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Risk Perception, Dread, and the Value of Statistical Life: Evidence from Occupational Fatalities

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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. The correlation is negligible among workers with no high school diploma, consistent with underestimating risk in more dangerous occupations, and strongest among more educated workers when objective risk is specific to harmful and noxious substances, which in psychological studies rank high in dread. Biased perceptions of risk may also lead to biased estimates of value of statistical life. VSL estimates are negligible across all education levels using the all cause fatality rate, but consistently greater among more educated workers using the fatality rate due to harmful and noxious substances, upwards of $70 million and more. Optimal policy is considered, including an illustrative simulation of a risk ceiling.

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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 perceptions of occupational fatality risk.[1] Behavioral economics, in contrast, considers the possibility that perceptions of risk may be biased (Rabin, 2002).[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.

This paper first examines empirically whether perceptions of occupational fatality risk exhibit bias. Although anecdotal evidence suggests that workers in dangerous

[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).

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 two dimensions. The first is 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. If so, the correlation between objective and subjective risk should be greater among more educated workers.

The results confirm this prediction 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. Among workers with some college or more, an increase in the all-cause fatality rate by one per 10^5 full-time equivalent workers is associated with a 0.134 percentage point increase in self-reported exposure to death on the job, in comparison to a 0.020 decrease among workers with no high school diploma. These findings are consistent with less educated workers underestimating risk in more dangerous occupations.

The second dimension is fatalities attributable to harmful and noxious substances. According to the NHIS data, 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. Thus, the correlation between subjective and objective risk should be greater when objective risk is limited to harmful and noxious substances.

The results also confirm this prediction. Among all workers, an increase in the all-cause fatality rate by one per 10^5 full-time equivalent workers is associated with a 0.035 percentage point increase in self-reported exposure to death on the job. In contrast, an increase in the fatality rate specific to harmful and noxious substances is associated with a 1.53 percentage point increase. Again this difference is driven by more educated workers, specifically those with a high school diploma or more.

Next, this paper explores the implications of biased perceptions for estimating the VSL. The VSL is estimated by regressing hourly wages on occupational fatality risk. The models include the all-cause fatality rate as well as the fatality rate specific to harmful and noxious substances. The empirical question is whether the compensating wage differential - and thus the estimated VSL - is greater for harmful and noxious substances. The data come from the National Longitudinal Survey of the Youth (NLSY) 1979, which allow for fixed-effect and first-difference models intended to control for unobservable factors that affect both wages and occupational fatality risk.

The results reveal that the estimated VSL is greater with respect to harmful and noxious substances. Among all workers, the VSL with respect to all-cause mortality is negligible and statistically insignificant. In contrast, the VSL with respect to harmful and noxious substances is $29.0 million. Again, this difference is driven mostly by more educated workers, specifically with some college or more, where the VSL estimate reaches $70 million and more.

Finally, this paper incorporates biased perceptions of occupational fatality risk into the economics of workplace safety. 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.

This paper makes three main contributions to the existing literature. First, the results contribute to the empirical literature on biased perceptions of risk. The results suggest occupational fatality risk may be underestimated among less educated workers and for fatality risks that are common in non-fatal form. One possible mechanism is overconfidence or optimism (Weinstein, 1989), combined with a heuristic to evaluate risk, deeming fatality risks that are common in non-fatal form as less probable.[3] This is consistent with Slovic et al. (1990), who find that people overestimated risks that were dramatic, sensational, and dreadful, and underestimated risks that were unspectacular. Second, the results contribute to the empirical literature on estimating the VSL. In particular, underestimating risks in more dangerous would bias down estimates of the VSL, and overestimating risks due to dread would bias upward estimates of the VSL. 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). One possible policy is a risk ceiling or quota, similar to an existing program of the United States Occupational Safety and Health Administration titled 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. Taken together, the results from this study suggest that workers may not have accurate perceptions of occupational fatality risk, which not only justifies government regulation, but complicates the estimation and interpretation of the VSL.

2 Empirical Analysis of Biased Perceptions

Bias in risk perceptions is modeled using the following notation: $\rho(r) = r + v(r)$, 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

[3] This is consistent with Oster et al. (2013), who find that individuals at risk for Huntington disease exhibit optimistic beliefs about their health, which can reconciled with a model of optimal expectations by Brunnermeier and Parker (2005).

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 initial focus of the empirical analysis.

2.1 Model

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:

$$Death_{ij} = \alpha + \beta FatalityRate_j + \gamma X_{ij} + u_{ij}. \quad (1)$$

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, and X_{ij} is a vector of control variables. 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 robust to heteroskedasticity.

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.

To examine whether β differs by types of fatalities, $FatalityRate_{ij}$ is interacted with the proportion of fatalities attributable to harmful and noxious substances. The coefficient on this interaction term measures the difference between harmful and noxious substances and all causes.

2.2 Data and Sample

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 the CFOI. The CFOI tabulates deaths by occupation annually from 1992 to 2020, 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.[4] 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).[5]

[4]To calculate the denominator of fatality rates, the US Bureau of Labor Statistics also uses data from the Current Population Survey (Northwood, 2010). 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. This is consistent with a new methodology introduced by the US Bureau of Labor Statistics in 2009 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).

[5]As Kniesner et al. (2012) note, fatality rates by occupation are likely better than rates constructed

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.[6]

The proportion of fatalities attributable to harmful and noxious substances by occupation is constructed using the CFOI series separated by event and exposure. These series are not disaggregated by sex and thus must be calculated among all workers. Given the rarity of fatalities due to substances, the proportion is calculated using years 1992 to 2002.

For controls, the model includes variables commonly used in wage regressions in the VSL literature (Viscusi and Aldy, 2003): 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. Industries are grouped into 14 categories. The results are qualitatively similar when industries are grouped into 43 categories.

