Wages and Risks at the Workplace: Evidence from Linked Firm-Worker Data

Rafael Lalive*, University of Zurich Oliver Ruf, University of Zurich

Josef Zweimüller, University of Zurich

May 2006

PRELIMINARY VERSION

Abstract One of the oldest views on wage determination holds that wage differences reflect compensation for hedonic aspects of jobs such as the risk of injuries and occupational diseases. This paper studies the importance of such compensating wage differentials using longitudinal information on workers and firms. This data allows us to disentangle the wage and risk components that are attached to the worker from the wage and risk components that are specific to the firm. Results indicate first that there is a strong positive correlation between wages and the risk of workplace accidents as has been observed in the previous literature. Second, we find a compensating wage differential that is roughly equal to the one obtained in the standard cross-sectional wage regression when we correlate the firm-specific wage component with the firm-specific risk component. Third, we find no evidence in favor of the hypothesis that more productive workers sort themselves into more secure jobs.

JEL-Classification: J17, J31

Keywords: Industry wage differentials, Compensating wage differentials, Linked Firm-Worker Data, Worker sorting

*Financial support by the Swiss National Science Foundation (No.100012-103970) is gratefully acknowledged.
Addresses: Rafael Lalive, Bluemlislapstr. 10, CH-8006 Zuerich, e-mail: rlalive@iew.unizh.ch,. Oliver Ruf, Bluemlislapstr. 10, CH-8006 Zuerich, e-mail: oliruf@iew.unizh.ch,. Josef Zweimüller, IEW, Bluemlisalpstr. 10, CH-8006 Zurich, Switzerland, e-mail: zweim@iew.unizh.ch.

"Virtually no matched worker-firm records are available for empirical research, but obviously are crucial for the precise measurement of job and personal attributes required for empirical calculations. Not only will the availability of such data produce sharper estimates of the wage-job attributes equalizing differences function, but also will allow more detailed investigations of the sorting and assignment aspects of the theory ..."

Rosen (1986), p.688.

1 Introduction

One of the oldest views on wage determination holds that wage differences reflect compensation for hedonic aspects of jobs such as the risk of injuries and occupational diseases. This paper studies the importance of such compensating wage differentials using longitudinal information on workers and firms. While 20 years ago, almost linked firm-worker data were available, in recent years many now linked firm-worker data sets have become available (for a survey, see Abowd and Kramarz, 1999). However, so far these data have not been used to shed new light on the question of compensating wage differentials. To large extent the reason is still the limited availability of data as suggested by Rosen (1986). While linked firm-worker data set are informative workers' wage histories at different firms, it typically does not report the corresponding information on job attributes. In this paper, we use a linked firm-worker data set that is informative on one particular dimension of job attributes: the risk of injury.

We argue that such matched employer-employee data allow identifying the building blocks of the theory – the firm-specific components of wages and risk. The risk of injury results from the interplay between the risk inherent in the workplace and the risk behavior of the workers. The theory of compensating wage differentials holds that workers subject to a higher firm-specific risk should be compensated by higher wages. In contrast, the risk that is attached to the worker, for instance, due to lack of dexterity, precaution, or diligence, should show up in lower wages. A worker more likely to cause a workplace accident has a lower expected productivity which1 should result in a wage penalty.

Our empirical analysis relies on administrative data from Austria covering about 660,000 male blue collar workers employed in more than 60,000 firms. A unique feature of our data is that we can observe, for each individual in this dataset, the number, the exact timing (on a daily basis), and severeness (as measured by duration off work) of workplace accidents over the period January 2000 to December 2002. Since our dataset covers the universe of Austrian employees and since we know for each worker at which date he or she is employed at which firm, we have also exhaustive information on injuries at the firm-level. This allows us to disentangle risk components that are attached to the worker from risk components that are specific to the firm.

Our empirical strategy is as follows. We then make use of the information provided by linked firm-worker data. Using econometric techniques developed by Abowd, Creecy, and Kramarz (2001) we split up observed wages into a worker-component (a "fixed" worker wage-effect) and firm-component (a "fixed" firm wage-effect). We proceed in an analogous way for observed injuries to disentangle the risk inherent to the workplace from the risk implied by the behavior of the worker. While neither the fixed firm risk-effects nor the fixed worker risk-effects are informative at the individual level (because they reflect mainly good or bad luck), we argue that these measures are informative when they are aggregated. When aggregated at a sufficiently high level, the random component is averaged out and variation across industries in the resulting indicators should reflect, respectively, differences in both true workplace risks and differences in risk behavior of workers.

Hence our empirical strategy adds two elements to existing studies. First, by identifying the relationship between firm-wage components and workplace-specific injury risks it identifies the building blocks of the theory and provides refined empirical estimates for the hedonic wage injury risk hedonic wage function. Second, by identifying the worker wage-components and the risk-components that are due to worker behavior, our results also shed new light on the hypothesis that workers with higher earnings capacities sort themselves into more secure jobs.

Our empirical analysis produces several interesting results. *First*, our data set reproduces the typical findings obtained from cross-sectional hedonic wage regressions. These studies regress individual wages on aggregate industry (or occupational) injury risk from which the value of a statistical injury can be calculated. The implied value of a statistical (non-fatal) injury in our data set is about 64,000 USD which is within the range of 20,000 to 70,000 USD that is found in samples from other industrialized countries (Viscusi and Aldy, 2003). *Second*, the estimated compensating differential (and the estimated value of a statistical injury) does not change strongly when we focus on the building blocks of the theory. Regressing the firm-specific wage component on (aggregated) firm-specific risk-components, we find a compensating wage differential that is of roughly equal size as the one obtained in the standard cross-sectional wage regression. This result turns out rather robust and holds for workers in different age groups. We also find that our results remains unchanged when we use the expected days off work (rather the expected number of injuries) per 100 workers as the relevant risk indicator. *Third*, we find no evidence for a bias of the compensating differential obtained from a standard cross-sectional hedonic wage function that can be attributed to unobserved worker productivity. More precisely, we find that workers with a higher earnings capacity (a higher fixed worker wage-effect) are not more likely to be employed in industries with a lower workplace risks. In the construction industry, we even find that workers with higher earnings capacity are even willing to take higher risks. In non-construction industries, no significant relationship between (aggregated) firm-specific risks and workers' earnings capacities exists.

The paper is organized as follows. Section 2 discusses related literature. Section 3 presents a very simple model of wage determination where workers differ in their ability to avoid workplace accidents and firms differ in the riskiness of workplaces they offer. Section 4 presents the data and gives first descriptive evidence on the relationship between the injury risk and earnings. Section 5 briefly discusses the econometric methodology to disentangle worker and firms effects for both earnings and injury risks. Section 6 presents the main results and checks their robustness. Section 7 concludes.

2 Related Literature

Among the early papers that study the role of on-the-job risk of wage on the U.S. labor market are Thaler and Rosen (1975), Brown (1980), Leigh (1981), and Arnould and Nichols (1983) who use risk data collected by Society of Actuaries for 1967. Other papers, like Hamermesh (1978), Viscusi (1979, 1980), and Fairris (1989) find that self-reported riskiness of one's job is significantly positively related to on an individual's wage. Duncan and Holmlund (1983), using Swedish data, show that longitudinal data may be necessary to reveal any significant compensating differential of job disamenties.

A major issue in the empirical literature of estimating compensating wage differentials is the issue of sorting. Many authors have argued (e.g. Hwang, Reed, and Hubbard, 1992) that worker's unobservable (to the researcher) productivity characteristics (such as talent, innate ability) fundamentally bias downward the estimated compensating differential for job disamenities. The reason is that, when workplace safety is a normal good, workers with a high earnings potential will select themselves into the less risky jobs. Using simulation techniques Hwang et. al (1992) show that failing to account for such differences in unobservable productivity may lead to a strong downward bias of compensating differential and even to ”wrongly signed” coefficients. However, Shogren and Stamland (2002) show that when workers differ in the ability to avoid risk, the standard hedonic wage regression may bias the compensating wage differential upwards. They show that also this bias could be very large.

