are significantly different than predictions for those over 40 at $p < .01$. In the OLS models, these point estimates are different from those for men over 40 at $p < .05$ and $p < .10$, respectively. In addition, in the FE model, the estimated marginal change in earnings for a point change in BMI for men 26-30 and 31-35 is different from the estimated change for men 36-40 at $p < .01$ and $p < .05$, respectively.

Taken as a whole, these results strongly suggest that the previous literature understates

[17] Hausman tests confirm both the correlation of the unobserved time-invariant factors with the $X's$ and the appropriateness of the fixed effect rather than random effect specification. These tests were significant at $p < .001$.

the effect of BMI or obesity on men's wages by dint of the fact that it has not, in general, examined older workers. My results indicate that, while men in their late 20s to late 30s may not experience any detriment to wages for extra body mass, men over 40 experience a significant 0.5 percent decline in wages for each extra point of BMI. Similarly, men under 35 may experience little or no decrease in wages for being obese, but men 35-40 experience a 4.9 percent decline in wages for being obese, and men over 40 experience a 5.6 percent decrease in wages for being obese. These estimates also indicate that differences between age group estimates are also statistically significant.

6 Semiparametric Results

As mentioned above, there are good *a priori* and empirical reasons to suspect that linear models might not be ideal for modeling wages as a function of body mass. In general, models linear in BMI will only give an average effect, which could miss important aspects of the wage-BMI distribution, especially if low and high BMI are indicative of poor health and thus cause lower wages. Piecewise linear models (i.e. those that use weight category dummy variables) may be better, but are still only as good as the cutpoints they assume. Recent empirical work (especially Gregory and Ruhm (2009)) and the unconditional estimates shown in Figures 3 and 4 suggest that linear or conventional non-linear indicator models might not perform well in this application, especially for men.

Figures 5 and 6 show results from model 4 for women and men, respectively. I plot this specification along with model 3, as well as with a model that also includes a quadratic in BMI as well as age interactions with quadratic terms. I include the quadratic to compare the partial linear models with a much more easily estimable, but also more flexible estimate with respect to BMI. The graphs also show vertical lines at the first and third quartile values, as in Figures

3 and 4.

I use the bootstrapped semiparametric estimates of $\hat{f}(BMI_{it})$ to simulate the effect of BMI on conditional earnings over narrow ranges of BMI. For women, I use the ranges 18-20, 20-25, 25-30, 30-35, and 35-40. For men, since the BMI distribution is more compact than for women and since the peak of the conditional wage function is at or near a BMI of 27, I have used ranges 19-22, 22-27, 27-32, 32-37, and 37-40. The results of these simulations for women and men are shown in the top and bottom panels of Table 3, respectively.

6.1 Women

Visual inspection of the panels in Figure 5 suggests that, especially for women over 30, the parametric linear and/or quadratic models do well at approximating the distribution of conditional earnings. Whatever non-linearities there were in unconditional wages for women (as shown in Figure 3) are largely accounted for by other controls.[18] Only estimates for the youngest two age cohorts differ markedly from the linear and quadratic models. For women 21-25 years old, however, the estimated marginal effect of BMI on wages is significant only in the BMI range from 25-30. For women 26-30, the marginal effects shown in Table 3 are between the OLS and FE estimates from Table 2. They indicate that women in this group see a decrease in wages of about 0.5 percent for each extra point of body mass. Women who would have a BMI greater than 35 at this age (who are "obese 2" by NIH standards) see a decrease in wages of about .075 percent for a similar increase in body mass. [19]

In general, the estimates of the marginal effect of BMI on earnings lie somewhere in between

[18]This is consistent with results shown by Gregory and Ruhm (2009), who found that, in a comparison of conditonal earnings for restricted samples in the NLSY and PSID, conditional wages were closer to being linear for women in the NLSY than the PSID.

[19]This latter result, in particular, seems driven by values of wages in the right tail of the BMI distribution. Roughly 5 percent of this sample has a BMI greater than 35; however, the marginal effect in this tail of the distribution is not statistical noise, as is suggested by the significance level of the estimate.

the OLS and FE models shown in Table 2, but, as can be seen in the Figure 5 they do not differ markedly from the parametric linear or quadratic models. The results for women over 40 show an odd convexity in both the partial linear and quadratic FE models; the effect measured by the linear model in this sense is a weighted average of a strong negative effect for women in the 20-25 BMI range (-.012), negligible effects in the range from 25-30 and 30-35 (-.0045 and -.0024, respectively), and a small positive effect for women with a BMI over 35 (.0055). This odd functional shape notwithstanding, this estimate, compared to the others, reaffirms the conclusion that we draw from the above estimates. As women age, the penalty to increased body mass or obesity tends to increase until women reach their early to mid 30s and then decreases and may abate altogether for women over 40.

6.2 Men

There are two features of the estimates for men, shown in Figure 6, that are particularly interesting. First, these results strongly suggest that models of wages that use linear or even quadratic models miss a lot of the variation over the BMI distribution.[20] In each of the panels in the figure, the linear and the quadratic models do a good job of capturing what is happening in the middle of the BMI distribution, as can be seen by comparing the linear and/or quadratic with the semiparametric estimates in the region bounded by the first and third quartiles. However, the linear and quadratic models do less well at capturing the distribution in the bottom and top quartiles. For example, the simulated results for men 21-25 years old suggest that the marginal effect of BMI is large and positive for men in the body mass ranges from 19-22 and 22-27. The point estimates of these effects are .046 and .011, respectively, and both are significant at $p < .01$. The latter is similar to the marginal effect measured in the linear model,

[20]This result is consistent with results shown by Gregory and Ruhm (2009), whose comparison of semiparametric regressions on restricted NLSY and PSID samples indicated a high degree of concavity in the NLSY79 men's sample results.

for which the point estimate (standard error) is .0101 (.0026). For men in body mass ranges 27-32, 32-37, and 37-40, however, the measured effects of BMI are -.0003, -.0136, and -.0167; the estimates for the last two BMI ranges are significant at $p < .01$.

Similar patterns emerge in all of the age cohorts. Below a BMI of about 27, there are positive effects of additional BMI, but above that BMI level there are large and significant penalties for additional body mass. For example, for men in the 31-35 year old age group, the estimate of the marginal effects of extra BMI for those in the BMI ranges of 19-22 and 22-27 are .0525 and .0310, respectively. However, for men whose BMI is above 27, these marginal effects of extra BMI are estimated to be -.0113, -.0041, and -.0047 for those in the BMI ranges 27-32, 32-37, and 37-40, respectively.

Second, the BMI level at which earnings peak declines with age. The BMI levels at which wages are at their maximum for those aged 21-25, 26-30, 31-35, and 36-40 are 29.3, 28.1, 27.3, and 26.0, respectively. (For men over 40 years old, the peak of conditional earnings is at a BMI of 26.7.) At the same time, as the plotted interquartile ranges suggest, the "middle" of the distribution is trending rightward as men get older. Thus, the stronger negative effect of BMI on wages as measured by the linear model is not so much due to the penalty BMI increasing *per se*. Rather, as men get older, more of them are in the part of the earnings distribution in which wages are penalized at all, partly because they are getting heavier and partly because the peak of the earnings distribution is shifting to the left.