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.[7] 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 8,709 observations.[8]

2.3 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 ob-

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.

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

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

[8]The sample size decreases from 8,964 to 8,709 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.

jective 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 11.97 among workers without a high school diploma, compared to 8.98 and 5.25 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 3.11 percent of workers without a high school diploma report exposure to death on the job, compared to 4.90 and 3.36 percent work among workers with only a high school diploma and some college or more, respectively.[9]

To further understand the relationship between self-reported exposure to death and occupational fatality rates, Figure 1 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. Taken together, the difference in self-reported exposure to death on the job by education, reported in Table 1, is concentrated among more dangerous occupations.

To examine self-reported exposure to death by type of exposure, Table 2 reports exposures for three broad categories: substances, physical environment, and physical injuries, falls, slips, etc.[10] Interestingly, most of the self-reported exposures stem from

[9]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.

[10]Substances include chemicals, dust, fibers, gases, fumes; physical environment includes loud of ex-

substances, and, within this category, to "chemicals" and "other gases, fumes, vapors, or mists" (not shown). In contrast, harmful and noxious substances account for a small proportion of occupational fatalities according to the CFOI data. As shown in Table 1, whereas the all-cause fatality rate among all workers is 7.76, the fatality rate attributable to harmful and noxious substances is only 0.38. This proportion decreases with education, from 0.56 among workers with no high school diploma to 0.24 among workers with some college or more.

2.4 Regression Results

Table 3 presents estimates of β in equation (1) by educational attainment. 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 0.121 and is statistically significant at the one percent level. The second column interacts the fatality rate with educational attainment. Consistent with Figure 1, 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 0.029, which increases by 0.097 and 0.154 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 0.029 to -0.025, 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.

Table 4 presents the estimates of β in equation (1) by educational attainment and the fatality rate specific to harmful and noxious substances. This fatality rate is missing for some occupations, reducing the sample from 8,709 in Table 3 to 8,225 in Table

cessive noise, extreme heat or cold, physical stress; and physical injuries include powered equipment, contact with electrical equipment, injuries from falling or flying objects.

4 . Using this reduced sample, panel A of Table 4 reports estimates from the baseline model with control variables and industry fixed effects, confirming the robustness of the results in Table 3. Panel B introduces the interaction between the fatality rate and the proportion of fatalities attributable to harmful and noxious substances. As shown, the estimates of β are substantially larger for fatalities attributable to harmful and noxious substances in comparison to all-cause fatalities. Among all workers, an increase in the all-cause fatality rate by one per 10^5 full-time equivalent workers is associated with a 0.035 percentage point increase in self-reported exposure to death on the job. In contrast, an increase in the fatality rate specific to harmful and noxious substances is associated with a 1.53 percentage point increase. This difference is driven by more educated workers, specifically those with a high school diploma or more.

2.5 Robustness

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.[11] This concern in relation to equation (1), 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 not possible to measure the correlation in rates between 1985 and 1992 to 1995 by occupation using the CFOI, it is possible to measure the correlation between the period 1992 to 1995 and 1999 to 2002, when workplace safety was also improving. Despite a decline in the mean from 7.75 to 6.80, the correlation across these two periods is 0.91.

Both Table 1 and Figure 1 show that less educated workers are skewed towards more dangerous occupations. To ensure that the different results by educational attain-

[11] 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).

ment in Table 3 are not due to distributional differences in fatality rates, the models in Table 3 are estimated among fatality rates of 15 or less, eliminating roughly the top quintile of the distribution. If anything, the results suggests a greater gradient by education, though the esimates are more imprecise. For example, for column (4), the first three estimates are -0.044 (0.172), 0.497 (0.217), and 0.259 (0.199). Thus, the results in Table 1 are not driven by the extremes of the fatality rate distribution.

2.6 Mechanism

The empirical analysis reveals two main findings. First, the correlation between self-reported exposure to death and the all-cause fatality rate is negligible among workers with no high school diploma. Second, among more educated workers, the correlation between self-reported exposure to death and the fatality rate is substantially greater when the latter is specific to harmful and noxious substances in comparison to all causes.

Although these findings provide insights into risk perceptions, the empirical strategy and data have two important limitations regarding the mechanism, particularly the extent of bias. One limitation is that the CFOI does not report fatalities by educational attainment, so the fatality rate is measured among all workers, even when analyzing within education groups. This raises the possibility that the negligible correlation between objective and subjective risk among workers with no high school diploma reflects that objective risk is constant across occupations.

To address this possibility, hazard rates of work-limiting and work-preventing disabilities due to workplace accidents are estimated using the Survey of Income and Program Participation (SIPP).[12] Table 5 reports annual hazard rates of work-limiting and

[12]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

work-preventing disabilities among males ages 18 to 64. The numerator is the estimated number of disabilities in the population over five years prior to the survey, 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 the aggregate occupational fatality rates among all workers.[13]

Table 5 shows that, despite differences in levels across education groups, disability hazard rates increase with aggregate occupational fatality rates within all education groups. Workers with less than a high school diploma experience the highest rates of work-related disability. Overall, the rate of work-limiting disability is 0.453 percent, and the rate of work-preventing disability is 0.217 percent. Additionally, the rate of work-preventing disabilities increases from 0.166 percentage points in the lowest fatality rate category (between zero to six) to 0.316 in the highest fatality rate category (14 and greater). Thus, the negligible correlation between objective and subjective risk among workers with no high school diploma cannot be explained by constant objective risk.

A second limitation is that 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 between objective and subjective risk only 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). Additionally, among more educated workers, the stronger correlation between objective and subjective risk when the latter is specific to harmful and noxious substances could reflect that workers are overestimating the risk of substances, underestimating the risk of all causes,

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.

[13] In contrast to Figure 1, which aggregate the data to integers of occupational fatality rates, Table 5 aggregates the data to wider ranges of fatality rates, i.e. between zero and six. 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.

or both.

