Worker Investments in Safety, Workplace Accidents, and Compensating Wage Differentials

José R. Guardado
American Medical Association
Economic and Health Policy Research
Nicolas R. Ziebarth
Cornell University
Policy Analysis and Management

Abstract

Standard theory assumes that workplace accident risk is exogenous to workers, predicting a positive association between risk and wages. This paper incorporates safety investments by workers into the canonical model, which predicts a negative association between individual accident risk and wages. We test the model predictions using weight gains as a proxy for disinvestments in “risky job-specific” human capital. In addition to the standard positive compensating wage differential (CWD) and consistent with our model, we observe a significant negative association between individual risk and wages, but only in high risk jobs. Our findings may help explain inconsistent findings of CWDs.

Key Words worker investment, safety, human capital disinvestment, nonfatal risk, compensating wage differentials, obesity

JEL Classification I10, I12, J24, J31, J62, J71

José R. Guardado
Economic and Health Policy Research
American Medical Association
330 N. Wabash Ave.
Chicago, Illinois 60611
312.464.4559
joseguardado11@gmail.com

Nicolas Ziebarth
Cornell University
Policy Analysis and Management
106 MVR
Ithaca, NY, 14850
607.255.1180
nrz2@cornell.edu
1. Introduction

The theory of compensating wage differentials (CWD) posits that workers must be compensated with higher wages for accepting unpleasant job conditions. The risk of accidents is one such undesirable attribute. This leads to the standard prediction of a positive association between on-the-job risk and wages (Thaler and Rosen 1975).¹

Economists are interested in the relationship between job risk and wages because it informs us about the way the labor market works (cf. Viscusi 1978; Kniesner et al. 2012). Policymakers care about it because it is used as an estimate of workers’ valuation of job conditions and their health.

Importantly, the canonical model treats workplace safety as exogenous to the worker. Only firms have the ability to change the workplace environment. Firms can either pay workers higher wages for accepting the higher risk of accidents, or they can reduce the risk by investing in safety and pay lower wages.

Intuitively, this sharp distinction between workers and firms seems odd. There may be opportunities for workers to lower the risk of accidents in ways unknown to firms, or they may be too costly for firms to exploit. For example, in 2014, the most common job in 28 U.S. states was being a truck driver, and a quarter of fatal occupational injuries consist of highway accidents (Census of Fatalities Occupational Injuries 2004; NPR 2015). It is clearly possible that drivers can take action that their employers cannot undertake, and make safety investments in averting accidents.

This paper enhances the canonical CWD model by allowing for worker investment in safety. The enhanced model leads to important implications for the relationship between safety and wages, and may help explain why there is inconclusive empirical evidence about the existence and size of

¹ In this paper, we refer to "risk" and "safety" somewhat interchangeably, acknowledging that risk and safety are the converse of each other.
CWDs, especially for nonfatal risk. As standard CWD theory predicts, job risk and wages will be positively associated, but only when the risk is “produced” by the firm (or technology). In contrast, when risk is “produced” by workers, our enhanced model predicts a negative association between the individual risk of accidents and wages. This finding also has implications for estimates of the value of a statistical life (VSL), which are typically derived from CWD estimates (Shogren and Stamland 2002; Black and Kniesner 2003, Lalive 2003; Leeth and Ruser 2003; Kniesner et al. 2010; Kochi and Taylor 2012; DeLeire et al. 2013; Lavetti 2014). Failure to account for workers’ influence on undesirable job attributes such as accident risk may mask or downward bias previous CWD estimates.

Examples from industry compensation policies support the notion that workers can invest in safety and are rewarded for it. The clearest examples are safety bonuses. Chappelle (1991) reports that firms offer monetary incentives to make workers more careful. Wilde (2000) notes that firms have been increasingly turning to safety incentive programs as a way to control accident costs. In a survey of 40 long haul trucking firms in Canada, 70% of them had a safety incentive program, and the use of such programs is growing. NATIONWIDE INSURANCE, CHARTER COMMUNICATIONS and GENERAL MOTORS have programs that reward seat belt use. DENARK CONSTRUCTION's hourly employees receive a bonus check every quarter if their particular project avoids any serious OSHA citations, individual violations of company safety policies, and accidents on that project. There are also many large consulting firms that advise employers on how to motivate employees to improve their safety behavior.

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2 Wage premiums have been found more consistently for fatal risk, yet some studies do not find evidence of this either (see, e.g., Leigh 1991; Viscusi and Aldy 2003; Kniesner et al. 2012; Doucouliagos et al. 2012).
4 http://safetymanagementgroup.com/
Several studies suggest that bonuses are indeed associated with reductions in accident rates. Gregersen et al. (1996) finds that bonuses for safe driving significantly reduce the number and costs of accidents. Nafukho et al. (2004) examine the performance of tractor-trailer truck drivers in a U.S. trucking company and find that bonuses are associated with a reduction in accidents. Furthermore, companies report client testimonials of how programs have reduced their accident rates and costs (Cable 2005). In sum, there is widespread and growing use of paying workers for improved safety.

Somewhat surprisingly, only a few previous studies formally model workplace risk as endogenous to workers (Rea 1981; Moore and Viscusi 1990; Krueger 1990; Lanoie 1991; 1994). Those studies typically model this in the context of Workers’ Compensation (WC) benefits, as they are usually concerned with ex ante moral hazard. They also tend to focus on safety investments through worker demand (Seabury, Lakdawalla and Reville 2005). We provide a similar model, but with notable differences. In our model, even a fully insured worker makes investments in safety because it increases worker productivity, thus firm profits, and also wages. As in previous models, such safety investments increase workers’ utility by decreasing the probability of the hazardous state, which entails a personal financial loss. In addition, our model incorporates a direct incentive for both firms and workers to demand such human capital investments given they are valuable to the firm regardless of workers preferences for wages, safety or WC benefits.5

The second part of this paper tests the model’s predictions empirically. Since worker safety investments are very difficult to measure, we take an indirect empirical approach to examine their effects. We employ (observable) increases in body weight over time as an indicator for worker

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5 Previous studies only focus on the safety of the worker, and accident costs faced by the firm are typically thought to be WC benefits and lower wage costs. However, firms may face direct costs of accidents. Consider the hedonic methodology used in previous empirical studies. In this approach, firms are sellers and workers are buyers of safety. Our model is different in that firms are not only sellers, but also buy safety produced by workers.
disinvestment in risky-job-specific human capital. The use of obesity as a proxy for worker disinvestment makes sense for several reasons.

