CENTER FOR POLICY RESEARCH
THE MAXWELL SCHOOL

WORKING PAPER SERIES

Behavioral Bias in Occupational Fatality Risk: Theory, Evidence, and Implications

Perry Singleton

Paper No. 242
November 2021

ISSN: 1525-3066
426 Eggers Hall
Syracuse University
Syracuse, NY 13244-1020
T 315.443.3114 **E** ctrpol@syr.edu
https://www.maxwell.syr.edu/CPR_Working_Papers.aspx

Syracuse University
Maxwell School of
Citizenship & Public Affairs
Center for Policy Research

CENTER FOR POLICY RESEARCH - Fall 2021

Leonard M. Lopoo, Director
Professor of Public Administration and International Affairs (PAIA)

Associate Directors

Margaret Austin
Associate Director, Budget and Administration

John Yinger
Trustee Professor of Economics (ECON) and Public Administration and International Affairs (PAIA)
Associate Director, Center for Policy Research

SENIOR RESEARCH ASSOCIATES

Badi Baltagi, ECON
Robert Bifulco, PAIA
Carmen Carrión-Flores, ECON
Sean Drake, SOC
Alfonso Flores-Lagunes, ECON
Sarah Hamersma, PAIA
Madonna Harrington Meyer, SOC
Colleen Heflin, PAIA
William Horrace, ECON
Yilin Hou, PAIA
Hugo Jales, ECON
Jeffrey Kubik, ECON
Yoonseok Lee, ECON
Amy Lutz, SOC
Yingyi Ma, SOC
Jerry Miner, ECON
Shannon Monnat, SOC
Jan Ondrich, ECON
David Popp, PAIA
Stuart Rosenthal, ECON
Michah Rothbart, PAIA
Alexander Rothenberg, ECON
Rebecca Schewe, SOC
Amy Ellen Schwartz, PAIA/ECON
Ying Shi, PAIA
Saba Siddiki, PAIA
Perry Singleton, ECON
Yulong Wang, ECON
Peter Wilcoxen, PAIA
Maria Zhu, ECON

GRADUATE ASSOCIATES

Rhea Acuña, PAIA
Graham Ambrose, PAIA
Mariah Brennan, SOC. SCI.
Brandon Charles, PAIA
Ziqiao Chen, PAIA
Yoon Jung Choi, PAIA
Stephanie Coffey, ECON
Adam Cucchiara, PAIA
William Clay Fannin, PAIA
Giuseppe Germinario, ECON
Myriam Gregoire-Zawilski, PAIA
Joshua Grove, SOC
Hyojeong Kim, PAIA
Mattie Mackenzie-Liu, PAIA
Maeve Maloney, ECON
Austin McNeill Brown, SOC. SCI.
Qasim Mehdi, PAIA
Nicholas Oesterling, PAIA
Claire Pendergrast, SOC
Lauryn Quick, PAIA
Michael Quinn, ECON
Radine Rafols, ECON
Christopher Rick, PAIA
Sam Saltmarsh, ECON
Spencer Shanholtz, PAIA
Sarah Souders, PAIA
Yue Sun, SOC
Joaquin Urrego, ECON
Yao Wang, ECON
Zhanhan Yu, ECON
Xiaoyan Zhang, Human Dev.
Bo Zheng, PAIA
Dongmei Zuo, SOC. SCI.

STAFF

Willy Chen, Research Associate
Michael Dunaway, Postdoctoral Scholar
Katrina Fiacchi, Administrative Specialist
Michelle Kincaid, Senior Associate, Maxwell X Lab
Emily Minnoe, Administrative Assistant
Hannah Patnaik, Managing Director, Maxwell X Lab
Candi Patterson, Computer Consultant
Xiaohan Sun, Postdoctoral Scholar
Samantha Trajkovski, Postdoctoral Scholar
Laura Walsh, Administrative Assistant

Abstract

Behavioral bias in occupational fatality risk is introduced to the theoretical framework of hedonic wages, yielding an endogenous risk ceiling that increases social welfare. Empirically, bias is most evident among workers with no high school diploma, who do not report relatively greater exposure to death in high fatality rate occupations. These findings suggest that extant population estimates of value of statistical life are biased downwards and should be factored by at least 1.35. Under reasonable assumptions, simulations suggest an optimal risk ceiling between 73.0 to 85.9 percentile of the population distribution of occupational fatality risk.

JEL No.: J31, J81

Keywords: Compensating Wage Differentials, Value of Statistical Life, Workplace Safety, Occupational Safety

Authors: Perry Singleton, Department of Economics and Center for Policy Research, Maxwell School of Citizenship & Public Affairs, Syracuse University, psinglet@syr.edu

*The data used in this project are available online

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 the structural mechanisms of a class of goods that differ by a vector of objectively measured characteristics. He shows that, in equilibrium, the relationship between price and quantity of characteristics reflects - and therefore reveals - consumer preferences. The model has direct implications for workplace safety in the labor market. Workers differ by risk tolerance, and firms differ 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] 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 behavioral economics, misperceptions of risk is a bias referred to as nonstandard belief, and experimental evidence suggests that the bias arises in at least three ways: overconfidence, law of small numbers, and projection bias (DellaVigna, 2009). 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 behavioral bias due to nonstandard beliefs into the economics of workplace safety. The aims are similar to Akerlof and Dickens (1982), who introduce cognitive dissonance into the theory of workplace safety, and

[1] The issue of risk perception in VSL studies is discussed in reviews by Blomquist (2004), Kniesner and Leeth (2014), and Viscusi and Aldy (2003). A recent study by (Johnson, 2020) examines a recent practice of the Occupational Safety and Health Administration of issuing press releases regarding violations and penalties of individual establishments. He finds that publicizing the violations of one establishment improves regulation compliance and workplace safety of nearby establishments.

a study by O'Donoghue and Rabin (2006), who introduce behavioral biases into the theory of optimal sin taxes. Section 2 builds upon Rosen's (1974) theory on hedonic prices and implicit markets with respect to wages and occupational fatality risk. If agents are rational, workers sort optimally into employment based on risk aversion, and government policies and regulations that effectively cap employment risk only decrease welfare. Behavioral agents are introduced to the model by assuming workers systematically underestimate or overestimate risk. As shown, workers who systematically underestimate risk choose riskier employment than optimal, and workers who systemically overstate risk choose safer employment than optimal. In both cases, welfare decreases, and government policies and regulations can potentially increase social welfare. Whereas Rosen (1974) considers exogenous restrictions on choice that only decrease social welfare, this study shows that an optimal risk ceiling may increase welfare and is endogenous to the distribution of workers' risk preferences and behavioral biases.

Section 3 provides new empirical evidence on behavioral biases in occupational fatality risk. Although anectdotal evidence suggests that workers in dangerous jobs are often oblivious to the dangers (Akerlof and Dickens, 1982), empirical evidence on the magnitudes remains scant.[2] The empirical questions are whether self-reported exposure to death on the job is correlated with objective rates of occupational fatality risk and, more specifically, whether the correlation varies by education. 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, more educated workers may better assess occupational fatality risk, which would increase the correlation between self-reported exposure to death and occupational fatality risk. The data come from the National Health and Interview Survey (NHIS) of 1985, which includes a one-time survey supplement in which survey respondents report exposure

[2]In an oft-cited study in experimental psychology, Lichtenstein et al. (1978) examine how well individuals judge risk by comparing perceived risk of death to actual risk across various causes, including fireworks (3 per 10^8 population), drowning (3,600 per 10^8), and stroke (102,000 per 10^8). They find that subjects tend to overestimate small frequency events and overstate large frequency events. Moreover, subjects were unable to correct for potential sources of bias - specifically due to imaginability and memorability - when prompted to avoid them.

to death on the job. These data are linked to occupation fatality rates according to a respondent's reported occupation. Occupation 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 2002. The empirical analysis confirms the predictions regarding subjective risk, objective risk, and education: while subjective and objective measures of occupational fatality risk are highly correlated among more educated workers, the partial correlation is a relatively precise zero among workers with less than a high school diploma.

