Workplace Safety:
Estimating Workers' Marginal Willingness to Pay

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Abstract

The aim of the present paper is to empirically estimate the monetary value workers place on safer working conditions. The marginal willingness to pay for workplace safety is estimated using data on job durations together with data on accident risks and wages. The results indicate that individuals value safety to 0.65-4.1 percent of annual wages. Male workers in service occupations are found to have the highest marginal willingness to pay. Female blue-collar workers are found to value workplace safety higher than male blue-collar workers.

JEL classification: J17; J28; J31; J81

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1 Introduction

The analysis in the present paper attempts to quantify the monetary value of reducing the risk of on-the-job accidents by focusing on workers' preferences. Do workers themselves have a positive willingness to pay for increases in workplace safety? Hazardous working conditions and their effects on worker health continue to be an important issue for public policy and the work to reduce working hazards is an ongoing concern. In Sweden, almost 8 out of 1,000 workers[1] suffered injuries causing a loss of workdays in 2006. Risk reduction measures are costly. It is important to quantify the monetary value on the marginal benefits of accident risk reduction, which can be contrasted with the costs of workplace risk reduction measures.

Earlier research have focused mainly on the value of life, i.e. the monetary value of reducing accidents with a fatal outcome. However, the monetary value of non-fatal accidents is also important as accidents can have debilitating and life-changing effects for the individual worker.

To estimate the individual willingness to pay for workplace safety, workers are considered to change jobs during their working life whenever they are offered a job with better work conditions. Here, work conditions are defined as earnings and other job characteristics, such as workplace safety. Using information on work histories obtained from the Swedish Level of Living Survey in 1991, the effect of job characteristics on time spent on a job are estimated. Marginal willingness to pay estimates can then be obtained by using the marginal effects of different job characteristics on the hazard rate, as pointed out by Gronberg and Reed (1984).

Previous research regarding the valuation of workplace safety has focused on estimating hedonic wage functions. In that framework, workers require wage compensation in order to accept a risky job. All other things equal, a higher risk level is coupled with a higher wage (Viscusi, 1992). The main criticism of this approach, as has been pointed out by Viscusi (1992), Garen (1988) and Hwang et al. (1992) among others, is the difficulty to

[1] All industries. National Board of Occupational Safety and Health (2008)

observe all relevant characteristics of workers and firms. Since safety can be considered a normal good it can be expected that workers with higher human capital could possibly select jobs with both higher wages and better working conditions. Hwang et al. (1992) show that if it is not possible to observe workers human capital, estimates of the compensating differential will be biased. The size of this bias can be substantial and may even result in parameter estimates with unexpected signs (Hwang et al., 1992). In a recent paper using Norwegian data, Dale-Olsen (2006) found that search frictions cause a sizeable downward bias when estimating the marginal willingness to pay using a hedonic wage framework.

In the present paper, workers do not necessarily change to a job with higher wages and lower risk. The improvement in wages could be sufficient to offset an increase in risk when estimating the marginal willingness to pay for workplace safety in a search context. By using data on job spells the effect of wages on job durations, and hence on the probability of leaving a job, is separated from the probability of leaving due to hazardous working conditions.

A flexible specification for job durations is applied here. Job durations are considered to be generalized gamma distributed. The specification also allows variables to vary with time and parameters to vary across groups.

The results suggest that workers tend to stay longer in jobs with lower risk rates and higher wages. The average marginal willingness to pay for workplace safety is SEK 415, which is 0.65 percent of annual wages, when workplace safety is measured as the reduction in the number of accidents by 1/1000 employees. When allowing MWP estimates to vary across subgroups, only blue-collar workers and males in service occupations have positive and significant effects of risk on expected duration. Blue-collar female workers are on average willing to forego a larger part of their wages to increase workplace safety, 1.32 percent compared to 0.93 percent for male blue-collar workers. The highest MWP estimates are for male workers in service occupations. They are willing to give up on average SEK 1,703 (4.1

percent of wages) to reduce the number of workplace accidents by 1/1,000 employees.

The outline of the study is as follows. Section 2 describes a model of job-to-job transitions. Data are presented in Section 3, while Section 4 describes the econometric method. Section 5 contains the results while Section 6 concludes.

2 A Model of Job Transitions

Consider a labor market, with imperfections in the sense that workers can not freely choose among jobs, with different wages and nonpecuniary attributes. The current employment is not only a matter of choice, but it also depends on the arrival of job offers. Dissatisfaction with the present job induces workers to search for new jobs to improve their wages and working conditions. Workers will be sorted into employment and unemployment depending on market opportunities. If the offered job is better than the current job, in terms of offering a higher utility, the worker is observed to change jobs, otherwise the offer is rejected and the worker continues with the present job and continues to search. The utility from a job is here considered to depend on wages as well as nonpecuniary job attributes, for instance workplace safety.[2]

The focus is here on modeling the probability of a worker leaving the current job for a new job. The value to a worker of having a specific job can at each instant be summarized by a utility function where the arguments consist of wages and a vector of nonpecuniary job attributes. This instantaneous utility in the present job can be written as $u(w, \boldsymbol{z})$.

Workers are assumed to receive job offers that are random draws from the joint distribution of wages, w, and nonpecuniary attributes, $\boldsymbol{z}$, with distribution function $F(u(w, \boldsymbol{z}))$. Each new job offer arrives according to a

[2]The standard search framework has been extensively described. See, e.g., Rogerson et al. (2005) for an extensive survey of search-theoretic models of the labor market and Eckstein and van den Berg (2007) for a survey of empirical applications of search theory.

Poisson process.

The probability of quitting is given by the product of the probability of receiving a new offer, δ, and the probability that the offered job yields a higher utility than the present job, $1 - F(u(w, \boldsymbol{z}))$. This transition rate from a job can be written

$$\lambda(u(w, \boldsymbol{z})) = \delta[1 - F(u(w, \boldsymbol{z}))]. \tag{1}$$

The transition rate is then the product of a chance element, i.e. the probability of receiving a new job offer, and a choice element, which is the probability that the worker finds the new job better than the current one.