First of all, given that body weight is to a large degree modifiable, gaining weight and becoming obese can be seen as a form of human capital disinvestment in safety-related productivity, particularly in risky jobs. We view this set of skills as “risky-job-specific,” akin to firm-specific human capital. It loses its value in jobs that have no risk.

Second, obesity has been shown to significantly increase the risk of accidents (Stoohs et al. 1994; Froom et al. 1996; Craig et al. 1998; Engkvist et al. 2000; Corbeil et al. 2001; Xiang et al. 2005; Yoshino et al. 2006; Finkelstein et al. 2007; Ostbye 2007; Lakdawalla et al. 2007; Pollack et al. 2007; Guardado 2008). The medical literature also provides a plenitude of reasons why obese workers are more prone to accidents. Among the reasons are higher risk of drowsiness, a higher likelihood of falling, lack of concentration, and more physical limitations (cf. Corbeil et al. 2001; Shutan 2003; Pollack 2007).

Third, we bolster that evidence by examining the association between workers’ obesity status and their personal risk of experiencing a workplace injury. Using the NLSY 1979 data and estimating a rich model that includes person, industry and occupation fixed effects, we find that becoming obese is significantly associated with an increased risk of having an accident by 21%.

The empirical part exploits a uniquely compiled dataset. It links panel data from the NLSY 1979 to 3-digit occupational risk data from the Bureau of Labor Statistics, as well as data from the Current Population Surveys. First, we obtain a remarkably precise positive CWD estimate for nonfatal risk. For every additional injury per 100 full-time workers, wages increase by 0.5%. Second,

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6 Note that our economic model and empirical tests do not hinge on whether one interprets gaining weight more broadly as a form of human capital disinvestment, or more narrowly as a form of disinvestment in workplace safety.
and entirely in line with the model predictions, we obtain a similarly strong _negative_ association between an increase in the individual accident risk—through body weight gains—and wages. However, this wage penalty for observable risky-job-specific human capital disinvestment only appears in high-risk occupations, which reinforces our theory of compensating wages as a response to endogenous safety (dis)investments. While we do not claim our empirical results can be given a causal interpretation, the wage effects are identified by an extremely rich individual, occupational, and industry-specific fixed effects model. This model nets out unobserved time-invariant worker heterogeneity and focuses on changes in body weight for employees who do not switch jobs.

In addition to its contributions to the CWD literature, this paper also contributes to the obesity-wage gap literature in economics (Cawley 2004). We find that the obesity wage penalty only exists in high risk, physically demanding jobs, and importantly, does not vary by gender. This implies that occupational sorting is likely to be largely responsible for the typically observed pay gap for females found in the literature. In fact, recent work by Shinall (2015) finds evidence that females sort into physically demanding jobs. In addition, DeLeire and Levy (2004) find that variation in occupation-specific fatality risk explains a quarter of gender sorting into occupations. In this sense, our paper bridges the literatures on CWDs, occupational gender sorting, and obesity-related wage differentials. Our findings are consistent with DeLeire (2001), who suggests that discrimination likely plays a minor role in health and gender-specific pay gaps. Instead, our findings support the notion that obese workers earn lower wages due to their lower safety-related productivity.

The next section presents our model of worker investments in safety. The empirical application, research design, data and empirical analysis are presented in Section 3. The results are reported in section 4. Section 5 concludes.
2. A Model of Worker Investments in Safety

2.1 Worker's Incentives to Invest in Safety

It is known that firms have an incentive to invest in safety because it lowers accident and wage costs, as workers are willing to accept lower wages for a lower risk of accidents. However, workers also have an incentive to invest in safety that is independent of the firm’s objectives. Worker safety investments increase utility by decreasing the probability of an accident and the associated loss of wages (Ehrlich and Becker 1972). These safety investments, however, will only be valuable if there exists a (significant) workplace accident risk. They lose their value in jobs with no risk. Hence, they are investments in what we call “risky-job-specific” human capital (or safety-related productivity).

To make this point more formally, we begin by considering the worker’s incentives drawing on the model by Ehrlich and Becker (1972). There is a probability \( p \) that an accident occurs resulting in the worker's nonfatal injury, \( 0 \leq p < 1 \). Workers can make human capital investments in safety, \( e \), which will reduce the probability of an accident. The safety production function is \( p(S,e,p^E) \), where \( S \) is employer investments in safety and \( p^E \) is the endowed on-the-job injury risk that is determined by technology. We assume that \( \frac{\partial p(S,e,p^E)}{\partial e} < 0 \), and \( \frac{\partial^2 p(S,e,p^E)}{\partial e^2} > 0 \), i.e., human capital investments reduce the probability of an accident and there is a decreasing marginal productivity of investment. The price of a unit of investment in safety is \( q \). If there is no accident, the worker earns wage \( W \) and his utility is \( U(W - qe) \), where \( U(\cdot) \) is a twice-differentiable, increasing and concave function. If there is an accident, there is a loss \( l \), so the worker’s utility is \( U(W - l - qe) \).

The worker’s problem is to choose investments in safety, \( e \), to maximize expected utility \( EU \) as follows:

\[
(1) \quad EU^* = \max_e EU = [1 - p(S,e,p^E)]U(W - qe) + p(S,e,p^E)U(W - qe - l)
\]
The first-order condition is given in equation (A3) (see Appendix B). The marginal benefit of worker safety investments—a reduced accident probability—has to equal its marginal costs, which is its price, \( q \), weighted by the expected marginal utility of income in the accident and non-accident state, respectively. Those investments will be higher, the more productive workers are in producing safety and the lower their price \( q \).

If the quantity of worker investments demanded by the firm exceeds the optimal level of investment that the worker would choose on her own, the employer can induce further investments by compensating workers with higher wages. This wage change is obtained formally by differentiating the expected utility function with respect to wages and worker investments to obtain

\[
(2) \quad \frac{dW}{de} = \frac{\partial p}{\partial e} (U_1 - U_0) + q[(1 - p)U_1' + pU_0'] \geq 0
\]

Equation (2) shows the magnitude of the return to investments in risky-job specific human capital. It is non-negative.

2.2 Firm’s Incentives to Invest in Safety

Now consider the firm’s incentives to invest in safety (\( S \)). Building on models by Smith (1974) and Oi (1974), we assume the employer produces output \( Q \), which is an increasing function of labor \( L \), \( \frac{\partial Q(L)}{\partial L} > 0 \), \( \frac{\partial^2 Q(L)}{\partial L^2} < 0 \). The price of a unit of output is \( m \). An accident can occur with probability \( p \), and the safety production function is the same as above: \( p(S, e, p^E) \).

