Jochen Kluve and Sandra Schaffner

Gender Wage Differentials and the Occupational Injury Risk

Evidence from Germany and the US

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Jochen Kluve and Sandra Schaffner*

Gender Wage Differentials and the Occupational Injury Risk – Evidence from Germany and the US

Abstract

Numerous studies, in particular for the US, have shown that individuals in occupations with high injury risk are compensated for that risk by corresponding bonus payments. At the same time, male workers are overrepresented in the most dangerous occupations like scaffolders or miners, while females typically work in relatively safe occupations with respect to occupational injuries. It is therefore remarkable that almost all studies analyzing the gender wage gap have disregarded different occupational injury risks as a potential explanatory variable for observed gender wage differentials. By merging data on occupational injury risks to German and US panel data on individual workers, this study analyzes gender wage differentials in Germany and the US considering fatal occupational injury risk. The Blinder-Oaxaca method for tobit models is used to decompose the gender wage gap with and without consideration of the fatal injury risk. Our results indicate that the compensating wage differentials for risky jobs are reflected in the resulting gender wage gap, which is caused by the unequal distribution of occupational injury risks among men and women.

JEL Classification: J16 J17 J31 J7

Keywords: Gender wage differentials, occupational injury risk, compensating wage differentials, Blinder-Oaxaca decomposition

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1 Introduction

The gender wage gap is a topic in labor economics that has received much attention, and a substantial body of research exists that intends to identify the factors that can help explain the observed differentials in male and female earnings (see Altonji & Blank, 1999 for an overview). In this paper we add to the analysis of gender wage differentials by focusing on an additional explanatory variable that has received little, if any, attention in previous analyses: the occupational injury risk.

Several studies estimating the value of a statistical life with labor market data (for a summary see Viscusi & Aldy, 2003) have shown that individuals in occupations with high injury risk are compensated for that risk by corresponding bonus payments. At the same time, it is mainly men that work in the most dangerous occupations (such as scaffolders, miners, sailors, etc.), while women tend to work in relatively safe occupations as regards the on-the-job risk of injury or death. If compensating wage differentials for high injury risks exist for both genders, and the distribution of the occupational risks differs between male and female workers, then part of the gender pay gap can be explained by the differences in the injury risks men and women experience. We therefore investigate the extent to which differences in the occupational injury risk of the jobs that men and women occupy, and the corresponding compensation, can help explain observed gender wage differentials.

Whereas the results obtained by Groshen (1991) indicate for the US that sex segregation into occupations, industries and establishments can explain almost the entire wage gap, the study by Bayard, Hellerstein, Neumark, and Troske (1999) suggests that only a fraction of the gender pay gap is accounted for by that segregation, and a substantial part of the gender pay gap remains. This last result is in line with the findings of Black, Kunze, and Salvanes (2004) using Norwegian employer-employee data. The study by DeLeire and Levy (2001) suggests that the sex segregation into occupations is dependent on different features of the jobs such as the occupational risks of injury and fatality. The results show that women choose safer jobs. If the occupational injury risk accounts for the sex segregation into occupations, and the segregation explains part of the gender pay gap, then it can be concluded that the unequal distribution of occupational injury risks causes part of the gender wage differential.

In accordance with the evidence for the US (surveyed in (Viscusi & Aldy, 2003)), recent studies for Germany also find compensating wage differentials for occupational injury risks (Bellmann, 1994, Spengler, 2004, Schaffner & Spengler, 2005). To our knowledge, Lorenz and Wagner (1989) is the only study in which the occupational injury risk is considered as part of the explanation of the gender pay gap. The study uses the first wave of the German socioeconomic panel along with data from the statutory accident insurance organizations. The results do not confirm the hypothesis that including a variable for the occupational injury risk reduces the unexplained part of the gender pay gap. The dataset they use is rather small, and Lorenz and Wagner (1989), also suspect to have some measurement error in their risk data. Hence, their results certainly require further examination. In doing this, we take advantage of more recent and more extensive data: specifically, large panel datasets and information on injuries for several years. Merging the latter with the administrative panel data provides a more reliable way of calculating occupational rates of injuries and fatalities.

In our study we use two panel data sets for Germany and one for the US, each giving us necessary information for an analysis of gender wage differentials, i.e. occupational choice and characteristics of the job and the individual. The data cover the years 1995 – 2001, and are then merged to complementing data on occupational injuries in Germany and the US, respectively. Adopting the standard human capital model (Becker, 1971) we use sociodemographic and occupational factors to explain the gender pay gap. The method by Blinder (1973) and Oaxaca (1973) and the Blinder–Oaxaca Decomposition for tobit models by Bauer and Sinning (2005) are used to decompose the gender pay gap into a part caused by differences in human capital and the occupational settings and into an unexplained surplus. Our data document a substantial gender wage gap of about 21.2–26.3 percent for full-time workers in West–Germany and the US. Using the Blinder-Oaxaca decomposition a part of this gender pay gap can be explained. This part increases when we include the occupational injury risk as an explanatory variable. In East-Germany the gender wage gap of full–time workers is quite small of about 8.5 to 11 percent and cannot be explained by the sociodemographic factors we used, independent therof we include the occupational injury risk or not.