In the basic on-the-job search model the Poisson process generating the job offers is assumed to be time-inhomogeneous. The arrival of new job offers is not dependent on time spent in employment. The process has no memory and each new job offer is independent of all previous offers. Additionally, if the distribution of wage offers is constant we have a stationary model of job search. The transition rate is then constant implying exponentially distributed employment spells.

However, a constant transition rate is restrictive. It could very well be that δ and/or $F(w, \boldsymbol{z})$ change with time. This will result in a non-stationary transition rate. It has been shown that a non-stationary transition rate will arise in a number of different settings, for instance if the reservation wage depends on time (Mortensen, 1986; Jovanovich, 1984), or if there are effects of learning, changes in the cost of search, and changes in the availability of job offers (Lancaster, 1990). van den Berg (1990) analyzed a non-stationary model where the utility of unemployment in the present state, the arrival rate of job offers, and the wage offer distribution are allowed to vary over time. In a non-stationary model of job search the transition rate from job-to-job is given by

$$\lambda(u(w, \boldsymbol{z}), t) = \delta(t)[1 - F(u(w, \boldsymbol{z})|t)], \tag{2}$$

where either or both the probability of receiving a new offer and the instantaneous utility now depend on time.

The transition rate can yield information about workers monetary evaluation of different nonpecuniary job attributes. The marginal willingness to pay for job attributes is given by the marginal utility of the job attribute divided by the marginal utility of wages. As pointed out by Gronberg and Reed (1984), this will equal the marginal effect of the job attribute on the transition rate divided by the marginal effect of wages on the transition rate

$$MWP_k = \frac{\partial u(w, \boldsymbol{z})/\partial z_k}{\partial u(w, \boldsymbol{z})/\partial w} = \frac{\partial \lambda/\partial z_k}{\partial \lambda/\partial w}, \tag{3}$$

where w is wages and z_k is one of $k = 1, 2, ..., K$ non-wage attributes. In a paper by van Ommeren et al. (2000), the validity of Eq.(3) is considered for a number of extensions to the basic search model. They show that the result presented by Gronberg and Reed (1984) will hold in a general model of on-the-job search. Eq. (3) can also be shown to be time-invariant for the generalized gamma family of distributions used in this paper (see Appendix).

3 The Sample and the Variables

Information on employment histories is obtained from the retrospective questions of the 1991 Swedish Level of Living Survey. Individuals are asked about their work experience. All persons that have had, at least, one job lasting six months or more are interviewed about their complete employment history. Besides employment there is information on the following activities: unemployment, education, military service, parental leave, and self-employment. In all, there are complete employment histories for 3,624 individuals. The earliest spell started in 1931 and the latest began in 1991. Durations are measured in months.

The interest here is in the effects of different variables on the probability of changing jobs. The initial sample of job spells consists of a total of 13,406 observations. Job changes are considered to occur when an individual changes employer. Only job spells that began after 1970 are included

Table 1: Sample reduction

		Reduction	Remaining
Initial sample			13,406
	- start year before 1970	4,796	8,610
	- missing start/end date	255	8,355
	- missing risk	644	7,711
	- missing wages	76	7,635
Final sample			7,635

in the analysis due to lack of data on wages before that year. Table 1 gives a complete description of the reductions of sample size. Not very many individuals experience 8 spells or more. These spells are all labeled as job spell 8. The final sample consist of 7,635 job spells.

Descriptive statistics and variable definitions are given in Table 2. Information on wages is obtained from official tax registers and is matched to the interview data. Data on wages are available for the years 1970-1991 and are deflated to the 1991 price level using the Consumer Price Index. Wages are measured in SEK 1,000s.

The risk of injury is used as a measure of workplace safety, where risk of injury are all nonfatal injuries reported to the National Board of Occupational Safety and Health. Reported injuries are those which cause lost workdays. The risk rates are matched to the employment data on the basis of 5-digit industry codes. The risk rate is the annual number of reported work accidents per 1,000 employees in each industry. The number of accidents is available for each year 1970-1991. Using industry averages instead of individual risk data will introduce measurement errors as different types of workers in each industry most likely face different risks, e.g., administrative staff and welders most likely face different risk although employed in the same industry. The type and severity of injuries may also differ both within and across industries. Workers are classified according to occupation type in an attempt to control for these factors. Three distinct

Table 2: Variable description

Variable name	Mean	St.dev.	Description
Job duration	43.96	50.29	duration in months
Wages	104.35	62.83	real annual wages (SEK 1,000s)
Risk of injury	26.80	20.20	accident incidence rate
Excess risk	0.54	0.50	=1 if high risk occupation
Experience	7.03	7.33	work experience in 10's of years
Turnover	5.45	1.14	job turnover manufacturing
Female	0.54	0.50	=1 if female
University	0.07	0.26	=1 if university degree
Small workplace	0.23	0.42	=1 if $<$ 10 workers
Large workplace 2	0.43	0.50	=1 if $>$ 50 workers
Spell 2	0.18	0.38	=1 if worker's $2nd$ job
Spell 3	0.17	0.38	=1 if worker's $3rd$ job
Spell 4	0.14	0.35	=1 if worker's $4th$ job
Spell 5	0.11	0.31	=1 if worker's $5th$ job
Spell 6	0.08	0.27	=1 if worker's $6th$ job
Spell 7	0.06	0.23	=1 if worker's $7th$ job
Spell 8	0.10	0.30	=1 if worker's $\geq 8th$ job
Censoring indicator	0.65	0.48	=1 if not censored

Job turnover has been multiplied by 100 for computational reasons.
Descriptive statistics are for start year when applicable.

groups are identified: white-collar workers, blue-collar workers and service workers. White-collar workers include administrative, executive, sales, and technical workers as well as doctors and nurses. Blue-collar workers comprise production and maintenance staff. Police and firemen, cleaning staff, hairdressers are some of the groups considered as service workers.[3]

Malker (1990) identifies a number of occupations as having excess risk using indirect standardized incidence ratios. The standardized incidence ratios are given by the number of accidents for each occupation divided by the expected number of cases, stratified on age cohorts and geographic region. An indicator variable, excess risk, is created taking the value of one for the occupations identified as having a standardized incidence ratio

[3]White-collar workers (NYK1-NYK339, except NYK42, NYK43, NYK47, NYK48), blue-collar workers (NYK401-NYK889), and service workers (NYK911-NYK981 and NYK42, NYK43, NYK47, NYK48).