Accidents cost the firm \( A \) dollars per worker, and include costs of training and replacing injured workers, lost production time of the victim and other workers, lost output and interrupted production. The price of a unit of firm investment in safety is \( c \).
In addition to the firm’s incentives to make its own investments as in the standard model, the firm also has an incentive to induce worker safety investments because this would increase profits. However, competition for workers would bid away these rents and they would have to be returned to the worker. Therefore, the employer would be willing to pay a higher wage for worker investments and would to do so until the wage increase for the last unit of investment equals the decrease in accident costs.\(^7\)

To complete the firm’s problem, we incorporate the constraint that the value of workers’ utility resulting from firm choices is equal to the value of workers’ utility that they can achieve on their own \((EU^*). The latter is obtained from the solution to the worker problem given by equation (1). This captures the idea that workers must be compensated for investing beyond their own optimal investment. The employer’s problem is to choose labor \((L)\), investments in safety \((S)\), and worker investments in safety \((e)\) to maximize profits subject to a constraint that workers’ utility is equal to \(EU^*\) (the alternative):

\[
\begin{align*}
\max_{L,S,e} \pi &= mQ(L) - WL - p(S,e,p^E)AL - cSL \\
\text{s.t.} \quad \{ [EU^* = (1 - p(S,e,p^E))U_1(W - qe) + p(S,e,p)U_0(W - qe - l)]L \}
\end{align*}
\]

Note that the employer does not incur the worker’s cost \((qe)\) of investment but compensates workers with higher wages for undertaking it. The first-order conditions w.r.t. safety investments by firms \((S)\) and workers \((e)\) are given by equations (A7) and (A8) in Appendix B, respectively. The

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\(^7\) To see this, consider the employer’s profit function given by \(\pi = mQ(L) - WL - p(S,e,p^E)AL - cSL\). Using the implicit function theorem, obtain an expression for the wage change needed to keep profits constant when workers invest in safety (i.e., zero profit constraint of competition)

\[
\frac{dW}{de} = -\frac{\partial p(S,e,p^E)}{\partial e} A > 0
\]

This equation shows wages would rise in response to an increase in worker safety investments, where the magnitude of the wage increase would equal the expected reduction in accident costs. Note that worker investments in safety are no different than any other form of human capital investment. Investment raises worker productivity and is rewarded by higher wages.
optimal level of those investments in safety requires that their marginal benefits equal the marginal costs.

Differentiating equation (3) with respect to labor \((L)\), and solving for the wage \((W)\) yields a linear association between wages \((W)\), the injury risk \((p)\), and the firm costs of safety investment, \((cS)\):

\[
W = m \frac{\partial Q(L)}{\partial L} - p(S, e, p^E)A - cS.
\]

Equation (4) illustrates that wages depend on the level of firm and worker investments in safety through their effects on risk, \(p\). Our empirical model will be mainly motivated by equations (4) and (2) above.

Although firm-level safety investment and risk measures are not included in our model, we incorporate firm size dummies, a set of 417 occupational dummies at the 3-digit level, 236 industry dummies at the 2-digit level as well as year fixed effects. These variables capture the effects of risk \((p)\) and firm investment costs \((cS)\) in equation (4) above. Note that one could easily reformulate the firm’s problem and aggregate it up to the occupational or industry level.

In addition to their own investments, firms can induce safety investments by workers over and above the optimal level they would choose on their own as derived from equation (A3). As mentioned, this may be necessary and efficient since employers \((a)\) cannot make these investments or \((b)\) workers can make them more efficiently, i.e. \(\frac{\partial p(S, e, p^E)}{\partial S} < \frac{\partial p(S, e, p^E)}{\partial e} < 0\) and \(q <= c\). Real world examples may be mining, logging, clerking or driving.

The wage increase required to keep worker utility constant when the worker invests in safety is given by equation (2). An alternative formulation is derived in Appendix B and given by:

\[
- \frac{\partial p}{\partial e} A = \frac{dW}{de} [(1 - p)U_1' + pU_0'] \chi.
\]
The left-hand-side of equation (5) represents the reduction in accident costs through the increased safety investment, i.e., its marginal benefit. The right-hand-side of equation (5) represents the marginal cost and is the wage increase required to compensate workers for their investment, weighted by their marginal utility of income and the value of changing utility by $1 (\chi).^8

2.3 Summary of Theory and Predictions to be Tested in the Empirical Analysis

The key insight of our model is that workers can invest in safety and such risky-job-specific human capital investments raise the value of workers to the firm. Employers induce those investments by paying for them with higher wages. Analogously, firms pay lower wages in the case of (observable) human capital disinvestments of their workers. 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 (Dorman and Hagstrom 1998).

An important prediction of the model is that the net effect of accident risk on wages is a priori ambiguous. The standard prediction is that risk and wages are positively associated because firms offer CWDs to attract workers to risky jobs. This is true if risk is exogenously determined, e.g., by technology, and cannot be influenced by workers. However, when workers have the possibility to invest or disinvest in risk-job-specific human capital, the association between wages and (worker-produced) risk becomes negative.

The next section tests the model empirically. To derive testable predictions, we assume that from the perspective of the worker, an occupation’s nonfatal injury risk is exogenous. Thus, across

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^8 Note that our simple model does not allow for worker heterogeneity. Obviously, in reality and in our data, there is variation of worker investment in safety at the individual level. Our model could generate this type of variation if one introduced heterogeneity and allowed 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.
occupations, we hypothesize that there is a positive association between occupational risk and wages since firms with higher accident risk have to offer CWDs to attract workers.

However, in line with our model, we also assume that workers can individually modify this exogenously given occupational risk through personal investment in risky-job-specific human capital. Because it’s risky-job-specific, this safety-related productivity will lose its value in non-risky jobs. Hence, we hypothesize that there is a positive association between measures of worker investments in safety and wages, but only in risky jobs. Since our empirical indicator is weight gain and measures human capital disinvestment, we expect a negative association between safety disinvestments and wages in high risk jobs.

3. Human Capital Disinvestments, Accident Risk, and CWD: An Empirical Application

The empirical application exploits weight gains and becoming obese as a proxy for worker disinvestment in risky-job-specific human capital. Because obesity is to a significant degree individually modifiable, preventing it can be thought of as an investment in self-protection (Kenkel 2000). Likewise we can think of becoming obese as a disinvestment in human capital and job safety (Bhattacharya and Bundorf 2009), the result being lower safety-related productivity. We view this set of skills as “risky-job-specific,” akin to firm-specific human capital. It loses its value in jobs that have no risk.

