THE INDIRECT EFFECTS OF OBESITY

The Wage Effects of Obesity in the U.S. Labor Market: Are Obese Paid Less Because of Health Insurance?

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ABSTRACT

Past economic literature has consistently found depressant effects of obesity on wage levels. However, the research provides mixed results on both the magnitude of the obese wage differential as well as a conclusive explanation for its occurrence. In this article, I use data from the Panel Study of Income Dynamics to further investigate the relationship among obesity, wages, and the hypothesis that obese workers with employer-provided health insurance pay for their higher medical expenditure through reduced wages. The results present evidence that obesity is a significant factor in determining women's wage rates, reducing wages by 3.2%. Using a quantile regression approach, I find obesity to have larger depressant effects on wages at higher paying jobs for both men and women. Moreover, the interaction effects of obesity and employer-provided health insurance suggest women's obese wage penalty is confounded in jobs offering health insurance.

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I. Introduction

The incidence of obesity in the United States is a growing public health concern.[1] While in the 1970's an estimated 15% of the U.S. population was obese, by the early 2000's the prevalence more than doubled to an alarming 30%.[2] These trends have significant financial consequences. Increased weight is linked to chronic diseases such as type II diabetes, hypertension, cardiovascular disease, and several types of cancer (Finkelstein, Fiebelkorn & Wang 2003). According to a recent study, nearly 9% of U.S. total medical expenditure, an estimated $51.5 billion, is attributed to the prevalence of these overweight and obese-related chronic diseases (Finkelstein et al. 2003). These increased costs imply obese individuals spend 36% more on annual medical expenditure than non-obese individuals (Sturm 2002).

While the prevalence of obesity is growing, the number of employers offering health insurance has been declining due to rising healthcare costs (Gilmer & Kronick 2005). In the past two decades, the costs of employer-provided health insurance (EPHI) have increased 10% per year and are among the most expensive benefits employers offer (Fong & Franks 2008). Empirical evidence suggests the increasing costs of health insurance are deriding labor market outcomes. Baicker and Chandra (2006) estimate that a 10% increase in EPHI reduces employees' wages by 2.4% and employment opportunities by 1.9%.

While more economic literature has emerged to explore the impact of the rising costs of EPHI and its effects on earnings, less has focused specifically on the coincidence of the growing

[1] The commonly used method to measure obesity and overweight is a ratio of height to weight, the body mass index (BMI). The World Health Organization classifies individuals with a BMI of 30 or more as obese, 25 to 29.9 as overweight, and 18.5 to 24.9 as healthy and of normal weight.
[2] Center of Disease Control: http://www.cdc.gov/obesity/data/trends.html

prevalence of obesity in the workforce along with higher health insurance costs. Given that obesity is an observable health risk and is attributed to higher medical expenditure, profit-maximizing employers offering health insurance could view obese employees as more costly due to their higher healthcare costs. For instance, some literature suggests employers are incentivized either not to hire obese workers (Han et al. 2008; Fong & Franks 2008) or individually reduce obese employees' wages to cover these increased costs (Bhattacharya & Bundorf 2009; Baum & Ford 2004; Atella et al. 2008).

The main purpose of this paper is to explore the wage effects of obesity in the U.S. labor market, specifically when obese workers receive EPHI. The economic literature has consistently found depressant effects of increased weight on wages and has suggested alternative explanations for this association, but fewer studies have focused directly on whether obese workers with EPHI pay for their higher medical expenditure through lower wages. Generally speaking, economists agree that workers pay for the costs of health insurance through reduced wages, but less is known about how employers shift the costs of the health insurance to employees. Essentially, each worker's wages could be offset by an amount equal to their healthcare costs or by the averaged healthcare costs among all workers in the firm. The significant question remains: Are employers individually offsetting wages for specific, high-health risk workers, such as the obese?

The aim of my analysis is to examine the obese wage penalty under the hypothesis that obese employees receive lower wages than non-obese employees because of higher obese-attributed medical expenditure and the subsequent more expensive EPHI. To perform this research, I primarily estimate the wage effects of obesity under the maintained assumption that the obese wage penalty is not due to EPHI. The existing studies on the obese wage penalty find obese employees receive lower wages than their non-obese colleagues; but the magnitude of the differential is debatable. I use a quantile regression approach to estimate where along the wage distribution obesity most affects wages. Applying this method, I find obesity to have heterogeneous effects along the wage distribution for men and women, but with more significant effects at higher paying jobs. Secondly, I examine the obese wage differential when controlling for obese individuals receiving EPHI. The results imply obese women receiving EPHI receive a 4.3% wage penalty. The results for men, however, show no significant effects on wages.

The paper is organized as follows: Section II reviews the literature on the obese wage penalty. It provides the framework to understand the existence of the obese wage differential and covers alternative explanations for its existence. This section also covers additional labor market studies that examine the cost-shifting of incremental health insurance costs to individual, higher-health risk employee wages. Section III presents the theoretical framework of EPHI and its effects on wage determination. Section IV introduces the data and presents the descriptive statics used in this analysis. Section V introduces the hypothesis and empirical model. Section VI presents the estimation procedure and results of the analysis. Section VII summarizes the results and suggests areas for further research. And lastly, Section VIII presents policy implications based on the results.

II. Literature Review

The economic literature investigating the wage impacts of obesity suggests obese employees receive lower wages relative to their normal weight colleagues in the U.S. labor market. While the literature agrees that increased weight is associated with lower wages, and find the wage penalty to range from 3% to 17%, studies do not agree on a definitive explanation for its occurrence. Along with the hypothesis that obese employees' wages are reduced due to higher medical expenditure, the literature proposes alternative explanations for the wage gap. Obesity can affect wages due to internal factors, such as obese workers having higher morbidity rates and thus lower productivity at work,[3] or external factors, such as customer or employer discrimination.

i. Model of Hourly Wage Determinants

To investigate the differences in obese and non-obese wage rates, the majority of the literature on the obese wage penalty has applied the human capital equation, as modeled by Jacob Mincer (1974), and used a mean regression approach. While the primary application of this model is to study the effects of investment in schooling and job-training on wage rates, it also has been applied to studies of wage discrimination and theories of wage differentials (Willis 1986). To determine the wage effects of weight, economists have enhanced the model to include individual body weight. This equation is constructed as:

$$\ln W_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 O_{it} + \varepsilon_{I,}$$

Where W_{it} is the individual's hourly wage, O_{it} is a measure of the individual's weight, and X_{it} is a vector of the standard variables that influence wages, such as education, work experience, occupation, industry, region, age, race, gender, and family characteristics. The underlying theory of this model assumes variables measuring educational attainment and work experience positively affect wages because they increase labor productivity (Willis 1986). While weight is not a standard variable to include in wage rate regression, the literature suggests this component of health capital is a significant factor in explaining wage rate variation.

[3] Studies have shown that obesity is directly impacting labor market outcomes because of health limitations. For instance, Friedman and Tucker (1998) estimate that because obesity is attributed to higher morbidity rates, obese workers are more than twice as likely to miss work during a year as their non-obese colleagues. For the U.S. labor market as a whole, Cawley, Rizzo, and Haas (2007) estimate that the absentee costs associated with obesity and consequential reduced productivity costs $4.3 billion annually.

ii. Empirical Evidence

The seminal works on the obese wage penalty began in the early 1990's and sought to explain the wage differential based on the physical attributes of individuals. In response to social science and psychological studies that find physical attributes to affect others' perceptions (Loh 1993), economists hypothesized that weight could lead to discriminatory wage effects. That is, the social stigma of obesity may signal to employers that obese workers have lower productivity, even given equal education and work experience, leading to discriminatory outcomes. Most generally, employer discrimination results in lower wages when employers underestimate the productivity of certain workers (Cain 1986). Under this assumption, employers may assume obese workers have lower marginal productivity than non-obese workers. The pioneering works on the wage penalty suggest obese workers are penalized through reduced wages because employers underestimate obese workers' productivity.

Register and Williams (1990), Loh (1993), and Gortmaker et al. (1993) are among the first economists to estimate the hourly wage variation for physical attractiveness under the hypothesis that attractive workers, such as those with socially accepted weight and height, are more likely to have favorable labor market outcomes. To investigate the wage effects of obesity, Register and Williams (1990) use a relative weight approach and data from the National Longitudinal Study of Youth (NLSY).[4] Employing the human capital equation and observing both part-time and full-time workers, they find differing effects of weight on wages based on gender. The results imply overweight women receive 12% less in wages compared to those of

[4] The majority of the literature on the obese wage penalty has utilized individual level data from the National Longitudinal Study of Youth (NLSY). The NLSY surveys 12,000 men and women in the U.S. and has been conducted annually since 1979, when the individuals were 14 to 21 years old and biannually since 1994.

normal weight and it is significant at the 99% level of significance. For overweight men, however, the wage penalty is 5%, but not statistically significant. To control for productivity differences that may explain the wage differential, the authors find the wage offset of obesity to be greater than the wage offset of productivity differences.

Moreover, to determine the true proportion of the wage differential due to increased weight that is not explained in control variables,[5] Register and Williams (1990) re-estimate the wage differentials by running a separate regression for the obese and non-obese samples.[6] The authors find a -30% differential for males and a 90% differential for females. This implies that 90% of the wage differential between obese and non-obese females is due to unobservable factors not included in the vector of control variables. This seminal work suggests obesity negatively impacts wages, more so for women. Register and Williams argue that their findings have important gender-based wage discrimination implications, and conclude that at least some of the discrimination against women in the labor market is a result of discrimination against the obese.

Similarly, Loh (1993) uses the 1982 and 1985 waves of the NLSY, but examines only full-time workers to estimate both wage level differentials and wage growth differentials associated with increased weight. Loh's results indicate increased weight has no significant effect on wage levels for both men and women in 1982, but he does find a significant differential in wage growth. Observing obese and non-obese wage growth from 1982 to 1985, Loh finds

[5] The control variables used in Register and Williams' study include only the basic human capital accumulation factors. The vector of control variables, X_i, includes black, local unemployment rate, years of education, age, health status (an indicator variables for if the respondent's health limits their type or quantity of work), married, number of dependents, south, urban, English spoken at home, enrolled in school, work experience, government employee, and professional or managerial occupation.

[6] The re-estimation method, based on the Oaxaca decomposition method, requires running two regressions, one for the overweight respondents $W_o = \beta_0 + \beta_1 X_{o,}$ and one for the normal weight respondents $W_n = \beta_0 + \beta_1 X_{n,}$. Register and Williams then take the difference D of the estimated coefficients β and mean values of the control variables X for each group, $D = X_o(\beta_n - \beta_o)/(W_n - W_o)$. The difference D is explained to be the effect of discrimination based on weight, as it measures the proportion of the wage differential not explained by the control variables.

obese men have a significant 5.5% wage growth penalty, while for women the growth differential is negative, but insignificant. Because employers may perceive heavier individuals as less productive, Loh controls for the presence of health limitations along with the other control variables. Loh's study concludes increased weight may not directly lower wage levels, but it slows wage growth. He proposes the slower wage growth as a consequence of discrimination.

Gortmaker et al. (1993) investigate the wage effects of weight, but expand the model to compare attainment probabilities-- such as marital status, household income, and education-- between overweight individuals and normal weight individuals over a seven-year span. While not specifically addressing hourly wages, the results suggest further disadvantageous outcomes for men and women for being overweight during adolescence. Gortmaker et al. find the effects of weight to be more significant in determining women's future outcomes. Examining the relationship between being overweight in 1981 and social and economic attainment in 1988, the results imply overweight women during adolescence are 20% less likely to be married, have 0.3 years less education, and $6,000 less in household income than women who had not been overweight during adolescence (Gortmaker et al. 1993).

To control for health factors and productivity differences, Gortmaker et al. (1993) assume overweight workers have health conditions that interfere with future attainment probabilities. However, after controlling for chronic diseases, such as asthma and musculoskeletal abnormalities, the regression results suggest that individuals with these conditions do not have lower socio-economic outcomes compared to overweight individuals. This implies the wage differential is not confounded by health status factors that lower productivity. Thus, Gortmaker et al. (1993) propose that discrimination best explains the obese and non-obese attainment differentials.

iii. Estimation Improvements

While the earlier literature on the obese wage differential provides evidence that weight affects hourly wages, the results can be misleading because the endogeneity of weight and concerns of reverse causality are not addressed. That is, while this earlier literature shows increased weight causes lower wages, the negative relationship could also be a result of lower wages causing weight gain or due to unobservable factors not included in the regression. For instance, studies have shown lower socioeconomic outcomes, like lower wages, can result in weight gain. Chen and Meltzer (2009) find the decrease in real minimum wage over the past thirty years has impacted the growth of obesity prevalence.[7] Furthermore, while Cutler, Glaeser, and Shapiro (2003) find the technological advancement of food preparation and lower food prices have increased U.S. obesity rates, they also point out individual factors, like motivation and self-discipline, can have significant effects on weight gain. Presumably, these individual factors that which affect weight, also impact an individual's willingness to earn higher wages.

The association between lower wages and obesity could also be due to certain occupational characteristics. For instance, while Lakdawalla and Philipson (2007) find occupational characteristics to be a significant determinant in weight gain, and specifically that men who spend eighteen years in strength-demanding jobs to be 15% heavier than men in the least strength-demanding jobs, the authors also propose a causal relationship. That is, heavier workers may have an incentive to select into jobs where increased weight is beneficial. If these

[7] Chen and Meltzer's (2009) study on the effects of decreasing real minimum wage on weight, which decreased from $9.15 in 1968 to $5.80 in 2007, finds that a $1 decrease in real minimum wage is associated with a .06 increase in BMI. This study provides evidence that wages, at least partly, impact weight gain.

jobs are paid less, then the sorting into these jobs will result in obese workers having lower wages.

In order to statistically account for the possibility of obese workers sorting into specific jobs, some studies, such as Register and Williams' (1990), have employed the Heckman correction to adjust for this selection bias. The Heckman correction is a statistical method used first to adjust the probabilities of employment so it is equal among the individuals in a sample and second to use predicted individual probabilities to correct the self-selection bias (Heckman 1979). Because the sample could be biased if obese workers either self-select into certain occupations or choose not to work at all, the results will be biased due to non-random selected samples. Using this method, however, requires identifying variables correlated with employment probability, but not correlated with the control variables. For instance, Cawley (2004) used this correction specification to improve estimating the wage effects of obesity. Cawley, however, finds the Heckman correction to have minimal influence on the results. Furthermore, the majority of the literature has not employed the Heckman correction and thus estimates the wage effects of obesity conditional on employment status.

However, other methods have been used to address these estimation biases. The more recent research addresses issues of reverse causality by employing instrumental variables, such as lagged-body weight and sibling-differences. Essentially, the use of these instrumental variables will reduce concerns of reverse causality because lagged-body weight and sibling-differences affect individual weight status, without affecting wages. Applying the lagged-body weight approach simply requires replacing O_{it} with the individual's weight in the past under the assumption that lagged-body weight is not affected by current wages. The sibling-difference approach is used to minimize the unobservable factors, such as genetics and lifestyle choices, which are presumably similar between siblings (Cawley 2004). With this approach, it is assumed that all unobservable heterogeneity, accounting for genetic and non-genetic factors, is constant between the two siblings and thus differenced away.

Averett and Korenman (1996) build on the influences of physical attributes and their effects on family income, marital status, and hourly wage rates. Using lagged-body weight and employing an indicator variable for overweight and obesity in 1981, the results show obese women have a statistically significant 15% wage penalty, and obese men have an 8% wage penalty. Using current indicators for weight, the wage differentials decrease and indicate a 10% wage penalty for obese women and a 3% wage penalty for obese men. Averett and Korenman find the largest wage penalty, a 17% differential, for women who were obese both in 1981 and 1988, as compared to normal weight women in both time periods. However, when the authors attempt to use the sibling-difference approach, they obtain insignificant results, most likely due to a much smaller sample size.

