Biased Perceptions of Occupational Fatality Risk: Theory, Evidence, and Implications*

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Abstract

In a model of occupational safety, biased perceptions of risk decrease welfare, which may justify government regulation. Bias is examined empirically by the correlation between subjective and objective risk, the former measured by self-reported exposure to death on the job. This correlation is negligible among workers with no high school diploma, consistent with underestimating risk in more dangerous occupations. This negligible correlation implies that population estimates of value of statistical life may be biased downwards. An optimal risk ceiling is examined through an illustrative simulation.

Keywords: compensating wage differentials, value of statistical life, workplace safety, occupational safety
JEL Codes: J31, J81

*The data used in this project are available online: the National Health Interview Survey at https://www.cdc.gov/nchs/nhis/index.htm, and the Census of Fatal Occupational Injuries at https://www.bls.gov/iif/oshcfoi1.htm. The author has no disclosures to report. For helpful comments, the author thanks Meltem Daysal, V. Joseph Hotz, Aron Tobias, Mircea Trandafir, Nicolas Ziebarth and seminar participants at the University of Copenhagen and the annual meeting of the Society of Labor Economists. For helpful assistance, the author thanks Ehsan Dowlatabadi.

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1 Introduction

Rosen's (1974) theory on hedonic prices and implicit markets has greatly shaped economic thought on workplace injury, illness, and death. The theory characterizes implicit markets for goods that differ by objectively measured characteristics. He shows that, in equilibrium, the relationship between price and quantity of characteristics depends on - and thus reveals - consumer preferences. The model has direct implications for workplace safety in the labor market (Thaler and Rosen, 1976). Workers vary by risk tolerance, and firms vary by risk-based productivity. In equilibrium, more risk-averse workers sort into low wage, low risk jobs, and less risk-averse workers sort into high wage, high risk jobs. Moreover, the wage-risk tradeoff at the margin reveals workers' value of statistical life (VSL), defined as the collective compensation required by workers for exposure to one additional fatality in expectation. Numerous studies estimate the VSL using observational data on wages and risk, and the estimates are crucial to cost-benefit analyses involving loss of life.

A critical assumption of hedonic price theory and subsequent studies on the VSL is that workers have accurate information about occupational fatality risk.[1] Behavioral economics, in contrast, considers the possibility that perceptions of risk may be biased (Rabin, 2002b).[2] Biased perceptions are referred to as nonstandard beliefs and can arise from three sources: overconfidence, law of small numbers, and projection bias (DellaVigna, 2009) While studies suggest that workers accumulate and respond to risk information (Viscusi, 1992; Viscusi and O'Connor, 1984), these studies do not rule out that misperceptions of risk persist. In the context of workplace safety, Akerlof and Dickens (1982) focus specifically on cognitive dissonance, whereby workers select information to confirm desired beliefs.

The first aim of this paper is to incorporate biased perceptions of occupational fatality risk into the economics of workplace safety. The aim is similar to Akerlof and

[1] Rosen (1974) assumes "all consumers' perceptions or readings of the amount of characteristics embodied in each good are identical."

[2] The concern for subjective versus objective risk in VSL studies is discussed in reviews by Blomquist (2004), Kniesner and Leeth (2014), and Viscusi and Aldy (2003).

Dickens (1982), who introduce cognitive dissonance into the theory of workplace safety, and a study by O'Donoghue and Rabin (2006), who introduce self-control into the theory of optimal sin taxes. If workers perceive risk accurately, they sort into risk optimally. Moreover, government regulations that restrict risk from exceeding a threshold - referred to as a risk quota or ceiling - only decrease welfare. This consequence is noted by Rosen (1974), who discusses the welfare effects of minimum quality standards in product markets. Biased perceptions are introduced to the model by allowing perceived risk to differ from objective risk. As shown, workers who generally underestimate risk choose riskier employment than is optimal, and workers who generally overstate risk choose safer employment than is optimal. In both cases, welfare decreases, and a risk ceiling can potentially increase social welfare.

The second aim is to examine empirically whether perceptions of occupational fatality risk exhibit bias. Although anecdotal evidence suggests that workers in dangerous jobs are often oblivious to the dangers (Akerlof and Dickens, 1982), empirical evidence on the magnitudes remains scant. The primary question is whether self-reported exposure to death on the job is correlated with objective rates of occupational fatality risk. The data come from the National Health Interview Survey (NHIS) of 1985, which includes a one-time survey supplement on self-reported measures of workplace safety. These data are merged to occupational fatality rates according to a respondent's reported occupation. Occupational fatality rates are tabulated from the Census of Fatal Occupational Injuries (CFOI) and the March Supplement of the Current Population Survey (CPS), both from 1992 to 1995. The sample is restricted to males, who are substantially more likely to die on the job than females.

The empirical analysis emphasizes differences across educational attainment. Evidence suggests that education causally improves health (Cutler and Lleras-Muney, 2006; Lleras-Muney, 2005), and one possible mechanism is that education increases the efficiency of health production (Grossman, 1972), including the ability to acquire and understand health information. Additionally, some less educated workers may be constrained to high risk occupations, lacking the skills required for high wage, low risk occupations. In this case, workers may optimally believe their occupation is safer than it really is, a form of cognitive dissonance (Akerlof and Dickens, 1982).

The results confirm the predictions regarding subjective risk, objective risk, and education. First, although workers with less than a high school diploma work disproportionately in dangerous occupations, they are least likely to report exposure to death on the job. Second, while subjective and objective measures of occupational fatality risk are highly correlated among more educated workers, the partial correlation is negligible among workers with less than a high school diploma. These findings are consistent with less educated workers underestimating risk in more dangerous occupations.

The empirical strategy and data have several important limitations. First, the CFOI does not report fatalities by educational attainment. This raises the concern that objective risk among workers with less than a high school diploma is uncorrelated with aggregate fatality risk among all workers, thereby accounting for the negligible correlation between subjective and objective risk. To address this concern, hazard rates of work-limiting and work-preventing disabilities are calculated using the Survey of Income and Program Participation (SIPP). As shown, hazard rates increase with aggregate fatality risk similarly among less and more educated workers. Second, the measures of subjective and objective risk are not directly comparable. As a result, the empirical strategy can only identify relative bias, not absolute bias. In particular, a negligible correlation means that bias becomes more negative as objective risk increases, but workers may be underestimating risk, overestimating risk, or both (i.e. overestimating risk in safer occupations but underestimating risk in more dangerous occupations). However, a scenario in which less educated workers in dangerous jobs are not underestimating risk requires all other workers to be overestimating risk. A simpler and more likely scenario is that, to some extent, less educated workers in dangerous occupations are underestimating risk. Finally, the data are particular to the 1980s, which may not be relevent to contemporary public policy. However, Rosen (1974) and Thaler and Rosen (1976) date to the 1970s, yet continue to influence economic thought, research, and policy. An important question for science is whether the assumptions of the model are valid, both then and now.

The third aim is to explore the implications of biased perceptions in occupational fatality risk. Section 4 examines implications for estimating the VSL. If subjective risk is uncorrelated with objective risk, then the expected value of the VSL estimate would be zero, biasing downward VSL estimates. Given the empirical evidence, this seems most likely among less educated workers. Additionally, these workers would have an outsized effect on the estimated VSL because the bias depends on their share of the conditional variance in fatality risk, not their share in the population, where the former exceeds the latter. Under certain assumptions, the population estimate of the VSL should be factored by 1.3. This downward bias may be mitigated, however, if a few informed workers can discipline the entire market for dangerous occupations. As Rabin (2002b) notes, a common argument against psychological economics is that "markets will wipe any unfamiliar psychological phenomenon out". While this argument is beyond the scope of this study, it raises an important direction for further research.

Section 5 explores the implications of biased perceptions on the optimal risk ceiling. An illustrative simulation is based on the assumption that more educated workers accurately perceive occupational fatality risk, but less educated workers have biased perceptions. Additionally, risk aversion is assumed homogeneous among less educated workers, but less educated workers are less risk averse than more educated workers on average. As the risk ceiling is lowered, the marginal cost among more educated workers increases, whereas the marginal benefit among less educated workers may increase or decrease. The latter reflects that the marginal benefit per worker decreases, on one hand, but more workers benefit from the risk ceiling, on the other. As shown, the optimal risk ceiling decreases with risk aversion of less educated workers and with the VSL.

The final section discusses three main contributions of this study to the existing literature. First, the results contribute to the empirical literature on biased perceptions of risk. The tendency of less educated workers to underestimate fatality risk may reflect overconfidence or optimism (Weinstein, 1989). For example, Oster et al. (2013) find that individuals at risk for Huntington disease exhibit optimistic beliefs about their health, which they reconcile with a model of optimal expectations by Brunnermeier and Parker

(2005). Additionally, the majority of self-reported exposures to death stem from substances, rather than physical injuries or the physical environment. This is consistent with Slovic et al. (1990), who find that people overestimated risks that were dramatic and sensational and underestimated risks that were unspectacular and common in non-fatal form. Second, this study explores alternative explanations for the tendency for VSL estimates to be greater among workers with higher income (Viscusi and Aldy, 2003). One possible explanation is that safety is a normal good (Viscusi, 1978). Another explanation, supported by the results from this study, is that income is correlated with education, and education decreases biased perceptions of risk. Finally, the results contribute to the literature on non-standard economic models and their implications for public policy (Mullainathan et al., 2012; O'Donoghue and Rabin, 2006). In fact, the risk ceiling or quota considered in this study is consistent with an existing program of the United States Occupational Safety and Health Administration, the Site Specific Targeting (SST) plan, implemented in 1999. The plan targets establishments with accident rates exceeding a threshold for inspection and, if applicable, financial penalties. Although more recent data are required to fully understand how biased perceptions should inform public policy, this study provides theoretical and empirical frameworks for further study.

2 Theory

2.1 Standard Model

The standard model follows Thaler and Rosen (1976), who apply Rosen's (1974) model of hedonic prices to workplace safety in the labor market.[3] A worker's expected utility depends endogenously on wages w and occupational injury risk r and exogenously on risk aversion η and consumption d if injured: $E[u(w, r; \eta, d)] = (1 - r)u(w) + ru(d)$, where the risk aversion parameter η is subsumed in the utility function.[4] The slope of the

[3]The model in Thaler and Rosen (1976) includes endogenous insurance coverage against occupational injury or death, which can be ignored to focus on biased perceptions of risk.

[4]Consumption d if injured may be interpreted as a demogrant in linear income tax models. The model can be reframed to reflect occupational fatality risk, rather than injury risk, by interpreting $u(d)$ as a

indifference curve at (w, r) is given by $\frac{dw}{dr} = \frac{u(w)-u(d)}{(1-r)u'(w)} > 0$, where $\frac{d^2w}{(dr)^2} > 0$. In equilibrium, wage is function of risk $w(r)$, and a worker maximizes utility at $w'(r^*) = \frac{u(w(r^*))-u(d)}{(1-r^*)u'(w(r^*))}$.