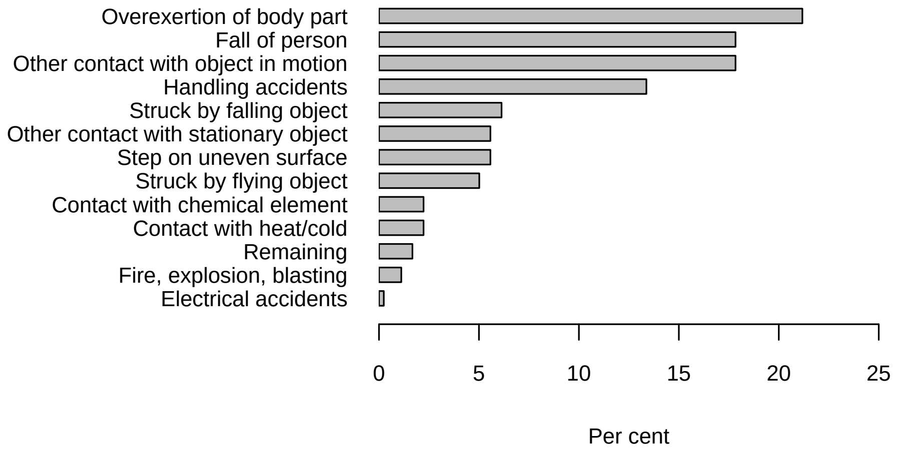

Figure 1: Accidents by type (1991: all industries)

larger than one at least one type of injury.[4]

As can be seen in Figure 1, the most common type of accident is overexertion of body part, closely followed by fall of person and accidents involving moving objects. A comparison of risk rates among industries is given in Figure 2. The number of accidents per 1,000 employees is highest in some manufacturing sectors, fire rescue, and metal ore mining. For the manufacturing sectors butcheries and iron and steel works the accident rate is more than four times as high as the total rate for all industries. The safest sectors are banking, education, and retail.

The exogenously given probability of receiving a job offer δ changes over time as labor market conditions vary. As δ is not known, the rate of job turnover for Swedish manufacturing for the years 1970-1991 is matched to the data. Job turnover rates are from a study by Andersson et al. (2000). For computational reasons this measure is multiplied with 100.

[4]Other variables indicating severity of accidents were also considered. But neither the rate of fatal accidents nor duration of sick leave were found to have any significant effect on the expected employment duration.

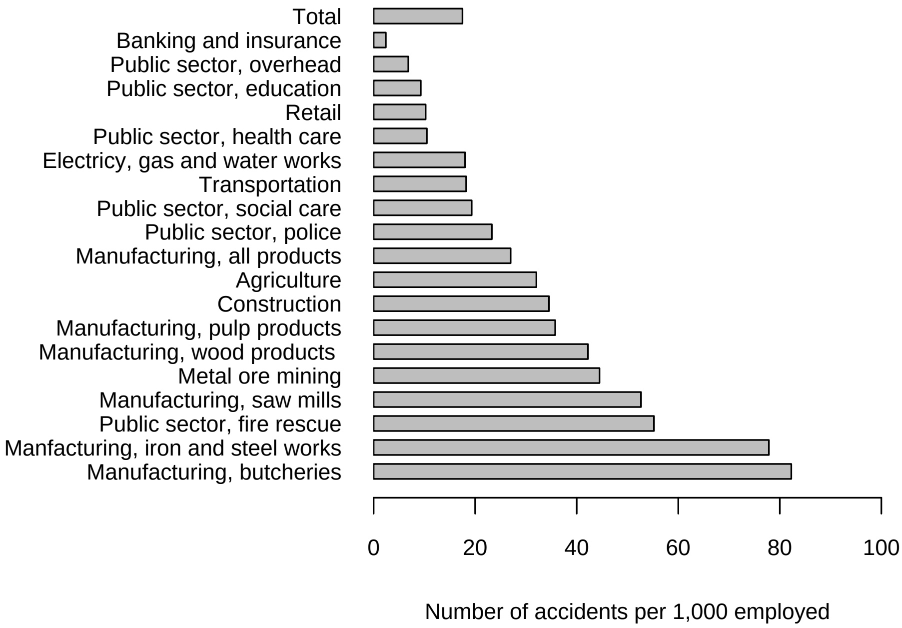

Figure 2: Risk values for different industries (1991)

More recent values of wages, risk, and turnover are more likely to be important than values in the starting year. Also, both the probability of receiving a job offer and the wage offer distribution are likely to change over time. Wages, risk, and turnover are allowed to vary over the course of a job spell to accommodate this. These variables are updated annually, while remaining constant during each calendar year. This expansion result in a data set with 42,317 observations.

A distinction is made between voluntary and involuntary job changes. All moves to unemployment, retirement, or to an unspecified activity are considered to be involuntary. Involuntary job separations are treated as censored observations since the time the individual would have chosen to stay is unknown.