A further related paper is Garen (1988) who emphasizes the importance of the issue that individuals may systematically differ in productivity-relevant characteristics, specific to dangerous job. Garen mentions that some workers are ”coolheaded” making them more productive on a dangerous job but such characteristics may not be relevant in a safe job. Garen (1988) and DeLeire and Levy (2004) use instruments such as family characteristics. The idea is that being responsible for others lets individuals choose less dangerous jobs. These papers find evidence for the sorting hypothesis.

A further related strand of the literature explores to which extent observed industry wage premiums are associated with wages compensating for on-the-job risk. Leigh (1995) and Dorman and Hagstrom (1998) compare models with and without dummy variables for industry affiliation and conclude that industry-wage differentials reflect to a large extent risk-premiums.

The recent literature addresses the problems with measuring compensation for risk. Ashenfelter and Greenstone (2004) and Ashenfelter (2006) use mandated speed limits to measure the value of a statistical life. Halliwell and Huang (2005) use information on life satisfaction, wages, and workplace characteristics to identify compensating wage differentials. Linked firm-worker data have not been used to study the importance of compensating wage differential for workplace injury risks. The only exception known to us is the paper by Dale-Olsen (2005) who estimates workers' the marginal willingness to pay for safety using linked firm-worker data from Norway. However, the focus in his paper is on dynamic aspects of worker and firm behavior such as quits and job durations whereas our paper focuses on the issue of distentangling worker and firm effects in the hedonic wage equation and discuss the involved sorting issues.

3 A Simple Model

Consider a simple model of wage determination and non-fatal injury risk, inspired by Viscusi and Aldy (2003). Denote by w a worker's wage and, respectively, the utility with and without an injury by $U(w)$ and $V(w)$ with standard assumptions $U'(w) > 0 > U''(w)$ and $V'(w) > 0 > V''(w)$. The probability that an injury occurs is given by p. Assume for simplicity that the utility in the case of an injury $V(w) = (1-k)U(w)$ where k should be thought of as a measure of the severeness of an injury. This lets us write the worker's expected utility as $EU = [1 - p(1-k)]\,U(w)$.

Now assume that the hedonic wage function is linear and given by $w = h + \beta p$ where h denotes a worker's earnings capacity and β is the compensating wage differential. Substituting the budget constraint into the expected utility expression, the optimal level of risk chosen by the worker is implicitly given by the first order condition

$$\frac{\partial EU}{\partial p} = -(1-k)U(w) + [1 - p(1-k)]\,\beta U'(w) = 0.$$

Using this condition, we can now easily study how the optimal level of risk-taking varies with a worker's earnings capacity. Implicitly differentiating the p with respect to h shows that

$$\frac{dp}{dh} = -\frac{1}{\beta}\frac{(1-k)U'(w) - [1 - p(1-k)]\,\beta U''(w)}{2(1-k)U'(w) - [1 - p(1-k)]\,\beta U''(w)} < 0$$

workers a higher earnings capacity unambiguously reduces the degree of risk that workers are willing to take. A corollary of this result is that, when variation in wages is to a large extent due to unobserved productivity of workers, estimating compensating wage differentials from cross-sectional data suffer from ability bias and will underestimate the true compensating differential.

A further potentially important dimension of sorting concerns the ability of individuals to cope with risky workplaces. The reason why an industry can have a high number of injuries is twofold. On the one hand, there are differences in injury rates because there are differences in risks embodied in the workplace. This is emphasized by the standard compensating wage differentials theory. On the other hand, there are differences in industry injury rates because different industries select different workers. When workers differ in their ability to cope with workplace risks – because of differences in worker's dexterity, precaution, and diligence, there may be further sorting of workers across high- and low-risk industries. It is straightforward to explore this argument in the context of the above model. Assume workers differ in the ability to avoid an injury and that the probability that a worker of type π experiences an injury is given by

$$p(\pi) = p\pi$$

where $\pi > 0$ says that a worker of type π is π times as likely to experience an injury than the average worker. (Of course, it must be that $\pi^{\max} < 1/p$).

The objective function now is $EU = [1 - p\pi(1-k)]\, U(w)$ which the worker maximizes under the same hedonic wage equation as above.[1] Under this assumption the first order conditions changes only slightly to

$$\frac{\partial EU}{\partial p} = -(1-k)\pi U(w) + [1 - p\pi(1-k)]\, \beta U'(w) = 0.$$

Implicitly differentiating the first order condition for p with respect to π yields

$$\frac{dp}{d\pi} = -\frac{1}{\beta} \frac{(1-k)U(w) + p(1-k)\beta U'(w)}{2(1-k)\beta U'(w) - [1 - p(1-k)]\, \beta^2 U''(w)} < 0,$$

which implies that high-risk workers will sort themselves into low-risk workplaces.

4 Data

We assess the extent to which wages compensate for injury risks with linked employer-employee data from Austria. We use data from two different sources: (i) the Austrian social security data (ASSD) and (ii) the Austrian statutory accident insurance (Allgemeine Unfallversicherungsanstalt, AUVA). These datasets were merged for the purpose of this study on an individual (and anonymized) basis. The available data include the universe of Austrian private sector wokers who were employed at some date between January 1, 2000 and December 31, 2002. The ASSD reports the workers' complete employment and work history since January

[1] One could further assume that it matter for the compensation of a worker how able he or she is in coping with workplace risks. Realistically, the occurrence of an injury will be associated with lower output, so the expected productivity of a high-risk workers will be lower. On a perfect labor market (where a worker's risk is common knowledge) this should result in a lower output. Hence, ceteris paribus, a worker with low ability to cope with workplace risks should also get lower wages. One possibility to include this argument into the above framework is to assume a hedonic wage equation of the form. $w = h + \beta p - \gamma\pi$. Assuming such a hedonic wage equation does not, however, change the results concerning the sorting of high-wage and high-risk workers across industries.

1, 1972 and the AUVA-data report the complete history of occupational injuries (incidence and duration) between the period January 1, 2000 and December 31, 2002. Both data sets are linked via an individual identifier (the workers' anonymous social security number). Because the ASSD reports, on a daily basis, during which dates a worker was employed at which firm and because our dataset includes the universe of all private sector workers, we can infer the firms' history of occupational injuries over the period January 1, 2000 to December 31, 2002.

The AUVA data report the complete history of occupational injuries for each worker, the severeness of the injury (as measured by degree of disability) and the duration of the injury, and the exact date of the injury. Moreover, the data report the amount and duration of disability benefits that an individual has been drawing over this period.

The ASSD covers all private sector employees and reports the full employment and earnings history on a daily basis since January 1, 1972. The ASSD contains all data necessary to calculate old age social security benefits. (Benefits levels depend both on previous earnings and on the number of months during which social security contributions were paid.) Since contributing to the old age insurance fund is mandatory and since non-compliance with reporting rules are subject to sanctions (fines), this data set contains high-quality information on workers employment and earnings history.

Our empirical analysis is confined to workers in the age group 25-65. As the data report daily earnings but does not provide information on average working hours per day, we focus on male workers (where variation in wages results predominantly from variation in hourly wages rather than variation in daily hours worked) and exclude female workers (many of whom work part-time). Furthermore, occupational injuries are much more prevalent in blue collar-jobs, we exclude white collars. We also excluded multiple job-holders, workers with wages below the social security threshold (*Mindestgrenze*) and above the social security earnings cap (*Höchstbemessungsgrundlage*).[2] Furthermore, as identification of firm- and worker-components in earnings and risks can only accomplished for workers moving between firms, we could only concentrate on those subset of workers and firms for which identification of both worker and firm effects could be accomplished. We ended up with 618,174 male blue collar workers working in 62,497 firms. We split the three years period 2000 - 2002 into six semesters (using wage

[2]For earnings below the Mindestgrenze and the part of the earnings above the Höchstbemessungsgrundlage, workers do not have to pay social security contributions. For the former group, records are incomplete. For the latter group, we do not know the exact amoung of earnings (we only know that earnings are above the cap). Applying both criteria lead to exclusion of 4014 workers.

observations at May 10 and November 10 of each year) and calculating flow variables (such as the number of injuries, days of work experience, etc. on a semester basis). In total this lead to 2,846,102 observations.