A firm's expected profit depends endogenously on wages w and occupational injury risk r and exogenously on risk-based productivity μ: $E[\pi(w, r; \mu)] = R(r) - w$, where the risk-based productivity measure μ is subsumed in the revenue function.[5] The slope of the isoprofit curve at (w, r) is given by $\frac{dw}{dr} = R'(r) > 0$, where $\frac{d^2w}{(dr)^2} = R''(r) < 0$. In equilibrium, wage is function of risk $w(r)$, and a firm maximizes profits at $w'(r^*) = R'(r^*)$.

In equilibrium, for all combinations of (w, r), $\frac{u(w(r))-u(d)}{(1-r)u'(w(r))} = R'(r)$, and labor supply equals labor demand (Rosen, 1974). To provide intuition for this equilibrium condition, the model is simplified by considering two types of workers: high risk-averse workers with preferences u^A and low risk-averse workers with preferences u^B. The difference in risk aversion implies that, at a given combination of (w, r), $\frac{dw^A}{dr} > \frac{dw^B}{dr}$. The model is further simplified by assuming that firms have only one type of risk-based technology mapping risk to marginal productivity. Additionally, the labor market is competitive, and firm profits are zero. An equilibrium under this scenario is illustrated in panel A of Figure 1. As shown, workers sort into two types of employment based on wages and risk: more risk-averse workers maximize expected utility at $E[u^A(w(r^*_A), r^*_A)]$, and less risk-averse workers maximize expected utility at $E[u^B(w(r^*_B), r^*_B)]$. Thus, risk-averse workers choose safer jobs.

In the standard model, exogenous safety standards imposed by the government only decrease social welfare (Rosen, 1974). For example, Panel B of Figure 1 illustrates the welfare consequences of a quota such that risk cannot exceed the ceiling r_c. Because this quota is binding for less risk-averse workers, they are forced to accept employment at risk r_c and wage $w(r_c)$, thereby decreasing welfare.

bequest motive. The utility function may also be state dependent such that, for all levels of consumption, both utility and marginal utility are greater in the non-injured state.

[5]The profit function assumes constant returns to scale. Safety costs can also be subsumed in the revenue function so that $R(r)$ represents revenue net of safety costs.

2.2 Biased Perceptions

Biased perceptions arise when a worker's subjective injury risk differs from objective injury risk. A general notation for biased perceptions is given by $\rho(r) = r + v(r)$, where ρ is perceived risk and v is the bias. The bias may vary by objective risk r and can be either positive, leading to overestimation of risk, or negative, leading to underestimation.

Bias leads workers to choose employment risk suboptimally, thereby decreasing welfare. To characterize the effect of the bias on risk choice and welfare, denote (w^*, r^*) as the optimal choice with no bias. This choice is a function of η and d, which are dropped from the notation. As a simplification, the bias is assumed a constant v in the neighborhood of (w^*, r^*). In this case, the worker chooses employment by maximizing $E[u(w, r; \eta, d, v)] = (1 - \rho)u(w) + \rho u(d)$, with indifference curves $\frac{dw}{dr} = \frac{u(w)-u(d)}{(1-\rho)u'(w)}$. The optimal choice with bias is denoted r^{**}. If $v \neq 0$, then the worker would not choose (w^*, r^*). Specifically, if $v > 0$, then $R'(r^*) < \frac{u(w(r^*))-u(d)}{(1-(r^*+v))u'(w(r^*))}$, and the worker would instead seek safer employment $r^{**} < r^*$ such that $R'(r^{**}) = \frac{u(w(r^{**}))-u(d)}{(1-(r^{**}+v))u'(w(r^{**}))}$. Conversely, if $v < 0$, the worker would seek more dangerous employment $r^{**} > r^*$. Importantly, while bias affects employment choice, experienced utility is evaluated under actual degrees of risk, and because welfare is maximized at r^*, $E[u(w^{**}, r^{**})] < E[u(w^*, r^*)]$ regardless of whether workers overestimate or underestimate risk. Thus, biased perceptions reduce worker welfare.

The case where workers underestimate risk ($v < 0$) is illustrated in panel C of Figure 1. The optimal choice of risk is r^*, but the underestimation of risk causes workers to choose r^{**}. The welfare loss from the bias is illustrated by the shift from utility curve that is tangent to $w(r)$ at r^* to the utility curve that runs through $w(r)$ at the optimal choice with bias r^{**}.

2.3 Optimal Policy

The loss of welfare due to biased perceptions may justify government policy and regulation that restrict risk. In a utilitarian model, government maximizes a social welfare function that places equal weight on all workers:

$$E_F[u(w^{**}, r^{**}; \eta, d, v)] = E_F[(1 - r^{**})u(w^{**}) + r^{**}u(d)]. \tag{1}$$

Expectations are integrated across the joint distribution of η and v, denoted $F(\eta, v)$. In this framework, the government maximizes experienced utility, while workers employment choice (w^{**}, r^{**}) is influenced by bias. By construction, welfare is maximized when $r^{**} = r^*$, so the government's objective amounts to minimizing the externality that results from biased perceptions (O'Donoghue and Rabin, 2006). The government's objective is complicated by the fact that some workers can overestimate risk while others can underestimate risk. Therefore, any policy that shifts workers from one risk level to another may increase welfare for some workers while decreasing welfare for others.

One policy strategy is to improve access to and quality of risk information so that workers can make more informed decisions. For example, the US Occupational Safety and Health Administration (OSHA) requires many employers with ten or more employees to keep records of serious work injuries and illnesses and to make these records available to workers and their representatives. Policies that provide information may be ineffective for several reasons. First, workers may exhibit statistical bias, whereby individual risk is incorrectly inferred from risk of larger groups (i.e. establishments or industries). Second, workers may be optimistic or pessimistic about their individual risk relative to a group. Third, according to the law-of-small numbers, in the absence of recent accidents or fatalities, workers may believe their employment is safer than reality (Rabin, 2002a). Finally, workers may disregard accurate information that is inconsistent with prior beliefs (Nisbett and Ross, 1980). For example, in an experimental study on judging risk, Lichtenstein et al. (1978) find that individuals were unable to correct for potential sources of bias even when prompted to avoid them.

Another policy strategy is Pigouvian taxation. To characterize a first-best policy, workers are assumed homogeneous with respect to risk misperception v as well as risk aversion η. Social welfare is maximized by imposing penalty $P(r)$ on firms based on risk that solves the first-order ordinary differential equation:

$$P'(r) = \frac{u(R(r)) - u(d)}{(1-r)u'(R(r))} - \frac{u(R(r) - P(r)) - u(d)}{(1-r-v)u'(R(r) - P(r))}. \tag{2}$$

The zero-profit condition then becomes

$$w(r) = R(r) - P(r). \tag{3}$$

Finally, workers maximize utility using the biased utility function so that

$$w'(r^{**}) = \frac{u(w(r^{**})) - u(d)}{(1 - r^{**} - v)u'(w(r^{**}))} \tag{4}$$

Combining equations (2), (3), and (4) yield

$$R'(r^{**}) = \frac{u(R(r^{**})) - u(d)}{(1 - r^{**})u'(R(r^{**}))}. \tag{5}$$

It follows that $r^{**} = r^*$. Of course, if workers are heterogeneous with respect to bias and risk aversion, first-best policies may not be feasible.

A third policy strategy is to enforce a risk ceiling, similar to a quota on the consumption or production of goods that impose externalities. Specifically, the government could determine a maximum risk ceiling on objective risk at r_c, and enforce the ceiling by establishing workplace standards, conducting workplace inspections, and levying financial penalties.[6] The focus on the right-tail of the risk distribution is because the share of workers who underestimate risk likely exceeds the share of workers who overestimate risk. To evaluate the welfare consequences of a risk ceiling, define $I(r^{**} > r_c; \eta, v, d)$ as an indicator of working at a risk level above r_c with bias but in the absence of a risk ceiling. The government chooses r_c to maximize a social welfare function

[6] Kniesner and Leeth (2014) discuss and review the literature on the deterrence and abatement effects of OSHA on workplace safety. Levine et al. (2012) and Li and Singleton (2019) find that workplace inspections improve workplace safety, and Li (2020) finds that penalties improve workplace safety.

$$E_F[u(w^{**}, r^{**}; \eta, v, d)] =$$

$$E_F[(1 - I(r_c))[(1 - r^{**})u(w^{**}) + r^{**}u(d)] + I(r_c)[(1 - r_c)u(w(r_c)) + r_c u(d)]]. \quad (6)$$

The first-order condition for the optimal ceiling r_c^* is given by

$$E_F\left[I(r_c^*)\left[w'(r_c^*) - \frac{u(w(r_c^*)) - u(d)}{(1 - r_c^*)u'(w(r_c^*))}\right]\right] = 0. \quad (7)$$

At the optimum, there are no welfare effects on the margin among workers who choose $r^* = r_c^*$ without bias.[7] Instead, the welfare effects occur among two types of workers. The first is workers with $r^* > r_c$, whose welfare decreases from the ceiling. In this case, $\frac{u(w(r_c))-u(d)}{(1-r_c)u'(w(r_c))} < w'(r_c)$, so relaxing the ceiling increases social welfare. The second is workers with $r^* < r_c$ and $r^{**} \geq r_c$, whose welfare increases from the ceiling. In this case, relaxing the constraint decreases social welfare. At the optimum, the positive marginal welfare effects exactly offset the negative marginal welfare effects so that, in effect, the average indifference curve at r_c^* is tangent to the isoprofit curve.

The first-order condition also provides sufficient conditions for any regulatory ceiling on risk. In the absence of a ceiling, the maximum risk with biases is denoted as r_{max}^{**}. At this point, workers may be overestimating the risk ($r^* > r_{max}^{**}$), underestimating risk ($r^* < r_{max}^{**}$), or neither ($r^* = r_{max}^{**}$). A sufficient condition for a regulatory ceiling is that no worker who chooses the maximum risk is overstating risk and at least one worker is understating risk. In this case, the first-order condition would be negative at r_{max}^{**}, so $r_c^* < r_{max}^{**}$. In fact, the sufficient condition implies that a binding risk ceiling is not only optimal, but Pareto optimal, since marginal welfare at r_{max}^{**} is either positive for workers with $r^* < r_{max}^{**}$ or zero for workers with $r^* = r_{max}^{**}$.

The sufficient condition and optimal risk ceiling is illustrated in panel D of Figure 1. There are two types of workers at r_{max}^{**}: workers with no bias, whose indifference

[7] In this case, $w'(r_c^*) = \frac{u(w(r_c^*))-u(d)}{(1-r_c^*)u'(w(r_c^*))}$.

curves are tangent to the wage curve at r^{**}_{max}, and workers who underestimate risk, whose indifference curves run through the wave curve at r^{**}_{max}. As a risk ceiling is imposed, welfare decreases for the former, but increases for the latter. The optimal risk ceiling, denoted r^*_c, occurs where the marginal welfare gain equals the marginal welfare loss.

