Worker Investments in Safety, Workplace Accidents, and Compensating Wage Differentials[‡]

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Abstract

The theory of compensating wage differentials (CWDs) assumes that firms supply and workers demand workplace safety, predicting a positive relationship between accident risk and wages. This paper allows for safety provision by workers, which predicts a countervailing negative relationship between individual risk and wages: firms pay higher wages for higher safety-related productivity. Using National Longitudinal Survey of Youth panel data and data on fatal and nonfatal accidents, our precise CWDs imply a value of a statistical injury of $45.4 thousand and a value of a statistical life of $6.3 million. In line with our model, individual risk and wages are negatively correlated.

Keywords: occupational safety, nonfatal risk, hedonic wage models, workplace accidents, compensating wage differentials, Value of a Statistical Life (VSL), Value of a Statistical Injury (VSI), obesity wage penalty, productivity, discrimination

JEL classification: I10, I12, J24, J31, J62, J71

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1 Introduction

The theory of compensating wage differentials (CWD) posits that workers must be compensated with higher wages for accepting unpleasant job conditions. Occupational risk of accidents is one such undesirable attribute. This leads to the standard prediction of a positive association between workplace accident risk and wages (Thaler and Rosen 1976).[2]

Since Adam Smith, economists have studied the relationship between accident risk and wages because it informs us about the way the labor market works (Viscusi and Aldy 2003; Kniesner et al. 2010). Policymakers care about it because CWDs provide an estimate of workers' valuation of job conditions and their health. The economic approach to risk valuation is to use empirical estimates of wage-risk tradeoffs to infer the value of a statistical injury (VSI) and the value of a statistical life (VSL). In turn, government regulators use VSL estimates to value the benefits associated with risk reduction policies. Kenkel (2003) discusses several examples of this practice.

The standard CWD model treats workplace safety as exogenous to the worker. Only firms have the ability to provide safety. Firms can either pay workers higher wages for accepting the risk of accidents, or they can provide more safety and pay lower wages. The majority of empirical studies base their analyses on this CWD theory and typically abstract away from the possibility that *workers* have the ability to reduce accident risk as well.[3]

In reality, however, there may be opportunities for workers to lower the risk of accidents and thereby supply safety to the firm. Firms would demand such worker-provided safety ("safety-related productivity") because accident costs reduce their profits. As an example, consider that in 2014, the most common job in 28 U.S. states was being a truck driver and that roadway fatalities make up a quarter of all fatal occupational injuries (Bureau of Labor Statistics 2016; National Public Radio 2016). Employees can obviously take action (that their employers cannot undertake) to avert workplace accidents. Large consulting firms exist that advise employers on how to motivate employees to improve their safety behavior (Safety Management Group 2016).[4] Industry compensation policies also support the notion that workers have the ability to engage in risk reduction efforts and get rewarded for it. Examples are safety bonuses and wellness programs (Baicker et al.

[2]In this paper, we refer to "risk" and "safety" somewhat interchangeably, acknowledging that risk and safety are the converse of each other.

[3]An earlier literature recognizes the importance of worker behavior in affecting the risk of accidents (Oi 1974; Chelius 1974).

[4]Companies also report client testimonials of how programs have reduced their accident rates and costs (Cable 2005). Gossner and Picard (2005) derive cost–benefit rules for automobile safety regulation when drivers may adjust their driving behavior.

2010). In a survey of 40 long haul trucking firms in Canada, 70 percent of them had a safety incentive program (Transport Canada 2012). Denark Construction's employees receive a bonus check if they avoid violations of safety policies, accidents, and citations by the Occupational Safety and Health Administration (OSHA). Clearly, it is very plausible that workers can invest in safety and get compensated for it.

In this paper, we first extend the theory of compensating wage differentials by allowing workers to supply workplace safety. In the standard model, firms supply safety and workers demand it; the price for safety is a lower wage that workers accept for a safer workplace. In contrast, in our model, workers supply safety and firms demand it. In turn, the firm pays higher wages for workers' provision of safety. As in the standard model, accident risk and wages will be positively correlated, but only to the extent that risk is "produced" by the firm or exogenously determined by technology. In contrast, when safety is produced by workers, our model predicts a *negative* relationship between the individual accident risk and wages. To the extent that workers' provision of safety prevents accidents, riskier jobs then appear safer than they actually are. The theoretical insight that worker- and firm-produced workplace safety affects wages in opposite directions carries over to the empirical estimation of CWDs. CWDs and the implied VSI and VSL estimates could be downward biased when ignoring workers' safety-related productivity. Part of what has been estimated as the compensating wage differential for risk may actually be a return to workers' safety-related productivity.

Next, we investigate the model predictions empirically. Specifically, we estimate CWDs for fatal and nonfatal risk using panel data from the United States. We also investigate the roles of (a) time-invariant unobservable worker characteristics, for example risk preferences, as well as (b) time-variant observable changes in workers' safety-related productivity. The empirical part exploits a uniquely compiled dataset using four different data sources. We link panel data from the NLSY 1979 to occupational fatal and nonfatal risk data from the Bureau of Labor Statistics (BLS) and normalize by occupation counts from the Current Population Survey (CPS). This is one of a very few papers that examines wage effects of both nonfatal and fatal risk.

Our findings show a precisely estimated positive CWD for nonfatal and fatal risk. For every additional nonfatal accident per 100 full-time workers, wages are 0.4 percent higher. For every additional fatal accident per 100,000 full-time workers, wages are 0.3 percent higher. The implied VSI is \$45.4 thousand and the implied VSL is \$6.3 million; they fall into the range of existing estimates (Viscusi and Aldy 2003; Kniesner et al. 2010).

We then examine the wage effects of worker investments in safety. Because safety-related productivity is very difficult to measure, we take an indirect approach. We use changes in body weight as a proxy for changes in safety-related productivity. Body weight changes have some desirable properties for our purposes: They are observable to the employer, they are to a large degree modifiable by the individual, and they can be interpreted as changes in human capital. Perhaps more importantly, there is evidence that obesity significantly increases the risk of accidents (Stoohs et al. 1994; Craig et al. 1998; Xiang et al. 2005; Yoshino et al. 2006; Finkelstein et al. 2007; Ostbye et al. 2007; Lakdawalla et al. 2007). The medical literature provides a plenitude of mechanisms underlying this relationship, such as a higher likelihood of drowsiness and falling, a lack of concentration, and more physical limitations (Corbeil et al. 2001; Shutan 2003; Pollack et al. 2007). Using NLSY data and estimating a rich fixed effects model, we add to this literature by showing that becoming obese is significantly associated with a 21 percent higher risk of having a workplace accident.

Next, using changes in body weight as a proxy for changes in safety-related productivity, we empirically investigate wage changes of workers who become obese across occupations with varying degrees of accident risk. In line with our theoretical predictions and in addition to the standard positive CWD estimates, we find a significant negative association between lower safety-related productivity ("becoming obese") and wages. Most notably, this wage penalty for an observable depreciation of safety-related productivity only appears in high-risk occupations, which reinforces our theoretical insights. While we do not claim that our empirical results can be given a direct causal interpretation, we emphasize that the effects are identified by a rich fixed effects panel model, which nets out unobserved time-invariant worker characteristics and focuses on changes in body weight and accident risk over time.

After discussing the specific contributions of the paper to various literature strands, Section 3 presents our model of worker investments in safety. Section 4 presents the data and Section 5 contains the empirical model and results. Section 6 concludes.

2 Specific Contributions to the Literature

Viscusi and Aldy (2003) provide an excellent discussion and meta-analysis of CWD studies. Categorizing dozens American and international fatal risk studies, they show that VSL estimates vary from basically zero to $20 million.[5] In addition, more than 30 American and international nonfatal

[5]And Viscusi and Gentry (2015) provide evidence that VSL labor market estimates generalize across transport and non-transport contexts in the US.

risk studies yield VSI estimates that vary from zero to $200,000. Many studies do not yield any significant VSL or VSI estimates—plus, publication bias has been shown to exist (Ashenfelter and Greenstone 2004; Doucouliagos et al. 2012; Viscusi 2015). One reason for the wide range of estimates may be that researchers do not account for what Kip Viscusi calls "workers' safety-related productivity" (Hersch and Viscusi 1990; Viscusi and Hersch 2001). Shogren and Stamland (2002) refer to that productivity as "skill"—the personal ability to reduce risk of injury or death (Ehrlich and Becker 1972). This paper contributes to the literature by explicitly modeling such worker provision of safety. We also refer to such set of skills as "risk-specific human capital:" it loses its value in non-risky jobs.

Other reasons for why VSL and VSI estimates differ so widely across studies include the role of unobservables and sorting into occupations (Hamermesh and Wolfe 1990; Black and Kniesner 2003; Lalive 2003; Leeth and Ruser 2003; Ashenfelter 2006; Kniesner et al. 2010; Bommier and Villeneuve 2012; Kochi and Taylor 2011; DeLeire et al. 2013; Lavetti 2017; Lavetti and Schmutte 2017b). For example, Shogren and Stamland (2002) argue that VSL estimates would be likely upward biased if they do not account for worker heterogeneity in both risk preferences and skill at reducing risk. (However, they ignore that workers could earn higher wages in return for that skill.) Lavetti and Schmutte (2017a) present an approach to correct for endogenous job mobility bias in CWD estimates as a result of unobserved firm heterogeneity. Kniesner et al. (2010) show empirically that controlling for unobserved worker heterogeneity makes a difference for VSL estimates.

Our paper confirms the importance of controlling for unobserved time-invariant worker heterogeneity. Doing so increases the size and significance of our fatal and nonfatal CWD estimates. DeLeire et al. (2013) show empirically that standard VSL estimates are biased downwards when not correcting for non-random sorting into occupations. The main insight of our paper also implies downward biased VSI and VSL estimates: if the underlying relationship between individual accident risk and wages is *negative*, it operates against and thus downward biases the standard compensating wage differential.