Table 1 reports descriptive statistics for this sample. The yearly risk of an injury per 100 full-time workers is 7.2. Notice that this is a rather high number when compared to statistics from other data sources. The reason is twofold. First, we focus on male blue collar workers, a group that is typically employed in more risky workplaces. Second, we define the risk of an injury as the number of workplace injuries within one year, divided by the number of calendar days during which workers were in employment. This implies that spells of unemployment (or other non-employment) are not counted in the denominator of the risk-variable. The number of lost working days per 100 workers is about 97 days. Again, this number is somewhat higher than those found in other data sets because we focus on male blue collars. The average daily wage in the sample is about 97 Euros (or 120 USD). On average, workers in our data set have 16.8 years of work experience since January 1972, were employed since 7.3 years with their current firm, and are 39 years old. The size of the firm in which the typical worker is employed is 467.

Table 2

5 Methodology and Empirical Strategy

This section discusses the decomposition of the log of earnings per day into a worker effect, a firm effect, and an error term. Moreover, the section discusses how to separate the risk of injury into worker and firm effects.

5.1 Decomposing Wages

Let w_{it} be the log earnings per day of worker i at time t, let x_{it} denote the time-varying characteristics, and let $J(i,t)$ be the identification number of the firm at which worker i is emplolyed at time t. We assume that

$$w_{it} = x_{it}\beta^w + \theta_i^w + \psi_{J(i,t)}^w + \epsilon_{it}^w \tag{1}$$

and

$$E[\epsilon_{it}^w | i, t, J(i,t), x_{it}] = 0 \tag{2}$$

The wage policy of the firm is modelled as simple as possible.[3] The firm effect in the wage rate, ψ_j^w, captures the wage differential earned in the present firm compared to the average firm in the dataset. The worker's wage component, θ_i^w, reflects differences in pay due to time-invariant characteristics of each worker such as ability but also education.[4] Thus, the worker effect in the wage rate measures the extent to which compensation for skill is important. Finally, the parameter β^w measures economy-wide returns to experience or productivity increases (see the following section for a definition of the vector x).

Intuitively, the worker effect on the wage and the firm effect on the wage can be separated by observing workers moving between firms. The wage change associated with a job change provides information on the firm effect of the new firm relative to the firm effect in the old firm. The main statistical assumption is the assumption of exogenous mobility between employers (equation 2). This assumption basically ensures that the model is identified. The exogenous mobility assumption rules out correlation between unmeasured time-varying effects on the wage rate captured by ϵ_{it}^w with the person effect θ_i^w, the firm effect $\psi_{J(i,t)}^w$ or the time-varying observed effects x_{it}. Note, however, that this assumption does not rule out that workers move to better paying firms. Correlation between the firm effect and the mobility decision does not imply that the assumption of exogenous mobility is invalid. Furthermore, in previous work we find that endogenous mobility does not lead to a strong bias in decomposing wages (Gruetter, and Lalive, 2004).

Direct estimation of the model (1) by least squares is impossible because this is a large two-way fixed effect problem. While we can eliminate the worker fixed effect by taking deviations from worker means, there are still more than 60,000 firm effects that need to be estimated (Abowd et al., 1999). This paper uses a modified version of the iterative algorithm proposed in (Abowd et al., 2002) to solve for the least squares parameter estimates $\widehat{\beta}, \widehat{\theta}_i, \widehat{\phi}_j$, and $\widehat{\gamma}_j$ (see appendix for a description of our algorithm).

[3] A more elaborate model for the wage policy allows for firm-specific returns to tenure. However, keeping the wage policy of the firm as simple as in equation 1 allows identifying the wage policy for a larger number of firms because only one parameter per firm needs to be estimated. Moreover, allowing for firm-specific returns to seniority does not affect results of the wage decomposition (Gruetter and Lalive, 2004).

[4] Recall that our data do not have information on education.

5.2 Decomposing Injury Risk

This paper argues that injuries or illnesses are generated by factors which are firm specific (technology, safety regulations, work stress, ...) and by factors which are worker specific (ability, skill level, ...). Because workers need to be compensated only for the risk of injury or illness that is imposed on them by the job, we are also interested in measuring the firm's contribution to the risk of an injury or illness. We therefore propose the following statistical model for the relative risk of an injury or illness of worker i in the half-year t, R_{it}

$$R_{it} = x_{it}\beta^R + \theta_i^R + \psi_{J(i,t)}^R + \epsilon_{it}^R \tag{3}$$

and

$$E[\epsilon_{it}^R | i, t, J(i,t), x_{it}] = 0 \tag{4}$$

Equation (3) holds that the risk of an injury or illness is generated by time-varying individual characteristics, x_{it}, by the firm-effect in risk psi_j^R, and by the worker effect in risk θ_i^R. The exogenous mobility assumption (4) is required for identification of this model. We estimate this model again using the iterative algorithm that finds the least squares solution. Fitting ordinary least squares is appropriate even though the dependent variable is censored at zero because we are interested in measuring the expected relative risk conditional on the characteristics x, the firm identifier, and the worker identifier. (We do not have a model for underlying propensity to have an injury or illness.) Moreover, note that average predicted risk of a worker or a firm turns out to be non-negative because ordinary least squares fits the average risk of each worker or firm. Thus, there is no problem with 'non-sensical' risk predictions.

Note that our estimates of the underlying firm effect and worker effect in risk are noisy because our data cover only a three year period. For instance, a worker who happens to have an accident in half-year t will have a very high estimated worker effect $\hat{\theta}_i^R$ even though the underlying true worker effect might be small. This is a problem, however, that is common to all objective measures of risk. The literature has commonly dealt with this problem of noise by aggregating the risk measure either to the firm or the industry dimension (Viscusi and Aldy, 2003).

We therefore aggregate the estimated firm effects, $\hat{\psi}_{it}^R$, and worker effects, $\hat{\theta}_i^R$, in risk to the industry / large firm level (see following section for details). The industry average firm effect in risk captures the average risk imposed on workers by the characteristics of their workplace. Arguably, this is the component of overall risk in the industry that needs to be compensated. In contrast, the industry average worker effect captures the average ability to avoid risks of workers in a particular industry. Importantly, these industry average firm and worker risk measures are much less strongly affected by noise than the individual data. We can therefore reliably assess the compensating wage differential for risk using the industry risk measure.

6 Estimating the Compensating Differential for Injury Risk

In this section we use the decompose both observed injury-risk and observed wages into firm- and worker-components. We then use these estimated quantities and explore the relationship between on-the-job risks and wages. Taking these estimated worker fixed effects at face value we are able to say more about sorting of workers across industries. In particular, we will interpret the estimated fixed worker wage-effect as a measure of a workers productivity and the industry mean of the estimated fixed worker risk-effect as a measure of the ability to avoid risk of the average worker within an industry. Provided these interpretations are correct, we are able to characterize in more detail than previous studies the sorting of workers across industries.

6.1 Main Results

We are now able to present our main results. Figure 1 plots, at the 2-digit industry level, the mean log-wage against the mean injury risk. Clearly there is a positive association between these two variables, albeit there is also considerable variation around the regression line. A simple (weighted) linear regression of the wage- on the risk-measure reveals a positive and significant association between wages and workplace risks.

Figure 1

Table 2 shows the corresponding regression results. Column 1 in Table 2 reports the coefficient of a standard hedonic wage function, that regresses this aggregate industry risk indicator on the individual wage rate. We include age, the duration of the current job (tenure), and calendar-time dummies as additional regressors. It turns out that, after controlling for these characteristics, workers who are employed in industries with a greater injury risk earn higher wages. However, estimating industry-clustered robust errors, it turns out that the coefficient of the risk variable is barely significant. The coefficient of 0.0202 means that, for avoiding one additional accident in 100 within a year, a worker is willing to sacrifice 1.9 percent of his yearly earnings. Put differently, to avoid 1 injury per year, 100 workers would be willing to pay 2.02 times a yearly income. A yearly income of an Austrian blue collar workers is about 25,000 Euros (32,000 USD). Hence the value of a statistical injury would be roughly 50,000 Euros (64,000 USD). This number is within the range of 20,000 to 70,000 USD that is reported in Viscusy and Aldy (2003) for other studies. Hence we find that Austrian data reproduce studies from other industrialized countries rather well.

