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ABSTRACT

The Value of a Statistical Injury: New Evidence from the Swiss Labor Market*

We study the monetary compensation for non-fatal accident risk in Switzerland using the number of accidents within cells defined over industry x skill-level of the job and capitalizing on the partial panel structure of our data which allows us to empirically isolate the wage component specific to the employer. Our results show that using accident risk at a lower level of aggregation, using narrower samples of workers, and using the wage component that is specific to the firm all yield higher estimates of risk compensation. Our preferred estimate gives an estimate of about 36,000 Swiss francs per prevented injury per year.

JEL Classification: J17, J28, J31

Keywords: compensating wage differentials, value of a statistical injury, risk measurement

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1 Introduction

Empirical studies document a remarkable increase in the value of life in the past few decades (Costa and Kahn, 2004) and a more general increase in the value of nonmarket goods like health and longevity (Costa and Kahn, 2003; Murphy and Topel, 2006). One important part of this more general trend in the price of health is workers' willingness to pay for the prevention of workplace-related accidents, both fatal and non-fatal. It is also the compensation for workplace safety which has attracted most interest in the empirical literature, and there is a large number of empirical studies which try to pin down the compensation for accident risks, as well as for a wide range of other job amenities and disamenities (the surveys by Viscusi and Aldy (2003) and Viscusi (1993) are of special interest here; see also the more recent survey by Ashenfelter (2006)).[1] Most empirical studies find a positive compensation for fatal accident risk, often yielding high implicit values of a statistical life. For example, Viscusi and Aldy (2003) report that half of the studies from the U.S. labor market surveyed in their article give a value of a statistical life within the range of \$3.8 to \$9.0 million (in prices of 2000), the median estimate being about \$7 million. Most studies from outside the U.S. labor market give estimates within the same range. It is difficult to assess the exact reasons for this wide range of estimates, since the studies differ in various ways, for example with respect to the available data and risk measure[2], or in the econometric methods applied. The evidence on the compensation for non-fatal accident risk is much less coherent, which is somewhat surprising since most studies that present estimates of such compensation are based on the same data as estimates for the compensation for fatal accident risk. Viscusi and Aldy (2003) report, for both the U.S. as well as other labor markets, a probable range for the value of a statistical injury of about \$20,000 to about \$70,000 per injury.[3] Very similar estimates of the value of injury are reported in Leeth and Ruser (2003). Moreover, they also point out considerable differences between different demographic groups. Relatedly, a recent study by Wei (2007) reports substantial wage compensation for job-related illness periods, ranging from 27% up to 140% of annual earnings per prevented illness episode per year.

The key problem from the empirical point of view is the potential sorting of workers into jobs differing in their risk of accidents. Hwang *et al.* (1992), among others, argue that the problem of main concern are differences in unobservables which in turn relate to the productivity of workers and thus may lead to sorting of workers into jobs with different risks. The sorting of workers in turn is endogenous due to the fact that the income elasticity of the value of a

[1] Compensating wage differentials have also been found, for example, for the risk of unemployment (Lalive *et al.*, 2006; Moretti, 2000), for shift work (Kostiuk, 1990), and uncertainty with respect to future earnings (Feinberg, 1981). Stern (2004) studies the compensating wage differential for being a scientist.

[2] Most importantly perhaps, some studies rely not on direct measures of risk (i.e. number of accidents), but base their analyses on tradeoffs outside the labor market, e.g. on the tradeoff between traffic accidents and the price of automobiles (Dreyfus and Viscusi, 1995) or fatalities related to bicycle accidents and the prize of bicycle helmets (Jenkins *et al.*, 2001). Other studies have used subjective assessments of risk, as for example Viscusi and O'Connor (1984) and Viscusi and Hersch (2001).

[3] See table 5(a) and table 5(b) in Viscusi and Aldy (2003) for an overview of the relevant literature and the corresponding estimates of the value of a statistical injury.

statistical life or injury is positive, i.e. more productive workers sort themselves into less risky jobs by accepting ceteris paribus lower wages. Viscusi and Aldy (2003), for example, report an income elasticity of about 0.5-0.6. On the other hand though, Shogren and Stamland (2002) argue that the bias in estimating the compensating wage differential could run in the other direction, assuming that workers not only differ in their productivity, but also with respect to their skill in avoiding accidents. Thus, workers in risky jobs could be either more tolerant to risk or more skilled in avoiding risk (or both). Thus they show that the estimated risk compensation might actually be upward biased, rather than downward biased. Some studies have tried to approach the problem of endogenous sorting by using instrumental variables (DeLeire and Levy, 2004; Garen, 1988, for example,).[4] One potentially promising way of dealing with the problem of sorting is to rely on panel or, ideally, matched employer-employee data (Dale-Olsen, 2006; Woodcock, 2008). The second important empirical issue concerns the measurement of the risk of an accident. First, as pointed out by Mellow and Sider (1983) for example, typical survey data are more often than not plagued by measurement error, i.e. it seems to be the case that workers often misreport their industry affiliation and/or their exact occupation. Assuming that this kind of measurement error is random, this causes the compensating differential to be biased towards zero (Black and Kniesner, 2003). Second, there clearly is a trade-off of the following form. On the one hand, risk measurements at a low level of aggregation are preferred, as otherwise one might mix workers with very different occupations into the same risk categories, giving rise to aggregation bias (Lalive, 2003). On the other hand though, risk measures at a low aggregation level run into the problem that many cells will have zero risk, at least for shorter periods of time. This is specifically true for fatal accident risk, yet obviously also applies to non-fatal injuries.

