Online Appendix to “A life-cycle model of risk-taking on the job”

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Replication code for the empirical and simulation results reported here and in the main text is available at https://doi.org/10.5281/zenodo.15838971.

A.1 Estimating the age-mortality profile

We assume that the conditional mean of the distribution of fatalities D_j in each cell j satisfies

$$\mathbf{E}[D_j|\mathcal{X}_j] = \mu(\mathcal{X}_j)N_j \tag{A.1}$$

where N_j is the number of workers in full-time equivalents. The function $\mu(\mathcal{X}_j)$ determines the mortality rate for given cell characteristics $\mathcal{X}_j$ and is assumed to be log-linear,

$$\ln \mu(\mathcal{X}) = \ln \mu(a, i, X) = \beta_a + \gamma_i + \delta X, \tag{A.2}$$

where β_a is an age group fixed effect, γ_i is the fixed effect pertaining to occupation i, and X is a vector of demographic characteristics. Conditional on (i, X), the ratio between the mortality rate of age group a and the mortality rate of age group a' is

$$\frac{\mu(a, i, X)}{\mu(a', i, X)} = \frac{\exp(\beta_a + \gamma_i + \delta X)}{\exp(\beta_{a'} + \gamma_i + \delta X)} = \exp(\beta_a - \beta_{a'}). \tag{A.3}$$

Since the latter expression does not depend on (i, X), we shall henceforth denote it by $\Delta(a, a')$. Fixing an age group a', equation (A.3) pins down the age profile of mortality when occupation and additional demographic effects are controlled for.

We estimate the conditional expectations model (A.1)–(A.2) by maximum likelihood, assuming a Poisson distribution for $D_j|\mathcal{X}_j$, compare Cameron and Trivedi (2013). Table A2 reports the coefficient estimates of four alternative regressions together with their robust standard errors. The coefficient of age group 35–44 was normalized to 0. The descriptive statics of all variables are given in Table A1.

To obtain the fitted age profile $\hat{\Delta}(a, a')$ depicted in Figure 1, the estimated age fixed effects from Table A2 replace the unknown coefficients, i.e., $\hat{\Delta}(a, a') = \exp(\hat{\beta}_a - \hat{\beta}_{a'})$. To indicate the uncertainty of these fitted values, a confidence interval for $\hat{\Delta}(a, a')$ can be constructed from the variance-covariance matrix of $\hat{\beta}$ by noting that for any real-valued random variable Z and $p \in [0,1]$ it holds that

$$p = P[\exp(Z) < \xi_p] = P[Z < \ln(\xi_p)].$$

Hence if $[c, d]$ is a confidence interval for Z with coverage probability $1-\alpha$, then $[\exp(c), \exp(d)]$ is a confidence interval for $\exp(Z)$ with the same coverage probability. In our application, $Z = \hat{\beta}_a - \hat{\beta}_{a'} = r'\hat{\beta}$ where $\hat{\beta} \sim N(\beta, \Sigma)$ is the vector of age group fixed effects. Hence $Z \sim N(r'\beta, r'\Sigma r)$ and the pth quantile of $\hat{\Delta}(a, a') = \exp(Z)$ is

$$\xi_p = \exp(r'\beta + z_p\sqrt{r'\Sigma r}) = \Delta(a, a')\exp(z_p\sqrt{r'\Sigma r})$$

where z_p is the pth quantile of the standard normal distribution. The error bars shown in Figure 2 illustrate the so constructed 95% confidence interval $[\xi_{0.025}, \xi_{0.0975}]$ where $\Delta(a, a')$ is replaced by $\hat{\Delta}(a, a')$ and Σ by the robust variance-covariance matrix estimate of $\hat{\beta}$.

Table A1: Sample statistics

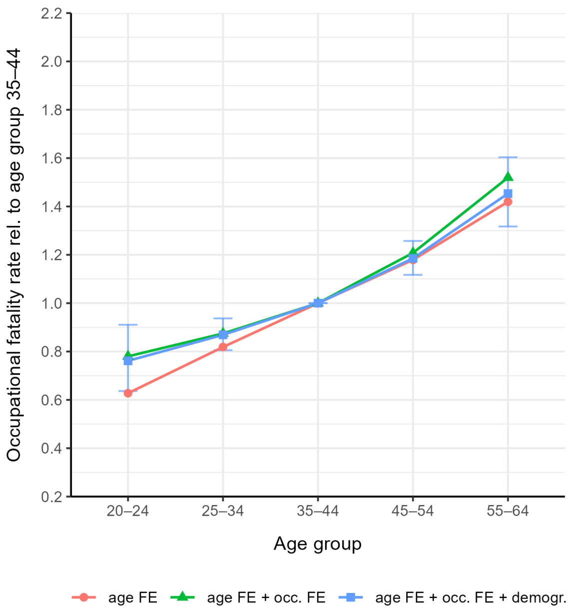
Variable	Population-level	Cell-level			
		Mean	S.D.	Min	Max
Deaths from occupational injuries	32,650	37.102	62.613	0.00	373.00
Full time equivalents (in 100,000)	10,297	11.701	9.748	0.30	52.15
Share male workers	0.565	0.575	0.246	0.09	0.99
Share white workers (non-Hispanic)	0.648	0.636	0.120	0.31	0.89
Share black workers (non-Hispanic)	0.110	0.111	0.057	0.01	0.33
Share Asian workers (non-Hispanic)	0.061	0.062	0.045	0.00	0.29
Share Hispanic workers	0.163	0.172	0.112	0.03	0.64
Share self-employed workers	0.095	0.084	0.088	0.00	0.41
Share high-school graduates	0.928	0.920	0.105	0.49	1.00
Share college graduates	0.485	0.498	0.283	0.06	0.93
Share health: excellent	0.313	0.333	0.129	0.04	0.84
Share health: very good	0.359	0.353	0.082	0.07	0.70
Share health: good	0.252	0.243	0.096	0.00	0.64
Share health: fair	0.061	0.057	0.048	0.00	0.37
Share health: poor	0.014	0.013	0.022	0.00	0.21

Notes: Occupational deaths computed from the Census of Fatal Occupational Injuries (CFOI) public use files, all other variables from the Current Population Survey (CPS) provided by Flood et al. (2021), pooled years 2011–2018. Population-level figures are computed over the pooled working population, while cell-level figures are computed from the 880 year-occupation-age cells used in the regression analysis.