3 Evidence of Bias: Exposure to Death

The theoretical model of biased perceptions raises questions about whether, and to what extent, perceptions are biased. This question can be framed using the notation above, $\rho(r) = r + v(r)$, where perceived or subjective risk ρ equals objective risk r plus bias $v(r)$. A linear specification of the bias is given by $v(r) = v_0 + (v_1 - 1)r$, so that $\rho(r) = v_0 + v_1 r$. The parameter v_0 accounts for systemic bias, whereby workers overestimate or underestimate risk across all values of r similarly, and the parameter v_1 accounts for bias that varies with r. If workers accurately perceive risk, then $v_0 = 0$ and $v_1 = 1$. The parameter v_1, which scales the covariance between subjective and objective risk, is the focus of the empirical analysis.

3.1 Model and Data

To examine potential bias in risk perception, the empirical analysis examines the correlation between self-reported exposure to death on the job and objective rates of occupational fatality risk. This relationship is estimated using the following model:

$$Death_{ij} = \alpha + \beta FatalityRate_j + \gamma X_{ij} + u_{ij}. \tag{8}$$

The unit of analysis is individual i in occupation j. $Death_{ij}$ is an indicator of exposure, equaling one if death is mentioned as an on-the-job risk and zero otherwise. $FatalityRate_j$ is the occupational fatality rate per 100,000 full-time equivalent workers. X_{ij} is a vector of control variables commonly used in wage regressions in the VSL literature (Viscusi and Aldy, 2003): age, age squared, race (indicator of white), education (indicators of high school diploma and some college or more, with high school drop as the left-out group), marital status (indicators of married, widowed, and divorced, with never married as the left-out group), and indicators of veteran status, self-employment, and industry.[8] These variables are included in wage regression to mitigate omitted variable bias, since they have a direct effect on wages and may be correlated with occupational safety. The term u_{ij} is the error.

The coefficient of interest is β, which reflects the partial covariance between self-reported exposure to death and objective fatality rates. The covariance is estimated from variation in objective risk across workers and their respective occupations. Intuitively, if workers perceive increased risk, then self-reported exposure of death should increase with objective fatality rates: β should be positive. There is no prediction regarding the magnitude of β because exposure to death is a discrete response whereas the fatality rate is continuous; nonetheless, a negligible correlation would be consistent with workers misperceiving risk. Importantly, the slope coefficient β does not capture systemic bias across all occupations, represented by v_0, which would be subsumed in the coefficient α.

To examine whether β differs by education, indicators of education are interacted with $FatalityRate_{ij}$. This approach assumes that the effect of the control variables are constant by education. To relax this assumption, the model is also estimated separately by education.

Data on self-reported exposure come from the NHIS of 1985. This survey includes a one-time supplement on health promotion and disease prevention that asks numerous questions about risk exposure. Importantly for this study, the supplement includes questions on exposure to "substances in present job" and "work conditions in present job". Survey respondents first report whether they are exposed to substances or conditions; if so, respondents then report which specific substances or conditions are present and their possible health effects, including death.

Fatality rates by occupation are measured as the number of fatalities annually per 100,000 full-time equivalent workers. Data on the number of deaths come from

[8]Industries are grouped into 14 categories. The results are qualitatively similar when industries are grouped into 43 categories.

the CFOI. The CFOI tabulates deaths by occupation annually from 1992 to 2001, but the analysis utilizes only years 1992 to 1995, corresponding closer to the NHIS survey year 1985. Data on the number of full-time equivalent workers comes from the March Supplement of the CPS, survey years 1992 to 1995.[9] Full-time equivalent is calculated by factoring the sample weight by weeks worked last year multiplied by the usual hours worked per week divided by 2,000, where the latter is 50 weeks per year multiplied by 40 hours per week.[10] The fatality rate is calculated as the sum of fatalities from 1992 to 1995, divided by the sum of full-time equivalent employment, multiplied by 100,000. Fatality rates are tabulated and merged to NHIS data by 330 standardized occupation codes constructed by Autor and Dorn (2013).[11] These codes serve as a crosswalk between the 1980 Census Detailed Occupation Codes used in the NHIS and the 1990 Census Occupational Classification System used in the CFOI.[12]

The sample is restricted to males who are ages 18 to 64 and employed at the time of the survey. The focus on males reflects that occupational fatality rates are substantially lower among females.[13] Importantly, CFOI data are disaggregated by sex, so population fatality rates by occupation are calculated specifically for males. The sample is further restricted to observations that match to tabulated fatality rates, yielding 8,455 observations.[14]

Unfortunately, the CFOI data are not disaggregated by educational attainment. Thus, when estimating equation (8) by education, an important issue is whether occupational fatality risk among all workers is a valid proxy for subsets of workers. This will be an important issue when when discussing the potential mechanisms for the empirical

[9]To calculate the denominator of fatality rates, the US Bureau of Labor Statistics also uses data from the Current Population Survey (Northwood, 2010).

[10]In 2009, the US Bureau of Labor Statistics introduced a new methodology for calculating fatality rates based on hours rather than employment. The methodology assumes that a full-time equivalent worker works 40 hours per week, 50 weeks per year (Northwood, 2010).

[11]As Kniesner et al. (2012) note, fatality rates by occupation are likely better than rates constructed from industry alone, a common practice in the literature. In their study, they consider 720 industry-occupation groups, comprising 72 industries, but only 10 one-digit occupations.

[12]The CPS also uses the 1990 Census Occupational Classification System.

[13]The average occupational fatality rate for males is 8.10 per 100,000, compared to just 0.77 for females.

[14]The sample size decreases from 8,964 to 8,455 because the occupation code in the NHIS is missing values, the occupation code in the NHIS does not match to a standardized occupation code constructed by Autor and Dorn (2013), or because the fatality rate could not be calculated from the CFOI and CPS data.

findings.

3.2 Summary Statistics

Summary statistics of the analysis sample by education are presented in Table 1. The statistics immediately reveal a paradox regarding self-reported exposure to death and objective occupational fatality rates: although workers with less than a high school diploma work in occupations with the highest fatality rates, they are least likely to report exposure to death on the job. The mean occupational fatality rate per 100,000 workers is 12.42 among workers without a high school diploma, compared to 9.39 and 5.45 among workers with only a diploma and some college or more, respectively. The higher fatality rate among workers with less than a high school diploma reflects that they are less likely to work in professional and technical occupations and more likely to work in service, production, and operator occupations. In contrast, only 3.05 percent of workers without a high school diploma report exposure to death on the job, compared to 5.08 and 3.40 percent work among workers with only a high school diploma and some college or more, respectively. The difference between workers without a high school diploma and those with only a high school diploma is statistically significant.

To further understand the relationship between self-reported exposure to death and occupational fatality rates, Figure 2 illustrates a scatter plot of the data by education groups. The figure plots rates up to 30, which excludes just 3.5 percent of the sample at the extreme end of the fatality rate distribution. The fatality rate is discretized as integers so that self-reported exposure to death is tabulated by integer bins. The marker size is proportional to the number of workers within education groups.

The figure reveals two notable patterns. First, at occupational fatality rates near zero, the share of workers who report exposure to death is similar across all three education groups. Second, the share of workers who report exposure to death increases with the occupational fatality rate, but the increase appears steeper among more educated workers in comparison to workers with no high school diploma. Thus, the difference in self-reported exposure to death on the job by education, reported in Table 1, is concentrated among more dangerous occupations.

Exposure to death is a simple Bernoulli variable, without regard to intensity or type. To examine the intensity of exposure, Table 1 also reports the average number of exposures to death. As shown, workers without a high school diploma also report fewer exposures than more educated workers. To examine the type of exposures, Table 2 reports exposures for three broad categories: substances, physical environment, and physical injuries, falls, slips, etc. Substances include chemicals, dust, fibers, gases, fumes; physical environment includes loud of excessive noise, extreme heat or cold, physical stress; and physical injuries include powered equipment, contact with electrical equipment, injuries from falling or flying objects. Interestingly, most of the self-reported exposures stem from substances, and, within this category, to "chemicals" and "other gases, fumes, vapors, or mists" (not shown). To put these findings into context, in 2022, work-related deaths due to harmful substances account for 15.3% of all work-related deaths, well behind transportation incidents (29.5%), but comparable to falls, slips, and trips (15.8%) and contact with objects and equipment (13.5%). These findings are consistent with Slovic et al. (1990), who find that people overestimated risks that were dramatic and sensational and underestimated risks that were unspectacular and common in nonfatal form.

3.3 Regression Results

Table 3 presents the estimates of β in equation (8). The first column is a regression of self-reported exposure to death on occupational fatality risk with no control variables or industry fixed effects. The point estimate is 0.108 and is statistically significant at the one percent level. At the mean of 3.99 percent, a one standard deviation in fatality risk of 11.89 increases the likelihood of self-reported exposure to death by 1.28 percentage points. The second column interacts the fatality rate with educational attainment. Consistent with Figure 2, the correlation between self-reported exposure to death and occupational fatality risk is strongest among more educated workers. The estimated relationship among workers with no high school diploma is 0.017, which increases by 0.100 and 0.152 among workers with a high school diploma only and some college or more, respectively. This finding is robust to including control variables (column 3), including industry fixed effects (column 4), estimating the model separately by education (columns 5 through 7), and the probit and logit models (not shown). Interestingly, the inclusion of industry fixed effects from column (3) to (4) reduces the estimate among workers without a high school diploma from 0.017 to -0.024, whereas the estimates for more educated workers are robust. These results indicates that the variation in self-reported exposure to death among workers without a high school diploma is largely between industries, rather than between occupations within industries.

The differences in estimates between education groups are both statistically and economically significant. In column (3), where all the estimates are positive, a one standard deviation in fatality risk increases the likelihood of self-reported death by 1.76 percentage points among workers with some college or more, but just 0.20 percentage points among workers with no high school diploma. The negative estimate in column (5) among less educated workers suggests a similarly weak relationship between objective and subjective risk, even at the upper bound of the 95 percent confidence interval of 0.036.