These estimates suggest that the literature has understated the wage penalty for men in two ways. First, it has not examined older workers. Second, it has relied on linear specifications that may not capture the magnitude of the wage penalty, but only give an average effect (in the linear case) or a mis-specified estimate (in the piecewise linear case). According to my estimates, wages are increasing for men with BMIs lower than about 27 and decreasing above that; as men age and have higher BMIs, the negative effects predominate. The linear FE model suggests that men who are over 40 receive about 0.5 percent less in earnings for every extra BMI point. The partial linear FE model, however, suggests that for the 75 percent of men whose BMI is over 27 at this age, the effect of BMI will be to decrease wages between 0.75 and about 1.0 percent. Similarly, the partial linear model suggests that the effect of additional BMI for men 36-40 with a BMI above 27 will be between a 1 and 1.2 percent decrease, three times that predicted by the linear model.

7 Discussion

The literature on the effect of BMI or obesity on wages has for the most part found significant effects of body mass for women and none for men. However, most of these studies do not include older workers–those over 35 years old–and most do not examine how the effect of BMI or obesity might change with age. This study addresses this gap in the literature. In general, the findings presented here suggest that the wage penalty to body mass for women peaks when women are relatively young and diminishes after that, and that the penalty for young men is small or negligible, but large and signficant as they get beyond 40 years old.

For women, unconditional measures, linear OLS and FE regressions, as well as partial linear FE regressions point strongly to the same conclusion. As women get older, the negative effect of having extra body mass diminishes and may disappear completely. Moreover, the negative association of BMI with wages is not an obesity effect: the negative effects of extra body weight are present at all levels of BMI. Unconditional nonparametric regressions suggest that this effect is accompanied by two dynamics in the distribution of BMI: first, women are getting heavier as they get older, and, independent of that, more extreme BMI is becoming more prevalent, and less penalized.

Of the unobserved mechanisms that might drive the negative effect of BMI on wages, two imply increasing penalties as women get older: decreasing marginal productivity and health care costs. My results suggest that these are likely not alone in driving the negative effects of BMI and/or obesity on earnings. The effects on earnings for women over 40 are less than the effects for younger women. If the health costs or marginal productivity stories were correct, we should expect to see increasing–or, at least, non-decreasing–effects as women get older. On the other hand, if the causes were appearance or consumer preferences for thinner workers, then we would expect to see what my results show, a declining effect as women age.

For men, the estimates presented here suggest a very dynamic process underlying the relationship between wage and BMI. Unconditional means and linear OLS and FE estimates point to the fact that, while extra BMI may have a positive or no effect for younger men, the effect of BMI or obesity on earnings for men over 40 is unequivocally negative, large, and significant. While much of the literature has found no effect of BMI on earnings for men, these results find that each extra BMI point implies a decrease in wages of about 0.5 percent for men over 40; similarly, I show that obese men over 40 earn 5.6 percent less than their normal weight counterparts, and that similar penalties are found for those in their late 30's.

My results for men also indicate that our current understanding of the effect of BMI on wages for men is almost certainly limited by linear models used heretofore in the literature. All of the results for men suggest highly non-linear conditional earnings, with positive marginal effects of BMI measured at BMI levels less than 27, and strong and negative effects for those with BMIs above 27. For the youngest men, positive effects predominate; as men age and get heavier, the negative effects become increasingly important. Simulations using semiparametric estimates of conditional wages suggest that the true effect of BMI on earnings for men with BMIs above 27 may be almost three times as large as those estimated by linear models.

The results for men offer mixed evidence on the causes of the effect of body weight. On one hand, it appears that the health effects of body mass may be the cause of the wage penalty. Not only do wages begin to decline at a BMI level near the obesity cutoff, but the negative effect grows stronger as men age. However, the semiparametric estimates suggest negative effects at high levels of BMI in all age groups, which could suggest that something other than health effects–like consumer preferences or appearance–play a role for young men.

The men's results also bear on the aforementioned strand of the literature that highlights the deficiencies of BMI as a measure of body adiposity (Burkhauser and Cawley, 2008; Wada and Tekin, 2007; Johannson et al., 2009). It is well understood that BMI does not distinguish between body fat and muscle mass, a fact that is a particular problem for understanding the effect of body fat on wages for men. Whereas we normally presume that a high BMI is evidence of high body fat, which is assumed to be detrimental to health and appearance and thus wages, men–particularly young men–who have high BMIs may be very athletic and healthy, and thus be expected to have higher–or certainly not lower–wages than their normal weight peers. But we also might expect BMI to do a better job of measuring body fat as men get older, at least if we assume that men are less physically active as they age. In this case, BMI ought to better reflect body fat as men age, and the measured effect of BMI on earnings ought to better reflect the penalty to body-fatness as they age. The results shown here could suggest that there is a penalty to body-fatness for men at all ages, but BMI is not really measuring it until men reach their 40's. This would also partly explain the large positive effect of obesity and BMI on earnings for young men: men 21-25 years old who are obese have 11 percent higher wages than normal weight men of the same age; men in this age group also show an increase in wages of about one percent for each BMI point. These could reflect returns to health or appearance.

These results suggest several avenues for future research. First, more research is needed into the joint relationships between earnings, health expenditures, and BMI. Recent research by Bhattacharya and Bundorf (2005) suggests that the incidence of health costs explain much of the effect of BMI or obesity on earnings. These estimates suggest something quite different. Future research might seek to use data such as MEPS that contains information on earnings as well as health insurance, health expenditure, and health status to model these relationships. Second, these results for men suggest that one of the reasons for the increased negative association of BMI with wages for men is the better job that BMI is doing at measuring body-fatness as men age. Although it would be useful to have better measurements of body-fatness in social science data sets, as suggested by Burkhauser and Cawley (2008), it would also be good to understand in what ways various measures fail, relative to some gold standard of measurement, such as denistometry. Both these lines of research would enhance our understanding of the effects of BMI or obesity on earnings, as well as other outcomes of interest to health and labor economists.