4 Econometric Method

The aim is to estimate the effect of risk and wages on the transition rate of leaving a job in Eq. (2) using data on individuals, each with one or more employment spells. A general formulation of the transition rate allowing for multiple spells, time-varying variables as well as left truncation is

$$h = h(t^*; \boldsymbol{x}_t^m \boldsymbol{\beta}, \theta) \tag{4}$$

where h is a function of $t^* = (t_{0i}, t_i)$, conditional on explanatory variables $\boldsymbol{x}_t^m$, parameters $\boldsymbol{\beta}$, and distribution specific parameters θ. The variables in $\boldsymbol{x}_t^m$ include wages, w, nonpecuniary job characteristics, $\boldsymbol{z}$, and other variables controlling for individual, workplace, as well as labor market characteristics. They may vary with time t and job spell m. Each spell starts at time t_{0i} and ends at time t_i. Left truncation is present as for the first job only spells lasting longer than six months are included in the retrospective survey. Time is measured since the start of each spell.

A parametric approach is used, having the advantage of being more efficient than semi-parametric approaches (Cleves et al., 2004). Given the availability of different distributions, a parametric approach can be very flexible in allowing for different shapes of the hazard function.

As the retrospective study only covers time until 1991, there are a number of job spells that are ongoing (censored) at the time of the survey and for which t^* is not fully observed. The likelihood contribution (Cleves et al., 2004) for observation, i, is

$$L_i = \frac{\{S(t_i; \boldsymbol{x}_t^m \boldsymbol{\beta}, \theta)\}^{1-d_i} \{f(t_i; \boldsymbol{x}_t^m \boldsymbol{\beta}, \theta)\}^{d_i}}{S(t_{0i}; \boldsymbol{x}_t^m \boldsymbol{\beta}, \theta)} \tag{5}$$

where d_i is a censoring indicator equal to one for observations that are not censored. The term in the denominator accounts for truncation.

Durations, t, are considered to be generalized gamma distributed $GG(\theta)$, $\theta = (\tau, \sigma, \kappa)'$. This is a flexible distribution that allows for a variety of shapes of the hazard function and it contains other common distributions as special cases. The $GG(\theta)$ has probability density function

$$f(t) = \frac{|\kappa|}{\sigma t\Gamma(\kappa^{-2})}[\kappa^{-2}(e^{-\tau}t)^{\kappa/\sigma}]^{\kappa^{-2}} \exp[-\kappa^{-2}(e^{-\tau}t)^{\kappa/\sigma}] \tag{6}$$

and survival function

$$S(t) = \begin{cases} 1 - \Gamma(\kappa^{-2}(e^{-\tau}t)^{\kappa/\sigma}; \kappa^{-2}), & \text{for } \kappa > 0 \\ 1 - \Phi(\text{sgn}(\kappa)(\ln(t) - \tau)/\sigma), & \text{for } \kappa = 0 \\ \Gamma(\kappa^{-2}(e^{-\tau}t)^{\kappa/\sigma}; \kappa^{-2}), & \text{for } \kappa < 0 \end{cases} \tag{7}$$

where $\Gamma(b)$ is the gamma function, $\Gamma(a; b)$ is the incomplete gamma function[5], and $\Phi(c)$ is the standard normal distribution.[6]

In the case of the generalized gamma distribution it is easier to parameterize the logarithm of durations, $\ln t$, instead of allowing variables to directly affect the hazard rate. Variables affect t such that $\tau = \ln t - \nu = \boldsymbol{x}_t^m \boldsymbol{\beta}$, where ν is a random disturbance term. This is the standard accelerated failure time formulation.[7]

The transition rate for the generalized gamma distribution can be obtained analytically by dividing Eq. (6) by Eq. (7)), $f(t)/S(t)$. Although the resulting expression for the transition rate is mathematically cumbersome, the marginal willingness to pay for reducing the risk of injury can, using the result in Eq. (3), be shown to be (see appendix A) of the following simple form

$$MWP^{risk} = -\beta^{risk}/\beta^{w}. \tag{8}$$

To facilitate interpretation the minus sign is added to the MWP expression. The interpretation will then be as the marginal willingness to pay for workplace safety and it is the monetary amount workers are willing to forego in order to get a job with increased safety.

Specification tests also indicated that the full generalized gamma specification was found necessary as the model did not collapse into any of

[5]The gamma function is $\Gamma(b) = \int_0^\infty v^{(b-1)}e^{-v}\, dv$ and the incomplete gamma function is $\Gamma(a; b) = \Gamma(b)^{-1} \int_0^a v^{(b-1)}e^{-v}\, dv$.

[6]See Cox et al. (2007) and Stata Corporation (2003) for this parametrization of the generalized gamma distribution.

[7]The model is estimated using the STATA statistical software.

the models nested within the generalized gamma specification (log-normal, Weibull and gamma, respectively).[8]

The linear specification of the mean function was questioned and the inclusion of quadratic terms for risk and wages was tested. For the range of values that is of interest here, this did not alter parameter estimates. Further, the inclusion of quadratic terms lead to a violation of the underlying utility theory as marginal willingness to pay estimates for workplace safety were negative for a substantial number of observations.

Due consideration was paid to testing and allowing for heteroskedasticity. Heteroskedasticity will make parameter estimates inconsistent and will also unpredictably affect the power of the t-test. It is not unlikely that variances differ across groups. An attempt to test and control for heteroskedasticity is made by allowing some of the explanatory variables to affect the scale parameter σ, such that the skedastic function is $\sigma_t^m = \exp(\boldsymbol{y}_t^m \boldsymbol{\gamma})$ (Greene, 2000). When variables enter σ_t^m, the model is no longer an accelerated failure time model (Cox et al., 2007).