Our study presents empirical evidence on the compensation for non-fatal accident risk in Switzerland. Our study has three main features. First, we will exclusively focus on non-fatal accidents. This focus reflects the fact that most accidents have non-fatal consequences and thus, from the viewpoint of public health and safety, merit the most attention. We though acknowledge that our focus is also due to data availability well as the empirical approach we take, as we will discuss in more detail below. In the year 2004 (which is the year of our empirical analysis), for example, the Swiss Accident Insurance Fund reports about 246,000 non-fatal accidents related to work, but only 188 fatal accidents. The relative risk of experiencing a non-fatal accident versus a fatal accident in a given year is thus about 1300 times higher. Second, we observe the number of non-fatal accidents not only within entire industries, but also within cells defined by industry×skill-level of the job. This is a tremendous advantage from an empirical point of view, since risks at (too) high levels of aggregation mix the risks of very different groups of workers and different willingness to pay for avoiding risk, which might lead to biased estimation of the compensation for risk in the workplace. Third, we capitalize on the

[4] The study by Garen (1988), for example, tries to correct for the endogeneity of job risk by using a system of simultaneous equations where marital status and the number of dependents are used as instruments for the preference over risk. However, one might argue that both marital status and family size are not very good instruments because they are potentially correlated with risk preferences.

availability of longitudinal wage information, which allows us to use simple panel estimation methods in order to isolate the firm wage component. We believe that our empirical approach, on the one hand using the number of non-fatal accidents within narrower cells than usually available, and on the other hand combining panel data estimation methods with simple non-parametric stratification, transcends the typical hedonic wage function approach often used in the literature on the subject. Besides, we also complement previous evidence for Switzerland. To the best of our knowledge, there is only a single published study on the compensation of accident risk for Switzerland by Baranzini and Ferro-Luzzi (2001), though focusing on fatal accident risk only. The main findings of our empirical analysis are the following. First, we find that a simple hedonic wage regression yields a compensation for non-fatal accident risk which is statistically zero, a result that is in line with some previous empirical studies. The leading explanation for this result (which runs counter to theory) is presumably the sorting of workers which differ in their unobserved productivity. Second, moving on to, in a sense, more sophisticated (but, we believe, in this case also more reliable) methods, we find a positive point estimate for the compensation of non-fatal accident risk. Our preferred point estimate yields an implicit value of a statistical injury of about 36,000 Swiss francs (which lies well within the range given by studies from the U.S. labor market, as well as from studies outside the U.S.). On the other hand, using different estimation methods yields considerably different values for the value of a statistical injury.

The remainder of this paper is organized as follows. In section 2, we discuss the two data sources we rely on and the construction of the key variables – along with some descriptive statistics. The empirical analysis is presented and discussed in section 3. Specifically, we will discuss three different approaches to identification and estimation. We start with a simple hedonic wage regression model, where the wage is simply regressed on individual- and firm-specific characteristics. The second approach is based on the idea that we can control for individual unobserved heterogeneity by an appropriate stratification of the sample. The third approach capitalizes on the longitudinal structure of the wage data. We isolate the wage component, which is specific to the firm and then use only this part of the wage to estimate risk compensation. Based on our econometric results, we further present estimates of the value of a statistical injury in Switzerland. Section 4 concludes.

2 Data

Our primary data source is the Swiss Wage Structure Survey (SWSS; "Lohnstrukturerhebung (LSE)"), a biannual survey among firms which is administered and made available by the Swiss Federal Statistical Office. The SWSS is one of the largest official surveys in Switzerland focused mainly on employment-relevant information.[5] The SWSS is a survey of firms, covering

[5]The second important labor market survey is the Swiss Labor Force Survey (SLFS; "Schweizerische Arbeitskräfteerhebung (SAKE)"). There are two main advantages of using the SWSS over the SLFS: First, the SWSS allows isolating the wage firm fixed effect, which is the part of the observed wage where risk compensation should show up. Second, the SWSS is (as opposed to the SLFS) mailed to employers, and misclassification of

the population of large firms along with a random sample of small firms. We use three different waves of the SWSS (from the years 2000, 2002, and 2004) and we extract individual monthly earnings along with several individual-specific characteristics (see section 2.1 below on details). The SWSS includes average gross monthly wages for full-time employment (i.e. 172 hours per month), including mandatory social security contributions and extra pay (e.g. for night work, 13. monthly wage). The SWSS also includes several socio-demographic characteristics (e.g. age, gender, tenure, educational attainment (highest degree), citizenship) and different firm characteristics (most importantly, the size of the firm along with it's geographic location).

Our risk measure corresponds to the number of non-fatal accidents within cells defined over industry (forty different industries on a two-digit level) and skill-level of the job (four different levels). The data have been provided by the Swiss Accident Insurance Fund (SAIF; "Schweizerische Unfallversicherungsanstalt (Suva)"), which is the most important accident insurance fund in Switzerland. The number of non-fatal accidents within industry×skill-level cells are available for the year 2004. One of the main features of our analysis is that our risk measure r_k gives the number of non-fatal accidents per year and per 1,000 workers within a given industry×skill-level cell k (instead of within-industry only). Data on the absolute number of non-fatal accidents for the year 2004 is available within cells defined over industry×skill-level of job. Now, because the SAIF does not directly have the number of workers within these cells and because workers are not uniformly distributed over these cells, we also need to know the distribution of workers over these cells in order to compute the risk of a non-fatal accident. To this end, we simply use the distribution of workers in the SWSS (from the year 2004), and then approximate the population distribution of workers by multiplying the number of workers within a given cell with the total number of workers which are covered by the SAIF (about 1.827 millions in the year 2004).[6] One main advantage of our data is that measurement error in the risk data and industry-affiliation of workers is arguably of minor significance (as already mentioned, Mellow and Sider (1983) have pointed out the problem of misclassification of both industry and occupation). This is important because measurement error in the risk variable tends to bias the compensating wage differential towards zero (measurement error in the dependent variable (i.e. wage) is, of course, also common but of less concern). We are confident that measurement error for both our risk measure and industry-affiliation is of no great importance, since the SWSS does not involve employees but obtains the data from the employer directly (such that misclassification of either industry and/or occupation is unlikely to occur). For the same reason, we also believe that our wage information is more reliable

occupations and industries should therefore be of minimal order only (the same is arguably true for wages).