Section 4 explores the implications of behavioral bias on the estimation of VSL. The analysis shows that aggregate measures of risk should only be applied to populations from which they are derived and that, even if this were the case, VSL estimates may still be biased downwards if some workers increasingly underestimate risk in high-risk occupations. Given the empirical evidence, this seems most likely among less educated workers. In multiple regression, the bias not only reflects that less educated workers underestimate risk, but also that they account for a disproportionately larger share of the conditional variance in occupational fatality risk. Based on the empirical evidence of behavioral bias among less educated workers, population estimates of VSL should be factored by at least 1.35.

Section 5 explores the implications of behavioral bias on the optimal risk ceiling. The simulation is based on the assumption that more educated workers have no behavioral bias in perception of occupational fatality risk, but less educated workers have behavioral bias. Additionally, risk aversion is assumed constant among less educated workers - so preferences for risk are homogeneous - but less educated workers are less risk averse than more educated workers on average. Under reasonable assumptions, the optimal risk ceiling ranges from 7 to 15 fatalities per 10^5 workers, which correspond respectively to the 73.0 to 85.9 percentile of the population distribution of occupational fatality risk.

Section 6 concludes by discussing broader issues related to behavioral bias in occupational fatality risk and various public and private mechanisms to mitigate bias.

2 Theoretical Framework

2.1 Rational Agents

This section introduces behavioral agents to Rosen's (1974) model on hedonic prices, applied specifically to occupational fatality risk in the labor market. Workers' expected utility depends endogenously on wages w and occupational injury risk r and exogenously on risk aversion η and consumption floor d if injured: : $E[u(w, r; \eta, d)] = (1-r)u(w) + ru(d)$. 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 $w'(r) = \frac{u(w(r))-u(d)}{(1-r^*)u'(w(r^*))}$.

Firms expected profit depends endogenously on wages w and occupational injury risk r and exogenously on risk-based productivity μ: $E[\pi(w, r; \mu)] = R(r) - w$. 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, $\frac{u(w(r))-u(d)}{(1-r^*)u'(w(r^*))} = R'(r)$, and supply equals demand at all combinations of (w, r) (Rosen, 1974). To provide intuition for this equilbrium 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. Additionally, firms have only one type of risk-based productivity, and firm profits are zero in equilibrium assuming the labor market is competitive. An equilibrium under this scenario is illustrated in the Figure 1. As shown, workers sort into two types of employment based on wages and risk. Specifically, more risk-averse workers maximize expected utility at $E[u^A(w_0, r_0)]$, and less risk-averse workers maximize expected utility at $E[u^B(w_1, r_1)]$. Government policies or regulations that cap risk at $r_c < r_1$ only reduces welfare, as $E[u^B(w_c, r_c)] < E[u^B(w_1, r_1)]$.

2.2 Behavioral Agents

Behavioral biases may arise if a worker's subjective perception of injury risk differs from objective injury risk. In Figure 1, for example, suppose more risk-averse workers A perceive risk to be r_0 for all employment between r_0 and r_1. In this case, such workers would strictly prefer any employment with $w > w_0$ and risk $(r_0, r_1]$. Additionally, firms will offer any terms of employment as long as profits are non-negative. Based on these two criteria, feasible terms of employment lie below the isoprofit curve and above w_0 between r_0 and r_1. Thus, in the short run, firms can profit by exploiting behavioral biases of workers. If firm profits are zero in equilibrium, the feasible set of employment terms is further limited to the isoprofit curve. In these cases, expected utility is strictly lower for more risk-averse workers who deviate from (w_0, r_0), as $E[u^A(w,r)] < E[u^A(w_0, r_0)]$ within the set $[w, r : \pi = 0, r_1 \geq r > r_0]$. Firms, on the other hand, are indifferent between all (w, r) combinations along the isoprofit line. Thus, encouraging more risk-averse workers to settle closer to (w_0, r_0) would be Pareto improving.

More generally, all workers may systematically overestimate or underestimate risk. To characterize the effect of the behavioral bias on employment terms and welfare, denote (w^*, r^*) as the optimal choice with no bias. Noted above, the equilibrium is characterized by $R'(r^*) = \frac{u(w(r^*))-u(d)}{(1-r^*)u'(w(r^*))}$.

Now suppose that individuals systematically overestimate or undestimate risk, so that $\rho = r + v$. The worker now chooses employment by maximizing $E[u(w, r; \sigma, v)] = (1-\rho)u(w) + \rho u(d)$, with indifference curves $\frac{dw}{dr} = \frac{u(w)-u(d)}{(1-\rho)u'(w)}$. 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 $r^{**} > r^*$. In both cases, $E[u(w^{**}, r^{**})] < E[u(w^*, r^*)]$, so behavioral biases reduce worker welfare regardless of whether they overestimate or underestimate risk.

2.3 Optimal Policy

The presence of behavioral agents may justify government policy and regulation that restrict risk. First, government maximizes a social welfare function that places equal weight on all workers:

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

Expectations are integrated across the joint distribution of σ and v, denoted $F(\sigma, v)$. In this framework, the government maximizes utility absent behavioral bias (r), whereas the optimal choice of employment by workers (w^{**}, r^{**}) reflects behavioral bias (ρ). Indirect utility is maximized when (w^{**}, r^{**}) equals (w^*, r^*), so the government's objective amounts to minimizing the distortion in employment choice that results from behavioral bias (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 restricts workers from choosing (w^{**}, r^{**}) potentially increases welfare of some workers while decreasing welfare of others.

One obvious policy strategy is to improve access and quality of risk information so that workers can make more accurate choices. The US Occupational Safety and Health Administration (OSHA), for example, 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. Additionally, the BLS reports work-related injury and fatality rates annually by industry and occupation. A limitation of these policies to improve welfare is that workers may exhibit small sample bias, whereby risk in smaller groups is incorrectly inferred from risk in larger groups, or may be optimistic or pessimistic about their individual risk relative to a group. Moreover, 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.

The government can also consider imposing the costs of workplace injuries on firms. In the model above, for example, firms could be required to pay for the consumption floor of injured workers, so profits become $R(r) - w(r) - rd$, and the slope of the isoprofit curve becomes $R'(r) - d$. While this policy would shift the distribution of objective risk towards safer employment, it reduces welfare across the entire wage-risk distribution without addressing welfare losses due to behavioral biases.