The MWP estimates will now differ across spells (see appendix A). Define $a = \kappa^{-2}(e^{-\tau}t)^{\kappa/\sigma_t^m}$ and $s = a^{\kappa^{-2}}e^{-a}/\int_0^a v^{(\kappa^{-2}-1)}e^{-v}\,dv$, where $\tau = \boldsymbol{x}_t^m \boldsymbol{\beta}$ and $\sigma_t^m = \exp(\boldsymbol{y}_t^m \boldsymbol{\gamma})$. The marginal willingness to pay is given by

$$MWP^{risk} = -\frac{\sigma_t^m \gamma^{risk} + \kappa[\kappa^{-2} - a - s][(-\tau + \ln t)\gamma^{risk} + \beta^{risk}]}{\sigma_t^m \gamma^{wages} + \kappa[\kappa^{-2} - a - s][(-\tau + \ln t)\gamma^{wages} + \beta^{wages}]}. \tag{9}$$

Each job spell will have a separate value of the marginal willingness to pay calculated for the final year of each spell.

5 Empirical Results

The estimation results are shown in Table 3. The β parameters are transformed to show the percentage change in expected duration t of a unit

[8]Attempts to test for unobserved heterogeneity by including a heterogeneity term were unsuccessful as the estimation did not converge.

Table 3: Estimation results (percentage changes in t)

	I		II	
Wages	0.74	(16.95)		
Wages-wc, m, u			0.48	(4.10)
Wages-wc, m, nu			0.70	(9.65)
Wages-wc, f, u			0.47	(3.90)
Wages-wc, f, nu			0.60	(8.60)
Wages-bc, m			0.94	(13.75)
Wages-bc, f			0.94	(8.64)
Wages-s, m			0.99	(7.79)
Wages-s, f			0.70	(8.17)
Risk	-0.18	(-2.09)		
Risk-wc, m, u			0.67	(0.87)
Risk-wc, m, nu			-0.10	(-0.40)
Risk-wc, f, u			0.17	(0.26)
Risk-wc, f, nu			0.18	(1.04)
Risk-bc, m			-0.40	(-3.16)
Risk-bc, f			-0.71	(-3.26)
Risk-s, m			-1.45	(-2.17)
Risk-s, f			-0.19	(-0.45)
Excess risk	-7.13	(-2.08)	-10.55	(-2.36)
Turnover	-12.38	(-7.79)	-12.25	(-7.57)
Experience	11.53	(19.19)	11.36	(18.78)
Female	6.76	(1.67)	17.30	(1.44)
University degree	-10.76	(-1.68)	12.25	(0.66)
Small workplace	-12.23	(-3.06)	-12.67	(-3.18)
Large Workplace	13.78	(3.10)	12.67	(2.86)
Job spell 2	-24.06	(-5.82)	-23.44	(-5.66)
Job spell 3	-28.78	(-6.38)	-28.40	(-6.31)
Job spell 4	-43.50	(-10.44)	-43.12	(-10.28)
Job spell 5	-46.53	(-10.59)	-46.26	(-10.43)
Job spell 6	-46.17	(-9.13)	-46.21	(-8.75)
Job spell 7	-49.36	(-8.23)	-48.89	(-8.04)
Job spell 8	-67.02	(-20.35)	-65.90	(-19.20)
Constant	2.92	(21.00)	3.04	(21.36)
ln σ	Details in Table A-1 in Appendix			
κ	-0.208	(-4.08)	-0.213	(-4.00)
Pseudo log-L		-10,226.684		-10,192.961
Number of observations		35,352		35,352
Number of spells		7,635		7,635

Standard scores in parentheses (robust standard errors).
wc=white-collar, bc=blue-collar, s= service.
m=male, f=female, u=university, nu=no university.
Pseudo log-L: since obs are not independent (Sribney, 2005).

change in the independent variables.[9] The results indicate that wages significantly affect job duration. An increase in annual wages by SEK 1,000 implies that expected job duration in months increases by 0.74 percent. Workers with a higher risk tend to stay shorter on a job, albeit this is not significant at the 5 percent level. An increase in the accident rate by 1/1,000 employees will shorten expected duration by 0.18 percent. The other parameters are consistent with prior expectations. Workers in occupations considered to have excess risk have shorter expected durations. In times of high turnover, job durations are shorter. Workers with more work experience have longer job spells. Women have on average 6.76 percent longer durations than men. Workplace size is important. Workers tend to stay longer the larger is the workplace, possibly due to more opportunities for advancement and versatility in work tasks that can be offered in larger organizations. Workers have on average the longest expected duration in the first job as indicated by the parameters for the job spell indicator variables.

Variables are allowed to affect σ in an attempt to control for heteroskedasticity. The parameter estimates for the skedastic function are given in Table A-1 in the Appendix. To summarize, all of the continuous variables and the job spell indicator variables were found to have significant parameter estimates. Estimation results when variables are not allowed to affect σ are given in Table A-2 in the Appendix.

The aggregated risk measure based on industry risk rates does not take into account that the severity and type of prevalent injuries may differ across subgroups. The effects of wages and risk are in model II allowed to vary across subgroups. The wages and risk variables are split into eight separate variables, respectively. The effects may differ across occupational groups, between men and women, and between workers with and without a university degree.

The estimation results, given in the second column of Table 3, indicate

[9]This is achieved by multiplying the parameter estimate by 100 for the continuous variables and by multiplying by $\exp(\beta) - 1$ by 100 for the indicator variables (Hardy, 1993).

that the effect of wages on expected duration differs among the eight groups; an F test for equality of the parameters of the eight wages variables was rejected ($\chi^2(7) = 33.11$), indicating that the parameters are significantly different. Also, all wages parameters are significantly different from zero. The effect of wages on expected duration is largest for blue-collar workers and males in service occupations. The estimates for these groups are about twice the magnitude of that for white-collar workers with a university degree (0.94-0.99 compared to 0.47-0.48). There are no significant differences in estimates between males and females within occupational groups except for workers in service occupations ($\chi^2(1) = 3.89$).