Table 2

Figure 2 makes use of information provided by linked firm-worker data. We first decompose, for each observation in our data set, the observed wage into a firm- and a worker-component (using the procedure described in the last Section). We then aggregate the estimated firm- and worker-effects to the industry level and plot the resulting industry means against the average industry injury risk. Panel A of Figure 2 shows the relationship between the (industry-mean of the) firm wage-component and industry injury risk, whereas Panel B shows the corresponding relationship between the (industry-mean of the) worker wage-component and the industry injury risk. From Figure 2, panel A we see that – corresponding with the theory of compensating wage differentials – there is a positive relationship between the firm wage component and the injury risk. We also see that no such relationship can be detected from plotting the worker wage-component against the industry injury risk.

In columns 2 and 3 of Table 2 we regress the estimated (individual) firm- and worker-component of the wage on the injury risk. The explanatory variables in these regressions are identical to the one use in the standard hedonic wage regression reported in column 1 of Table 2. The firm-component wage regression, column 2 of Table 2 shows results very similar to column 1. The coefficient of .0209 is slightly higher but statistically significant. Our estimate of the value of a statistical injury of about 50.000 Euro (64.000 USD) is the same as before. This is support for the theory of compensating differential. From a theoretical point of view any wage differential that compensates for workplace hazards should affect the firm-component but not the worker-component of the wage. To attract a worker, the firm has to pay the compensating differential to ensure that the (marginal) worker is at least as well off at the current workplace as on relevant other jobs.

Column 3 of Table 2 regresses the injury risk indicator on the worker componente of the wage. We do not expect a causal effect of the former on the latter but these two indicators should be correlated if there is sorting. Under the unobserved productivity hypothesis we would expect that high-productivity worker (those with a high worker wage-component) should be found in low-risk environments. The results do not support this hypothesis. The point estimate shows the expected negative but is not significantly different from zero.

One reason for this result could be that injury risk at the (two-digit) industry level is a poor estimate for the injury risk to which the typical worker is exposed. The fact that our dataset allows us to attribute each observed injury to one particular firm, lets us aggregate the risk indicator at any arbitrarily level. Note, however, that calculating this indicator at the firm level is not meaningful because the typical firm is small and using the firm-specific number of accidents per employee is more likely to reflect noise rather than true injury risks. Hence a level of aggregation that is lower than the (two-digit) industry[5] but higher than the firm-level may give us a more precise estimate of a worker's actual injury risk. We divide, each of the 36 two-digit industries into 5 firm-size categories (-14, 15-49, 50-99, 100-999, 1000-), and calculate the injury risk for each of the resulting 180 labor market segments.

Figure 3 shows how industry risk and mean (log) wages are related using such a classification of risk-relevant labor market segments. The figure shows again a clear positive relationship between wages and injury risks. Figure 4 decomposes, for each industry / firm-size cell, the mean (log) wage into a firm- and a worker-component and plots these two indicators against the injury risk in the same industry / firm-size cell. Panel A of Figure 3 shows that there is a positive relationship between the firm-wage component and the injury risk whereas panel B of Figure 4 shows that there is no such relationship between the worker component and injury risk.

Table 3 reports regression results corresponding to Figures 3 and 4. The regression control for the same characteristics as before. We see that the finer disaggregation does not change the point estimates of the risk indicator. In column 1 of Table 3 the dependent variable is the log daily wage and the estimated coefficent of our more disaggregated risk measure is very similar as before, the point estimate being close to 0.02. However, unlike before this coeffcient

[5]The data set reports industry affiliation only at the two-digit level. A finer disaggregation of industries is not available.

is more precisely estimated suggesting an increase in efficiency by using a finer classification of the (risk-)relevant labor market segment. Colums 2 and 3 of Table 3 show that the more disaggregate risk measure does not alter our results concerning the relationship both risk and firm- versus worker-specific wage components. Just like before, higher risk increases the firm-specific wage component but is unrelated to the worker-specific component of the wage. This supports the hypothesis that firms compensate workers for their workplace hazard, but does not support the hypothesis of sorting.

Table 3

A further reason why we do not find support for the unobserved productivity hypothesis may be that workers differ in their ability to cope with risks. Hence sorting of high-productivity workers to low-risk industries may be confounded by sorting of high-risk workers to low-wage industries. When high-productivity workers are more willing to take (or more able to cope with) risks the sorting mechanism described by the unobserved productivity hypothesis may be confounded by the sorting of workers according to attitudes towards (or abilities to cope with) risks.

Our linked firm-worker data allow us to shed light on these issues. The fact that we can link firms and workers not only with respect to wages but also with respect to injuries allows us to decompose the observed injuries into a part that is attributable to the firm and another part that is attributable to the workers using the same procedure that we have applied to decompose wages. In column 1 of Table 4 we rerun our basic hedonic wage regression but not split up the injury risk within an industry / firm-size cell into a component attributable to the firm and a component that is attributable to the worker. It turns out that only the firm risk component has a significant impact on the wage rate whereas the risk component that is attributable to the worker has no effect on the wage. The point estimate of firm-risk is 0.015 and somewhat smaller than in the baseline hedonic regression. While the baseline regression suggests an implied value of a statistical injury of 50.000 Euros (64.000 USD), the corresponding number in the present regression would amount to 38.000 Euros (49.000 USD).

Columns 2 and 3 of Table 4 run separate regressions using the estimated firm- and worker-effects from the first-stage decomposition as dependent variables. The firm wageis signficiantly positively affected by the risks that are attributable to the firm. But the risk component that is attributable to workers has no significant effect on the firm wage component. This is perfectly consistent with the theory of compensating differentials. Attributes of the workers should show up in the worker wage component but not in the firm wage component. Moreover, the fact that this coefficient is insignficant suggest that there is no systematic sorting of worker risk-types into high- or low-wage firms.

Column 3 of Table 4 regresses the worker-effect of the wage on firm- and worker-risks. It turns out that the coefficients of both risk variables are small and statistically not different from zero. Workers of different productivity do not appear to sort themselves systematically to high- or low-risk firms. Moreover, we do not see any systematic correlation between productivity-types and risk-types. More precisely, workers who are more willing to take (or more able to cope with) risks are not necessarily workers who are more productive.

Table 4

In sum, our results indicate that the relationship between injury risks and wages is consistent with the theory of compensating wage differentials. We do not find support for the hypothesis that worker sorting lead to a strong bias in the basic hedonic wage regression.

6.2 Sensitivity Analysis

In this section we explore the sensitivity of our results. In Table 5, we run similar regressions as in Tables 3, using accident duration (the time off work that is induced by a workplace accident) as the relevant risk indicator. One could argue that indicence of injuries is a weak indicator as it does not take account of the severity of an accident. A good proxy for the latter may be accident duration. The first three columns in Table 5 use the log wage as the dependent variable, columns 4 to 6 report regression results using the estimated firm wage-component as the dependent variable. For ease of comparison, we include in column 1 and 4 the results we got from Table 3. It turns out that using accident duration as the relevant measure of risk does not have a signficant impact on the quality of our results. In all cases we find that both wages and the firm component of the wage are signficantly affected by the risk indicators. Moreover, the results are very similar when we use the wage and when we use the firm-component as the dependent variable. This suggests that sorting of workers cannot strongly affect our results.