Cawley (2004) focuses primarily on the causality issue and examines wage differentials separately by race-gender groups. Using standard mean regression and both body weight in pounds and an indicator variable based on standard body mass index (BMI) classifications for overweight and obesity, he finds weight to have substantially different effects depending on race; the obese wage differentials vary from a negative 11.9% for white females, negative 8.2% for Hispanic females, negative 3.3% for white males, to a positive 4% for black men. Using the point estimate, Cawley finds a two standard deviation increase from the mean weight to decrease wages by 9%. The results using the indicator variables for being overweight and obese suggest that the wage penalty increases at higher BMI levels. For instance, while overweight black females face a 1.2% wage penalty, obese black females face a 6.1% wage penalty. Furthermore, he re-estimates the race-gender wage penalties using lagged-body weight. The results from the indicator variables show larger wage penalties, consistent with Averett and Korenman's findings that increased weight in the past adversely affects current wages. However, the results from the point estimate are also similar enough to infer current wages minimally impact current weight (Cawley 2004).

In summary, the uses of the lagged-body weight and sibling-differences instrumental variables are important in understanding alternative methods to estimate unbiased effects of weight on wages. However, as the literature demonstrates, the ability to use these variables correctly is difficult. As pointed out by Han, Norton and Stearns (2008), the lagged-body weight approach will not be valid if it is correlated with the error term in the wage equation. Similarly, while the assumption for the sibling-difference approach is that sibling BMI is uncorrelated with the error term, it is impossible to prove. Thus, the sibling-difference approach will not be valid if the siblings have the same unobservable wage factors (Han et al. 2008).

iv. Alternative Explanations for the Wage Effects of Obesity

The previous literature on the obese wage penalty rationalized the existence of the obese wage differential as a result of employer discrimination, since most controlled for productivity differences between obese and non-obese workers. However, the more recent studies on the obese wage differential have focused more specifically on determining alternative explanations for the incidence of lower wages and obesity. Using the aforementioned research as framework, the following studies explore if the wage effects of obesity are consequences of customer discrimination or the higher health insurance costs attributed to obesity.

Customer Discrimination

Baum and Ford (2004) estimate the obese wage penalty using data from the NLSY and find obesity to lower men's wages by 3.2% and female's wages by 5.8%.[8] However, the authors focus primarily on the theoretical mechanisms for why obesity adversely affects wages, such as customer discrimination. Baum and Ford hypothesize that if the obese wage penalty is due to customer discrimination, the wage penalty will be greater in jobs with more customer interaction than in those with less. Accordingly, if the wage penalty is the same across all occupations, then the wage penalty is due to employer discrimination. To test this hypothesis, the authors interact an indicator variable for obesity with an indicator variable for jobs with higher customer interaction. The results show no changes in the differential when subjectively controlling for jobs with higher interpersonal interaction with customers.

Similar to Baum and Ford (2004), a study by Han, Norton and Stearns (2008), again examines if the obese wage penalty is due to customer discrimination, but extensively control for job characteristics. Using NLSY data from 1982 through 1998, the authors use the U.S. census occupational codes to separate jobs depending on the amount of interpersonal skills required. Following Cawley's (2004) findings that the wage penalty varies based on race-gender groups, the results indicate that jobs requiring more interpersonal skill have greater obese wage penalties, of which is largest for white and black obese females, at 6.7% and 11.9% respectively.

Similarly, DeBeaumont (2009) observes the wage effects of obesity exclusively for women and finds that obese women are paid less than non-obese women in jobs with higher customer interaction, such as sales and service occupations. Using the production field as a baseline comparison, DeBeaumont finds obese women in jobs with higher customer interaction

[8] Baum and Ford (2004) pool the 1979 through 1994 waves of the NLSY.

to receive an estimated 11% less than non-obese women in the same job. He argues the obese wage penalty is due to customer discrimination.

Healthcare Costs

Because obesity is an observable health risk and is linked to higher medical expenditure, profit-maximizing employers may identify obese workers as more costly to employ due to higher medical expenditure. Accordingly, employers providing health insurance may penalize obese workers through lower wages to cover the incremental costs of EPHI. While legal constraints, such as the Health Insurance Portability and Accountability Act of 1996 (HIPPA), prohibit employers to deny certain individuals health insurance coverage or to charge these individuals higher health insurance premiums,[9] employers then have incentive to not hire the obese worker or to individually offset wages to cover the increased costs.

While U.S. anti-discrimination laws make it difficult to individually adjust wages based on individual-specific healthcare expenditure, Gruber (2000) acknowledges the possibility lies in just how finely employers can individually shift costs of health insurance on wages.[10] Individual firms, for instance, could offset wages in other manners, such as during hiring placements or promotions (Cain 1986). Given that employers are incentivized to lower wages when offering health insurance, the question remains if employers individually offset wages for specific, high-health risk employees.

[9] United States Department of Labor website provides full and amended versions of this law: http://www.dol.gov/ebs a/FAQs/fa q_hipaa_ND.html

[10] The American's with Disability Act (ADA), for instance, restricts employers to ask an applicant questions about disability or require the applicant to take a medical examination before making a job offer. This law makes it unlawful for employers to discriminate against employees with disabilities through pay, hiring, firing, promotion, and other employment related activities.

Of the relatively few studies examining if the obese wage penalty is the result of employers passing on the incremental healthcare costs to obese employees through lower wages, the results are mixed. However, other economic literature has examined comparable wage effects of employing higher-health cost workers. The shifting of healthcare costs to individual wages has been studied among maternity-aged workers and older-aged workers.

Gruber (1994) studies the effects of mandated maternity benefits on relative wages of maternity-aged workers. From 1975 through 1979, twenty-three states in the U.S. mandated comprehensive coverage for childbirth in health insurance coverage. In a similar manner to obesity, Gruber (1994) investigates if the costs associated to these higher-health cost workers are shifted to these individuals through lower wages. To examine if the costs of the mandate are shifted to maternity-aged workers, he compares relative wages from the states that passed the legislation to provide mandated maternity benefits to those that did not. Essentially, Gruber finds that while the goal of the mandate was to redistribute resources to benefit this targeted group, the cost-shifting of the incremental costs of the benefit resulted in reduced wages for the maternity-aged workers. While this research differs from the effects of health insurance on obese wages because it is a mandated benefit, rather than employer's voluntary offering of health insurance, this empirical evidence shows the incremental costs for specific, higher cost workers can be shifted to wages.

Similarly, Sheiner (1999) investigates the cost-shifting of health insurance among older-aged workers. Because healthcare expenditure increases with age, Sheiner (1999) examines the incremental healthcare costs associated to employing older-aged workers and if these additional costs reduce older-aged workers' wages. She uses data on cross city-variation in health insurance costs to observe whether cities with more expensive healthcare impact the wages of older-aged workers more than those of younger workers. Her results provide strong evidence that the wages of older-aged workers reflect their higher healthcare costs. Observing separate estimates by age group, the wage offsets get larger as age increases. Sheiner (1999) finds that her results are robust to the inclusion of other variables and that older workers pay for their higher healthcare costs through reduced wages.

Of the studies investigating the cost-shifting of EPHI to obese workers' wages, the results are mixed. Baum and Ford (2004) investigate if employers offering health insurance reduce obese wages to cover their presumably higher health insurance premiums. Baum and Ford use an indicator variable for health insurance status and interact it with an obesity indicator variable. Hypothesizing the wage penalty to increase for obese employees obtaining EPHI, Baum and Ford's results show a negative coefficient on the interaction term for females, but a positive coefficient on the interaction term for males. For men, this suggests obese employees with health insurance actually receive less of a wage penalty than those without health insurance. However, the authors point out that the model may not specify what was intended.[11]

While each of the mentioned studies focuses on the obese wage penalty in the U.S. labor market, a study by Atella, Pace, and Vuri (2008) investigates the existence of the wage penalty among European workers. While the primary principal of the analysis is to use a quantile regression approach to observe the varying wage effects of obesity along the wage distribution,[12] Atella et al. (2008) also explore if the European obese wage penalty is explained by the higher medical costs of obesity charged on obese employees' wages. Although European countries are

[11] Baum and Ford's data set included 1979-1994 waves of the NLSY. Beginning in 1989, the NLSY added a more detailed question on the respondent's type of health insurance coverage, specifically if it is employer-provided.

[12] For women, Atella et al. (2008) find the quantile regression results to be of similar magnitude as the results from the mean regression. They find a relatively consistent 4% to 5% wage penalty for obesity along the wage distribution, but with the highest wage penalty in the central part of the distribution. For men, the results suggest obesity to be more heterogeneous across quantiles. For European men, there is a wage penalty at the lowest quantile, -2%, and a wage premium at the highest quantile, 2%.

covered by universal healthcare coverage, the authors investigate the health insurance hypothesis to account for the additional health benefits covered by employers. Again using an interaction variable for obesity and health insurance status, Atella et al. (2008) find that health insurance costs are not able to explain the obese wage penalty.

In the most recent research examining the health insurance hypothesis, Bhattacharya and Bundorf (2009) pool the most recent available waves of the NLSY, 1989 through 2002, and unlike Baum and Ford (2004), find evidence that additional costs of insuring obese workers is passed on to obese workers through lower wages. Specifically, Bhattacharya and Bundorf find evidence that employers at least partially individually offset obese workers' wages to reflect the higher medical expenditure, and thus higher health insurance premiums, of obese workers.

Primarily, Bhattacharya and Bundorf (2009) find the obese wage differential to be $1.21 for men and $1.66 for women before controlling for obese individuals with EPHI. However, once the authors control for those with EPHI, the differentials change significantly and increase to $2.64 for women and decrease to an insignificant $.58 for men.[13] Accordingly, Bhattacharya and Bundorf find the obese wage penalty to be greater in jobs offering health insurance, suggesting the higher heath insurance premiums are adjusted through lower wages to these workers. To determine why the wage penalty is larger for women with EPHI than for men, the authors observe gender differences in medical expenditure using data from the Medical Expenditure Panel Survey. They find the wage differentials to be consistent with gender-specified medical expenditure. While privately insured obese women spend an estimated $583 more than non-obese women, the difference for men is only $52.

[13] While the other studies on the obese wage penalty use the log transformation of hourly wages, Bhattacharya and Bundorf use wage levels directly to better represent the incremental healthcare costs associated with obesity. Bhattacharya and Bundorf argue the incremental healthcare costs should offset hourly wages in magnitude, not in proportion to hourly wages.

The results from Bhattacharya and Bundorf's (2009) study, unlike Baum and Ford's (2004), support the hypothesis that employers offering health insurance individually reduce obese employee wages. Due to this finding, Bhattacharya and Bundorf (2009) further examine the wage differential depending on firm size. Under the assumption obese workers' wages are individually reduced to cover higher health insurance premiums, than presumably the wage differentials exists at all firm sizes. Examining firms with fifty or more employees to those with less than fifty, the results indicate a wage penalty in both firm sizes. Because the wage penalty exists in both firm sizes suggests individual wage offsets rather than group incidence. Bhattacharya and Bundorf's (2009) study lends support to the hypothesis that obese wages are individually reduced to cover the increased costs of medical expenditure.

Rather than observing wage differentials, Fong and Franks (2008) evaluate if obesity affects the likelihood of obtaining a job with EPHI. Utilizing a different data set, the 2004 Household Components of the Nationally Representative Medical Expenditure Panel Survey, the authors use logistic regression model, but use employment with EPHI as the dependent variable. Fong and Franks assume that employers are less likely to hire obese workers because of the greater financial risk to insure a high-health risk worker. The results of the regression, however, suggest the opposite. When using a continuous variable for BMI, results showed a direct association between increasing BMI and the increasing likelihood of holding a job with health insurance. The authors posit that obese workers may value health insurance more because they are aware of their medical needs and thus self-select into jobs offering health insurance.

Summary

Of the aforementioned studies exploring obese wage penalty in the U.S., the broad finding is that obesity is associated with lower wages, but the magnitude of the penalty varies, depending on occupational characteristics, age, or race. Broadly speaking, the past literature estimates the direct wage effects of obesity to range from 3% to 17% and more often to affect women's wages more than men's. As mentioned, while some studies have focused on the causal relationship between weight and wages by employing instrumental variables, this paper will primarily examine the association between obesity status and wages. In any case, these studies provide a general framework to model the wage effects of obesity.

At the same time, the literature has posited some shortcomings. The majority of the existing literature on the obese wage penalty has utilized the same dataset, the NLSY, and pooled multiple years, many over ten year periods. In doing so, the research on the wage effects of weight has yet to focus exclusively on the most recent data to capture the current trends in obesity growth. Because the U.S. workforce has consistently gained weight over the years, the wage effects of obesity may have different effects due to the increasingly higher proportion of obese workers in the labor market. Unlike the past research, I study the obese wage penalty using only the most current years, 2005 and 2007, and use a different dataset, the Panel Study of Income Dynamics, to observe the most recent wage effects of obesity in the U.S. labor market.

Additionally, each of these studies applied only a mean regression analysis to observe the wage effects of obesity. The research by Atella et al. (2008) demonstrates an additional way to examine the obese wage effects that has yet to be used with a U.S. sample. Employing the quantile regression approach can show hidden complexities in understanding where obesity most affects wages and illustrate variations in the wage penalty along the wage distribution.[14] This

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[14] The purpose of quantile regression is to expose the relationship between the dependent variable (log wages) and the explanatory variable when the distribution is heterscedastic, highly skewed, or has non-random residuals, and thus is more robust to large outliers. For instance, mean regression analysis estimates the conditional mean of y_i given x_i in the following model: $E(y_i| x_i) = \beta_0 + \beta_1 x_i + \varepsilon_I$. Using a quantile regression, the potential differential effects of the independent variables are estimated at various quantiles of the conditional distribution and the regression predicts the median. A quantile regression follows the model: $Q^{(p)} (y_i|x_i) = \beta_0^{(p)} + \beta_1 x_i^{(p)} + \varepsilon^{(p)}_I$ where p is the proportion of the population with scores below the quantile at p (Hao & Naiman 2007).

method indicates if obesity affects wages more at lower paying jobs, where presumably more physical activity is required, or less at higher paying jobs, where other human capital, such as education, is more significant.

Most importantly, while the aforementioned literature finds obese workers earn less than those of normal weight, it also demonstrates the complexities in explaining the mechanisms through which obesity affects wages. While the incidence of cost-shifting health insurance premiums to individual wages has been studied among other groups, only Baum and Ford (2004) and Bhattacharya and Bundorf (2009) have investigated the incidence among obese workers in the U.S. labor market. Inevitably, given the increasing medical expenditure attributed to obesity (Finkelstein et al. 2003) and the rising health insurance costs (Fong & Franks 2008), these simultaneous trends will impact labor market outcomes. While the economic theory of labor economics predicts that costs of fringe benefits, like health insurance, are paid by workers through reduced wages, further research is needed to investigate if employers individually offset wages for specific, high-health risk workers to cover the incremental costs of health insurance.

III. Theoretical Framework

The literature on the obese wage differential provides evidence that obesity is an important determinant in estimating wages. While studies have attempted to explain why this wage differential occurs, the results are mixed on whether the differential is due to productivity differences, discrimination, or to cover higher health insurance costs. While my analysis accounts for the alternative explanations through adequate control variables, the aim of this paper is to investigate if the wage differential is due to the incremental costs of employing a high-health risk worker with EPHI. To understand if the existence of the wage penalty is due to EPHI requires understanding of the health insurance market and the theoretical framework of the wage-setting model with employer-provided benefits.