The paper is structured as follows: In section 2 we describe the data on individual workers and the occupational injury risk. Section 3 presents the empirical specification. Estimation results are discussed in section 4. Section 5 concludes.

2 Data

For an analysis combining an assessment of risk-induced wage differentials with an assessment of the gender wage gap, two sources of information are required. First, individual-level data on sociodemographic characteristics, in particular human capital acquisition, as well as characteristics of the job. For Germany, these micro data come from the IAB employment subsample and from the German SocioEconomic Panel GSOEP (see below). For the US, we use data from the Panel Study of Income Dynamics PSID. Second, these data need to be complemented by information on the injury risk in certain occupations. For Germany, we obtain corresponding data from insurance carriers. For the US, data from the Census of Fatal Occupational Injuries CFOI are used. We discuss these data sets in turn.

2.1 Data on worker and job characteristics

As mentioned above, our study uses data from both Germany and the US to assess and compare risk-induced gender wage differentials in both countries. We will first discuss two data sources on worker and job characteristics from Germany, then turn to the US.

The **IAB Employment Subsample (IABS)** is a 2% random sample of all employees registered by the German social insurance system since 1973. The data are stored by the IAB (Institut für Arbeitsmarkt- und Berufsforschung, Institute for labor market research), which is part of the German *Federal Employment Service* (Bundesanstalt für Arbeit). Supplementary information on establishments and on unemployment spells during which a claimant received transfer payments was added to the sample. The IABS we use covers a total period of 27 years from January 1, 1975, until December 31, 2001, and contains daily flow information. we restrict our data on the years 1995–2001. The data originate in corresponding notifications regarding individual worker status that each employer has to make available for the compulsory health, annuity and unemployment insurances.

The IABS does not record individuals who are self-employed, family workers, judges, civil servants, soldiers, conscripts, individuals in community service as an alternative to military service, individuals who are marginally employed (i.e. below a certain threshold income, cf. below), and students enrolled in higher education. The large majority of the working population, however, is covered by the data: For instance, in 1995 79,4% of all people in paid work in West Germany appear in the data (Bender, Haas, & Klose, 1999). The version of the IABS that is available for scientific use has been made anonymous in several ways, a procedure which is described in detail in Bender, Haas, and Klose (2000). The IABS covers roughly 200,000 individuals.

As mentioned above, the IABS is characterized by the legal obligation of the employers to report data on their employees for the health, pension and unemployment insurance schemes. This leads to a rather high reliability of the stored information, especially concerning the data necessary for the social security system.[1] The measured earnings in the IABS are the mean daily earnings (gross earnings of the whole period divided by number of days in the period). Decimal places are cut, leading to a maximum error of 0.99 Euros per day and 30.69 Euros per month. Incomes are right–censored because all workers and employees with earnings above the assessment threshold of the social insurance are assigned the respective threshold as earnings. This upper limit is 1,432 Euros in 1975 and 4,448 Euros (West-Germany) and 3,732 Euros (East-Germany) in 2001. The lower limit of earnings is given by the threshold for marginal employment and during our observation period takes on values between 179 Euros (1975) and 297 Euros (1995). Until the year 1998, however, the marginally employed do not form part of the IABS and therefore the earnings are left–truncated in the older waves. Because our analysis focusses on full–time workers the right censoring of the wages is the more important problem to address, and we discuss this further below.

[1]This applies to earnings, sex, age, and dates. Other variables are collected for statistical evaluation.

The second German data source is the **German Socioeconomic Panel (GSOEP)**, a representative annual survey of private households in Germany that was started in 1984 in West Germany. East German households have been interviewed since 1990. On average the GSOEP covers 4,500 households with 11,000 indivduals (of which about 6,000 are employed) per year. Panel attrition generally arises if a person dies or goes abroad, and is low in the GSOEP: For West Germany, of the initial 5921 households with 12290 individuals in the year 1984, 3724 households with 6811 persons are still in the sample in 2004. For East Germany, from the initial 2179 households with 4453 individuals in 1990, in 2004 1813 households with 3435 persons remain (see www.diw.de/english/sop/index.html). New households emerge if an individual separates from a previously interviewed household, e.g. by moving out, and forms or becomes part of a new household. The GSOEP is a rather comprehensive data source, containing up to 100 variables for the household and more than 250 variables for the individual. Comparable to the IABS we restrict our analysis to the waves 1995-2001.

The data are collected at a specific due date each year and the earnings reported refer to the last month before this date. To adapt the GSOEP to the IABS all marginally employed individuals are disregarded in the following analysis and earnings are calculated as daily wages.

Comparing the two data sets, the GSOEP has the advantage that it is much richer in variables, covering nearly every theme of the daily life. Whereas the IABS data on the other hand mainly cover employment, unemployment and related variables, it has the advantages of a large sample size and the reliability of the reported information. The data sets thus complement each other.