Table 5

In Table 6 we consider the relationship between wages and workplace risks for different age groups. It could be argued that young workers have to be compensated more strongly for taking a given amount of risk as their time horizon is longer – and therefore the welfare consequences of an injury is more severe. To shed light on this issue we split our data set into workers younger than 30 years of age, between 30 and 50 years of age and between 50 and 64 years of age. It turns out that the relationship between injury risk and wages is indeed somewhat weaker among older workers, although the difference in the estimated coefficients is small. Using the estimated firm wage-component (rather than the observed wage) as the dependent variable equalizes the estimated coefficient across age groups. Hence we conclude that the compensating wage differential does not vary strongly over different age categories. One reason could be that older workers are more risk-averse and hence more willing to pay for safety - hence the effect of a shorter time-horizon is countervailed. Just like in the main results for the whole population, we do not find any significant relationship between the worker component of the wage and injury risk suggesting that sorting is of minor importance.

Table 6

Table 7 includes different additional control variables into the basic regression. In column 1 we repeat the results of our basic model (Table 3), column 2 introduces industry dummies, column 3 controls for firm size, and column 4 controls for industry affiliation and region. In all regression it turns out that injury risk has a significant impact on the observed wage and the estimated firm wage-component but not on the worker wage-component.

Table 7

Finally, Table 8 runs separate regressions for construction workers. This is a potentially interesting segement of the labor market as construction workers are more exposed to risk than workers in other industries. In fact, we find that the compensating wage differential in construction is higher than in other industries. This result remains once we use the estimated firm wage-component as the dependent variable. Moreover, we find that the industry risk and the worker-component of the wage are positively correlated. One explanation would be that high-wage workers in the construction industry tend to be workers willing to take higher risks. This could be rationalized by taking more risks leads to higher pay.

7 Conclusions

In this paper, we have presented evidence from a linked firm-worker data set that reports not only an individual earnings at various employers but also the worker's history of workplace injuries at various employers. We have argued that such information allows us to identify the building blocks of the theory of compensating wage differences – the firm-specific components of wages and risk. The risk of injury results from the interplay between the risk inherent in the workplace on the one hand and the risk behavior (i.e. the ability to avoid risk) of the workers on the other hand. The theory of compensating wage differentials holds that workers subject to a higher firm-specific risk should be compensated by higher wages. In contrast, the risk that is attached to the worker, for instance, due to lack of dexterity, precaution, or diligence, should show up in lower wages. A worker more likely to cause a workplace accident has a lower expected productivity which should result in a wage penalty.

Our empirical strategy decomposes observed wages and workplace injuries into firm and worker components using econometric techniques developed by Abowd, Creecy, and Kramarz (2001). Hence our empirical strategy has added two elements to existing studies. First, by identifying the relationship between firm-wage components and workplace-specific injury risks it identifies the building blocks of the theory and provides refined empirical estimates for the hedonic wage injury risk hedonic wage function. Second, by identifying the worker wage-components and the risk-components that are attached to the worker, our results also shed new light on the sorting of worker-types across industries.

Our empirical analysis produces several interesting results. *First*, our data set reproduces the typical findings obtained from cross-sectional hedonic wage regressions. These studies regress individual wages on aggregate industry (or occupational) injury risk from which the value of a statistical injury can be calculated. The implied value of a statistical (non-fatal) injury in our data set is about 64,000 USD which is well within the range of 20,000 to 70,000 USD that is found in samples from other industrialized countries (Viscusi and Aldy, 2003). *Second*, the estimated compensating differential (and the estimated value of a statistical injury) remains unchanged when we focus on the building blocks of the theory. Regressing the firm-specific wage-components on firm-specific risk-components, we find a compensating wage differential that is of roughly equal size than the one obtained in the standard cross-sectional wage regression. This result turns out rather robust and holds for workers in different age groups. We also find that our results remains unchanged when we use the expected days off work (rather the expected number of injuries) as the relevant risk indicator. *Third*, taking the estimated from linked firm-worker data at face value, we find no evidence in favor of sorting. This suggests that the bias of the compensating differential obtained from a standard cross-sectional hedonic wage function that is due to unobserved productivity of workers or unobserved ability to cope with risks is small.

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Appendix

This appendix discusses the estimation algorithm. The least squares estimator of β, θ, ϕ, and γ solves the following normal equations

$$\begin{bmatrix} X'X & X'D & X'F & X'S \\ D'X & D'D & D'F & D'S \\ F'X & F'D & F'F & F'S \\ S'X & S'D & S'F & S'S \end{bmatrix} \begin{bmatrix} \beta \\ \theta \\ \phi \\ \gamma \end{bmatrix} = \begin{bmatrix} X'y \\ D'y \\ F'y \\ S'y \end{bmatrix} \tag{5}$$

It is not possible to invert the cross-product matrix due to the large number of person and firm effects and due to computer memory constraints. In this paper we apply a modified version of the iterative gradient method proposed in Abowd et al. (2002) to find the solution to the normal equations. The idea of this estimator is simple. Rearranging the system of linear equations in (5) yields

$$\begin{bmatrix} X'X\beta \\ D'D\theta \\ F'F\phi \\ S'S\gamma \end{bmatrix} = \begin{bmatrix} X'(y - D\theta - F\phi - S\gamma) \\ D'(y - X\beta - F\phi - S\gamma) \\ F'(y - X\beta - D\theta - S\gamma) \\ S'(y - X\beta - D\theta - F\phi) \end{bmatrix} \tag{6}$$

These are four blocks of normal equations that yield the required least squares solution given the least squares solution of the remaining three sets of parameters.

The iteration protocol is as follows. Choose starting values $\beta_0, \theta_0, \phi_0$, and γ_0. Let l index iterations. Solve for $\beta_l, \theta_l, \phi_l$, and γ_l using (6) based on the estimate of the other parameters in iteration $l-1$. This gives the following updating rule

$$\begin{bmatrix} \beta_l \\ \theta_l \\ \phi_l \\ \gamma_l \end{bmatrix} = \begin{bmatrix} [X'X]^{-1} X'(y - D\theta_{l-1} - F\phi_{l-1} - S\gamma_{l-1}) \\ [D'D]^{-1} D'(y - X\beta_l - F\phi_{l-1} - S\gamma_{l-1}) \\ [F'F]^{-1} F'(y - X\beta_l - D\theta_l - S\gamma_{l-1}) \\ [S'S]^{-1} S'(y - X\beta_l - D\theta_l - F\phi_l) \end{bmatrix} \tag{7}$$

Intuitively, the current estimate of β, for instance, is found by regressing the residuals $y - D\theta_{l-1} - F\phi_{l-1} - S\gamma_{l-1}$ on the matrix X.