A more promising policy strategy to address behavioral bias is to focus on the right tail of the risk distribution, where the share of workers who underestimate risk likely exceeds the share of workers who overestimate risk. For example, the government could place a ceiling on objective risk at r_c, and enforce the ceiling by establishing workplace standards and enforcing them through workplace inspections and financial penalties.[3] To evaluate the welfare consequences of a risk ceiling, define a $I(r^{**} > r_c; \sigma, v)$ as an indicator of working at a risk level above r_c with a behavioral bias but in the absence of a risk ceiling. The government chooses r_c to maximize a social welfare function

$$E_F[u(w^{**}, r^{**}; \sigma, v)] = E_F[(1-I(r_c))[(1-r^{**})u(w^{**})+r^{**}u(d)]+I(r_c)[(1-r_c)u(w(r_c))+r_c u(d)]. \tag{2}$$

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

$$E_F\left[I(r_c^*)\left[w'(r_c^*) - \frac{u(w(r_c^*)) - u(d)}{(1-r_c^*)u'(w(r_c^*))}\right]\right] = 0. \tag{3}$$

At the optimum, there is no welfare gain on the margin among workers who either choose $r^{**} = r_c$ with behavioral bias or choose $r^* = r_c$ without behavioral bias. In the latter case, $w'(r_c) = \frac{u(w(r_c))-u(d)}{(1-r_c)u'(w(r_c))}$, so the term inside the integral of the first-order condition is zero. Instead, the welfare effects occur among workers with $r^{**} > r_c$ and $r^* \neq r_c$. If $r^* > r_c$, then $\frac{u(w(r_c))-u(d)}{(1-r_c)u'(w(r_c))} < w'(r_c)$, so relaxing the ceiling increases social welfare. If $r^* < r_c$, then relaxing the constraint decreases social welfare. At the optimum, the positive marginal welfare effects exactly offset the negative marginal welfare effects, so the average indifference curve is tangent to the isoprofit curve.

The first-order condition also provides sufficient conditions for any regulatory ceiling on risk. Denote the maximum employment risk with behavioral biases and in the absence of a ceiling 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

[3]Kniesner and Leeth (2014) discuss and review the literature on the deterrance and abatement effects of OSHA on workpalce safety. More recently, 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.

condition for a regulatory ceiling is that no worker who chooses the maximum risk also systematically overstates risk. In this case, the first-order condition would be negative at r_{max}, so $r_c^* < r_{max}$.

3 Evidence of Behavioral Biases in Risk Perception

3.1 Model and Data

To examine behavioral biases in risk perception, self-reported exposure to death on the job is compared to objective rates of occupational fatality risk. The partial regression coefficient between self-reported exposure and objective rates is estimated using the following model:

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

The subscripts correspond to individual i in occupation j. $Death_i$ is an indicator of exposure, equaling one if death is mentioned as an on-the-job risk and zero otherwise. $FatalityRate_i$ is the occupation fatality rate per 100,000 workers. X_{ij} is a vector of control variables commonly used 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. The term u_{ij} is the error. The coefficient of interest is β, the partial correlation between self-reported exposure and objective fatality rates. For ease of interpretation, $Death_i$ is factored by 100, so β is interpreted as percentage points.

To examine whether the correlation differs by education, indicators of education are interacted with $FatalityRate_i$. This approach assumes the 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 year includes a one-time survey supplement on health promotion and disease prevention that asks numerous questions about risk exposure. Importantly for this study, the supplement includes questions pertaining to health risks on the job. Survey respondents first report whether they are exposed to substances or conditions at their present job. If so, respondents then report which substances or conditions are present and their possible health effects, including death. The sample is restricted to males at ages 25 to 64 who are employed at the time of the survey, yielding 8,479 observations.

Objective rates of occupational fatality risk are measured as the number of fatalities annually per 100,000 workers. Data on the number of deaths come from the CFOI, which tabulates deaths by occupation annually from 1992 to 2001. Data on the number of workers comes from the March Supplement of the CPS, survey years 1992 to 2001. Using males only, the fatality rate is calculated as the sum of fatalities from 1992 to 2001, divided by sum of employment and multiplied by 100,000. Fatality rates are tabulated and merged to NHIS data by 330 standardized occupations codes constructed by Autor and Dorn (2013), which serves 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.[4] The sample is further restricted to observations successfully matched to tabulated fatality rates, yielding 8,229 observations.[5]

Table 1 presents summary statistics of the analysis sample by education. Demographic characteristics differ by education - for example, age decreases with education - which will be controlled using multiple regression. Most notable are the differences in occupation, self-reported exposure to death and accidents on the job, and occupational fatality rates based on CFOI data. Workers with less than a high school diploma are less likely to work in professional/technical occupations, and more likely to work in service and production/operator occupations. Among all workers, reported exposure to death is substantially lower than exposure to accidents: 4.0 percent versus 51.2 percent. While

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

[5]The sample size decreases by 250 because the occupation code in the NHIS is missing values (64 observations) or does not match to a standardized occupations codes constructed by Autor and Dorn (2013).

exposure to accidents systematically decreases with education, exposure to death is highest among workers with a high school diploma only and lowest among workers with less than a high school diploma. In contrast, average occupational fatality is highest among among workers with less than a high school diploma (12.0) compared to workers with a high school diploma (8.9) and some college or more (5.0). These results indicate that self-reported exposure to death is not systematically related to occupational fatality rates when measured across education groups.

3.2 Results

Figure 2 illustrates the relationship between self-reported exposure to death and occupational fatality risk separately by education. To address extreme values of the fatality rate - with the highest rate reaching 115.0 - the rate is winsorized at 50, which corresponds to the 99th percentile. The rate is also discretized as integers. The figure shows the share who report exposure to death by the discretized occupational fatality rate, and the marker size is proportional to the number of workers within education groups.

The figure reveals three notable patterns. First, among all education groups, the share of workers who report exposure to death is low at occupational fatality rates near zero. Thus, workers in low fatality rate occupations do not appear to overestimate the risk of death. Second, among workers with no high school diploma, the share who report exposure to death does not increase with the occupational fatality rate. This suggests that workers with no high school diploma underestimate risk in high fatality rate occupations.[6] Finally, among workers with a high school diploma and some college or more, the share who report exposure to death increases with the occupational fatality rate. This suggests that more educated workers appreciate, to some extent, increased risk of death in high fatality rate occupations.

The regression results from equation (4) are presented in Table 2. The first column is a regression of self-reported exposure to death on occupational fatality risk.

[6] An alternative explanation, which seems unlikely, is that the increase in the occupational fatality rate is only on the intensive margin, so while the fatality rate increases the share of exposure remains constant.

At the mean of 3.96 percent, a one standard deviation in fatality risk of 11.16 increases the likelihood of self-reported exposure to death by 1.42 percentage points. The second column interacts the fatality rate with indicators of education and includes education fixed effects. Consistent with Figure 2, the association between self-reported exposure to death and occupational fatality risk is mostly evident among more educated workers. The estimated relationship among workers with no high school diploma is 0.030, which increases by 0.122 and 0.148 among workers with a high school diploma only and some college more, respectively. This finding is robust to the including of 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). In comparison to more educated workers in columns (6) and (7), the partial correlation for workers with less than a high school diploma in column (5) is a relatively precise zero.

To explore risk perceptions further, Figure 3 illustrates the relationship between self-reported exposure to accidents and occupational fatality risk separately by education. As shown, a substantial share of workers in low fatality rate occupations report exposure to accidents, and the share is greater among workers with no high school diploma. This may reflect objective risk, an overestimation of risk, or both. As the occupational fatality rate increases from zero to approximately 20, the share of workers who report exposure to accidents increases among all education groups, but appears to increase more steeply among more educated workers. Beyond 20, the share of workers who report exposure to accidents remains high for all education groups.