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9 There are a few things to keep in mind when using obesity as a proxy for individual disinvestment in workplace safety. First, it has been shown that obesity measures generated from self-reported height and weight include substantial measurement error and are not perfectly correlated with the real degree of body fat (cf. Burkhauser and Cawley 2009). Second, there is the possibility that obese workers are systematically more careful on the job since they may be aware of their higher risk, which could potentially offset the higher risk induced by obesity. Finally, obesity is only an indirect proxy measure of worker disinvestment in safety. It should be noted, however, that employing direct measures would also require certain assumptions, such as the effectiveness of the safety training or non-sorting into training participation.
This application is also motivated by mounting evidence that weight gain and obesity increases the risk of accidents (Stoohs et al. 1994; Froom et al. 1996; Craig et al. 1998; Engkvist et al. 2000; Corbeil et al. 2001; Xiang et al. 2005; Yoshino et al. 2006; Finkelstein et al. 2007; Ostbye 2007; Lakdawalla et al. 2007; Pollack et al. 2007; Guardado 2008). Using our NLSY dataset to examine the association between becoming obese and the risk of workplace accidents, we find strong supporting evidence of this notion. Regressing an indicator of individual-level workplace accidents on a rich set of socioeconomic characteristics and fixed effects for industries, occupations, years, and individuals, we find that obesity increases the risk of a workplace accident by 21% (results available upon request). In the empirical analysis, we investigate whether obese workers get penalized for such higher on-the-job risk of accidents.

3.1 Research Design and Methods

The empirical analysis compares obese and non-obese workers’ wages in high- and low-risk jobs. Specifically, we use the following linear specification, which is motivated by equations (2) and (4) above:

\[ \ln W_{ijkt} = \alpha_i + \pi_j + \sigma_k + X_{it} \beta + \delta OB_{it} + \gamma RISK_j + \lambda (OB_{it} \times RISK_j) + \epsilon_{ijkt} \]

(6)  
\[ i = 1, \ldots, N \quad \text{(index of employee; } N = 7,006) \]
\[ j = 1, \ldots, J \quad \text{(index of 3-digit occupation; } J = 417) \]
\[ k = 1, \ldots, K \quad \text{(index of 2-digit industry; } K = 217) \]
\[ t = 1992, \ldots, 2000 \quad \text{(index of years)} \]

In equation (6), \( X \) is a vector of an extensive set of regional, demographic, educational and workplace characteristics (see Appendix A). These characteristics are expected to affect wages and proxy for worker productivity, the price of worker investment in safety, and worker productivity in producing those investments.
\( \alpha_i, \pi_j \) and \( \sigma_k \) are person, occupation and industry fixed effects, respectively. These are proxies for accident costs and for the productivity and cost of workers' and firms' safety investments (see equation (4)). Those factors are further captured by the firm size dummies included in \( X \). Importantly, note that including individual fixed effects nets out any unobservable, time-invariant personal factors, such as individual worker productivity and risk preferences.

\( OB \) is a measure of obesity (body mass index >30). Note that \( X \) additionally includes a continuous measure of BMI. This is to capture non-obesity-related weight effects.\(^\text{10}\) \( RISK \) is the nonfatal injury rate at the 3-digit occupational level per 100 full-time workers (FTW). It varies across the 417 occupations and over time between 1992 and 2000. \( OB \times RISK \) is the interaction term between our safety disinvestment and risk measures and is our main variable of interest.

**Testing hypotheses.** Recall the model predictions and the derived hypotheses that we intend to test empirically (see Section 2.3):

(i) First, across occupations, we expect to find a positive association between occupational accident risk and wages. The first-difference coefficient on \( RISK \) yields the CWD for riskier occupations; thus we expect \( \gamma \) to be positive.

(ii) Second, we assume that workers can individually modify the exogenously given occupational injury risk through own human capital investments. We proxy for worker disinvestment in risky-job-specific human capital with \( OB \)—becoming obese. Note, however, that there are competing hypotheses here, depending on the reason why obesity would affect wages. If obesity only captures risky-job-specific human capital, then we expect \( \delta \) to be small in size and insignificant. Risky-job-specific human capital is only valuable in risky jobs. Alternatively, a negative coefficient

\(^{10}\) However, the results are robust to excluding the continuous BMI measure.
on \( OB \) would instead suggest that the wage penalty is due to other factors, such as discrimination, or productivity unrelated to safety.

\( (iii) \) Third, this gets us to the core idea of the paper. We hypothesize that worker investments in risky-job-specific human capital will be valuable only in high-risk occupations. We aim to test whether becoming obese, which we see as an observable and individually modifiable disinvestment in risky-job-specific human capital, triggers a wage penalty that varies across the exogenously given occupational job risk. Because the human capital is risky-job specific, it would lose its value in non-risky jobs. A priori, there is no reason to believe that any of the possible alternative explanations under \( (ii) \) which would explain a negative relationship between obesity and wages—e.g. discrimination—should differ significantly by the riskiness of the job. Our main coefficient of interest in equation (6) is the interaction term between obesity \( (OB) \) and \( RISK \). We expect \( \lambda \) to be negative.

3.2 Data

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

**Dependent variable.** The dependent variable is the natural logarithm of the respondent's real hourly wage at his current/most recent job. We calculate the real hourly wage using the Consumer Price Index (CPI) for all urban consumers where the base period is 1982-1984. As shown in Appendix A, the average logarithm of the hourly wage is about $2 (i.e., $7.50). However, the smallest reported hourly wage was $1.05 and the highest $56.83. This illustrates that our dependent variable exhibits a significant degree of variation.
**Obesity Measure.** One key independent variable is obesity, which we calculate from the body mass index (BMI) using reported weight in each year and the reported height in 1985. We then create a dummy variable for obesity status (BMI$\geq 30$). The average BMI is 26.9, but values range from 10.9 to 91.2 (see Appendix A). About 23% of all respondents are classified as obese.

**Nonfatal Risk Measure.** We obtain nonfatal injury rates by 3-digit occupation from the *The Survey of Occupational Illnesses and Injuries* (SOII) of the *Bureau of Labor Statistics* (BLS).\(^{11}\) The SOII provides information on nonfatal occupational injuries and illnesses resulting in at least one day away from work. The SOII is a federal/state program in which reports are collected 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 data are available for the years 1992 to 2000.\(^{12}\)

To turn the injury counts into rates, we divide them by annual 3-digit occupation employment counts provided by the March CPS. In what follows, we always report injury rates per 100 full-time workers (FTW). As Appendix A demonstrates, the variation in this crucial variable for our analysis is large; it ranges from 0.006 to 102 nonfatal injuries or accidents per 100 FTW, occupation, and year. This risk measure is skewed to the right, with an average of 1.9, a median of 1.1, a 90\(^{th}\) quintile of 4.7 and a 99\(^{th}\) quintile of 10.5.