Nonetheless, the potential for bias can be inferred by combining objective and subjective risk. For example, subjective risk among less educated workers is denoted 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, where the subscript l indicates 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 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 is whether workers with no high school diploma are understimating risk in dangerous occupations. If they are not underestimating risk in dangerous jobs, then $v_l(r_d) \geq 0$. In this 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.

3 Implications for VSL

Given the evidence on biased perceptions of risk, an important question is whether biased perceptions affect the estimation of compensating wage differentials and the VSL. Ideally, the VSL would be estimated using the following structural model:

$$Wage_{ij} = \alpha + \beta\rho^s_{ij} + \gamma X_{ij} + \epsilon_{ij}. \tag{2}$$

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 individual subjective risk of death perceived by the worker.[14] The coefficient β represents the trade-off between wages and perceived fatality risk and thus is proportional to the VSL.[15] 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 or death among all workers.

These two complications yield the following estimatable equation:

$$w_{ij} = \alpha + \beta r^o_j + \beta\left[(r^o_{ij} - r^o_j) + v_{ij}\right] + \epsilon_{ij}, \tag{3}$$

where $\beta\left[(r^o_{ij} - r^o_j) + v_{ij}\right]$ is included in the composite error term. The equation highlights

[14] As noted by Blomquist (2004), individual subjective risk is preferred to objective risk when estimating hedonic wage models involving workplace safety.

[15] 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.

two potential biases when estimating β. The first bias depends on the correlation between r_j^o and $(r_{ij}^o - r_j^o)$, which reflects how individual objective risk varies relative to aggregate objective risk. Bias is not an issue if r_j^o is measured among all workers and the model is estimated among all workers. 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 is also not an issue if r_j^o is the population mean, the model is estimated for subgroups, and the correlation between r_j^o and $(r_{ij}^o - r_j^o)$ is constant across subgroups. This constant correlation assumption is supported by Table 5, which shows hazards rates of work-related disabilities increase similarly with aggregate risk within education groups.

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.[16] Bias becomes an issue, however, when perceived bias varies with risk. In particular, if workers increasingly underestimate risk in more dangerous occupations, then v_{ij} would be more negative as r_j^o increases, biasing downward the estimate of β. In the extreme case where workers are oblivious to risk, the correlation between v_{ij} and r_j^o is negative one, and $E(\hat{\beta}) = 0$. Conversely, if workers overestimate risk associated with harmful and noxious substances, then the correlation between v_{ij} and r_j^o is positive, biasing upward the estimate of β.

3.1 Model

The value of statistical life is estimated using the following fixed-effects model:

$$Wage_{ij} = \alpha + \beta FatalityRate_{ij} + \gamma X_{ij} + \alpha_i + u_{ij}. \tag{4}$$

$Wage_{ij}$ is the hourly wage, $FatalityRate_{ij}$ is the occupation fatality rate per 100,000

[16] 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).

full-time equivalent workers, and the vector X_{ij} includes time varying control variables, including demographic characteristics, industry, and occupation-specific working conditions. The term α_i is an individual fixed effect and controls for unobservable, time-invariant factors that affect both wages and selection into fatality risk. Again, the coefficient of interest is β, which measures the relationship between wages and objective risk. The identification assumption is that, conditional on the fixed effect and time-varying controls, the fatality rate is uncorrelated with u_{ij} except through biased perceptions of risk. To examine whether β differs by types of fatalities, $FatalityRate_{ij}$ is interacted with the proportion of fatalities attributable to harmful and noxious substances.

3.2 Data and Sample

The data come from the National Longitudinal Survey of the Youth (NLSY) 1979. The survey is available annually from 1979 to 1994 and biannually from 1996 to 2018. The unit of observation is individual by year, and the wage and fatality rate correspond to the "CPS" job, defined as the current or most recent job. The sample is restricted to individual by year observations in which the individual has a current or most recent job, has non missing values for education, marital status, region, occupation, and industry, and works in either the government, a private for profit company, or a non-profit. The sample is further restricted to males ages 18 to 62 who are empoyed at least part-time (hours greater than or equal to 20) and whose wages range from \$2 and \$100 in 2017 dollars.[17]

In contrast to the NHIS analysis, where fatality rates were calculated using CFOI data from 1992 to 1995, the fatality rates for the NLSY analysis are calculated using five-year moving averages. One complication is that, while the NLSY data span from 1979 to 2018, the CFOI data span from 1992 to 2020. To address this limitation, the fatality rate estimates for year 1994, estimated from years 1992 to 1996, are extrapolated to all years prior to 1994. Similar to the NHIS analysis, fatality rates are tabulated and merged to NHIS data by 330 standardized occupation codes constructed by Autor and

[17] Age 62 is the highest by year 2018.

Dorn (2013).

The model includes a set of time-varying control variables. To control for age-related trends, the model includes age, age squared, as well as age and age squared interacted with indicators for education (high school diploma and some college or more) and race (black and hispanic). The model also includes an indicator for married, 28 industry fixed effects, and year and region fixed effects. To control for occupation specific working conditions, the analysis uses data from the Dictionary of Occupational Titles for 1980 Census Detailed Occupations, specifically the measures of physical demand and environmental factors.[18] These control variables are intended to isolate variation in the fatality rate associated with fatality risk, separate from variation associated with working conditions.

In addition to the sample restrictions based on NLSY data, the sample is further restricted to observations with non-missing values for the fatality rate and working conditions. With these restrictions combined, the sample contains 6,068 individuals and 76,632 individual by year observations.

3.3 Summary Statistics

Table 6 presents summary statistics of the analysis sample by education. A major difference between the NLSY and the NHIS is that the NLSY sample is substantially younger. This is because the NLSY is comprised of individuals who were ages 14 to 22 in 1979 when the survey began. This has implications for other characteristics such as the percent married, which is higher in the NHIS than the NLSY. As shown, wages increase with educational attainment, whereas occupational fatality risk decreases.