The regression results from equation (4) for exposure to accidents are presented in Table 3. The results confirm that exposure to accidents is initially greater among workers with no high school diploma: in column (4), the coefficient on some college or more is -21.2 percentage points. The results also confirm that the relationship between exposure to accidents and the occupational fatality rate is greater among more educated workers: the coefficient on the fatality rate is 0.51 among workers with no high school diploma and 0.98 among workers with some college or more. Figures 2 and 3 together suggest that, although workers with no high school diploma perceive high fatality risk occupations as more dangerous with respect to accidents, they do not perceive them as more dangerous with respect to death.

4 Implications for Value of Statistical Life

Behavioral biases in occupational fatality risk have implications for estimating the value of statistical life. Ideally, the value of statistical life would be estimated using the following structural model:

$$w_{ij} = \alpha + \beta r_{ij}^{s} + \epsilon_{ij} \tag{5}$$

The outcome variable w_{ij} is the wage for individual i in occupational j, r_{ij}^{s} is the subjective risk of death perceived by the individual worker, and β represents the causal effect of subjective risk. Blomquist (2004) discusses the preference for subjective risk over objective risk when estimating VSL.

At least two complications arise when measuring risk. First, a worker's behavioral bias may result in individual subjective risk differing from individual objective risk, denoted r_{ij}^{o}. Deviations of subjective and objective risk is characterized by $r_{ij}^{s} = r_{ij}^{o} + v_{ij}$, where v_{ij} represents the bias. Second, due to data availability, individual subjective risk is often replaced with aggregate objective risk, denoted $r_{j}^{o} = f_j(r_{1j}^{o}, ..., r_{N_j}^{o})$, where N_j is the number of workers in occupation j.

These two complications yield the following estimable equation:

$$w_{ij} = \alpha + \beta r_{j}^{o} + \beta \left[(r_{ij}^{o} - r_{j}^{o})) + v_{ij} \right] + \epsilon_{ij} \tag{6}$$

The equation highlights two potential sources of bias when estimating β. First, the term $(r_{ij}^{o} - r_{j}^{o})$ may be positively or negatively correlated with r_{j}^{o}. This is generally not be an issue if r_{j}^{o} is average risk among the population used for estimation, since $(r_{ij}^{o} - r_{j}^{o})$ would equal zero in expectation for all r_{j}^{o}. This becomes an issue, however, if the aggregate measure is used for subgroup analysis, but risk at the subgroup level rises more or less steeply with aggregate risk. For example, in Figure 3 on self-reported exposure to accidents, exposure among less educated workers is initially higher at low occupational fatality rate occupations, but increases less steeply than average as the occupational fatality rate increases. This would result in a negative correlation between r_j^o and $(r_{ij}^o - r_j^o)$, biasing downward the estimate of β.

Second, the behavioral bias v_{ij} may be systematically correlated with objective risk. For example, in Figure 2 on self-reported exposure to death, exposure among less educated workers does not increase with occupational fatality risk. In this special case, the correlation between r_j^o and v_{ij} is -1, and the bias in the estimate of β is $-\beta$.

The empirical model has two implications for estimating the VSL. First, aggregate measures of risk should should only be applied to populations from which they are derived. As the empirical model presented here demonstrates, using aggregate measures for subgroup analysis may lead to overestimating VSL for some groups and underestimating it for others. Second, even if aggregate risk measures are applied to their respective populations, VSL estimates may still be biased downwards if some workers increasingly underestimate risk in high-risk occupations.

These issues may account for different VSL estimates between subgroups of the population. In a review of the VSL literature by Viscusi and Aldy (2003), studies tend to find larger VSL estimates among workers with higher income. On one hand, this may reflect that safety is a normal good Viscusi (1978). On the other, this may reflect that income is highly correlated with education, which has direct effects on the relationship between wages and risk. As this evidence presented here suggests, objective safety risk increases more steeply than average risk among more educated workers, and more educated workers may be more informed about risk compared to less educated workers. Both factors would lead to higher VSL estimates among higher income workers.

If the nature of behavioral bias is known, one solution is to adjust the estimate of β upwards, as in Miller (2000) following Lichtenstein et al. (1978). An adjustment strategy for the bias can be derived from a model of multiple regression with heterogeneous treatment effects (Aronow and Samii, 2016). The model is given by the following equation:

$$Y_i = \alpha + \beta D_i + X_i \gamma + \epsilon_i, \tag{7}$$

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:

$$\hat{\beta} \xrightarrow{p} \frac{E[w_i \tau_i]}{E[w_i]}, \tag{8}$$

where τ_i is the treatment effect for individual i, and $w_i = (D_i - E[D_i|X_i])^2$. Intuitively, when estimating β in multiple regression with heterogeneous treatment effects, observations are weighted by the conditional variance of D_i on X_i.

The question is how to adjust population estimates of VSL assuming that workers with no high school diploma do not perceive differences in occupational fatality risk, so that among them $E[\hat{\beta}] = 0$. On one hand, workers with no high school diploma represent only 16.6 percent of the population. On the other, these workers account disproportionately for employment in high fatality risk occupations. To quantify the matter, occupational fatality risk is regressed on the control variables and industry fixed effects from equation (4):

$$FatalityRate_{ij} = \delta X_{ij} + \mu_{ij}. \tag{9}$$

As expected, $\bar{\hat{\mu}}^2_{ij}$ decreases with education: 0.55 among workers with no high school diploma, 0.34 among workers with a high school diploma only, and 0.29 among workers with some college or more. Although workers with no high school diploma represent only 16.6 percent of the population, they account for 26.2 percent of the variation in $\hat{\mu}^2_{ij}$.

The share of conditional variance in occupational fatality risk attributable to behavioral agents is useful for adjusting VSL estimates. For example, if VSL is constant in the population, but 26.2 percent of the conditional variance is attributable to low educated workers with $E[\hat{\beta}] = 0$, then $E[\hat{\beta}] = 0.74\beta$ from a population-level regression.

In this case, estimates of VSL should be factored by 1.35. If more educated workers also underestimate risk, the factor would be greater.

5 Implications for Optimal Policy

Behavioral biases in occupational fatality risk also have implications for the optimal risk ceiling. An example of the optimal risk ceiling is simulated based on several 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. Second, firm revenues with respect to risk increase at a decreasing rate, $w(r) = ar^b$, where $0 < b < 1$. Third, more educated workers have no behavioral bias in perception of occupational fatality risk, so the distribution of workers across the wage-risk distribution is due only to risk aversion. Finally, less educated workers have behavioral bias, so employment choice reflects both risk aversion and perception bias. To simplify matters, risk aversion is assumed constant among less educated workers - so preferences for risk are homogeneous - but less educated workers are less risk averse than more educated workers on average. The latter accounts for the tendency for lower educated workers to select riskier employment.

The simulation is conducted using the NHIS sample. Low 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 $g - 1 < r \leq g$. Discretized risk $r_g = 1$ for continuous risk between 0 and 1. Based on the data, g spans 41 risk categories from 1 to 114.

The first step is to calibrate the values of a and b of the revenue function. If more educated workers are fully informed, then the average marginal revenue product should equal the VSL. Denote $\tilde{p}_g^m$ as the conditional share of more educated workers with employment risk g, so $\sum_g \tilde{p}_g^m = 1$. The equation for VSL is given by the following equation:

$$\sum_g \tilde{p}_g^m abr_g^{(b-1)} = VSL \tag{10}$$

The shares $\tilde{p}_g^m$ are estimated from the data, and the VSL is set equal to \$74. Because risk is measured per 10^5 workers, the value of statistical life is \$7.4 million, which falls between the range of \$4 and \$10 million estimated by Kniesner et al. (2012). The term a is now an implicit function of b. For this simulation, $b = 0.9$, so $a = 30$.