This paper also adds to the literature theoretically. Only a few previous studies formally model workplace risk as endogenous to workers (Rea 1981; Moore and Viscusi 1990; Krueger 1990; Lanoie 1991, 1994; Ruser and Butler 2010). Those studies typically model it in the context of Workers' Compensation benefits, as they are usually concerned with ex ante moral hazard. They also tend to focus on safety investments through worker demand (Seabury et al. 2005), not because of firms' demand. In some respects, our model is similar to these existing models but it also exhibits some notable differences. In our model, even a fully insured worker makes safety investments that increase worker productivity, thus firm profits, and also wages. As in previous models, worker investments in safety increase workers' utility by decreasing the accident probability. However, our model incorporates a direct incentive for firms to demand worker-produced safety because fewer accidents lower firms' accident costs as well.[6]

In addition to its contributions to the CWD and workplace accident literature (Seabury et al. 2005; Braakmann 2009; Boone et al. 2012; Levine et al. 2012; Sullivan and To 2013; Bronchetti and McInerney 2012, 2015; Sojourner and Yang 2015; Seabury and Powell 2015; Hansen 2016; Johnson 2017), this paper also contributes to the literatures on beauty and the labor market (Hamermesh and Biddle 1994; Biddle and Hamermesh 1998; Hamermesh and Biddle 2012), discrimination (Anwar and Fang 2006; Fang and Norman 2006; Anwar and Fang 2015) and the obesity wage gap (Cawley 2004; Lindeboom et al. 2010; Harris 2018; Caliendo and Gehrsitz 2016). We find that the well-documented obesity wage penalty only exists in high risk jobs. Importantly, it does not vary by gender within those jobs. Our findings are consistent with DeLeire (2001), who suggests that discrimination likely plays a minor role in health and gender-specific wage gaps. Instead, our findings support the notion that obese workers may earn lower wages due to their lower (safety-related) productivity. The findings also imply that occupational sorting may be largely responsible for the gender wage gap found in the literature. For example, DeLeire and Levy (2004) find that variation in occupation-specific fatality risk explains a quarter of gender sorting into occupations.

In short, our paper bridges the literatures on compensating wage differentials, obesity-wage penalties as well as occupational and gender-based sorting into jobs.

3 Theoretical Model

This section presents a simple model that extends the basic framework in Ehrlich and Becker (1972). We apply this model to study workers' incentives to invest in safety and how wages are related to their safety provision. The model is static with representative rational agents.[7] There is a probability p that a workplace accident occurs ($0 < p < 1$). Workers can lower risk p via safety

[6]The hedonic methodology used in previous studies consider firms are sellers and workers are buyers of safety. Our model is different in that firms are not only sellers, but also buyers of safety produced by workers.

[7]Our simple model abstains from worker heterogeneity. We could introduce heterogeneity and allow worker safety productivities to differ across individuals. However, in a competitive labor market with heterogeneity in job risks, we would need to introduce costs of job search, mobility or switching to avoid complete worker sorting into different occupations. Thus, we decided to keep the model tractable. Note that the model does not rely on the absence of a competitive labor market to explain the absence of a wage premium for risk of accidents (Peter and Hagstrom 1998).

inputs e. The safety production function is $p(e)$ with $p' < 0$, $p'' > 0$, where p' is the marginal productivity of safety investments. The worker chooses optimal safety inputs e^* to maximize expected utility.

The main objective of the model is to study the relationship between worker investments in safety and wages. Workers produce the safety when the firm cannot provide it or when it is more cost-effective for workers to provide it (e.g., safe driving or operating machinery). The model endogenizes workplace accident risk and assumes that workers have the ability to effectively provide workplace safety, not just the firm. One main insight of the model is that, under this assumption, the overall relationship between accident risk and wages is theoretically ambiguous. This is because of two forces working in opposite directions: (a) the positive relationship between wages and (exogenous) job risk, and (b) the negative relationship between wages and (endogenous) "worker-produced" risk.

3.1 Firm's Demand for Safety

Consider the firm's profit function:

$$\Pi = Q - W - S - p(e)A \tag{1}$$

where Π are firm profits and Q is output. W is the worker's wage. In case of a work accident with probability $p(e)$ (which can be lowered by worker safety inputs e) the firm incurs accident costs A per worker. To simplify, we assume that firms' safety investments S are exogenously given, as is the workplace accident risk that is determined by technology and the type of job. Also for simplicity, labor and all prices are normalized to one.

Using the firms profit function (1) and the implicit function theorem, we obtain the total differentials:

$$\frac{dW}{dp} = -A < 0 \tag{2}$$

$$\frac{dW}{de} = -\frac{\partial p(e)}{\partial e}A > 0 \tag{3}$$

With respect to equation (2): Note that $dW/dp < 0$, which is of the opposite sign than the standard prediction. From the firm's perspective, standard theory assumes that $dW/dp > 0$ because the firm can make costly safety investments S in order to lower p. Firms would do so only if they can pay lower wages to keep profits constant. However, standard theory does not consider reductions in risk that are not produced by the firm. Our extension of the basic framework illustrates that firms are willing to pay *higher* wages for reductions in risk produced by workers (equation (2)), given that firms are not making the costly expenditures to lower the risk. Accident costs A lower firms' profits, which gives rise to a firm demand for safety, not just supply of safety as is traditionally assumed.

With respect to equation (3): Traditional CWD models assume that $\partial p(e)/\partial e = 0$, implying that workers do not have the ability to endogenously affect risk p. However, given that $\partial p(e)/\partial e < 0$, equation (3) illustrates that $dW/de > 0$. Wages increase in response to worker investments in safety. This gives workers an incentive to invest in safety as they can "sell it" to the firm. Similarly, if workers provide less safety, firms would lower wages. Workplace investments in safety can also be seen as a special ("safety-related") case of worker productivity or human capital.

Equation (3) is the motivating equation for our empirical analysis. It shows the incentive for workers to provide safety to the firm.

Proposition 1 *Firms pay higher wages if workers provide workplace safety and decrease the risk of a workplace accident. Under the assumption that workers have the ability to endogenously influence the accident risk, $p' < 0$, their wages will be positively correlated with higher safety-related productivity. The wage increase will be higher, the higher the marginal productivity of worker safety investments, and the higher the firms' accident costs.*

3.2 Workers' Supply of Safety

The worker maximizes utility $U(.)$ by choosing her level of workplace safety input e, subject to the zero profit constraint which holds in equilibrium due to perfect competition:

$$\max_{e} U = [1 - p(e)]U_1(W - e) + p(e)U_0(W - e - l) + \lambda[Q - W - S - p(e)A] \tag{4}$$

The first term equals worker utility when no accident occurs with probability $1 - p$. In the no-accident state, worker utility depends on wages W minus safety effort e.

The second term equals worker utility when an accident occurs. In the accident state, the worker incurs an additional utility loss l (which can be of pecuniary or non-pecuniary nature). Simplifying notation, equation (4) becomes $U = (1-p)U_1 + pU_0$, where $U' > 0$, $U'' < 0$. The final term is the firm's zero profit constraint.

The first order condition (FOC) is then given by:

$$-\frac{\partial p}{\partial e}(U_1 - U_0) - \lambda \frac{\partial p}{\partial e} A = (1-p)U_1' + pU_0' \tag{5}$$

The FOC states that the marginal benefits of the worker's safety investments have to equal the marginal costs. The right hand side (RHS) of equation (5) represents the marginal costs. They are the sum of the marginal utilities in both states, weighted by the accident probabilities and the price of safety provision (which has been normalized to one).

The left hand side (LHS) of equation (5) represents the marginal benefits of the worker's safety investment. The first term is the difference in worker utility between the accident and non-accident state, weighted by the marginal productivity of the safety investment. The second term is the worker utility from providing safety to the firm—it represents the firm's reduced accident costs. As we saw above, the firm pays the worker higher wages for the worker's supply of safety. Thus, we can substitute equation (3) into equation (5) to obtain:

$$-\frac{\partial p}{\partial e}(U_1 - U_0) + \lambda \frac{dW}{de} = (1-p)U_1' + pU_0' \tag{6}$$

The second term now represents the wage increase for an additional unit of safety input by the worker.

Proposition 2 *Workers invest in workplace safety until the marginal benefits equal the marginal costs.* Ceteris paribus, *they invest more in safety the higher the marginal productivity of their safety investments, the higher the utility loss in case of an accident, and the more firms are willing to pay for it.*

Note the special case of $U_1 = U_0$: This represents the case of a fully insured worker, e.g., through generous public insurance (and abstaining from non-pecuniary utility losses). In this case, worker investments to lower the risk of accidents will be lower. Likewise, government mandated safety regulations could decrease the marginal productivity of worker investments in safety, p', thereby lowering e^*. Note that even if the worker were to not get any utility loss from an accident and $U_1 = U_0$ would strictly hold up, as long as the firm incurs accident costs, the worker would still invest in safety. This is because the firm would *demand* worker-provided safety and compensate workers for such provision, as seen by the second terms of the LHS in equations (5) and (6).

On the other hand, safety investments by workers will also decrease when accidents costs are shifted from firms to taxpayers as it lowers firms' incentives to compensate workers for their safety provision (equation (5)).

Proposition 3 *Reducing workers' accident costs, for example through public insurance, lowers workers' safety investments (ex ante moral hazard). Similarly, to the extent that safety regulations decrease the marginal productivity of workers' safety investments, p', they also lower workers' accident prevention efforts. Likewise, insuring firms' accidents costs reduces firms' incentives to compensate workers for higher safety-related productivity. However, as long as the firm still incurs some accident costs and as there are opportunities for workers to prevent accidents, the firm will still demand and the workers still supply safety.*

3.3 Testable Model Predictions

The key assumption and insight of our model is that, in general, workers have the ability to invest in safety and endogenously determine the risk of a workplace accident. Such safety investments are a special case of human capital investments. Firms demand safety supplied by workers and pay for it with higher wages in return. *Ceteris paribus*, worker safety investments are higher (i) the more productive workers' safety investments are, (ii) the bigger workers' utility loss in case of an accident, and (iii) the more the firm is willing to pay for worker provision of safety.

The standard prediction of the CWD literature is that workplace risk and wages are positively correlated because firms offer higher wages to compensate for riskier jobs. This is true to the extent that risk is exogenously determined from the perspective of the worker, e.g., by technology or safety investments by the firm. Our model predicts that, when workers can effectively prevent workplace accidents, wages and (worker-produced) risk are *negatively* correlated. Hence, the overall relationship between workplace accident risk and wages is *a priori* ambiguous.

The next section tests the model predictions empirically. To derive testable predictions, we assume that the accident risk at the occupational level is exogenous from the worker's perspective. Thus, our **Hypothesis I** suggests a *positive* association between occupational accident risk and wages. Riskier jobs pay higher wages to attract workers. We test this hypothesis in a standard CWD setting using variation in fatal and nonfatal accident risk at the occupation level.

In line with our model, we assume that workers can alter this exogenously given occupational accident risk with their risk-specific human capital. **Hypothesis II** suggests a positive association between worker provision of safety and wages.

Worker panel data that contain time-variant measures of safety-related work productivity are very sparse. Thus, we take an indirect empirical approach. Our empirical approximation uses weight gain of workers over time. Weight gain is observable to employers and can be considered a reasonable measure of safety-related productivity as we will show. As gaining weight proxies for a reduction in risk-specific human capital, we will test whether a negative association between gaining weight and wages exists in high risk jobs.

4 Data

Data for the empirical analysis come from four different sources. The primary source is the 1979 *National Longitudinal Survey of Youth (NLSY)*. The NLSY is a sample of 12,686 people aged 14 to 22 years in 1979. The survey was conducted annually until 1994 and biennially thereafter. All the variables, with the exception of nonfatal and fatal injury risk, were obtained from the NLSY.