One concern with the analysis is that self-reported exposure to death is measured in 1985, whereas occupational fatality rates are calculated for years 1992 to 1995. The concern is that occupational safety improved during this time and, as such, the results may be sensitive to these changes. From 1980 to 1995, for example, the number of annual deaths declined by 28 percent to 5,314, and the average rate of deaths declined by 43 percent to 4.3 per 100,000 workers (US Center for Disease Control, 1999). This concern in relation to equation (8), however, should not be whether rates for years 1992 to 1995 are equal to rates in 1985, but whether rates for years 1992 to 1995 are highly correlated with rates in 1985. This is similar to the logic of Blomquist (2004) and Kniesner et al. (2012), who note that workers need not perceive risk accurately, but their perceptions must be correlated with objective risk. While it is impossible to measure the correlation in rates from 1985 and 1992 to 1995, it is possible using the CFOI to measure the correlation in rates from 1992 to 1995 and from 1999 to 2002, when workplace safety was also improving.[15] This correlation among the sample of men in 1985 is 0.93. Thus, despite a decline in the mean and variance of rates over time, rates are highly correlated. Furthermore, the results in Table 3 are qualitatively similar when using rates from 1999 to 2002 instead of 1992 to 1995. In the final three columns, the estimates are -0.015 (standard error: 0.033), 0.161 (0.060), and 0.161 (0.062).

Both Table 1 and Figure 2 show that less educated workers are skewed towards more dangerous occupations. To ensure that the different results by educational attainment in Table 3 are not due to distributional differences in occupational safety, the models in Table 3 are estimated among fatality risks of 5 or more, eliminating roughly half of the sample. The results are qualitatively similar. For example, for column (4), the first three estimates are -0.047 (0.028), 0.083 (0.058), and 0.138 (0.061). Thus, the relationship between subjective and objective risk is stronger among more educated workers, even among the more dangerous occupations.

The results may also vary by age, because occupational fatality rates generally increase with age, and because risk information may improve with tenure in the labor market.[16] The qualitative results, however, are similar between younger and older workers. In the final three columns, the estimates are -0.028 (0.044), 0.074 (0.048), and 0.102 (0.055) among workers ages 18 to 44 and -0.020 (0.041), 0.160 (0.124), and 0.127 (0.072) among workers ages 45 to 64.

3.4 Mechanism

Self-reported exposure to death reflects both objective risk and bias. Thus, before considering the potential for bias, it is necessary to consider how objective risk varies with the occupational fatality rate, particularly across education groups and across occupations within education groups.

Among less educated workers, the correlation is negligible between self-reported risk and the aggregate fatality rate among all workers. This could reflect two possible

[15] The mean declines from 8.10 to 6.94, and the standard deviation declines from 11.94 to 10.45.

[16] According to BLS data, the occupational fatality rate (per 100,000 full-time equivalent workers) increases monotonically with age, from 2.4 at ages 20 to 24 to 8.4 at ages 65 and over.

mechanisms, which are illustrated in Figure 3. The aggregate fatality rate is on the x-axis, the objective rates by education are on the y-axis, and the 45-degree line indicates how rates by education compare to the aggregate.

Under the first mechanism, objective rates are greater among less educated workers, but increase similarly among both education groups with respect to the aggregate fatality rate. Since the correlation is negligible between self-reported risk and aggregate risk, subjective risk, if plotted in Figure 3, would be a horizontal line.[17] This horizontal line may be placed above objective risk, so that workers are overestimating risk, or placed below objective risk, so that workers are underestimating risk. This means that, under mechanism one, bias must decrease as occupations become more dangerous, either by overestimating more dangerous occupations less or by underestimating more dangerous occupations more.

Under the second mechanism, objective rates among less educated workers do not vary substantially across occupations, despite variation at the aggregate level. This mechanism is plausible since the share of less-educated workers is small overall and is smallest among the safest occupations, thus having a minimal impact on the mean. Since subjective risk is represented by a horizontal line, bias must be systemic across all occupations, either by overestimating risk in all occupations, underestimating risk in all occupations, or no bias at all.

To differentiate between these two mechanisms, occupational fatality rates would ideally be calculated separately by education. This is not possible with the available data, unfortunately, as the CFOI does not report fatalities by educational attainment. As an alternative, two other measures of risk are considered: self-reported exposure to accidents and disability onset due to workplace accidents.

[17] The horizontal line assumes that the neglibile relationship between self-reported exposure to death and objective fatality rates found in the empirical analysis implies a negligible relationship between subjective fatality rates, which are plotted on the y-axis but not observed in the data, and objective fatality rates.

3.4.1 Accidents

One strategy to evaluate objective risk is to examine self-reported exposure to accidents using the same data and models above. For two reasons, self-reported exposure to accidents may be less prone to bias than exposure to death: workplace accidents are more common than workplace fatalities, and the risk of accidents may be more salient. As shown in Table 1, while only 3.99 percent of workers report exposure to death on the job, 52.45 percent report exposure to an accident.

The data on accidents are consistent with an intermediate version of the two mechanisms in Figure 3. Figure 4 illustrates the relationship between self-reported exposure to accidents and occupational fatality risk separately by education. The x-axis is fatality risk, rather than accident risk, to determine whether less educated workers perceive greater accident risk, if not fatality risk, in more fatal occupations. As shown, a substantial share of workers report exposure to accidents, even in low fatality-rate occupations. At near-zero fatality rates, the share is approximately 50 percent for workers with no high school diploma and with a high school diploma only, and closer to 30 percent among workers with some college or more. Additionally, exposure to accidents increases with the aggregate fatality rate, even among workers with less than a high school diploma. This means that, although workers with less than a high school diploma do not associate more dangerous occupations with an increased risk of death, they do associate them with an increased risk of accidents.

As with self-reported exposure to death, the slope is steepest among more educated workers. In fact, among more dangerous occupations, workers with less than a high school diploma are least likely to report exposure to accidents, similar to the reports for death in Table 1. For example, among occupations with a fatality rate greater than 10, 68.32 percent of workers with less than a high school diploma report exposure to an accident, in comparison to 76.41 and 78.54 percent among workers with a high school diploma only and with some college or more.

Table 4 reports regression results from equation (8) with exposure to accidents as the outcome variable. The results confirm that exposure to accidents in low-fatality occupations is greater among less educated workers, but increases more steeply with the fatality rate among more educated workers. In column (4), for example, the main effect on some college or more is 19.11 percentage points less in comparison to no high school diploma, but the slope coefficient is 0.712 more, both of which are statistically significant.

3.4.2 Work-Limiting and Work-Preventing Disabilities

Another strategy to evaluate objective risk by education is to examine workplace safety outcomes. In particular, hazard rates of work-limiting and work-preventing disabilities due to workplace accidents are estimated using the Survey of Income and Program Participation (SIPP). The SIPP is a nationally representative, longitudinal survey of the US population. The analysis utilizes SIPP panel years 1990, 1991, 1992, and 1993. The frequency of disabilities by occupation is tabulated using the topical modules on disability and employment history. The module on disability history is conducted in wave two for all panels, which corresponds to the eighth month of a panel. The module asks respondents whether they have a health condition that limits or prevents work and, if so, the date of disability onset, whether the disability was the result of an accident, and the location of the accident, including possibly at work. The module on employment history is conducted in either wave one (panel years 1992 and 1993) or two (panel years 1990 and 1991). The module asks respondents the month and year they started their current employment as well as the month and year they started and ended their previous employment. Respondents also report the occupation of their current and previous employments. The analysis is restricted to five years prior to the survey, which increases the frequency of disability onsets while minimizing recall error and increasing the likelihood that a disability onset occurred during the current or previous employment, for which occupation data are available. By merging SIPP data to administrative data on longitudinal earnings, Singleton (2012) shows that these retrospective reports of work-limiting and work-preventing disabilities are associated with a precipitous decrease in employment and earnings.

Table 5 reports annual hazard rates of work-limiting and work-preventing disabilities among males ages 18 to 65. The numerator is the estimated number of disabilities in the population over the five-year period, derived by summing the sampling weights. The denominator consists of three factors: the number of SIPP panels (four); the number of years over which disabilities are tabulated (five); and the estimated number of full-time equivalent workers, derived from the 1992 CPS. The rates are calculated separately by education and occupational fatality rates among all workers. In contrast to Figures 2 and 4, which aggregate the data to integers of occupational fatality rates, Table 5 aggregates the data to wider ranges of fatality rates. This is due to the low frequency of disabilities resulting from workplace accidents during the previous five years: 719 work-limiting disabilities, and 311 work-preventing disabilities.

The hazard rates are consistent with mechanism one in Figure 3. First, workers with less than a high school diploma experience higher rates of work-related disability, even within subcategories of occupational fatality risk. Overall, the rate of work-limiting disability is 0.453 percent, and the rate of work-preventing disability is 0.217 percent. In comparison, these rates are 0.111 and 0.035 percent, respectively, among workers with some college or more. Second, workers with less than a high school diploma exhibit substantial rates of work-related disability, even in relatively safe occupations. Among occupations with a fatality rate between zero and six, the rate of work-limiting disabilities is 0.353 percent, and the rate of work-preventing disabilities is 0.166. Finally, disability rates increase with occupational fatality rates within all education groups, and, in levels, the increases are comparable across education levels. From the lowest to highest occupational fatality categories, the latter between zero to six and the former 14 and greater, the rate of work-limiting disabilities increases by 0.259 percentage points among workers with no high school diploma and by 0.262 percentage points among workers with some college or more. These results support that objective risk increases across occupations within all education levels.

3.4.3 Biased Perceptions

The potential for bias can be inferred by combining objective and subjective risk. For example, denote subjective risk among less educated workers as $\rho_l(r_s) = r_l(r_s) + v_l(r_s)$ in safe occupations and $\rho_l(r_d) = r_l(r_d) + v_l(r_d)$ in dangerous occupations. The subscripts l indicate that risk and bias is particular to less educated workers relative to aggregate risks r_s and r_d. According to Table 5, objective risk among less educated workers increases with aggregate risk, so $r_l(r_s) < r_l(r_d)$; yet, according to Table 3, subjective risk is approximately constant, so $\rho_l(r_s) = \rho_l(r_d)$. This implies that bias must decrease with aggregate risk: $v_l(r_s) > v_l(r_d)$.

The same logic can be applied across education groups. For example, in safer occupations, subjective risk appears similar across educational attainment; yet, according to Table 5, objective risk is greater among less educated workers. Taken together, bias among more educated workers must be greater than bias among less educated workers: $v_m(r_s) > v_l(r_s)$, where the subscript m corresponds to more educated workers.

Because subjective risk (self-reported exposure to death) is not directly comparable to objective risk (occupational fatality rate), this framework reveals only relative bias, i.e. that $v_l(r_s) > v_l(r_d)$ and that $v_m(r_s) > v_l(r_s)$. It is not possible to identify whether workers are overestimating risk, underestimating risk, or some combination of both.