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

$$abr_g^{(b-1)} = \frac{\frac{w_g^{1-\eta}-1}{1-\eta} - \frac{d^{1-\eta}-1}{1-\eta}}{(1-r_g)w^{-\eta}}, \tag{11}$$

where $w_g = ar_g^b$. If consumption when injured d is known, this equation identifies the value η_g for each risk group g. For this simulation, d is a constant and replaces 75 percent of wages of the lowest risk group: $d = 0.75w_1$. Based on the data, η ranges from 54.5 for $g = 1$ to 2.56 for $g = 114$, with a mean of 16.6.

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.[7] Denote the risk ceiling as r_c, which corresponds to wage $w_c = w(r_c)$, and denote the population share of more educated workers observed in risk g as p_g^m. The social marginal welfare cost at risk ceiling r_c is given by

$$SMC(r_c) = \sum_{r_g > r_c} p_g^m \left[abr_g^{(b-1)} - \frac{u(w(r_c,\eta_g)) - u(d,\eta_g)}{(1-r_c)u'(w(r_c,\eta_g))} \right]. \tag{12}$$

Figure 4 plots the social marginal cost at different values for the risk ceiling, from $r_c = 1$ to $r_c = 20$. The social marginal cost is lowest at $r_c = 20$. This reflects that the share of more educated workers at or above $g = 20$ and $g = 30$ is just 8.5 percent and 2.6 percent of the population, respectively, and that the risk ceiling does not restrict risk substantially relative to optimal risk. As the risk ceiling is lowered, the social marginal

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

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

$$SMB(r_c) = \sum_{r_g > r_c} p_g^l \left[abr^{(b-1)} - \frac{u(w(r_c, \eta^l)) - u(d, \eta^l)}{(1 - r_c)u'(w(r_c, \eta^l))} \right], \tag{13}$$

where p_g^l is the population share of less educated workers in risk group g, and η^l is the constant level of risk aversion. Figure 4 plots the social marginal benefit at different values for the risk ceiling r_c and risk aversion η^l, the latter evaluated at 5.5, 6.5, and 7.5. These values represent less risk aversion than more educated workers: approximately 70.6 percent of more educated workers are more risk averse than 5.5, and approximately 55.2 percent are more risk averse than 7.5. By definition, the social marginal benefit equals zero if the socially optimal risk for workers with risk aversion η^l is r_c. As the r_c increases relative to the socially optimal risk, more workers choose r_d between the optimal risk and the risk ceiling according to p_g^l, which increases the social marginal benefit of the ceiling.

According to equation (3), the optimal risk ceiling occurs where the social marginal benefit equals social marginal cost. This occurs in Figure 4 where the benefit curves cross. As shown, the optimal risk ceiling depends on the risk aversion of less educated workers. In the more risk averse scenario ($\eta^l = 7.5$), the optimal risk ceiling is approximately 7 per 10^8 population, which corresponds to the 73.0 percentile of the risk distribution. In the less risk averse scenario ($\eta^l = 5.5$), the optimal risk ceiling is approximately 15 per 10^8 population, which corresponds to the 85.9 percentile of the risk distribution.

Figure 4 illustrates the simulation from raising VSL from \$74.0 to \$98.8, the upper-bound esetimate from Kniesner et al. (2012). As shown,the optimal risk ceiling does not change substantially. This reflects that raising the VSL increases both the social marginal cost and the social marginal benefit across values of r_c.

6 Conclusion

The results from this study contribute to the literature on behavioral economics and its implications for public policy (Mullainathan et al., 2012; O'Donoghue and Rabin, 2006). The empirical results reveal substantial bias among less educated workers, who do not report greater exposure to death in high fatality rate occupations. Under reasonable assumptions, government policy can improve social welfare by enforcing a ceiling on occupational risk.

One strategy to enforce a risk ceiling is through workplace inspections and penalties through OSHA. Before 1999, OSHA targeted "programmed" inspections at 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 Site Specific Targeting (SST) plan, which first collected injury rates at the establishment level, then targeted establishments with the highest rates for a programmed inspection. The cutoff for an inspection corresponded to the 86.3 percentile of the distribution (Li and Singleton, 2019), similar to the risk ceiling in the less risk averse simulation of this study.

Such blanket enforcement of a risk ceiling potentially helps behavioral workers who underestimate risk, but hurts rational workers who are accurately informed. The emprical evidence presented here, however, does not rule out the possibility that more educated workers underestimate risk, especially at the extreme right tail of the risk distribution. Moreoever, workers who underestimate risk may pose a negative externality on rational workers through added carelessness on the job. In any case, to target behavioral workers, enforcement efforts can focus specifically on high risk industries and establishments with disproportionate shares of less educated workers and where wages do not appear commensurate with risk.

An important consideration is whether the negative welfare consequences of behavioral bias can be addressed privately. Labor unions, for example, may be more efficient at providing workers with more accurate information about risk (Dickens, 2004; Olson, 1981; Viscusi, 1979). This may account for the greater VSL estimates among union workers: in a review of the literature, Viscusi and Aldy (2003) note that nine out of ten studies that estimate VSL by union status found that unions workers receive a greater wage premium for fatality risk. Relatedly, union workers are more likely to have a non-fatal occupational injury (Donado, 2015), and unionization increases regulatory enforcement (Sojourner and Yang, 2020) and improves workplace safety (Li et al., 2020).

Finally, workers may collect their own information regarding workplace safety through repeated transactions, private networks, advertising, and the media. In 2009, for example, OSHA began issuing press releases on establishments with egregious workplace safety violations and penalties, which improved workplace safety in nearby establishments (Johnson, 2020). In contrast, informing employers privately that their accident case rates were above the national average had no effect on workplace safety (Li and Singleton, 2019). Information may also be improved through quality dislosures and certifications. Dranove and Jin (2010) review the literature on disclosures and certifications for consumper products. Relatively understudied is the effect of quality disclosures and certifications on wages and workplace safety.

References

Akerlof, G. and Dickens, W. (1982). The economic consequences of cognitive dissonance. *American Economic Review*, 72(3):307–319.

Aronow, P. and Samii, C. (2016). Does regression produce representative estimates of causal effects? *American Journal of Political Science*, 60:250–267.

Autor, D. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5):1553–1597.

Blomquist, G. (2004). Self-protection and averting behavior, values of statistical lives, and benefit cost analysis of environmental policy. *Review of Economics of the Household*, 2:89–110.

Cutler, D. and Lleras-Muney, A. (2006). Education and health: Evaluating theories and evidence. National Bureau of Economic Research, Working Paper 12352.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, 47(2):315–372.

Dickens, W. (2004). Differences between risk premiums in union and nonunion wages and the case for occupational safety regulation. *Quarterly Journal of Economics*, 119:1383–1442.

Donado, A. (2015). Why do unionized workers have more nonfatal occupational injuries? *Industrial and Labor Relations Review*, 68:153–183.

Dranove, D. and Jin, G. Z. (2010). Quality disclosure and certification: Theory and practice. *Journal of Economic Literature*, 48(4):935–963.

Greene, W. (2008). *Econometric Analysis*. Pearson, Upper Saddle River, NJ.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, 80:223–255.