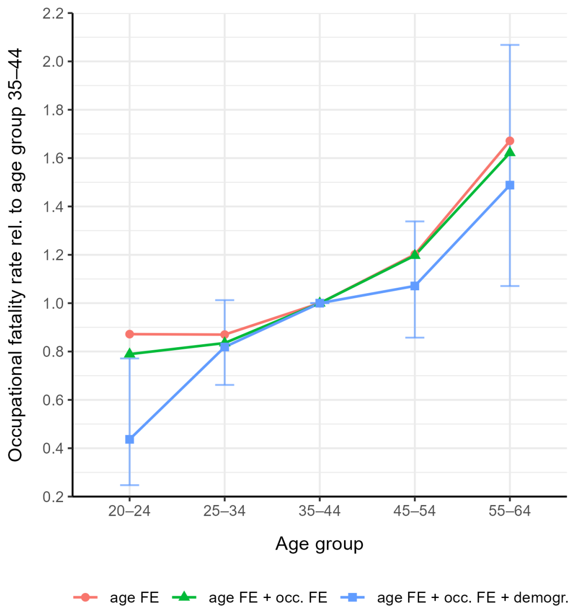
Table A2: Estimated age profiles of the mortality rate from occupational injuries

	Dependent variable: fatal injuries			
	(1)	(2)	(3)	(4)
Age group 20–24	−0.200	−0.238***	−0.276***	−0.260***
	(0.165)	(0.045)	(0.088)	(0.092)
Age group 25–34	−0.151	−0.129***	−0.116***	−0.110***
	(0.162)	(0.024)	(0.036)	(0.036)
Age group 45–54	0.204	0.203***	0.183***	0.178***
	(0.169)	(0.021)	(0.029)	(0.031)
Age group 55–64	0.428**	0.473***	0.431***	0.423***
	(0.168)	(0.027)	(0.045)	(0.047)
Share male workers			0.616	0.615
			(0.385)	(0.397)
Share white workers (non-Hispanic)			−2.104	−2.132
			(1.718)	(1.747)
Share black workers (non-Hispanic)			−2.271	−2.338
			(1.969)	(2.020)
Share Asian workers (non-Hispanic)			−5.246***	−5.283***
			(1.874)	(1.929)
Share Hispanic workers			−2.175	−2.196
			(1.699)	(1.732)
Share workers with high school degree			−0.194	−0.199
			(0.530)	(0.543)
Share workers with college degree			−0.480	−0.459
			(0.374)	(0.377)
Share self-employed workers			1.024**	1.026**
			(0.405)	(0.411)
Share health: very good				0.033
				(0.196)
Share health: good				0.112
				(0.175)
Share health: fair				0.109
				(0.241)
Share health: poor				−0.075
				(0.458)
Constant	−10.457***	−11.294***	−9.130***	−9.148***
	(0.118)	(0.067)	(1.717)	(1.763)
Additional controls				
Occupation-fixed effects		✓	✓	✓
Observations	880	880	880	880

Notes: Poisson regressions on occupation-year-age group cells with different sets of control variables. Coefficients are relative to age group 35–44 in excellent self-reported health and can be interpreted as marginal effects on log(mortality rate). Robust standard errors in parenthesis. Coefficient significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.



(A) Low-skilled occupations



(B) High-skilled occupations

Figure A1: Estimated age profile of the fatal occupational injury rate for low-skilled (Panel A) and high-skilled occupations (Panel B)

A.2 Descriptive statistics

Table A3: Descriptive statistics of four alternative simulations with one skill group (period: month)

Variable		Benchmark		Experiment I[a]		Experiment II[b]		Experiment III[c]	
(a) Population characteristics									
Population	N	59,382		59,366		59,383		61,246	
Employed	L	39,514		43,243		39,514		39,733	
Unemployed	U	3,188		3,465		3,188		3,204	
Retired	R	16,680		12,658		16,681		18,309	
Unemployment rate	$\frac{U}{L+U}$	7.47%		7.42%		7.47%		7.46%	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
(b) Endogenous variables (conditional on being employed and below age 65)									
Probability of dying†									
– total	$1-\boldsymbol{\pi}(\mathcal{L})$	28.42	(27.68)	28.55	(27.85)	28.42	(27.67)	24.40	(23.68)
– on-the-job	m	0.26	(0.05)	0.25	(0.04)	0.25	(0.04)	0.25	(0.05)
On-the-job mortality rate†	μ	3.11	(0.57)	3.00	(0.51)	3.03	(0.46)	3.03	(0.56)
Wage level	w	2,873	(293)	2,844	(289)	2,810	(285)	2,890	(294)
Labor productivity	F/H	4,353	(444)	4,309	(438)	4,257	(432)	4,379	(446)
Consumption	c	1,841	(298)	1,988	(351)	1,767	(343)	1,795	(276)
Wealth (in 1,000s)	a	145	(102)	146	(101)	135	(91)	145	(102)
Value of Life (in 1,000s)	VoL	11,742	(1,329)	12,840	(1,268)	11,094	(880)	11,917	(1,340)
Capital–labor ratio	K/H	467.66		455.87		437.31		484.23	
Tax rate	τ	0.1976		0.1453		0.2398		0.2130	
Real interest rate	r (in %)	0.14		0.15		0.16		0.13	
(c) Exogenous variables									
Baseline mortality	$\ln(\alpha_\pi)$	−9.63		−9.63		−9.63		−9.63	
Pension replacement rate	ϕ_R	0.4		0.4		0.5		0.4	
Retirement age (years)	$\frac{T_R}{12}+20$	65.0		70.0		65.0		65.0	

Notes: †Values reported per 100,000 individuals. [a] Experiment I: higher retirement age; [b] Experiment II: higher pension replacement rate; [c] Experiment III: lower baseline mortality.