**Other Covariates.** In our preferred specifications, we control for the following personal characteristics in addition to the individual fixed effects. A first category of controls refers to

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\(^{11}\) For 3% of all occupation-year observations, no risk measure could be assigned since no count of nonfatal injuries and diseases was available. Another reason we could calculate rates for just 97% of all observations is that there were missing CPS employment counts. More specifically, for our time period covered, 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 3-digit *industry*-specific risk measures for the missing values. The results are very robust.

\(^{12}\) 1995, 1997, and 1999 are not covered.
demographics and includes covariates such as age, gender, race, marital status, and #kids in the household (see Appendix A).

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 accordingly.

A third category of controls makes use of 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 and characteristics that may affect the value of the worker's marginal product (cf. Bender and Mridha, 2011), i.e., the local unemployment rate ($\leq 6\%$, 6 to 8.9\%, $>9\%$) as well as the region of residence (northeast, north central, west and south; urban or rural residence).

Note that we always consider the survey year in form of year fixed effects. In more sophisticated models, we additionally incorporate a full set of 3-digit occupation fixed effects (417 dummies) as well as a full set of 2-digit industry fixed effects (236 dummies).

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 3-digit occupation and 2-digit industry codes, had non-missing data on key variables, and did not have a real hourly wage less than $1$ or greater than $100$. We drop observations with extreme values of the

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13 We exclude those in the armed forces as is common in the previous literature. After the aforementioned selection restrictions, the following variables have missing data: wage (N=451), occupation (N=120), industry (N=163), weight or height (bmi) (N=710).
real hourly wage as they are likely coding errors. After all restrictions, we have a sample of 26,016 person-year observations on 7,006 persons.

4. Results

4.1 Nonparametric Evidence

We begin the empirical analysis by showing mean differences between obese and non-obese workers in Table 1. This descriptive exercise shows that obese workers earn lower wages on average than their non-obese counterparts ($6.97 vs. $7.74). We can also see from Table 1 that on average, obese people work in slightly riskier occupations. However, considering the huge standard deviation of nonfatal risk of 2.6, the difference in average injury risk per 100 FTW is actually minor (1.9 vs. 2.0).

[Insert Table 1 about here]

An important question is whether our panel data set is well balanced. Perhaps surprisingly, Table 1 shows that the relevant covariates seem to be reasonably well balanced. Column (3) of Table 1 shows that all normalized differences are significantly below 0.25; for most variables, the values are even below 0.1. For example, consider the indicator for whether or not employees changed their job. There is little difference in switching between obese and non-obese workers, and the obese are actually less likely to switch (23.6% vs. 24.6%); the normalized difference is only 1.6%.14

Figure 1 plots the relationship between the normalized nonfatal occupational accident rate on the x-axis and the hourly wage on the y-axis. One observes a strictly increasing significant association between the occupational accident risk and wages. This is the graphical CWD representation and reinforces the according first model prediction of a positive CWD.

14 Imbens and Wooldridge (2009) propose to assess the covariate balance based on scale-free “normalized differences” (see notes to Table 1 for more details). According to their rule of thumb, values below 0.25 suggest a well covariate balance.
[Insert Figures 1 and 2 about here]

Next, Figure 2 shows a nonparametric plot of the relationship between employees’ BMI and their individual accident risk. We find a monotonically increasing individual accident risk for workers with BMIs of about 24 and 34, which reinforces the notion that a body mass above 25 and especially 30 can be interpreted as a form of workplace safety disinvestment. On the other hand, keep in mind that Figure 2 is just a nonparametric unconditional correlation that does not exploit the panel structure of the data and may additionally be confounded by selection issues.

Figure 3 shows the association between BMIs and wages separately for males (3a) and females (3b). One observes monotonically decreasing relationships for both genders. However, for males, the negative and almost linear association is observed between BMIs of 25 and 40 whereas, for females, we observe it from BMIs of 20 to 35. Again, recall that these pure unconditional associations in levels may mix true causal relationships with employee sorting into occupations and other unobservable confounders (c.f. DeLeire and Levy, 2004; Shinall, 2015). Therefore, in Figure 4 we plot changes in the BMI of employees (conditional on being overweight) with changes in hourly wages. We can see that the relationship flattens substantially and it is hard to detect any significant association.

The nonparametric visual diagnostics do not control for important factors that may be correlated with job risk, obesity and wages, such as unobservable worker productivity and preferences toward risk. Thus, we proceed with parametric fixed effects models that net out time-invariant unobservables across industries, occupations, and employees and which additionally adjust the sample with time-variant socio-demographics and firm characteristics. Netting out worker as well as industry, occupation, and firm-specifics seems to be crucial in this setting. Recall that we intend to approximate equations (2) and (4) which include firm-specific safety investment costs as well as marginal worker safety benefits and investment costs.
4.2 Parametric Evidence

Table 2 presents parametric estimates of equation (6). In all specifications, the outcome variable is the logarithm of the hourly wage. Following our three hypothesis in Section 3.1, the regressors of interest are (i) the normalized occupational injury risk to test for positive CWDs, (ii) the BMI and obesity status that indicate observable changes in human capital investments, as well as (iii) interactions between (i) and (ii). The interaction term tests the model prediction that risky-job-specific human capital investments lead to wage changes but only in jobs in which this risk-job-specific human capital is valuable.

The first three columns of Table 2 report results from simple OLS regressions that only differ by the inclusion of sets of covariates as indicated in the bottom of the table. While column (1) only includes year fixed effects, column (2) incorporates 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 wages, job risk, and obesity. Column (3) of Table 3 additionally controls for a rich array of individual-level controls with respect to demographics, education, and the workplace (see Appendix A). Individual-level factors may likewise confound the relationship between wages, on-the-job risk, and obesity. Note that the $R^2$ strongly increased from 0.05 in column (1) to 0.41 and 0.52 in columns (2) and (3), illustrating that the most saturated model explains more than 50% of the variation in wages.

The findings show that (i) the association between occupational injury risk and wages becomes insignificant and very small in size once occupation and industry fixed effects are added to the model. In addition, (ii) the obesity-wage penalty shrinks dramatically in size, from 14% in column (1) to 4% in column (3) but remains statistically significant. Finally, (iii) the interaction term between
firm-specific injury risk and being obese is positive and significant, and thus at odds with our model prediction.