Johnson, M. (2020). Regulation by shaming: Deterrence effects of publicizing violations of workplace safety and health laws. *American Economic Review*, 111(6):1866–1904.

Kniesner, T. and Leeth, J. (2014). Regulating occupational and product risks. In Machina, M. J. and Viscusi, W. K., editors, *Handbook in Economics: Economics of Risk and Uncertainty*, volume 1, pages 493–600. Elsevier.

Kniesner, T., Viscusi, W. K., Woock, C., and Ziliak, J. (2012). The value of statistical life: Evidence from panel data. *Review of Economics and Statistics*, 94(1):74–87.

Levine, D., Toffel, M., and Johnson, M. (2012). Randomized government safety inspections reduce worker injuries with no detectable effect on job loss. *Science*, 336:907–911.

Li, L. (2020). Workplace safety and worker productivity: Evidence from the MINER Act. Forthcoming in Industrial and Labor Relations Review.

Li, L., Rohlin, S., and Singleton, P. (2020). Labor Unions and Workplace Safety. Forthcoming in Industrial and Labor Relations Review.

Li, L. and Singleton, P. (2019). The effect of workplace inspection on worker safety. *Industrial and Labor Relations Review*, 72(3):718–748.

Lichtenstein, S., Slovic, P., Fishchoff, B., Layman, M., and Combs, B. (1978). Judged frequency of lethal events. *Journal of Experimental Psychology: Human Learning and Memory*, 4(6):551–578.

Lleras-Muney, A. (2005). The relationship between education and adult mortality in the united states. *Review of Economic Studies*, 72:189–221.

Miller, T. (2000). Variations between countries in values of statistical life. *Journal of Transport Economics and Policy*, 34(2):169–188.

Mullainathan, S., Schwartzstein, J., and Congdon, W. (2012). A reduced-form approach to behavioral public finance. *Annual Review of Economics*, 4:511–540.

O'Donoghue, T. and Rabin, M. (2006). Optimal sin taxes. *Journal of Public Economics*, 90:1825–1849.

Olson, C. (1981). An analysis of wage differentials received by workers on dangerous jobs. *Journal of Human Resources*, 16(2):167–185.

Rosen, S. (1974). Hedonic prices and implicit markets: Produce differentiation in pure competition. *Journal of Political Economy*, 82(1):34–55.

Sojourner, A. and Yang, J. (2020). Effects of union certification on workplace-safety enforcement: Regression-discontinuity evidence. *Industrial and Labor Relations Review.*

Viscusi, K. and Aldy, J. (2003). The value of a statistical life: A cricial review of market estimates throughout the world. *Journal of Risk and Uncertainty*, 27:5–76.

Viscusi, W. K. (1978). Market valuations of life and limb: Evidence and policy implications. *Public Policy*, 26(3):359–386.

Viscusi, W. K. (1979). *Employment Hazards: An Investigation of Market Performance.* Harvard University Press, Cambridge, MA.

Viscusi, W. K. (1992). *Fatal Tradeoffs: Public and Private Responsibilities for Risk.* Oxford University Press, New York.

Viscusi, W. K. and O'Connor, C. (1984). Adaptive responses to chemical labeling: Are workers bayesian decision makers? *American Economic Review*, 74(5):942–956.

Table 1: Summary Statistics of NHIS Sample, Males Ages 20 to 64

Education	Less than HS diploma	High School Diploma	Some College More	Total
Age (years)	44.71	39.45	39.43	40.31
	(0.30)	(0.20)	(0.16)	(0.12)
White	81.56	88.53	89.60	87.88
	(1.06)	(0.60)	(0.48)	(0.36)
Married	81.32	81.07	77.50	79.40
	(1.06)	(0.73)	(0.66)	(0.45)
Self Employed	13.46	11.67	11.21	11.75
	(0.93)	(0.60)	(0.50)	(0.35)
Professional/Technical	13.39	29.03	73.16	47.64
	(0.93)	(0.85)	(0.70)	(0.55)
Serivce	18.97	12.88	7.83	11.47
	(1.07)	(0.63)	(0.42)	(0.35)
Production/Operator	67.64	58.08	19.01	40.89
	(1.27)	(0.92)	(0.62)	(0.54)
Death Exposure	3.08	5.19	3.36	3.96
	(0.47)	(0.42)	(0.28)	(0.22)
Accident Exposure	60.93	62.72	39.39	51.17
	(1.35)	(0.91)	(0.78)	(0.56)
Occupational Fatality Rate	12.03	8.93	5.06	7.59
(per 10^5 workers)	(0.39)	(0.21)	(0.14)	(0.12)
0 to 1.5	13.55	18.91	34.74	25.62
	(0.93)	(0.73)	(0.75)	(0.48)
1.5 to 4	6.30	10.51	21.90	15.28
	(0.66)	(0.57)	(0.65)	(0.40)
4 and above	80.15	70.58	43.36	59.09
	(1.09)	(0.85)	(0.78)	(0.54)
Observations	1,351	2,860	4,018	8,229

The sample is derived from the National Health Interview Survey, restricted to males ages 20 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 2002. Estimates are in percentage points unless otherwise noted. Standard errors are in parentheses.

Table 2: Linear Probability Model of Death Exposure, Males Ages 20 to 64

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					No HS	HS	
Education	All	All	All	All	Diploma	Diploma	College
Fatality Rate	0.127***	0.030	0.031	-0.012	-0.006	0.198***	0.106**
	(0.026)	(0.036)	(0.036)	(0.033)	(0.039)	(0.065)	(0.049)
Fatality Rate - HS Diploma		0.122**	0.126**	0.164***			
		(0.059)	(0.059)	(0.062)			
Fatality Rate - College		0.148**	0.142**	0.138**			
		(0.060)	(0.060)	(0.059)			
HS Diploma		1.298*	0.689	0.133			
		(0.785)	(0.802)	(0.859)			
College		0.055	-0.497	-0.818			
		(0.672)	(0.693)	(0.765)			
Mean Death	3.96	3.96	3.96	3.96	3.08	5.19	3.36
Control Variables	No	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Observations	8229	8229	8229	8229	1351	2860	4018

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 workers. The sample is derived from the National Health Interview Survey, restricted to males ages 20 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 2002. 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. Robst standard errors are in parentheses.

Table 3: Linear Probability Model of Accident Exposure, Males Ages 20 to 64

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					No HS	HS	
Education	All	All	All	All	Diploma	Diploma	College
Fatality Rate	0.960***	0.546***	0.507***	0.452***	0.511***	0.792***	0.976***
	(0.057)	(0.089)	(0.087)	(0.085)			
Fatality Rate - HS Diploma		0.318**	0.331***	0.294**			
		(0.127)	(0.124)	(0.117)			
Fatality Rate - College		0.845***	0.822***	0.708***			
		(0.148)	(0.145)	(0.136)			
HS Diploma		1.379	-2.895	-2.776			
		(2.156)	(2.157)	(2.365)			
College		-20.680***	-24.637***	-21.210***			
		(1.982)	(1.983)	(2.277)			
Mean Accident	51.17	51.17	51.17	51.17	60.93	62.72	39.39
Control Variables	No	No	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Observations	8229	8229	8229	8229	1351	2860	4018

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 workers. The sample is derived from the National Health Interview Survey, restricted to males ages 20 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 2002. 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. Robst standard errors are in parentheses.