A.3 Proof of Proposition 1

Rewriting condition (12), noting $\chi = 0$, yields

$$\xi \frac{f(t)}{y_t'(m_t)} = \frac{f(t)}{\hat{\pi}_t \mathrm{VoL}_{t|\mathcal{L}}} \tag{A.4}$$

where $\xi = \frac{\beta}{(1-\tau)F_H(K,H)}$ is a positive constant. Substituting the production function (14), recalling $\overline{y}_t = \overline{y} f(t)$, reveals that the left-hand side of (A.4) is independent of age t and we will henceforth refer to it as $\psi(m_t)$. Using (14), we observe that $\lim_{m_t \to 0} \psi(m_t) = 0$ as well as $\lim_{m_t \to \tilde{m}} \psi(m_t) = \infty$ since $y_t(m_t)$ has a local maximum at $\tilde{m}$. Furthermore, $\psi(m_t) > 0$ and $\psi'(m_t) > 0$ for $m_t \in (0, \tilde{m}_t)$ by Assumption 1. Therefore, the inverse function of ψ is well-defined and satisfies the properties demanded by Proposition 1.

A.4 The relationship between VSL and VoL

In this section we show that at any given age t, the value of a statistical life, VSL_t, and the value of life, VoL_t, are proportional in our model. The proof uses the particular structure of the model and the observation that conditional on age, the dispersion in simulated wages and on-the-job mortality rates is small.

As explained in Section 4.2.2, the VSL at age t is computed as $\text{VSL}_t = \hat{\beta}_t \times \bar{w}_t \times 10^5$ where $\hat{\beta}_t$ is obtained from the regression $\log(w_{it}) = \alpha_t + \beta_t(m_{it} \times 10^5) + \varepsilon_{it}$ across employed individuals i of age t and $\bar{w}_t$ is their average wage. It is straightforward obtain the OLS estimate for β_t as

$$\hat{\beta}_t = \frac{\sum_i (m_{it} - \bar{m}_t)[\log(w_{it}) - \overline{\log(w_t)}]}{\sum_i (m_{it} - \bar{m}_t)^2} \times 10^{-5}.$$

where $\bar{m}_t = \frac{1}{L_t}\sum_j m_{jt}$ and $\overline{\log(w_t)} = \frac{1}{L_t}\sum_j \log(w_{jt})$. Next, note that condition (9) implies $\log(w_{it}) = \log(F_H(K,H)) + \log(y_t(m_{it}))$. Substituting this above yields

$$\hat{\beta}_t = \frac{\sum_i (m_{it} - \bar{m}_t)[\log(y_t(m_{it})) - \overline{\log(y_t(m_{it}))}]}{\sum_i (m_{it} - \bar{m}_t)^2} \times 10^{-5}.$$

where $\overline{\log(y_t(m_{it})} = \frac{1}{L_t}\sum_j \log(y_t(m_{jt}))$. A first order Taylor approximation of the logarithmic term around $\bar{m}_t$ yields $\log(y_t(m_{it})) \approx \log(y_t(\bar{m}_t)) + \frac{y_t'(\bar{m}_t)}{y_t(\bar{m}_t)}(m_{it} - \bar{m}_t)$. Averaging this across i reveals $\overline{\log(y_t(m_{it}))} \approx \log(y_t(\bar{m}_t))$. Plugging both into the above expression gives

$$\hat{\beta}_t \approx \frac{y_t'(\bar{m}_t)}{y_t(\bar{m}_t)} \times 10^{-5}, \tag{A.5}$$

such that the value of a statistical life at age t can be approximated as $\text{VSL}_t \approx \frac{y_t'(\bar{m}_t)}{y_t(\bar{m}_t)}\bar{w}_t$.

On the other hand, the individual's first order condition for optimal on-the-job mortality (7) is

$$w_t'(m_{it}) = \frac{\hat{\pi}_t}{1-\tau}\left[\frac{\chi}{U'(c_{it})} + \beta \text{VoL}_{it|\mathcal{L}}\right].$$

Condition (9) implies $\frac{w_t'(m_{it})}{\bar{w}_t} = \frac{y_t'(m_{it})}{\bar{y}_t}$ where $\bar{w}_t = \frac{1}{L_t}\sum_j w(m_{jt})$ and $\bar{y}_t = \frac{1}{L_t}\sum_j y(m_{jt})$ which, similar to above, can be approximated as $\bar{y}_t \approx y_t(\bar{m}_t)$. Therefore,

$$\frac{\bar{w}_t}{y_t(\bar{m}_t)} y_t'(m_{it}) \approx w_t'(m_{it}) = \frac{\hat{\pi}_t}{1-\tau}\left[\frac{\chi}{U'(c_{it})} + \beta \text{VoL}_{it|\mathcal{L}}\right] \approx \frac{1}{1-\tau}\text{VoL}_{it|\mathcal{L}},$$

where the last step uses the fact that in our calibration $\chi = 0$, $\beta = 1$, and $\hat{\pi}_t \approx 1$ during working age. Averaging across employed individuals of age t yields

$$\frac{\bar{w}_t}{y_t(\bar{m}_t)} \frac{1}{L_t} \sum_i y_t'(m_{it}) \approx \frac{1}{1-\tau}\text{VoL}_{t|\mathcal{L}}.$$

The first order approximation of $y_t'(m_{it})$ is $y_t'(\bar{m}_t) + y_t''(\bar{m}_t)(m_{it} - \bar{m}_t)$. Averaging over i, the second term vanishes and we observe that $\frac{\text{VoL}_{t|\mathcal{L}}}{1-\tau} \approx \frac{y_t'(\bar{m}_t)}{y_t(\bar{m}_t)}\bar{w}_t$. As a result, $\text{VSL}_t \approx \frac{\text{VoL}_{t|\mathcal{L}}}{1-\tau}$.

A.5 Empirical support for the shape of the production function

Applying (A.5) to the net production function introduced in (14) reveals

$$\hat{\beta}_t \approx \frac{y_t'(\bar{m}_t)}{y_t(\bar{m}_t)} \times 10^{-5} = \left(\frac{\sigma_y}{\bar{m}_t} - \lambda\right) \times 10^{-5} = \sigma_y \cdot \frac{1}{\bar{m}_t \times 10^5} - (\lambda \times 10^{-5}) \tag{A.6}$$

Therefore, the marginal effect of mortality on wages is a linear function of the inverse of the mortality rate (per 100,000 workers) of the considered group. Groups with higher mortality receive a lower compensation (relative to their wage), while groups with low mortality receive a higher compensation. This is consistent with the empirical evidence of Aldy and Viscusi (2008) where the marginal effects reported in Table 1 are indeed decreasing in age.