This framework is important for a number of reasons. As the health insurance market is currently structured, premiums are not adjusted to account for individual risk factors like obesity. Premiums, the monthly payments that reflect the costs of medical bills and cover expenses to manage the health insurance, are often community-rated among all individuals in the pool (Larson 2009). While some behavioral high-health risk factors, such as smoking, are adjusted through higher individual premiums,[15] the health risks associated with obesity are not. For instance, because obesity is not risk-rated to determine prices of health insurance premiums, it is estimated that obese-related excess healthcare expenditure is subsidized by the insurance pool, resulting in a negative externality. Bhattacharya & Sood (2005) estimate this negative externality to be $150 per capita in 1998 dollars. Under the assumption the obese wage penalty is a result of obese individual's higher healthcare expenditure, than presumably part of this negative externality is shifted to obese individuals through lower wages.

i. Wage-Setting Determination: Fringe Benefits

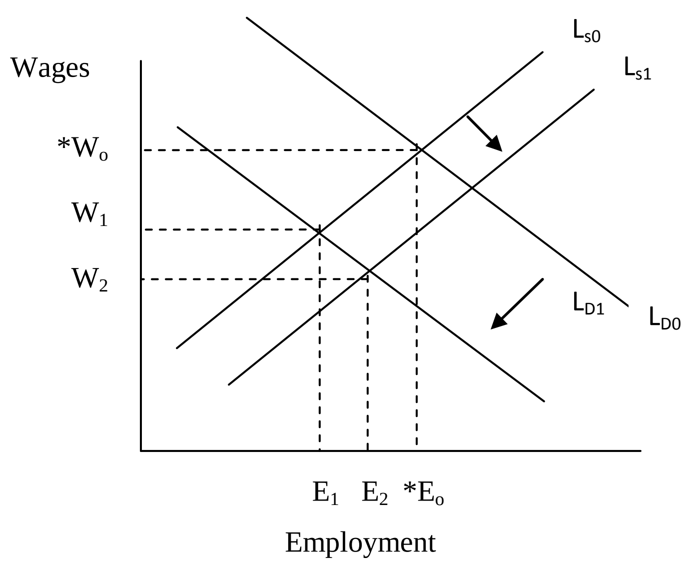
In the simplest model, wage-setting in a competitive labor markets is ultimately a transaction between two agents. Employers demand workers based on the workers' productive characteristics and hire workers as long as their marginal productivity does not exceed marginal cost. At the same time, workers supply labor based on preferences, opportunities, and worker choice in attempt to maximize utility (Rosen 1986). In competitive labor markets, wages are

[15] While most health insurance companies charge smokers higher health insurance premiums when individually insured, smokers then can avoid these higher rates by obtaining employer-provided health insurance. However, it is interesting to note that more private and public employers are requiring employees who smoke to pay higher premiums. Meijer Inc., American Financial Group Inc., PepsiCo Inc. and Northwest Airlines are among the companies already charging or planning to charge smokers higher premiums (Arbogast 2006).

determined when the labor supply of workers equals the labor demand of workers. Accordingly, the equilibrium wage rate W_o* is equal to the marginal revenue of product (MRP).

However, when employers offer fringe benefits like health insurance, the higher costs to provide this benefit are reflected in lower wages. The theoretical framework to examine the shifting of health insurance costs to wages draws on the seminal analysis of Summers (1989). Figure 1 illustrates Summers' (1989) analysis and shows how the offering of health insurance lowers wage levels. Primarily, equilibrium wages without EPHI are at W_0* where labor demand equals labor supply. When healthcare costs increase or employers decide to offer health insurance, the additional costs of providing this benefit will raise labor costs and shift the demand curve inward leading to lower wages (W_1) and lower employment (E_1). Summers assumes that because of the cost increase, workers value health insurance more and thus the labor supply shifts outwards leading to lower wages (W_2), but a higher employment level (E_2). The result of this increase in health insurance costs will thus be fully shifted to wages, resulting in the lower equilibrium wage rate (W_2).

Figure 1:



ii. Health Insurance and Community-Rating

Summers' (1989) analysis of the effects of EPHI on labor market outcomes demonstrates the important implication that rising healthcare costs lead to lower wages. The new equilibrium with lower wages due to the higher costs of EPHI assumes workers must value the obtainment of EPHI at its cost, or more. And while employers voluntarily offer health insurance, EPHI is currently the dominant source of health insurance coverage in the country.[16] One explanation for this is that EPHI provides large economies of scale due to community rating (Gruber 2000). With EPHI, each individual's unobservable health components are averaged among all employees and the group cost of health insurance is adjusted based on the pooled health status of all members of the firm. To determine wage compensation, employers pool the average premiums of all workers' health risks to equally reduce wage rates among all employees (Gruber 2000).

However, this structure of workplace pooling demonstrates labor market inefficiencies. Bhattacharya and Bundorf's (2009) analysis of the wage effects of obesity and EPHI illustrates that this structure is unsustainable when health insurance premiums do not reflect individual-risk factors like obesity. When employers pool insurance premiums, wages are reduced by the average cost of insuring each member of the firm, $\bar{P}$, where $\bar{P}$ is equal to the average medical expenditure of all employees. Thus, the wage for each employee is equal to:

$$W_i = MRP_i - \bar{P}$$

Conversely, if wages can freely adjust and employers and employees can negotiate over terms of the compensation package, then individuals who value health insurance more will be more willing to pay for the health benefits through lower wages (Summers 1989). In this case, if

[16] The 2008 estimate from the Kaiser Family Foundation show that 68% of adults receive health insurance through their employer. The remaining 10% have Medicare, 16% are uninsured, 4% are individually covered, and 2% have other public health coverage: http://www.statehealthfacts.org/comparetable

the wage offsets vary for each worker and employers reflect health insurance premiums on individual wage rates, then wages will be reduced by the exact cost of insuring each worker. In this case, each worker's individual health insurance premium, P_i, is equal to their medical expenditure. Thus, the wage for each employee is equal to:

$$W_i=MRP_i-P_i$$

This framework has important implications for both obese employees, given their presumably higher needs in medical care, and employers, given the higher costs of insuring an obese employee. Because obese individuals are aware of their health risks, obese workers may value jobs offering EPHI.[17] In this case, obese workers may chose employers with health insurance with the understanding that these jobs offer lower wages. For employers, the structure of workplace pooling among healthier employees leads to lower health insurance premiums. That is, employers could presumably pay higher wages if all employees are low-health risk and consequentially use less medical care. Because obesity is an observable health risk and is linked to higher medical expenditure, profit-maximizing employers may identify obese individuals as more costly to employ due to higher medical expenditure. As mentioned, while legal constraints, such as HIPPA, prohibit employers certain wage offsets, individual firms, for instance, could offset wages in other manners, such as during hiring placements or promotions (Cain 1986). In the case of promotions, the incidence of lower wages could be a result of slower wage growth, as Loh (1993) investigated, with wage offsets occurring overtime to cover the incremental costs of health insurance.

[17] This finding is consistent with the empirical analysis by Fong and Franks (2008).

IV. Data and Descriptive Statistics

To capture the most current trends in obesity and represent a new set of individuals compared to the majority of the aforementioned literature, this study uses only the most recent waves, 2005 and 2007, from the Panel Study of Income Dynamics (PSID). The PSID is representative dataset of U.S. households and focuses on the economic and demographic behaviors of both individuals and families in the U.S. from 1968 through 2007.

While the preliminary dataset includes over 24,000 observations, I restrict the data as specified by the literature to obtain the most unbiased results. The dataset is restricted to include only individuals who are currently working, work more than twenty hours a week, and employed by someone else in order to adequately account for the wage effects of weight. I further restrict the sample to include only individuals between the ages of 20 and 60. Observing this age group will reduce concerns in self-reported height and weight measurement error. According to Thomas and Frankenburg (2001), the difference between self-reported height and weight and true height and weight is relatively constant for this age range. Thomas and Frankenburg (2001) find that while women tend to report lower weights and men tend to report to be taller and heavier, there are minimal differences between the reported and the clinically-measured height and weight variables in this age group. After making these restrictions and omitting missing observations, the final sample consists of 11,296 individual observations.[18, 19]

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[18] Definitions of variables and summary statistics used in the regressions, separated by obese and non-obese respondents, are presented in *Table 1* of the Appendix. The histogram of the log of hourly wages is in the Appendix, *Graph 1*. The Data Appendix provides detailed definitions of all variables.

[19] The reduction of sample size from the original 24,476 observations is due to the following set of restrictions. A.) currently employed and employed by other: 17,353 remaining observations B.) Age 20 to 60: 16,345 remaining observations D.) Wage rate and BMI restrictions: 12,923 remaining observations E.) Miscellaneous missing data: 11,296 , of which 5,512 are men and 5,784 are women.

Variables of Interest

Our primary variables of interest are hourly wage rate, body mass index (BMI), and an indicator variable for whether the individual receives health insurance through their current employer. Hourly wage rate is based on the respondent's first-mention main job. If the respondent's main job is salaried, the hourly wage is computed as annual labor income divided by annual hours. All 2007 wage rates are adjusted to 2005 dollars. Following Cawley's (2004) and Bhattacharya and Bundorf's (2009) framework, I only observe individuals with hourly wage rates between $1 and $200. This will both correct errors in coding and restrict severe outliers. To account for obesity status, I convert the each respondent's self-reported height and weight to BMI. [20] I assign an indicator variable to account for all respondents who are classified as obese. For health insurance status, I assign an indicator variable if the respondent receives EPHI through their current employer. Based on the sample, 27.5% of the individuals are classified as obese, relatively equal among women and men. The average hourly wage rate for the obese individuals is $13.99 and the average for the non-obese individuals is $15.41. Furthermore, 78% of the sample receives EPHI, equal among the obese and non-obese individuals.[21]

Standard Variables

The control variables used are standard among labor economic studies. I include socioeconomic variables and family background characteristics. The control variables include age, age squared, gender, race, number of children in the household, an indicator variable for

[20] Body mass index is calculated as defined by the Center of Disease Control: BMI= $\frac{(wt.lbs)}{(ht.in)^2} * 703$. Obese is classified as those with BMI greater than or equal to 30.

[21] While 78% of the sample used in this regression receives employer-provided health insurance, only 68% of the original 24,000 receive employer-provided health insurance. This large proportion of individuals with employer-provided health insurance is most likely due to restricting observations to those who are only currently employed and not self-employed.

whether the children are under the age of six, marital status, union status, an indicator variable for if the respondent is salaried, health insurance status, region of residence, urban residency, mother's education, and father's education. To account for human capital accumulation, I include variables for the respondent's highest grade completed, years employed with their present employer, and years of full-time work experience. Based on our sample, the non-obese individuals have higher college graduation rates than the obese individuals, 35% and 23% respectively, and a higher proportion of salaried individuals, 41% and 32% respectively.

Occupational Variables

As mentioned in the literature review, controlling for occupational differences is important in order to control for occupation-specific wage premiums and possible selection biases into certain occupations. I include extensive control variables for nineteen industries, and nine occupations.[22] Based on the descriptive statistics, 32% of non-obese respondents have white-collar jobs, compared to 24% of the obese respondents.

Health Status Variables

Controlling for individuals health condition is crucial in this study. The lower wages for obese workers could reflect health status differences that result in lower marginal productivity. If the variables accounting for health status differences cause lower marginal productivity, then presumably the depressant wage effects will be captured in the health status variables. Also, the

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[22] The industry variables are agriculture/forestry/fishing, mining, utilities, manufacturing, construction, wholesale trade, retail trade, transportation/warehousing, information, finance and insurance, real estate/leasing, professional/scientific/ technical services, management/administration and support, educational services, healthcare/social assistance, arts/entertainment, food services/accommodation, other services, and public administration. The base variable indicating the respondent does not know his industry or it is not available
The occupational variables are officials and managers, professionals, technicians, sales workers, administrative support workers, craft workers, operatives, laborers and helpers, and service workers. The base variable indicating the respondent does not know their occupational code or it is not available. White collar jobs are classified as officials and managers or professionals.

inclusion of these variables will control for behavioral differences that affect wage rates. As specified by Baum and Ford (2004), the use of these supplemental background characteristics will limit the potential of unobserved heterogeneity. In this study, the health status variables include a physical limitation variable, indicating if the respondent has a physical limitation that limits their type or amount of work, and a health status variable, indicating how the respondent views their general health. Based on our sample, only 13% of the obese individuals indicate to be in excellent health, compared to 24% of the non-obese individuals. Furthermore, 10% of the obese individuals indicate to have a physical limitation, compared to 6.5% of the non-obese. Additionally, the dataset provides detailed information on obese-related chronic diseases such as heart disease, hypertension, asthma, and diabetes and whether these illnesses limit each respondent's daily activity. Parallel with the obesity research that increased weight is attributed to higher incidences of these diseases; based on our sample, the obese individuals are nearly twice as likely to have these chronic diseases.

V. Hypothesis and Empirical Model

i. Obese Wage Penalty

The analysis consists primarily of two parts. First, I focus specifically on the wage penalty to quantify the effects of weight on hourly wage rates. To estimate the wage effects of obesity, I apply the standard labor market equation as the past literature has specified. I estimate the coeffient β_2 using the model:

Model 1: $lnhourlywage_i = \beta_0 + \beta_1 X_i + \beta_2 obese_i + \varepsilon_{I,}$

Where $lnhourlywage_i$ is the natural log of hourly wage rate, $obese_i$ is an indicator variable for obesity, and X_i is a vector of wage-related variables to control for wage differentials. The estimated coefficient β_2 is interpreted as the percent increase or decrease in hourly wages when an individual is classified as obese.[23] The primary hypothesis is that β_2 will be negative, meaning that while holding all other wage-related variables constant, the estimated coefficient β_2 will indicate the magnitude of the obese wage penalty.

I use a quantile regression approach as demonstrated by Atella et al. (2008) to observe the effects of weight along the wage distribution. The application of the quantile regression will test whether the effects of obesity vary along the wage distribution. Unlike the mean regression approach which assumes each explanatory variable behaves in the same relation to the log hourly wages, the quantile approach examines the the effects of each explanatory variable at each specified quantile of hourly wage rates. I analyze if there are varying effects of obesity at the 10th, 25th, 50th, 75th and 90th percentiles of hourly wage rates.[24]

In both the quantile regression analysis and the mean regression analysis, I use the t-test to determine if this individual partial regression coeffiecient, β_2*obese*, has a significant influence on hourly wage rate determination. The null hypothesis states H_o: $\beta_2=0$, suggesting obesity to have no impact on wage rates, and the alternative hypothesis states H_1: $\beta_2 \neq 0$. Given the t-value of estimated coefficient β_2 in our model exceeds the critical t-value at the chosen level of significance, I can reject the null hypothesis and conclude obesity is a significant factor in hourly wage determination (Gujarati & Porter 2009).

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[23] Since the natural log of hourly wage is the dependent variable, percent changes in hourly wage rates can be obtained from $e^{\beta 2}$-1.

[24] For men, the median hourly wage rate at each percentile is $8.76 at the 10th percentile, $11.50 at the 25th percentile, $16.05 at the 50th percentile, $23.33 at the 75th percentile, and $34.00 at the 90th percentile. For women, the median hourly wage rate at each percentile is $7.46 at the 10th percentile, $9.42 at the 25th percentile, $13.26 at the 50th percentile, $19.00 at the 75th percentile, and $26.91 at the 90th percentile.

ii. *Effects of Employer-Provided Health Insurance*

Next, I expand the model to observe the wage effects of being obese and obtaining health insurance through a current employer. That is, given that obese are paid less, is it due to higher costs of EPHI? Following Baum and Ford's (2004) framework, I include an interaction variable for obesity and EPHI. In Model 2, the interaction variable, $ephi_i*obese_{i,}$ will capture the wage effects of obese individuals receiving EPHI. If the wage penalty is due to the increased costs of obese employee's higher health costs, then the t-value on the estimated coefficient on the interaction variable, $\beta_3 obese*ephi$, will be negative and significant. Furthermore, to analyze if there are varying effects of obesity and EPHI along the wage distribution, I again apply the quantile regression approach.