3.4 Regression Results

Table 7 reports estimates of equation (4) under various sample and model specifications. Panel I reports estimates from the baseline sample and model. The baseline model does

[18] Again, these data are aggregated and merged to the NLSY data by 330 standardized occupation codes constructed by Autor and Dorn (2013). The date are aggregated using the weighted average, where the weight is male employment reported in the data.

not include the interaction term of the fatality rate with the proportion of harmful and noxious substances, and the baseline sample is not adjusted for missing values of this proportion. Column (1) reports the estimate among all workers, and the remaining three columns report estimates seprately by education. As shown, the estimate of β is negligible and statistically insignificant across all sample specifications. Because wages are hourly, and because the fatality rate is measured per 100,000 full-time equivalent workers, the estimate of β is converted to the VSL by factoring by \$200 million: 100,000 workers factored by 2,000 hours per year. Applied to column (1), the estimated VSL is -\$800,000.

Panel II reports estimates of equation (4) restricted to observations with non-missing values of the proportion of harmful and noxious substances. The estimates from the baseline model using this restricted sample, reported in panel II.A, are similar to estimates from the unrestricted sample. Panel II.B reports estimates from the model that includes the interaction between the fatality rate and the proportion of harmful and noxious substances. As shown, the estimates on the interaction term are substantially larger than the estimates on the all-cause fatality rate, where the latter are comparable to the baseline model. In column (1), the estimate on the interaction term is 0.145 and statistically significant at the five percent level, yielding a VSL estimate of \$29.0 million. This finding is driven mainly by workers with some college or more, reported in column (4). In that column, the estimate is 0.352 and statistically significant at the one percent level, yielding a VSL estimate of \$70.4 million.

Panel III reports estimates using first differences rather than fixed effects.[19] The first differences model addresses the concern that wages are non-stationary, which is reasonable given the long time horizon. Because the NLSY data are reported biannually since 1996, the data are differenced across two calendar years. As shown, the estimates from the baseline model are similarly negligible, but increase in statistical significance. In the interaction model, the estimates on the interaction term are considerably smaller. In column (1), the estimate reduces to 0.025 and is statistically insignificant. In column (4), the estimate reduces to 0.158 and is statistically significant at the ten percent level,

[19]In the first-differences model, the control variables are indicators for age and year, differences in indicators for industry, and differences in the measures of physical demand and environmental factors.

yielding a VSL estimate of \$31.6 million.

Table 8 reports estimates similar to Table 7 after restricting the sample to ages 30 to 62. This addresses the concern that the fatality rate estimates for year 1994, estimated from years 1992 to 1996, are extrapolated to all years prior to 1994, up to 1979. By restricting to ages 30 to 62, the earliest year is 1987. Similar to Table 7, the estimate of β is negligible with respect to the all-cause fatality rate. The estimate of β on the interaction term, however, appears slightly larger and is robust between the fixed effects model in panel II and the first differences model in panel III. In panel II, the estimate of β on the interaction term is 0.242 among all workers and 0.423 among workers with some college or more, yielding VSL estimates of \$48.4 million and \$84.6 million, respectively. In contrast to Table 7, large estimates on the interaction term emerge for workers with no high school diploma. In the first differences model, the estimate is 0.987 and statistically significant at the one percent level, yielding a VSL estimate of \$197.4 million. In the fixed effects model, however, this estimate is only 0.438 and statistically insignificant.

The results for workers with no high school diploma raise an important question: how can large compensating wage differentials emerge for these workers if they underestimate risk? One possibility is that, to some extent, informed workers can discipline market, yielding positive externalities in the form of compensating wage differentials for uninformed workers. This is consistent with a common argument against psychological economics, noted by As Rabin (2002), that "markets will wipe any unfamiliar psychological phenomenon out." While this issue is beyond the scope of the empirical analysis, it remains an important direction for future research.

4 Theory

4.1 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.[20] A worker's expected utility

[20] 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.

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.[21] The slope of the 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.[22] 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 2. 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 2 illustrates the welfare consequences of a quota such that risk cannot exceed the ceiling r_c. Because

[21] 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 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.

[22] 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.

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.

4.2 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 2. 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^{**}.

4.3 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:

$$E_F[u(w^{**}, r^{**}; \eta, d, v)] = E_F[(1 - r^{**})u(w^{**}) + r^{**}u(d)]. \tag{5}$$

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 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:

$$P'(r) = \frac{u(R(r)) - u(d)}{(1 - r)u'(R(r))} - \frac{u(R(r) - P(r)) - u(d)}{(1 - r - v)u'(R(r) - P(r))}. \tag{6}$$

The zero-profit condition then becomes

$$w(r) = R(r) - P(r). \tag{7}$$

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

$$w'(r^{**}) = \frac{u(w(r^{**})) - u(d)}{(1 - r^{**} - v)u'(w(r^{**}))} \tag{8}$$

Combining equations (6), (7), and (8) yield

$$R'(r^{**}) = \frac{u(R(r^{**})) - u(d)}{(1 - r^{**})u'(R(r^{**}))}. \tag{9}$$

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.

Another policy 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.[23] 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

$$\begin{aligned} &E_F[u(w^{**}, r^{**}; \eta, v, d)] = \\ &\qquad E_F[(1 - I(r_c))[(1 - r^{**})u(w^{**}) + r^{**}u(d)] + I(r_c)[(1 - r_c)u(w(r_c)) + r_c u(d)]]. \end{aligned} \tag{10}$$

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

$$E_F\left[I(r_c^*)\left[w'(r_c^*) - \frac{u(w(r_c^*)) - u(d)}{(1 - r_c^*)u'(w(r_c^*))}\right]\right] = 0. \tag{11}$$

At the optimum, there are no welfare effects on the margin among workers who choose $r^* = r_c^*$ without bias.[24] 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,

[23] 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.