4.1 Risk Measures

Nonfatal Risk. We calculate nonfatal injury rates from the *The Survey of Occupational Illnesses and Injuries (SOII)* of the BLS. The SOII provides information on nonfatal occupational injuries and illnesses resulting in at least one day away from work. The SOII is a government program that collects reports from private industry employers. State agencies collect and process the survey data and prepare estimates using standardized procedures established by the BLS to ensure uniformity and consistency between states. The nonfatal risk data are available separately by occupation and gender for the years 1992 to 2000.[8]

To turn the nonfatal accident counts into rates, we divide them (separately by gender) by annual three-digit occupation employment counts provided by the March CPS.[9] In what follows,

[8] The data are available here: https://www.bls.gov/iif/oshcdnew.htm.

[9] For three percent of all occupation-year observations, no nonfatal risk measure could be assigned due to missing data (nonfatal risk or CPS employment counts). More specifically, for our time period, the CPS still used the 1980 Census Occupation Code, whereas the SOII used the 1990 Census Occupation Code. Despite crosswalks, the concordance is not perfect and not all codes could be matched. However, as a robustness check, we imputed three-digit industry-specific risk measures for the missing values. The results are very robust.

we always report injury rates per 100 full-time workers (FTW). We merge nonfatal risk by three-digit occupation, gender and year with the NLSY.

As seen in Figure 1a and Table A1 (Appendix), nonfatal risk is skewed to the right, with an average of 1.9 accidents per 100 FTW, a median of 1.1, a 90^{th} percentile of 4.7 and a 99^{th} percentile of 10.5. The variation is large and ranges from 0.006 to 102 nonfatal accidents per 100 FTW.

[Insert Figure 1 about here]

Fatal Risk. We calculate fatal injury rates from the *The Census of Fatal Occupational Injuries (CFOI)* of the BLS. The CFOI provides the most comprehensive inventory of all work-related fatalities in the United States. The data are collected from various sources including the Occupational Safety and Health Administration, Workers' Compensation reports, death certificates and medical examiner reports. The BLS uses source documents and follow-up questionnaires to ensure that the fatalities are indeed work-related.

We obtain annual fatality counts at the three-digit occupation level for 1992 to 2000 and aggregate them to correspond to the two-digit occupation.[10] To turn the fatality counts into rates, we divide them by annual CPS employment counts and express rates per 100,000 FTW. Finally, to reduce noise and the impact of outliers, we calculate a five-year average fatality rate. We merge fatal risk by two-digit occupation with the NLSY.

As seen in Figure 1b and Table A1 (Appendix), on average, we count 5 fatal accidents per year and 100,000 FTW in the United States. As with nonfatal risk, the variation in fatal risk across occupation is large and ranges from 0.33 to 118.

Body Weight. We calculate each worker's body mass index (BMI) using self-reported weight in each year and the reported height in 1985. We then create a dummy variable for obesity status (BMI$\geq$30). As seen in Table A1, the average BMI is 26.9. About 23 percent of all workers are obese. Guardado and Ziebarth (2013) provide evidence on the covariate balance by obesity status. Somewhat surprisingly, all normalized differences are below the rule-of-thumb threshold of 0.25 (Imbens and Wooldridge 2009); for most variables, the values are even below 0.1. Varying the obesity threshold yields robust results (available upon request).

4.2 Dependent Variable and Socio-Demographics

Hourly Wages. As the dependent variable, we calculate the real hourly gross wage of each respondent by year using the Consumer Price Index (CPI) for all urban consumers where the base

[10] The data are available here: https://www.bls.gov/iif/oshcfoi1.htm.

period is 1982 to 1984. As shown in Table A1, at this time, the average hourly gross wage was \$8.71 but varied from \$1 to \$81.71.

Other Covariates. The empirical specifications adjust the variation in hourly wages for several sets of worker characteristics. A first category refers to demographics and includes age, gender, race, marital status, and #kids in the household (see Appendix, Table A1).

A second category refers to education and includes dummies for high-school degree, some college education, or being a college graduate. We also split the Armed Forces Qualification Test Score (AFQT) into quartiles and include dummy variables for each quartile.

A third category refers to workplace characteristics and includes four firm size dummies ($\leq$25, 26-99, 100-499,$>$500 employees), an indicator for whether there was a job change, and a dummy indicating whether the person holds a private or public sector job.

Finally, we also include regional controls for economic conditions that may affect the value of the worker's marginal product (Bender and Mridha 2011; Boone et al. 2012). This includes the local unemployment rate ($\leq$6 percent, 6 to 8.9 percent, $>$9 percent) as well as the region of residence in the United States (northeast, north central, west and south; urban or rural residence).

Note that all models include year fixed effects. In some saturated specifications, we additionally include worker fixed effects, three-digit occupation fixed effects or two-digit industry fixed effects.

4.3 Sample Selection

We focus on six NLSY waves from 1992 to 2000 and restrict the sample to those who worked for pay, worked at least 40 weeks in the year prior to the survey, usually worked at least 24 hours a week, were not self-employed, were not in the armed forces, reported valid three-digit occupation and two-digit industry codes, had non-missing data on key variables, and did not have a real hourly wage less than \$1 or greater than \$100.[11] After all sample restrictions, we have a sample of 26,016 worker-year observations on 7,006 unique workers.

[11] The following variables have missing data: wage (N=451), occupation (N=120), industry (N=163), weight or height (BMI) (N=710).

5 Empirical Model and Results

5.1 Empirical Model

We estimate two main empirical wage models, one for nonfatal risk and one for fatal risk. Both models are very similar; the nonfatal risk model can be written as:

$$(7) \qquad y_{ijkt} = \gamma Risk_{ijt} + \kappa Risk_{ijt}^2 + \delta OB_{it} + \lambda Risk_{ijt} \times OB_{it} + X_{it}\beta + \phi_t + \alpha_i + \sigma_k + \rho_j + \epsilon_{ijkt}$$

where y_{ijkt} stands for the natural logarithm of the gross hourly wage of worker i in occupation j of industry k in year t.

Each of the two wage-risk models routinely includes year fixed effects ϕ_t. In addition, our preferred specifications include worker fixed effects (α_i) and time-variant regional, demographic, educational and workplace covariates included in X_{it} (see Table A1). Year fixed effects net out common time shocks and worker fixed effects net out time-invariant unobserved worker characteristics that may affect wages, such as worker productivity and risk preferences. For the nonfatal risk model, we also control for industry and occupation fixed effects ($\sigma_k + \rho_j$). We routinely cluster standard errors at the individual level but clustering at the occupational level (Bertrand et al. 2004) yields robust results (available upon request).

Our first regressor of interest is $Risk_{ijt}$. For the nonfatal risk model, $Risk_{ijt}$ represents the nonfatal accident rate at the three-digit occupational level per 100 FTW. It varies by gender, year, and across 417 occupations. In the fully saturated model with year, worker, industry and occupation fixed effects, the coefficient estimate for $Risk_{ijt}$ is thus identified by within-occupation changes in risk of the worker's job over time—after netting out all time-invariant worker characteristics and all time-variant predictors of wage changes in X_{it}. In robustness checks, we exclude job changers and show that the results are not driven by workers who change jobs but workers whose jobs become safer (or riskier) over time (Guardado and Ziebarth 2013). $Risk_{ijt}$ then identifies the compensating wage differential for nonfatal risk and yields an estimate of the VSI. It also tests **Hypothesis I** (Section 3.3) according to which occupational accident risk and wages would be positively correlated.

For the fatal risk model, $Risk_{ijt}$ becomes $Risk_j$ and represents the fatal accident rate at the two-digit occupational level per 100,000 FTW. It only varies across occupations. In the fully saturated fatal risk model, we include year and worker fixed effects, but omit industry and occupation fixed effects (because occupation fixed effects are not identified and industry fixed effects are highly collinear). The coefficient estimate for $Risk_j$ is then identified by between-occupation variation in the fatal risk of workers' jobs. When including worker fixed effects, $Risk_j$ is solely identified by workers who switch occupations. $Risk_j$ identifies the compensating wage differential for fatal risk and yields an estimate of the VSL. Again, this coefficient estimate tests **Hypothesis I** and we expect $\gamma > 0$. (Note that all our models also include a quadratic risk term to capture non-linearities.)

OB_{it} measures obesity. Note that X_{it} includes the continuous BMI measure and its quadratic term to capture non-obesity-related weight effects.[12] With worker fixed effects, OB_{it} identifies the wage penalty of gaining weight and becoming obese. (Experimenting with different BMI thresholds yields robust results which are available upon request.) Because we use weight gain and becoming obese as an (observable) proxy for lower safety-related productivity, δ (partly) tests **Hypothesis II**. However, because gaining weight is correlated with other wage determining factors (including stigma, discrimination, and lower general productivity) finding a wage penalty for becoming obese is not an unambiguous test of our model predictions. It would rather confirm the standard estimate of the obesity-wage literature (Cawley 2004; Caliendo and Gehrsitz 2016).

Therefore, we introduce the interaction term between becoming obese and the workplace risk measure, $Risk_{ijt} \times OB_{it}$, as our main variable of interest. If weight gain proxies for lower safety-related productivity of workers, then we would expect to observe a wage penalty for heavier people particularly in riskier jobs. Because this safety investment is risk-specific, it would lose its value in non-risky jobs. Accordingly, **Hypothesis II** predicts a negative correlation between wages and the interaction term, $\lambda < 0$. Note that the identification assumes (a) that becoming obese is a significant predictor of having a work accident (this is shown in Figure 3 below), and (b) that there exist no unobservables or other non-safety related productivity factors that are correlated with both λ and y_{ijkt}.

The size and significance of δ and λ are also indicative of some of the underlying driving forces of the obesity-wage gap. If obesity primarily captured risk-specific human capital, we would expect the general obesity estimate δ to be small in size and insignificant. By contrast, a negative estimate would suggest that the wage penalty is driven by general factors, such as discrimination or productivity unrelated to safety. *A priori*, there is no reason to believe that these alternative explanations for the obesity-wage penalty should differ significantly by the riskiness of the job, which is why $\lambda < 0$ would be fully in line with **Hypothesis II**.

[12] However, the results are robust to excluding these continuous BMI measures.

5.2 Nonparametric Results

We begin this section by investigating the nonparametric relationship between workplace safety and wages as well as body weight and wages. Figure 2 plots the occupational risk on the x-axis and hourly wages on the y-axis. Figure 2a shows the relationship for nonfatal risk and Figure 2b shows the relationship for fatal risk.