Turning to the US data, the **Panel Study of Income Dynamics** has followed a core set of households since 1968, complemented by newly formed households as members of the core households have split off into new families. The PSID provides individual-level data on demographics, wages, industry and occupation. Since the time interval between interviews does not always correspond to one year, we use the 1995, 1997, 1999, and 2001 waves for our analysis. We exclusively consider full-time workers, excluding the marginally employed and apprentices.

2.2 Data on the occupational injury risk

Data on occupational accidents are separately available for fatal and non-fatal accidents at the workplace as well as travel accidents. The latter are dependent on the distance to work and not on the occupation. But both, the fatal and non-fatal accidents at the workplace are determined by the occupation. Those risks are highly correlated among each other. We decide to use only the fatal injury risk because non-fatal injuries are compensated by the insurances in Germany. The wage will be paid by the insurance as long as a worker has to stay out of work. Additional compensations are paid for permanent injuries. There exist also some compensation for the surviving dependents. But the worker himself is not compensated for a high fatal risk.[2]

The data from the IABS, GSOEP, and PSID described in the previous section provide us with crucial information on sociodemographic and job characteristics at the individual level. For the purposes of our analysis this information needs to be complemented with **Industrial Injury Data** from other sources.

In Germany all occupational injuries, travel accidents and occupational diseases that

[2]We also did our analysis with the non-fatal injury risk instead of the fatal risk and found out that there would be no significant difference in our main findings if we decided to use the non-fatal risk.

cause an individual to be absent from work for at least three days are reported to the accident insurance if the concerned person is insured. The insurance associations, association of commercial and industrial workers' compensation insurance carriers (Hauptverband der gewerblichen Berufsgenossenschaften, HVBG), the Federal Association of Accident Insurers (Bundesverband der Unfallkassen, BUK), and the association of agricultural workers' compensation insurance carriers (Bundesverband der landwirtschaftlichen Berufsgenossenschaften, LSV) collect all these data about work accidents. All employed persons who are not insured with the LSV or BUK are insured at the HVBG. Contrary to employees, self-employed persons (with the exception of self-employed individuals in agriculture, who have to be insured with the LSV) can voluntarily choose to become member of a HVBG insurance. Especially entrepreneurs in handicraft and the small business sector are voluntarily insured because they often work together with their employees and face an increased injury risk.

The data from the insurance associations give the total number of accidents each year in each occupation. In order to measure the occupational injury risk on the basis of the total number of injuries for each occupation each year it would be necessary to know the total number of insured workers in each occupation. This information, however, is not available, and not even the insurers themselves know these numbers. They only learn about the occupation of an insurant if he has an injury and they receive notification of the accident. Hence, the total number of insurants per occupation has to be extrapolated from the number of employees in each occupation.

We implement this extrapolation using the IABS. Whereas, in principle, other equally feasible data sources exist (such as the "Mikrozensus", i.e. German census data, used by Spengler (2004)), we believe that the decisive factor for using the IABS is the possibility of counting full-time-man-years worked in each occupation. For instance, several types of work such as part-time jobs exist that are not full-time occupations on every single day of the year. The measured number of injuries, however, is for the entire year. Work in the construction sector, to give another example, follows a seasonal pattern and more jobs exist in the summer than in the winter. At the same time, such seasonal work implies an occupation with increased injury risk. Using the daily information in the IABS it is possible to approximate how many full-time-man-years are worked in each year in each occupation.

Table 1: Occupational injury risk severity of an fatal injury per 1.000 fulltime-man-years of each occupation, in Germany: the 10 occupations with the highest fatal injury risk (out of 241 occupations)

occupation	*rk.*	mean	std.	min.	max.
Inland waters navigator	*1*	0.6854	0.3577	0.1426	1.1505
Scaffolders	*2*	0.4946	0.1615	0.1804	0.7150
Deckhands	*3*	0.3940	0.1891	0.1403	0.6530
Blasters	*4*	0.3423	0.5857	0.0000	1.2638
Building labourer (non-specified)	*5*	0.3346	0.0872	0.2319	0.4444
Quarrymen	*6*	0.3254	0.2852	0.0000	0.7073
Air traffic occupations	*7*	0.2721	0.2262	0.1050	0.7208
Sundry civil engineering occupations	*8*	0.2702	0.0792	0.1787	0.4237
Motor vehicle drivers	*9*	0.2407	0.0179	0.2164	0.2629
Roofers, slaters	*10*	0.2387	0.0497	0.1363	0.2915

Table 1 shows the 10 occupations with the highest fatality risk in Germany. Note, however, that not all available occupations are part of the statistics and the following analysis. Occupations mainly taken by civil servants and employees (firemen, . . .), agricultural occupations, and occupations mainly taken by self-employed (innkeepers, entrepreneurs, . . .) are not considered because they are not included at all, or with too few observations, in the IABS, which would lead to a bias in the calculated risk. Gardeners are also excluded because the LSV does not distinguish the different occupations in their injury data.