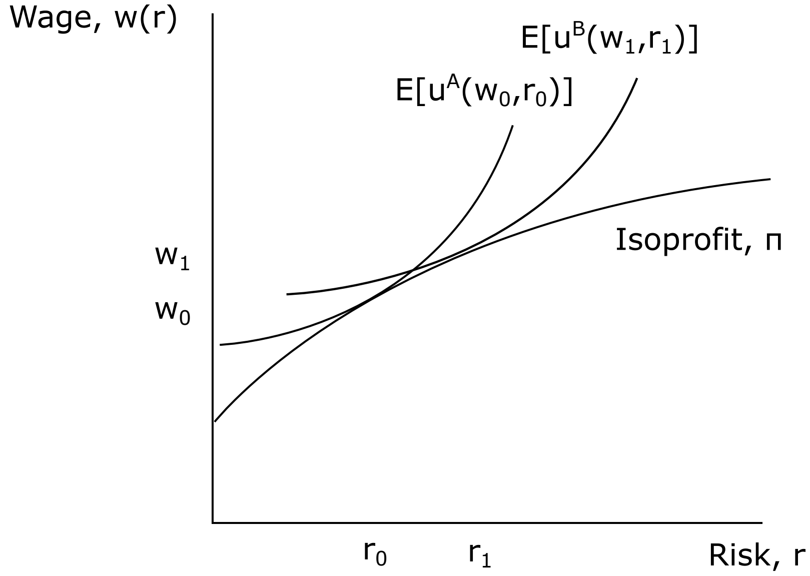

Figure 1: Market Equilibrium with Rational Agents

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 males ages 20 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 2002. The size of the markers are proportional to the number of workers within education categories.

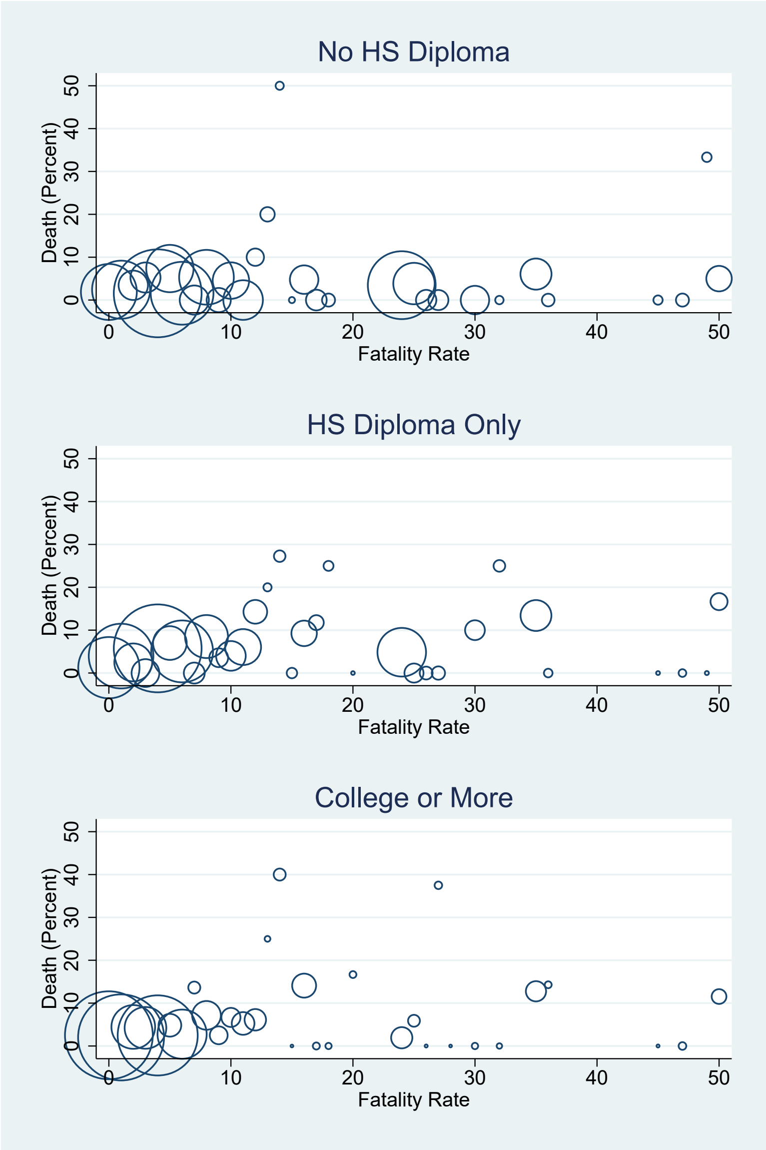

Figure 2: Death Exposure by Education and Occupational Fatality Risk, Males 20 to 64

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 males ages 20 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 2002. The size of the markers are proportional to the number of workers within education categories.

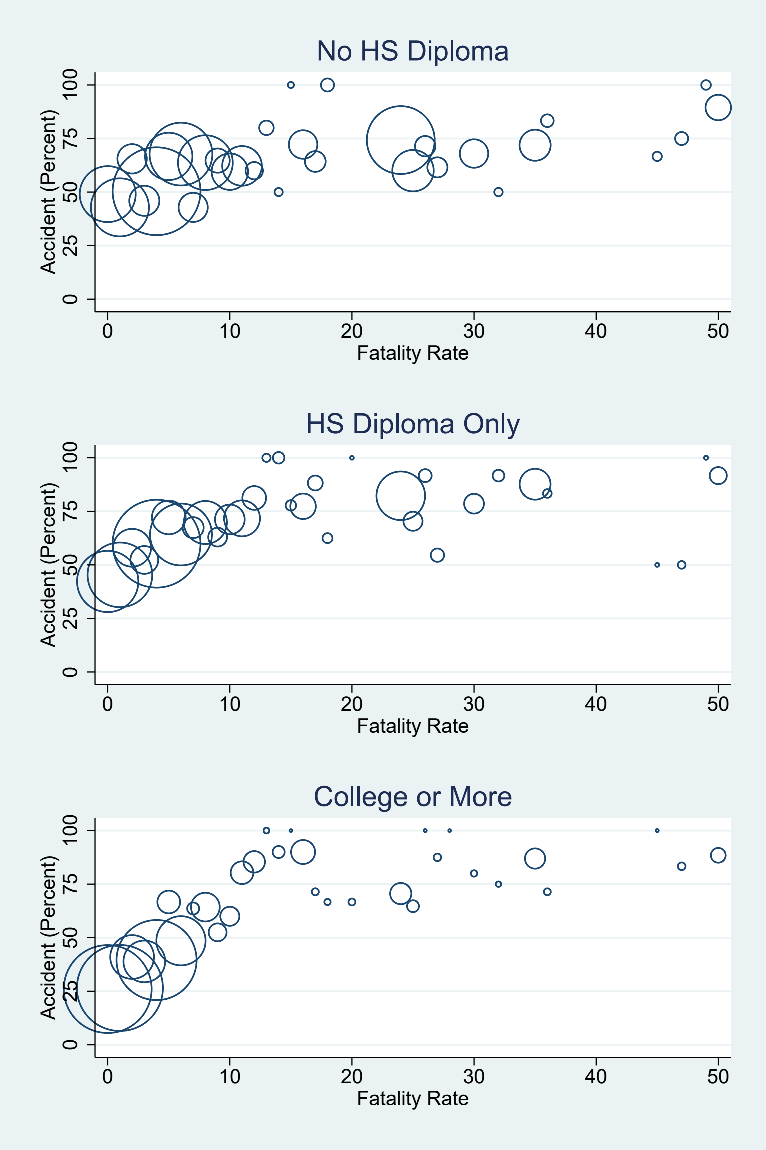

Figure 3: Accident Exposure by Education and Occupational Fatality Risk, Males 20 to 64

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 males ages 20 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 2002. The size of the markers are proportional to the number of workers within education categories.