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8 Tables and Figures

Sample Means				
	Women		Men	
Variable	Mean	Std. Dev.	Mean	Std. Dev
Log Wage	2.529	0.566	2.795	0.592
BMI	25.708	5.687	26.646	4.345
Northeast Region	0.185	0.388	0.188	0.390
Midwest Region	0.271	0.445	0.303	0.459
West Region	0.162	0.369	0.169	0.375
SMSA	0.783	0.412	0.778	0.416
Married	0.564	0.496	0.546	0.498
Divorced/Sep.	0.179	0.383	0.127	0.333
Rural Residence	0.234	0.423	0.230	0.421
Number of Children	1.109	1.155	0.883	1.158
Hours Worked/Wk.	36.86	11.24	43.63	10.48
Job Tenure	225.80	256.36	255.89	280.75
Enrolled in School	0.072	0.258	0.055	0.228
Working Part Time	0.087	0.282	0.035	0.184
Highest Grade Completed	13.465	2.304	13.301	2.473
Total Labor Mkt. Experience (Wks.)	506.14	265.41	560.40	270.78
Age: 21-25	0.183	0.386	0.176	0.380
Age: 26-30	0.230	0.421	0.238	0.426
Age: 31-35	0.219	0.413	0.226	0.418
Age: 36-40	0.176	0.381	0.170	0.376
Age: 41 & Up	0.192	0.394	0.189	0.392
BMI @ Age 21-25	23.274	4.233	24.519	3.586
BMI @ Age 26-30	24.596	5.155	25.746	3.884
BMI @ Age 31-35	25.897	5.654	26.781	4.138
BMI @ Age 36-40	27.085	5.994	27.792	4.448
BMI @ Age 41& Up	27.865	6.047	28.560	4.523
N	28,128		29,129	

Table 1: Weighted Sample Means in NLSY

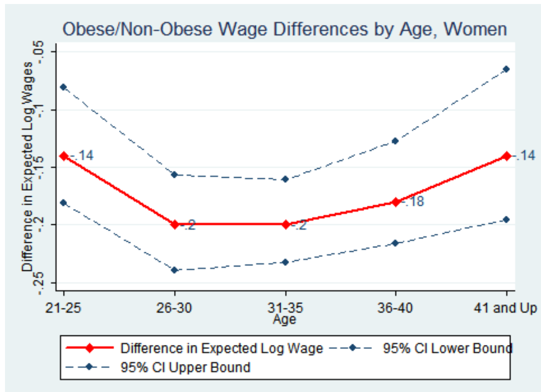

Figure 1: Differences in Expected Log Wages: Women in NLSY79

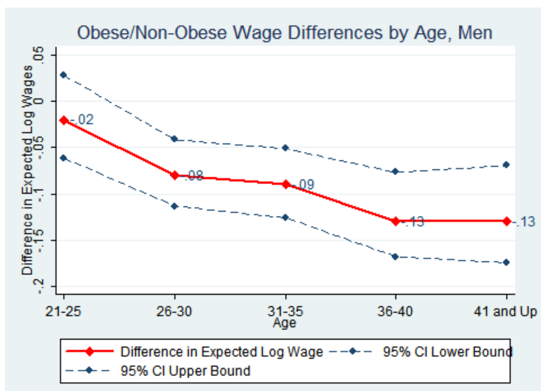

Figure 2: Differences in Expected Log Wages: Men in NLSY79

Table 2: Marginal Effect of BMI/Obesity on Wages at Different Ages[1]

Age Group Interaction	Models Using Obesity		Models Using BMI	
	OLS	FE	OLS	FE
	Women			
Age 21-25	-0.0663	-0.0232	-0.0065	-0.0007
	(0.0212)	(0.0242)	(0.0013)	(0.0018)
Age 26-30	-0.0872	-0.0393 ∘	-0.0071	-0.0021∘
	(0.0156)	(0.0173)	(0.0010)	(0.0014)
Age 31-35	-0.1175⋆†	-0.0768⋆†	-0.0078†	-0.0052†
	(0.0148)	(0.0160)	(0.0010)	(0.0013)
Age 36-40	-0.0788	-0.0456	-0.0062	-0.0036
	(0.0180)	(0.0173)	(0.0012)	(0.0013)
Age 41 & Up	-0.0696	-0.0394	-0.0047	-0.0024
	(0.0228)	(0.0218)	(0.0015)	(0.0015)
N	28,128			
	Men			
Age 21-25	-0.0146	0.1132	0.0025	0.0096
	(0.0194)	(0.0222)	(0.0015)	(0.0022)
Age 26-30	-0.0467	0.0159***⋆⋆⋆‡‡	-0.0027***‡	0.0023***•⋆⋆⋆‡‡
	(0.0161)	(0.0167)	(0.0014)	(0.0018)
Age 31-35	-0.0377	-0.0069***⋆⋆ ‡	-0.0032***†	-0.0002***‡‡⋆⋆
	(0.0158)	(0.0158)	(0.0014)	(0.0017)
Age 36-40	-0.0684	-0.0494***	-0.0056***	-0.0033***
	(0.0205)	(0.0187)	(0.0018)	(0.0018)
Age 41 & Up	-0.0646	-0.0566***	-0.0077***	-0.0051***
	(0.0268)	(0.0235)	(0.0020)	(0.0020)
N	29,129			

[1] Table shows the marginal effect of obesity (relative to normal weight) and BMI on log hourly earnings for women and men in the NLSY sample. Independent variables include race (in OLS models), education, total labor market experience, job tenure, hours worked per week, Census region, SMSA indicator, rural indicator, number of children, part-time indicator, school enrollment indicator, marital status, and year indicators. All models use Huber-White sandwich estimates of standard errors. Standard errors in parenthesis. † Different from Age 41 & Up at p<.10. ‡ Different from Age 41 & Up at p< .05. ‡‡ Different from Age 41& Up at p< .01. ⋆ Different from Age 36-40 at p< .10.⋆⋆ Different from Age 36-40 at p< .05 ⋆⋆⋆ Different from Age 36-40 at $p < .01$ • Different from Age 31-35 at p< .10 ∘ Different from Age 31-35 at p< .01.***Different from Age 21-25 at p< .01.

Table 3: Simulated Marginal Effect of BMI on Wages[1]

	Women				
	BMI Range				
	18-20	20-25	25-30	30-35	35-40
Age 21-25	-0.0007	-0.0012	-0.0025*	-0.0009	-0.0006
	(0.0063)	(0.0014)	(0.0010)	(0.0021)	(0.0016)
Age 26-30	0.0118	-0.0048**	-0.0043**	-0.0050**	-0.0075**
	(0.0088)	(0.0017)	(0.0011)	(0.0014)	(0.0023)
Age 31-35	0.0174	-0.0074**	-0.0051**	-0.0048**	-0.0018
	(0.0083)	(0.0023)	(0.0013)	(0.0009)	(0.0016)
Age 36-40	0.0002	-0.0037	-0.0052**	-0.0052**	-0.0039**
	(0.0063)	(0.0022)	(0.0008)	(0.0009)	(0.0013)
Age 41 & Up	0.0025	-0.0118**	-0.0045	-0.0024	0.0055**
	(0.0082)	(0.0035)	(0.0014)	(0.0012)	(0.0017)
	Men				
	BMI Range				
	19-22	22-27	27-32	32-37	37-40
Age 21-25	0.0460***	0.0110***	-0.0003	-0.0136***	-0.0167***
	(0.0054)	(0.0014)	(0.0014)	(0.0029)	(0.0030)
Age 26-30	0.0179**	0.0113***	-0.0073***	-0.0277***	-0.0326***
	(0.0088)	(0.0022)	(0.0019)	(0.0027)	(0.0046)
Age 31-35	0.0525***	0.0310***	-0.0113***	-0.0041***	-0.0047
	(0.0072)	(0.0022)	(0.0018)	(0.0025)	(0.0051)
Age 36-40	0.0116***	0.0171***	-0.0120***	-0.0097***	-0.0124
	(0.0075)	(0.0027)	(0.0016)	(0.0022)	(0.0059)
Age 41 & Up	-0.0017	0.0254***	-0.0073***	-0.0098***	0.0077
	(0.0196)	(0.0037)	(0.0019)	(0.0022)	(0.0039)