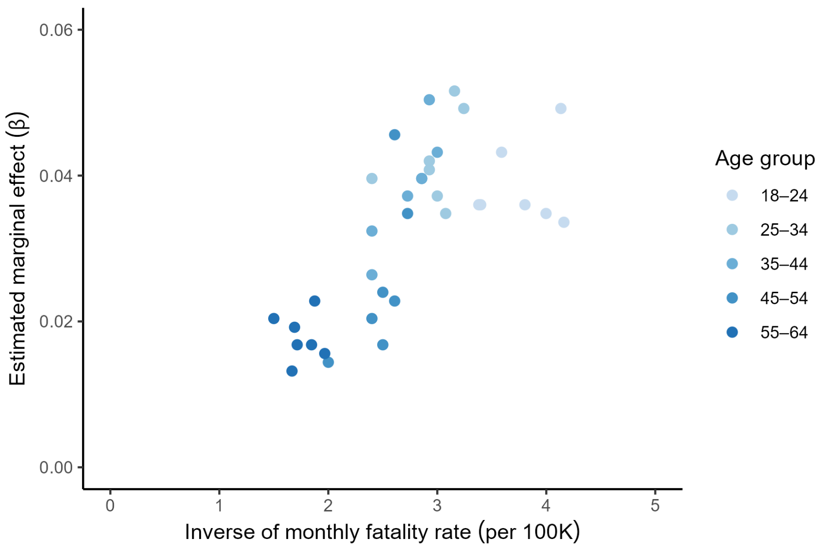


Figure A2: Scatter plot of the monthly marginal effects estimated by Aldy and Viscusi (2008) for 1994–2000 and the inverse of the corresponding monthly CFOI mortality rates per 100,000 workers

Figure A2 plots the marginal effects estimated by Aldy and Viscusi (2008) for the years 1994–2000 against the inverse of the monthly age-specific mortality rates extracted from historical CFOI records.[1] The relationship indeed appears to be linear, except for three outliers in the youngest age group (18–24 years). A regression analysis excluding these points yields point estimates of $\hat{\sigma}_y = 0.0157$ and $\hat{\lambda} = 899.6$ at an R^2 of 0.66.[2] While σ_y is estimated rather precisely (standard error = 0.0021), the point estimate of λ is not statistically significant from zero at the 10% level. Nevertheless, both point estimates are close to our calibrated values, which have been derived in an alternative way, compare Section 4.1.

[1] We disregard the results for 1993 since they differ markedly from the remaining years in 3 of the 5 age groups under consideration. The historical employment-based mortality rates were obtained from https://www.bls.gov/iif/fatal-injuries-tables/archive.htm.

[2] Since in this paper, β_t captures the relative compensation for an increase of the *monthly* probability of dying by 1 in 100,000 workers, the regression coefficients of Aldy and Viscusi (2008), which reflect the yearly relationship, must be multiplied by 12. The estimate for σ_y is given by the slope of the imagined regression line through the data points of Figure A2, while λ corresponds to the intercept multiplied by the factor -10^5.

A.6 Empirical estimates of the parameter λ

A.6.1 Estimation from data on work absences

To explain our estimation strategy, we first develop further intuition for our production function (14). Assume more generally that

$$y_t(m_t) = \overline{y}_t m_t^{\sigma_y} \phi_t(m_t) \tag{A.7}$$

where $\phi_t(m_t)$ is the fraction of days worked during a month, which may depend on age and on-the-job mortality. Assume further that there is a latent process that generates work absences at a daily rate $\eta_t(m_t)$. Whenever such an event occurs, the individual is absent for the whole upcoming day. The probability of being absent on a given day is then $1-e^{-\eta_t(m_t)}$ and the mean share of non-absent workdays within a month is $\phi_t(m_t) = e^{-\eta_t(m_t)}$. Assuming that the absence rate is a linear function of on-the-job mortality, $\eta_t(m_t) = a_t + \lambda m_t$, yields $\phi_t(m_t) = e^{-a_t-\lambda m_t}$. Substituting this into (A.7), absorbing e^{-a_t} into the exogenous component $\overline{y}_t$, yields (14).

An estimate for λ can therefore be constructed as $\frac{\eta-a}{m}$ where η, a, and m are the population-wide means of the respective variables. For our benchmark calibration of Section 4.1, we compute the absence rates η and a from the Survey of Occupational Injuries and Illnesses (SOII), since occupation-level data suggests that a high incidence of fatal injuries correlates positively with a high incidence of absences due to non-fatal injuries. As both mortality and absence rates are close zero in the safest occupation, we set $a = \eta(0) = 0$ and estimate λ as

$$\hat{\lambda} = \frac{\eta}{m} = \frac{\text{Total days lost due to non-fatal occupational injuries and illnesses / 365}}{\text{Total occupational fatalities per month}}. \tag{A.8}$$

To compute the numerator in equation (A.8), we use the SOII records from 2011–2018 available from the BLS website.[3] We define total days lost as the sum of (i) full days away from work, (ii) effective days lost due to job restriction or job transfer, and (iii) the fraction of the day lost on which the event occurred.

Concerning events that lead to absences, job restriction or job transfer, only the median duration of absences is published, which does not easily allow to recover the mean duration or the total number of days lost. Since the SOII is an employer survey and therefore prone to underreporting, we use the published information to construct an upper bound of the total working time lost using the following steps.