[6]Note that there is a fundamental trade-off with respect to the risk measure chosen: On the one hand, risk measures on a highly disaggregated level are preferred, such that we do not pool accident risks of individuals working in very different occupations and jobs. This has been pointed at, for example, by Viscusi (1993, p.1928), noting that "[t]he main deficiency of industry-based data is that they pertain to industry-wide averages and do not distinguish among the different jobs within that industry [...]". On the other hand, accidents observed at a very low level of aggregation also give rise to estimation problems, because the number of accidents tends towards zero for most cells if we shrink the size of the risk-relevant cells. That, in fact, is the reason why we decided not to use the information about fatal accidents for this study. Disaggregating the number of fatal accidents over the skill-level of job actually yields far too many cells with zero number of accidents.

than the information available in typical survey data (although presumably less reliable than administrative data). Additionally, our risk measure is directly obtained from administrative sources and should thus cover all relevant accidents.

2.1 Descriptive Statistics

Table 1 shows descriptive statistics for both the overall sample as well as the sample of individuals in jobs of the lowest skill-level (that will be used in the empirical analysis discussed below). In both samples, we only consider workers aged between 16 and 64 (for men) and between 16 and 61 (for women). A second restriction applies to the size of the employer. Because we are estimating wage fixed effects for each firm, we also restrict the sample to workers from firms which have at least ten workers in each of the four job skill-levels in each year. The overall sample includes more than one million individual workers, the subsample of workers in the lowest skill-level (with respect to the job, *not* with respect to the educational attainment of the worker) consists of about 300,000 individual workers. In both cases, there are about 3,500 different firms (due to the restriction on firms). As we will discuss in-depth in section 3 below, our preferred estimation approach will focus exclusively on workers within a given skill-level as collected in the SWSS, as we believe that such a stratification of the workers yields more reliable estimates of the compensating wage differential.

Table 1

We begin with describing the overall sample, which is representative of the Swiss labor market as a whole. The typical worker in the Swiss labor market has gross earnings equal to 6,300 Swiss francs a month, is about 40 years old and has about 9.5 years of tenure and is more likely to be a man. The average employer has more than 2,800 workers (reflecting the sampling structure of the SWSS as well as the restriction with respect to the selection of the employers). About two thirds of the workers are married, the other third single. The distribution of workers with respect to educational attainment highlights two important characteristics of the Swiss labor market in terms of education. First, compared to other countries, the number of workers with tertiary education is rather low (e.g. only about 5.5% of the workers have a university degree). Second, about half of the workers hold a vocational training. Another important characteristic of the Swiss labor market is the large fraction (about 20%) of workers without Swiss citizenship.

Focusing on individuals working in jobs with the lowest skill-level yields the expected result that some groups are overrepresented in the analysis sample relative to the overall sample of individuals (although this subset of individuals is similar to the overall sample with respect to some characteristics, for example age and size or the geographic location of the employer).[7] Here, average monthly earnings are only about 70% of the overall average earnings (about 4,500 Swiss francs per month). Moreover, a worker from skill-level four is more likely to be a woman,

[7]The distribution of workers over the skill-level of jobs looks as follows: About 6% work in the highest level, about 20% in the second-highest level. 46% work in skill-level 3, and the remaining 28% of the workers are in jobs of lowest skill-level.

more likely to be married and much more likely not to have Swiss citizenship, compared with a worker from the overall sample. The most striking difference between the overall sample and the lowest skill-level sample though is the distribution of workers with respect to educational attainment. As table 1 shows, there are practically no workers with an educational degree above vocational training. This, in fact, is a desired result with respect to the empirical approach we take (see section 3 below): Given that education (of course not exclusively) reflects differences in productivity, focusing on workers with similar educational attainment also implies that these workers are more similar with respect to unobserved productivity-relevant characteristics (compared to workers from all job skill-levels). We believe that the variance of unobserved productivity is presumably lowest within the group of workers in the lowest skill-level (although this presumption obviously is fundamentally empirically untestable).

Figure 1

As table 1 also shows, the typical worker in the year 2004 was faced with the risk of a non-fatal, work-related accident of about 8.8% (i.e. there were 88 accidents on average per 1,000 workers). In the sample of workers with lowest skill-level, the average risk was about half (about 43 accidents per 1,000 workers). Figure 1 shows a simple scatterplot between the average logarithmic monthly wage and the number of non-fatal accidents for workers from the lowest skill-level jobs at the level of industry×skill-level. The scatterplot shows no relation whatsoever between the two variables (if anything, the association goes the "wrong" way), which is underlined by the estimated slope coefficient from a regression of the average log earnings on the number of accidents – yielding essentially a zero point estimate, both in economic and statistical terms (the corresponding t-value is approximately zero). This result is not especially surprising though since average wages within industries clearly may not only reflect differences with respect to accident risks, but also differences in the composition of workers and jobs. We thus now move on to issues of identification and econometric estimation.

3 Empirical Analysis

We now discuss issues of identification and estimation of the compensating wage differential for (non-fatal) accident risk using different alternative empirical approaches along with the corresponding results. We start with a simple hedonic wage regression of the following form:

$$y_{ijk} = \alpha + x_i'\beta + z_j'\gamma + \delta r_k + u_{ijk}, \tag{1}$$

where y_{ijk} is the natural logarithm of the gross monthly wage of individual i, working in firm j and industry×skill-level cell k. x is a column vector of individual characteristics including citizenship, educational attainment, age (and its square), tenure (and its square), a gender-dummy and marital status. z is a column vector of characteristics describing the firm (and thus reflecting the characteristics of the job), and includes the size of the firm (and its square) and the geographical location of the firm. r is our risk measure, corresponding to the number of non-fatal accidents in industry×skill-level cell k per 1,000 workers in the year 2004. u_{ijk} is the unobserved error term. The parameter of main interest is δ, which, under appropriate assumptions, corresponds to the compensating wage differential for non-fatal accident risk. As mentioned before, the number of non-fatal accidents is only available for a single point in time, so that we can essentially only run a cross-sectional hedonic wage regression.[8] However, we do have a partial panel structure with respect to wages, which we will try to capitalize on later. However, as has been pointed out by several authors (e.g. Hwang *et al.*, 1992), there is good reason to act on the assumption that there is unobserved individual heterogeneity related to wages (that is, these differences somehow reflect differences in productivity not taken into account for by observed variables) *and* that "safety" is a normal good (i.e. the demand for "safety" increases as income rises). Thus, workers of high productivity sort themselves into less risky jobs by accepting lower wages ceteris paribus. To stick with the model from equation (1), the hedonic wage regression with unobserved individual heterogeneity made explicit can be written as:

$$y_{ijk} = \alpha + x_i'\beta + z_j'\gamma + \delta r_k + \theta_i + \epsilon_{ijk} \tag{2}$$

where $(\theta_i + \epsilon_{ijk})$ corresponds to the error term u_{ijk} in equation (1) whereby now we make the problem of individual heterogeneity explicit (for simplicity, θ is rescaled such that the partial effect of θ on y is equal to 1).[9] Now, even if we can assume that ϵ_{ijk} *is* mean independent of the regressors, identification of the compensating wage differential δ is only achieved if the unobserved effect θ is also mean independent. Whenever there is reason to believe otherwise, parameter δ is not identified (and neither are the other parameters identified, but that is of minor importance for our purposes, since we are not per se interested in these parameters).

As discussed in the introduction, the leading reason for a correlation between θ and the accident risk r is that θ reflects unobserved productivity, which is obviously related to the wage y. If the demand for safety actually increases with income and if we are, at the same time, unable to adequately control for productivity differences, then this could quite plausibly lead to a correlation between θ and r. That is, more productive workers (i.e. workers with above-average θ) sort themselves into less-risky jobs by accepting lower wages, which in turn leads to a correlation between the productivity measure θ and the risk measure r, meaning that identification of the risk compensation parameter δ must ultimately fail.

Also note that the key regressor, the accident risk r, is measured at a higher level of aggregation than the dependent variable and this needs to be taken into account when doing statistical inference (Moulton, 1986). We therefore use robust standard errors, clustered at the

[8] Many, if not most, other empirical studies face the same problem of not observing the relevant risk measure over time, as pointed out by Hwang *et al.* (1992, p.836): "While studies of this sort [i.e. panel studies] represent improvements over standard cross-sectional studies, their applicability is restricted by the availability of longitudinal data sets that include the relevant nonwage job attribute variables. In most cases, this is a binding constraint."

[9] Note that the error term ϵ_{ijk} potentially also includes unobserved heterogeneity with respect to the firm (Woodcock, 2008). We will take up this issue below.

same level as the risk measure, i.e. either on the industry level or on the level of industry×skill-level of the job.

3.1 Sample Stratification

A first and straightforward way of dealing with the problem of sorting is to stratify the sample in such a way as to minimize the variation in the unobserved error component θ. That is, we run the very same hedonic wage regression as given by equation (1), but only on a narrow(er) subset of individuals. Ideally, this subset consists of individuals presumably as similar as possible with respect to θ. That is, stratification is the simple non-parametric variant of the hedonic wage regression before. However, since most often it is very difficult to control for θ, we think that stratifying the sample is probably a more fruitful approach. Our stratification variable of primary interest is the skill-level of the job, which is recorded in the SWSS. Let $s_{ij} \in \{1, 2, 3, 4\}$ be the skill-level of individual i working in job j, where $s = 1$ ($s = 4$) corresponds to the highest (lowest) skill-level of a given job. We thus run the same hedonic wage regression as in equation (1), but only on a subset of individuals within a given skill-level s. Specifically, we will run the following regressions:

$$y_{ijk} = \alpha + x_i'\beta + z_j'\gamma + \delta r_k + u_{ijk} \quad s_{ij} \geq s \in \{1, 2, 3, 4\} \tag{3}$$

Note that this approach to estimation is basically the same as the control function approach, the main difference being that stratification allows *all* parameter estimates to vary between different subsets of the sample[10]. However, we think it plausible that the main advantage of the stratification is that we can minimize variation in θ in this way, which ideally renders a consistent estimate of the compensating wage differential δ.[11]

Table 2

Table 2 shows the estimated parameters of the compensation for non-fatal accidents. The first column in each panel of table 2 shows estimates when using accident risk at the level of industry×skill-level of the job, while the second column uses accident risk at the industry level only. Estimated parameters of the hedonic wage function, as given by equation (1), are given in column (1) and (2) of table 2. The point estimate of the non-fatal accident risk is negative in both cases (-0.00005 and -0.00015, respectively), although statistically not different from zero (t-value of about 0.8 and 1.3, respectively). This result is in fact in line with either

[10] That is, the control function approach yields the same estimates as sample stratification if all parameters would be interacted with the variable on which stratification is based on. However, such a fully interacted regression model is, due to the large number of parameters to be estimated, often difficult to interpret.

[11] As we will show later, our stratification approach actually reduces the differences between groups of workers with respect to the observed wage (on this point, see table 4). For example, in the overall sample the difference in mean monthly earnings between men and women amounts to about 1,700 Swiss francs (about one third relative to the female average). In the subsample of workers within the lowest skill-level, the difference in average earnings amounts to only about 630 Swiss francs (relative to the female average, a bit less than 15%). Although this is only suggestive evidence, we still believe that this exactly what one would expect if the presumption holds that the variance in θ is lower in the lower skill-levels of jobs.

endogenous sorting of workers. As already discussed, the leading explanation for the "wrong" sign of the risk variable is endogenous sorting of workers into jobs with different risks. As we do not put much confidence in this simple hedonic wage regression, so we quickly move on to the next results.

The remaining columns in table 2 also show parameter estimates from a simple hedonic wage regression, but only for a subset of workers each. As we narrow the range of the skill-level, the point estimate of risk compensation moves towards the expected direction. Focusing on workers in the lowest skill-level only yields a positive point estimate on the risk measure ($\hat{\delta} = 0.00024$), which moreover is almost statistically significant on the 10% level (t-value of 1.63). Using the risk measure at the industry level also yields a positive, but much smaller and statistically not significant point estimate in this group of workers. Indeed, the point estimate using the finer risk measure is almost five times as large as the point estimate based on the industry-level accident risk.