[1] Table shows marginal effect of BMI for specified BMI ranges for different age groups. Point estimates derived from semiparametric FE models. Independent variables include education, total labor market experience, job tenure, hours worked per week, Census region, SMSA indicator, rural indicator, number of children, part-time indicator, school enrollment indicator, marital status, and year indicators. Standard errors derived from 500 bootstrap replications; significance levels calculated using the percentile approach.

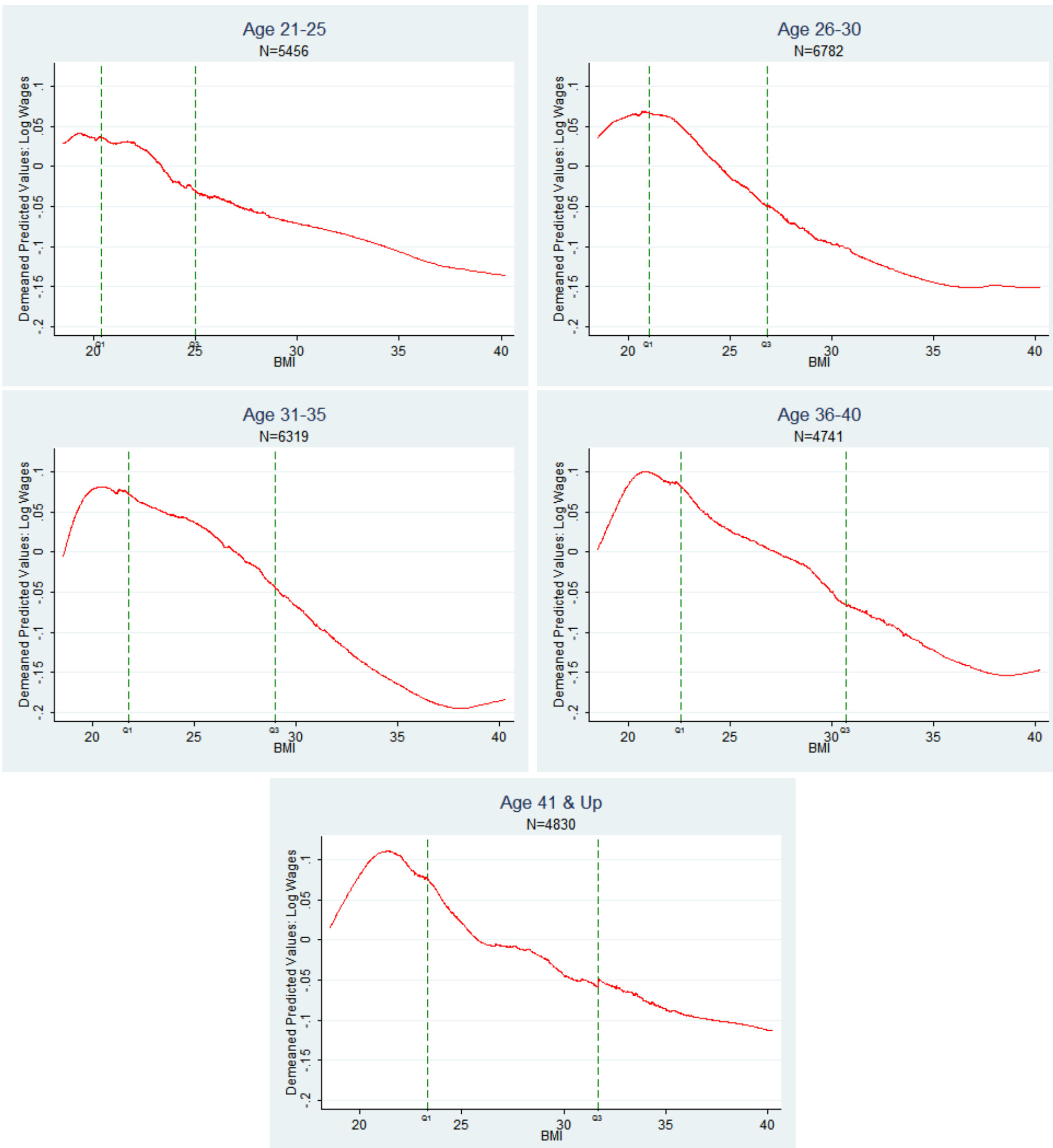

Figure 3: Univariate Local Linear Smoothing Estimates, Women 21-25, 26-30, 31-35, 36-40, 41 and Older