[Insert Table 2 about here]

Columns (4) to (6) report results from our preferred specifications. Those specifications similarly include sets of covariates in a stepwise fashion, but most importantly, they additionally include employee fixed effects. This approach is crucial in our context since it nets out all time-invariant unobservable factors at the employee level that may be correlated with both obesity and wages and that may lead to spurious statistical correlations, such as risk preferences or unobserved productivity. The effects are now identified by individuals who gain weight and become obese. Similarly, the CWD effects are identified by variation in job risk at the occupation and industry level. One finds the following:

First, workers in high risk occupations earn wage premiums. Columns (4) to (6) show that high risk jobs raise wages by 0.5% to 0.6% per additional accident per 100 full time workers. Moving from the median risky job (1.1 accidents) to the 90th percentile (4.7 accidents) implies a wage premium of about 2%, and moving to the 99th percentile (10.5 accidents) carries a CWD of about 5%. This finding is in line with our hypothesis (i) according to which workers in high risk jobs would earn CWDs. Note that this wage premium is identified by workers who either switch occupations or whose occupations become riskier over time and who thus see a change in their occupational risk. Below we show that the effect is not driven by job switchers but changes in occupational risk. The finding adds to the economics literature on the existence of a CWD nonfatal risk which has not been consistently found (cf. Viscusi and Aldy 2003).

Second, the general statistical association between obesity and wages vanishes. This is consistent with our hypothesis (ii) in Section 3.1. There is no return to risky-job-specific human
capital in non-risky jobs. The absence of a general obesity-wage penalty also rules out alternative explanations for the wage penalty, such as discrimination or productivity unrelated to safety.

Third, the coefficient of the main variable of interest—the interaction term between obesity and job risk—is negative, highly significant and very robust across all three specifications. We interpret these estimates as the wage effects of worker disinvestments in risky-job-specific human capital. Specifically, they indicate that becoming obese reduces wages by about 0.4%—but only in high risk jobs. By excluding job changers we show in a robustness check below that this is not due to an alternative explanation of obese workers switching jobs. The finding that becoming obese leads to a wage penalty only in high risk jobs is absolutely in line with our model and hypothesis (iii).

A highly significant wage penalty of 0.4% appears to be 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% discount rate, this yields a lifetime wage penalty of more than $8,000. Moreover, it is possible that a more direct measure of worker investment in safety would yield estimates of larger magnitude. In addition, our sample consists of relatively young workers and below we find evidence that the effect increases with age. Finally, classical measurement error in the obesity or job risk measures could bias our coefficient of interest toward zero.

4.3 Robustness Checks

We now assess whether there could be alternative explanations for our main findings. First, column (1) of Table 3 excludes workers who changed their jobs. The negative coefficient on our main variable of interest \(OB*RISK\) may either stem from workers who become obese or from obese workers who switch jobs and sort into occupations. Table 1 shows that the covariates between obese and non-obese workers are surprisingly well balanced, which supports the view that the negative association is not primarily a result of worker sorting (cf. DeLeire and Levy 2004, Harris 2014). Here
we bolster that evidence. We find that excluding job switchers yields a surprisingly robust and highly significant negative relationship between becoming obese, job risk, and wages (column (1)). Becoming obese results in a wage penalty of about 0.5% in higher risk occupations—specifically, in jobs with one additional injury per 100 FTW.

[Insert Table 3 about here]

Column (2) of Table 4 re-estimates the model using lagged values of all the independent variables. We find that the main coefficient of interest—$OB*RISK$—shrinks in magnitude but remains statistically significant at conventional levels. The shrinking of the coefficient makes sense since the NLYS data does not include the years 1995, 1997, and 1999. This means that, for 1996, 1998 and 2000, there is a lag of two years, not just one, and the obesity-risk-wage association thus decreases over time.

Finally, column (3) clusters the standard errors at the occupation instead of the individual level (Bertrand et al. 2004). Both the magnitude and statistical significance of the estimates are highly robust. In short, by showing that the covariates between obese and non-obese workers are well balanced and by excluding job changers in a robustness check, we provide evidence against the notion that the wage penalty for obese workers in high risk occupations is a result of sorting.

### 4.4 Heterogeneity in Effects

Next we explore whether there is heterogeneity in the main effects of interest. First, we test whether the results differ by gender. We generate and add an additional triple interaction term between $female$ and $OB*RISK$ to the model. Other evidence finds that obesity increases the risk of accidents for both males and females (e.g., Guardado 2008). If weight changes reflect changes in human capital-related productivity, then one should not expect to find a wage differential by gender. Column (4) of Table 3 shows no evidence that the main estimate differs by gender. This bolsters the
idea that the wage penalty is rather a result of lower risk-job-specific productivity. The finding is also in line with DeLeire (2001) who uses US IPP data from the 1980s and 1990s and finds that only 3.7 percentage points of the earnings gap between healthy and unhealthy workers is due to discrimination.

Next, we test whether the results differ by race by including two additional triple interaction terms between OB*RISK as well as black and Hispanic, respectively. Similar arguments to those made above (with respect to gender) apply here as well. The results (available upon request) show that all workers—in this case across race-ethnicity status—earn lower wages in high risk jobs when they gain weight. We do not find any evidence that the results differ by race.

Column (5) interacts age with OB*RISK and adds this triple interaction term to the model. Note that all respondents are between 27 and 43 years old. Nevertheless, we find a marginally significant and negative triple interaction, which suggests that the high job risk wage penalty for the obese increases by 0.4% for every 5 life years. Put differently, the return to worker investment in safety increases with age and thus work experience.

4.5 The Role of Job Requirements

Thus far we have considered accident risk across occupations and over time. However, certain characteristics of jobs, such as being physically demanding or strenuous, are a plausible channel of transmission underlying the risk-obesity-wage relationship. Strenuousness may lower obese workers’ safety-related productivity and thereby increase their risk of workplace accidents.

To investigate this possibility, we generate a variable JobPhysicallyDemanding, which takes on values 0 to 3 and varies across occupations. Higher values represent more strenuous jobs. It indicates whether the job requires (i) climbing, (ii) reaching, or (iii) stooping, kneeling, crouching or
We re-estimate our standard models with the addition of this variable in levels along with a triple interaction term. We hypothesize that the wage penalty for obese workers in high risk occupations is particularly pronounced in jobs with these physical requirements since they would increase the risk of accidents.