It is possible, however, to characterize the conditions necessary for a certain risk profile to exist and then to consider whether those conditions are reasonable relative to alternative explanations. Of particular importance for an optimal risk ceiling is whether workers in dangerous jobs underestimate risk. Given the foregoing analysis, this seems most plausible for less educated workers: subjective risk does not increase with objective risk, and, in dangerous occupations, subjective risk is lower compared to more educated workers, despite higher objective risk. If less educated workers are not underestimating risk in dangerous jobs, then $v_l(r_d) \geq 0$. If this is the case, several additional conditions must be met. First, less educated workers in safe occupations must overestimate risk : $v_l(r_s) > 0$. Second, more educated workers in safe occupations must not only overestimate risk, but overestimate risk more than less educated workers in similar occupations: $v_m(r_s) > v_l(r_s) > 0$. Third, more educated workers in dangerous occupations must not only overestimate risk, but overestimate risk more than less educated workers in similar occupations: $v_m(r_d) > v_l(r_d) \geq 0$. Thus, a scenario in which less educated workers in dangerous jobs are not underestimating risk requires all other workers to be overestimating risk. A simpler and more likely scenario is that, to some extent, less educated workers in dangerous occupations are underestimating risk.

4 Implications for Value of Statistical Life

Biased perceptions in occupational fatality risk have implications for estimating the VSL. Ideally, the VSL would be estimated using the following structural model:

$$w_{ij} = \alpha + \beta\rho^s_{ij} + \gamma X_{ij} + \epsilon_{ij}. \tag{9}$$

The outcome variable w_{ij} is the wage for individual i in occupational j; X_{ij} is a set of observable characteristics; and ρ^s_{ij} is the subjective risk of death perceived by the worker. As noted by Blomquist (2004), subjective risk is preferred to objective risk when estimating hedonic wage models involving workplace safety. The coefficient β represents the trade-off between wages and perceived fatality risk and thus is proportional to the VSL.[18] As a structural model, β represents the causal effect of risk on wages, holding all other factors constant.

At least two complications arise when measuring risk. First, biased perceptions means that individual subjective risk may differ from individual objective risk, denoted r^o_{ij}. Deviations of subjective and objective risk is characterized by $\rho^s_{ij} = r^o_{ij} + v_{ij}$, where v_{ij} represents the bias. Second, due to data availability, individual subjective risk is often replaced with objective risk at the aggregate level, denoted $r^o_j = f_j(r^o_{1j}, ..., r^o_{N_j})$, where N_j is the number of workers in occupation j. In many VSL studies, r^o_j is the rate of injury

[18]For example, if the outcome variable is the hourly wage, and risk measure is annual deaths per 100,000 full-time equivalent workers, then the VSL is calculated as β multiplied by annual hours for a full-time worker and 100,000.

or death among all workers.

These two complications yield the following estimable equation:

$$w_{ij} = \alpha + \beta r_j^o + \beta \left[(r_{ij}^o - r_j^o) + v_{ij} \right] + \epsilon_{ij}, \tag{10}$$

where $\beta \left[(r_{ij}^o - r_j^o) + v_{ij} \right]$ is included in the composite error term. The equation highlights two potential biases when estimating β. The first bias depends on the correlation between $(r_{ij}^o - r_j^o)$ and r_j^o, which reflects how objective risk across occupations varies among individuals relative to the population. Bias is not an issue if r_j^o is the population mean and the model is estimated among the population. In this case, the mean of $(r_{ij}^o - r_j^o)$ is zero for each occupation j and thus is uncorrelated with r_j^o. Bias may be an issue, however, when r_j^o is the population mean, but the model is estimated for subgroups. For example, regarding accidents among less educated workers, the correlation between $\beta(r_{ij}^o - r_j^o)$ and r_j^o is likely negative because, as shown in Figure 4, risk increases less steeply relative to the aggregate. This implies that the correlation between r_{ij}^o and r_j^o is less than one, so the correlation between $\beta(r_{ij}^o - r_j^o)$ and r_j^o is negative. As a result, the estimate of β would be biased downward.

The second bias depends on the correlation between v_{ij} and r_j^o, which reflects how perceived bias varies across occupations among individuals relative to aggregate risk. Of course, bias is not an issue if workers accurately perceive risk, since v_{ij} would equal zero for all individuals and occupations. Additionally, bias is not an issue if perceived bias is systemic because, by definition, v_{ij} is a constant and thus does not vary across occupations.[19] Bias becomes an issue, however, when perceived bias varies with risk. For example, if workers increasingly underestimate risk in more dangerous occupations, then v_{ij} would be more negative as r_j^o increases, so the correlation between v_{ij} and r_j^o would be negative. Again, the estimate of β would be biased downward.

These two potential biases correspond with the two mechanisms illustrated in Figure 3. Under mechanism two, objective risk among less educated workers is weakly

[19]This is consistent with the relaxed assumption that workers need not perceive risk accurately, but their perceptions are nonetheless correlated with objective risk (Blomquist, 2004; Kniesner et al., 2012).

correlated with objective risk in aggregate. In this case, the correlation between $(r^o_{ij} - r^o_j)$ and r^o_j is approximately negative one. Under mechanism one, objective risk among less educated workers is strongly correlated with objective risk in aggregate, but bias is strongly negatively correlated with objective risk. In this case, the correlation between v_{ij} and r^o_j is approximately negative one. Under either extreme case, the bias is $-\beta$, and $E(\hat{\beta}) = 0$.

Importantly, if subjective risk among less educated workers is uncorrelated with objective risk, as argued above, then $E(\hat{\beta}) = 0$, regardless of the mechanism. This is because the bias depends on the correlation between the composite term $\left[(r^o_{ij} - r^o_j) + v_{ij}\right]$ and r^o_j, which would equal negative one.

If the bias is known, one solution is to adjust the estimate of β, as in Miller (2000) following Lichtenstein et al. (1978).[20] Here, an adjustment strategy is derived from a model of multiple regression with heterogeneous treatment effects (Aronow and Samii, 2016). The model is given by the following equation:

$$Y_i = \alpha + \beta D_i + X_i \gamma + \epsilon_i, \tag{11}$$

where Y_i is the outcome variable, and D_i is the treatment variable. Utilizing results for partial regression (Greene, 2008), they show that multiple regression generates a weighted average of causal effects:

$$\hat{\beta} \xrightarrow{p} \frac{E[w_i \tau_i]}{E[w_i]}, \tag{12}$$

where τ_i is the treatment effect for individual i, and $w_i = (D_i - E[D_i|X_i])^2$ is the conditional variance of D_i on X_i. Intuitively, when estimating β in multiple regression with heterogeneous treatment effects, more weight is placed on observations whose treatment values are less explained by the covariates (Aronow and Samii, 2016).

One implication of the model for estimating the VSL among the population is that workers with no high school diploma will be over-represented in the effective

[20] Blomquist (2004) provides a thorough discussion about adjusting VSL estimates for biased perceptions of risk.

sample weighted by w_i. This is because the variation in occupational fatality risk not explained by the covariates is greater among less educated workers. In the NHIS sample, for example, workers with no high school diploma represent only 16.3 percent of the population. Their representativeness in an effective sample, however, is determined by regressing occupational fatality risk on the control variables and industry fixed effects in equation (8):

$$FatalityRate_{ij} = \delta X_{ij} + \mu_{ij}. \tag{13}$$

The conditional variation in occupational fatality risk decreases with education: the mean of $\hat{\mu}_{ij}^2$ is 0.21 among workers with no high school diploma, 0.13 among workers with a high school diploma only, and 0.12 among workers with some college or more. Denote s_l as the sum of $\hat{\mu}_{ij}^2$ among workers with no high school diploma and s_m as the sum among all other workers. The representativeness of the former in the effective sample is calculated as $\frac{s_l}{s_l+s_m}$, which equals 0.233. Thus, although workers with no high school diploma represent only 16.3 percent of the population, they account for 23.2 percent of the effective sample.

The model can also be used to characterize the potential bias in VSL estimates. Denote β_l and β_m as the treatment effects for less and more educated workers in equation (8), respectively, which are proportional to the VSL. Using the intuition from equation (12), the estimated treatment using partial regression is given by

$$E[\hat{\beta}] = \beta_l \cdot \frac{s_l}{s_l + s_m} + \beta_m \cdot \frac{s_m}{s_l + s_m}. \tag{14}$$

Two assumptions are made both to characterize the bias and to correct for it. First, perceived bias among less educated workers arises from the extreme case of mechanism two. This allows for $E[\hat{\beta}_l] = 0$ among less educated workers and $E[\hat{\beta}_m] = \beta_m$ among more educated workers. Second, treatment effects are homogeneous: $\beta_l = \beta_m = \beta$. Under these assumptions, the population estimate of equation (8) based on equation (14) is $E[\hat{\beta}] = \beta \cdot \frac{s_m}{s_l+s_m}$. Thus, an unbiased estimate can be obtained by factoring the biased estimate by $\frac{s_l+s_m}{s_m}$. Based on the results from equation (13), this factor equals 1.30.

Without these two assumptions, the bias is more difficult to characterize. If mechanism one were also operating, then the estimate of β_m would be overestimated. This is because fatality risk among more educated workers would have to increase more across occupations than the aggregate measure would suggest. Additionally, if β_l and β_m are different, then an estimate of the latter is not an estimate of the former. If safety were a normal good, for example, then $\beta_l < \beta_m$. Under both scenarios, factoring the population estimate by 1.3 would overstate the VSL in aggregate. Thus, this adjustment strategy, interpreted more conservatively, provides an upper bound to the VSL. Nonetheless, the foregoing discussion contributes to the understanding of bias in VSL estimates stemming from biased perceptions of risk.

5 Implications for Optimal Policy

Discussed in Section 2, biased perceptions in occupational fatality risk also have implications for the optimal risk ceiling. An example of the optimal risk ceiling is simulated based on several simplifying assumptions. First, worker utility exhibits constant relative risk aversion, $u(w) = (w^{1-\eta} - 1)/(1-\eta)$, with η as the measure of risk aversion.[21] Second, firm revenues with respect to risk increase at a decreasing rate, $w(r) = ar^b + c$, where $0 < b < 1$. Third, all workers face the same wage and objective risk within an occupation regardless of education.[22] While a stark departure from reality, this assumption ensures that the optimal risk ceiling reflects differences in risk aversion and bias perceptions rather than wages and risk. Fourth, more educated workers accurately perceive occupational fatality risk, so the distribution of workers across the wage-risk distribution is due only to risk aversion. Fifth, less educated workers have biased perceptions by assuming risk aversion is constant. This implies only one optimal wage-risk combination

[21]Eeckhoudt and Hammitt (2004) note that, while VSL is independent of local risk aversion, an increase in risk aversion increases VSL when the marginal utility of bequest is zero. This condition is effectively satisfied here since the utility of bequest is independent of wage.

[22]This assumption contradicts Table 5, where less educated workers face greater disability risks than more educated workers within occupations; however, constructing risk distributions by education requires fatality rates by educational attainment, which is not possible with the CFOI data.

for all less educated workers, yet they sort suboptimally into other risk levels. Finally, risk aversion among less educated workers is lower than the average risk aversion among more educated workers. This attributes some of the riskier employment observed for less educated workers to risk aversion, rather than bias.