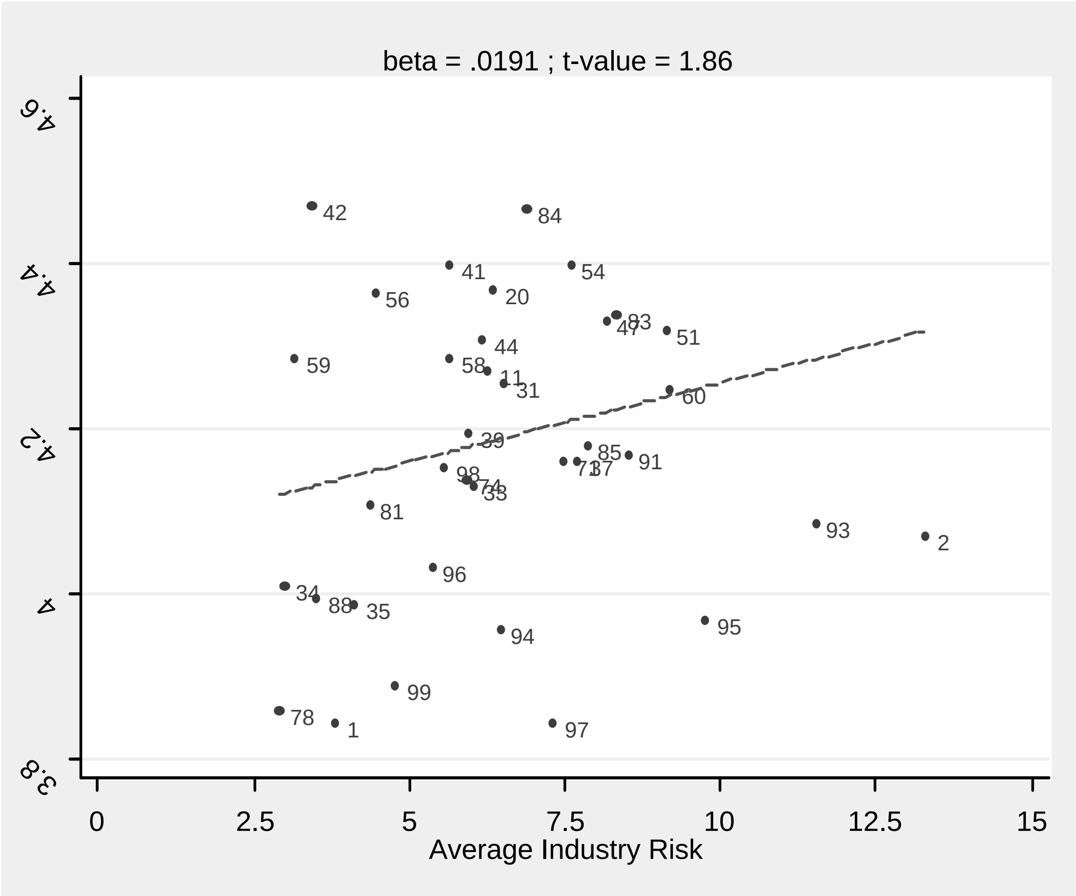
The algorithm is partially recursive in using the fact that the current value of β, β_l, can already be used in estimating θ_l. In estimating ϕ_l, the current values of β_l and θ_l are used to form the residuals, etc. The algorithm converges to the true least squares solution because parameter updates are chosen to fulfill the normal equations given the values of the other parameters. We determine convergence to be achieved when the absolute change in the sum of squared errors between iteration l and $l-1$ falls below $1 \cdot 10^{-11}$.

Moreover, Abowd et al. (2002) show that it is necessary to identify connected groups of firms and workers in the dataset. A connected group is defined as the set of firms and workers such that every worker in the set is connected to every other worker in the set by at least one move (either directly or indirectly) between their respective employers. Within a connected group, the model identifies all worker effects and firm effects up to one effect in each dimension. In the empirical analysis we focus on the largest group (group 1) which covers more than 85 % of all observations, more than 85 % of all workers, and more than 55 % of all firms. (Smaller groups typically consist of one worker being employed with the same one person firm in the entire sample period). We normalize all effects such that they can be interpreted as the deviation of the firm effect from the average firm effect in the group.

We apply this procedure separately, to the log of daily earnings w_{it}, and the risk of an injury or illness, R_{it}.

Figure 1:

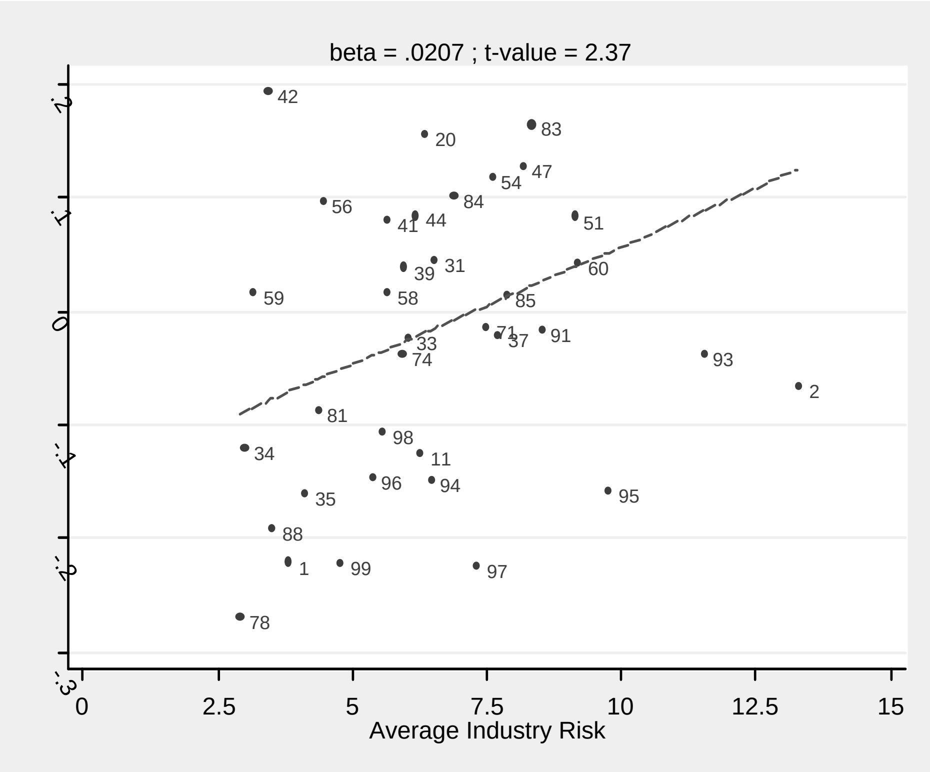
Wages and injury risks, 2-digit industries



Note: Vertical axis measures mean log daily wage per industry, horizontal axis measures agregate industry injury risk (yearly injuries per 100 employees)

Figure 2:

A. Firm wages component and injury risk, industries



B. Worker wages component and injury risk, industries

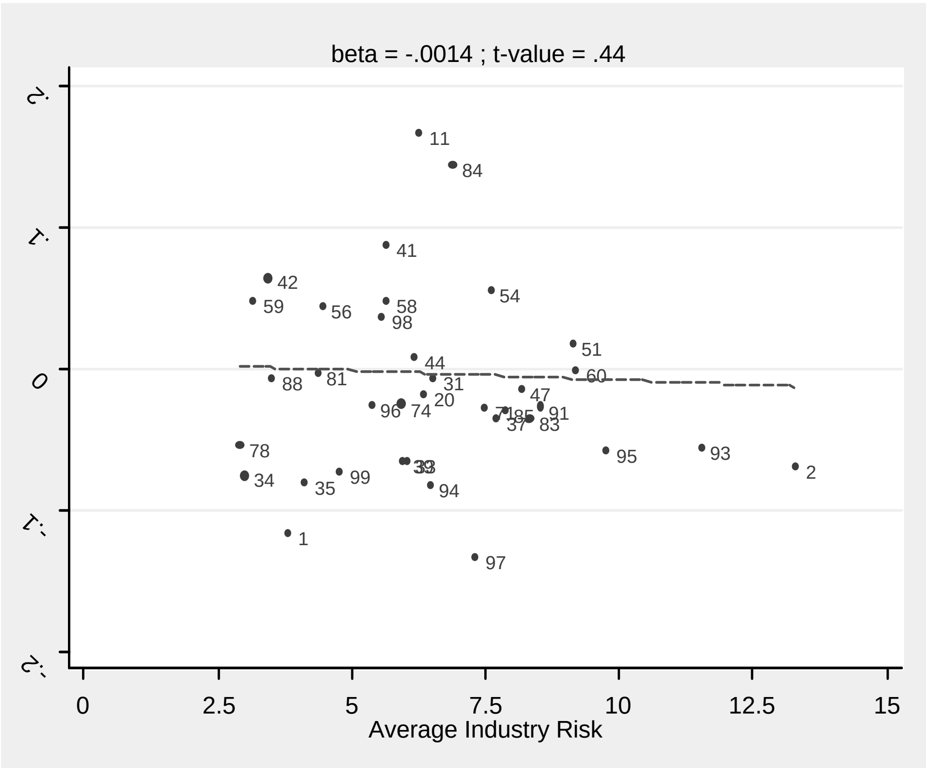


Figure 3: Wages and workplace injury risks, (industry X firm-size cells)