Table 2: Selected Summary Statistics

	West-Germany								**East-Germany**								**US**			
	GSOEP				IABS				GSOEP				IABS				PSID			
	male workers		female workers		male workers		female workers		male workers		female workers		male workers		female workers		male workers		female workers	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
daily wage[in 2001€/in 2001$]	88.49	44.33	65.24	25.47	94.85	29.14	72.38	28.01	62.30	23.60	56.41	20.80	65.16	22.91	59.78	23.49	85.50	52.80	67.67	46.48
log daily wage	4.409	0.380	4.112	0.377	4.500	0.344	4.196	0.446	4.071	0.345	3.965	0.376	4.117	0.351	4.003	0.442	4.324	0.478	4.079	0.491
7–year fatal injury risk $\times 10^3$	0.076	0.015	0.025	0.026	0.047	0.073	0.011	0.080	0.086	0.015	0.028	0.035	0.079	0.097	0.014	0.035	1.212	3.235	0.373	2.130
age 15-20	0.008	0.090	0.019	0.135	0.008	0.090	0.015	0.122	0.006	0.078	0.006	0.078	0.009	0.095	0.007	0.085	0.006	0.078	0.011	0.106
age 20-25	0.069	0.253	0.138	0.345	0.067	0.249	0.128	0.334	0.068	0.252	0.102	0.303	0.073	0.260	0.075	0.263	0.093	0.290	0.088	0.283
age 25-30	0.135	0.342	0.178	0.382	0.134	0.340	0.172	0.378	0.126	0.332	0.104	0.306	0.123	0.328	0.104	0.306	0.141	0.348	0.103	0.304
age 30-35	0.185	0.388	0.141	0.348	0.178	0.383	0.153	0.360	0.150	0.357	0.122	0.328	0.159	0.366	0.149	0.356	0.153	0.360	0.135	0.342
age 35-40	0.161	0.368	0.117	0.322	0.164	0.370	0.133	0.339	0.171	0.376	0.178	0.383	0.164	0.370	0.173	0.378	0.146	0.354	0.162	0.368
age 40-45	0.130	0.337	0.129	0.336	0.136	0.342	0.126	0.332	0.155	0.362	0.178	0.383	0.152	0.359	0.167	0.373	0.147	0.355	0.152	0.359
age 45-50	0.117	0.321	0.119	0.323	0.116	0.320	0.114	0.317	0.130	0.336	0.143	0.350	0.125	0.331	0.138	0.345	0.132	0.338	0.138	0.345
age 50-55	0.093	0.290	0.088	0.283	0.099	0.298	0.089	0.284	0.106	0.308	0.103	0.304	0.103	0.304	0.110	0.312	0.082	0.275	0.095	0.293
age 55-60	0.078	0.269	0.065	0.246	0.080	0.271	0.064	0.245	0.076	0.265	0.060	0.237	0.080	0.271	0.074	0.262	0.050	0.217	0.054	0.227
age 60-70	0.024	0.152	0.007	0.083	0.020	0.140	0.007	0.085	0.013	0.113	0.003	0.054	0.012	0.110	0.003	0.052	0.042	0.200	0.056	0.231
white																	0.744	0.436	0.719	0.450
no vocational qualification, no upper secondary degree	0.184	0.388	0.232	0.422	0.153	0.360	0.167	0.373	0.031	0.172	0.035	0.183	0.044	0.205	0.040	0.196				
no vocational qualification, upper secondary degree	0.008	0.090	0.010	0.102	0.008	0.087	0.010	0.097	0.004	0.062	0.004	0.062	0.003	0.052	0.003	0.059				
with vocational qualification, no upper secondary degree	0.637	0.481	0.610	0.488	0.712	0.453	0.718	0.450	0.738	0.440	0.583	0.493	0.823	0.382	0.821	0.384				
with vocational qualification, upper secondary degree	0.031	0.172	0.051	0.219	0.033	0.179	0.057	0.232	0.034	0.182	0.038	0.191	0.026	0.159	0.046	0.210				
university of applied science degree	0.057	0.232	0.044	0.205	0.045	0.208	0.020	0.139	0.097	0.296	0.264	0.441	0.044	0.205	0.048	0.214				
university degree	0.083	0.275	0.052	0.223	0.049	0.216	0.028	0.166	0.096	0.295	0.076	0.265	0.061	0.239	0.042	0.201				
years of education																	12.33	2.198	12.69	2.194
unskilled worker	0.234	0.423	0.222	0.416	0.228	0.420	0.170	0.376	0.141	0.348	0.091	0.288	0.124	0.330	0.079	0.270				
skilled worker	0.330	0.470	0.047	0.213	0.348	0.476	0.059	0.236	0.500	0.500	0.131	0.337	0.564	0.496	0.146	0.354				
master craftsman	0.038	0.191	0.003	0.051	0.031	0.173	0.002	0.047	0.045	0.207	0.006	0.075	0.026	0.161	0.003	0.059				
white collar, salaried	0.398	0.490	0.728	0.445	0.393	0.488	0.769	0.421	0.314	0.464	0.772	0.420	0.286	0.452	0.772	0.419				
tenure	11.17	9.779	8.848	8.166	7.979	5.329	6.994	5.070	8.071	8.826	8.667	8.430	3.950	2.624	4.337	2.617	7.783	8.391	6.130	7.189
work experience	14.72	9.423	12.12	8.331					12.46	9.801	11.93	8.831								
job covered by union																	0.282	0.450	0.137	0.344
union member																	0.260	0.439	0.116	0.320
work for government																	0.090	0.287	0.244	0.429
number of observations	15,571		6,913		1,339,534		676,802		5,202		3,396		258,042		182,264		3,837		3,730	