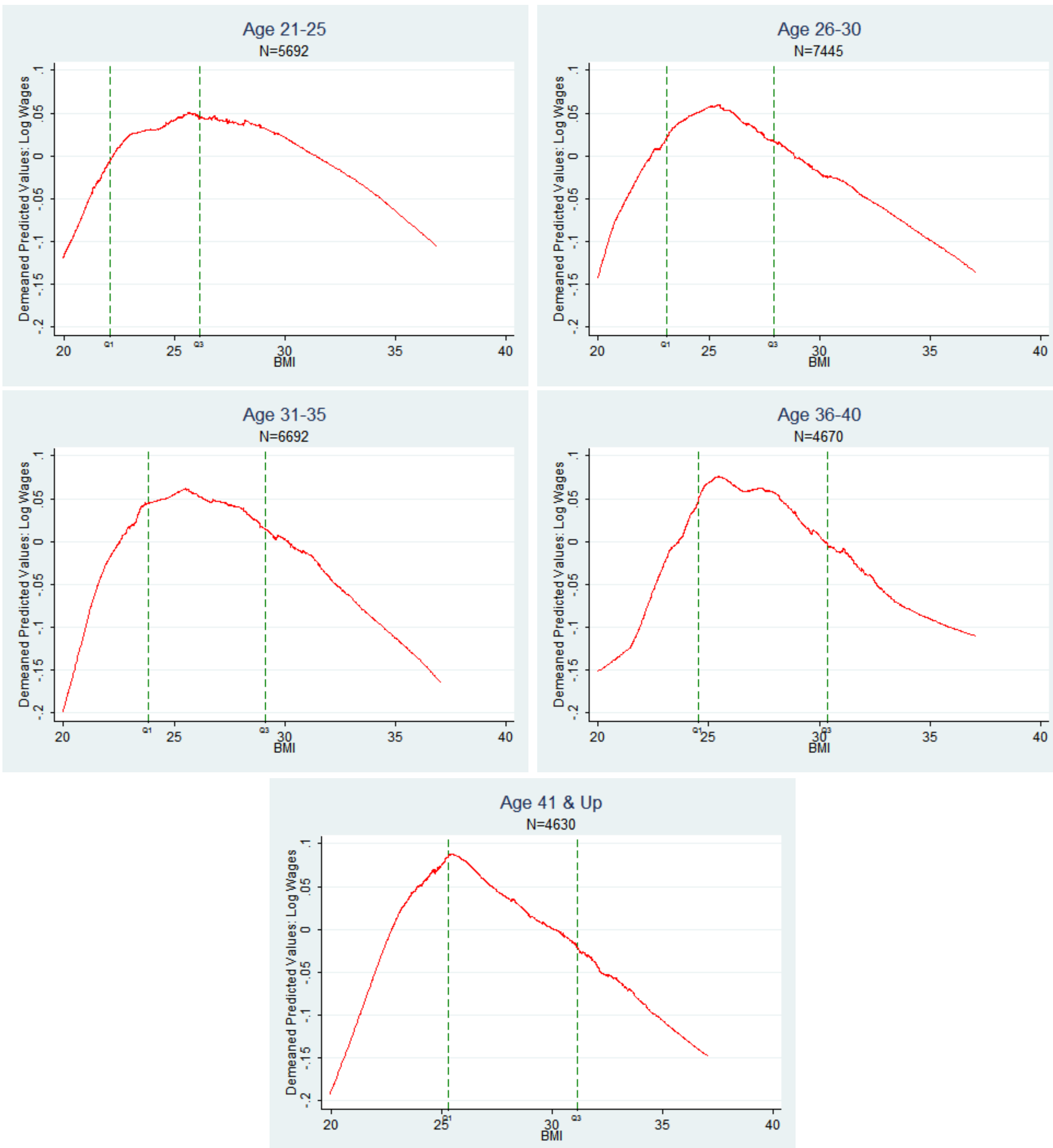

Figure 4: Univariate Local Linear Smoothing Estimates, Men 21-25, 26-30, 31-35, 36-40, 41 and Older