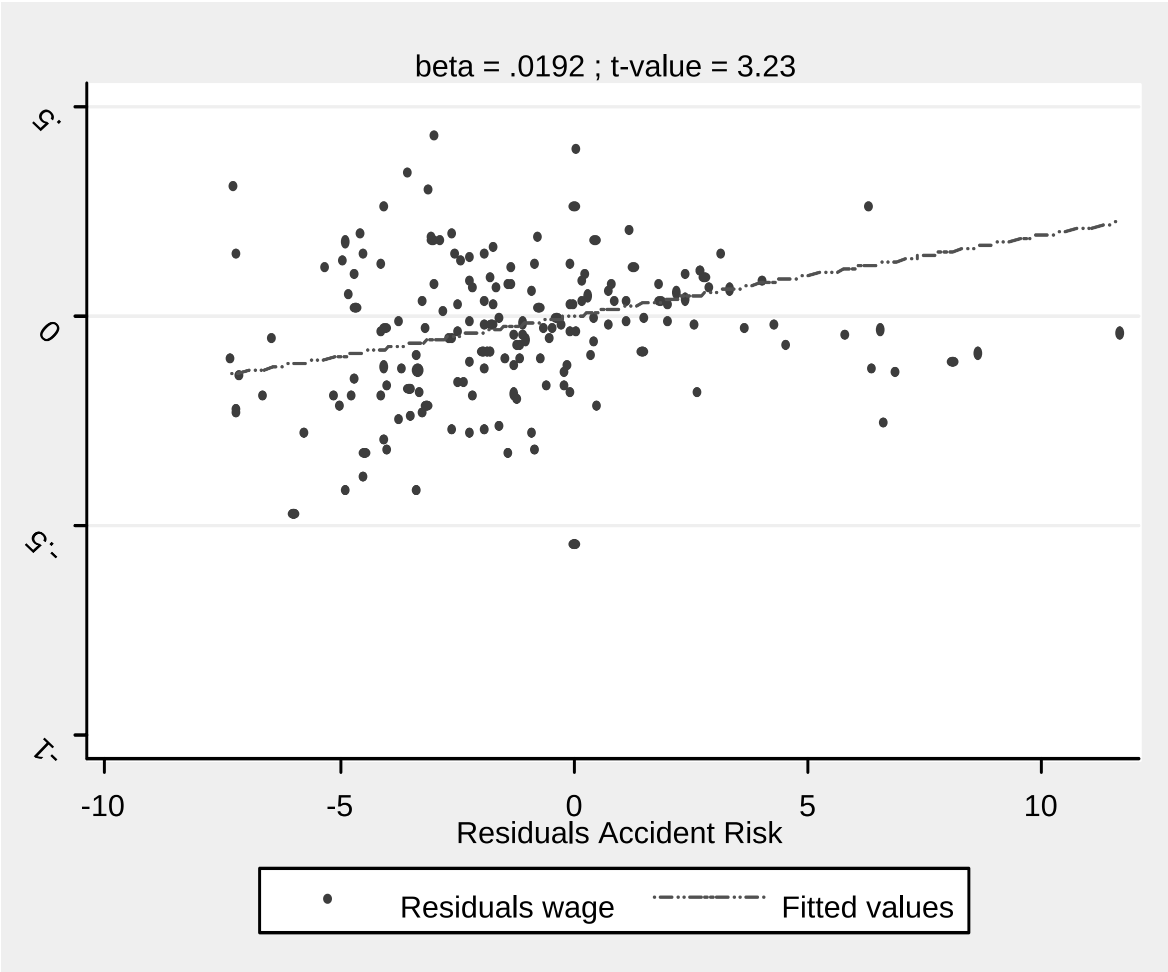
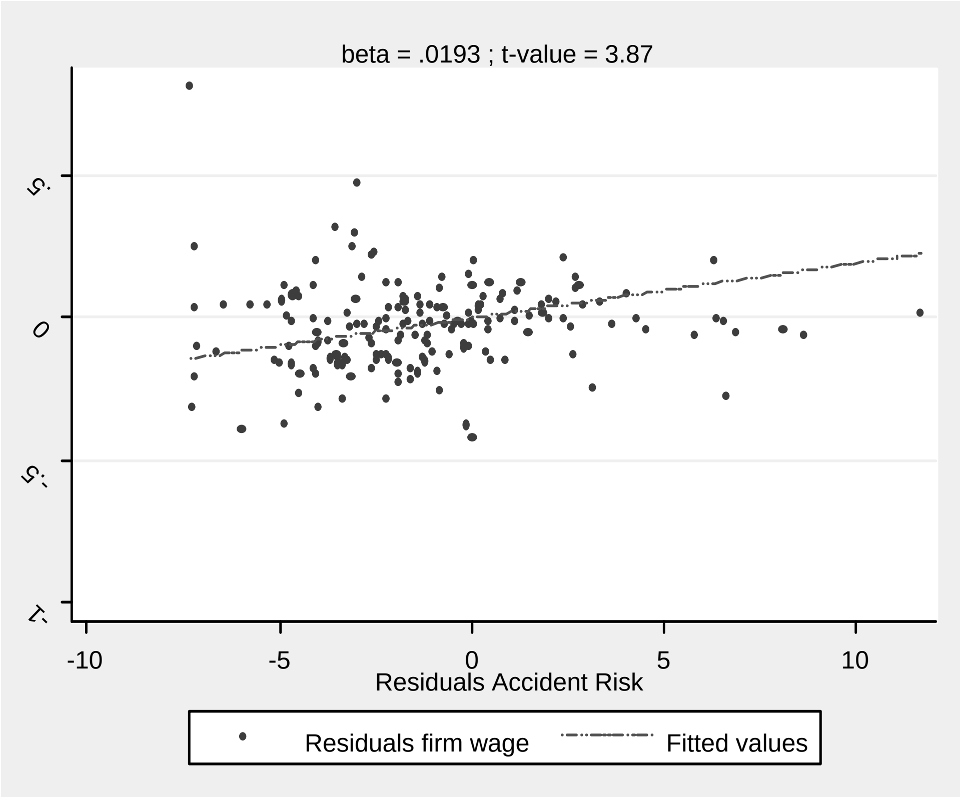


Figure 4:

A. Firm wages component and injury risk, industry x firmsize categories



B. Worker wages component and injury risk, industry x firmsize categories

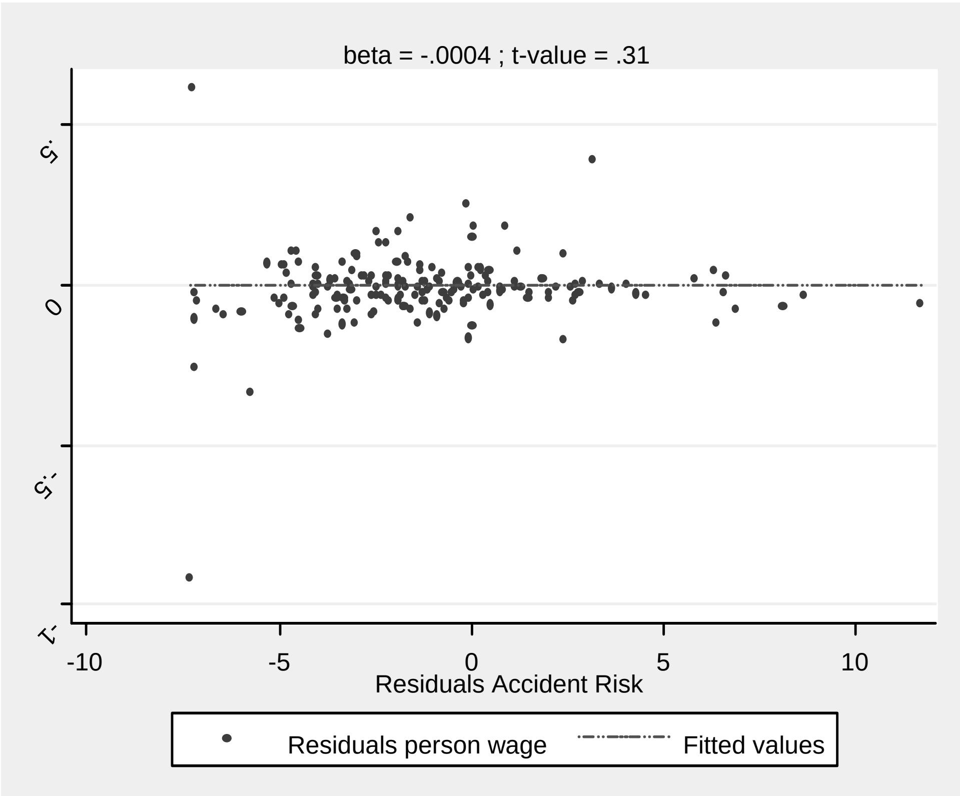


Table 1: Descriptive statistics

Accident risk	7.238	(44.703)
Duration	97.002	(983.642)
Wage rate	69.906	(20.112)
Work experience[a]	16.753	(8.039)
Tenure[a]	7.354	(7.396)
Age	39.073	(8.963)
Firmsize	466.723	(1583.463)
N(obs)	2'846'102	
N(firms)	62'497	
N(workers)	618'174	