The results from this exercise are presented in column (6) of Table 3. The triple interaction term is significant at conventional levels and of the same size in magnitude as the $OB*RISK$ coefficient in Table 2, column (6). Note that the $OB*RISK$ coefficient in this model is no longer significant. This illustrates that the obesity-wage-penalty is not only specific to high-risk occupations, but also to high-risk occupations that are physically demanding. This is totally in line with our model and hypothesis: becoming obese indicates a depreciation of risky-job-specific human capital (safety-related productivity) which translates into a decrease in wages, but only in high risk, physically demanding jobs.

5. Summary and Conclusions

The standard economic theory of compensating wage differentials (CWDs) assumes that firms and workers face tradeoffs between the risk of accidents and wages. Firms can pay higher wages to compensate workers for accepting this risk, or they can invest in safety to lower the wages they pay. Importantly, that model makes the strong assumption that risk is exogenous to workers, as only firms can reduce risk. We depart from most past research by incorporating worker investments in safety characteristics.

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15 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). This consisted of first matching 1990 US Census occupation codes (used in the NLSY) to the occupations in the DOT, and then assigning DOT scores to the US Census occupation codes. Because DOT occupations can be more narrow and 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.
into the standard model. A key prediction of the enhanced model is that accident risk is positively associated with wages only to the extent that it is produced by the firm or determined by technology. However, if risk is produced by workers, then higher risk will be associated with lower wages.

We test the model predictions empirically using NLSY data, linked with the March CPS and detailed BLS nonfatal risk measures at the annual 3-digit occupation level. We proxy for worker disinvestment in risky-job-specific human capital with significant weight gains over time and becoming obese. Because obesity is an individually modifiable attribute, weight control can be thought of as an investment in risky-job-specific human capital. In addition, there is strong evidence in the literature that obesity increases the risk of accidents (Stoohs et al. 1994; Froom et al. 1996; Craig et al. 1998; Engkvist et al. 2000; Corbeil et al. 2001; Xiang et al. 2005; Yoshino et al. 2006; Finkelstein et al. 2007; Pollack et al. 2007). Indeed, using our data and a rich fixed effects model, we find that becoming obese increases the individual-level risk of a workplace accident by 1.5 percentage points or 21%.

Our empirical results are in line with our model predictions. Most important, we find a highly significant negative relationship between weight gains, occupational job risk, and wages. When workers become obese, they face a wage penalty of about 1.5% in high risk as compared to median risk jobs (90th vs. 50th risk percentile). For every additional injury per 100 FTW and year, the wage penalty for obese workers increases by about 0.5%. Put differently, human capital disinvestment is associated with wage losses, but only in risky jobs, where risky-job-specific human capital matters.

It is worthwhile to stress that we obtain a remarkably precisely estimated positive relationship between nonfatal occupational risk and individual wages. This is the standard (and sometimes elusive) CWD finding. In our empirical model, moving from an occupation with the median risk to one in the 90th risk percentile is associated with a CWD of 2%. One main empirical contribution of this paper is to disentangle this positive relationship between occupational risks and wages from
another precisely estimated negative relationship between a measure of individual accident risk and wages. The latter additionally varies by overall workplace risk, is in line with our model, and has the same size as the standard CWD estimate. In an extension, we show that the transmission channel is likely related to job requirements since becoming obese only leads to a wage penalty in strenuous high risk jobs.

Although our empirical model includes hundreds of occupational and industry fixed effects along with individual fixed effects and is identified by workers who become obese and do not change jobs, we do not interpret our empirical findings as strictly causal. However, they are absolutely in line with our model predictions and the idea of worker investment in risky-job-specific human capital.

In summary, our empirical evidence indicates that obese workers earn lower wages than their non-obese counterparts, particularly in physically demanding high risk occupations. It is consistent with DeLeire (2001), who suggests that discrimination plays a minor role in health and gender-specific pay gaps. Our findings support the notion that obese workers earn lower wages due to their lower risky-job-specific productivity. More importantly, they are consistent with an extension of the standard CWD model in which workers invest in safety and firms pay higher wages for those investments. Worker investments in risky-job-specific human capital generate a negative relationship between wages and individual accident risk, an effect that operates against the standard CWD prediction. Failure to account for this possibility may be one explanation for varying and sometimes imprecisely estimated CWDs estimates. To the extent that these results carry over to fatal risk, they also suggest that failure to account for worker investments in risky-job-specific human capital could downward bias estimates of the value of a statistical life (VSL).
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References


Figure 1: Nonparametric Association between Occupational Injury Risk and Wages

Figure 2: Nonparametric Association between BMI and Individual Injury Risk
Figure 3a and b: Nonparametric Association between BMI and Wages for (a) Males and (b) Females

Figure 4: Nonparametric Association between Weight Gain and Wage Changes
Table 1: Balancing Properties of Covariates by Obesity Status

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Source: NLYS and SOII 1992-2000; the last column shows the normalized difference which was calculated as $\Delta s = (s_1 - s_0) / \sqrt{\sigma_1^2 + \sigma_0^2}$, where $s_1$ and $s_0$ are the average covariate values for obese and non-obese workers, respectively, and $\sigma$ is the variance. As a rule of thumb, normalized differences exceeding 0.25 indicate non-balanced observables that might lead to sensitive results (Imbens and Wooldridge, 2009).
Table 2: CWDs and the Association between Wages and Worker Disinvestments in Risky-Job-Specific Human Capital

<table>
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<th>Covariates</th>
<th>OLS</th>
<th>Worker FE</th>
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<td>Nonfatalrisk*obese</td>
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<td></td>
<td>(0.0073)</td>
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<td>Obese</td>
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Source: NLYS and SOII 1992-2000; *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors, clustered at the individual level, are in parentheses. The first three columns estimate an OLS version of equation (6), i.e., includes no individual fixed effects. Those three models only differ by the sets of covariates included, as indicated. The last three columns estimate worker Fixed Effects models. The three worker FE models also only differ by the sets of covariates included. Obese is a dummy variable equal to 1 if the person’s body mass index (BMI) exceeds 30. By contrast, BMI is a continuous measure of BMI. Nonfatalrisk indicates the number of workplace accidents at the yearly 3-digit occupation level per 100 full time employees.
### Table 3: Robustness Checks and Heterogeneity in Effects