Model 2: $lnhourlywage_i = \beta_0 + \beta_1 X_i + \beta_2 obese_i + \beta_3 ephi_i*obese_i + \varepsilon_I$

To determine whether obesity and its interaction with EPHI have statistically significant influence on wage determination, I use an f-test to test the overall significance of including these variables in the model. To test whether these variables improve the goodness of fit, the null hypothesis states H_o: $\beta_2=\beta_3= 0$, suggesting the joint effect of each variable is simultaneously equal to zero; while the alternative hypothesis states both coefficients are not simultaneously equal to zero. If the joint effect has a systematic influence on the model, I can reject the null hypothesis and conclude that the variables improve the goodness of fit and are significant to include while estimating wage differentials (Gujarati & Porter 2009).

iii. *Further Observations*

As pointed out by Bhattacharya and Bundorf (2009), the incidence of the cost-shifting of health insurance to wages could differ depending on firm size. Because employers generally pool the average health expenditure among all employees in the workplace, smaller firms may have more incentive to individually offset wages. In other words, since larger firms have more workers to pool risk, one individual's higher medical expenditure will have minimal impact on the averaged premium, $\overline{P}$, as the firm size grows larger. That is, because larger firms have more employers to average health risk, individual wage offsets will be less significant and thus the wage penalty may exist only in smaller firms. To test the hypothesis that the wage penalty differs at firm sizes, I run separate regressions for those employed at firms with fifty or less employees and those with more than fifty employees.

Lastly, as mentioned in Section IV, legal constraints hinder employer's likelihood in shifting the costs of higher health insurance premiums to obese employees' wages. However, the wage offsets could occur through other mechanisms, such as promotional differences, that arise over time. To investigate if the obese wage penalty is a result of employers incrementally offsetting the higher costs of health insurance, I observe the differences in the interaction variable depending on the number of years each respondent has been employed with their current employer. If this is the case, presumably the wage offset will be greater for those employed longer with their current employer. I run separate regressions for individuals employed with their current employer for more than five years, to those employed with their current employer for five or less years. While this method will not directly account for the ways in which employers lower wages, it will provide further insight on the cost-shifting mechanisms.[25]

[25] Ideally, to better test this hypothesis, I would observe only obese and non-obese workers employed with the same employer. Observing the wage level differences between obese workers and non-obese workers in the same firm for the same amount of time would provide a better explanation for if the wage offset is due to employers incrementally offsetting wages to cover higher medical premiums associated to obesity.

VI. Estimation and Results

Using multiple regression analysis requires various assumptions to be met for unbiased estimates. As mentioned in the literature review, there are concerns that weight is an endogenous variable and there may be unobservable factors that affect wages and weight. Factors, such as motivation and self-discipline, could have simultaneous effects on weight and wages (Cutler et al. 2003). While our health status variables are included to account for some of these behavioral differences, without adequately controlling for all unobservable factors, there may be correlation between the error term and the obesity variable. Thus heteroscedasticity may be present. If heteroscedasticity is present, the estimators will no longer be minimum variance or efficient. To test for heteroscedasticity in the model, I run a preliminary regression, pooled with both males and females, and observe the scatter plot of estimated squared residuals and the predicted log hourly wages. The data exhibits a non-constant variance in the error term.[26] To confirm the presence of heteroscedasticity, I use Stata to perform the Breusch-Pagan-Godfrey test.[27] The obtained p-value is zero. This suggests rejecting the null hypothesis that there is no heteroscedasticity at the 1% level.

Furthermore, normality of the residuals is an underlying assumption in regression analysis. To test if the residuals are normally distributed, I use the same preliminary regression and the estimated residuals. The scatter plot illustrates some non-normality in the error term. While the normal probability plot illustrates the errors terms are normally distributed about the mean, the normal quantile plot shows signs of outliers. I precede using Huber-White adjusted

[26] To test for heteroscedasticity I include the standard covariates, health status variables, and occupational and industry controls. The variables and estimated coefficients used in this model are in the Appendix, *Regression 1: Pooled Regression*. Based on this preliminary regression, obesity is significant at the 99% level of significance indicating a 2.1% decrease in hourly wages.

[27] Using the Stata command "estat hettest," the obtained chi-squared value is large and the p-value is zero, indicating to reject the null hypothesis that there is no heteroscedasticity at the 99% level of significance (Chen et al 2003).

robust standard errors for the ordinary mean regressions.[28] Using the robust option will generate consistent standard errors, even when the data is not normally distributed or homoscedastic (Yafee 2002). Furthermore, it should be noted that because the data is heterscedastic and the error terms are not normally distributed, using a quantile regression will account for each of these concerns. The quantile regression approach predicts coefficients based on the median (Yafee 2002). Thus, when outliers are present and the residuals not normally distributed, a quantile regression is an efficient approach to estimate the effects of weight on wages.[29]

The past literature found weight to have differing effects on wages based on gender. To formally test if specifying models separately by gender is significant, rather than pooling all individuals, I conduct the Chow test. The Chow test specifies if there are significant differences between the pooled regression and regressions separated by gender. In other words, if the hourly wage determinants are essentially the same for both men and women, then the sum of the residual sum of squares from the women's and men's regressions will not be significantly different from residual sum of squares from the pooled regression (Gujarati & Porter 2009). After conducting the Chow test, the calculated f-statistic is 9.25. At the 99% level of significance, I reject the null hypothesis that there is no difference between genders. I precede specifying models separately by gender.[30] Furthermore, as the past literature has demonstrated,

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[28] Because the residuals do not appear to be normally distributed, I also perform the White test to verify heteroscedasticity. Using this test does not rely on the normality of the residuals. While the White test requires the squared residuals to be regressed on the cross products of the explanatory variables, I use the modified test because of the large amount of variables in our regression. Following the modified version, $\hat{u}^2_i=\beta_0 + \beta_1 \textit{predictedhourlywage} + \beta_2 \textit{predictedhourlywage}^2+\varepsilon_I$, the results again support rejecting the null hypothesis that there is no heteroscedasticity, the critical chi-squared value at the 99% level of significance exceeds the obtained chi-squared value from $n*R^2$ (Gujarati & Porter 2009).

[29] When using quantile regression in Stata, standard errors are computed as robust.

[30] The Chow test procedure requires calculating an f-statistic based on three separate regressions: A regression for male individuals only, regression for female individuals only, and a pooled regression with both genders. The maintained assumption in the test is that the error terms are normally distributed, have the same variance, and each error term is normally distributed. The f-statistic = $(RSS_{pool} - (RSS_{males}+RSS_{females}))/k)/((RSS_{males}+RSS_{females})/(n_{males+}n_{females}-2k))$. From the regressions, RSS_{males} =738.1, $RSS_{females}$= 717.0, RSS_{pool}= 1511, k=47, n_{males}= 5512, $n_{females}$= 5784. Thus, the computed f-value is 9.25. The critical F-value at the 99% level of significance is

the wage effects of weight are generally different depending on gender, with greater influence on women's wages.

i. *Model Specification*

I follow the model specification procedure used by Atella et al. (2008) to evaluate the robustness of the estimated coefficients due to possible endogenous variables. Following this model specification requires incrementally including supplemental variables, those accounting for health status differences and occupational differences, to observe changes in the obesity coefficient and determine a proper model. In the following this procedure, I estimate β_2 with Model 1, $lnhourlywage_i = \beta_0 + \beta_1 X_i + \beta_2 obese_i + \varepsilon_I$. Model 1.a, the reference model, includes only the standard variables in the vector X_i. We can interpret the estimated coefficient β_2 in this model as the effect of obesity on wages that could occur through omitted unobservable variables. Model 1.b then adds only the variables for health status and physical limitation, and Model 1.c. then adds only occupational and industry variables. Finally, Model 1.d includes all variables.[31]

ii. *Obese Wage Penalty Results*

Women

Table 2 presents the estimated obese coefficient in each of the specified models for women. The reference model suggests the largest wage penalty of 5.1%. However, while in each model obesity has a negative effect on wage levels and is significant at the 99% level of significance, it is clear the inclusion of additional variables changes the magnitude of the wage

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f(47,10000)=1.59. Because the calculated f-statistic exceeds the critical f-value at the 99% level of significant, I reject the null hypothesis that there is no significant difference between the two genders (Gujarati & Porter 2009).

[31] The list of the preliminary variables included in each model is listed in the Appendix, *Model Specification*. Full tables for all estimated coefficients included in Models 1.d are in the Appendix; *Regression 2: Women Model 1.d Results* and *Regression 3: Men Model 1.d Results*.

differential. The addition of the occupational variables shows relatively no differences from the reference model, suggesting that the aforementioned selection-effect of obese individuals into certain occupations is not worrisome. Conversely, the inclusion of the health status variables decreases the magnitude of the wage effects of obesity by 2%. While the effects of obesity are still significant at the 99% level of significance, this suggests part of the depressant effect of obesity on wages is absorbed by differences in health factors. When controlling all variables, obesity has a significant depressant effect on women's wages.[32] The t-statistic of 3.06, and p-value of 0.002, implies rejecting the null hypothesis at the 99% level of significance. Accordingly, the results show a significant obese wage penalty for women; wages for obese women are 3.2% less than those of non-obese women.

Table 2	OLS Estimates of the Effect of Obesity on Women's Wages Dependent Variable: Log Hourly Wage No. of Observations: 5784			
	Model 1.a (Reference)	**Model 1.b (Health)**	**Model 1.c (Occupation)**	**Model 1.d (All)**
Obese Coefficient β_2	-.051*** (.011)	-.031*** (.011)	-.051*** (.011)	-.032*** (.011)
R-Squared Value	.429	.435	.547	.551

Note: All estimates are adjusted for heteroscedasticity with robust standard errors. Robust standard errors are shown in parenthesis. * Indicates significant at 10%, ** significant at 5%, and *** significant at 1%. Full table of all estimated coefficients from Model 1.d is in the Appendix, *Regression 2: Women Model 1.d Results*.

Men

Following the same procedure, the model specification results for men show the estimated effect of obesity on wages becomes less significant as more control variables are included. Table 3 presents the results. While obesity consistently has a negative effect on wages, the effect is not significant at the 90% level of significance in the final model. The

[32] In following this procedure I omitted variables that did not improve the goodness of fit. I tested the overall significance of the regression using the f-test under the null hypothesis that the slope coefficients of possible omitted variables are simultaneously equal to zero. For women, I omitted the following variables from each model. *Fatherhs*, *ne*, *nevermarried*, *mothercollege*, and *west* were omitted from the standard covariates, and *retailtrade*, *technicians*, *arts*, *otherservices*, *agricultural* and *officialsandmanagers* were omitted from the occupational model. The final list of variables is presented in the Appendix, *Regression 2: Women Model 1.d Results*.

addition of health status variables and the occupational variables both reduce the magnitude of the obese wage differential by about 2%, again suggesting the effects of obesity are absorbed by the inclusion of other variables. In the final model, the results indicate there is no significant obese wage penalty for men.[33] At the 90% level of significance, the t-statistic of 1.33 suggests accepting the null hypothesis that obesity does not have a significant influence on determining men's wage rates.

Table 3	OLS Estimates of the Effect of Obesity on Men's Wages Dependent Variable: Log Hourly Wage No. of Observations: 5512			
	Model 1.a (Reference)	**Model 1.b (Health)**	**Model 1.c (Occupation)**	**Model 1.d (All)**
Obese Coefficient β_2	-.036*** (.012)	-.023** (.012)	-.025** (.011)	-.014 (.010)
R-Squared Value	.417	.415	.541	.544

Note: All estimates are adjusted for heteroscedasticity with robust standard errors. Robust standard errors are shown in parenthesis. *Indicates significant at 10%, ** significant at 5%, and *** significant at 1%. Full table of all estimated coefficients from Model 1.d is in the Appendix, *Regression 3: Men Model 1.d Results*.

This model specification demonstrates that controlling for a more inclusive vector of control variables X_i affects inferences about the magnitude in which obesity depresses wages. The differences in magnitude in the obese wage penalty, particularly between the reference model and the model controlling for health status, suggests health status differences carry some of the depressant effects of obesity on wages. For both men and women, I precede with Model 1.d for the quantile regressions and interaction effects with EPHI. Overall, each model performs well for both men and women. Each model is adjusted for heterskedasticity with robust standard errors, tests for multicollinearity imply accepting the null hypothesis that there is no

[33] I followed the same procedure to omit variables that did not improve the goodness of fit. For men, I omitted the following variables from each model. *Motherhs*, *married*, *ne*, *mothercollege*, and *fathercollege* were omitted from the standard covariates, and *retailtrade*, *management*, *arts*, *craftworker*, and *technicians* were omitted from the occupational model. The final list of variables is presented in the Appendix, *Regression 3: Men Model 1.d Results*.

multicollinearity,[34] and the estimated coefficients for the control variables have wage effects as predicted, which are statistically significant by conventional standards.[35] Moreover, while the residuals obtained from each regression appear to be normally distributed (by examining histograms and scatter plots), the Jacque-Bera statistic rejects the null hypothesis that the error term terms are normally distributed. However, given the large sample size of over 5,500 observations in each regression and no severe outliers, I proceed with each specified model.[36] Even without the normality assumption, mean regression estimates are still the best linear unbiased estimated under the Gauss-Markov assumptions (Gujarati &Porter 2009). Furthermore, the f-statistic for both the men's and women's model is significant at 99% level of significance and the model is robust to the inclusion of specified variables.[37]

Using Models 1.d, I also investigate if the wage penalty increases at higher BMI levels. Following Cawley's (2004) framework, I substitute an indicator variable for morbid obesity, those with BMI greater than 35, in place of the obesity variable in both models. However, the effects of being morbidly obese have slightly lower depressant wage effects than being obese. For women, morbid obesity is significant at the 95% level of significance and indicates a wage

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[34] To test for multicollinearity, I use the Stata command, vif, variable inflation factor. The results suggest no severe multicollinearity in each model as each vif is less than 10 (Chen et al 2003).

[35]While some of the included variables are not significant at the 90% level of significance, I chose to include them because they are included in the majority of the past literature. *White*, for instance, did not come up significant in both regressions. This could be because a large proportion (66%) of our observed waves of the PSID indicates to be white, and thus there are a small number of minority respondents. *Age, highestgrade, inunion, salaried,* and *yrspresemployer* are all significant at the 99% level of significance. However, the results suggest *fulltimeexp* is only significant for men. It is also interesting to note that *ephi* is also highly significant and implies a wage premium of 15% to 18% for women and men respectively. While labor economic theory predicts wages to decrease in jobs offering employer-provided health insurance, our data suggests jobs with health insurance offer higher wages. This finding is consistent with Baum and Ford's (2004) results. Baum and Ford (2004) suggest this wage premium is due to worker value where valuable workers receive fringe benefits and higher wages.

[36] I use Stata to perform the Jacque-Bera test using the residuals from each regression the command, sktest. Also using Stata, I observe outliers in each regression using the command, iqr. Observing each continuous variable, there are no extreme outliers (Chen et al. 2003).