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

$\frac{u(w(r_c))-u(d)}{(1-r_c)u'(w(r_c))} < w'(r_c)$, 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 2. There are two types of workers at r^{**}_{max}: workers with no bias, whose indifference 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.

4.4 Optimal Policy Simulation

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.[25] 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

[25] 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.

same wage and objective risk within an occupation regardless of education.[26] Although unrealistic, 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 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 $g - 0.001 < r \leq g$.[27] 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:

$$\sum_g p_{g|m} ab r_g^{(b-1)} \cdot 2,000 \cdot 100 = VSL \tag{12}$$

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

[26] 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.

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

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:

$$abr_g^{(b-1)} = \frac{\frac{w_g^{1-\eta_g}-1}{1-\eta_g} - \frac{d^{1-\eta_g}-1}{1-\eta_g}}{(1-r_g)w_g^{-\eta_g}}, \tag{13}$$

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.[28] 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

$$SMC(r_c) = \sum_{g>c} p_{gm} \left[abr_c^{(b-1)} - \frac{u(w(r_c);\eta_{g,m})) - u(d;\eta_{g,m})}{(1-r_c)u'(w(r_c);\eta_{g,m}))} \right]. \tag{14}$$

Figure 3 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,

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

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

$$SMB(r_c) = \sum_{g>c} p_{gl} \left[abr_c^{(b-1)} - \frac{u(w(r_c);\eta_l)) - u(d;\eta_l)}{(1-r_c)u'(w(r_c);\eta_l))} \right], \tag{15}$$

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 3 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 (11), the optimal risk ceiling occurs where the social marginal benefit equals social marginal cost. In Figure 3, 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.

To examine how the VSL affects the optimal risk ceiling, the ceiling is simulated with a VSL of $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. 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 (not shown). In the least risk averse case, $\eta_l = 11$, the optimal risk ceiling decreases from approximately 20 to 18.

5 Conclusion

This paper makes three main contributions to the existing literature. First, the results contribute to the empirical literature on biased perceptions of risk. One key finding is that bias may differ by educational attainment. Whereas the correlation between objective and subjective risk is positive among more educated workers, this correlation is negligible among workers with less than a high school diploma. Another key finding is that the correlation between objective and subjective risk is greater for fatalities due to harmful and noxious substances, which rank high on dread risk, in comparison to all cause fatalities. Dread risk relates to whether a risk is uncontrollable, catastrophic, and involuntary (Slovic et al., 1985). According to Slovic et al. (1990), people tend to overestimate risks that are dramatic and sensational, but underestimate risks that are unspectacular and common in nonfatal form.

Second, the results contribute to the literature on the VSL. In general, biased perceptions may lead to overestimating or underestimating the VSL, depending on whether workers underestimate or overestimate risk. This is consistent with results on compensating wage differentials between education groups and between fatalities due to harmful and noxious substances and all causes. In general, the estimated VSL is negligible among all education groups using the all cause fatality rate, but is larger for using the fatality rate due to harmful and noxious substances, specifically among workers with some college or more. These results may account for the finding, noted by Viscusi and Aldy (2003) in a review of the VSL literature, that VSL estimates tend to be smaller among workers with lower income. One possible explanation is that safety is a normal good (Viscusi, 1978). Another possible explanation is that workers with less education, who have lower incomes, also tend to underestimate risk in more dangerous occupations.

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). One possible policy to prohibit extreme levels of risk is to enforce a risk ceiling or quota. Without biased perceptions, an exogenous risk ceiling decreases welfare;

with biased perceptions, an endogenous risk ceiling may increase welfare. 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. According to Li and Singleton (2019), the risk cutoff for an inspection corresponded to the 86.3 percentile of the distribution. 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	All	No HS Diploma	HS Diploma	College
Age (years)	37.88	41.52	35.98	38.18
	(0.13)	(0.35)	(0.21)	(0.17)
White	87.80	82.05	88.27	89.44
	(0.35)	(1.04)	(0.57)	(0.48)
Married	73.41	76.91	70.93	74.24
	(0.47)	(1.14)	(0.80)	(0.68)
Self Employed	10.74	11.77	10.14	10.87
	(0.33)	(0.87)	(0.53)	(0.49)
Professional/Technical	45.79	14.15	27.40	72.20
	(0.53)	(0.94)	(0.78)	(0.70)
Service	12.35	19.69	14.09	8.32
	(0.35)	(1.07)	(0.61)	(0.43)
Production/Operator	41.86	66.16	58.51	19.48
	(0.53)	(1.28)	(0.87)	(0.62)
Death Exposure	3.90	3.11	4.90	3.36
	(0.21)	(0.47)	(0.38)	(0.28)
Death Exposure (Number)	4.94	3.84	6.32	4.17
	(0.30)	(0.62)	(0.55)	(0.41)
Accident Exposure	52.09	59.96	63.07	40.26
	(0.54)	(1.34)	(0.86)	(0.77)
Accident Exposure (Number)	91.62	94.85	112.57	73.07
	(1.21)	(2.82)	(2.02)	(1.74)
Occupational Fatality Rate				
All Cause	7.76	11.97	8.98	5.25
	(0.12)	(0.38)	(0.21)	(0.15)
Harmful and Noxious Substances	0.38	0.56	0.47	0.24
	(0.01)	(0.02)	(0.02)	(0.01)
Observations	8,709	1,375	3,234	4,100

The data come from the National Health Interview Survey of 1985, restricted to males 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. Occupations are aggregated according to standardized occupations codes constructed by Autor and Dorn (2013). Age is reported in years, and the occupational fatality rate is measured per 10^5 full-time equivalent workers. All other estimates are percentage points. Standard errors are in parentheses.