Accident risk significantly reduces expected duration only for blue-collar workers and male service workers. The F test for the equality of the risk parameters was rejected ($\chi^2(7) = 17.42$), indicating that the effect of risk on expected duration is significantly different across groups. Males in service occupations have the largest reduction of expected duration, three times the magnitude of that for males in blue-collar occupations. The difference in risk parameter estimates between male and female blue-collar workers is not significant ($\chi^2(1) = 1.48$).

The parameters for the indicator variables female and university degree are now different from the results in model I. Neither of them are significant and the university degree parameter has the opposite sign. The parameters for the remaining variables are similar to those of model I and will not be elaborated upon.

The goodness of fit has been evaluated utilizing Cox-Snell residuals.[10] Both models were considered to provide an adequate fit to the data. Also, the possible presence of multicollinearity was considered. Estimation results were not altered by excluding variables that could be suspected to be collinear.

Marginal willingness to pay estimates are obtained for both models

[10]The goodness of fit has been evaluated by plotting the transformed Cox-Snell residuals $-\ln(1 - S(t))$ against the expected exponential score (Brännäs, 1992) for all uncensored spells (Nelson, 2003).

Table 4: MWP statistics

	# of spells	Mean	St.dev.	%-mean	%-st.dev.
I: all	4,995	415	130	0.65	1.81
II: bc, m	1,128	695	201	0.93	1.58
II: bc, f	363	748	1	1.32	3.14
II: serv, m	232	1,703	200	4.10	19.38

bc=blue-collar, serv=service, m=male, f=female
Accidents: 1/1,000 employees.
Uncensored observations.
Calculated for the final year of each spell.

according to Eq. (9). Summary statistics are given in Table 4. In model I, assuming homogenous preferences regarding wages and risk, the MWP is on average SEK 415 when accidents are measured as 1/1,000 employees. When allowing preferences to be heterogenous, MWP estimates range from SEK 695 for blue-collar male workers to SEK 1,703 for males in service occupations. This is more than three times the average MWP for model I. The averages are significantly different when performing pairwise two-sample t tests.

The full densities of marginal willingness to pay estimates can be examined in Figure 3. The density for males in service occupations is, however, only slightly overlapping with the densities of the other subgroups. A majority of male workers in service occupations have higher MWP estimates than workers in the other subgroups. Kernel density estimates of the MWP for model I only partly overlap the distributions for the three subgroups. The densities for male and female blue-collar workers overlap, albeit the density for females has less spread.

The MWP estimates are also calculated as percentages of annual wages to get a perspective on the magnitude of the estimates. This also facilitates comparison with estimates from other studies (see below). The mean percentages in Table 4 are significantly different when evaluated by pairwise two-sample t tests. Blue-collar workers are willing to forego on average 0.93/1.32 percent of their wages to increase safety by reducing the number

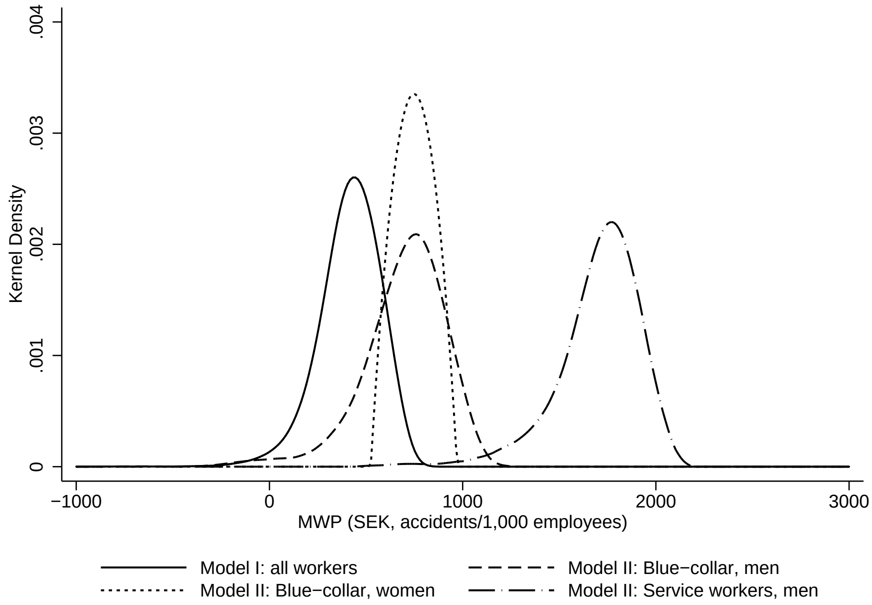

Figure 3: Kernel density estimates of the MWP: by groups
Epanechnikov kernel, bandwidth=100. Uncensored obs.

of accidents by $1/1,000$ workers. Male service workers are willing to forego 4.10 percent of their wages. The average for all workers based on model I is 0.65 percent.

There are significant differences in MWP estimates across subgroups. The results indicate that controlling for the severity and type of injuries is important. The male service workers value safety higher than both other subgroups although the average risk level is less than half (Table 5) (albeit firemen do have on of the highest risk rates, see Figure 2). Workplace injuries encompass a whole range of different types of injuries as briefly described in Section 3. Consider, i.e., injuries caused by kick or blow from person or animal. The occupations represented in the male service subgroup had a much higher percentage in 1981 compared to the overall percentage for the blue-collar subgroup (6.6 percent compared to 1 percent).[11] This type of injury could have more severe consequences for the injured worker. It could also be that this type of injury is perceived as more risky. According to Geller (2001), perceived rather than actual risk is important. Workplace hazards that are considered as, catastrophic, uncontrollable, unusual, and inconsequential are perceived as more dangerous than hazards which are considered controllable, familiar, and understandable. It can be argued that kick/blow injuries to a larger extent have the characteristics described by Geller (2001) than some of other types of injuries.