[37] For instance, I also try each regression by including more robust health status variables, such as variables accounting for obese-related diseases and whether these diseases limit each respondent's amount or type of work. However, the inclusion of these variables does not impact the obesity variable.

penalty of 2.6%. For men, the effect of increased weight on wages is again insignificant. I also run the regression with the continuous variable BMI in place of the obesity indicator variables. Again, for women only, increased weight is associated with lower wages. The estimated coefficient on BMI is negative and significant the 95% level of significance. The coefficient for the continuous variable BMI is -0.002 and is interpreted as a .2% decrease in hourly wages for a one point increase in BMI.

Obese Wage Penalty: Quantile Regression

To observe if the effects of obesity change depending on hourly wage rates, I use the use the same variables in Model 1.d, but observe the effects of obesity along the wage distribution.[38] Table 4 presents the results for women.   While obesity is consistently significant at the 90% level of significance at higher wage rates, it is statistically insignificant only at the lowest paying jobs. The results show the effects of obesity have the greatest wage penalty at the 75th percentile and exceed the wage penalty of obesity using mean regression analysis (4.3% vs. 3.2%). Table 5 shows the estimated obesity coefficient at each quantile for men. While the results from the mean regression suggest an insignificant obese wage penalty, the quantile regression uncovers a wage penalty at the 50th, 75th, and 90th percentiles.   The t-statistics suggest obesity to be most significant in the central part of the wage distribution, significant at the 99% level of significance, resulting in a 3.4% wage penalty. Obesity continues to be a significant factor at higher wage rates, although the magnitude of the penalty decreases.

[38] I employ the quantile regression approach using the Stata command, sqreg. This regression command estimates a bootstrapped variance-covariance matrix of the estimators that includes between-quantiles blocks. In other words, it coefficients are estimated by minimizing the absolute deviations from the median, rather than mean. (Chen et al. 2003)

Table 4	Quantile Regression Estimates of the Effect of Obesity on Women's Wages Dependent Variable: Log Hourly Wage No. of Observations: 5784				
	10th	**25th**	**50th**	**75th**	**90th**
Obese Coefficient β_2	-.021 (.016)	-.025** (.013)	-.030*** (.010)	-.043*** (.012)	-.032** (.015)
Constant	1.12	1.33	1.37	1.41	1.42
R-Squared Value	.303	.328	.363	.383	.383

Table 5	Quantile Regression Estimates of the Effect of Obesity on Men's Wages Dependent Variable: Log Hourly Wage No. of Observations: 5512				
	10th	**25th**	**50th**	**75th**	**90th**
Obese Coefficient β_2	.00 (.017)	.00 (.010)	-.034*** (.010)	-.026** (.013)	-.031** (.014)
Constant	.84	1.20	1.41	1.49	1.37
R-Squared Value	.271	.323	.364	.396	.407

Note: In Table 4 and Table 5 all estimates are adjusted with robust standard errors. Robust standard errors are shown in parenthesis. *Indicates significant at 10%, ** significant at 5%, and *** significant at 1%. Full table of all estimated coefficients from the quantile regressions are in the Appendix, *Quantile Regression 1: Women Results* and *Quantile Regression 2: Men Results.*

Moreover, the quantile regressions provide additional noteworthy results on other explanatory variables affecting wage levels. For female workers, while obesity is not significant at the lowest paying jobs, the variable for physical limitation is significant only at this quantile of hourly wage rates, indicating a 5% decrease in wages. Likewise, for men, while the physical limitation variable is consistently significant at the 90% level of significance, the results indicate decreasing effects as wage rates increase. In any case, the standard control variables appear to be consistent along the wage distribution for both men and women and not to differ significantly from the mean regression results. The control variables, age, highest grade, in union, salaried, number of years with present employer, and health status, are all significant at the 99% level of significance along the distribution.

iii. Employer-Provided Health Insurance Results

I expand Model 1.d to include the interaction between EPHI and obesity. Model 2 includes the same vector of control variables, X_i, from Models 1.d, but includes the interaction variable $\beta_3 ephi_{i*}obesity_i$. Table 6 shows the estimated coefficients from Model 2 with the Model 1.d results for reference. For women, the mean regression results show the interaction variable to be significant at the 90% level of significance, indicating obese women with EPHI receive a wage penalty of 4.7%. Furthermore, the estimated coefficient on obesity is no longer significant, strengthening our finding that obese women with EPHI are penalized through reduced wages compared to obese women without EPHI. For men, the results are insignificant. The interaction variable indicates to have no effect on the model proposing any depressant wage effects of obesity is not explained by higher costs of health insurance. In any case, I employ a quantile regression to the model to observe if the effects of obesity and EPHI have varying effects along the wage distribution. For women, obesity and the interaction variable are at not significant at the 90% level of significance along the wage distribution. For men, again, obesity and the interaction variable are insignificant at all wage rates.

Table 6	Model 2: OLS Estimates with Interaction Variable Dependent Variable: Log Hourly Wage			
	Women		**Men**	
	Model 1.d	**Model 2**	**Model 1.d**	**Model 2**
Obese Coefficient β_2	-.032*** (.011)	0.00 (.02)	-.014 (.01)	-.011 (.02)
EPHI*Obese β_3	-	-.047* (.03)	-	.00 (.03)
EPHI Coefficient β_4	.15*** (.01)	.15*** (.02)	.18*** (.01)	.18*** (.02)
Constant	1.26	1.26	1.21	1.21
R-Squared Value	.551	.551	.544	.544
No. of Observations	5784	5784	5512	5512

Note: In Table 6 all estimates are adjusted for heteroscedasticity with robust standard errors. Robust standard errors are shown in parenthesis.* Indicates significant at 10%, ** significant at 5%, and *** significant at 1%. Full table of all estimated coefficients from the regression with the interaction variables are in the Appendix, *Regression 4: Women Interaction Results* and *Regression 5: Men Interaction Results.*

To determine the joint effect of *obese* and *ephi**obese* in Model 2, I conduct an f-test to test the overall significance of our model of hourly wage determinants. I test the overall significance of the obesity variable and the interaction variable under the null hypothesis that each coefficient simultaneously equals zero. For women, the computed f-value is f(2, 5739)= 6.88 with a p-value of 0.1%. Given these results, I reject the null hypothesis and conclude that collectively controlling for obese women and obese women receiving EPHI has a significant impact on our model of hourly wage determinants. This test indicates the inclusion of these variables increases the explanatory power in determining women's wages. The results for men are, unsurprisingly, insignificant. The computed f-value is f(2, 5465) = 0.89 with a p-value of 41%. I thus do not reject the null hypothesis and conclude that collectively including obese men and obese men receiving EPHI do not have a significant impact in estimated hourly wage rates. In other words, excluding these variables from the model of hourly wage determination increases the model's explanatory power. Accordingly, obesity and its interaction with EPHI should not be included while estimating men's hourly wage rates.

iv. Further Observations

Firm Sizes

As mentioned in Section V, the effects of EPHI presumably vary depending on firm size. Because larger firms have more workers, individual workers with higher medical expenditure will have a smaller influence on the averaged premium, $\bar{P}$, and thus there is less incentive for employers to individually offset wages. Running separate regressions for those employed at small and large firms, the estimated coefficients of the obesity variable and the interaction variable are presented in the Appendix, *Table 7: Firm Size Regression Results.* For women, while the interaction term is negative among both large and small firms; it is only statistically significant at the 90% level of significance in smaller firms, indicating a 6.7% wage penalty. Unlike the results from the Bhattacharya and Bundorf's (2009) analysis that suggest the existence of this wage offset in both small and large firms, our results provide evidence for the group incidence of cost-shifting. Because the wage offset is not present in large firms lends support that the incremental costs of health insurance are charged on all workers wages at the firm. In other words, our results provide evidence that because higher-health risk individuals have more influence on the pooled premiums in small firms, the higher costs associated to insure an obese worker is only shifted to obese workers' wages in small firms. Again, for men, firm size does not make a systematic difference on the interaction variable. The coefficient remains insignificant among both small and large firms.

Years with Present Employer

Similarly, the mechanisms through which the obese wage differentials arise could also vary depending on how long a worker has been employed with their current employer. To investigate if employers slow obese workers' wage growth over time to cover higher costs of health insurance, I observe differences in the interaction variable among individuals working with their employer for five or less years, to those for more than five years. The results are presented in the Appendix, *Table 8*: *Years with Present Employer Regression Results.* Again, the results for men remain insignificant. However, the results for women support this theoretical framework. For women employed with her present employer for more than five years, the estimated coefficient on the interaction variable β_3 indicates that obese women with EPHI receive a wage penalty of 9.9% and again is significant at the 90% level of significance.[39]

VII. Conclusion and Future Research

Using the most recent data from the 2005 and 2007 waves of the PSID, this study fills in gaps of the existing literature on the wage effects of obesity and the incidence of EPHI costs. While the previous studies on the obese wage penalty have consistently found depressant effects of obesity on wage levels, they have yet to observe only the most recent data to capture the growing prevalence of obesity in the labor force and observe the heterogeneous effects of weight along the wage distribution.

Consistent with the past research, our results suggest the obese wage penalty to differ significantly depending on gender. Given our model specification, the mean regression results suggest obesity only to be significant in women's wage rate determination. Whereas for men, our results indicate increased weight has no significant influence on hourly wages, even when observing the morbid obese individuals. Although we recognize our data does not perfectly satisfy the mean regression assumptions, presumably the large sample size is robust enough to capture these imperfections. Furthermore, the extent to which our estimates measure the direct depressant effects of obesity on wage levels depends on the reliability of our control variables. As mentioned, a common concern while estimating the wage effects of obesity is accounting for unobservable factors that simultaneously affect weight and wages and address reverse causality. In our case, the inclusion of health status variables presumably captures productivity differences that ultimately lead to lower wages. If, however, our health status variables do not capture lower

[39] It should be noted that when investigating the interaction effects depending on firm size and years with present employer, the number of observations decreases by about half in each of the regressions. Thus, the results may be biased due to a smaller sample size.

marginal productivity associated with lower wages, then our results would be biased. Likewise, while the extensive industry and occupational variables are to capture the job-specific wage premiums, these variables do not directly account for obese workers self-selecting into certain jobs. To improve upon our estimation method, ideally we would like to include more variables sensitive to behavioral differences to control for both obesity causing lower wages and lower wages causing obesity.[40]

In any case, the empirical evidence in this study suggests the obese wage penalties have decreasing depressant effects on wages as compared to the results from the past research. Presumably, given the increasing obesity rates in the U.S., employers now have less flexibility to reduce obese workers' wages. Whether the incidence of the obese wage penalty is due to productivity differences, customer or employer discrimination, or higher healthcare expenditure, the larger proportion of obese workers in the U.S. workforce proposes decreasing wage effects associated with obesity. Future research should more adequately control for the changes in the obese wage penalties over the past decades to determine if the bias against weight is decreasing.

Moreover, this study advances research on the wage effects of obesity by employing a quantile regression approach. Until now, the existing studies on the wage effects of obesity have only employed a mean regression approach to estimate the wage differential. For both men and women, our results suggest obesity to have significantly larger effects on wages at higher paying jobs. Perhaps, this is due to minimum wage laws that constrain employers from further reducing wages. Nevertheless, according to the comparative results from European study by Atella et al.

[40] For instance, as in Averett and Korenman's (1996) study, includes a self-esteem variable to account for personal attitudes and aspirations. To measure self-esteem, Averett and Korenman (1996) use a question from the NLSY that measures self-esteem based on the Rosenberg self-esteem scale; an index of ten statements to reflect and quantify respondent's beliefs about themselves. This is based on the assumption that individuals with lower self-esteem are more likely to have lower wages.

(2008), they also do not find a definitive explanation for the heterogeneous effects of weight at various wage rates.

Moreover, while past studies have proposed alternative explanations for the existence of the obese wage penalty, less have focused specifically on the impacts of EPHI. Our results lend support that the association between obesity and lower wages for women is concentrated in jobs providing health insurance. However, concerns still remain. As mentioned, our study is not able to control for the mechanisms in which this negative association arises. The negative association could be demand-side driven, due to obese workers self-selecting into lower wage jobs offering health insurance, or supply-side driven, due to employers incrementally offsetting wages to cover the higher health insurance costs. Still, our investigations depending on firm size and the number of years with her present employer provide further insight. The data suggests women's obese wage penalty is significant only for those employed in smaller firms and employed longer with her current employer.

While this study provides evidence that there are depressant effects on wages for obese women receiving EPHI, we need to realize this explanation for lower wages is not exclusive. That is, while we do find evidence that women's obese wage penalty is concentrated in jobs with health insurance, there is no reason to exclude employer-discrimination as an explanation for the wage differential as well. Ideally, to better control if the wage offset is driven exclusively by higher health insurance costs, further research should explore the direct association only between obese workers with higher medical expenditure and wages. While obesity is attributed to higher healthcare, presumably not all obese individuals spend more on medical care. In this case, the incidence of lower wages for obese workers not spending more on healthcare should not be penalized through reduced wages. If, however, lower wages for these obese workers are present, then we can assume other explanations, such as employer-discrimination.

VIII. Policy Implications

This research provides suggestive, but not conclusive, policy implications regarding the current structure of the health insurance market. Given health insurance premiums do not adjust for individual weight (Bhattacharya & Sood 2005) and obese individuals spend 36% more on annual medical expenditure than non-obese individuals (Sturm 2002), the incremental costs of obesity are charged on all individuals in the community-rated pool. In regards to the labor market, profit-maximizing employers offering health insurance are left with minimal options to adjust the increasing costs of health insurance and higher rates of obesity. As we have studied, employers can offset wages for these high-health risk workers to cover the associated increased costs. However, as we have found, the cost-shifting of health insurance is present only among women and is concentrated in small firms. In other cases, for men for instance, our results suggest the incremental medical expenditure is not individually-adjusted. Accordingly, the higher associated health costs are born on all workers' wages. Alternatively, another option is for employers to incorporate health promotion programs to reduce higher health insurance premiums. The promotion of healthy lifestyles within the workplace is associated with lower medical costs. For instance, growing numbers of employers have adopted health promotion programs to decrease the costs of insurance premiums (Anderson et al. 2009).[41]

[41] There are a number of ways employers can implement health promotion programs into the workplace. Jesson (2008) reviews different approaches currently used by U.S. employers to decrease health insurance costs while also obeying legal constraints such as the Health Insurance Portability and Accountability Act of 1996 (HIPPA) . While a detailed description is beyond the scope of this paper, it is worth noting that there are exceptions to HIPPA's nondiscrimination rules prohibiting different cost-sharing arrangements based on individual health factors. Employer adopting wellness programs meeting certain criteria can vary benefits depending on health factors. For example, some employers offer monetary rewards for employees with a BMI between 19 and 26. However, for any

In any case, the results of this paper, and those of past studies on the obese wage penalty, have consistently found an adverse relationship between obesity and wages. No matter the explanation for the obese wage penalty, it posits the need of discrimination laws to protect obese workers from labor market discrimination. While the Equal Pay Act of 1963 and Civil Rights Acts of 1964 prohibit employers from racial discrimination in any employment-related opportunities,[42] there are no national laws protecting obese individuals from comparable discriminatory outcomes.[43] Currently, Michigan is the only state with a law prohibiting weight discrimination (Puhl 2008). In response to the consistent finding of a negative association between obesity and wages, public policy research should consider the inclusion of obese individuals in discrimination laws.

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employee who is not medically advised to meet this BMI qualification, other options must be offered to obtain the monetary reward. Jesson's (2008) article provides further detail on employer wellness programs.