[Insert Figure 2 about here]

In both cases, we observe a U-shaped pattern: The relationship between nonfatal risk and wages is negative up to nonfatal risk of about 4 accidents per 100 FTW after which the relationship flattens up to a value of about 8. For higher nonfatal risk, we observe a strictly positive relationship between risk and wages. The same U-shape is depicted in Figure 2b for fatal risk between 10 and 20 accidents per 100,000 FTW.

[Insert Figure 3 about here]

Next, Figure 3 provides evidence on whether workers' BMI can be considered a good predictor of the individual accident risk. Figure 3 plots the relationship between workers' BMI and their self-reported probability of having a work accident. We find a (statistically significant) increasing risk for workers with BMIs between 24 and 34. This is in line with the medical literature (Craig et al. 1998; Xiang et al. 2005; Finkelstein et al. 2007) and reinforces the notion that a body mass index above 25, and especially 30, is a good proxy for lower safety-related productivity. Recall that Figure 3 is just a nonparametric plot that does not control for individual background characteristics or exploits the panel structure of the data. However, when running a rich fixed effects model similar to equation (7) with accident risk as the outcome measure, we find that becoming obese is associated with a highly significant 1.5 percentage points (or 21 percent) higher risk of having an accident.

[Insert Figure 4 about here]

Next, Figure 4 plots the relationship between BMI and wages separately for males (Figure 4a) and females (Figure 4b). We observe relatively monotonic decreasing relationships between body weight and wages for both sexes. For males, this negative association holds between BMIs of 25 and 40 whereas, for females, it holds between BMIs of 20 and 35. Again, recall that these are pure associations that may mix causal effects with employee sorting into occupations and other unobservable confounders (DeLeire and Levy 2004; Shinall 2015; Harris 2018).

5.3 Parametric Results

Because the nonparametric visual diagnostics do not control for potentially important factors that may be correlated with job risk, obesity and wages (such as risk preferences, discrimination or worker productivity), we proceed with parametric fixed effects models as shown in equation (7). These models control for time-variant individual-level or regional-level wage determinants as well as time-invariant worker unobservables. Following our model hypotheses (Section 3.3) and the discussion on how we test for these (Section 5.1), the relevant regressors are (i) the occupational risk—to test for compensating wage differentials γ, (ii) the BMI and obesity status—to test for changes in risk-specific work productivity δ, and (iii) the interaction between (i) and (ii) λ. The interaction coefficient λ assesses the model prediction that accident prevention investments by workers are rewarded with higher wages, but only in jobs in which this risk-specific human capital is valuable.

[Insert Table 1 about here]

Table 1 presents the results for the nonfatal risk model and equation (7). Each column represents one model. The outcome variable is always the logarithm of the hourly wage and the columns only differ by the covariates that are included, as indicated in the bottom of the table. The first three columns report results without worker fixed effects, and the last three columns report results with worker fixed effects.

Column (1) only includes year fixed effects and yields a significantly negative compensating wage differential γ and a significantly positive coefficient of the risk-obesity interaction term λ, the opposite of what our model predictions suggest.

Column (2) adds a rich set of 417 occupational and 236 industry fixed effects to control for time-invariant occupational and industry factors that may bias the statistical relationship between risk and wages. Recall that the variation in nonfatal risk is particularly rich and varies by occupation, gender and year. When adding occupational and industry fixed effects, the sign of the compensating wage differential γ becomes positive and marginally significant, but the risk-obesity interaction term λ is also still positive.

Column (3) now additionally controls for a rich array of individual-level controls with respect to demographics, education, and the workplace (Appendix, Table A1). However, the coefficient estimates in column (3) are still not in line with our model predictions.

Note that the (adjusted) R2 strongly increases from 0.06 in column (1) to 0.41 in column (2) and further to 0.53 in column (3), illustrating that the most saturated model explains half of the variation in wages between workers.

[Insert Figure 5 about here]

Columns (4) to (6) add worker fixed effects and report results from our preferred specifications. The compensating wage differentials γ are now identified by within-occupation and within-worker changes in job risk over time, and the obesity wage penalty δ is identified by workers who gain weight. Figure 5 illustrates the relationship between within-occupation variation in nonfatal risk and wages. As seen in the figure, the within-occupation variation in nonfatal risk from one year to the next is rich (x-axis) and the relationship with wages (y-axis) is clearly upward sloping and positive, suggesting a positive compensating wage differential.

Indeed, our preferred specifications in columns (5) and (6) now clearly show that workers in high risk occupations earn wage premiums. Each additional nonfatal accident per 100 FTW is associated with 1.1 percent higher wages. Moving from the median risky job (1.1 accidents) to the 90^{th} percentile (4.7 accidents) implies a wage premium of about 4 percent, and moving to the 99^{th} percentile (10.5 accidents) implies a wage premium of about 10 percent. This finding is in line with **Hypothesis I** according to which workers in high risk jobs would earn higher wages. This wage premium is identified by workers whose occupations become riskier over time. Robustness checks show that the effect is not driven by workers who change jobs (Guardado and Ziebarth 2013).

Second, the general negative statistical association between obesity and wages (which we observe in columns (1) to (3)), δ, vanishes. At most, becoming obese is associated with a very small general wage penalty of 0.3 percent which is, however, not statistically significant (column (6)). The absence of a general wage penalty for gaining weight is consistent with **Hypothesis II**. There is no return to risk-specific human capital in non-risky jobs. The absence of a general obesity-wage penalty also rules out some alternative explanations for the wage penalty, such as general discrimination or lower productivity unrelated to safety.

Third, in the models with worker fixed effects, the interaction term between occupational risk and obesity, λ , is negative, significant, and very robust across all three specifications. We interpret these estimates as the return to risk-specific human capital. Specifically, the estimates indicate that becoming obese reduces wages by about 0.4 percent—but only in high risk jobs. The estimate remains stable when we exclude workers who switched jobs (available upon request). The finding that becoming obese leads to a wage penalty only in risky jobs is absolutely in line with our model and **Hypothesis II**.

A significant wage penalty of 0.4 percent appears small in magnitude; however, it translates into $200 per year for an annual income of $50,000. After a work life of 30 years and assuming a 2 percent discount rate, this yields a lifetime wage penalty of more than $8,000. Also note that it is a third of the size of the CWD estimate γ. Moreover, it is possible that a more direct measure of safety-related productivity would yield estimates of larger magnitudes. Also recall that our sample consists of relatively young workers. Finally, classical measurement error in the obesity or job risk measures could downward bias the estimate.

The finding contributes to the economics literature on the existence of a CWD for nonfatal risk, which has not been consistently found. Viscusi and Aldy (2003) report (published) VSI estimates that range between zero and $200,000. Applying a $21 hourly wage and a fixed point of 2,000 annual hours as in Kniesner et al. (2010), the nonfatal CWD estimate in column (6) of Table 1 would translate into a VSI of $45.4 thousand. This estimate falls within the range of estimates reported by Viscusi and Aldy (2003), but at the lower end, analogously to the reduced VSL estimate in Kniesner et al. (2010) when considering unobserved worker heterogeneity.

When we run the same model as in equation (7), but do not control for workers' body weight, obesity status and its interaction with risk, λ, then the γ CWD coefficient shrinks in size (although not in a statistically significant sense). This is in line with our priors and the theory, according to which the standard VSI/VSL estimates could be downward biased when ignoring the relationship between individual risk and wages, which operates opposite the standard occupational risk-wage correlation. When ignoring this correlation empirically, the VSI is $42.4 thousand and 7 percent smaller.[13]

[Insert Table 2 about here]

Table 2 presents the results for the fatal risk model. The setup of the table is the same as in Table 1. Recall that fatal risk exhibits significantly less variation (Figure 1) because (i) it rarely occurs; on average only 5 fatal accidents per 100,000 FTW have been recorded (vs. 1,900 per 100,000 FTW for nonfatal risk), (ii) we average over the years to minimize the impact of outliers, and (iii) the data are not available by gender. Because the variation in the fatal risk measure is significantly smaller, so is the statistical power. In addition, we cannot include occupation and industry fixed effects in

[13] Note that this test does not have the power to empirically correct for an underestimated VSI/VSL. The reason is that *Risk* is an equilibrium outcome. Imagine that workers have the ability to invest in safety and are effective in preventing work accidents. Then occupations appear safer than they actually are and $Risk < TrueRisk$.

the empirical model. Furthermore, when including worker fixed effects, the compensating wage differential γ is solely identified by workers who switch occupations.

As above, when we just control for year fixed effects, the coefficient estimates are at odds with our model predictions (column (1) of Table 2): the compensating wage differential γ is negative and significant, and the interaction term λ is positive and significant. In column (2), when adding individual-level controls, X_{it}, λ remains positive but γ has the hypothesized positive sign and is statistically significant.

The most saturated specifications in columns (3) and (4)—our preferred specifications—add worker fixed effects and thus identify the CWD γ by workers who switch occupations over time—while correcting wage differences for time shocks, unobserved time-invariant worker characteristics, and observed time-variant socio-demographic, educational and job-related controls. Now, in both models, the estimate for δ (obesity) has shrunk and lost significance. Our main variable of interest λ (risk-obesity interaction) has the hypothesized sign and is negative, but lacks statistical power. Given the lower variation in the fatal risk measure and our relatively rich fixed effects model, the low statistical power is not surprising. However, note that we do obtain a statistically significant and large interaction term $\lambda = -0.0327^{**}$ when we create a binary measure of fatal risk being above the mean ($RiskHigh_j$) and interact this dummy with being obese (detailed results available upon request). We consider this statistically significant estimate (and the imprecise estimate of the standard model in columns (3) and (4)) in line with the nonfatal risk model and **Hypothesis II**. Workers with lower safety-related productivity earn lower wages.

In column (4), we obtain a compensating wage differential of 0.15 percent for every additional fatal accident per 100,000 FTW. This estimate is statistically significant at the 5 percent level. When applying a \$21 hourly wage and 2,000 annual hours of work (as above for nonfatal risk and in Kniesner et al. (2010)), this CWD estimate translates into a VSL estimate of \$6.3 million. Such a VSL estimate is almost identical to the first differenced estimate in Kniesner et al. (2010) using the PSID. It also lies within the range of recent meta-analyses for the United States. For example, Robinson and Hammitt (2016) provide a range between \$4.2 and \$13.7 million. Finally, as above with nonfatal risk, when not controlling for workers' obesity status and its interaction with risk, the CWD coefficient and the implied VSL shrink in size (but not in a statistically significant sense) to \$5.9 million. In contrast and also in line with our priors, in the extended model with the additional $RiskHigh_j$ control and when correcting for the significant $HighRisk_j \times OB_{it}$ proxy for worker investments in safety, the fatal CWD estimate increases in size to 0.21 percent and yields a VSL estimate of \$8.8 million (detailed results available upon request).