The simulation is conducted using the NHIS sample. Less educated workers are defined as no high school diploma, and more educated workers are defined as at least a high school diploma. Additionally, the risk space is discretized into integer categories g so that discretized risk $r_g = g$ if continuous risk r satisfies $g - 0.001 < r \leq g$.[23] Risk r is measured as fatalities per 100 workers, whereas fatality rates thus far have been reported per 100,000. Based on the data, g spans 41 risk categories from 0.001 to 0.152.

The first step is to calibrate the values of a and b of the revenue function. If more educated workers accurately perceive risk, then the average marginal revenue product should equal the VSL. Denote $p_{g|m}$ as the share of workers with employment risk g conditional on being more educated. The equation for VSL is given by the following equation:

$$\sum_g p_{g|m} a b r_g^{(b-1)} \cdot 2,000 \cdot 100 = VSL \tag{15}$$

The factors reflect that fatality rates must be expressed per 100 workers annually, whereas wages are measured as earnings for a single worker per hour. The factor 2,000 is the number of weeks in a year (50) multiplied by 40 hours per week. The values of $p_{g|m}$ are estimated from the data, and the VSL is set equal to \$7.27 million, which falls between the range of \$4 and \$10 million estimated by Kniesner et al. (2012). With these values, a is an implicit function of b. For this simulation, $b = 0.70$, so $a = 10$.

The next step is to determine the distribution of η among more educated workers. In equilibrium, marginal revenue product equals the indifference curve at each level of risk:

[23] To account for occupations with a zero fatality rate, r_g equals 1 for $0 \leq r \leq 0.001$.

$$abr_g^{(b-1)} = \frac{\frac{w_g^{1-\eta_g}-1}{1-\eta_g} - \frac{d^{1-\eta_g}-1}{1-\eta_g}}{(1-r_g)w_g^{-\eta_g}}, \tag{16}$$

where $w_g = ar_g^b + c$. If the lowest wage c and consumption when injured d are known, then η_g is identified for each risk group g. For this simulation, c is the federal minimum wage in 1985 ($c = 3.35$), and d replaces 75 percent of wages of the lowest risk group ($d = 0.75 \cdot w_1$). Based on the data, η among more educated workers in risk group g, denoted $\eta_{g,m}$, ranges from $\eta_{0.001,m}$=21.1 to $\eta_{0.152,m}$=2.3. Based on the conditional distribution of more educated workers $p_{g|m}$, the conditional mean of η is 15.69.

With the distribution of η identified among more educated workers, it is now possible to calculate the welfare losses among more educated workers due to a risk ceiling.[24] Denote the risk ceiling as r_c, which corresponds to wage $w_c = w(r_c)$, and denote the unconditional share of more educated workers observed in risk g as p_{gm}. The social marginal welfare cost at risk ceiling r_c is given by

$$SMC(r_c) = \sum_{g>c} p_{gm} \left[abr_c^{(b-1)} - \frac{u(w(r_c);\eta_{g,m})) - u(d;\eta_{g,m})}{(1-r_c)u'(w(r_c);\eta_{g,m}))} \right]. \tag{17}$$

Figure 5 plots the social marginal cost at different values for the risk ceiling, from $r_c = 1$ to $r_c = 21$. The social marginal cost is lowest at $r_c = 21$. This reflects that the share of more educated workers at or above $g = 21$ is just 4.62 percent and that the risk ceiling does not restrict risk substantially relative to optimal risk. As the risk ceiling is lowered, the social marginal cost increases. This reflects that more workers are affected by the ceiling and that the ceiling restricts risk more substantially relative to optimal risk.

The next step is to determine the social marginal benefit of the risk ceiling. Stated above, η is assumed constant among less educated workers. Thus, the social marginal welfare benefit at risk ceiling r_c is given by

[24] By assumption, more educated workers display no behavioral bias and therefore only lose welfare due to a risk ceiling.

$$SMB(r_c) = \sum_{g>c} p_{gl} \left[abr_c^{(b-1)} - \frac{u(w(r_c);\eta_l)) - u(d;\eta_l)}{(1-r_c)u'(w(r_c);\eta_l))} \right], \tag{18}$$

where p_{gl} is the unconditional share of less educated workers in risk group g, and η_l is the constant level of risk aversion. For this simulation, η_l is set equal to 11, 13, and 15, less than the average of $\eta_{g,m}$ of 15.69 using the observed distribution of less educated workers $p_{g|l}$. Figure 5 plots the social marginal benefit at different values of the risk ceiling r_c. As shown, the social marginal benefit is greatest at $g = 21$. The benefit decreases as the risk ceiling decreases, reaching zero at the optimal risk for less educated workers.

According to equation (7), the optimal risk ceiling occurs where the social marginal benefit equals social marginal cost. In Figure 5, the optimum occurs where the benefit curves cross. In the least risk averse case, $\eta_l = 11$, the optimal risk ceiling is approximately 20. This optimal ceiling would affect approximately 12.05 percent of the population: 4.09 percent who are less educated workers and thus would benefit from the policy, and 7.95 percent who are more educated and thus would be harmed by the policy. As risk aversion among less educated workers increases, the optimal risk ceiling decreases. The optimal risk ceiling for $\eta_l = 13$ and $\eta_l = 15$ is approximately 15 and 10, respectively. In the latter case, the risk ceiling would affect 24.33 percent of workers.

Figure 6 illustrates the optimal risk ceiling when the VSL is increased to \$10.90 million. This is achieved by slightly increasing the value of a from 10 to 15, which increases the values of $\eta_{g,m}$ at each risk level, raising the conditional mean from 15.69 to 16.05. As shown, an increase in the VSL generally decreases the optimal risk ceiling, and the decrease appears slightly greater with less risk aversion among less educated workers. In the least risk averse case, $\eta_l = 11$, the optimal risk ceiling decreases from approximately 20 to 18.

6 Conclusion

This study explores the theory, evidence, and implications of biased perceptions in occupational fatality risk. First, biased perceptions decrease worker welfare, which raises the potential for government policies to regulate risk. A particularly promising approach is to enforce a risk ceiling at the extreme tail of the risk distribution, where workers are more likely to be underestimating risk. Second, self-reported exposure to death is uncorrelated with objective risk among workers with no high school diploma. The simplest explanation is that, to some extent, these workers underestimate risk in more dangerous occupations. Finally, biased perceptions have direct implications for estimating VSL and designing optimal policy. This study explores these implications through illustrative examples.

The results make three important contributions to the literature. First, the results contribute to the empirical literature on biased perceptions. One source of bias is overconfidence or optimism (Weinstein, 1989). Another source of bias is "dread risk," which relates to whether a risk is uncontrollable, catastrophic, and involuntary (Slovic et al., 1985). As a result, people tend to overestimate risks that are dramatic and sensational, but underestimate risks that are unspectacular and common in nonfatal form Slovic et al. (1990). In this light, the finding that less educated workers may be underestimating risk in dangerous occupations may reflect overconfidence or that they do not associate exposures that commonly cause accidents as being fatal, i.e. exposures from physical injuries or the physical environment.

Second, this study supports an alternative mechanism for different VSL estimates by socioeconomic status. In a review of the VSL literature by (Viscusi and Aldy, 2003), studies tend to find larger VSL estimates among workers with higher income. One possible explanation is that safety is a normal good (Viscusi, 1978). An alternative explanation is that, among less educated workers, risk does not vary substantially with occupational fatality rates at the aggregate level. This explanation is not supported by this study, however, as the hazard rate of disability onset increases with the occupational fatality rate. Another explanation is that workers underestimate risk in more dangerous occupations, either by a lack of information or cognitive dissonance. This explanation is supported by this study, as subjective risk is uncorrelated with objective risk.

Finally, the results contribute to the literature on non-standard economic models and their implications for public policy (Mullainathan et al., 2012; O'Donoghue and

Rabin, 2006). Without biased perceptions, an exogenous risk ceiling decreases welfare; with biased perceptions, an endogenous risk ceiling may increase welfare. In fact, a risk ceiling is consistent with an existing program of the United States Occupational Safety and Health Administration, the Site Specific Targeting (SST) plan, implemented in 1999. Before 1999, OSHA targeted "programmed" inspections at establishments in industries with high rates of accidents and injuries; however, many establishments in high-risk industries were found to be relatively safe. In the mid 1990s, OSHA created the SST plan, which first collected injury rates at the establishment level, then targeted establishments with the highest rates for a programmed inspection. The risk cutoff for an inspection corresponded to the 86.3 percentile of the distribution (Li and Singleton, 2019). This study begins to build theoretical and empirical frameworks for evaluating such policies.

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Table 1: Summary Statistics of NHIS Sample, Males Ages 18 to 64

Education	Less than HS diploma	High School Diploma	Some College More	Total
Age (years)	41.56	35.92	38.19	37.86
	(0.36)	(0.22)	(0.17)	(0.13)
White	82.15	88.32	89.32	87.79
	(1.06)	(0.58)	(0.49)	(0.36)
Married	77.83	70.72	74.58	73.63
	(1.15)	(0.82)	(0.70)	(0.48)
Self Employed	12.10	10.20	10.55	10.66
	(0.90)	(0.54)	(0.49)	(0.34)
Professional/Technical	14.19	27.29	71.83	45.61
	(0.97)	(0.80)	(0.72)	(0.55)
Service	20.07	14.50	8.59	12.68
	(1.11)	(0.63)	(0.45)	(0.37)
Production/Operator	65.74	58.21	19.58	41.71
	(1.31)	(0.89)	(0.64)	(0.54)
Death Exposure	3.05	5.08	3.40	3.99
	(0.48)	(0.39)	(0.29)	(0.21)
Accident Exposure	59.92	63.51	40.64	52.45
	(1.36)	(0.87)	(0.79)	(0.55)
Death Exposure (count)	3.82	6.57	4.24	5.06
	(0.64)	(0.57)	(0.42)	(0.31)
Accident Exposure (count)	98.38	115.73	75.07	94.31
	(2.91)	(2.08)	(1.80)	(1.25)
Occupational Fatality Rate	12.42	9.39	5.45	8.07
(per 10ˆ5 FTE workers)	(0.42)	(0.22)	(0.15)	(0.13)
0 to 3	16.78	24.04	44.71	32.35
	(1.03)	(0.77)	(0.80)	(0.51)
3 to 6	26.88	30.02	31.40	30.15
	(1.23)	(0.82)	(0.74)	(0.50)
6 and above	56.33	45.94	23.89	37.50
	(1.37)	(0.90)	(0.68)	(0.53)
Observations	1,348	3,144	3,963	8,455

The sample is derived from the National Health Interview Survey, restricted to ages 18 to 64. Occupations are aggregated according to standardized occupations codes constructed by Autor and Dorn (2013), and occupational fatality rates are constructed from the Census of Fatal Occupational Injuries (CFOI) and the March Supplement of the Current Population Survey (CPS), both from 1992 to 1995. Estimates are in percentage points unless otherwise noted. Standard errors are in parentheses.