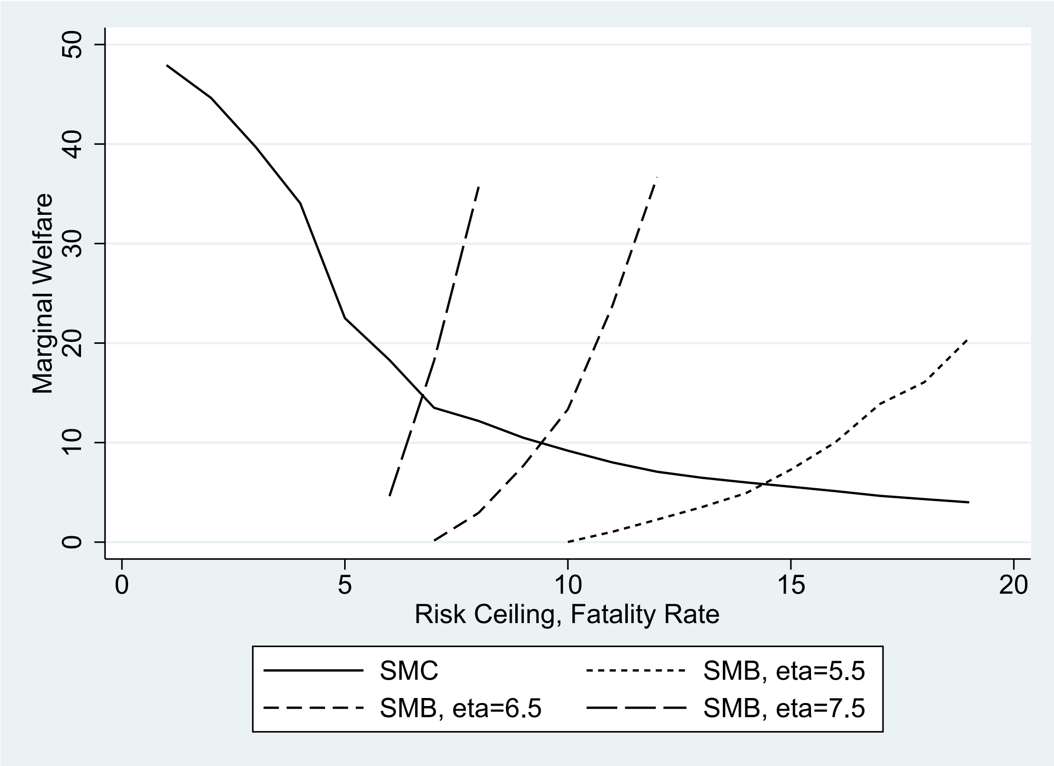

Figure 4: Simulation of Optimal Risk Ceiling, VSL=$7.4 million

The figure illustrates the optimal ceiling on occupational fatality risk measured per 10^5 workers, which occurs where where social marginal cost equals social marginal benefit. The social marginal cost occurs among more educated workers who, by assumption, have no behavioral bias. The social marginal benefit occurs among less educated workers who do have behavioral bias. Risk aversion η among the latter is assumed constant, and the simulation considers three values: 5.5, 6.5, and 7.5. Value of statistical life is assumed $7.4 million. In the more risk averse scenario ($\eta^l = 7.5$), the optimal risk ceiling is approximately 7 per 10^8 population, which corresponds to the 73.0 percentile of the risk distribution. In the less risk averse scenario ($\eta^l = 5.5$), the optimal risk ceiling is approximately 15 per 10^8 population, which corresponds to the 85.9 percentile of the risk distribution.

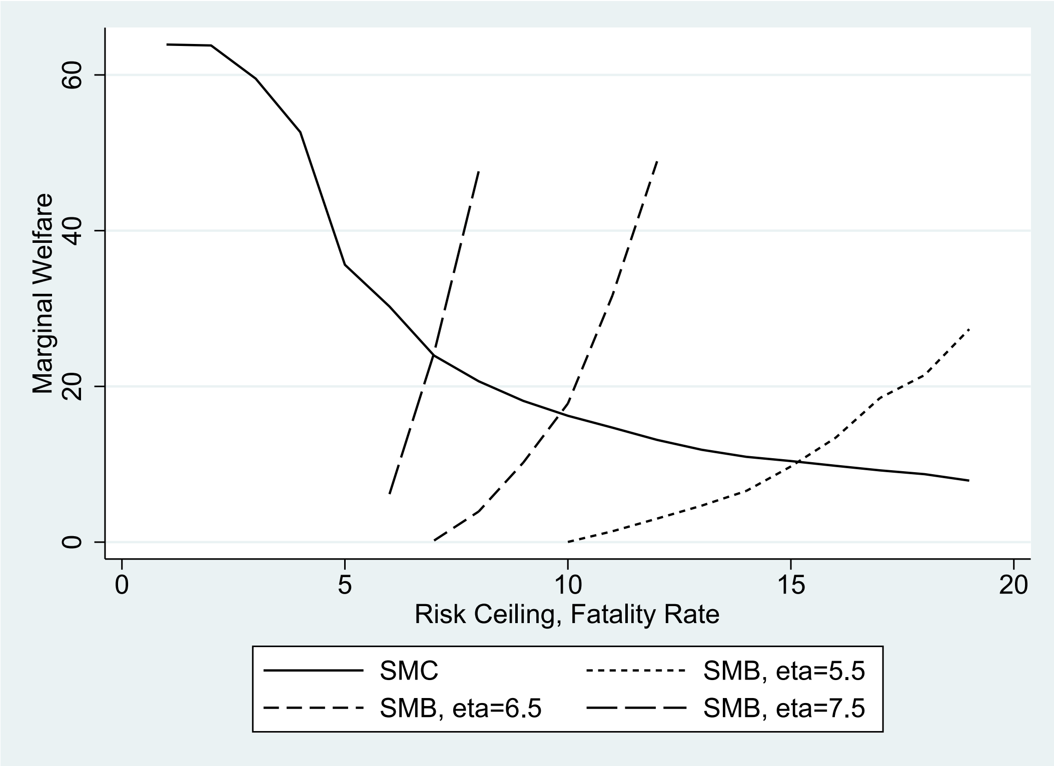

Figure 5: Simulation of Optimal Risk Ceiling, VSL=$10.0 million

The figure illustrates the optimal ceiling on occupational fatality risk measured per 10^5 workers, which occurs where where social marginal cost equals social marginal benefit. The social marginal cost occurs among more educated workers who, by assumption, have no behavioral bias. The social marginal benefit occurs among less educated workers who do have behavioral bias. Risk aversion η among the latter is assumed constant, and the simulation considers three values: 5.5, 6.5, and 7.5. Value of statistical life is assumed \$10.0 million. In the more risk averse scenario ($\eta^l = 7.5$), the optimal risk ceiling is approximately 7 per 10^8 population, which corresponds to the 73.0 percentile of the risk distribution. In the less risk averse scenario ($\eta^l = 5.5$), the optimal risk ceiling is approximately 15 per 10^8 population, which corresponds to the 85.9 percentile of the risk distribution.