The positive MWP estimates for female blue-collar workers are interesting. Many earlier studies using hedonic wage equations have failed to find a significant effect of workplace risk on wages for women (Viscusi and Aldy, 2003). One exception is Hersch (1998), who found that female workers do value safety to the same magnitude as male workers (Viscusi and Aldy, 2003). Here, female blue-collar workers value safety more than male blue-collar workers on average.

Most earlier research concerning workplace safety and the monetary valuation of accident risk have estimated wage equations. Viscusi and Aldy (2003) provide a comprehensive review of the research concerning the valuation of both fatal and nonfatal accidents. When comparing results, the concept of the value of a statistical injury is used. The value of a statistical injury (VSI) is the annual amount the average individual would be willing to pay to reduce the number of accidents by one each year. The average MWP of SEK 415 (Table 4) would then correspond to a VSI of SEK 415,000 (in 1991 SEK). The value of a statistical injury is then approximately 650 percent of the annual average income in the present sample. The VSI values reported by Viscusi and Aldy (2003) are mostly in the range USD 20,000-USD 70,000 measured in 2000 USD. The average annual income of the included studies are mostly in the range USD 20,000-USD 35,000.

[11]Typical male service occupations are firemen, police, and wardens in criminal and psychiatric facilities. Blue-collar occupations are predominantly in manufacturing, construction, and transportation.

Table 5: Values of a Statistical Injury

Study	Method	Mean risk	VSI	VSI (% of wages)
Biddle and Zarkin (1988)	Wage eq.	37	USD 155,582	369
Viscusi and Moore (1987)	Wage eq.	38	USD 70,650	162
Dorsey and Walzer (1983)	Wage eq.	30	USD 60,581	280
Dorsey and Walzer (1983)	Wage eq.	30	USD 69,235	320
Dale-Olsen (2006)	Wage eq.	49	NOK 660,372	383
Dale-Olsen (2006)	Duration	49	NOK 5,251,192	3,047
Dale-Olsen (2006)	Duration	49	NOK 8,782,592	5,096
I: all	Duration	27	SEK 415,000	650
II: bc, m	Duration	48	SEK 695,000	930
II: bc, f	Duration	38	SEK 748,000	1,320
II: serv, m	Duration	16	SEK 1,703,000	4,100

Mean risk: the average number of accidents per 1,000 employees.
VSI(% of wages): the VSI divided by average annual wages times 100.
Dale-Olsen (2006) use risk imputed from certified accidents (≥ 3 lost workdays).

Three of the studies (Biddle and Zarkin, 1988; Viscusi and Moore, 1987; Dorsey and Walzer, 1983) use a similar risk measure as the present study; the rate of nonfatal accidents causing a loss of workdays. In Table 5, the results of these three studies are summarized. The studies have VSI values that are in the upper range of the results reviewed by Viscusi and Aldy (2003). In order to make the results comparable, the VSI estimates reported for each study have been recalculated as a percentage of wages[12] for the respective study (the rightmost column in Table 5). The higher VSI to income for the present study could be evidence of the downward bias that was pointed out by Hwang et al. (1992), that arise when human capital is not fully observed in a hedonic wage equation model.

Also reported, are results from a Norwegian study by Dale-Olsen (2006), who compares results using both a hedonic wage equation and a search framework. The wage equation estimates from Dale-Olsen (2006) are also in the upper range when compared to average wages. The VSI estimates from the duration regressions are substantially higher, however. One explanation

[12] The same calculation is used by Cahuc and Zylberberg (2004) to compare results across studies. They call it the price expressed in years of wages.

could be the difference in risk measures that is used compared to the other studies in Table 5. Dale-Olsen (2006) use an imputed risk measure based on physician certified injuries with at least three lost workdays. The average risk is also higher.

6 Concluding Remarks

The results indicate that Swedish workers have substantial willingness to pay for increased workplace safety. The willingness to pay to reduce the number of accidents by one each year range from SEK 415,000 to SEK 1,703,000 (1991 prices).

The results confirm earlier research concerning the underestimation of the MWP using hedonic wage equations. The MWP estimates here are higher and in line with other studies using a job search framework. The present study further indicate that using an aggregated risk measure, such as industry risk rates, poses questions regarding the reliability of estimates, especially when a wide group of workers is included. Allowing MWP estimates to differ across subgroups is important. An area for further research is to extend the analysis by allowing preferences to vary over a wider range of subgroups. With access to less aggregated data, interesting conclusions regarding differences in workers' preferences could be reached. It would also be interesting to analyze workers willingness to pay for specific types of injuries.

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Appendix

The marginal willingness to pay in Eq. (3) for the generalized gamma distribution will, in the case where variables enter $\tau = \boldsymbol{x}_t^m \boldsymbol{\beta}$, be

$$MWP^{risk} = \frac{\beta^{risk}}{\beta^{wages}}. \tag{A-1}$$

This is obtained by taking the quotient of the derivative of the transition rate for each of the variables risk and wages. The transition rate for the generalized gamma distribution can be written

$$r(\sigma)s(a) \tag{A-2}$$

where $r(\sigma) = |\kappa|/\sigma t$, $s(a) = p(a)/q(a)$ (where $p(a) = a^{\kappa^{-2}} e^{-a}$ and $q(a) = \int_0^a v^{(\kappa^{-2}-1)} e^{-v}\ dv$), and $a = \kappa^{-2}(e^{-\tau}t)^{\kappa/\sigma}$. Then the derivative of the transition rate with respect to x_j is

$$r(\sigma)\frac{\delta s}{\delta a}\frac{\delta a}{\delta \tau}\frac{\delta \tau}{\delta x_j} \tag{A-3}$$

and Eq. (A-1) immediately follows.