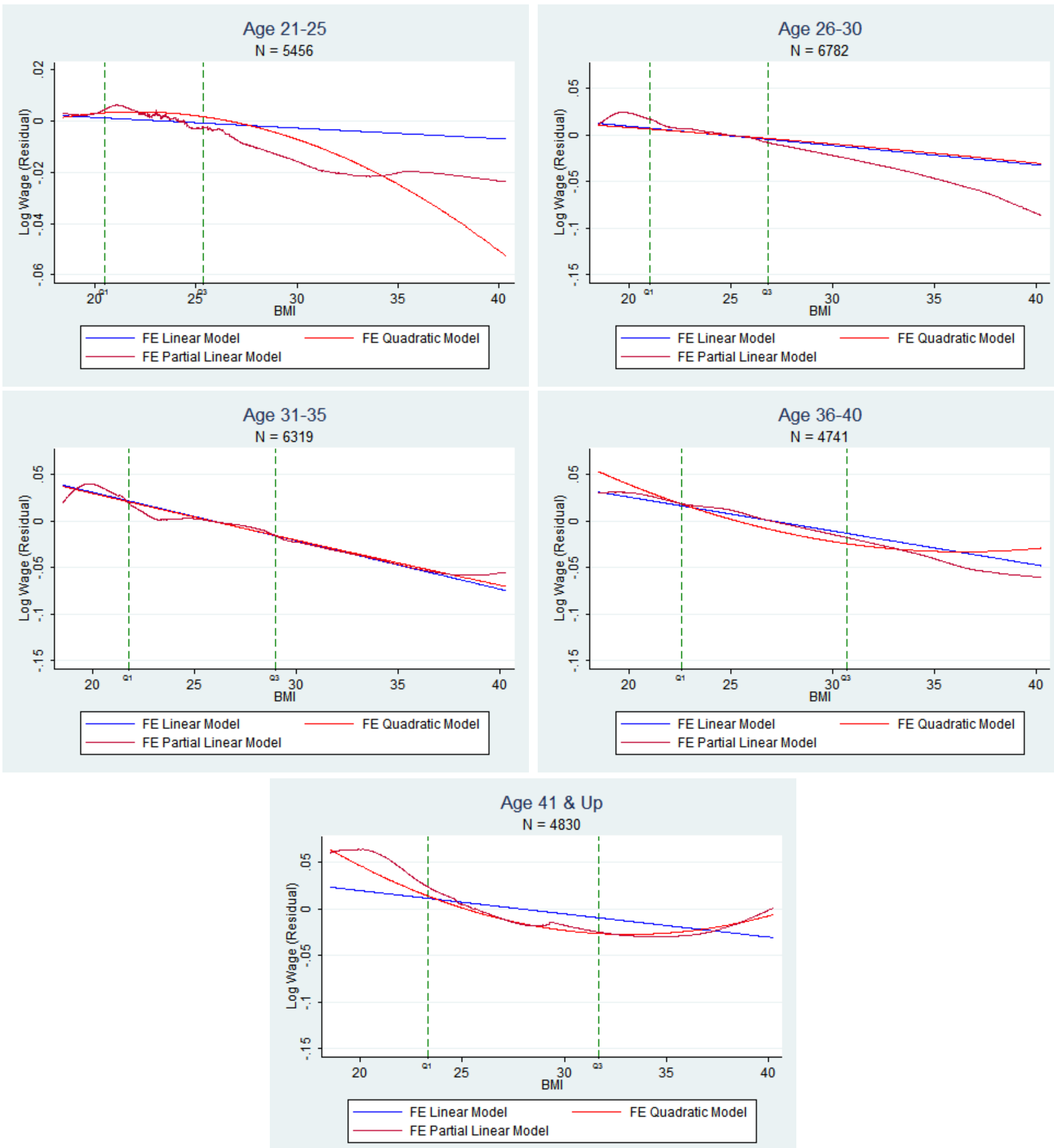

Figure 5: Three Models of Wages, Women 21-25, 26-30, 31-35, 36-40, 41 and Older

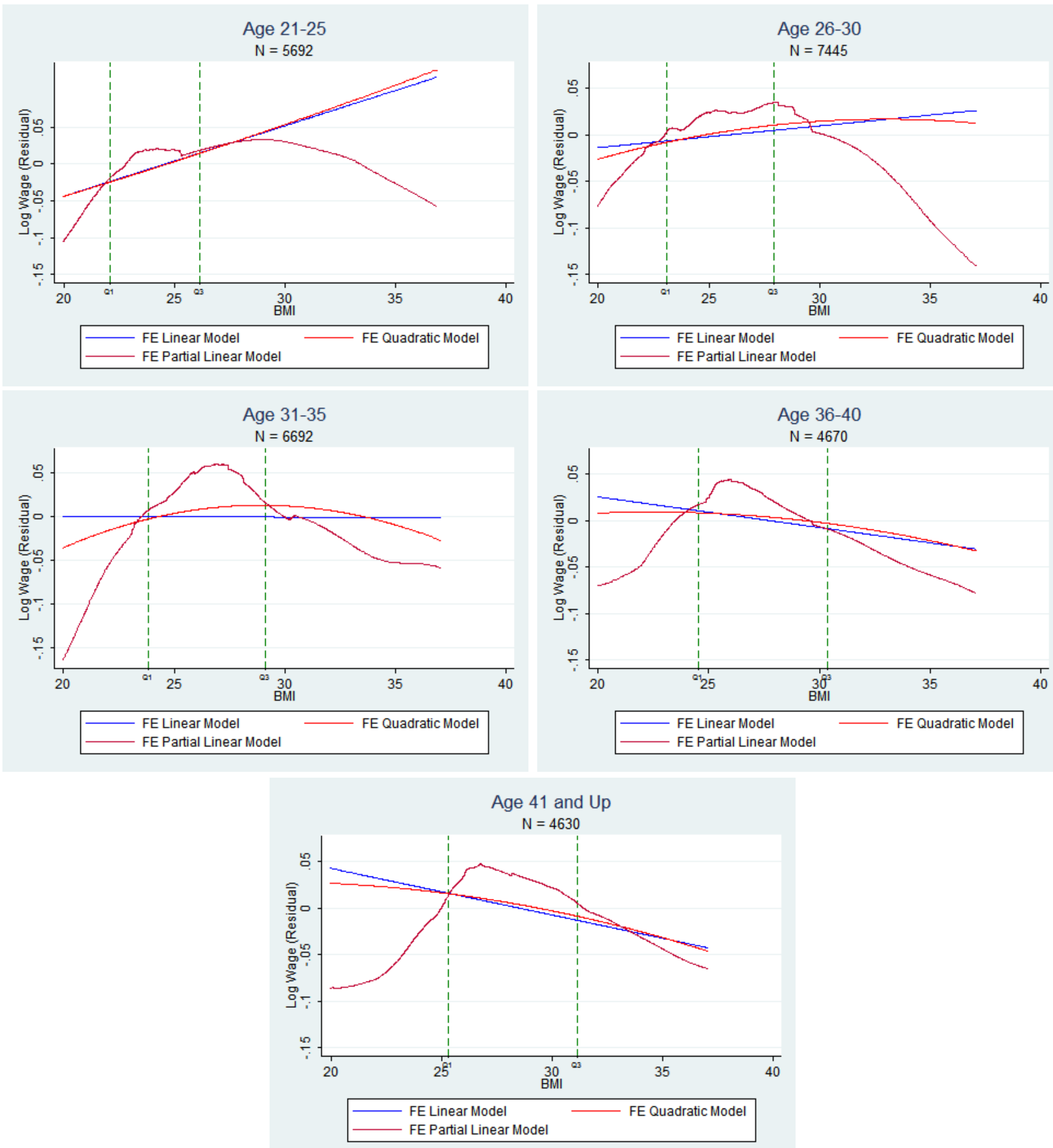

Figure 6: Three Models of Wages, Men 21-25, 26-30, 31-35, 36-40, 41 and Older

Appendix A

Sample Choice

Although the NLSY has been the workhorse data set for the examination of the effect of body weight on wages, relatively little has been said in the obesity/BMI-wage literature about its design, the choices faced by researchers using the data, and the effects of these choices on the outcomes studied. In particular, three subsamples comprise the NLSY: a representative subsample (6,185 people in 1979), supplementary subsamples (5,295 people in 1979), and a military subsample (1,206 people in 1979). The supplementary subsamples include over-samples of black, Hispanic, and economically disadvantaged white respondents. The NLSY dropped the military and economically disadvantaged white subsamples in 1985 and 1991, respectively, a fact which has led the NLSY, following the publication of a thorough review of the data by MacCurdy et al. (1998), to revise the sample weights published with the survey. Currently, for the representative and supplementary samples there are distinct sample weights: a set of weights for the representative sample only, updated for the probability of interview each wave, and a set of weights for the representative sample and all of the supplementary samples, also updated for the probability of attrition from the sample.

In this study, I employ the representative subsample for the main estimates, for the most part to retain sample consistency with the partial linear models. However, I have also estimated the main regression results with the full sample. The results for the fixed effect models from both samples are shown below in Table A-1.

Table A-1: Marginal Effect of BMI/Obesity on Wages at Different Ages[1]

	Sample			
Age Group Interaction	Full	Representative	Full	Representative
	Models Using Obesity		Models Using BMI	
	Women			
Age 21-25	-0.0039	-0.0223	0.0008	-0.0007
	(0.0213)	(0.0241)	(0.0016)	(0.0018)
Age 26-30	-0.0359∘	-0.0375 ∘	-0.0016	-0.0021
	(0.0149)	(0.0173)	(0.0012)	(0.0014)
Age 31-35	-0.0706⋆‡‡	-0.0767⋆†	-0.0040 †	-0.0052 †
	(0.0143)	(0.0161)	(0.0011)	(0.0013)
Age 36-40	-0.0494	-0.0458	-0.0034	-0.0036
	(0.0154)	(0.0173)	(0.0011)	(0.0013)
Age 41 & up	-0.0209	-0.0392	-0.0014	-0.0024
	(0.0196)	(0.0218)	(0.0013)	(0.0015)
N	47,135	28,182	47,135	28,182
	Men			
Age 21-25	0.1030	0.1132	0.0089	0.0096
	(0.0196)	(0.0222)	(0.0018)	(0.0022)
Age 26-30	0.0097***⋆⋆⋆‡‡	0.0159*** ⋆⋆⋆‡‡	0.0021***•⋆⋆⋆‡‡	0.0023***•⋆⋆⋆‡‡
	(0.0143)	(0.0167)	(0.0015)	(0.0018)
Age 31-35	-0.0030***⋆⋆ ‡	-0.0069***⋆⋆ ‡	0.0006***•⋆⋆⋆‡‡	-0.0002***‡‡⋆⋆
	(0.0139)	(0.0158)	(0.0014)	(0.0017)
Age 36-40	-0.0357***	-0.0494***	-0.0020***	-0.0033***
	(0.0162)	(0.0187)	(0.0015)	(0.0018)
Age 41 & up	-0.0423***	-0.0566***	-0.0033***	-0.0051***
	(0.0211)	(0.0235)	(0.0016)	(0.0020)
N	48,865	29,129	48,865	29,129

[1] Table shows marginal effect of BMI/Obesity on wages for full and representative samples in the NLSY. Independent variables include education, total labor market experience, job tenure, hours worked per week, Census region, SMSA indicator, rural indicator, number of children, part-time indicator, school enrollment indicator, marital status, and year indicators. All models use Huber-White sandwich estimates of standard errors. Standard errors in parenthesis. † Different from Age 41 & Up at p<.10. ‡ Different from Age 41 & Up at p< .05. ‡‡ Different from Age 41& Up at p< .01. ⋆ Different from Age 36-40 at p< .10.⋆⋆ Different from Age 36-40 at p< .05 ⋆⋆⋆ Different from Age 36-40 at $p < .01$ • Different from Age 31-35 at p< .10 ∘ Different from Age 31-35 at p< .01.***Different from Age 21-25 at p< .01.