So far, we have estimated the models separately for nonfatal and fatal risk. Table 3 serves as a robustness check and includes all nonfatal and fatal risk measures as well as their interactions with obesity simultaneously. While, in theory, this approach allows us to disentangle the nonfatal and fatal risk parameters, in practice, one could run into econometric issues such as multicollinearity or overfitting, given that we include year, industry, occupation and worker fixed effects in some specifications (the bivariate correlation between nonfatal and fatal risk is 0.3). Other than that, the setup of Table 3 is similar to the setup of Tables 1 and 2—each column represents one regression model as in equation (7)

[Insert Table 3 about here]

Columns (1) and (3) of Table 3 are the equivalent joint models to columns (1) and (4) of Table 1 for nonfatal risk, and columns (1) and (3) of Table 2 for fatal risk. A comparison reveals that the coefficients are very similar in size and significance and are robust. In the most parsimonious specification with just year fixed effects (column (1)), as above, most of coefficients do not carry the expected sign. When adding worker fixed effects in column (3), however, the nonfatal risk model yields a highly significant and negative λ of size 0.4 percent as hypothesized and as in Table 1. In line with Table 2, the fatal risk coefficients for γ and λ lack statistical power when adding worker fixed effects in column (3).

Columns (2) and (4) additionally control for occupation and industry fixed effects. However, for the fatal risk model this is not very meaningful as the fatal risk measure only varies at the two-digit occupation level (and is now solely identified by very little residual variation over time, see Section 4.1). For the nonfatal risk model, the coefficient estimates are very robust whether we simultaneously control for fatal risk and its interaction with obesity, or not (column (4) of Table 3 vs. column (6) of Table 1): In line with **Hypothesis II**, the λ coefficient is negative, of size 0.4 percent, and statistically significant at the 5 percent level. In line with **Hypothesis I**, the γ coefficient is positive, of size 1.1 percent, and also statistically significant at the 5 percent level.

5.4 Effect Heterogeneity

Now we explore effect heterogeneity by gender, age, race, and job requirements. Because of its richer variation, we focus on the nonfatal risk model for this exercise. Technically, we generate and add an additional triple interaction term between the stratifying covariate and the risk-obesity interaction term λ, in addition to the according two-way interactions. Otherwise, the setup of Table 4 is the same as above.

[Insert Table 4 about here]

Column (1) stratifies by gender. If weight changes reflected changes in safety-related productivity, then we would not expect the results to differ by gender. Indeed, column (1) provides no evidence that this is the case. This finding bolsters the idea that the wage penalty is a result of lower risk-specific productivity rather than general discrimination against obese workers. Although the $OB \times female$ interaction is relatively large and negative, it is not statistically significant and thus rather *suggests* the existence of a general obesity wage penalty for women (Cawley 2004; DeBeaumont 2009).

Next, we test whether the results differ by race. Similar arguments to those made with respect to gender apply here as well. Columns (2) and (3) show that all workers earn lower wages in high-risk jobs when they gain weight. We do not find any evidence that the results differ by race.

Column (4) tests for age-related heterogeneity effects. Again, there is no evidence that the wage penalty for people who work in high-risk jobs and gain weight differ by age. This, however, could be an artifact of the compressed age distribution of the NLSY which varies only between 27 and 43 (see Appendix, Table A1).

Thus far we have considered accident risk across occupations, gender, and over time. Certain job characteristics, such as being physically demanding or strenuous, could be a potential transmission channel of the underlying relationship. To investigate this possibility, we generate a variable *PhysicallyDemandingJob* (which takes on values 0 to 3 and varies across occupations) and interact it with our main variables of interest. Higher values represent more strenuous jobs. The variable indicates whether the job requires (i) climbing, (ii) reaching, or (iii) stooping, kneeling, crouching or crawling.[14]

Column (5) of Table 4 presents the results. The triple interaction term is not statistically significant and is relatively small in size. However, the two-way interaction between risk and obesity remains significant and increases in size. The new two-way interaction between obesity and *PhysicallyDemandingJob* is large, significant, and negative. This suggests that gaining weight leads to lower wages, particularly in physically demanding jobs and in jobs with higher occupational acci-

[14] We assigned these job characteristics to the occupations in the NLSY using the Dictionary of Occupational Titles (DOT), Revised Fourth Edition, following the work of Lakdawalla and Philipson (2009) (who generously shared their data with us). Using the NLSY, we first matched 1990 US Census occupation codes to the occupations in the DOT, and then assigned DOT scores to the US Census occupation codes. Because DOT occupations can be more specific than the Census occupations (Census occupations can match to multiple DOT occupations) we averaged the DOT scores within each 1990 US Census code to obtain an average score for each Census code. We were unable to assign job characteristics for 147 individuals.

dent risk. It bolsters this paper's main idea of endogenizing job risk from the workers' perspective and allowing for worker investments in safety. It also makes it reasonable to believe that the correlation between occupational risk, obesity and wages is not driven by unobserved variables or productivity unrelated to safety, but by changes in safety-specific productivity of workers.

6 Conclusion

The standard theory of compensating wage differentials assumes that firms and workers face tradeoffs between workplace safety and wages. Firms can pay higher wages to compensate workers for higher accident risk, or they can invest in safety and pay lower wages. Importantly, the standard model assumes that workplace risk is exogenous to workers, as only firms are able to alter this risk.

In this paper, we depart from most past research by allowing for investments in safety made by workers. A key prediction of this enhanced model is that accident risk is positively associated with wages, but only to the extent that it is produced by the firm or determined by technology. In contrast, if risk is "produced" by workers, then risk will be *negatively* associated with wages. Firms would compensate workers for their accident prevention efforts and provision of safety.

We empirically investigate the model predictions using a uniquely compiled dataset based on worker panel NLSY data linked to fatal and nonfatal occupational risk measures from the BLS. Our empirical results are in line with our model predictions. We obtain precisely estimated compensating wage differentials for fatal and nonfatal risk. Using a mean wage of $21, our VSI estimate is $45.4 thousand and our VSL estimate is $6.3 million.

In addition to these CWD estimates and in line with the main idea of this paper, we find a highly significant negative relationship between obesity (proxying for lower risk-specific productivity) and wages, but only in high risk occupations. When workers become obese, they face a wage penalty of about 4 percent in high risk as compared to median risk jobs (90^{th} vs. 50^{th} nonfatal risk percentile). Lower safety-related productivity is associated with wage losses, but only in risky jobs, where such productivity ought to matter. This finding is consistent with our prediction that "worker-produced" risk is associated with *lower* wages.

One implication of workers being able to invest in safety is that some jobs will appear safer than they actually are if workers are effective in preventing accidents. Also, the negative wage-risk correlation at the individual level may operate against the positive wage-risk correlation at the occupational level. This may have downward biased previous VSI and VSL estimates and explain imprecise or null findings. Although we can only rely on an incomplete measure of safety-related productivity, in line with our theory, our VSI and VSL estimates increase slightly in size once we control for individual-level variation in safety-related productivity.

Finally, our findings also contribute to the obesity-wage literature. We show that the wage penalty primarily exists in risky occupations, which suggests that it is due to lower (risk-specific) productivity. This finding is at odds with alternative explanations for the obesity-wage penalty, such as general discrimination.

The intersection of workplace safety, accident prevention, and compensating wage differentials continues to provide ample research opportunities. Obtaining more precise measures of worker safety-related productivity is a fruitful avenue for future research.

References

Anwar, S. and H. Fang (2006). An Alternative Test of Racial Prejudice in Motor Vehicle Searches: Theory and Evidence. *American Economic Review 96*(1), 641–658.

Anwar, S. and H. Fang (2015). Testing for Racial Prejudice in the Parole Board Release Process: Theory and Evidence. *The Journal of Legal Studies 44*(1), 1–37.

Ashenfelter, O. (2006). Measuring the Value of a Statistical Life: Problems and Prospects. *Economic Journal 116*(510), C10–C23.

Ashenfelter, O. and M. Greenstone (2004). Estimating the Value of a Statistical Life: The Importance of Omitted Variables and Publication Bias. *American Economic Review 94*(2), 454–460.

Baicker, K., D. M. Cutler, and Z. Song (2010). Workplace Wellness Programs Can Generate Savings. *Health Affairs 29*(2), 2304–2311.

Bender, K. A. and H. Mridha (2011). The Effect of Local Area Unemployment on Compensating Wage Differentials for Injury Risk. *Southern Economic Journal 78*(2), 287–307.

Bertrand, M., E. Duflo, and M. Sendhil (2004). How Much Should We Trust Differences-in-Differences Estimates? *Quarterly Journal of Economics 119*(1), 249–275.

Biddle, J. E. and D. S. Hamermesh (1998). Beauty, Productivity, and Discrimination: Lawyers' Looks and Lucre. *Journal of Labor Economics 16*(1), 172–201.

Black, D. A. and T. J. Kniesner (2003). On the Measurement of Job Risk in Hedonic Wage Models. *Journal of Risk and Uncertainty 27*(3), 205–220.

Bommier, A. and B. Villeneuve (2012). Risk Aversion and the Value of Risk to Life. *Journal of Risk and Insurance 79*(1), 77–104.

Boone, J., J. C. van Ours, J.-P. Wuellrich, and J. Zweimüller (2012). Recessions are Bad for Workplace Safety. *Journal of Health Economics 30*(4), 764–773.

Braakmann, N. (2009). Is There a Compensating Wage Differential for High Crime Levels? First Evidence from Europe. *Journal of Urban Economics 66*(3), 218–231.

Bronchetti, E. T. and M. McInerney (2012). Revisiting Incentive Effects in Workers' Compensation: Do Higher Benefits Really Induce More Claims? *Industrial and Labor Relations Review 65*(2), 288–315.

Bronchetti, E. T. and M. McInerney (2015). What Determines Employer Accommodation of Injured Workers? The Importance of Employer Workers' Compensation Costs, State Policies, and Case-Specific Characteristics. *Industrial and Labor Relations Review 68*(3), 558–583.

Bureau of Labor Statistics (2016). *National Census of Fatal Occupational Injuries in 2015*. https://www.bls.gov/news.release/pdf/cfoi.pdf, retrieved June 24, 2017.

Cable, J. (2005). *Success Dispels Skepticism for Companies with Incentives Programs*. http://ehstoday.com/safety/incentives/ehs_imp_37524, last retrieved on May 9, 2016.

Caliendo, M. and M. Gehrsitz (2016). Obesity and the Labor Market: A Fresh Look at the Weight Penalty. *Economics and Human Biology 23*, 209–225.

Cawley, J. (2004). The Impact of Obesity on Wages. *Journal of Human Resources 39*(2), 451–472.

Chelius, J. R. (1974). The Control of Industrial Accidents: Economic Theory and Empirical Evidence. *Law and Contemporary Problems 38*(4), 700–729.