(i) For cases that involve one or more days away from work, the SOII provides case numbers n_i and median work absence m_i of the cases in various duration categories i (1, 2, 3–5, 6–10, 11–20, 21–30, 31–365 days). The distribution of the case numbers across these groups suggests that the underlying count distribution has a decreasing probability mass function (pmf), which will be exploited in the following. We seek to determine an upper bound on the total days away from work D, which can be computed as the sum of the days away

[3] The data has been retrieved using the tools https://data.bls.gov/cgi-bin/dsrv?ii and https://data.bls.gov/cgi-bin/dsrv?is.

from work in the categories, i.e., $D = \sum_i D_i$. Furthermore, $D_i = n_i \mu_i$ where μ_i is the mean duration of an absence in category i. To obtain an upper bound on μ_i, observe that for every random variable X supported on an interval $[a, b]$, the median m of X satisfies $\mathbf{E}[X] = P[X \leq m]\,\mathbf{E}[X|X \leq m] + P[X > m]\,\mathbf{E}[X|X > m] = \frac{\mathbf{E}[X|X \leq m] + \mathbf{E}[X|X > 0]}{2}$. Since a uniform distribution attains the highest mean among all distributions with bounded support and non-increasing pmf, it holds that $\mathbf{E}[X|X \leq m] \leq \frac{a+m}{2}$ and $\mathbf{E}[X|X > m] \leq \frac{m+b}{2}$ and therefore $\mathbf{E}[X] \leq \frac{a+2m+b}{4}$. Applied to the SOII data, this reveals

$$D = \sum_i \mu_i n_i \leq \frac{1}{4} \sum_i (a_i + 2m_i + b_i) n_i,$$

where a_i and b_i are the lower and upper boundaries of the absence intervals, respectively.

(ii) For days involving job restriction or job transfer, neither the duration (except for the population median) nor the extent of the productivity loss are known. For simplicity, we assume that the duration distribution is the same as for the days away from work and impose a productivity reduction of 50%.

(iii) The counting of absence days in the SOII starts with the day after the event. Furthermore, there is a large number of cases that does not lead to a full day of absence, job restriction or job transform. To take this into account, we further add half of the number of all recorded SOII incidences, assuming the incidence on average happened in the middle of the workday.

The sum of (i)–(iii) is then plugged into the numerator of (A.8) and divided by the monthly average of fatal occupational injuries in 2011–2018 available from the CFOI. Since the SOII excludes self-employed workers, only the fatalities of wage and salary workers enter the denominator of (A.8). The resulting value of $\hat{\lambda} = 612.84$ is used in the quantitative model in Section 4.

To obtain the skill-specific values of λ shown in Table A4, additional information by occupation is used.[4] Since the occupational breakdown of the SOII data only covers cases involving days away from work, we first construct the ratio between the absence rates of the two skill-groups. Assuming that this ratio also holds for the other two sources of lost working time, it equals $\frac{\eta^l}{\eta^h}$. The levels of η^l and η^h where then set such that (i) the estimated ratio is satisfied and (ii) the population-weighted average equals the value of η estimated above. Finally, λ^i is computed as $\frac{\eta^i}{m^i}$ for $i \in \{l, h\}$ where m^i is the monthly on-the-job mortality rate of the respective skill group.

A.6.2 Robustness checks

As a first robustness check, we obtain an alternative estimate of λ using the CPS. Since the CPS asks employees about their work absences, it is less affected by underreporting. Additionally,

[4] This data was accessed through https://data.bls.gov/cgi-bin/dsrv?cs.

it includes all work absences and therefore also covers potential absenteeism. However, at the occupational-level, the CPS features a much lower correlation between absence and mortality rates compared to the SOII.[5] Again, we compute lambda as $\lambda = \frac{\eta - a}{m}$, using for η the average absence rate of full-time workers and for $a = \eta(0)$ the absence rate of full-time workers in the safest occupation (computer and mathematical occupations). This yields $\hat{\lambda} = 1{,}714.29$. Using this value, the increase in on-the-job mortality above age 50 becomes slightly less pronounced compared to our baseline calibration. Our main results as well as the insights derived from the policy experiments remain unaltered. This additional set of results is available from the authors on request.

As a second robustness check, we consider additional costs of higher on-the-job mortality that go beyond the production loss of absences due to non-fatal injuries. We first consider additional direct costs of fatal injuries based on the total employer cost estimates reported by the Safety Pays Individual Injury Estimator provided by the Occupational Safety and Health Administration (OSHA).[6] Since no explicit cost estimate for fatalities is provided, we use the numbers for Asphyxiation, the most costly and potentially most lethal injury listed. We translate the monetary costs of 426,289 dollars into productive days lost by dividing through a worker's average daily labor productivity (145 dollars in our benchmark calibration). This number is multiplied by the number of fatalities per year and added to the total days lost in the nominator in (A.8), resulting in an increase of λ by 97.93. This indicates that each fatal injury leads to an additional loss equivalent to 97.93 months (8.2 years) of the deceased worker's production on top of the loss in expected future production that is already explicitly considered in the model. Since the OSHA cost estimates do not include fines and third-party liabilities, we add another 300,000 dollars per fatality, which equals the median settlement amount for wrongful death in the US between 2019 and 2024.[7] Transforming this cost into productive days lost in the same way as above leads to an additional increase in λ by 68.91, which increases the cost of a fatality to 13.9 years of the deceased worker's production on top of the loss in expected future production. Adding these cost estimates to the costs of production loss due to non-fatal work injuries leads to $\lambda = 710.77$ and $\lambda = 779.68$, respectively.

Panels B and C in Figure A3 show the simulated age profiles of on-the-job mortality with these alternative values. In each case, the model has been recalibrated as described in Section 4.1, taking the value of λ as given. The resulting calibrated value of σ_y, which together with λ determines the output-elasticity of on-the-job mortality is also reported in the figure.[8] Evaluated at the average m, the higher costs of fatal injuries slightly reduce the output elasticity from 0.0129 to 0.0127, while the reduction is higher in the oldest age group (from 0.0122 to 0.0118). This explains why the age profile of mortality becomes slightly flatter compared to the

[5] Once we condition on low- and high-skilled occupations, the correlation is practically zero within both groups.

[6] https://www.osha.gov/safetypays/estimator

[7] This figure is reported, for instance, in https://calculatemycase.com/wrongful-death, referring to statistics compiled by Thomson Reuters. While the primary source of these numbers could not be retrieved, the indicated amount seems plausible.

[8] Equation (15) implies that the elasticity of $y(m)$ equals $\sigma_y - \lambda m$.