Appendix B

Missing Data

Missing wage values for persons in the sample can be evidence of selection into the labor market in the sense developed by Heckman (1979) and can be modeled as such. However, missing values for right-hand side regression variables can be evidence of a selection mechanism that is not accounted for either by longitudinal weights or labor market selection, and can therefore bias results.

There are several ways to deal with missing values of right-hand side variables. Often, economists simply delete observations for which values are not reported for any reason. This method is inefficient and can induce bias. The missing dummy variable strategy that is sometimes used (Baum and Ruhm, 2007; Cawley, 2004) will preserve efficiency, but is clearly not appropriate for continuous variables for which zero is not a valid response. There is a large and growing literature outlining methods of data imputation that make explicit assumptions about the distribution of the parameters of the data, and model the full data by Gibbs sampling, Markov Chain Monte Carlo, or related methods.[21] These methods are attractive insofar as they make explicit rather than *ad hoc* assumptions about the distribution of the complete data; moreover, although the assumption underlying these methods–that the missing data are missing at random (MAR)–cannot be tested, alternative assumptions can easily be modeled. The main drawback of this approach is that multiple imputations imply multiple sets of parameter estimates, which can be cumbersome to present and interpret.

In the main parametric models above, I have used longitudinal data to fill in as many missing values as possible–particularly those for education, hours, and age. I have discarded observations for which BMI is missing. I test the sensitivity of the results to a multiple imputation strategy as outlined in Rubin (1987) and Van Buuren et al. (1999) in Table B-1 below. I form five complete data sets and show parameter estimates for each data set as well as for the original data used in the main body of this study.

[21] Canonical studies include Schafer (2000), Rubin (1987), and Van Buuren et al. (1999). More recent work on longitudinal data includes Daniels and Hogan (2008).

Table B-1: Marginal Effect of BMI on Wages at Different Ages Using Imputed Data[1]

	Main Estimates	Estimates Using Imputed Data				
		Women				
Age 21-25	-0.0009	0.0002	-0.0005	-0.0010	-0.0003	-0.0005
	(0.0018)	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0017)
Age 26-30	-0.0020	-0.0012	-0.0021*	-0.0022*	-0.0021*	-0.0019
	(0.0014)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Age 31-35	-0.0051***	-0.0038***	-0.0046***	-0.0052***	-0.0049***	-0.0045***
	(0.0013)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Age 36-40	-0.0038***	-0.0026**	-0.0033***	-0.0039***	-0.0032***	-0.0034***
	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Age 41 & Up	-0.0024	-0.0020	-0.0021	-0.0027*	-0.0024*	-0.0021
	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
N	28,128	29,057				
		Men				
Age 21-25	0.0096**	0.0091***	0.0097***	0.0089***	0.0083***	0.0084***
	(0.0022)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Age 26-30	0.0023	0.0020	0.0026	0.0022	0.0010	0.0015
	(0.0018)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Age 31-35	-0.0002	-0.0003	0.0006	-0.0005	-0.0016	-0.0007
	(0.0017)	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0016)
Age 36-40	-0.0033*	-0.0037**	-0.0028	-0.0037**	-0.0047***	-0.0037**
	(0.0018)	(0.0017)	(0.0018)	(0.0017)	(0.0017)	(0.0017)
Age 41 & Up	-0.0051**	-0.0057***	-0.0044**	-0.0051***	-0.0061***	-0.0054***
	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
N	29,129	30,015				

[1] Table shows estimated marginal effects of BMI on wages for women and men in the NLSY sample. The main estimates from the above study are shown in the first column. Other columns show results from imputed data sets. Independent variables include education, total labor market experience, job tenure, hours worked per week, Census region, SMSA indicator, rural indicator, number of children, part-time indicator, school enrollment indicator, marital status, and year indicators. All models use Huber-White sandwich estimates of standard errors. Standard errors in parenthesis. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix C

Non-Parametric Smoothing Techniques

The model that I have used for semiparametric estimates is

$$w_{it} = X_{it}\beta + [f(BMI_{it})|Age] + \mu_i + \varepsilon_{it}, \tag{C-1}$$

where Y_i is hourly wages of individual i, z_i is a vector individual characteristics and year effects, μ_i are person-level fixed effects, and $f(BMI)$ is the non-parametric function transforming BMI into wages. The method that I use is based on the "double residual" method outlined by Robinson (1988), modified for the fixed effect context as described by Li and Racine (2007). In this procedure, one first uses univariate non-parametric smoothing to purge the dependent and independent variables of the effect of BMI; second, one differences the raw variables and non-parametric predictions for each person; third, one takes the differences between the (person-level) differenced predictions and raw variables as regressors for an OLS regression. Using the estimated parameters from that equation, one then predicts $\hat{Y}_{it} = X_{it}\hat{\beta}_{\epsilon}$. With the differences between the observed and predicted values, $Y_{it} - \hat{Y}_{it} = \hat{v}_{it}$, one estimates $\hat{f}(BMI)$ using an iterative procedure. In this procedure, after getting an initial estimate of $\hat{f}(BMI)$, one updates the predictions by differencing the prediction errors over a person and then re-performing the smoothing operation. Usually, estimates converge in a few iterations.[22]

In particular, the local linear estimator that I use to estimate $\hat{f}$ can be defined as

$$\hat{r}_n(x) = \sum_{i=1}^{n} \ell_i(x) Y_i \tag{C-2}$$

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:

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

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

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

[22] In this context, estimates converged in not more than five iterations. Li and Racine (2007) develop a method based on a likelihood profile approach, whose advantage over the local linear approach that I use here is that it will be more efficient. However, it is also quite a bit more computationally intensive, and offers no advantage in terms of consistency to the local linear approach.

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

where

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

and

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

Finally,

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

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, I minimize the generalized cross-validation score over the range of the span as suggested by Craven and Wahba (1979). The cross-validation score is defined as

$$GCV(k) = \frac{n^{-1} \sum_{i=1}^{n} [Y_i - \hat{g}(X_i)]^2}{1 - n^{-1} tr[M_n(k)]^2} \tag{C-5}$$

where $[M_n(k)]$ is an nxn matrix with $(i, j)^{th}$ element given by $\frac{w_{ij}}{\sum_{l=1}^{n} w_{il}}$–i.e. the smoothing matrix for span k.[23]

I chose local linear regression because it relaxes the linearity assumption of OLS and minimizes both boundary bias and design bias introduced by kernel methods such as the Nadarya-

[23] When smoothing the dependent variables, I execute generalized cross-validation at the roughly 1000 percentile points apart in the middle 95 percent of the distribution of BMI.