[42] United States Department of Labor website provides full and amended versions of these laws: http://www.dol.gov/index.htm

[43] The results from Puhl's (2008) study on the perceptions of weight discrimination are parallel to the findings on the obese wage penalty. Puhl finds women to be more vulnerable to weight and height discrimination than men. However, for both genders, she finds weight and height discrimination in employment settings to be comparable to the prevalence of racial discrimination.

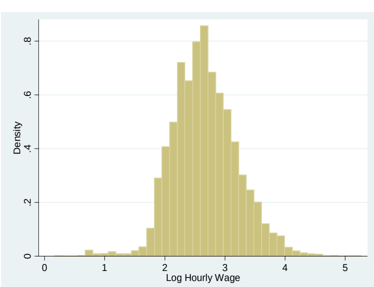
Appendix:

Table 1: Definitions and Summary Statistics of Variables Used in Regressions

			Full-Sample				Non-obese	Obese
		Definition of Variable	Mean	Min	Max	Std Dev.	Mean	Mean
Variables of Interest								
obese	=	1 if BMI greater than 30	.27	0	1	.44	0	1
hourlywage	=	Hourly wage rate	15.00	1.18	193.78	11.6	15.41	13.99
lnhourlywage	=	Natural log hourly wage rate	2.71	.169	5.27	.545	2.73	2.64
ephi	=	1 if receives employer-provided health insurance	0.78	0	1	.41	0.79	0.78
Standard Covariates								
Age	=	Age in years	39.2	20	60	10.8	38.9	40.2
sex	=	1 if male	0.49	0	1	.50	0.48	0.50
white	=	1 if white	0.66	0	1	.47	0.69	0.56
black	=	1 if black	0.29	0	1	.45	0.25	0.40
numchildren	=	The number of children in the household	0.99	0	7	1.16	0.96	1.08
haschildunder6	=	1 if has a child in the household under that age of six	0.27	0	1	.45	0.27	0.28
ne	=	1 if resides in a state in the northeast	0.14	0	1	.34	0.14	0.12
nc	=	1 if resides in a state in the north central	0.26	0	1	.44	0.27	0.24
south	=	1 if resides in a state in the south	0.41	0	1	.49	0.39	0.47
west	=	1 if resides in a state in the west	0.18	0	1	.39	0.19	0.16
urban	=	1 if lives in urban area	0.53	0	1	.50	0.54	0.52
married	=	1 if lives in urban area	0.64	0	1	.48	0.65	0.62
nevermarried	=	1 if lives in urban area	0.21	0	1	.41	0.21	0.21
yrspresemployer	=	The number of years with present employer	7.54	0	40	8.0	7.38	7.96
inunion	=	1 if belongs in union	0.15	0	1	.36	0.14	0.16
fulltimeexp	=	Years of full-time work experience	9.12	0	40	7.8	8.86	9.78
salaried	=	1 if current main job is salaried	0.39	0	1	.48	0.41	0.32
highestgrade	=	The highest grade completed: 1-16 is highest grade, 17 is at least some post graduate work	13.40	0	17	2.3	13.53	13.05
fatherhs	=	1 if father completed high school	0.32	0	1	.46	0.32	0.31
motherhs	=	1 if mother completed high school	0.39	0	1	.48	0.39	0.37
fathercollege	=	1 if father completed college	0.10	0	1	.30	0.11	0.07
mothercollege		1 if mother completed college	0.09	0	1	.28	0.10	0.07
Health Status Variables								
healthstatus	=	Health status rating : 5 indicates poor, 4 fair, 3 good, 2 very good, 1 excellent	2.23	1	5	.93	2.11	2.56
physlimit	=	1 if has physical or nervous condition that limits type of work or amount work	0.07	0	1	.25	0.06	0.10
Occupational Variable								
whitecollar	=	1 if classified as an official and manager, or professional	0.30	0	1	.45	0.32	0.24

* The full list of occupational variables and industry variables is not listed. Summary means for these variables are found in my data appendix.

Graph 1: Histogram of Log Hourly Wages



Regression 1: Mean Regression Pooled with Males and Females
Dependent Variable: Log Hourly Wage

lnhourlywage	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
obese	-0.021***	0.008	-2.600	0.009	-0.036	-0.005
age	0.03***	0.00	11.36	0.00	0.03	0.04
agesqu	0.00***	0.00	-9.10	0.00	0.00	0.00
sex	0.12***	0.01	14.86	0.00	0.11	0.14
numchildren	0.01*	0.00	1.70	0.09	0.00	0.01
haschildunder6	0.05***	0.01	4.90	0.00	0.03	0.07
nc	-0.10***	0.01	-9.04	0.00	-0.13	-0.08
south	-0.11***	0.01	-9.64	0.00	-0.13	-0.09
west	-0.03***	0.01	-2.74	0.01	-0.06	-0.01
married	0.02***	0.01	2.72	0.01	0.01	0.04
salaried	0.12***	0.01	12.68	0.00	0.10	0.14
yrspresemployer	0.01***	0.00	19.56	0.00	0.01	0.01
ephi	0.16***	0.01	16.49	0.00	0.14	0.18
inunion	0.13***	0.01	12.48	0.00	0.11	0.16
urban	0.05***	0.01	7.42	0.00	0.04	0.07
highestgrade	0.05***	0.00	23.81	0.00	0.04	0.05
fulltimeexp	0.00*	0.00	-1.80	0.07	0.00	0.00
white	0.00	0.02	-0.22	0.82	-0.04	0.03
black	-0.07***	0.02	-3.96	0.00	-0.10	-0.04
fatherhs	0.01	0.01	0.93	0.35	-0.01	0.02
fathercollege	0.05***	0.01	3.90	0.00	0.02	0.07
motherhs	0.01	0.01	1.32	0.19	-0.01	0.03
mothercollege	0.02*	0.01	1.64	0.10	0.00	0.05
physlimit	-0.05***	0.01	-3.80	0.00	-0.08	-0.03
healthstatus	-0.03***	0.00	-7.72	0.00	-0.04	-0.02
officmanags	0.28***	0.01	22.48	0.00	0.26	0.31
professionals	0.27***	0.01	21.50	0.00	0.25	0.30
technicians	0.18***	0.02	8.30	0.00	0.14	0.22
craftworkers	0.12***	0.02	7.32	0.00	0.08	0.15
operatives	-0.06***	0.01	-3.90	0.00	-0.08	-0.03
laborershelps	-0.10***	0.03	-3.81	0.00	-0.15	-0.05
serviceworks	-0.08***	0.01	-6.21	0.00	-0.10	-0.05
agricultural	-0.07**	0.04	-2.00	0.05	-0.15	0.00
mining	0.30***	0.05	5.91	0.00	0.20	0.41
utilities	0.24***	0.03	7.32	0.00	0.17	0.30
construction	0.20***	0.02	10.07	0.00	0.16	0.24
manufacturing	0.19***	0.01	12.72	0.00	0.16	0.22
wholesaletrade	0.11***	0.02	5.34	0.00	0.07	0.15
transportation	0.22***	0.02	11.19	0.00	0.18	0.26
information	0.22***	0.02	8.84	0.00	0.17	0.27
financeinsurance	0.17***	0.02	9.15	0.00	0.14	0.21
professervices	0.28***	0.02	14.42	0.00	0.25	0.32
management	0.11***	0.02	5.06	0.00	0.07	0.15
education	-0.13***	0.02	-7.75	0.00	-0.17	-0.10
healthcare	0.12***	0.01	7.78	0.00	0.09	0.14
foodservice	-0.21***	0.02	-10.57	0.00	-0.25	-0.17
otherservice	-0.06***	0.02	-2.68	0.01	-0.10	-0.02
publincadmin	0.20***	0.02	11.99	0.00	0.17	0.24
_cons	0.99	0.06	16.23	0.00	0.87	1.11
Source		**df**	**MS**	**Number of obs**	11296	
				F(48, 11247)	293.83	
Model	1859.11	48.00	38.73	**Prob > F**	0.00	
Residual	1482.53	11247.00	0.13	**R-squared**	0.56	
				Adj R-squared	0.55	
Total	3341.64	11295.00	0.30	**Root MSE**	0.36	

Model Specification: Preliminary Variables Used in Model Specification

Model 1.a Variables (Reference): *obese age agesqu sex numchildren haschildunder6 nc ne south west married salaried yrspresemployer ephi inunion urban highestgrade fulltimeexp white black fatherhs fathercollege motherhs mothercollege*

Preliminary Model 1.b Variables (Health): *obese age agesqu sex numchildren haschildunder6 nc south west married salaried yrspresemployer ephi inunion urban highestgrade fulltimeexp white black fatherhs fathercollege motherhs mothercollege physlimit healthstatus*

Preliminary Model 1.c Variables (Occupation): *obese age agesqu sex numchildren haschildunder6 nc south west married salaried yrspresemployer ephi inunion urban highestgrade fulltimeexp white black fatherhs fathercollege motherhs mothercollege officialsandmanagers professionals technicians sales administrativesupport craftworkers operatives laborersandhelpers serviceworkers agricultural mining utilities construction manufacturing wholesaletrade retailtrade transportation information financeandinsurance realestate professionalservices management education healthcare arts foodservice otherservice publincadministrative*

Regression 2: Women Model 1.d Results
OLS Estimates of the Effect of Obesity on Women's Wages
Dependent Variable: Log Hourly Wage

lnhourlywage	Coef.	Rob. Std. Err.	t	P>t	[95% Conf.	Interval]
obese	-0.032***	0.01058	-3.06	0.002	-0.0531	-0.01162
age	0.032***	0.004	8.51	0.00	0.02	0.04
agesqu	0.00***	0.00	-7.62	0.00	0.00	0.00
numchildren	-0.01**	0.01	-2.00	0.05	-0.02	0.00
haschildunder6	0.05***	0.01	3.45	0.00	0.02	0.07
nc	-0.10***	0.01	-7.46	0.00	-0.12	-0.07
south	-0.12***	0.01	-9.08	0.00	-0.15	-0.09
married	0.02	0.01	1.54	0.12	0.00	0.04
salaried	0.14***	0.01	9.81	0.00	0.11	0.16
yrspresemployer	0.01***	0.00	15.46	0.00	0.01	0.01
ephi	0.14***	0.01	9.99	0.00	0.11	0.17
inunion	0.12***	0.01	7.94	0.00	0.09	0.15
urban	0.07***	0.01	6.83	0.00	0.05	0.09
highestgrade	0.05***	0.00	16.60	0.00	0.04	0.05
fulltimeexp	0.00	0.00	1.04	0.30	0.00	0.00
white	-0.02	0.02	-0.92	0.3580	-0.06	0.02
black	-0.04*	0.02	-1.72	0.09	-0.09	0.01
fathercollege	0.02	0.02	0.93	0.35	-0.02	0.05
motherhs	0.01	0.01	1.42	0.16	-0.01	0.03
physlimit	-0.03	0.02	-1.52	0.13	-0.06	0.01
healthstatus	-0.04***	0.01	-6.98	0.00	-0.05	-0.03
professionals	0.01	0.02	0.60	0.55	-0.03	0.05
sales	-0.26***	0.02	-11.06	0.00	-0.30	-0.21
adminsupport	-0.24***	0.02	-15.71	0.00	-0.27	-0.21
craftworkers	-0.19***	0.06	-3.35	0.00	-0.30	-0.08
operatives	-0.31***	0.02	-12.68	0.00	-0.36	-0.27
laborershelps	-0.39***	0.05	-8.09	0.00	-0.48	-0.30
serviceworks	-0.35***	0.02	-18.71	0.00	-0.39	-0.32
mining	0.60***	0.09	6.34	0.00	0.41	0.78
utilities	0.23***	0.04	5.28	0.00	0.15	0.32
construction	0.24***	0.04	6.28	0.00	0.17	0.32
manufacturing	0.20***	0.02	8.98	0.00	0.16	0.25
wholesaletrade	0.16***	0.03	5.08	0.00	0.10	0.23
transportation	0.22***	0.03	6.92	0.00	0.16	0.28
information	0.17***	0.03	5.19	0.00	0.11	0.24
financeinsurance	0.16***	0.02	7.11	0.00	0.12	0.21
realestate	0.09**	0.04	2.13	0.03	0.01	0.17
professervices	0.29***	0.03	10.40	0.00	0.23	0.34
management	0.14***	0.03	4.69	0.00	0.08	0.20
education	-0.09***	0.02	-3.97	0.00	-0.14	-0.05
healthcare	0.14***	0.02	7.40	0.00	0.11	0.18
foodservice	-0.20***	0.03	-6.79	0.00	-0.26	-0.14
publincadmin	0.21***	0.03	7.68	0.00	0.15	0.26
_cons	1.26	0.08	14.94	0.00	1.10	1.43
Number of obs	=	5784				
F(43, 5740)	=	161.37				
Prob > F	=	0				
R-squared	=	0.5512				
Root MSE	=	0.35344				

Regression 3: Men Model 1.d Results
OLS Estimates of the Effect of Obesity on Men's Wages
Dependent Variable: Log Hourly Wage

lnhourlywage	Coef.	Rob. Std. Err.	t	P>t	[95% Conf.	Interval]
obese	-0.014	0.0104	-1.3300	0.1840	-0.0341	0.0066
age	0.033***	0.004	7.700	0.000	0.024	0.041
agesqu	0.00***	0.00	-5.24	0.00	0.00	0.00
numchildren	0.02***	0.01	3.50	0.00	0.01	0.03
haschildunder6	0.05***	0.01	3.68	0.00	0.02	0.08
nc	-0.10***	0.02	-5.71	0.00	-0.14	-0.07
south	-0.09***	0.02	-5.11	0.00	-0.12	-0.05
west	-0.04**	0.02	-2.40	0.02	-0.08	-0.01
nevermarried	-0.02	0.02	-1.57	0.12	-0.05	0.01
salaried	0.08***	0.02	5.44	0.00	0.05	0.12
yrspresemployer	0.01***	0.00	10.71	0.00	0.01	0.01
ephi	0.18***	0.01	12.39	0.00	0.15	0.20
inunion	0.15***	0.01	10.22	0.00	0.12	0.18
urban	0.04***	0.01	3.45	0.00	0.02	0.06
highestgrade	0.04***	0.00	14.43	0.00	0.04	0.05
fulltimeexp	0.00***	0.00	-4.51	0.00	-0.01	0.00
white	0.01	0.02	0.60	0.55	-0.03	0.06
black	-0.11***	0.02	-4.34	0.00	-0.15	-0.06
fatherhs	0.01	0.01	0.95	0.34	-0.01	0.03
fathercollege	0.09***	0.02	4.42	0.00	0.05	0.12
physlimit	-0.08***	0.02	-3.81	0.00	-0.12	-0.04
healthstatus	-0.03***	0.01	-4.96	0.00	-0.04	-0.02
officmanags	0.19***	0.02	8.52	0.00	0.15	0.23
professionals	0.17***	0.02	7.63	0.00	0.13	0.22
sales	-0.10***	0.03	-3.79	0.00	-0.16	-0.05
adminsupport	-0.15***	0.02	-7.82	0.00	-0.18	-0.11
operatives	-0.16***	0.02	-9.96	0.00	-0.20	-0.13
laborershelps	-0.19***	0.03	-6.76	0.00	-0.24	-0.13
serviceworks	-0.14***	0.02	-6.80	0.00	-0.18	-0.10
agricultural	-0.10**	0.04	-2.54	0.01	-0.17	-0.02
mining	0.23***	0.06	4.13	0.00	0.12	0.34
utilities	0.23***	0.04	6.47	0.00	0.16	0.30
construction	0.18***	0.02	8.58	0.00	0.14	0.22
manufacturing	0.18***	0.02	9.63	0.00	0.14	0.21
wholesaletrade	0.09***	0.03	3.13	0.00	0.03	0.14
transportation	0.22***	0.02	9.70	0.00	0.18	0.27
information	0.27***	0.04	7.41	0.00	0.20	0.34
financeinsurance	0.21***	0.04	5.77	0.00	0.14	0.28
realestate	0.12**	0.05	2.50	0.01	0.03	0.21
professervices	0.29***	0.03	8.52	0.00	0.22	0.35
education	-0.18***	0.03	-6.34	0.00	-0.24	-0.12
healthcare	0.05	0.03	1.61	0.11	-0.01	0.10
foodservice	-0.20***	0.03	-6.66	0.00	-0.26	-0.14
otherservice	-0.09**	0.04	-2.25	0.03	-0.17	-0.01
publincadmin	0.17***	0.02	7.07	0.00	0.12	0.22
_cons	1.21	0.09	12.77	0	1.03	1.40
Number of obs	=	5512				
F(45, 5466)	=	145.97				
Prob > F	=	0				
R-squared	=	0.5441				
Root MSE	=	0.36736				