<table>
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<tr>
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<td>cluster at occupational level</td>
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**Source:** NLYS and SOII 1992-2000; *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors, clustered at the individual level except for column (3), are in parentheses. Obese is a dummy variable equal to 1 if the person’s BMI exceeds 30. Nonfatalrisk indicates the number of workplace accidents at the yearly 3-digit occupation level per 100 full time employees. Column (1) excludes job changers. Column (2) uses all independent variables in the leftmost column as lagged independent variables. Column (3) clusters at the occupational level, instead of the individual level. Columns (4) to (6) add additional triple interaction terms between Nonfatalrisk*obese and the variable as indicated in the column header, along with the column header variable in levels. For example, in column (4) we add the triple interaction term Nonfatalrisk*obese*female to the model. The plain female covariate is included in all the models. The variable PhysicallyDemandingJob is generated using the DOT (see footnote 15). 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 A: Summary Statistics

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**Source:** NLYS and SOII 1992-2000; the leftmost column indicates the variable and the following column defines it. Columns 1-5 display the mean, standard deviation, minimum and maximum variable values, and the number of observations, respectively.
Appendix B: A Model of Worker Investment in Safety

The Maximization Problem of the Worker

In our model of workers’ investments in safety (Section 3), worker expected utility is given by

\[(A1) \quad EU = [1 - p(S, e, p^e)]U(W - qe) + p(S, e, p^e)U(W - l - qe)\]

The basic worker problem is to choose investments in safety, \(e\), to maximize expected utility \(EU\)

\[(A2) \quad EU^* \equiv \max_e EU = [1 - p(S, e, p^e)]U(W - qe) + p(S, e, p^e)U(W - l - qe)\]

The first-order conditions to this problem are given by

\[(A3) \quad -\frac{\partial p(e)}{\partial e} (U_1 - U_0) = q[(1 - p)U_1' + pU_0']\]

If the quantity of worker investments demanded by the firm exceeds the optimal level of investment that the worker would choose, the employer can induce further investments by compensating workers with higher wages. For example, a fully insured worker would not invest, but the employer may find additional investment profitable. Thus, the question becomes what wage increase is necessary to induce the worker to invest beyond the quantities implied by equation (A3).

This wage change can be obtained by differentiating the expected utility function with respect to wages and worker investments to obtain

\[(A4) \quad \frac{dW}{de} = \frac{\frac{\partial p}{\partial e} (U_1 - U_0) + q[(1 - p)U_1' + pU_0']}{(1 - p)U_1' + pU_0'} \geq 0\]

Equation (A4) indicates the magnitude of the wage change required to keep worker utility constant for a given change in worker investment in safety. If the employer demands the same quantity of worker investments as the worker would choose on his own, equation (A3) implies no change in the wage since this would make the numerator in equation (A4) equal to zero. To obtain further investments, equation (A4) shows the magnitude of the wage premium, which is positive because it
follows from equation (A3) that \( q[(1 - p)U_1' + pU_0'] \) exceeds \( \frac{\partial p}{\partial e}(U_1 - U_0) \). The employer would have to pay to obtain additional investment.

If the worker was fully insured, \( U_1 = U_0 \), he would have no personal incentive to invest: the first term on the right-hand-side of equation (A4) would be zero and the wage increase "charged" by the worker to invest would be given by \( dW/de=q \). This shows that for fully insured workers, the wage increase required to invest in safety would equal the cost of investment \( q \). This captures the idea that workers must be compensated for investing beyond their own optimal investment.

**The Maximization Problem of the Firm**

The employer's problem is to choose labor \((L)\), investments in safety \((S)\), and worker investments in safety \((e)\) to maximize profits subject to a constraint that workers' utility is equal to \( EU^\star \) (the alternative):

\[
\text{(A5) } \max_{L,S,e} \pi = mQ(L) - WL - p(S,E)AL - cSL \\
\text{s.t. } \{ [EU^\star = (1 - p(S,E)U_1(W - qe) + p(S,E)U_0W - qe - l)]L \}
\]

The first-order conditions to this problem are given by:

\[
\text{(A6) } m \frac{\partial Q(L)}{\partial L} = W + p(S,E)A + cS \\
\text{(A7) } - \frac{\partial p}{\partial S} A - \chi \frac{\partial p}{\partial S}(U_1 - U_0) = c \\
\text{(A8) } - \frac{\partial p}{\partial e} A - \chi \{ \frac{\partial p}{\partial e}(U_1 - U_0) = q[(1 - p)U_1' + pU_0'] \}
\]

Equation (A7) yields the optimal level of employer investments in safety \((S)\). The left-hand-side of the equation is the marginal benefit of investment, which is the sum of the reduction in accident costs and the increase in worker utility resulting from the risk reduction weighted by the value of
changing utility by $1 (\chi). The increase in utility resulting from the investment is a benefit to the employer because workers accept lower wages in return.

Equation (A8) yields the optimal level of worker investments in safety, $e$. The left-hand-side is the marginal benefit of such investment, which consists of the decrease in accident costs plus the increase in weighted utility stemming from the reduced injury risk. The right-hand-side is the investment's marginal cost, which is the worker's cost of investment ($q$) weighted by his marginal utility of income.

Equation (A6) states that the value of the marginal product of labor must equal its marginal cost, which is the sum of the wage, expected accident cost and cost of firm investment in safety. Solving for the wage ($W$) yields:

\begin{equation}
W = m \frac{\partial Q(L)}{\partial L} - p(S, e, p^E)A - cS,
\end{equation}

Equation 9 shows that wages depend on the level of employer and employee investments in safety through their effects on risk, $p$. Such investments in turn depend on a variety of factors. Equation (A7) shows that optimal employer investments in safety will differ depending on their price ($c$), productivity $\left(\frac{\partial p}{\partial S}\right)$, accident costs ($A$), and employees' tradeoff between wages and employer-determined risk. Equation (A8) yields the optimal level of employee investments in safety ($S$); they depend on their price ($q$), productivity $\left(\frac{\partial p}{\partial e}\right)$, accident costs ($A$), and the tradeoff between wages and employee-controlled risk.

Recall the firm will induce worker investments in safety by paying a higher wage. The wage increase required to keep worker utility constant when the worker invests in safety was given by equation (A4). Multiplying both sides of that equation by the marginal utility of income $[(1 - p)U_1' + pU_0']$ yields
(A10) \[ \frac{dW}{de} [ (1-p)U_1 + pU_0 ] = \frac{\partial p}{\partial e} (U_1 - U_0) + q( (1-p)U_1 + pU_0 ) \]

Substituting equation (A10) into equation (A8) gives another version of the first-order conditions for worker investment in safety:

\[ (A11) \quad \frac{\partial p}{\partial e} A = \frac{dW}{de} [ (1-p)U_1 + pU_0 ] \chi, \]

The right-hand-side of equation (A11) represents marginal benefits and the right-hand side marginal costs of worker investment in safety.