To obtain the fatality risk for the US we use US Bureau of Labor Statistics data from the Census of Fatal Occupational Injuries (CFOI) for 1992–2002. These publicly available data contain the number of fatal injuries by two-digit industries by one-digit occupations. The CFOI data come from reports by the Occupational Safety and Health Administration, workers' compensation reports, death certificates, and medical examiner reports. These data are combined with the number of employed persons published by the Bureau of Labor Statistics on the basis of the Current Population Survey. In contrast to the German injury data, industrial injury risks are used for the US data set. However, the main groups of the German occupational classification system and the US industrial classification system are similar (agriculture/forestry, mining, construction, manufacturing,...).

Two measures of fatality risk will be used. The first measure is the number of fatal injuries divided by the number of employed persons in each year in each occupation. The second measure is the 7–year average of the fatality risk. We expect to have less measurement error in the 7–year average relative to the annual rate. The CFOI data only contains the total number of injuries in the observed 7 years. Thus, we can only use the 7–year average in the PSID sample.

2.3 Descriptive Analysis

Table 2 contains summary statistics of the three data sets on worker and job characteristics, distinguishing also between West and East Germany. The raw difference in the daily wages of men and women amounts to about 20 euros (in 2001 euros) in West–Germany, for both the GSOEP and IABS data. In East–Germany this raw difference is much smaller (approximately 6 Euros), but it is certainly striking that the average wage of East German men is much lower than that of West–German women. In both the GSOEP and the IABS, West–German men earn on average about 30 Euros a day more than East–German men. According to the PSID data, male workers in the US on average earn about 18 dollars (in 2001 dollars) more than female workers.

A substantial difference in the mean fatal injury risk that men and women experience in their job can be seen in all samples. In all samples, i.e. both in Germany and in the US, the fatal injury risk for men is about three to four times as high as that of women. Looking at the other covariates, men in West-Germany on average have more educational attainment than women, while this difference is much smaller in East–Germany. In the US, the average years of education are almost the same across gender. Moreover, US female workers are much less likely to be covered by unions than their male counterparts, but more likely to work for the government.

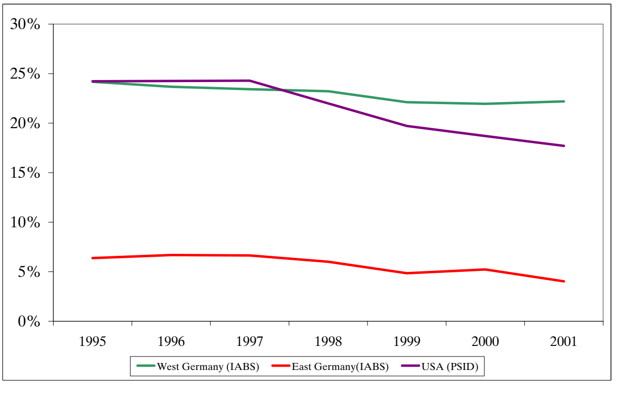

Figure 1: The observed Gender Pay Gap of fulltime workers in West–Germany, East–Germany and the US

The raw gender pay gap and its development during the years 1995 to 2001 in West-Germany, East-Germany and the US are drawn in figure 1. The figure compares wages of fulltime workers. The gap is expressed in relation to the mean male wage. It is noticeable that the observed pay gap is quite low in East–Germany compared to the US and West–

Germany. The pay gap in West–Germany remains almost stable over the years 1995 to 2001 while it decreases in the US and East–Germany.

3 Empirical Specification

The wage regressions are estimated separately for men and women, and the following regression equations are used:

$$\ln Y_{iM} = \beta_M * \mathbf{X}_{iM} + \varepsilon_{iM}; \qquad \ln Y_{iF} = \beta_F * \mathbf{X}_{iF} + \varepsilon_{iF} \tag{1}$$