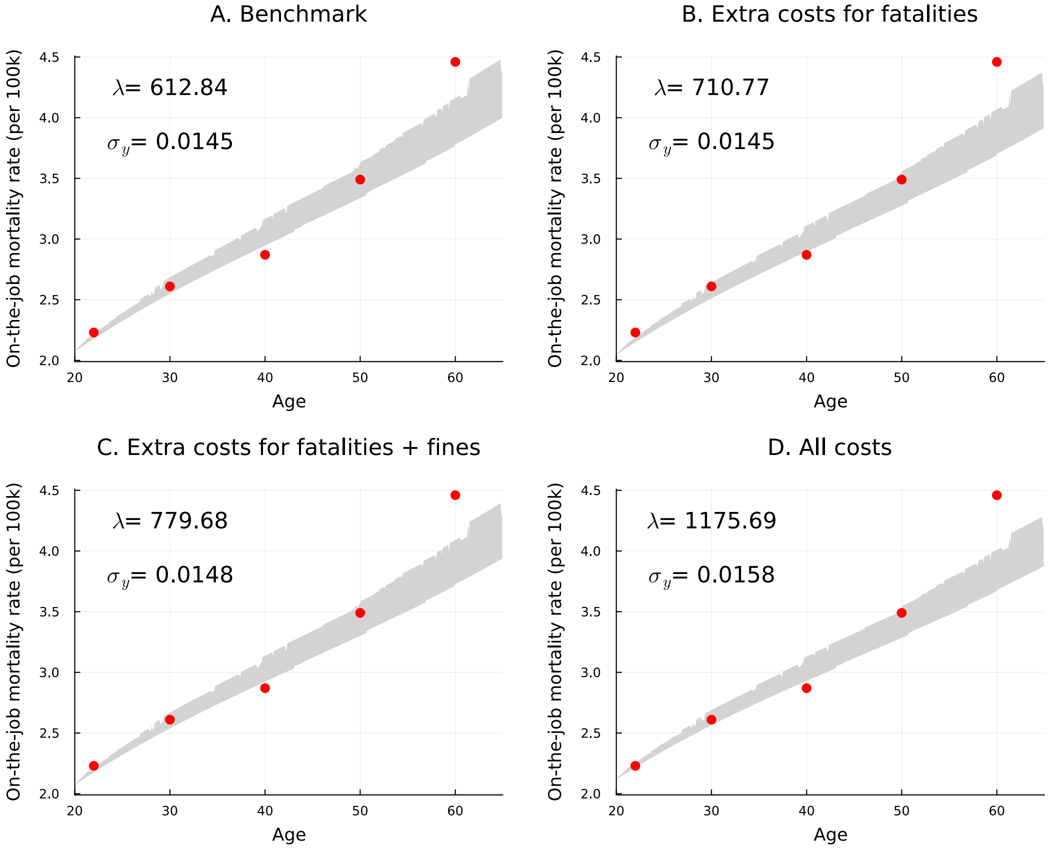


Figure A3: Age profiles of the on-the-job mortality rate for four different values of λ. Notes: Gray areas indicate the range of all simulated profiles. Red points indicate the data. Data source: CFOI and own simulations.

benchmark calibration depicted in Panel A of Figure A3.

To also account for additional costs of non-fatal work-related injuries, we follow a different approach. Our benchmark level of λ already takes into account the production loss from non-fatal injuries. Additionally, medical expenses, legal costs and the costs of production disruptions need to be considered. We use the detailed calculation of Miller (1997) to relate these costs to direct loss in production. Regarding medical expenses, we rely on the fact that Worker Compensation Insurance typically replaces two thirds of the worker's lost wage income.[9] Recent data from the National Council on Compensation Insurance indicate that in the years 2021 and 2022 wage replacement accounted for 47% of the total compensated sum, with the rest covering medical expenses.[10] Based on these numbers, we estimate that medical expenses on average amount to 74% of the worker's lost wages. To estimate legal expenses related to work injuries, we follow Miller (1997) and assume that these are covered by the administration costs of Worker Compensation, which amount to 13% of the compensated sum. Since the compensated sum includes wage replacement (67% of lost wages) as well as medical expenses (74% of lost wages), legal costs amount to 18% of lost wages. Moreover, occupational injuries have spillover

[9] See, for instance, https://www.ssa.gov/policy/docs/ssb/v65n4/v65n4p7.html.
[10] See https://injuryfacts.nsc.org/work/costs/workers-compensation-costs/

Table A4: Overview of the parameter values for the model with two skill groups

Parameter	Symbol	Value	
		Low-skilled	High-skilled
(a) Externally set parameters			
Share in population		0.692	0.308
Job separation probability	s	0.0410	0.0183
Job finding probability	p	0.4532	0.4428
(b) Calibrated parameters			
Output elasticity of on-the-job mortality	σ_y	0.0238	0.0029
Impact of absences on net productivity	λ	586.32	1,024.32
Labor productivity (scale)	$\overline{y}$	644.17	805.21
Age-profile of labor productivity			
	f_0	0.2519	0.0596
	f_1	3.123×10^{-2}	3.600×10^{-2}
	f_2	-2.995×10^{-4}	-3.208×10^{-4}