Quantile Regression 1: Women Results

Quantile Regression Estimates of the Effect of Obesity on Women's Wages
Dependent Variable: Log Hourly Wage

	q10		q25		q50		q75		q90	
obese	-0.021		-0.025	*	-0.030	***	-0.043	***	-0.032	**
age	0.03	***	0.02	***	0.03	***	0.04	***	0.04	***
agesqu	0.00	***	0.00	***	0.00	***	0.00	***	0.00	***
numchildren	-0.01		0.00		-0.01	***	-0.01	**	-0.02	**
haschildunder6	0.03	*	0.03	*	0.03	***	0.04	***	0.06	***
nc	-0.08	**	-0.08	***	-0.07	***	-0.11	***	-0.12	***
south	-0.10	***	-0.11	***	-0.09	***	-0.12	***	-0.16	***
married	0.00		0.00		0.01	***	0.02		0.04	**
salaried	0.06	***	0.11	***	0.17	***	0.19	***	0.19	***
yrspresemployer	0.01	***	0.01	***	0.01	***	0.01	***	0.01	***
ephi	0.15	***	0.14	***	0.13	***	0.12	***	0.12	***
inunion	0.12	***	0.11	***	0.12	***	0.13	***	0.08	***
urban	0.07	***	0.08	***	0.07	***	0.07	***	0.05	***
highestgrade	0.04	***	0.04	***	0.04	***	0.05	***	0.06	***
fulltimeexp	0.00		0.00		0.00		0.00	**	0.00	
white	-0.01		0.04		0.01		-0.01		-0.01	
black	-0.03		0.02		-0.02		-0.04		-0.01	
fathercollege	0.01		0.00		0.05	***	0.03		-0.01	
motherhs	0.03	**	0.01		0.02		0.03	***	0.01	
physlimit	-0.05	*	-0.02		-0.03		-0.02		-0.03	
healthstatus	-0.03	***	-0.03	***	-0.03	***	-0.04	***	-0.05	***
professionals	-0.06	*	-0.03		0.03		0.04		0.05	**
sales	-0.19	***	-0.23	***	-0.27	***	-0.30	***	-0.31	***
adminsupport	-0.17	***	-0.19	***	-0.23	***	-0.26	***	-0.29	***
craftworkers	-0.28	***	-0.27	***	-0.22	***	-0.11		0.11	
operatives	-0.28	***	-0.28	***	-0.30	***	-0.31	***	-0.33	***
laborershelps	-0.22	***	-0.31	***	-0.35	***	-0.45	***	-0.42	***
serviceworks	-0.33	***	-0.31	***	-0.33	***	-0.35	***	-0.36	***
mining	0.59	**	0.62	***	0.63	***	0.48	***	0.34	***
utilities	0.32	***	0.24	***	0.25	***	0.22	***	0.12	
construction	0.33	***	0.27	***	0.23	***	0.21	***	0.17	**
manufacturing	0.19	***	0.20	***	0.19	***	0.17	***	0.19	***
wholesaletrade	0.12	**	0.14	***	0.17	***	0.14	***	0.13	*
transportation	0.18	***	0.26	***	0.23	***	0.22	***	0.19	***
information	0.13	***	0.16	***	0.18	***	0.17	***	0.16	***
financeinsurance	0.17	***	0.17	***	0.15	***	0.14	***	0.11	***
realestate	0.13		0.13	**	0.11	***	0.03		0.10	
professervices	0.27	***	0.30		0.30	***	0.25	***	0.24	***
management	0.14	***	0.14	***	0.13	***	0.12	***	0.17	***
education	0.01		-0.01	***	-0.09	***	-0.16	***	-0.16	***
healthcare	0.15	***	0.15	***	0.15	***	0.13	***	0.12	***
foodservice	-0.61	***	-0.17	***	-0.09	***	-0.11	***	-0.14	***
publincadmin	0.25	***	0.19	***	0.17	***	0.21	***	0.25	***
_cons	1.12		1.33		1.37		1.41		1.42	
R-Squared	0.3032		0.3284		0.3631		0.3826		0.3825	

Quantile Regression 2: Men Results

Quantile Regression Estimates of the Effect of Obesity on Men's Wages

Dependent Variable: Log Hourly Wage

	q10		q25		q50		q75		q90	
obese	0.001		-0.001		-0.034	***	-0.026	**	-0.031	**
age	0.031	***	0.028	***	0.026	***	0.032	***	0.045	***
agesqu	0.00	***	0.00	***	0.00	***	0.00	***	0.00	***
numchildren	0.01		0.01	*	0.03	***	0.01	**	0.02	**
haschildunder6	0.08	***	0.06	**	0.04	***	0.06	***	0.05	**
nc	-0.06		-0.07	***	-0.08	***	-0.11	***	-0.13	***
south	-0.06	*	-0.08	***	-0.09	***	-0.10	***	-0.11	***
west	0.02		-0.02		-0.04	**	-0.07	***	-0.08	***
nevermarried	0.00		-0.02		-0.01		-0.06	***	-0.01	
salaried	-0.04		0.06	***	0.13	***	0.16	***	0.20	***
yrspresemployer	0.01	***	0.01	***	0.01	***	0.01	***	0.00	***
ephi	0.19	***	0.18	***	0.19	***	0.15	***	0.13	***
inunion	0.17	***	0.17	***	0.17	***	0.16	***	0.16	***
urban	0.03	**	0.05	***	0.04	***	0.04	***	0.02	
highestgrade	0.04	***	0.04	***	0.04	***	0.04	***	0.04	***
fulltimeexp	0.00		0.00		0.00	***	0.00	***	0.01	***
white	0.04		0.01		0.00		-0.01		0.04	
black	-0.06		-0.09	***	-0.11	***	-0.13	***	-0.11	***
fatherhs	0.02		0.02		0.01		0.01		0.03	*
fathercollege	0.10	***	0.09	***	0.10	***	0.08	***	0.04	**
physlimit	-0.08	**	-0.09	***	-0.06	***	-0.07	**	-0.06	*
healthstatus	-0.03	**	-0.03	***	-0.03	***	-0.04	***	-0.03	***
officmanags	0.14	***	0.13	***	0.16	***	0.19	***	0.22	***
professionals	0.13	***	0.11	***	0.19	***	0.19	***	0.20	***
sales	-0.16	***	-0.15	***	-0.10	***	-0.03		-0.06	**
adminsupport	-0.10	***	-0.16	***	-0.17	***	-0.15	***	-0.15	***
operatives	-0.15	***	-0.17	***	-0.16	***	-0.12	***	-0.12	***
laborershelps	-0.21	***	-0.20	***	-0.24	***	-0.21	***	-0.17	***
serviceworks	-0.15	***	-0.14	***	-0.13	***	-0.12	***	-0.14	***
agricultural	-0.01		-0.09	**	-0.04		-0.05		-0.20	***
mining	0.17	***	0.14	**	0.18	***	0.27	***	0.35	***
utilities	0.23	***	0.32	***	0.28	***	0.25	***	0.16	***
construction	0.20	***	0.15	***	0.19	***	0.18	***	0.16	***
manufacturing	0.19	***	0.17	***	0.17	***	0.15	***	0.13	***
wholesaletrade	0.10		0.12	***	0.13	***	0.08	**	0.05	
transportation	0.24	***	0.20	***	0.22	***	0.19	***	0.16	***
information	0.23	***	0.26	***	0.28	***	0.27	***	0.21	***
financeinsurance	0.24	***	0.24	***	0.16	***	0.14	***	0.22	***
realestate	0.09		0.11	*	0.15	**	0.16	***	0.15	***
professervices	0.19	***	0.26	***	0.26	***	0.32	***	0.31	***
education	-0.15	**	-0.14		-0.17	***	-0.16	***	-0.20	***
healthcare	-0.02		-0.03		0.05		0.07	**	0.16	***
foodservice	-0.30	***	-0.22	***	-0.14	***	-0.13	***	-0.20	***
otherservice	-0.19	*	-0.10	**	-0.02		-0.01		-0.04	
publincadmin	0.19	***	0.15	***	0.17	***	0.20	***	0.17	***
_cons	0.84		1.20		1.41		1.49		1.37	
R-Squared	0.271		0.323		0.364		0.396		0.407	

Regression 4: Women Interaction Results

OLS estimates of the Effect of Obesity and Employer-Provided Health Insurance on Wages

Dependent Variable: Log Hourly Wages

lnhourlywage	Coef.	Rob. Std. Err.	t	P>t	[95% Conf.	Interval]
obese	0.003	0.023	0.150	0.884	-0.041	0.048
ephiobese	-0.047*	0.03	-1.85	0.06	-0.10	0.00
age	0.03***	0.00	8.44	0.00	0.02	0.04
agesqu	0.00***	0.00	-7.56	0.00	0.00	0.00
numchildren	-0.01**	0.01	-2.07	0.04	-0.02	0.00
haschildunder6	0.05***	0.01	3.52	0.00	0.02	0.07
nc	-0.10***	0.01	-7.45	0.00	-0.12	-0.07
south	-0.12***	0.01	-9.06	0.00	-0.15	-0.09
married	0.02	0.01	1.51	0.13	0.00	0.04
salaried	0.14***	0.01	9.79	0.00	0.11	0.16
yrspresemployer	0.01***	0.00	15.47	0.00	0.01	0.01
ephi	0.15***	0.02	9.45	0.00	0.12	0.19
inunion	0.12***	0.01	7.93	0.00	0.09	0.15
urban	0.07***	0.01	6.82	0.00	0.05	0.09
highestgrade	0.05***	0.00	16.59	0.00	0.04	0.05
fulltimeexp	0.00	0.00	1.08	0.28	0.00	0.00
white	0.02	0.02	0.91	0.36	0.02	0.06
black	-0.04*	0.02	-1.72	0.09	-0.09	0.01
fathercollege	0.02	0.02	0.90	0.37	-0.02	0.05
motherhs	0.01	0.01	1.41	0.16	-0.01	0.03
physlimit	-0.03	0.02	-1.51	0.13	-0.06	0.01
healthstatus	-0.04***	0.01	-6.96	0.00	-0.05	-0.03
professionals	0.01	0.02	0.59	0.56	-0.03	0.05
sales	-0.26***	0.02	-11.08	0.00	-0.30	-0.21
adminsupport	-0.24***	0.02	-15.72	0.00	-0.27	-0.21
craftworkers	-0.19***	0.06	-3.33	0.00	-0.30	-0.08
operatives	-0.31***	0.02	-12.68	0.00	-0.36	-0.27
laborershelps	-0.39***	0.05	-8.09	0.00	-0.48	-0.30
serviceworks	-0.35***	0.02	-18.76	0.00	-0.39	-0.32
mining	0.60***	0.09	6.41	0.00	0.41	0.78
utilities	0.23***	0.04	5.27	0.00	0.15	0.32
construction	0.24***	0.04	6.23	0.00	0.16	0.32
manufacturing	0.20***	0.02	9.01	0.00	0.16	0.25
wholesaletrade	0.16***	0.03	5.09	0.00	0.10	0.23
transportation	0.22***	0.03	6.93	0.00	0.16	0.28
information	0.17***	0.03	5.18	0.00	0.11	0.24
financeinsurance	0.16***	0.02	7.10	0.00	0.12	0.21
realestate	0.09***	0.04	2.16	0.03	0.01	0.17
professervices	0.29***	0.03	10.40	0.00	0.23	0.34
management	0.14***	0.03	4.72	0.00	0.08	0.20
education	-0.09***	0.02	-3.98	0.00	-0.14	-0.05
healthcare	0.14***	0.02	7.42	0.00	0.11	0.18
foodservice	-0.20***	0.03	-6.80	0.00	-0.26	-0.14
publincadmin	0.21***	0.03	7.74	0.00	0.16	0.26
_cons	1.25807	0.084	14.89	0	1.09	1.423
Number of obs	=	5784				
F(44, 5739)	=	158.08				
Prob > F	=	0				
R-squared	=	0.551				
Root MSE	=	0.353				

Regression 5: Men Interaction Results

OLS estimates of the Effect of Obesity and Employer-Provided Health Insurance on Wages

Dependent Variable: Log Hourly Wages

lnhourlywage	Coef.	Rob. Std. Err.	t	P>t	[95% Conf.	Interval]
obese	-0.01	0.02	-0.48	0.63	-0.06	0.03
ephiobese	0.00	0.03	-0.11	0.91	-0.05	0.05
age	0.03***	0.00	7.69	0.00	0.02	0.04
agesqu	0.00***	0.00	-5.23	0.00	0.00	0.00
numchildren	0.02***	0.01	3.50	0.00	0.01	0.03
haschildunder6	0.05***	0.01	3.68	0.00	0.02	0.08
nc	-0.10***	0.02	-5.71	0.00	-0.14	-0.07
south	-0.09***	0.02	-5.11	0.00	-0.12	-0.05
west	-0.04**	0.02	-2.40	0.02	-0.08	-0.01
nevermarried	-0.02	0.02	-1.57	0.12	-0.05	0.01
salaried	0.08***	0.02	5.44	0.00	0.05	0.12
yrspresemployer	0.01***	0.00	10.71	0.00	0.01	0.01
ephi	0.18***	0.02	10.84	0.00	0.15	0.21
inunion	0.15***	0.01	10.22	0.00	0.12	0.18
urban	0.04***	0.01	3.45	0.00	0.02	0.06
highestgrade	0.04***	0.00	14.43	0.00	0.04	0.05
fulltimeexp	0.00***	0.00	-4.51	0.00	-0.01	0.00
white	0.01	0.02	0.60	0.55	-0.03	0.06
black	-0.11***	0.02	-4.34	0.00	-0.15	-0.06
fatherhs	0.01	0.01	0.95	0.34	-0.01	0.03
fathercollege	0.09***	0.02	4.42	0.00	0.05	0.12
physlimit	-0.08***	0.02	-3.82	0.00	-0.12	-0.04
healthstatus	-0.038***	0.01	-4.96	0.00	-0.04	-0.02
officmanags	0.19***	0.02	8.52	0.00	0.15	0.23
professionals	0.17***	0.02	7.64	0.00	0.13	0.22
sales	-0.10***	0.03	-3.79	0.00	-0.16	-0.05
adminsupport	-0.15***	0.02	-7.83	0.00	-0.18	-0.11
operatives	-0.16***	0.02	-9.97	0.00	-0.20	-0.13
laborershelps	-0.198***	0.03	-6.76	0.00	-0.24	-0.13
serviceworks	-0.14***	0.02	-6.82	0.00	-0.18	-0.10
agricultural	-0.10**	0.04	-2.54	0.01	-0.17	-0.02
mining	0.23***	0.06	4.13	0.00	0.12	0.34
utilities	0.23***	0.04	6.47	0.00	0.16	0.30
construction	0.18***	0.02	8.58	0.00	0.14	0.22
manufacturing	0.18***	0.02	9.63	0.00	0.14	0.21
wholesaletrade	0.09***	0.03	3.13	0.00	0.03	0.14
transportation	0.22***	0.02	9.69	0.00	0.18	0.27
information	0.27***	0.04	7.41	0.00	0.20	0.34
financeinsurance	0.21***	0.04	5.77	0.00	0.14	0.28
realestate	0.12**	0.05	2.51	0.01	0.03	0.21
professervices	0.29***	0.03	8.52	0.00	0.22	0.35
education	-0.18***	0.03	-6.34	0.00	-0.24	-0.12
healthcare	0.05	0.03	1.61	0.11	-0.01	0.10
foodservice	-0.20***	0.03	-6.67	0.00	-0.26	-0.14
otherservice	-0.09**	0.04	-2.24	0.03	-0.17	-0.01
publincadmin	0.17***	0.02	7.10	0.00	0.12	0.22
_cons	1.21	0.10	12.72	0.00	1.02	1.40
Number of obs	=	5512				
F(46, 5465)	=	143.22				
Prob > F	=	0				
R-squared	=	0.544				
Root MSE	=	0.367				