$\mathbf{X}$ is a vector of productivity related variables and ε is the error term. Using OLS it is assumed that the estimated regression curve goes to the arithmetic means of all variables and the expectation of the residual is zero. The difference of the logarithmic wages becomes:

$$\overline{\ln Y_M} - \overline{\ln Y_F} = \Delta^{OLS} = \widehat{\beta_M} * \overline{\mathbf{X}_M} - \widehat{\beta_F} * \overline{\mathbf{X}_F} \tag{2}$$

$$= \underbrace{\widehat{\beta_M} * (\overline{\mathbf{X}_M} - \overline{\mathbf{X}_F})}_{\textit{diff. capacities}} + \underbrace{\overline{\mathbf{X}_F} * (\widehat{\beta_M} - \widehat{\beta_F})}_{\textit{unexplained rest}} \tag{3}$$

$$= [E_{\beta_M}(\ln Y_{iM}|\mathbf{X}_{iM}) - E_{\beta_M}(\ln Y_{iF}|\mathbf{X}_{iF})] + [E_{\beta_M}(\ln Y_{iF}|\mathbf{X}_{iF}) - E_{\beta_F}(\ln Y_{iF}|\mathbf{X}_{iF})] \tag{4}$$

Equation 3 results from addition and subtraction of $\widehat{\beta_M}\overline{\mathbf{X}_F}$. The first part of the wage equation $\widehat{\beta_M} * (\overline{\mathbf{X}_M} - \overline{\mathbf{X}_F})$ is the part of the wage gap that arises from differences in the productivity of both sexes. The second term is the unexplained remainder, which could be interpreted as discrimination. In equation 3 addition and subtraction of $\widehat{\beta_F}\overline{\mathbf{X}_M}$ is also possible, leading to a different weighting. The basic assumption that women would reach the same wage as men if no discrimination existed leads to the version written down here.

This assumption is commonly used and sets the male wage as reference wage. Because of the right-censoring of the wages in the IABS (cf. section 2.1 above) we use the Blinder-Oaxaca–Decomposition for Tobit–Models developed by Bauer and Sinning (2005). The wages are right-censored with a censoring bound that changes each year:

$$\begin{aligned} \ln Y^*_{iM} &= \beta_M * \mathbf{X}_{iM} + \varepsilon_{iM} & \ln Y^*_{iF} &= \beta_F * \mathbf{X}_{iF} + \varepsilon_{iF} \\ \ln Y_{iM} &= a_t \text{ if } \ln Y^*_{iM} \geq a_t & \ln Y_{iF} &= a_t \text{ if } \ln Y^*_{iF} \geq a_t \\ \varepsilon_{iM} &\sim N(0, \sigma^2_M) & \varepsilon_{iF} &\sim N(0, \sigma^2_F) \end{aligned} \tag{5}$$

Bauer and Sinning (2005) show that the decomposition in equation 3 is not appropriate if the dependent variable is censored. In particular, the conditional expectations depend on the variance of the error terms σ_M and σ_F:

$$\begin{aligned} \Delta^{Tobit} &= [E_{\beta_M,\sigma_M}(\ln Y_{iM}|\mathbf{X}_{iM}) - E_{\beta_M,\sigma_F}(\ln Y_{iF}|\mathbf{X}_{iF})] \\ &\quad +[E_{\beta_M,\sigma_F}(\ln Y_{iF}|\mathbf{X}_{iF}) - E_{\beta_F,\sigma_F}(\ln Y_{iF}|\mathbf{X}_{iF})] \end{aligned} \tag{6}$$

If the wage is not censored equation 6 reduces to equation 3. Among the data sets we use only the IABS is right-censored with a time-variant upper bound. Thus, we use OLS for the GSOEP and PSID samples and an interval regression for the IABS dataset.

4 Results

The results of the pooled regressions are displayed in table 3. The estimated coefficients show the signs that would be predicted by human capital theory: A higher schooling degree is associated with higher wage differentials and middle-aged workers earn more than the other age groups. A longer job tenure also leads to a higher wage rate. These results apply to all three data sets used.