Corbeil, P., M. Simoneau, D. Rancourt, A. Tremblay, and N. Teasdale (2001). Increased Risk for Falling Associated with Obesity: Mathematical Modeling of Postural Control. *Law and Contemporary Problems 9*(2), 126–136.

Craig, B. N., J. J. Congleton, C. J. Kerk, J. M. Lawler, and K. P. McSweeney (1998). Correlation of Injury Occurrence Data with Estimated Maximal Aerobic Capacity and Body Composition in a High-Frequency Manual Materials Handling Task. *American Industrial Hygiene Association Journal 59*(1), 25–33.

DeBeaumont, R. (2009). Occupational Differences in the Wage Penalty for Obese Women. *Journal of Behavioral and Experimental Economics (formerly The Journal of Socio-Economics) 38*(2), 344–349.

DeLeire, T. (2001). Changes in Wage Discrimination against People with Disabilities: 1984-1893. *The Journal of Human Resources 36*(1), 144–158.

DeLeire, T., S. Khan, and C. Timmins (2013). Roy Model Sorting and Nonrandom Selection in the Valuation of a Statistical Life. *International Economic Review 54*(1), 279–306.

DeLeire, T. and H. Levy (2004). Worker Sorting and the Risk of Death on the Job. *Journal of Labor Economics 22*(4), 925–954.

Doucouliagos, C., T. D. Stanley, and M. Giles (2012). Are Estimates of the Value of a Statistical Life Exaggerated? *Journal of Health Economics 31*(1), 197–206.

Ehrlich, I. and G. S. Becker (1972). Market Insurance, Self-Insurance and Self-Protection. *Journal of Political Economy 80*(4), 623–648.

Fang, H. and P. Norman (2006). Government-Mandated Discriminatory Policies: Theory and Evidence. *International Economic Review 47*(2), 361–389.

Finkelstein, E. A., H. Chen, M. Prabhu, J. G. Trogdon, and P. S. Corso (2007). The Relationship between Obesity and Injuries among U.S. Adults. *American Journal of Health Promotion 21*(5), 460–468.

Gossner, O. and P. Picard (2005). On the Consequences of Behavioral Adaptations in the Cost–Benefit Analysis of Road Safety Measures. *Journal of Risk and Insurance 72*(4), 577–599.

Guardado, J. R. and N. R. Ziebarth (2013). A Model of Worker Investment in Safety and Its Effects on Accidents and Wages. IZA Discussion Papers 7428.

Hamermesh, D. S. and J. E. Biddle (1994). Beauty and the Labor Market. *American Economic Review 84*(5), 1174–1194.

Hamermesh, D. S. and J. E. Biddle (2012). Tall or Taller, Pretty or Prettier: Is Discrimination Absolute or Relative? *IZA Journal of Labor Economics 1*(2).

Hamermesh, D. S. and J. R. Wolfe (1990). Compensating Wage Differentials and the Duration of Wage Loss. *Journal of Labor Economics 8*(1), S175–S197.

Hansen, B. (2016). Californias 2004 Workers' Compensation Reform: Costs, Claims, and Contingent Workers. *Industrial and Labor Relations Review 69*(1), 173–198.

Harris, M. C. (2018). The Impact of Body Weight on Occupational Mobility and Career Development. *International Economic Review forthcoming.*, –.

Hersch, J. and K. W. Viscusi (1990). Cigarette Smoking, Seatbelt Use, and Differences in Wage-Risk Tradeoffs. *Journal of Human Resources 25*(2), 202–227.

Imbens, G. W. and J. M. Wooldridge (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature 47*(1), 5–86.

Johnson, M. S. (2017). Regulation by Shaming: Deterrence Effects of Publicizing Violations of Workplace Safety and Health Laws. Technical report. https://drive.google.com/file/d/0Bxr2qrvtxnbrZUhXVnBTa0JHV2c/view, retrieved January 14, 2018.

Kenkel, D. (2003). Using Estimates of the Value of a Statistical Life in Evaluating Consumer Policy Regulations. *Journal of Consumer Policy 26*(1), 1–21.

Kniesner, T. J., W. K. Viscusi, C. Woock, and J. P. Ziliak (2010). The Value of a Statistical Life: Evidence from Panel Data. *The Review of Economics and Statistics 94*(1), 74–87.

Kniesner, T. J., W. K. Viscusi, and J. Ziliak (2010). Policy Relevant Heterogeneity in the Value of Statistical Life: New Evidence from Panel Data Quantile Regressions. *Journal of Risk and Uncertainty 40*(1), 15–31.

Kochi, I. and L. O. Taylor (2011). Risk Heterogeneity and the Value of Reducing Fatal Risks: Further Market-Based Evidence. *Journal of Benefit-Cost Analysis 2*(3), Article 1.

Krueger, A. B. (1990). Incentive Effects of Workers' Compensation Insurance. *Journal of Public Economics 41*(1), 73–99.

Lakdawalla, D. N. and T. Philipson (2009). The Growth of Obesity and Technological Change. *Economics and Human Biology 7*(3), 283–193.

Lakdawalla, D. N., R. T. Reville, and S. A. Seabury (2007). How Does Health Insurance Affect Workers' Compensation Filing? *Economic Inquiry 45*(2), 286–303.

Lalive, R. (2003). Did We Overestimate the Value of Health? *Journal of Risk and Uncertainty 27*(2), 171–193.

Lanoie, P. (1991). Occupational Safety and Health: A Problem of Double or Single Moral Hazard. *Journal of Risk and Insurance 58*(1), 80 – 100.

Lanoie, P. (1994). A Note on Government Intervention in Occupational Safety and Health: The Case for an Accident Tax and a Safety Bonus Scheme. *Bulletin of Economic Research 46*(2), 185 – 191.

Lavetti, K. (2017). The Estimation of Compensating Wage Differentials: Lessons from the Deadliest Catch . Technical report. http://www.kurtlavetti.com/DLS_vc.pdf, retrieved June 24, 2017.

Lavetti, K. and I. Schmutte (2017a). Estimating Compensating Wage Differentials with Endogenous Job Mobility . Technical report. http://www.kurtlavetti.com/CDEM_vc.pdf, retrieved January 24, 2018.

Lavetti, K. and I. Schmutte (2017b). Gender Differences in Earnings and Sorting on Occupational Safety . Technical report. http://www.kurtlavetti.com/FVSL_vc.pdf, retrieved June 24, 2017.

Leeth, J. D. and J. Ruser (2003). Compensating Wage Differentials for Fatal and Nonfatal Injury Risk by Gender and Race. *Journal of Risk and Uncertainty 27*(3), 257–277.

Levine, D. I., M. W. Toffel, and M. S. Johnson (2012). Randomized Government Safety Inspections Reduce Worker Injuries with No Detectable Job Loss. *Science 336*(6083), 907–911.

Lindeboom, M., P. Lundborg, and B. van der Klaauw (2010). Assessing the Impact of Obesity on Labor Market Outcomes. *Economics & Human Biology 8*(3), 309–319.

Moore, M. J. and W. K. Viscusi (1990). *Compensation Mechanisms for Job Risks: Wages, Workers' Compensation, and Product Liability* (1 ed.). Princeton University Press.

National Public Radio (2016). *The Most Common Job in Every State*. http://www.npr.org/sections/money/2015/02/05/382664837/map-the-most-common-job-in-every-state, retrieved June 24, 2017.

Oi, W. (1974). On the Economics of Industrial Safety. *Law and Contemporary Problems 38*(4), 669–699.

Ostbye, T., J. M. Dement, and K. M. Krause (2007). Obesity and Workers' Compensation: Results from the Duke Health and Safety Surveillance System. *Archives of Internal Medicine 167*(8), 766–773.

Peter, D. and P. A. Hagstrom (1998). Work Compensation for Dangerous Work Revisited. *Industrial and Labor Relations Review 52*(1), 116–135.

Pollack, K. M., G. S. Sorock, M. D. Slade, L. Cantley, K. Sircar, O. Taiwo, and M. R. Cullen (2007). Association between Body Mass Index and Acute Traumatic Workplace Injury in Hourly Manufacturing Employees. *American Journal of Epidemiology 166*(2), 1–8.

Rea, S. A. (1981). Workmen's Compensation and Occupational Safety Under Imperfect Information. *American Economic Review 71*(1), 80–93.

Robinson, L. A. and J. K. Hammitt (2016). Valuing Reductions in Fatal Illness Risks: Implications of Recent Research. *Health Economics 25*(8), 1039–1052.

Ruser, J. and R. Butler (2010). The Economics of Occupational Safety and Health. *Foundations and Trends(R) in Microeconomics 5*(5), 301–354.

Safety Management Group (2016). *About Us*. http://safetymanagementgroup.com/, retrieved March 20, 2016.

Seabury, S. A., D. Lakdawalla, and R. T. Reville (2005). Gender Differences in Earnings and Sorting on Occupational Safety . RAND Working Paper 243.

Seabury, S. A. and D. Powell (2015). Medical Care Spending and Labor Market Outcomes: Evidence from Workers' Compensation Reforms. mimeo. https://sites.google.com/site/davidmatthewpowell/, retrieved June 24, 2017.

Shinall, J. H. (2015). Occupational Characteristics and the Obesity Wage Penalty. mimeo.

Shogren, J. F. and T. Stamland (2002). Skill and the Value of Life. *Journal of Political Economy 110*(5), 1168–1197.

Shutan, B. (2003). Obesity Debate Weighs on Workers' Compensation. *Risk and Insurance 5*(4), 1039. , retrieved November 24, 2016.

Sojourner, A. J. and J. Yang (2015). Effects of Unionization on Workplace-Safety Enforcement: Regression-Discontinuity Evidence. IZA Discussion Papers 9610.

Stoohs, R. A., C. Guilleminault, A. Itoi, and W. C. Dement (1994). Traffic Accidents in Commercial Long-Haul Truck Drivers: The Influence of Sleep-Disordered Breathing and Obesity. *Sleep 17*(7), 619–623.

Sullivan, P. and T. To (2013). Job Dispersion and Compensating Wage Differentials. Working Papers 469, U.S. Bureau of Labor Statistics.

Thaler, R. and S. Rosen (1976). The Value of Saving a Life: Evidence from the Labor Market. In N. Terleckyj (Ed.), *Household Production and Consumption*, pp. 265–302. NBER/Columbia University Press.

Transport Canada (2012). *Incentive Programs for Enhancing Truck Safety and Productivity: A Canadian Perspective*. http://data.tc.gc.ca/archive/eng/innovation/tdc-summary-13200-13256e-896.htm, retrieved March 20, 2015.

Viscusi, W. and E. Gentry (2015). The Value of a Statistical Life for Transportation Regulations: A Test of the Benefits Transfer Methodology. *Journal of Risk and Uncertainty 51*(1), 53–77.