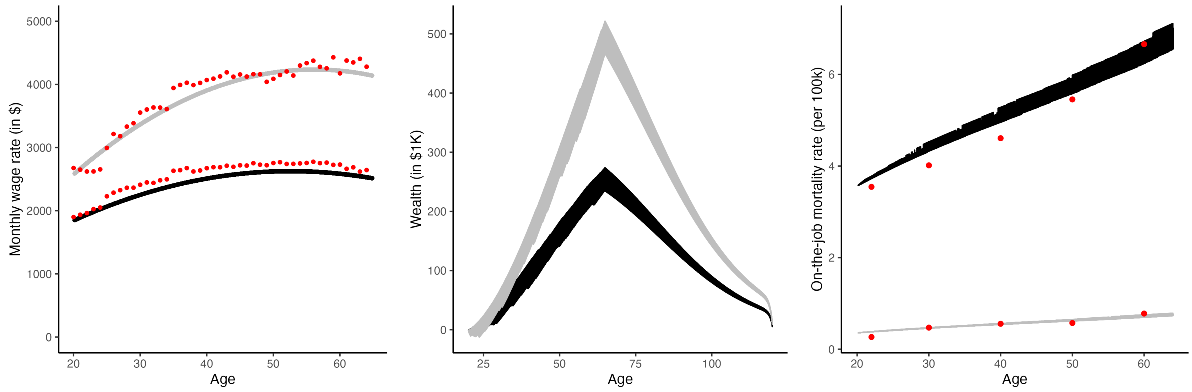
effects on other workers due to production stops, additional administrative duties as well as the reorganization of work schedules. The assumptions of Miller (1997) imply that these costs are around one fifth of the employer's fringe benefit costs.[11] In total, we conclude that medical and legal expenses as well as production disruptions associated with occupational injuries cause a financial loss equal to 122% of the worker's lost wage. Given a labor share of $1 - \alpha = 0.67\%$ in our model, this amounts to 81% of a worker's lost production value. To reflect these additional costs, we therefore multiply our benchmark estimate of $\lambda = 612.84$ by a factor of 1.81. Since Miller (1997) does not differentiate between the severity of injuries, the obtained factor already includes typical costs of fatal injuries. Not considered, however, are fines and lawsuits following the incidence, for which we assume a cost of 300,000 dollars as above. Taking all these costs into account leads to $\lambda = 1{,}175.69$. Although this is about twice the benchmark estimate, Panel D of Figure A3 shows that the model generates an age profile of on-the-job mortality that is only slightly flatter than in the benchmark case.

We also repeated the policy experiments of Section 4.2.4 for the three alternative values of λ presented in Figure A3 and did not find any quantitatively meaningful changes. These results are available from the authors on request. We therefore conclude that our conclusions drawn from the model are robust to a wide range of cost estimates for fatal injuries.

A.7 Benchmark results with two skill groups

In this section, we demonstrate that the model can be extended to capture two occupational groups. We label them as low-skilled occupations (l) and high-skilled occupations (h), which are targeted to workers of the appropriate skill level. This is drawn at birth and stays constant throughout life.

[11] We repeated Miller's calculation of this cost component using recent SOII data and obtained a quantitatively similar effect on λ.



(A) Wage (B) Wealth (C) On-the-job mortality

Figure A4: Age profiles of the monthly wage (Panel A), wealth (Panel B), and the on-the-job mortality rate (Panel C) for high-skilled workers (gray) and low-skilled workers (black). Notes: Shaded areas indicate the range of all simulated profiles. Red points indicate the data. Data source: CFOI, CPS, own simulations.

Calibration. The share of low-skilled workers in the population equals 0.692, which amounts to the share of workers in occupations with less than 50% college graduates in the CPS during 2011 and 2018.[12] The calibration procedure follows Section 4.1. To emphasize the effect of the labor market on mortality, we assume that high-skilled and low-skilled workers are identical except for the characteristics of the jobs they perform. This relates to the labor transition rates (s, p) and the parameters of the production technology ($\overline{y}$, f_0, f_1, f_2, σ_y, λ). For simplicity, we assume that low-skilled and high-skilled workers are perfect substitutes in production.

The labor transition rates for the two age groups were computed from the CPS using the methodology developed by Shimer (2005).[13] The skill-specific shape of the exogenous productivity profile $\{f_0^i, f_1^i, f_2^i \,|\, i \in \{l, h\}\}$ is inferred using the observed age profile of wages in the two occupational groups. The parameters λ^l and λ^h are taken from occupation-specific SOII data as described in Section A.6. The remaining parameters $\{\overline{y}^i, \sigma_y^i \,|\, i \in \{l, h\}\}$ are calibrated together with σ_C to match (i) the average wage in age group 35–44 in the two groups, (ii) the average occupational fatality rate in the two groups, and (iii) a population-wide average value of life of 12 million dollars. The calibrated skill-specific parameters can be found in Table A4 while all other model parameters are unchanged from Table 1. The descriptive statistics for the simulations with two skill groups are shown in Table A7.

Age profiles. Figure A4 shows the age profiles of the monthly wage, wealth, and the on-the-job mortality rate for high-skilled (gray) and low-skilled workers (black). The red dots indicate the data. While the two wage profiles have been used as target in the calibration,

[12]This cut-off point is suggested by the data as there are no occupations with a share of college graduates between 45% and 70%.

[13]Shimer (2005) uses data from 1951 to 2003, while our data only spans 2011 to 2018. To make the figures comparable, we scale the transition rates of the two skill groups such that their population-weighted average equals Shimer's values of s and p reported in Table 1.

Table A5: Value of a statistical life overall and by age and skill group

	Dependent variable: log(monthly wage)							
	Age=All		Age=40		Age=50		Age=60	
	Low-skilled	High-skilled	Low-skilled	High-skilled	Low-skilled	High-skilled	Low-skilled	High-skilled
On-the-job mortality (per 100k)	0.0400 (0.00005)	0.0400 (0.00009)	0.0500 (0.00002)	0.0500 (0.00003)	0.0400 (0.00002)	0.0400 (0.00003)	0.0400 (0.00002)	0.0400 (0.00004)
Mean monthly wage ($)	2,431	3,794	2,509	3,903	2,620	4,187	2,584	4,216
VSL (million $)	10.35	16.36	12.65	20.69	11.50	18.81	9.94	16.13
$\text{VoL}_{\mathcal{L}}$ (million $)	9.73	15.90	10.21	16.69	9.30	15.18	8.02	13.07

Note: Regressions on simulated data. Value of a statistical life (VSL) computed as VSL = $\hat{\beta} \times \bar{w} \times 100{,}000$, $\text{VoL}_{\mathcal{L}}$ as mean value of life (VoL) of all employed individuals.

only the average on-the-job mortality rate in each skill group was targeted. Yet, the model also replicates the slope of these profiles in both skill groups.

The value of a statistical life. Table A5 shows the age profile of the value of life (VoL) and the value of a statistical life (VSL). While both values are consistently higher in the high-skilled group, it is worth noting that this is mainly due to the higher wage earned in the high-skilled occupations. The trade-off between mortality and wages as measured by the regression coefficient $\hat{\beta}$ is almost identical in the two skill groups. This is consistent with Aldy and Viscusi (2008), who assume the same β coefficient in (18) for all individuals within an age group when estimating the value of a statistical life. While our model does not impose any restriction in this regard, equation (A.6) reveals that it is a result of the ratio of the calibrated σ_y values (σ_y^l/σ_y^h) being approximately equal to the ratio of the on-the-job mortality rates ($\bar{m}^l/\bar{m}^h$) since $\lambda^l \times 10^{-5}$ and $\lambda^h \times 10^{-5}$ are comparatively small.