Watson estimator.[24]

I use the "wild" bootstrap described by Härdle (1990). This bootstrapping procedure is appropriate for contexts in which heteroskedasticity is thought to be present, as it simulates sampling from N distributions of residuals, rather than one. At each draw of the bootstrap sample, one transforms the residuals using a two-point probability distribution, such that $\tilde{u}_{it} = [(1+\sqrt{5}/2)]\hat{u}_{it}$ with probability $p = (1+\sqrt{5})/(2\sqrt{(5)})$, and $\tilde{u}_{it} = [(1-\sqrt{5}/2)]\hat{u}_{it}$ with probability $1-p$, where $\hat{u}_{it}$ is the residual for the final iteration of the estimation procedure. One then uses these residuals in smoothing for that sample.[25]

[24] On this point, see Wasserman (2006), 73ff., and Fan and Gijbels (1996), pp.17-18, 60ff.

[25] Although some authors (Li and Racine, 2007; Yatchew, 2003) suggest using oversmoothed predictions and undersmoothed residuals for the bootstrap sampling procedure, I do not do that here. Pilot tests suggested no difference with this procedure.

Table D-1: Main Estimation Results, Women[1]

Variable	Models Using Obesity		Models Using BMI	
	OLS	FE	OLS	FE
Black	-0.0752***		-0.0733***	
	(0.0092)		(0.0091)	
Hispanic	0.0190		0.0179	
	(0.0123)		(0.0123)	
North East	0.1390***	0.0943***	0.1389***	0.0946***
	(0.0092)	(0.0264)	(0.0092)	(0.0264)
Midwest	-0.0009	0.0038	-0.0012	0.0045
	(0.0077)	(0.0233)	(0.0077)	(0.0233)
West	0.1151***	0.1169***	0.1155***	0.1165***
	(0.0097)	(0.0260)	(0.0097)	(0.0260)
SMSA	0.1054***	0.0372***	0.1050***	0.0368***
	(0.0079)	(0.0098)	(0.0079)	(0.0098)
Married	0.0261***	0.0510***	0.0247***	0.0509***
	(0.0079)	(0.0108)	(0.0079)	(0.0109)
Rural	-0.0588***	-0.0161*	-0.0582***	-0.0161*
	(0.0085)	(0.0096)	(0.0085)	(0.0096)
Divorce/Sep	0.0295***	0.0705***	0.0275***	0.0701***
	(0.0097)	(0.0136)	(0.0097)	(0.0136)
Number of Children	-0.0170***	-0.0334***	-0.0172***	-0.0335***
	(0.0034)	(0.0047)	(0.0034)	(0.0046)
Enrolled in School	-0.0991***	-0.1492***	-0.1005***	-0.1492***
	(0.0122)	(0.0125)	(0.0122)	(0.0125)
Highest Grade Completed	0.0708***	0.0376***	0.0704***	0.0375***
	(0.0018)	(0.0051)	(0.0018)	(0.0052)
Total Labor Mkt. Experience	0.0007***	0.0007***	0.0007***	0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Hours Worked/Wk.	0.0017***	0.0005	0.0021***	0.0005
	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Age 26-30	0.0295**	0.0811***	0.0389	0.1063***
	(0.0122)	(0.0133)	(0.0399)	(0.0374)
Age 31-35	-0.0103	0.1092***	0.0159	0.2056***
	(0.0168)	(0.0202)	(0.0424)	(0.0420)
Age 36-40	-0.0606***	0.1028***	-0.0625	0.1671***
	(0.0224)	(0.0276)	(0.0487)	(0.0491)
Age 41 & Up	-0.1437***	0.0672*	-0.1822***	0.1042*
	(0.0289)	(0.0363)	(0.0572)	(0.0589)
Constant	1.1513***	1.3084***	1.2815***	1.7278***
	(0.0331)	(0.0868)	(0.0436)	(0.0796)
N	28,182			

[1] Table shows regression coefficients for regressors other than BMI- or obesity-age interations. Year indicators not shown. *p< .10, **p< .05, ***p< .01.

Table D-2: Main Estimation Results, Men[1]

Variable	Models Using Obesity		Models Using BMI	
	OLS	FE	OLS	FE
Black	-0.1668***		-0.1663***	
	(0.0103)		(0.0103)	
Hispanic	-0.0818***		-0.0804***	
	(0.0125)		(0.0125)	
North East	0.1255***	0.0584*	0.1254***	0.0593*
	(0.0092)	(0.0303)	(0.0092)	(0.0303)
Midwest	0.0055	-0.0590***	0.0045	-0.0598***
	(0.0078)	(0.0207)	(0.0079)	(0.0207)
West	0.0974***	0.0505*	0.0971***	0.0492*
	(0.0101)	(0.0274)	(0.0101)	(0.0274)
SMSA	0.1292***	0.0272***	0.1290***	0.0269***
	(0.0084)	(0.0098)	(0.0084)	(0.0098)
Married	0.1611***	0.0923***	0.1643***	0.0929***
	(0.0087)	(0.0099)	(0.0087)	(0.0099)
Rural	-0.0575***	-0.0363***	-0.0569***	-0.0360***
	(0.0086)	(0.0091)	(0.0087)	(0.0091)
Divorce/Sep	0.0656***	0.0372***	0.0676***	0.0374***
	(0.0110)	(0.0136)	(0.0110)	(0.0136)
Number of Children	0.0295***	0.0176***	0.0289***	0.0175***
	(0.0038)	(0.0041)	(0.0038)	(0.0041)
Enrolled in School	-0.2205***	-0.2673***	-0.2233***	-0.2676***
	(0.0154)	(0.0155)	(0.0150)	(0.0155)
Highest Grade Completed	0.0757***	0.0465***	0.0757***	0.0464***
	(0.0016)	(0.0063)	(0.0016)	(0.0063)
Total Labor Mkt. Experience	0.0005***	0.0010***	0.0005***	0.0010***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Hours Worked/Wk.	0.0002	-0.0030***	0.0005	-0.0030***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)
Age 26-30	0.0641***	0.0867***	0.1919***	0.2513***
	(0.0140)	(0.0137)	(0.0540)	(0.0467)
Age 31-35	0.0584***	0.1018***	0.2072***	0.3276***
	(0.0182)	(0.0200)	(0.0555)	(0.0499)
Age 36-40	0.0562**	0.1045***	0.2639***	0.4015***
	(0.0250)	(0.0280)	(0.0649)	(0.0599)
Age 41 & Up	0.0315	0.0700*	0.2990***	0.4169***
	(0.0339)	(0.0366)	(0.0750)	(0.0683)
Constant	1.0573***	1.9198***	1.2710***	1.7054***
	(0.0429)	(0.0861)	(0.0494)	(0.0982)
N	29,129			

[1] Table shows regression coefficients for regressors other than BMI- or obesity-age interations. Year indicators not shown. *p< .10, **p< .05, ***p< .01.