Also note that the decrease in the R-Squared of the model from about 62% to about 32% reflects the fact that the stratification of the sample absorbs a large part of the variation in the regressors (e.g. educational attainment), which otherwise explain a significant part of the variation in wages.

3.2 Wage Decomposition and Firm Wage-Component

Our second approach to identification and estimation is based on quite another idea, which tries to capitalize on the availability of panel data with respect to the firm.[12] Still, we can use the additional source of variation in wages stemming from the fact that the SWSS has a longitudinal structure (at least with respect to the firm) such that we can apply simple panel data methods. To start with, let us assume that the observed natural logarithm of the wage y_{it} of individual i in a given year t can (conceptually) be decomposed in a linear model as follows:

$$y_{ijt} = \lambda_t + \phi_i + \psi_j + \epsilon_{ijt} \tag{4}$$

Abstracting from time fixed-effects (λ_t), equation (4) states that individual i's wage is the sum of an individual wage fixed-effect ϕ_i, a firm wage fixed-effect ψ_j, and a remaining random error component ϵ_{ijt}. The critical assumptions in this simple linear fixed effects model are the assumptions about the time invariance of both the individual and the firm fixed effect. However, since we are using panel data spanning only a short time period we believe that these assumptions are innocuous for our application – nonetheless allowing us to resort to the power of panel data methods. Importantly, note that the theory of compensating wage differentials essentially makes statements about the wage component specific to the employer (i.e. ψ_j), but not to the individual-specific part nor the random part of the wage. If it is possible to consistently estimate the wage firm fixed effect ψ_j from the available data, we can

[12] Of course, we could capitalize on repeated individual observations using for example the techniques proposed by Abowd and Kramarz (1999), but as explained in section 2, we only have temporal information about the employer but not the individual workers.

essentially get rid of individual heterogeneity by simply running a hedonic wage regressing using the estimated wage firm-fixed effect $\hat{\psi}_j$ instead of the observed wage y_{ijt} on our risk measure r, although we can not directly control for unobserved individual heterogeneity in the hedonic wage regression (because, remember, the risk measure is *not* observed over time and because there is no person-identifier in the SWSS). Thus, in a first stage, we run a simple regression model using the three consecutive waves of the SWSS:

$$y_{ijt} = \alpha + x'_{it}\beta + z'_{jt}\gamma + \lambda_t + \psi_j + u_{ijt} \quad \text{with} \quad s_{ij} = 4 \tag{5}$$

Here, as before, x and z are vectors of observed individual and firm characteristics and the parameter λ_t captures aggregate wage shifts over time. The vector x of observed individual characteristics is important here because we essentially use x to proxy for otherwise unobserved individual heterogeneity. Moreover, we run this regression on a subset of individuals working in jobs with the lowest skill-level only, such that we can further dampen the problem of unobserved heterogeneity. The regression model given by equation (5) is only of interest here because it allows us to estimate the firm wage fixed effects, represented by the vector ψ_j. Practically, ψ_j is estimated from the data by including a separate dummy variable for each firm in the sample. In the second stage, we run a regression very similar to the hedonic model from equation (1):

$$\hat{\psi}_{ijk} = \alpha + x'_i\beta + z'_j\gamma + r_k\delta + u_{ijk} \quad \text{with} \quad s_{ij} = 4 \tag{6}$$

where now the dependent variable is the estimated firm wage fixed effect $\hat{\psi}_{ijk}$ of individual i working in firm j. Note that the unit of observation is still the individual worker, although the firm fixed effect obviously does not vary between individuals working in the same firm. This procedure, though, directly applies the right weighting scheme. Again, r_k is the non-fatal risk measure in industry×skill-level cell k. Note that we still have to include both vector x and z, because the estimated wage firm fixed effect $\hat{\psi}$ is not independent of x and z. The main point is that the estimated wage firm fixed effect $\hat{\psi}$ should have been separated from the unobserved individual-specific component θ.

Figure 2 about here

As shown in figure 2, a simple scatterplot of the average firm wage fixed-effect (averaged within industries) versus the number of non-fatal accidents now shows a clear positive relation between the two variables (as opposed to figure 1, which showed no relation between the two measures at all).[13] A simple regression of the average wage firm fixed effect on the number of non-fatal accidents yields an estimated slope coefficient of 0.0034, which marginally reaches statistical significance (t-value of about 1.6).

Table 3 about here

[13]The last column in table A.1 in the chapter appendix shows the estimated firm wage fixed-effect by industry (at the two-digit level, only for the lowest skill-level of jobs).

Results from hedonic wage regressions using the wage firm fixed effect as the dependent variable are shown in table 3. The left panel of table 3 reproduces, for the purpose of comparison, the simple hedonic wage regression using the whole sample and using workers from the lowest skill-level only. The remaining columns show the corresponding estimates using the wage firm fixed effect as dependent variable instead. It turns out that using the firm fixed effect of the wage instead of the observed wage makes a huge difference with respect to the estimated compensation for workplace risk, but only in the subsample of least skilled workers. For example, using the accident risk at the more disaggregated level (i.e. at the level of industry×skill-level of the job), the point estimate of the risk parameter more then doubles when using $\hat{\psi}$ instead of y directly as the dependent variable in the regression, yielding a point estimate of 0.00067 (with a significant t-value of about 2.4). This result is moreover in line with the story of workers sorting into jobs based on their (partially) unobserved productivity, because the main difference between the left and the right panel of table 3 is that variation in y reflects to a substantial part variation in unobserved productivity, whereas variation in $\hat{\psi}$ much less so. In the overall sample, however, using the wage firm fixed effect yields almost the same estimates as when using the observed wage as dependent variable directly.

On the other hand, using risk measures at a less aggregated level has the same effect throughout of increasing the point estimate of risk compensation. This is true in the overall sample as well as in the subsample of less skilled workers, and it holds true whether the overall wage or the wage firm fixed effect is used as dependent variable.