a: measured in years, since 1.1.1972

Table 2: Wages and injury risks, two-digit industry

Depending variable	ln(wage rate)	Firm wage component	Worker wage component
Accident risk, industry categories ca	0.0202	0.0209	-0.0010
	(1.86)	(2.37)*	(0.44)
Age	0.0024	-0.0018	0.0021
	(1.29)	(1.00)	(3.30)**
Age squared	-0.00004	0.00002	-0.00004
	(2.32)*	(1.17)	(4.44)**
Tenure	0.2833	0.1050	0.1137
	(6.11)**	(3.39)**	(6.73)**
Tenure squared	-0.0592	-0.0275	-0.0269
	(5.16)**	(3.67)**	(5.88)**
Constant	3.8577	-0.1657	-0.0697
	(43.12)**	(2.40)*	(2.90)**
Time Dummies	YES	YES	YES
Observations	2'846'102	2'846'102	2'846'102
R-squared	0.14	0.07	0.03

Notes: **, * denotes significance at the 1\%, 5\% level respectively. Robust, industryclustered t-values in parentheses

Source: Own calculations, based on ASSD and AUVA

Table 3: Wages and Injury Risks, industry x firmsize categories

Depending variable	ln(wage rate)	Firm wage component	Worker wage component
Accident risk, industry x firmsize cat.	0.0192	0.0194	-0.0004
	(3.23)**	(3.87)**	(0.31)
Age	0.0024	-0.0018	0.0022
	(1.84)	(1.53)	(4.07)**
Age squared	-0.00004	0.00002	-0.00004
	(3.13)**	(1.53)	(5.92)**
Tenure	0.2769	0.0985	0.1139
	(9.19)**	(4.39)**	(11.35)**
Tenure squared	-0.0569	-0.0251	-0.0270
	(7.26)**	(4.33)**	(8.89)**
Constant	3.8716	-0.1482	-0.0739
	(77.37)**	(3.81)**	(4.93)**
Time Dummies	YES	YES	YES
Observations	2'846'102	2'846'102	2'846'102
R-squared	0.15	0.08	0.03

Notes: **, * denotes significance at the 1\%, 5\% level respectively. Robust, industryclustered t-values in parentheses

Source: Own calculations, based on ASSD and AUVA

Table 4: The effect of firm and worker risks on wage components

Depending variable	ln(wage rate)	Firm wage component	Worker wage component
Firm component of accident risk, industry x firmsize cat	0.0152	0.0157	-0.0007
	(2.68)**	(3.29)**	(0.58)
Worker component of accident risk, industry x firmsize	0.0048	0.0064	-0.0017
	(0.64)	(1.06)	(0.88)
Constant	4.0220	0.0022	-0.0756
	(169.98)**	(0.12)	(7.05)**
Control Variables	YES	YES	YES
Time Dummies	YES	YES	YES
Observations	2'846'102	2'846'102	2'846'102
R-squared	0.17	0.10	0.03

Notes: **, * denotes significance at the 1\%, 5\% level respectively. Robust, industryclustered t-values in parentheses

Source: Own calculations, based on ASSD and AUVA

Table 5: Injury risks vs. injury duration

Depending variable	ln/(wage rate)			Firm wage component		
Accident risk, industry x firmsize cat.	0.0192		0.0130	0.0194		0.0144
	(3.23)**		(2.40)*	(3.87)**		(3.22)**
Accident duration, industry x firmsize ca		0.0027	0.0018		0.0025	0.0014
		(3.14)**	(2.38)*		(3.21)**	(2.26)*
Constant	3.8716	3.7410	3.7455	-0.1482	-0.2537	-0.2487
	(77.37)**	(43.87)**	(49.77)**	(3.81)**	(3.51)**	(4.04)**
Control Variables	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES
Observations	2'846'102	2'846'102	2'846'102	2'846'102	2'846'102	2'846'102
R-squared	0.15	0.15	0.16	0.08	0.07	0.09

Notes: **, * denotes significance at the 1\%, 5\% level respectively. Robust, industryclustered t-values in parentheses

Source: Own calculations, based on ASSD and AUVA

Table 6: Compensating wage differentials across different age groups

Age group	25 -30	30 -50	50 -64
A. ln(wage rate)			
Accident risk, industries x firmsize ca	0.01940	0.01969	0.01669
	(3.02)**	(3.28)**	(3.17)**
Observations	476181	1912433	457488
R-squared	0.12	0.16	0.16
B. Firm wage component			
Accident risk, industries x firmsize ca	0.01869	0.01973	0.01832
	(3.48)**	(3.84)**	(4.19)**
Observations	476181	1912433	457488
R-squared	0.07	0.08	0.08
C. Worker wage component			
Accident risk, industries x firmsize ca	0.00039	-0.00026	-0.00165
	(0.32)	(0.24)	(1.03)
Observations	476181	1912433	457488
R-squared	0.03	0.03	0.02

Notes: **, * denotes significance at the 1\%, 5\% level respectively. Robust, industryclustered t-values in parentheses

Source: Own calculations, based on ASSD and AUVA

Table 7: Wages and workplace injury risks: additional controls

A. ln(wage rate)				
Accident risk.	0.0192	0.0179	0.0124	0.0178
industries x firmsize cat	(3.23)**	(4.50)**	(2.53)*	(4.64)**
R-squared	0.15	0.26	0.20	0.27
B. Firm wage component				
Accident risk, industries x firmsize c	0.0194	0.0169	0.0137	0.0166
	(3.87)**	(5.07)**	(3.33)**	(5.20)**
R-squared	0.08	0.21	0.15	0.22
C. Worker wage component				
Accident risk, industries x firmsize c	-0.0004	0.0010	-0.0015	0.0012
	(0.31)	(0.93)	(1.35)	(1.15)
R-squared	0.03	0.05	0.03	0.05
Industry dumies	NO	YES	NO	YES
ln(firmsize) included	NO	NO	YES	YES
Region dummies	NO	NO	NO	YES

Notes: **, * denotes significance at the 1\%, 5\% level respectively. Robust, industryclustered t-values in parentheses

Source: Own calculations, based on ASSD and AUVA

Table 8: Wages and workplace injury risks: construction versus non-construction workers

	Construction	Non construction
A. ln(wage rate)		
Accident risk	0.02708	0.0170
(industries x firmsize cat.)	(8.90)**	(2.40)*
Observations	648'703	2'197'399
R-squared	0.13	0.16
B. Firm wage component		
Accident risk	0.02320	0.0183
(industries x firmsize cat.)	(12.71)**	(3.03)**
Observations	648'703	2'197'399
R-squared	0.09	0.08
C. Worker wage component		
Accident risk	0.00353	-0.0016
(industries x firmsize cat.)	(2.11)*	(1.21)
Observations	0.01	2'197'399
R-squared	648'703	0.04

Notes: **, * denotes significance at the 1\%, 5\% level respectively. Robust, industryclustered t-values in parentheses

Source: Own calculations, based on ASSD and AUVA