The effect of wealth on mortality and wages. The dampening effect of wealth on on-the-job mortality increases in age in both skill groups, see the top part of Table A6. This effect is stronger for high-skilled workers for two reasons. First, Figure A4 shows that at any given age, they enjoy higher income and higher wealth, which makes it easier to give up part of their wage to reduce mortality. Second, our calibration implies that to reduce mortality by 1%, high-skilled need to give up a smaller share of their wage than low-skilled. To see this, observe that $\frac{\partial \ln w_t^i(m_t^i)}{\partial \ln m_t^i} = \sigma_y^i - \lambda^i m_t^i \approx \sigma_y^i$ for $i \in \{l, h\}$ since $\lambda^i m_t^i$ is comparatively small. Since $\sigma_y^l > \sigma_y^h$, reducing mortality is relatively more expensive for low-skilled workers. As evident from the bottom part of Table A6, low-skilled workers are nonetheless more willing to give up wages with increasing wealth compared to their high-skilled colleagues. The realized reduction in mortality, however, is smaller. To achieve the same mortality reduction as their high-skilled colleagues of the same age, low-skilled workers would need to accept an even higher wage cut. This makes it apparent that low-skilled workers have a high incentive to reduce their on-the-job mortality but they are limited by a lack of wealth and income as well as a tighter link between wages and on-the-job mortality.

Table A6: Marginal effect of wealth on on-the-job mortality and wages by skill group

	Dependent variable: log(on-the-job mortality)					
	Age=50		Age=55		Age=60	
	Low-skilled	High-skilled	Low-skilled	High-skilled	Low-skilled	High-skilled
log(wealth)	−0.281	−0.294	−0.360	−0.387	−0.454	−0.501
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.001)
Constant	2.640	0.750	3.717	2.068	4.987	3.678
	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.007)

	Dependent variable: log(wage)					
	Age=50		Age=55		Age=60	
	Low-skilled	High-skilled	Low-skilled	High-skilled	Low-skilled	High-skilled
log(wealth)	−0.006	−0.001	−0.008	−0.001	−0.009	−0.001
	(0.00001)	(0.00000)	(0.00001)	(0.00000)	(0.00001)	(0.00000)
Constant	7.942	8.348	7.963	8.362	7.973	8.362
	(0.0001)	(0.00001)	(0.0001)	(0.00001)	(0.0001)	(0.00002)

Note: Regressions on simulated data.

Table A7: Descriptive statistics of four alternative simulations with two skill groups (period: month)

Variable		Benchmark				Experiment I[a]				Experiment II[b]				Experiment III[c]			
		Low-skilled		High-skilled		Low-skilled		High-skilled		Low-skilled		High-skilled		Low-skilled		High-skilled	
(a) Population characteristics																	
Population	N	40,609		18,769		40,591		18,770		40,610		18,769		41,882		19,360	
Employed	L	26,646		12,887		29,145		14,119		26,646		12,887		26,793		12,958	
Unemployed	U	2,579		587		2,813		628		2,579		587		2,592		590	
Retired	R	11,384		5,295		8,633		4,024		11,385		5,295		12,496		5,812	
Unemployment rate	$\frac{U}{L+U}$	8.82%		4.36%		8.8%		4.26%		8.82%		4.36%		8.82%		4.35%	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
(b) Endogenous variables (conditional on being employed and below age 65)																	
Probability of dying†																	
– total	$1-\pi(\mathcal{L})$	28.5	(27.7)	28.4	(27.7)	28.7	(27.9)	28.5	(27.9)	28.5	(27.7)	28.4	(27.7)	24.5	(23.7)	24.4	(23.7)
– on-the-job	m	0.43	(0.07)	0.05	(0.01)	0.42	(0.07)	0.04	(0.01)	0.42	(0.06)	0.05	(0.01)	0.42	(0.08)	0.05	(0.01)
On-the-job mortality rate†	μ	5.17	(0.90)	0.56	(0.11)	5.05	(0.82)	0.53	(0.09)	5.03	(0.78)	0.55	(0.08)	5.04	(0.94)	0.55	(0.09)
Wage level	w	2,420	(224)	3,773	(490)	2,370	(244)	3,824	(382)	2,342	(241)	3,778	(377)	2,407	(249)	3,883	(387)
Labor productivity	F/H	3,667	(339)	5,716	(742)	3,591	(370)	5,793	(578)	3,548	(365)	5,724	(572)	3,647	(377)	5,884	(587)
Consumption	c	1,585	(258)	2,367	(387)	1,681	(294)	2,657	(467)	1,513	(291)	2,321	(448)	1,533	(235)	2,360	(363)
Wealth (in 1,000s)	a	116	(79)	201	(151)	113	(78)	216	(149)	100	(67)	210	(143)	109	(77)	223	(156)
Value of Life (in 1,000s)	VoL	9,772	(1,092)	15,966	(1,814)	10,452	(1,035)	18,307	(1,859)	9,171	(731)	15,484	(1,278)	9,823	(1,099)	16,660	(1,912)
Tax rate	τ	0.197		0.197		0.145		0.145		0.239		0.239		0.213		0.213	
Real interest rate	r (in %)	0.14		0.14		0.15		0.15		0.16		0.16		0.13		0.13	
(c) Exogenous variables																	
Baseline mortality	$\ln(\alpha_\pi)$	−9.63		−9.63		−9.63		−9.63		−9.63		−9.63		−9.63		−9.63	
Pension replacement rate	ϕ_R	0.4		0.4		0.4		0.4		0.5		0.5		0.4		0.4	
Retirement age (years)	$\frac{T_R}{12}+20$	65		65		70		70		65		65		65		65	

Notes: †Values reported per 100,000 individuals. [a] Experiment I: higher retirement age; [b] Experiment II: higher pension replacement rate; [c] Experiment III: lower baseline mortality.

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