3.3 The Value of a Statistical Injury

Given an estimate for the compensation for non-fatal accident risk, we can easily compute the value of a statistical injury (i.e. non-fatal accident). Because all our estimates of the risk parameter are based on semi-logarithmic regressions, the estimated risk coefficient corresponds to the *relative* wage which 1,000 workers are willing to forego in order to prevent one non-fatal accident (and thus is independent of the time period chosen). Thus, multiplying the estimated risk parameter by 1,000 yields the estimated *relative* value of a statistical injury (VSI). Since our risk measure refers to non-fatal accident per year, we will phrase the VSI in terms of average annual earnings (that is, we multiply VSI additionally with the average annual earnings in the corresponding group of workers).

Table 4 about here

Table 4 shows estimates for the value of a statistical injury computed from the different estimation methods discussed above (expressed in terms of the average annual earnings in the corresponding sample of workers). The main estimates are based on the point estimate of the risk variable. Lower and upper bounds on the value of a statistical injury are based on the 95% confidence interval of each point estimate of the parameter δ (based on robust standard errors). The simple hedonic wage regression based on the pooled sample actually yields a negative estimate for the value of a statistical injury (per injury per year). Only using the upper bound of the confidence interval yields the expected positive value (although still a small one).

Stratification of the sample by the skill-level of the job yields a higher value of a statistical injury, the narrower the sample. Focusing on workers in the lowest skill-level only gives an estimate of about 2,600 Swiss francs (accident risk at the level of industry only) and about 13,000 Swiss francs (accident risk at the level of industry×skill-level of the job), respectively. However, note that the estimate based on the lower bound of the confidence interval though still gives a negative estimate in both cases.

Finally, for the subsample of less skilled workers again, using the wage firm fixed effect gives a significant positive value of a statistical injury (even if we use the lower bound of the corresponding confidence interval). Based on the point estimate, we get an estimated value of a statistical injury of about 9,900 and about 36,000 Swiss francs per non-fatal accident averted per year, depending on the risk measure used. This value fits into the range reported by most other empirical studies (see Viscusi and Aldy, 2003, again).

4 Conclusions

We provide empirical estimates of the value of a statistical injury for Switzerland for the year 2004, using non-fatal accident risk within industry×skill-level cells and applying different approaches to identification. Specifically, we stratify the sample by the skill level of the job and we try to statistically isolate the firm-specific wage component, to which the theory of compensating wage differentials conceptually applies most directly.

It turns out that both the risk measure and the empirical method actually make a huge difference with respect to the estimation of risk compensation. Simple hedonic wage regressions actually yield negative or zero compensation for non-fatal accident risk at the workplace. Moving on to methods we believe are more reliable (i.e. consistent) pushes the risk compensation in the "right" direction (i.e. yielding positive compensation for accident risk). Our preferred estimation method, based on using a restricted sample of workers in jobs of lowest skill-level only and using the wage firm fixed effect instead of the observed wage, gives a substantial estimate for the value of a statistical injury of about 36,000 Swiss francs, which is within the range given by both studies from inside and outside the U.S. labor market. Consistent with existing evidence, individuals' willingness to pay for workplace safety is substantial - reflecting a more general trend in increasing prices in nonmarket goods (Costa and Kahn, 2003).

Our analysis, by comparing the magnitude of risk compensation, also sheds some light on the problem of endogenous sorting of workers based on their (unobserved) productivity-relevant characteristics. The more attention we pay to mitigating unobserved productivity differences (i.e. by focusing on narrower groups of workers), the larger the estimates for risk compensation we get. This pattern seems to be consistent with the hypothesis that high-productivity workers select into lower-risk jobs by accepting lower wages.

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Table 1: Descriptive statistics

	Skill-level 4		Skill-level 1-4	
Monthly wage	4,526.625	(1,069.261)	6,371.884	(3,466.716)
ln(monthly wage)	8.392	(0.226)	8.676	(0.381)
non_fatal_1000	45.400	(59.129)	93.007	(150.420)
non_fatal_1000_wirt_abt	103.176	(115.139)	93.110	(111.371)
Age	40.189	(11.661)	40.710	(11.143)
Female: Yes = 1	0.540	(0.498)	0.421	(0.494)
Tenure	7.633	(8.181)	9.058	(9.121)
Size of the firm	2,714.938	(7,820.838)	3,108.008	(7,890.729)
Marital status				
Single	0.267	(0.443)	0.317	(0.465)
Married	0.621	(0.485)	0.583	(0.493)
Others	0.112	(0.315)	0.100	(0.301)
Education				
University degree	0.003	(0.054)	0.055	(0.228)
College of higher education	0.003	(0.052)	0.048	(0.214)
Higher professional degree	0.006	(0.078)	0.074	(0.261)
Teachers' certificate	0.001	(0.039)	0.005	(0.068)
High School	0.012	(0.108)	0.020	(0.139)
Finished professional education	0.274	(0.446)	0.505	(0.500)
Firm intern professional education	0.138	(0.344)	0.067	(0.251)
Secondary school	0.480	(0.500)	0.176	(0.381)
Other degree	0.083	(0.277)	0.050	(0.219)
Citizenship				
Swiss citizenship	0.522	(0.500)	0.680	(0.466)
Short term residence authorization	0.012	(0.110)	0.007	(0.085)
Long term residence authorization	0.083	(0.276)	0.055	(0.227)
Permanent residence permit	0.290	(0.454)	0.167	(0.373)
Cross-border commuter	0.060	(0.238)	0.065	(0.247)
Others	0.033	(0.180)	0.026	(0.159)
Geographical region				
VD, VS, GE	0.186	(0.389)	0.163	(0.370)
BE, FR, SO, NE, JU	0.230	(0.421)	0.212	(0.409)
BS, BL, AG	0.123	(0.329)	0.142	(0.349)
ZH	0.236	(0.424)	0.267	(0.443)
GL, SH, AR, AI, SG, GR, TG	0.114	(0.318)	0.113	(0.317)
LU, UR, SZ, OW, NW, ZG	0.073	(0.260)	0.070	(0.255)
TI	0.038	(0.192)	0.032	(0.176)
Number of firms	3,533		3,533	
Numer of observations	130,976		468,328	

Notes: Table entries are sample means and standard deviations (in parentheses). Columns (1) and (2) refer to the subsample of workers in jobs of lowest skill-level, columns (3) and (4) to the full sample of workers. Sources: All variables are taken from the SWSS, except the number of non-fatal accidents. Risk measure gives the number of non-fatal accidents per 1,000 workers per year, within cells over industry×skill-level.