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

Education	All	No HS Diploma	HS Diploma	College
A. Death				
Substances	3.22	2.81	4.00	2.71
	(0.19)	(0.45)	(0.34)	(0.25)
Physical environment	0.41	0.20	0.38	0.52
	(0.07)	(0.12)	(0.11)	(0.11)
Physical injuries, falls, slips, etc.	0.38	0.17	0.65	0.23
	(0.07)	(0.11)	(0.14)	(0.07)
B. Accident				
Substances	1.59	0.56	1.60	1.95
	(0.13)	(0.20)	(0.22)	(0.22)
Physical environment	0.74	0.43	0.84	0.75
	(0.09)	(0.18)	(0.16)	(0.14)
Physical injuries, falls, slips, etc.	49.81	57.23	60.80	38.06
	(0.54)	(1.33)	(0.86)	(0.76)
Observations	8,709	1,375	3,234	4,100

The data come from the National Health Interview Survey of 1985, restricted to males ages 18 to 64. Substances refer to chemicals; dusts; fibers or fibrous materials; anesthetic gases; other gases, fumes, vapors, or mists; disease or biological hazard; and radiation. Physical environment refers to loud or excess noise; extreme heat or cold; physical stress; mental stress; uncomfortable work; vibration; and improper lighting. Estimates are in percentage points. 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)
					No HS	HS	
Education	All	All	All	All	Diploma	Diploma	College
Fatality Rate	0.121***	0.029	0.029	-0.025	-0.020	0.106**	0.134**
	(0.027)	(0.038)	(0.038)	(0.033)	(0.037)	(0.052)	(0.058)
Fatality Rate - HS Diploma		0.097*	0.100*	0.126**			
		(0.057)	(0.057)	(0.056)			
Fatality Rate - College		0.154**	0.151**	0.166**			
		(0.065)	(0.065)	(0.066)			
HS Diploma	2.191***	1.053	0.569	0.359			
	(0.620)	(0.784)	(0.800)	(0.804)			
College	1.266**	-0.150	-0.687	-0.986			
	(0.595)	(0.710)	(0.726)	(0.762)			
Mean Death	3.90	3.90	3.90	3.90	3.11	4.90	3.36
Control Variables	No	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Observations	8,709	8,709	8,709	8,709	1,375	3,234	4,100

The empirical objective is to measure the association between subjective and objective risk. The sample is derived from the National Health Interview Survey of 1985, restricted to males ages 18 to 64. 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 rate, measured per 10^5 full-time equivalent workers. 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 Death Exposure, Males Ages 18 to 64

Education	(1) All	(2) No HS Diploma	(3) HS Diploma	(4) College
A. Baseline model				
Fatality Rate	0.081***	-0.005	0.102*	0.129**
	(0.030)	(0.035)	(0.052)	(0.057)
B. Interaction model				
Fatality Rate	0.035	-0.008	0.036	0.087
	(0.030)	(0.037)	(0.057)	(0.053)
Fatality Rate - Substances	1.561***	0.147	1.915**	1.470*
	(0.503)	(0.785)	(0.812)	(0.756)
Mean Death	3.90	2.92	5.05	3.27
Control Variables	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,225	1,332	3,079	3,814

The empirical objective is to measure the association between subjective and objective risk. The sample is derived from the National Health Interview Survey of 1985, restricted to males ages 18 to 64. 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 rate, measured per 10^5 full-time equivalent workers. 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. Fatality rate due to substances is the interaction between the all cause fatality rate and the proportion of fatalities attributable to substances. 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 empirical objective is to determine whether the objective measure of risk among all workers, specifically the occupational fatality rate, is correlated with an objective measure of risk within education groups, specifically the hazard rate of disability onset due to a workplace accident. The hazard rate is the number of workplace accidents divided by full-time equivalent employment. The numerator is tabulated from the Survey of Income and Program Participation (SIPP), panel years 1990, 1991, 1992, and 1993, and the denominator is estimated from the 1992 Current Population Survey. The estimates are annual hazard rates of disability onset factored by 100. Standard errors are in parentheses and computed by bootstrapping the SIPP sample.

Table 6: Summary Statistics of NLSY 1979, Males Ages 18 to 62

Education	All	No HS Diploma	HS Diploma	College
Age (years)	32.15	29.74	32.07	33.03
	(0.04)	(0.09)	(0.06)	(0.06)
Black	27.52	25.60	31.18	24.95
	(0.16)	(0.40)	(0.27)	(0.23)
Hispanic	18.27	26.07	16.42	17.26
	(0.14)	(0.41)	(0.21)	(0.20)
Married	45.31	39.89	44.75	47.63
	(0.18)	(0.45)	(0.29)	(0.27)
Professional/Technical	29.34	7.21	14.97	49.35
	(0.16)	(0.24)	(0.21)	(0.27)
Service	17.08	18.87	17.97	15.70
	(0.14)	(0.36)	(0.22)	(0.20)
Production/Operator	53.59	73.93	67.06	34.95
	(0.18)	(0.41)	(0.27)	(0.26)
Hourly Wage (2017)	24.36	18.49	21.86	28.51
	(0.05)	(0.08)	(0.06)	(0.08)
Occupational Fatality Rate				
All Cause	8.92	12.81	10.38	6.34
	(0.05)	(0.15)	(0.08)	(0.06)
Harmful and Noxious Substances	0.47	0.64	0.54	0.35
	(0.00)	(0.01)	(0.01)	(0.01)
Individuals	6,068	1,090	2,287	2,691
Observations	76,632	11,682	30,291	34,659

The data come from the National Longitudinal Survey of Youth, 1979 Cohort, spanning years 1979 to 2018, restricted to males ages 18 to 42. Observations are individual by year. 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. Occupations are aggregated according to standardized occupations codes constructed by Autor and Dorn (2013). Age is reported in years, wages are in 2017 dollars, and the occupational fatality rate is measured per 10^5 full-time equivalent workers. All other estimates are percentage points. Standard errors are in parentheses.