Table 7: Firm Size Regression Results
OLS Estimates of the Effect of Obesity and Employer-Provided Health Insurance on Wages Dependent on Firm Size.
Dependent Variable: Log Hourly Wages

	Women		**Men**	
	Small Firm	**Large Firm**	**Small Firm**	**Large Firm**
Obese Coefficient β_2	0.00 (.03)	-.01 (.03)	-.02 (.03)	.02 (.04)
EPHI*Obese β_3	-0.067* (.04)	-.03 (.04)	.03 (.04)	-.06 (.04)
EPHI Coefficient β_4	.13*** (.02)	.16*** (.03)	.13*** (.02)	.18*** (.03)
Constant	1.22	1.19	1.13	1.16
R-Squared Value	.515	.551	.517	.556
No. Observations	2393	2706	2332	2583

Note: In Table 7 all estimates are adjusted for heteroscedasticity with robust standard errors. Robust standard errors are shown in parenthesis. * Indicates significant at 10%, ** significant at 5%, and *** significant at 1%. Small firms are defined as those with 50 or less employees. Large firms are defined as those with more than 50 employees. For women, 24% of the workers employed in small firms are obese and 30% of the workers in large firms are obese. For men, 27% of the workers employed in small firms are obese and 27% of the workers employed in large firms are obese. Also, it is important to note the number of observations dropped because not all respondents indicated the number of employees employed with their main job.

Table 8: Years with Present Employer Regression Results:
OLS Estimates of the Effect of Obesity and Employer-Provided Health Insurance on Wages Dependent on Number of Years Employed with Current Employer.
Dependent Variable: Log Hourly Wages

	Women		**Men**	
	Less than 5 Years	**More than 5 Years**	**Less than 5 Years**	**More than 5 Years**
Obese Coefficient β_2	0.00 (.03)	.063 (.05)	-.02 (.02)	-.02 (.03)
EPHI*Obese β_3	-.041 (.03)	-.099* (.05)	0.00 (.03)	.01 (.05)
EPHI Coefficient β_4	.13*** (.02)	.21*** (.02)	.18*** (.02)	.16*** (.02)
Constant	1.43	1.18	1.30	1.30
R-Squared Value	.514	.465	.513	.519
No. Observations	3355	2440	2847	2665

Note: In Table 8 all estimates are adjusted for heteroscedasticity with robust standard errors. Robust standard errors are shown in parenthesis. * Indicates significant at 10%, ** significant at 5%, and *** significant at 1%. Small firms are defined as those with 50 or less employees. Large firms are defined as those with more than 50 employees. For women, 26% of the workers have been employed for less than five years are obese and 28% of the workers have been employed for more than five years are obese. For men, 27% of the workers have been employed for less than five years are obese and 28% of the workers have been employed for more than five years are obese.

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Data Appendix:

Data is from the Panel Study of Income Dynamics webpage at: http://psidonline.isr.umich.edu/

Data is from the 2005 and 2007 waves and includes both the PSID Main Family Data and the PSID Individual Data for each year. From the Individual files, I obviously only observe the "head" and "wife" because only these individuals have the applicable information in the Family Data file.

All data is based on the head of household and wife's "first mention" responses. I use data from both the head of household responses and from the equivalent responses asked about the wife. For example, "ER36132 BC20 MAIN OCC FOR JOB 1: 2000 CODE (HD)" and "ER36390 DE20 MAIN OCC FOR JOB 1: 2000 CODE (WF)" are treated as the same variable, occupation. Likewise, the number of employees employed at work location, "ER25132 BC25A NUMBER EMPLOYED AT WORK LOCATION (HD)" and "ER25390 DE25A N NUMBER EMPLOYED AT WORK LOCATION (WF)," are treated as the same variable, firm size. And so forth, for all variables used.

The PSID Website has a variable search application with the codebook responses and means. It also provides full definitions of all variables.

Hourly Wage: For respondent's paid hourly, the wage rate is the given hourly wage. For salaried respondent's, hourly wage rate is computed as annual labor income divided annual work hours. The 2007 wages were adjusted for inflation to 2005 dollars using the CPI-U annual average. The cumulative annual inflation rate from 2005-2007 is 6.70%. The formula used to compute the inflation adjusted wage rate is [Wage07-(Wage07*.067)] [http://www.halfhill.com/inflation.html]

As specified by Cawley (2004) and Bhattacharya and Bundorf (2009), I omit severe outliers in wages and top and bottom the hourly wages rates to $1 and $200. Bhattacharya and Bundorf (2009) restricted the wage rates to $1-$290 and Cawley (2004) restricted the wage rates to $1 and $300.

BMI: Body mass index is computed using the calculation: BMI = $\frac{(wt.\,lbs)}{(ht.\,in)^2} * 703$. I assign indicator variables for 1 if the individuals' BMI is greater than 30. This is based on the standard definition from the Center of Disease Control at: http://www.cdc.gov/healthyweight/assessing/bmi/adult_BMI/index.html. As specified by the past literature, I omit severe outliers and errors in coding and observe only individuals with BMI between 15 and 50.

Race: The PSID asks: What is your race? Are you white, black, American Indian, Alaska Native, Asian, Native Hawaiian or other Pacific Islander?--FIRST MENTION and Is she white, black, American Indian, Alaska Native, Asian, Native Hawaiian or other Pacific Islander?--FIRST MENTION. I include white for those who respond [1 White] black for those who respond [2 Black, African-American, or Negro]. The unassigned are 3 American Indian or Alaska Native, 4 Asian, 5 Native Hawaiian or Pacific Islander, and 7 other.

Firm Size: Observing the histogram and summary statistics, there are many outliers. While the mean is 790 employees, the median is only 50 employees. When investigating the effects of the wage penalty cased on firm size, I restrict the regression to individuals in firms with more than 50 employees and 50 or less employees.

Urban and Rural: The survey asks for each respondent's size of largest city in county of residence. I assign an indicator variable of 1 for urban if the largest city is classified as an MSA, Metropolitan Statistical Area. I assign 0 if the largest city is not classified as an MSA.

Health Status: The PSID asks respondents how they view their general health, based on any serious limitations they may have. This is a continuous variable with 1 as excellent health, 2 as very good, 3 as good, 4 as fair and 5 as poor. I create sub groups with 1 as excellent, 2 and 3 as very good, and 4 and 5 as fair/poor.

Work Limiting Conditions: The variables that control for activity limiting health conditions are indicator variables based whether the respondent indicated that the specified obese-related health conditions (hypertension, diabetes, asthma, or heart disease) limit daily activity.

Industry: Industries are divided into the following groups and assigned a indicator variable for each: Agriculture, Mining, Utilities, Manufacturing, Construction, Wholesale Trade, Retail trade, Transportation, Information, Finance and Insurance, Real Estate, Professional Services, Management, Education, Healthcare and Social Assistance, Arts, Food Services, Other Services, Public Administration. The base variable indicates the respondent does not know his industry or it is not available.

White Collar: I assigned an indicator variable of 1 for white-collar occupations and 0 for blue-collar occupations. The PSID provides the three-digit occupation code from the 2000 Census of Population and Housing. I used the 2000 U.S. Census Bureau Special EEO -1 Job Categories to define white-collar workers as Officials and Managers and Professionals and blue-collar workers as the others. This is the definition used by the Kaiser state health facts: [http://www.statehealthfacts.org/comparemaptable.jsp?ind=748&cat=1].

Occupation: Along with white-collar status, occupations are divided among the nine job categories using the 2000 U.S. Census Bureau Special EEO -1 Job Categories. Each respondent's three-digit occupational code was classified into the following occupations: Officials and Managers, Professionals, Technicians, Sales Workers, Administrative Support Workers, Craft Workers, Operatives, Laborers and Helpers, and Service Workers. The base variable indicates the respondent does not know his occupational code or it is not available. The three digit occupation codes were obtained from:
[http://www.census.gov/hhes/www/eeoindex/jobgroups.pdf]

Full Table of all Variables with Definitions:

		Definition of Variable	Full-Sample			Non-obese	Obese
Variables of Interest			Mean	Min	Max	Mean	Mean
bmi	=	Body mass index, define obese as those with bmi≥30	27.5	15.3	49.9	24.8	34.7
hourlywage	=	Hourly wage rate	15.00	1.18	193.78	15.41	13.99
lnhourlywage	=	Natural log hourly wage rate	2.71	.169	5.27	2.73	2.64
ephi	=	1 if receives employer-provided health insurance	0.78	0	1	0.79	0.78
Standard Covariates							
age	=	Age in years	39.2	20.0	60	38.9	40.2
sex	=	1 if male	0.49	0	1	0.48	0.50
white	=	1 if white	0.66	0	1	0.69	0.56
black	=	1 if black	0.29	0	1	0.25	0.40
numchildren	=	The number of children in the household	0.99	0	7	0.96	1.08
haschildunder6	=	1 if has a child in the household under that age of six	0.27	0	1	0.27	0.28
ne	=	1 if resides in a state in the northeast	0.14	0	1	0.14	0.12
nc	=	1 if resides in a state in the north central	0.26	0	1	0.27	0.24
south	=	1 if resides in a state in the south	0.41	0	1	0.39	0.47
west	=	1 if resides in a state in the west	0.18	0	1	0.19	0.16
urban	=	1 if lives in urban area	0.53	0	1	0.54	0.52
married	=	1 if lives in urban area	0.64	0	1	0.65	0.62
nevermarried	=	1 if lives in urban area	0.21	0	1	0.21	0.21
yrspresemployer	=	The number of years with present employer	7.54	0	40	7.38	7.96
inunion	=	1 if belongs in union	0.15	0	1	0.14	0.16
fulltimeexp	=	Years of full-time work experience	9.12	0	40	8.86	9.78
salaried	=	1 if current main job is salaried	0.39	0	1	0.41	0.32
highestgrade	=	The highest grade completed: 1-16 is highest grade, 0 is no grades, 17 is at least some post graduate work	13.4	0	17	13.5	13.1
hsgrad	=	1 if graduated high school	0.81	0	1	0.81	0.80
collegedegree	=	1 if received college degree	0.31	0	1	0.35	0.23
fatherhs	=	1 if father completed high school	0.32	0	1	0.32	0.31
motherhs	=	1 if mother completed high school	0.39	0	1	0.39	0.37
fathercollege	=	1 if father completed college	0.10	0	1	0.11	0.07
mothercollege		1 if mother completed college	0.09	0	1	0.10	0.07
Health Status Variables							
healthstatus	=	Health status rating : 5 indicates poor, 4 fair, 3 good, 2 very good, 1 excellent	2.23	1	5	2.11	2.56
physlimit	=	1 if has physical or nervous condition that limits type of work or amount work	0.07	0	1	0.06	0.10
smoke	=	1 if smokes cigarettes	0.21	0	1	0.23	0.18
excellent	=	1 if in excellent health: corresponds to 1 in health status rating	0.24	0	1	0.28	0.13
verygood	=	1 if in very good health, corresponds to 2 and 3 in health status rating	0.68	0	1	0.65	0.73
fairpoor	=	1 if in fair or poor health, corresponds to 4 and 5 in health status rating	0.08	0	1	0.06	0.14
heartdisease	=	1 if been told by doctor to have heart disease	0.02	0	1	0.02	0.03
heartdiseasela	=	1 if the heart disease limits daily activity	0.01	0	1	0.01	0.01

hypertension	=	1 if been told by doctor to have hypertension	0.19	0	1	0.14	0.32
hypertensiionla	=	1 if hypertension limits daily activity	0.03	0	1	0.02	0.05
asthma	=	1 if been told by doctor to have asthma	0.09	0	1	0.08	0.12
asthmala	=	1 if asthma limits daily activity	0.03	0	1	0.02	0.04
diabetes	=	1 if been told by doctor to have diabetes	0.05	0	1	0.03	0.10
diabetesla		1 if diabetes limits daily activity	0.02	0	1	0.01	0.03
Occupational Variables							
whitecollar	=	1 if classified as an official and manager, or professional	0.30	0	1	0.32	0.24
officmanags	=	1 if classified as an official and manager	0.13	0	1	0.14	0.11
professionals	=	1 if classified as professional	0.17	0	1	0.19	0.14
technicians	=	1 if classified as technician	0.03	0	1	0.03	0.03
sales	=	1 if classified as sales worker	0.07	0	1	0.07	0.07
administrative	=	1 if classified as an administrative support worker	0.18	0	1	0.18	0.18
craftworkers	=	1 if classified as a craft worker	0.10	0	1	0.10	0.10
operatives	=	1 if classified as an operative	0.12	0	1	0.11	0.15
laborershelps	=	1 if classified as a laborer and helper	0.02	0	1	0.02	0.02
serviceworks		1 if classified as a service worker	0.16	0	1	0.15	0.19
Industry Variables							
agricultural	=	1 if in the agricultural, forestry, fishing, and hunting industry	0.01	0	1	0.01	0.01
mining	=	1 if in the mining industry	0	0	1	0	0.01
utilities	=	1 if in the utilities industry	0.01	0	1	0.01	0.02
construction	=	1 if in the construction industry	0.06	0	1	0.06	0.05
manufacturing	=	1 if in the manufacturing industry	0.15	0	1	0.15	0.15
wholesaletrade	=	1 if in the wholesale trade industry	0.04	0	1	0.04	0.03
retailtrade	=	1 if in the retail trade industry	0.08	0	1	0.09	0.08
transportation	=	1 if in the transportation and warehousing industry	0.04	0	1	0.04	0.05
information	=	1 if in the information industry	0.02	0	1	0.02	0.03
financeinsurance	=	1 if in the finance and insurance industry	0.05	0	1	0.06	0.04
realestate	=	1 if in the real estate, rental, and leasing industry	0.01	0	1	0.01	0.01
professervices	=	1 if in professional, scientific, and technical services	0.05	0	1	0.05	0.03
management	=	1 if in management, administrative support, and waste management services	0.03	0	1	0.03	0.04
education	=	1 if in education services	0.10	0	1	0.10	0.09
healthcare	=	1 if the healthcare and social assistance industry	0.15	0	1	0.14	0.18
arts	=	1 if in the arts, entertainment, and recreation industry	0.01	0	1	0.01	0.01
foodservice	=	1 if in the food services and accommodation industry	0.05	0	1	0.05	0.05
otherservice	=	1 if in other services, expect public administration	0.03	0	1	0.03	0.03
publincadmin		1 if in public administration and active duty military	0.08	0	1	0.08	0.08