Table 2: Hedonic wage regressions, by skill-level of the job

	ln(monthly wage)							
Skill-level(s) of job	1-4		2-4		3-4		4	
Mean	8.676		8.634		8.549		8.392	
Standard deviation	0.381		0.334		0.284		0.226	
Non-fatal accident risk (industry×skill)	−0.00005		−0.00003		0.00001		0.00024	
	(−0.883)		(−0.597)		(0.300)		(1.626)	
Non-fatal accident risk (industry)		−0.00015		−0.00012		−0.00005		0.00005
		(−1.318)		(−1.065)		(−0.427)		(0.423)
Additional controls included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	468,328		441,269		346,916		130,976	
R^2	0.623	0.624	0.556	0.558	0.459	0.459	0.321	0.318
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: ⋆, ⋆⋆, ⋆⋆⋆ denotes statistical significance on the 10%, 5% and 1% level, respectively. Robust t-values are given in parentheses. Skill-level 1 (4) corresponds to the highest (lowest) skill-level possible. Additional control variables are: Age and age squared, citizenship (5 dummy variables), educational attainment (8 dummy variables), female dummy, geographical region (6 dummy variables), job tenure and its square, marital status (2 dummy variables), size of the firm and its square. Full regression results are available upon request.

Table 3: Observed wage versus wage firm fixed effect, by skill-level of the job

	ln(monthly wage)				Firm fixed effect			
Skill-level(s) of job	1-4		4		1-4		4	
Mean	8.6758		8.3918		-0.2150		-0.1837	
Standard deviation	0.381		0.226		0.189		0.163	
Non-fatal accident risk (industry×skill)	−0.00005		0.00024		−0.00009		0.00067**	
	(−0.883)		(1.626)		(−1.126)		(2.410)	
Non-fatal accident risk (industry)		−0.00015		0.00005		−0.00014		0.00018**
		(−1.318)		(0.423)		(−1.055)		(2.031)
Additional controls included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	468,328		130,976		468,328		130,976	
R^2	0.623	0.624	0.321	0.318	0.417	0.419	0.201	0.163
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

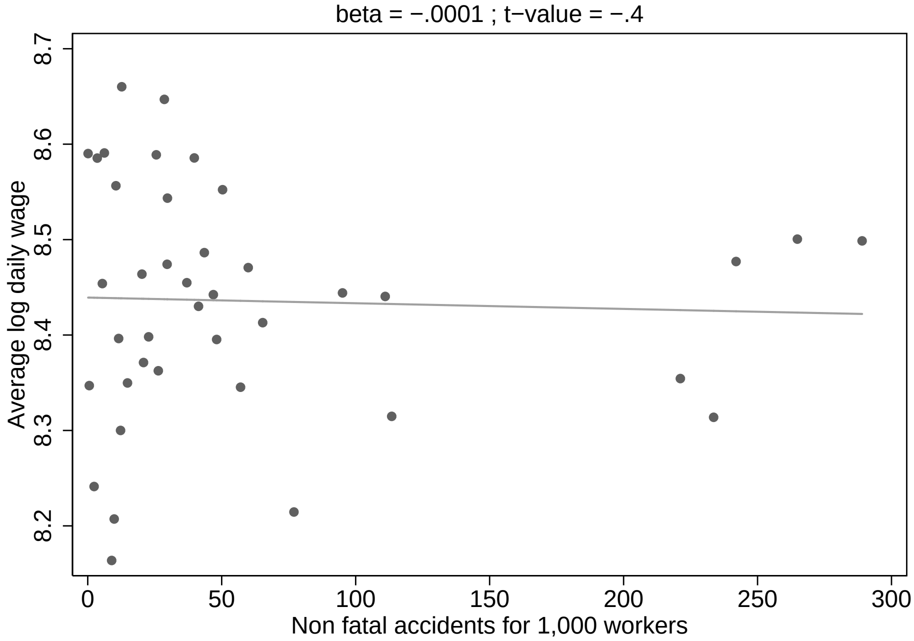
Notes: *, **, *** denotes statistical significance on the 10%, 5% and 1% level, respectively. Robust t-values are given in parentheses. Skill-level 1 (4) corresponds to the highest (lowest) skill-level possible. Additional control variables are: Age and age squared, citizenship (5 dummy variables), educational attainment (8 dummy variables), female dummy, geographical region (6 dummy variables), job tenure and its square, marital status (2 dummy variables), size of the firm and its square. Full regression results are available upon request.

Table 4: The estimated value of a statistical injury

		Estimated value of a statistical injury (VSI), based on		
	Yearly earnings	Lower bound of $\hat{\delta}$	Point estimate of $\hat{\delta}$	Upper bound of $\hat{\delta}$
A. Accident risk at the level of industry				
A.1 Observed wage				
Skill-level 1-4	76,463	−29,255	−11,761	5,734
Skill-level 2-4	71,502	−24,061	−8,472	7,117
Skill-level 3-4	64,570	−16,426	−2,937	10,551
Skill level 4	54,320	−9,428	2,592	14,611
A.2 Firm wage fixed effect				
Skill-level 1-4	76,463	−30,542	−10,685	9,173
Skill-level 2-4	71,502	−7,702	4,101	15,904
Skill-level 3-4	64,570	−13,932	−54	13,823
Skill-level 4	54,320	348	9,898	19,447
B. Accident risk at the level of industry×skill-level of the job				
B.1 Observed wage				
Skill-level 1-4	76,463	−12,442	−3,864	4,715
Skill-level 2-4	71,502	−9,312	−2,173	4,965
Skill-level 3-4	64,570	−4,869	879	6,627
Skill-level 4	54,320	−2,668	12,986	28,640
B.2 Firm wage fixed effect				
Skill-level 1-4	76,463	−18,057	−6,589	4,879
Skill-level 2-4	71,502	−5,036	1,337	7,710
Skill-level 3-4	64,570	−10,066	−1,701	6,663
Skill-level 4	54,320	6,749	36,162	65,575