The marginal willingness to pay in Eq. (3) for the generalized gamma distribution will, in the case where variables enter $\tau = \boldsymbol{x}_t^m \boldsymbol{\beta}$ and $\sigma = \exp(\boldsymbol{y}_t^m \boldsymbol{\gamma})$, be

$$MWP^{risk} = \frac{\sigma\gamma^{risk} + \kappa[\kappa^{-2} - a - s][(-\tau + \ln t)\gamma^{risk} + \beta^{risk}]}{\sigma\gamma^{wages} + \kappa[\kappa^{-2} - a - s][(-\tau + \ln t)\gamma^{wages} + \beta^{wages}]}. \tag{A-4}$$

Here the derivative of the transition rate Eq. (A-2) with respect to variable x_j is:

$$\frac{\delta r}{\delta \sigma}\frac{\delta \sigma}{\delta x_j}s + r((\frac{\delta p}{\delta a}q - p\frac{\delta q}{\delta a})/q^2)(\frac{\delta a}{\delta \sigma}\frac{\delta \sigma}{\delta x_j} + \frac{\delta a}{\delta \tau}\frac{\delta \tau}{\delta x_j}) \tag{A-5}$$

and Eq. (A-4) follows after some calculations.

Table A-1: Estimation results for the skedastic function (changes in ln σ)

	I		II	
ln σ: Wages	0.001	(5.27)		
ln σ: Wages-wc, m, u			0.001	(1.55)
ln σ: Wages-wc, m, nu			0.001	(1.58)
ln σ: Wages-wc, f, u			0.000	(0.53)
ln σ: Wages-wc, f, nu			0.001	(2.83)
ln σ: Wages-bc, m			0.001	(4.53)
ln σ: Wages-bc, f			0.001	(1.15)
ln σ: Wages-s, m			0.002	(3.50)
ln σ: Wages-s, f			0.000	(0.60)
ln σ: Risk	-0.001	(-2.11)		
ln σ: Risk-wc, m, u			-0.004	(-1.02)
ln σ: Risk-wc, m, nu			0.001	(0.52)
ln σ: Risk-wc, f, u			-0.005	(-0.67)
ln σ: Risk-wc, f, nu			-0.003	(-2.79)
ln σ: Risk-bc, m			-0.002	(-3.21)
ln σ: Risk-bc, f			0.000	(-0.42)
ln σ: Risk-s, m			-0.004	(-1.22)
ln σ: Risk-s, f			0.002	(1.08)
ln σ: Turnover	-0.020	(-2.34)	-0.015	(-1.79)
ln σ: Experience	0.028	(13.28)	0.028	(12.83)
ln σ: Job spell 2	0.268	(6.50)	0.262	(6.34)
ln σ: Job spell 3	0.301	(7.08)	0.296	(6.93)
ln σ: Job spell 4	0.314	(7.03)	0.318	(7.09)
ln σ: Job spell 5	0.258	(5.40)	0.260	(5.41)
ln σ: Job spell 6	0.282	(5.27)	0.281	(5.23)
ln σ: Job spell 7	0.329	(5.52)	0.338	(5.64)
ln σ: Job spell 8	0.216	(4.18)	0.225	(4.34)
ln σ: Constant	-0.040	(-0.70)	-0.047	(-0.81)

Standard scores in parentheses (robust standard errors).
wc=white-collar, bc=blue-collar, s= service.
m=male, f=female, u=university, nu=no university.
Pseudo log-L: since obs are not independent (Sribney, 2005).

Table A-2: Estimation results (σ constant, percentage changes in t)

	I		II	
Wages	0.58	(13.83)		
Wages-wc, m, u			0.33	(4.13)
Wages-wc, m, nu			0.55	(8.25)
Wages-wc, f, u			0.39	(3.10)
Wages-wc, f, nu			0.50	(6.94)
Wages-bc, m			0.82	(11.20)
Wages-bc, f			0.85	(7.20)
Wages-s, m			0.89	(6.60)
Wages-s, f			0.64	(7.41)
Risk	-0.23	(-2.41)		
Risk-wc, m, u			1.29	(2.15)
Risk-wc, m, nu			-0.26	(-0.95)
Risk-wc, f, u			0.01	(0.02)
Risk-wc, f, nu			0.11	(0.48)
Risk-bc, m			-0.43	(-2.98)
Risk-bc, f			-0.75	(-3.21)
Risk-s, m			-1.42	(-1.73)
Risk-s, f			-0.34	(-0.76)
Turnover	-11.13	(-6.95)	-11.25	(-6.95)
Experience	7.99	(17.20)	7.96	(17.12)
Excess risk	-4.95	(-1.29)	-2.52	(-2.70)
Female	8.90	(1.91)	19.09	(1.42)
University degree	-14.55	(-2.18)	9.36	(0.47)
Small workplace	-12.84	(-3.00)	-12.25	(-2.85)
Large Workplace	17.17	(3.40)	15.25	(3.07)
Job spell 2	27.94	(3.37)	27.06	(3.33)
Job spell 3	25.67	(2.93)	23.85	(3.79)
Job spell 4	3.48	(0.43)	2.09	(0.27)
Job spell 5	1.20	(0.14)	-0.49	(-0.06)
Job spell 6	0.29	(0.03)	-0.92	(-0.10)
Job spell 7	-7.25	(-0.71)	-8.07	(-0.80)
Job spell 8	-34.71	(-5.49)	-35.32	(-5.67)
Constant	2.99	(25.99)	2.97	(22.62)
ln σ: Constant	0.35	(23.50)	0.35	(22.55)
κ	0.17	(3.28)	0.19	(3.46)
log pseudo-L		-10,427.43		-10,401.70
Number of observations		35,352		35,352
Number of spells		7,635		7,635

Standard scores in parentheses (robust standard errors).
wc=white-collar, bc=blue-collar, s=service.
m=male, f=female, u=university, nu=no university.
Pseudo log-L: since obs are not independent(Sribney, 2005).