Table 3: Results of the pooled wage regressions with the different data sets

	West–Germany				**East–Germany**				**US**	
	GSOEP		IABS		GSOEP		IABS		PSID	
	male	female	male	female	male	female	male	female	male	female
fatal injury risk $\times 10^3$	0.389	-0.601	0.229	0.177	0.021	0.470	0.062	0.202	0.005	0.005
	(4.72)	(1.03)	(56.43)	(7.79)	(0.30)	(1.85)	(8.98)	(8.00)	(2.44)	(2.05)
white									0.098	0.009
									(6.59)	(0.55)
married	0.085	-0.044			0.041	-0.019				
	(7.64)	(3.40)			(2.49)	(1.26)				
number of children	0.014	-0.014			-0.008	-0.003				
	(3.01)	(1.06)			(0.91)	(0.23)				
age (Referenz: 15–20–aged)										
20–25	0.181	0.102	0.148	0.173	0.273	0.233	0.171	0.268	0.057	0.023
	(2.78)	(2.18)	(53.10)	(45.54)	(2.47)	(2.75)	(28.48)	(28.53)	(0.96)	(0.47)
25–30	0.193	0.220	0.251	0.269	0.411	0.268	0.264	0.362	0.139	0.186
	(2.90)	(4.60)	(92.45)	(71.20)	(3.78)	(3.15)	(44.87)	(38.89)	(2.32)	(3.83)
30–35	0.274	0.290	0.323	0.281	0.413	0.331	0.308	0.396	0.216	0.239
	(4.27)	(5.90)	(199.46)	(73.78)	(3.80)	(3.86)	(52.80)	(42.88)	(3.65)	(4.98)
35–40	0.257	0.277	0.360	0.266	0.406	0.327	0.324	0.436	0.277	0.253
	(3.98)	(5.51)	(132.54)	(69.03)	(3.73)	(3.80)	(55.51)	(47.31)	(4.66)	(5.29)
40–45	0.263	0.304	0.377	0.282	0.384	0.321	0.323	0.444	0.285	0.261
	(4.07)	(6.16)	(137.62)	(72.86)	(3.52)	(3.76)	(55.08)	(48.11)	(4.81)	(5.35)
45–50	0.278	0.279	0.388	0.291	0.343	0.293	0.308	0.427	0.256	0.221
	(4.29)	(5.48)	(140.92)	(74.76)	(3.12)	(3.40)	(52.26)	(46.07)	(4.34)	(4.66)
50–55	0.253	0.296	0.395	0.282	0.301	0.296	0.288	0.418	0.266	0.236
	(3.87)	(5.52)	(142.17)	(70.90)	(2.74)	(3.41)	(48.39)	(44.81)	(4.34)	(4.75)
55–60	0.229	0.280	0.376	0.247	0.297	0.303	0.267	0.407	0.289	0.176
	(3.49)	(4.99)	(133.72)	(60.37)	(2.69)	(3.51)	(44.39)	(43.03)	(4.68)	(3.41)
60–70	0.248	0.410	0.352	0.228	0.425	0.397	0.341	0.453	0.263	0.049
	(3.55)	(3.55)	(110.68)	(35.82)	(3.64)	(4.08)	(44.82)	(26.20)	(3.81)	(0.93)
highest educational achievement (Ref.: no vocational qualification, no upper secondary degree)										
no vocational qualification, upper secondary degree	0.002	0.367	0.027	0.024	0.107	0.175	0.03	0.003		
	(0.04)	(3.42)	(9.45)	(5.03)	(1.78)	(1.44)	(3.08)	(0.23)		
vocational qualification, no upper secondary degree	0.059	0.075	0.081	0.074	0.039	0.085	0.043	0.086		
	(5.70)	(4.22)	(101.79)	(48.07)	(1.07)	(2.29)	(14.94)	(20.03)		
vocational qualification, upper secondary degree	0.052	0.163	0.168	0.196	0.068	0.116	0.154	0.231		
	(2.13)	(5.61)	(105.59)	(80.23)	(1.38)	(2.51)	(34.36)	(41.41)		
university of applied science degree	0.349	0.355	0.318	0.332	0.228	0.253	0.259	0.297		
	(16.35)	(10.72)	(209.19)	(93.65)	(5.57)	(6.26)	(64.15)	(53.34)		
university degree	0.332	0.322	0.406	0.436	0.312	0.400	0.349	0.409		
	(11.47)	(8.63)	(267.25)	(138.87)	(6.76)	(9.44)	(90.97)	(71.14)		
years of education									0.036	0.054
									(9.03)	(12.18)
occupational status (Ref.: unskilled worker)										
skilled worker	0.111	0.199	0.085	0.067	0.099	0.063	0.062	0.019		
	(12.25)	(6.54)	(114.26)	(28.88)	(5.89)	(2.49)	(33.36)	(5.35)		
master craftsman	0.289	0.643	0.326	0.276	0.246	0.349	0.298	0.193		
	(16.35)	(9.35)	(213.26)	(28.93)	(8.20)	(4.88)	(78.89)	(14.35)		
white collar, salaried	0.350	0.297	0.327	0.305	0.274	0.261	0.335	0.332		
	(24.59)	(12.27)	(397.05)	(187.81)	(12.24)	(11.08)	(151.71)	(101.13)		
job tenure	0.007	0.004	0.022	0.016	0.015	0.019	0.025	0.020	0.010	0.017
	(4.18)	(1.54)	(105.98)	(41.83)	(5.59)	(6.95)	(37.13)	(19.46)	(3.81)	(5.83)
job tenure^2 $\times 10^{-1}$	0.000	0.000	-0.001	0.000	0.000	0.000	-0.001	-0.001	0.000	0.000
	(1.23)	(0.70)	(60.36)	(14.27)	(3.74)	(4.15)	(8.53)	(5.55)	(1.41)	(1.10)
job covered by union									0.140	0.028
									(3.37)	(0.68)
belonging to union									0.171	0.149
									(4.02)	(3.39)
work for government									0.054	-0.013
									(2.25)	(0.78)
firmsize dummies	+	+			+	+				
industry dummies	+	+	+	+	+	+	+	+		
occupation dummies									+	+
year dummies	+	+	+	+	+	+	+	+	+	+
region dummies			+	+			+	+	+	+
number of observations	15,571	6,913	1,339,534	676,802	5,202	3,396	258,042	182,264	3,730	3,837
right censored			136,453	12,904			10,292	2,164		

robust t-statistics in parentheses

The coefficient for the fatal injury risk is positive with high significance across gender and data sets. The only exceptions are for women based on the GSOEP, in which case the coefficient is insignificant for West-German women, and marginally significant for West German women. The table presents the pooled regression results using the 7–year injury risk as explanatory variable. The summary of results of applying the decomposition