Table 7: Model of Wages, Males Ages 18 to 62

Education	(1) All	(2) No HS Diploma	(3) HS Diploma	(4) College
I. Baseline Sample - Fixed Effects				
A. Baseline Model				
Fatality Rate	-0.004	-0.011	-0.004	-0.003
	(0.004)	(0.007)	(0.005)	(0.009)
Mean Wage	24.36	18.49	21.86	28.51
Observations	76,632	11,682	30,291	34,659
II. Substances Sample - Fixed Effects				
A. Baseline Model				
Fatality Rate	-0.004	-0.012*	-0.005	0.001
	(0.004)	(0.007)	(0.005)	(0.009)
B. Interaction Model				
Fatality Rate	-0.008*	-0.012**	-0.006	-0.011
	(0.004)	(0.006)	(0.005)	(0.010)
Fatality Rate - Substances	0.145**	0.028	0.037	0.352***
	(0.066)	(0.155)	(0.091)	(0.120)
Mean Wage	24.27	18.51	21.80	28.54
Observations	72,701	11,364	29,084	32,253
III. Substances Sample - First Differences				
A. Baseline Model				
Fatality Rate	-0.010***	-0.002	-0.013***	-0.012*
	(0.003)	(0.006)	(0.004)	(0.007)
B. Interaction Model				
Fatality Rate	-0.010***	-0.003	-0.011***	-0.018**
	(0.003)	(0.006)	(0.004)	(0.007)
Fatality Rate - Substances	0.025	0.078	-0.077	0.158*
	(0.047)	(0.110)	(0.064)	(0.086)
Mean Difference Wage	1.02	0.47	0.62	1.58
Observations	50,136	7,568	20,807	21,761

The empirical objective is to measure the association between the wages and the occupational fatality rate. The data come from the National Longitudinal Survey of Youth, 1979 Cohort, restricted to males ages 18 to 62. The outcome variable is hourly wages in 2017 dollars, and the regressor of interest is the occupational fatality rate, measured per 10^5 full-time equivalent workers. In the fixed effects models, control variables include age, age trends by education and race, marital status, region-by-year fixed effects, and industry fixed effects. Standard errors clustered at the individual level are in parentheses.

Table 8: Model of Wages, Males Ages 30 to 62

Education	(1) All	(2) No HS Diploma	(3) HS Diploma	(4) College
I. Baseline Sample - Fixed Effects				
A. Baseline Model				
Fatality Rate	-0.000	0.001	-0.008	0.008
	(0.006)	(0.016)	(0.006)	(0.013)
Mean Wage	27.29	19.02	22.96	32.88
Observations	37,571	4,512	14,847	18,212
II. Substances Sample - Fixed Effects				
A. Baseline Model				
Fatality Rate	0.001	0.002	-0.012	0.017
	(0.007)	(0.017)	(0.008)	(0.015)
B. Interaction Model				
Fatality Rate	-0.007	-0.012	-0.012	-0.000
	(0.008)	(0.014)	(0.009)	(0.017)
Fatality Rate - Substances	0.242**	0.438	0.007	0.423*
	(0.120)	(0.293)	(0.125)	(0.221)
Mean Wage	27.21	19.05	22.91	32.90
Observations	35,746	4,409	14,267	17,070
III. Substances Sample - First Differences				
A. Baseline Model				
Fatality Rate	-0.007	0.009	-0.019***	0.003
	(0.006)	(0.014)	(0.007)	(0.012)
B. Interaction Model				
Fatality Rate	-0.015**	-0.027	-0.016**	-0.013
	(0.007)	(0.017)	(0.008)	(0.014)
Fatality Rate - Substances	0.232***	0.987***	-0.112	0.373**
	(0.088)	(0.231)	(0.114)	(0.152)
Mean Difference Wage	0.23	-0.12	-0.03	0.53
Observations	24,375	2,773	9,977	11,625

The empirical objective is to measure the association between the wages and the occupational fatality rate. The data come from the National Longitudinal Survey of Youth, 1979 Cohort, restricted to males ages 30 to 62. The outcome variable is hourly wages in 2017 dollars, and the regressor of interest is the occupational fatality rate, measured per 10^5 full-time equivalent workers. In the fixed effects models, control variables include age, age trends by education and race, marital status, region-by-year fixed effects, and industry fixed effects. Standard errors clustered at the individual level are in parentheses.