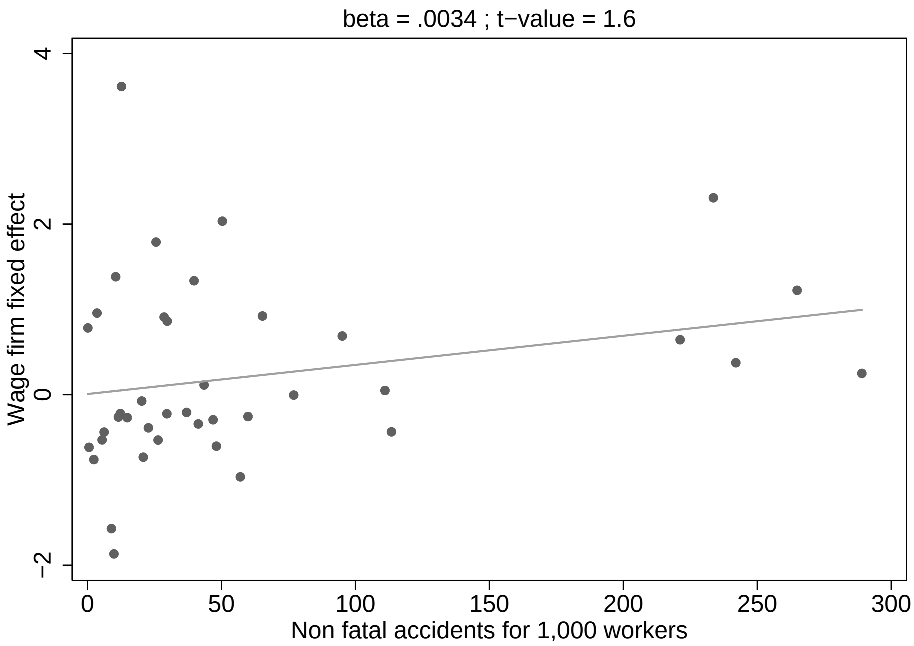
Notes: All entries are based on the point estimate $\hat{\delta}$, and the lower and upper bound of the 95% confidence interval of $\hat{\delta}$, respectively.

Figure 1: Log-Wage versus non-fatal injury risk, by industry



Notes: The y-axis shows the average logarithm of monthly gross earnings and the x-axis shows the number of non-fatal accidents per 1,000 workers per year. Workers in lowest job skill-level only. See also table A.1 in the appendix.

Figure 2: Firm fixed effect versus non-fatal injury risk, by industry



Notes: The y-axis shows the average of the wage firm fixed effect and the x-axis the number of non-fatal accidents per 1,000 workers per year. Workers in lowest job skill-level only. See also table A.1 in the appendix.

A Appendix

Table A.1: Main variables, by industry (lowest skill-level only)

Industry	Workers	Wage	Accidents	FFE
Petroleum refining and processing	4692	5,560.13	0.14	0.78
Office material production, data processing	4288	4,302.83	0.59	-0.62
Information technology services	6237	3,933.30	2.39	-0.76
Shipping	55	5,467.47	3.57	0.96
Metal production and processing	7201	4,781.81	5.46	-0.53
Aviation	12	5,496.25	6.22	-0.44
Production of leather goods and shoes	229	3,628.01	8.94	-1.57
Production of clothes and fur goods	270	3,741.27	9.89	-1.87
Insurance industry	2086	5,300.57	10.53	1.38
Production of medical technology	7421	4,523.07	11.55	-0.26
Retail business	19118	4,090.10	12.26	-0.22
Tobacco processing	636	5,977.87	12.70	3.61
Production of furniture, jewellery, musical intruments	1743	4,329.91	14.86	-0.27
Machinery, mechanical engineering	5441	4,851.64	20.24	-0.07
Textiles	1350	4,436.00	20.83	-0.73
Automobile industry	1075	4,508.15	22.73	-0.39
Energy- and watersupply	496	5,504.46	25.59	1.79
Traffic support	1502	4,360.78	26.35	-0.53
Credit business	3059	5,833.48	28.60	0.91
Paper and carton production	2153	4,917.06	29.64	-0.22
Credit business and insurance industry	70	5,373.94	29.76	0.86
Printing, publishing and distribution industries	3013	4,833.14	36.99	-0.21
Research and development	202	5,478.94	39.78	1.34
Whole sale	7621	4,683.02	41.36	-0.34
Wood processing	810	4,950.09	43.53	0.11
Transportation	2236	4,724.08	46.89	-0.29
Rubber and plastic production	2657	4,511.65	48.12	-0.60
Mining	80	5,277.08	50.33	2.03
Agriculture	6756	4,310.73	57.05	-0.96
Mining	1217	4,821.76	59.91	-0.26
Health and welfare system	19642	4,582.02	65.31	0.92
Hotel and restaurant industry	9676	3,743.90	76.98	-0.01
Real estate	581	4,784.07	95.10	0.69
Information transmission	55	4,707.71	111.04	0.05
Entertainment	814	4,208.07	113.46	-0.44
Education	744	4,394.47	221.19	0.64
Personal services	238	4,318.43	233.62	2.31
Waste management	95	4,953.19	242.00	0.37
Lobby, associations, organizations	512	5,067.35	264.88	1.22
Construction	4893	4,965.64	289.03	0.25

Notes: Table entries show sample averages within industries, sorted by accident risk. “Workers” shows the absolute number of observations. “Accidents” shows the number of non-fatal accidents per 1,000 workers. “Wage” is the average logarithm of gross monthly earnings. “FFE” denotes the average firm fixed effect, as given by equation (5), and is (in the table) standardized to mean 0 and variance 1.