Table 4: Blinder–Oaxaca–Decomposition of the different pooled regressions with and without taking into account the fatal injury risk

	West-Germany				**US**	
	IABS		GSOEP		PSID	
Raw Gender Pay Gap	26.34%		25.17%		21.17%	
	(499.04)		(38.60)		(17.62)	
	unexplained	explained	unexplained	explained	unexplained	explained
without the fatal risk	90.82%	9.18%	80.02%	19.98%	62.24%	37.76%
	(639.83)	(64.70)	(28.40)	(7.09)	(14.96)	(9.07)
with the mean fatal risk	89.69%	10.31%	77.10%	22.90%	61.62%	38.38%
	(642.15)	(72.44)	(28.98)	(8.61)	(14.66)	(9.13)
with cont. fatal risk	89.86%	10.14%	77.44%	22.56%		
	(630.73)	(71.15)	(31.50)	(9.18)		

	East-Germany			
	IABS		GSOEP	
Raw Gender Pay Gap	11.06%		8.73%	
	(84.60)		(9.78)	
	unexplained	explained	unexplained	explained
without the fatal risk	188.18%	-88.18%	179.80%	-79.80%
	(111.26)	(52.13)	(11.96)	(5.31)
with the mean fatal risk	186.91%	-86.91%	181.64%	-81.64%
	(111.75)	(51.96)	(12.05)	(5.42)
with cont. fatal risk	187.11%	-87.11	181.83%	-81.83%
	(111.83)	(52.06)	(11.91)	(5.36)

absolute z-values in parentheses

method delineated in section 3 are displayed in table 4. For all three data sets, and West- and East-Germany separately, we estimate pooled regressions both with different risk measures and without any risk measure, for male and female workers. The estimated coefficients are used to calculate the explained and unexplained part of the gender pay gap as described in the previous section.

In the West–German and the US samples part of the gender pay gap can obviously be explained without using the fatality risk as explanatory variable. Adding the fatality risk, however, leads to a further reduction of the unexplained part, on the size of about one to three percentage points.

In contrast to these results, the Blinder-Oaxaca-Decomposition of the pay gap in the East–German sample leads to a bigger unexplained part than the whole raw gender pay gap is. Reasons for this surprising result can be found in the fact that there are less differences in education between East-German women and their male counterparts than in West–Germany. But because of the high unemployment rate well-educated women work in low–paid jobs. In the data it can be seen that several women with a university or university of applied science degree work in the health care as nurses or elderly nurses. By decomposing the gender gap variable by variable the difference in the estimated constants is bigger than the raw gender pay gap. This seems to be a sign for omitted variables. High unemployment rates in the East lead to a bias between the educational degree and the fulfilled occupation. More information about the occupational status are needed. It is remarkable that there is a difference between men an women. This can be a result of different preferences with respect to unemployment or limited access to the labor force for one of the sexes in the concerned occupations and industries.

Of the raw gender pay gap of about 26% in the GSOEP data, 20% can be reduced by adjusting for sociodemographic factors. Taking into account the fatal injury risk explains an additional 3% of the gender pay gap. This seems remarkable in size relative to the part that can be explained by all other sociodemographic factors. In the PSID sample, however, the part of the gender wage gap that can be explained by standard sociodemographic factors is bigger than in the West-German datasets, but the additional part explained by the fatality risk is smaller.

5 Conclusion

In this paper, we have investigated the impact of compensating wage differentials for injury risks on the gender pay gap. Since women select themselves into more secure jobs than men do, and since workers in jobs with high injury risks are compensated for that risk, our analysis is motivated by the hypothesis that part of the observed gender pay gap results from a segregation into more and less secure occupations.

One panel data set for the US (PSID) and two panel data sets for Germany (GSOEP and IABS) for the years 1995 to 2001 are used, containing data on workers' sociodemographic attributes and job characteristics. We complement these data by information on the occupational fatality risk and industrial fatality risk, respectively. East–Germany and West–Germany are examined separately. In the data we find a substantial "raw" gender wage gap in the pooled samples, ranging from about 8.5 percent in East–Germany to 26.3 percent in West-Germany. This gap is decomposed using the Blinder-Oaxaca method for OLS and tobit models, respectively.

As expected, part of the gender pay gap can be explained by standard socioeconomic factors. Most importantly, however, we find that by considering the occupational injury risk an additional and substantial part of the gap can be explained. Including the injury risk increases the explained part of the gender wage gap by about one to three percentage points, which amounts to up to 12 percent of the whole explained part. This increase appears substantial for a single explanatory variable. We therefore think that for future studies it is advisable to include occupational fatality rates among other explanatory variables in wage regressions explaining the gender pay gap.

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