Viscusi, W. K. (2015). The Role of Publication Selection Bias in Estimates of the Value of a Statistical Life. *American Journal of Health Economics 1*(1), 27–52.

Viscusi, W. K. and J. E. Aldy (2003). The Value of a Statistical Life: A Critical Review of Market Estimates throughout the World. *Journal of Risk and Uncertainty 27*(1), 5–76.

Viscusi, W. K. and J. Hersch (2001). Cigarette Smokers As Job Risk Takers. *The Review of Economics and Statistics 83*(2), 269–280.

Xiang, H., G. A. Smith, J. R. W. III, G. Chen, S. G. Hostetler, and L. Stallones (2005). Obesity and Risk of Nonfatal Unintentional Injuries. *American Journal of Preventive Medicine 29*(1), 41–45.

Yoshino, A., M. Higuchi, F. Kawana, M. Kato, M. Kamata, S. Nakanishi, T. Kasai, and K. Narui (2006). Risk Factors for Traffic Accidents in Patients with Obstructive Sleep Apnea Syndrome. *Sleep and Biological Rhythms 4*(2), 144–155.

Figures and Tables

Figure 1 Histograms of Nonfatal and Fatal Occupational Accident Risk

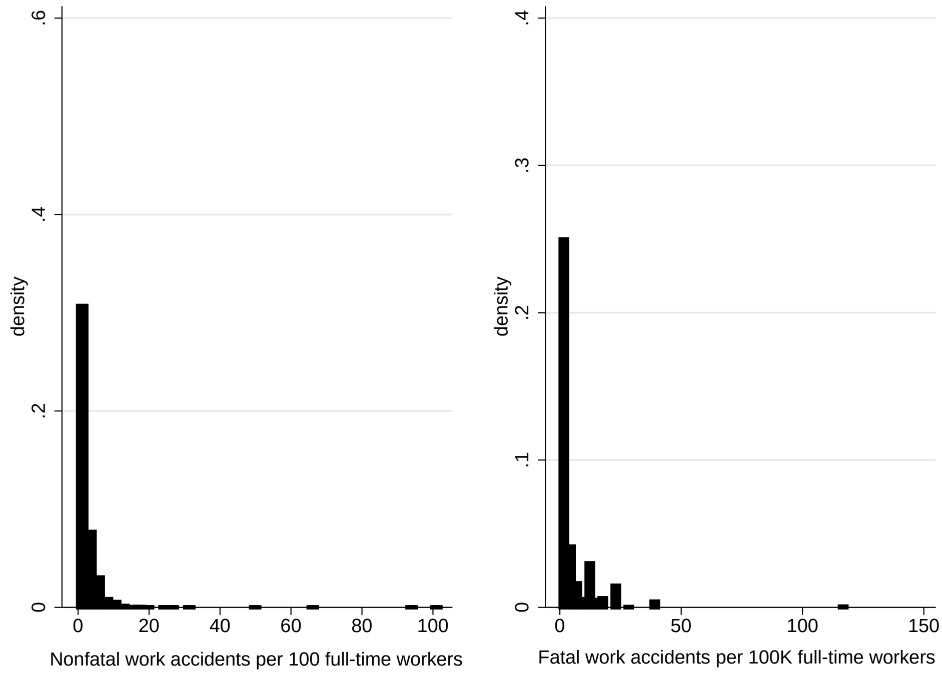

Figure 2 Nonparametric Association between Occupational Accident Risk and Wages

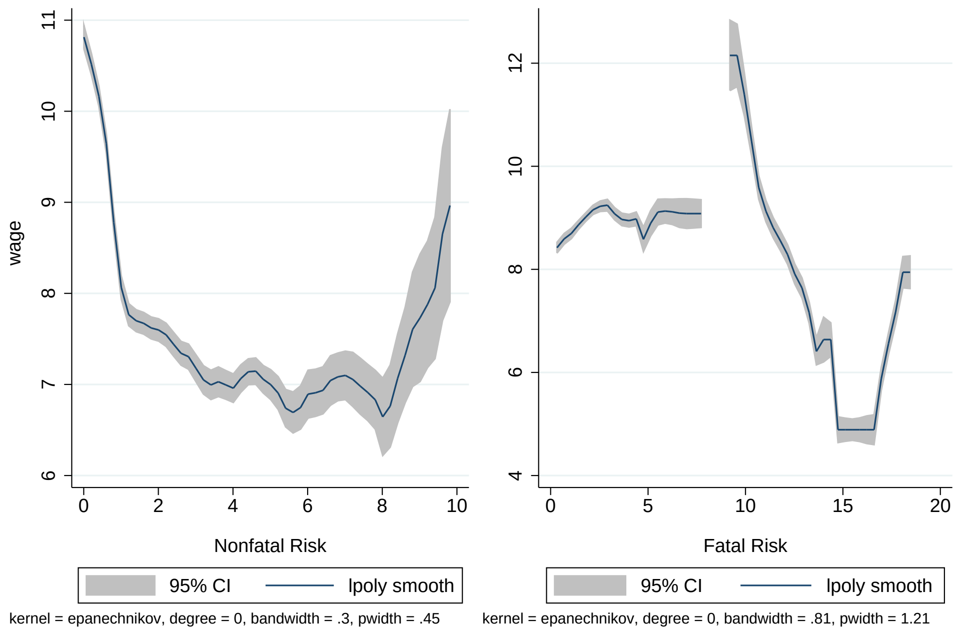

Figure 3 Nonparametric Association between BMI and Individual Injury Risk

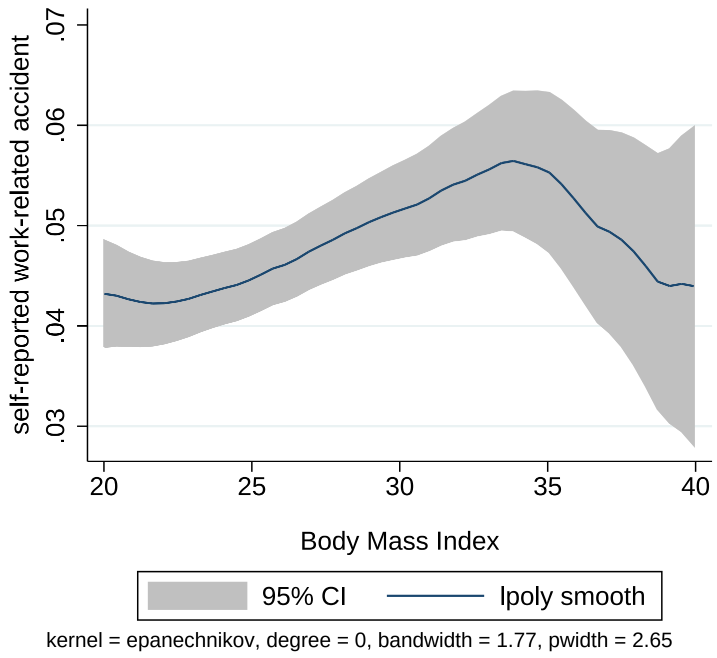

Figure 4 Nonparametric Association between BMI and Wages

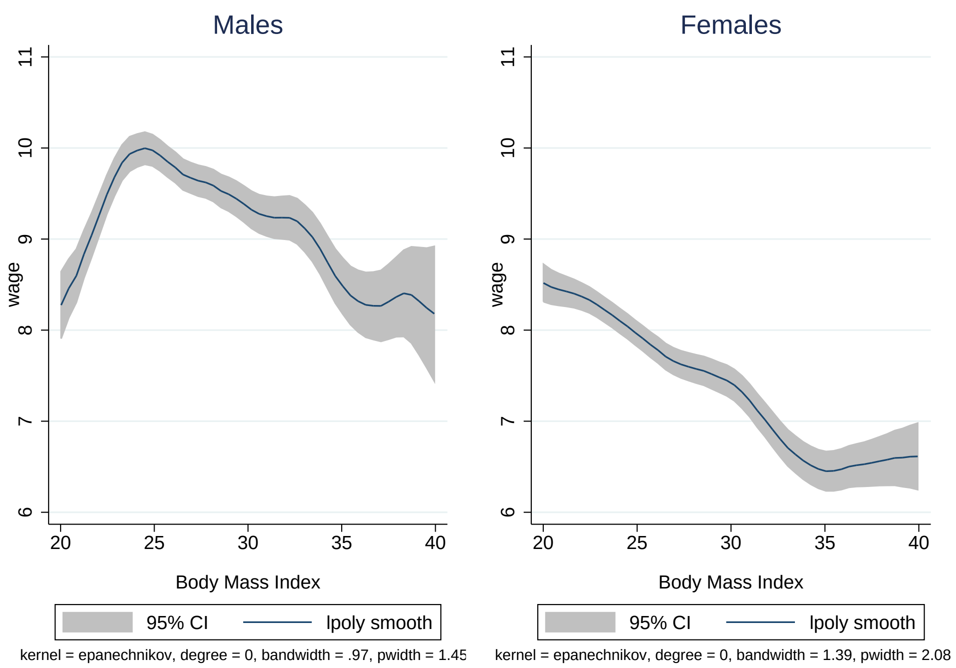

Figure 5 Within Occupational Changes in Nonfatal Accident Risk and Wages

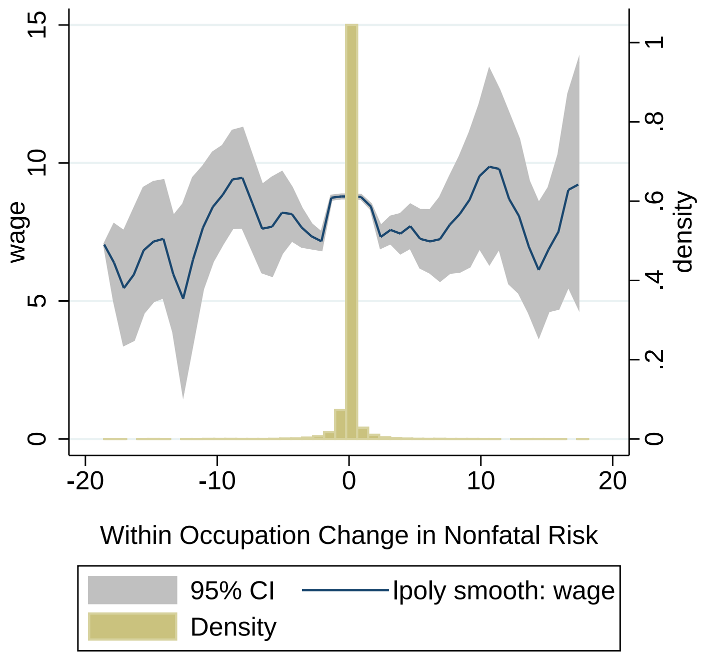

Table 1 Compensating Wage Differentials for Nonfatal Risk, Obesity, and their Interaction