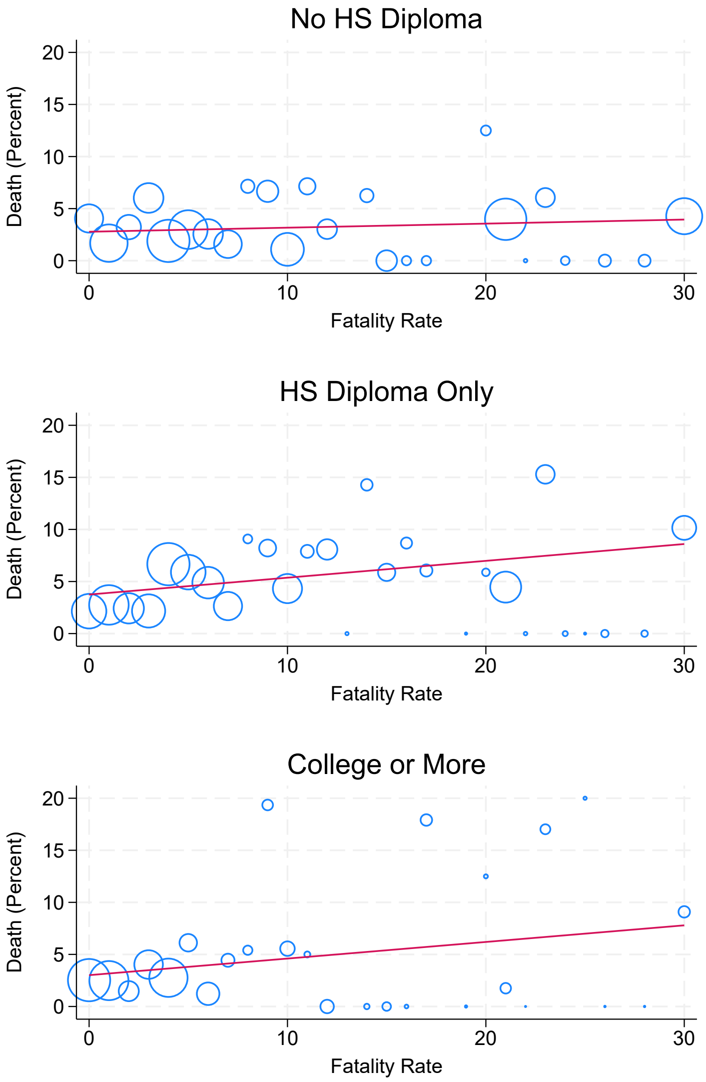

Figure 1: Self-Reported Exposure to Death Exposure by Occupational Fatality Rate and Education, Males Ages 18 to 64

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.

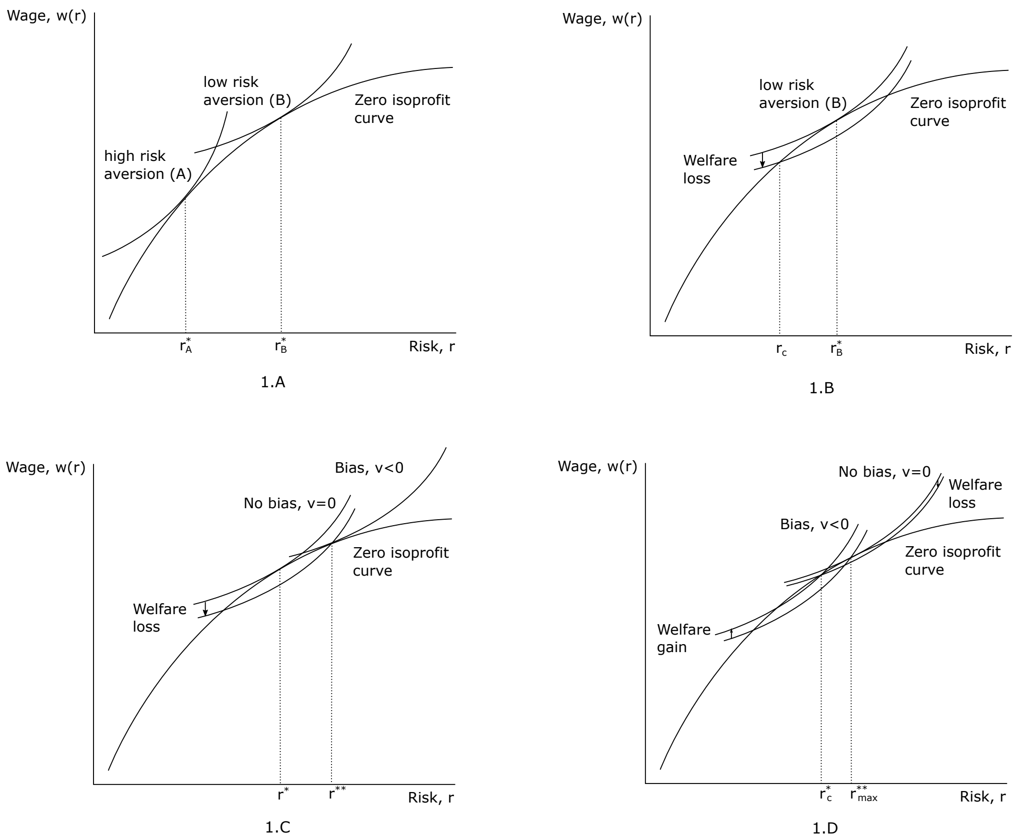

Figure 2: Labor Market Equilibria

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.

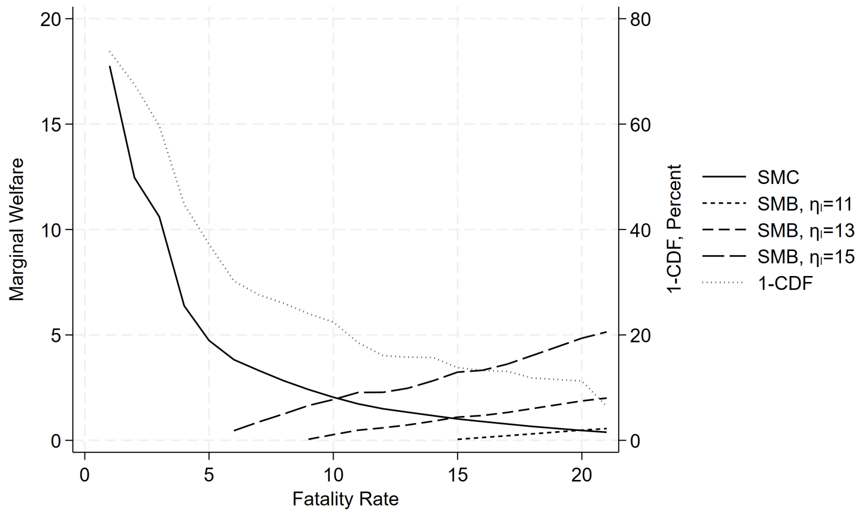

Figure 3: Simulation of Optimal Risk Ceiling, VSL=$7.27 million

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.