Table 2: Summary Statistics of NHIS Sample, Males Ages 18 to 64

Education	Less than HS diploma	High School Diploma	Some College More	Total
A. Death				
Substances	2.82	4.33	2.95	3.44
	(0.45)	(0.36)	(0.27)	(0.20)
Physical environment	0.15	0.35	0.56	0.41
	(0.10)	(0.11)	(0.12)	(0.07)
Physical injuries, falls, slips, etc.	0.22	0.64	0.25	0.39
	(0.13)	(0.14)	(0.08)	(0.07)
B. Accident				
Substances	0.82	1.65	2.30	1.82
	(0.25)	(0.23)	(0.24)	(0.15)
Physical environment	0.45	0.76	0.61	0.64
	(0.18)	(0.16)	(0.12)	(0.09)
Physical injuries, falls, slips, etc.	57.12	60.97	38.76	49.95
	(1.35)	(0.87)	(0.77)	(0.54)

The sample is derived from the National Health Interview Survey, restricted to ages 18 to 64. Occupations are aggregated according to standardized occupations codes constructed by Autor and Dorn (2013), and occupational fatality rates are constructed from the Census of Fatal Occupational Injuries (CFOI) and the March Supplement of the Current Population Survey (CPS), both from 1992 to 1995. Estimates are in percentage points unless otherwise noted. Standard errors are in parentheses.

Table 3: Linear Probability Model of Death Exposure, Males Ages 18 to 64

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Education	All	All	All	All	No HS Diploma	HS Diploma	College
Fatality Rate	0.108***	0.017	0.017	-0.024	-0.019	0.101**	0.109**
	(0.025)	(0.028)	(0.028)	(0.025)	(0.028)	(0.050)	(0.049)
Fatality Rate - HS Diploma		0.100**	0.102**	0.116**			
		(0.050)	(0.050)	(0.051)			
Fatality Rate - College		0.152***	0.148***	0.141**			
		(0.057)	(0.057)	(0.056)			
HS Diploma	2.357***	1.155	0.676	0.702			
	(0.625)	(0.747)	(0.762)	(0.755)			
College	1.237**	-0.211	-0.748	-0.718			
	(0.593)	(0.655)	(0.671)	(0.688)			
Mean Death	3.99	3.99	3.99	3.99	3.05	5.08	3.40
Control Variables	No	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Observations	8,455	8,455	8,455	8,455	1,348	3,144	3,963

The outcome variable is an indicator of exposure to death on the job (factored by 100), and the regressor of interest is the occupational fatality rates, measured per 10^5 full-time equivalent workers. The sample is derived from the National Health Interview Survey, restricted to ages 18 to 64. Occupational fatality rates are constructed from the Census of Fatal Occupational Injuries (CFOI) and the March Supplement of the Current Population Survey (CPS), both from 1992 to 1995. Control variables consist of age, age squared, race, education, marital status, veteran status, self-employment status. Industry fixed effects are created from 14 industry categories. Robust standard errors are in parentheses.

Table 4: Linear Probability Model of Accident Exposure, Males Ages 18 to 64

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					No HS	HS	
Education	All	All	All	All	Diploma	Diploma	College
Fatality Rate	0.845***	0.475***	0.439***	0.312***	0.331***	0.488***	0.946***
	(0.060)	(0.077)	(0.078)	(0.073)	(0.073)	(0.081)	(0.121)
Fatality Rate - HS Diploma		0.263**	0.268**	0.160			
		(0.120)	(0.118)	(0.107)			
Fatality Rate - College		0.790***	0.763***	0.712***			
		(0.157)	(0.155)	(0.139)			
HS Diploma	5.845***	2.312	-1.614	0.357			
	(1.605)	(2.107)	(2.105)	(2.289)			
College	-13.152***	-19.973***	-23.171***	-19.108***			
	(1.603)	(1.986)	(1.990)	(2.259)			
Mean Accident	52.22	52.22	52.22	52.22	59.85	63.25	40.93
Control Variables	No	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Observations	8,300	8,300	8,300	8,300	1,305	3,091	3,904

The outcome variable is an indicator of exposure to an accident on the job (factored by 100), and the regressor of interest is the occupational fatality rates, measured per 10^5 full-time equivalent workers. The sample is derived from the National Health Interview Survey, restricted to ages 18 to 64. Occupational fatality rates are constructed from the Census of Fatal Occupational Injuries (CFOI) and the March Supplement of the Current Population Survey (CPS), both from 1992 to 1995. Control variables consist of age, age squared, race, education, marital status, veteran status, self-employment status. Industry fixed effects are created from 14 industry categories. Robust standard errors are in parentheses.

Table 5: Annual Hazard Rate of Workplace Accidents by Education and Occupational Fatality Rate, Males Ages 18 to 64

Education	No HS Diploma	HS Diploma	College
A. Work limiting			
Fatality Rate: All	0.453	0.228	0.111
	(0.039)	(0.017)	(0.010)
Fatality rate: 0-6	0.353	0.156	0.069
	(0.053)	(0.019)	(0.009)
Fatality rate: 6+	0.539	0.302	0.234
	(0.057)	(0.029)	(0.030)
Fatality rate: 10+	0.551	0.312	0.297
	(0.068)	(0.037)	(0.048)
Fatality rate: 14+	0.612	0.320	0.331
	(0.088)	(0.046)	(0.068)
B. Work preventing			
Fatality Rate: All	0.217	0.078	0.035
	(0.028)	(0.011)	(0.006)
Fatality rate: 0-6	0.166	0.045	0.025
	(0.036)	(0.010)	(0.005)
Fatality rate: 6+	0.262	0.112	0.063
	(0.040)	(0.019)	(0.017)
Fatality rate: 10+	0.273	0.120	0.078
	(0.049)	(0.024)	(0.029)
Fatality rate: 14+	0.316	0.138	0.119
	(0.062)	(0.033)	(0.046)

The table reports estimated annual hazard rates of disability onset (factored by 100). The numerator is the number of disability onsets, tabulated from the Survey of Income and Program Participation (SIPP), panel years 1990, 1991, 1992, and 1993. The denominator is full-time equivalent employment, estimated from the 1992 Current Population Survey. The fatality-rate categories are in aggregate, not by education, and are measured per 10^5 full-time equivalent workers. This reveals how objective risk within education groups varies with population-level measures of risk. Standard errors are in parentheses and computed by bootstrapping the SIPP sample.

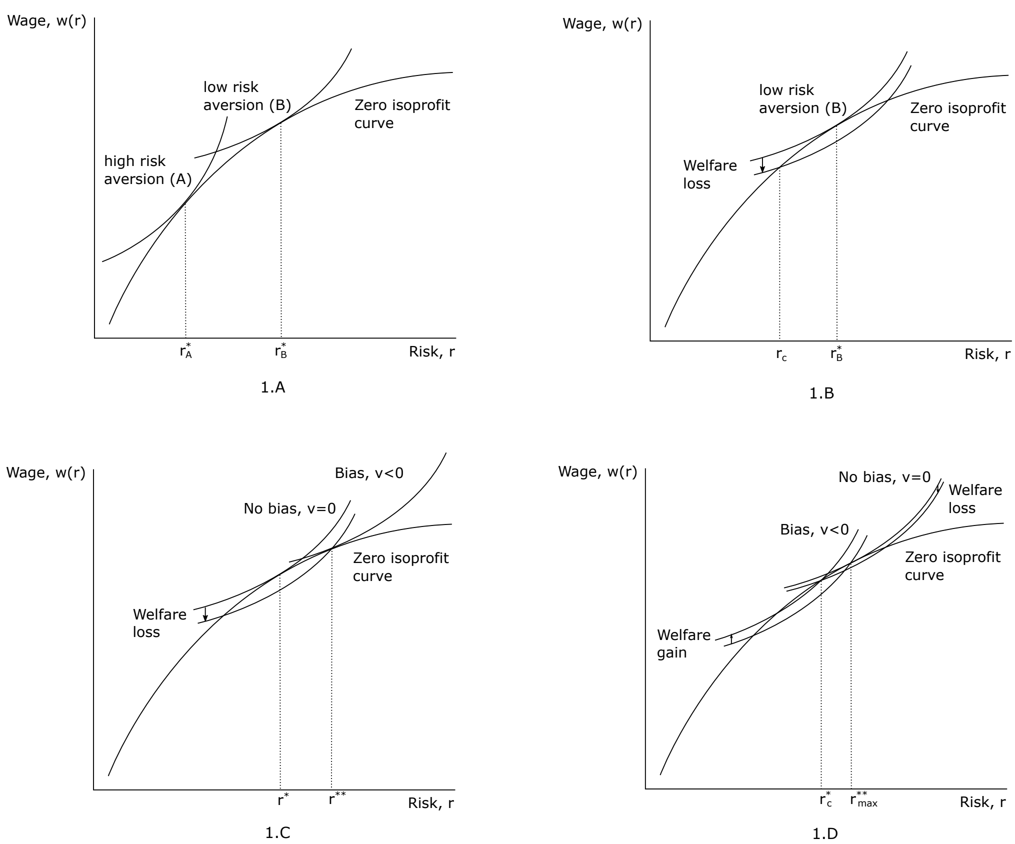

Figure 1: Labor Market Equilibria

1.A. The figure illustrates the equilibrium in the standard model of hedonic wages and occupational safey. Risk-averse workers sort into safer occupations. 1.B. This figure illustrates the welfare consequences in the standard model of an exogenous quota. Optimal risk is r_b^*, but is restricted to r_c, thereby decreasing welfare. 1.C. This figure illustrates negative bias in occupational fatality risk. Optimal risk is r^*, but optimal risk with bias is r^{**}, thereby decreasing welfare. 1.D. This figure illustrates the welfare consequences of an endogenous quota. At the optimal quota r_c^*, welfare is decrease among workers who accurately perceive risk, but is increased among workers who underestimate risk. At the optimum, marginal benefit equals marginal cost.