	Without Worker Fixed Effects			With Worker Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Nonfatal Risk×Obese	0.0088*	0.0092***	0.0075***	-0.0042**	-0.0042**	-0.0039**
	(0.0046)	(0.0027)	(0.0024)	(0.0018)	(0.0018)	(0.0018)
Nonfatal Risk	-0.0500***	0.0066*	0.0022	0.0019	0.0113***	0.0108***
	(0.0027)	(0.0034)	(0.0031)	(0.0015)	(0.0023)	(0.0023)
Nonfatal Risk^2	0.0006***	-0.0001***	-0.0001**	0.0000	-0.0001***	-0.0001***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Obese	-0.1362***	-0.0744***	-0.0400***	0.0024	-0.0000	-0.0028
	(0.0203)	(0.0144)	(0.0128)	(0.0103)	(0.0099)	(0.0099)
BMI	0.0329***	0.0145***	0.0029	0.0099**	0.0081**	0.0077**
	(0.0059)	(0.0041)	(0.0038)	(0.0040)	(0.0038)	(0.0039)
BMI^2	-0.0005***	-0.0002***	-0.0001	-0.0001*	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year FE	X	X	X	X	X	X
Industry FE		X	X		X	X
Occupation FE		X	X		X	X
Individual-level Covariates			X			X
Individual FE				X	X	X
R-squared	0.0593	0.4104	0.5274	0.1144	0.1871	0.1975

Source: NLSY, CPS, and SOII 1992-2000. Each model contains 26,019 worker-year observations with 7,009 unique workers.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Robust standard errors, clustered at the individual level, are in parentheses. Each column represents one model as in equation (7), estimated by OLS. The dependent variable is always the logarithm of the hourly gross wage. BMI is a continuous measure of the body mass index (BMI). Obese is a dummy variable equal to 1 if the worker's BMI exceeds 30. *Nonfatal Risk* measures nonfatal workplace accidents by gender at the yearly 3-digit occupation level per 100 full-time workers (see Table A1).

Table 2 Compensating Wage Differentials for Fatal Risk, Obesity, and their Interaction

	Without Worker Fixed Effects		With Worker Fixed Effects	
	(1)	(2)	(3)	(4)
Fatal Risk×Obese	0.0041***	0.0023***	-0.0001	-0.0002
	(0.0010)	(0.0009)	(0.0007)	(0.0007)
Fatal Risk	-0.0058***	0.0025***	0.0011	0.0015**
	(0.0009)	(0.0008)	(0.0007)	(0.0007)
Fatal Risk^2	0.0000	-0.0000***	-0.0000*	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Obese	-0.1373***	-0.0585***	-0.0049	-0.0070
	(0.0192)	(0.0147)	(0.0103)	(0.0102)
BMI	0.0285***	0.0093**	0.0098**	0.0096**
	(0.0059)	(0.0043)	(0.0040)	(0.0041)
BMI^2	-0.0005***	-0.0001**	-0.0001*	-0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year FE	X	X	X	X
Individual-level Covariates		X		X
Individual FE			X	X
R-squared	0.0269	0.3674	0.1143	0.1260

Source: NLSY, CPS, SOII 1992-2000, and CFOI 1992-2000. Each model contains 26,019 worker-year observations with 7,009 unique workers.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Robust standard errors, clustered at the individual level, are in parentheses. Each column represents one model similar to equation (7), but without industry and occupation fixed effects, estimated by OLS. The dependent variable is always the logarithm of the hourly gross wage. BMI is a continuous measure of the body mass index (BMI). Obese is a dummy variable equal to 1 if the worker's BMI exceeds 30. *Fatal Risk* measures fatal workplace accidents at the 2-digit occupation level per 100,000 full-time workers (see Table A1).

Table 3 Joint Model for Fatal and Nonfatal Risk, Obesity, and their Interactions

	Without Worker Fixed Effects		With Worker Fixed Effects	
	(1)	(2)	(3)	(4)
Nonfatal Risk×Obese	0.0061	0.0087***	-0.0043**	-0.0040**
	(0.0046)	(0.0026)	(0.0018)	(0.0018)
Nonfatal Risk	-0.0523***	0.0067**	0.0015	0.0113***
	(0.0029)	(0.0034)	(0.0015)	(0.0023)
Fatal Risk×Obese	0.0030***	0.0006	0.0002	-0.0003
	(0.0010)	(0.0009)	(0.0007)	(0.0007)
Fatal Risk	0.0028***	-0.0038	0.0010	0.0170
	(0.0010)	(.)	(0.0007)	(0.0135)
Obese	-0.1462***	-0.0768***	0.0017	0.0012
	(0.0207)	(0.0150)	(0.0108)	(0.0105)
Year FE	X	X	X	X
Industry FE		X		X
Occupation FE		X		X
Individual-level Covariates		X		X
Individual FE			X	X
R-squared	0.0607	0.4104	0.1146	0.1871

Source: NLSY, CPS, and CFOI 1992-2000. Each model contains 26,019 worker-year observations with 7,009 unique workers.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Robust standard errors, clustered at the individual level, are in parentheses. Each column represents one model similar to equation (7), estimated by OLS. The dependent variable is always the logarithm of the hourly gross wage. Obese is a dummy variable equal to 1 if the worker's BMI exceeds 30. *Nonfatal Risk* measures nonfatal workplace accidents by gender at the yearly 3-digit occupation level per 100 full-time workers. *Fatal Risk* measures fatal workplace accidents at the 2-digit occupation level per 100,000 full-time workers (see Table A1). Included in all models, but not displayed, are *Nonfatal Risk*^{2}, *Fatal Risk*^{2}, BMI and BMI^2.

Table 4 Effect Heterogeneity in Nonfatal Risk Model

	Female	Black	Hispanic	Age	Physically Demanding Job
	(1)	(2)	(3)	(4)	(5)
Nonfatal Risk×Obese×[column]	0.0049	0.0003	-0.0034	0.0004	0.0029
	(0.0050)	(0.0045)	(0.0054)	(0.0005)	(0.0020)
Obese×[column]	-0.0291	0.0012	0.0237	-0.0024	-0.0221**
	(0.0189)	(0.0219)	(0.0218)	(0.0019)	(0.0097)
Nonfatal Risk×Obese	-0.0050**	-0.0038*	-0.0034*	-0.0154	-0.0064*
	(0.0021)	(0.0023)	(0.0019)	(0.0183)	(0.0035)
Nonfatal Risk	0.0111***	0.0101***	0.0108***	0.0447***	0.0127***
	(0.0024)	(0.0024)	(0.0024)	(0.0081)	(0.0028)
Obese	0.0084	-0.0037	-0.0072	0.0793	0.0062
	(0.0126)	(0.0113)	(0.0110)	(0.0654)	(0.0116)
Year FE	X	X	X	X	X
Industry FE	X	X	X	X	X
Occupation FE	X	X	X	X	X
Individual-level Covariates	X	X	X	X	X
Individual FE	X	X	X	X	X
R-squared	0.1976	0.1975	0.1975	0.1985	0.1975

Source: NLSY, CPS, and SOII 1992-2000. Each model contains 26,019 worker-year observations with 7,009 unique workers (except for column (5) with 25,750 worker-year observations and 6,999 workers).

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Robust standard errors, clustered at the individual level, are in parentheses. Each column represents one model as in equation (7), estimated by OLS. The dependent variable is always the logarithm of the hourly gross wage. BMI is a continuous measure of the body mass index (BMI). Obese is a dummy variable equal to 1 if the worker's BMI exceeds 30. *Nonfatal Risk* measures nonfatal workplace accidents by gender at the yearly 3-digit occupation level per 100 full-time workers (see Table A1). Not displayed but included in the model is BMI in levels and squared, *Nonfatal Risk* squared, and *Nonfatal Risk*×[column]. The latter two-way interactions are small and insignificant, except for*Nonfatal Risk*×*age* in column (4) which is -0.0010***. *Physically Demanding Job* is generated using the DOT (see footnote 14). It varies across occupations, takes on values from 0 to 3 and indicates whether a job requires (i) climbing, (ii) reaching, or (iii) stooping, kneeling, crouching or crawling.

Appendix

Table A1 Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Dependent Variable					
Logarithm of hourly gross wage	2.0226	0.5166	0.0046	4.4032	26019
Hourly gross wage	8.7059	5.4679	1.004646	81.70809	26019
B. Variables of Interest					
Nonfatal risk per 100 full-time workers	1.9006	2.5942	0.0058	102.1088	26019
Fatal risk per 100K full-time workers	4.9606	7.9185	0.3265	118.0985	26019
Obese	0.227	0.4189	0	1	26019
BMI	26.8633	5.3363	10.9475	91.2293	26019
C. Covariates					
Age	34.3591	3.6001	27	43	26019
Female	0.4444	0.4969	0	1	26019
Hispanic	0.1869	0.3899	0	1	26019
Black	0.2766	0.4473	0	1	26019
#kids in household	1.2388	1.2181	0	8	26019
Married	0.5683	0.4953	0	1	26019
Never married	0.2306	0.4212	0	1	26019
Drop-out	0.101	0.3013	0	1	26019
High school	0.4383	0.4962	0	1	26019
Some college	0.2356	0.4244	0	1	26019
College	0.225	0.4176	0	1	26019
AFQT 2nd quartile	0.2562	0.4365	0	1	26019
AFQT 3rd quartile	0.2057	0.4042	0	1	26019
AFQT 4th quartile	0.1656	0.3717	0	1	26019
Public Sector	0.1028	0.3037	0	1	26019
Changed job	0.2434	0.4292	0	1	26019
Firm size 1 (<26 workers)	0.3286	0.4697	0	1	26019
Firm size 2 (25>workers¡100)	0.222	0.4156	0	1	26019
Firm size 3 (99>workers¡500)	0.2304	0.4211	0	1	26019
Firm size 4 (workers>499)	0.1848	0.3882	0	1	26019
Ordinal rating (1-5) of STRENGTH	2.019	0.9999	1	5	25750
Northeast	0.1583	0.365	0	1	26019
Northcentral	0.2412	0.4278	0	1	26019
South	0.4019	0.4903	0	1	26019
West	0.1873	0.3901	0	1	26019
Rural	0.2267	0.4187	0	1	26019
Unemp. Rate 6-8.9%	0.3473	0.4761	0	1	26019
Unemp. Rate > 8.9%	0.1519	0.3589	0	1	26019

Source: NLSY, CPS, SOFI, and SOII 1992-2000. BMI is a continuous measure of the body mass index (BMI). Obese is a dummy variable equal to 1 if the worker's BMI exceeds 30. *Nonfatal Risk* measures nonfatal workplace accidents by gender at the yearly 3-digit occupation level per 100 full-time workers. *Fatal Risk* measures fatal workplace accidents at the 2-digit occupation level per 100,000 full-time workers.