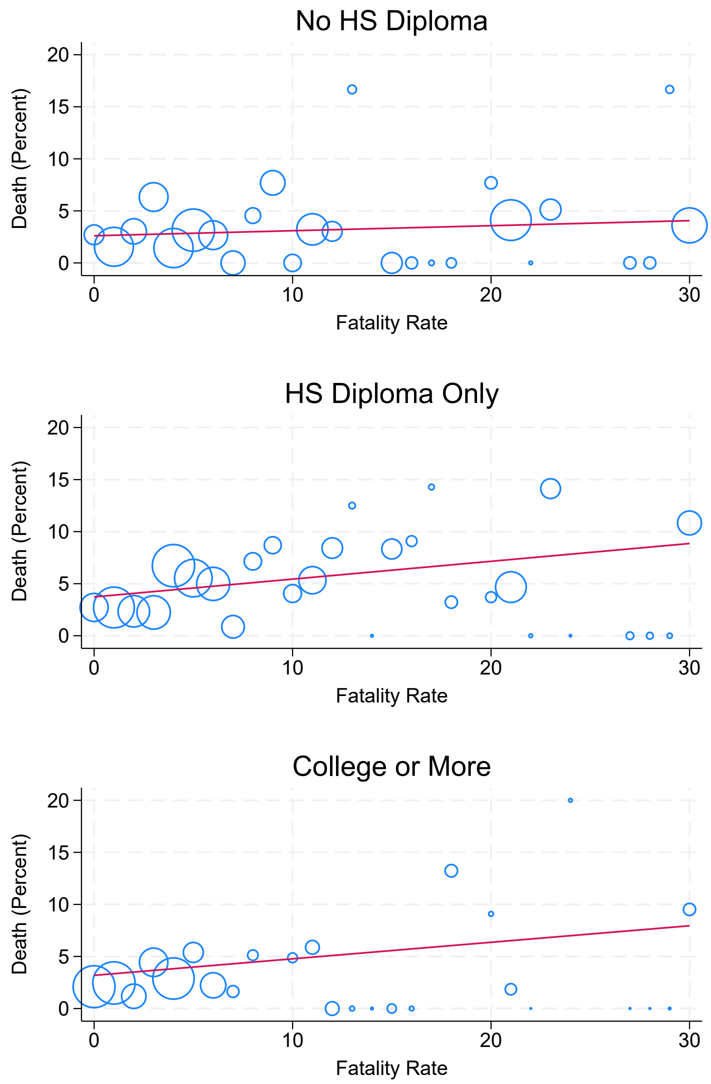

Figure 2: Death Exposure by Education and Occupational Fatality Risk, Ages 18 to 64

The figure illustrates the share of self-reported exposure to death on the job (factored by 100) by integer categories of occupational fatality rates, measured per 10^5 workers. The sample is derived from the National Health Interview Survey, restricted to ages 18 to 64. Occupational fatality rates are constructed from the Census of Fatal Occupational Injuries (CFOI) and the March Supplement of the Current Population Survey (CPS), both from 1992 to 1995. The size of the markers are proportional to the number of workers within education categories.

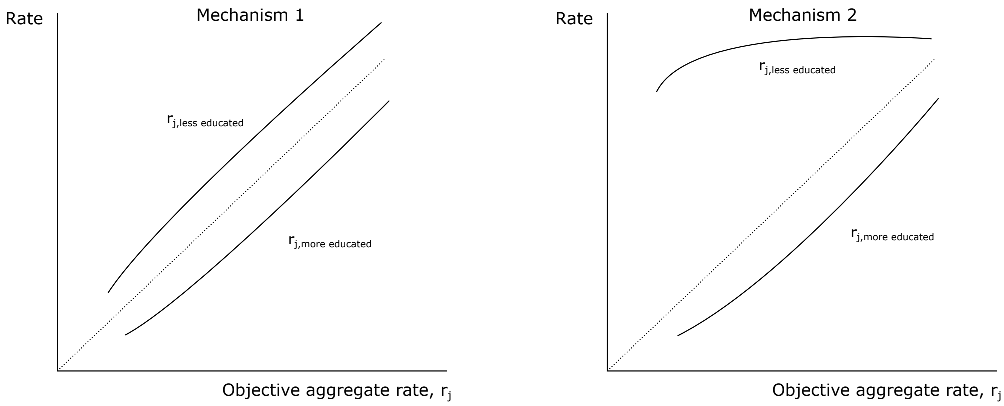

Figure 3: Mechanisms

Mechanism 1. Objective risk is greater among less educated workers, but increases similarly among less and more workers across occupations. Mechanism 2. Objective risk among less educated workers is approximately uncorrelated with objective risk at the aggregate level. This mechanism is plausible since less educated workers represent a small share of all workers.

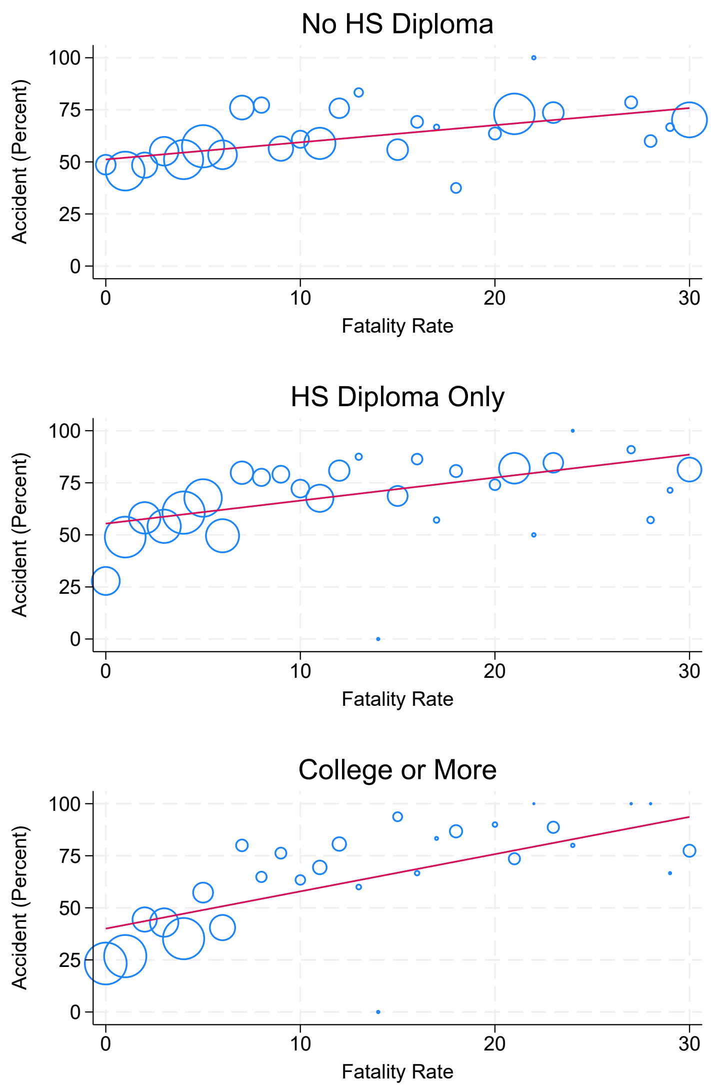

Figure 4: Accident Exposure by Education and Occupational Fatality Risk, Ages 18 to 64

The figure illustrates the share of self-reported exposure to an accident on the job (factored by 100) by integer categories of occupational fatality rates, measured per 10^5 workers. The sample is derived from the National Health Interview Survey, restricted to ages 18 to 64. Occupational fatality rates are constructed from the Census of Fatal Occupational Injuries (CFOI) and the March Supplement of the Current Population Survey (CPS), both from 1992 to1995. The size of the markers are proportional to the number of workers within education categories.

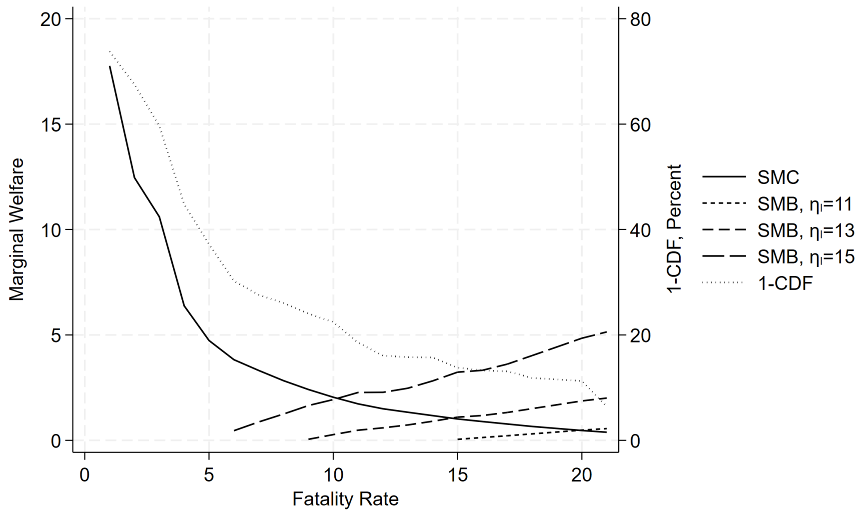

Figure 5: Simulation of Optimal Risk Ceiling, VSL=$7.26 million

The figure illustrates the optimal ceiling on occupational fatality risk measured as fatalities per 10^5 workers. The simulation assumes that more educated workers have accurate perceptions of risk, but less educated workers underestimate in more dangerous occupations. The optimum occurs where where social marginal cost equals social marginal benefit. The model is calibrated to a value of statistical life of $7.27 million.

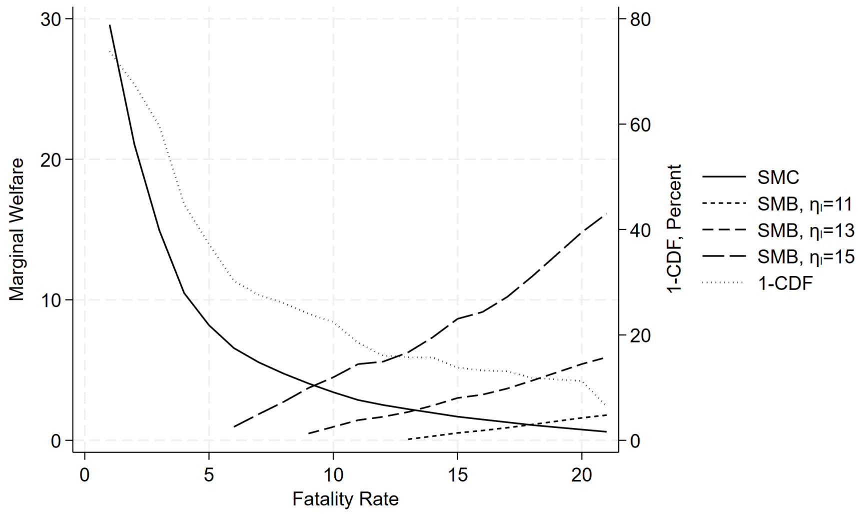

Figure 6: Simulation of Optimal Risk Ceiling, VSL=$10.90 million

The figure illustrates the optimal ceiling on occupational fatality risk measured as fatalities per 10^5 workers. The simulation assumes that more educated workers have accurate perceptions of risk, but less educated workers underestimate in more dangerous occupations. The optimum occurs where where social marginal cost equals social marginal benefit. The model is calibrated to a value of statistical life of $10.90 million.