

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

Preliminary Results - please do not quote

Sandra Schaffner[†]
Jochen Kluge[‡]

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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 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.

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[†]Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI), Hohenzollernstraße 1-3, 45128 Essen; Telefon: +49/201/8149-282; Fax: +49/201/8149-200; Email: sandra.schaffner@rwi-essen.de; <http://www.rwi-essen.de/schaffner>

[‡]Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI), Hohenzollernstraße 1-3, 45128 Essen; Telefon: +49/201/8149-202; Fax: +49/201/8149-200; Email: kluge@rwi-essen.de; <http://www.rwi-essen.de/kluge>

1 Introduction

The gender wage gap is a topic in labor economics that has received much attention, and heated debates have taken place regarding 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 of 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 the only time that the occupational injury risk is considered in the explanation of the gender pay gap is in Lorenz and Wagner (1989), who use the first wave of the German socioeconomic panel and data from the statutory accident insurance organizations. The results do not confirm the hypothesis that the involving of the risk reduces the unexplained part of the gender pay gap.

In our paper 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) is 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 21.6–26.5 percent for full-time workers. Using the Blinder-Oaxaca decomposition a small part of this gender pay gap can be explained. This part increases when we include the occupational injury risk as an explanatory variable.

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

2 Data and empirical specification

In order to implement our analysis 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.

The **IAB Employment Subsample (IABS)** is a 2% random sample of the data 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). The data cover all employees registered by the German social insurance system since 1973. Supplementary information on establishments and on unem-

ployment periods 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. 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, currently 400 Euros per month), 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 profession or occupation is coded into 130 occupational codes using code KldB75 from the Federal Statistical Office. 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

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

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.

The **German Socioeconomic Panel (GSOEP)** is 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 persons (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 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.

The data are collected at a specific due date each year and the earnings reported refer to the last month before this due 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. Compared to the IABS the GSOEP is much richer in variables and has substantially fewer observations. The GSOEP questionnaire covers nearly every theme

of the daily life, whereas the IABS data only cover employment, unemployment and corresponding themes.

The **Panel Study of Income Dynamics** in the US 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 except the marginally employed and apprentices.

The data from the IABS, GSOEP, and PSID 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 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

Table 1: Occupational fatality risk per 1.000 fulltime-man-years in Germany: the 20 occupations with the highest fatality risk (out of 241 occupations)

occupation	<i>rk.</i>	mean	std.	min.	max.
Scaffolders	1	0.924	0.429	0.212	1.861
Inland waters navigator, sundry waterways occupations	2	0.851	0.309	0.400	1.350
Deckhands	3	0.819	0.522	0.170	1.691
Nautical navigators	4	0.638	0.403	0.171	1.362
Roofers, slaters	5	0.484	0.151	0.202	0.712
Miners	6	0.424	0.152	0.173	0.750
Machine, electrical and shot colliers	7	0.389	0.289	0.000	1.080
Air traffic occupations	8	0.359	0.286	0.000	0.937
Blasters , sundry civil engineering occupations	9	0.324	0.082	0.144	0.475
Quarrymen, mineral oil and gas extractors, Earth, pyrite and sand excavators	10	0.320	0.166	0.000	0.596
Excavator drivers	11	0.316	0.117	0.131	0.479
Mineral processors	12	0.289	0.635	0.000	2.180
Carpenters	13	0.283	0.070	0.198	0.425
Motor vehicle drivers, coachman	14	0.283	0.023	0.245	0.314
Crane driver	15	0.257	0.115	0.000	0.415
Railtrack constructors	16	0.243	0.226	0.000	0.725
Brick and concrete makers	17	0.240	0.135	0.000	0.406
Concrete constructors	18	0.234	0.072	0.147	0.328
Excavators, building labourer (non-specified)	19	0.226	0.040	0.145	0.286
Stage, film and sound technicians	20	0.220	0.377	0.000	1.250

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. The occupations are allocated to a three-digit code from the code list KldB75. 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. In principle, two possibilities exist: the first is

to extrapolate using the Mikrozensus, i.e. the census data collected once every two years. The other possibility is to choose the IABS, described above, for extrapolating.

The Mikrozensus is a random sample of all working people in Germany, while the IABS is a random sample of all employees registered in the social insurance system. The insurance data include the same groups of working people as in the IABS. In addition, unfortunately, insured self-employed and marginally employed persons are also included. On the other hand, the Mikrozensus suffers from the fact that it includes all self-employed persons, also the non-insured. Hence, both approximations are deficient in different ways, and it cannot be said a priori which approach yields a better prediction of the total number of insurants by occupation.

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.

Spengler (2004), on the other hand, uses the Mikrozensus for extrapolating. His computations lead to different results especially in the high-risk occupations compared to the estimated risks calculated using the IABS in our study. These risks are partially illustrated in table 1 which shows the 20 occupations with the highest fatality risk. 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 severe bias in the calculated risk. Gardeners are also excluded because the LSV does not distinguish the different occupations in their injury data.

To obtain the fatality risk for US occupations 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 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. The industrial and occupational classification systems in Germany and the US are very different. However, the main groups of the German occupational classification system and the US industrial classification system are similar (agriculture/forestry, mining, construction, manufacturing,...).

Three 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, while the third measure is a 3-year average of the years surrounding a particular year. We expect to have less measurement error in the 3-year average and the 7-year average relative to the annual rate.

Tables 2 and 3 contain separate statistics of the three, and the following regression

Table 2: Selected Summary Statistics

	GSOEP				IABS				PSID			
	male workers mean	sd	female workers mean	sd	male workers mean	sd	female workers mean	sd	male workers mean	sd	female workers mean	sd
wage	80.92	<i>37.93</i>	62.57	<i>24.91</i>	90.12	<i>34.62</i>	70.62	<i>29.92</i>	85.50	<i>52.80</i>	67.67	<i>46.48</i>
log wage	4.310	<i>0.405</i>	4.063	<i>0.395</i>	4.431	<i>0.394</i>	4.168	<i>0.457</i>	4.324	<i>0.478</i>	4.079	<i>0.491</i>
Fatal injury risk	0.055	<i>0.070</i>	0.014	<i>0.024</i>	0.052	<i>0.066</i>	0.013	<i>0.024</i>	1.212	<i>3.235</i>	0.373	<i>2.130</i>
age 15–20	0.009	<i>0.095</i>	0.017	<i>0.130</i>	0.011	<i>0.104</i>	0.020	<i>0.140</i>	0.006	<i>0.078</i>	0.011	<i>0.106</i>
age 20–25	0.081	<i>0.272</i>	0.135	<i>0.341</i>	0.070	<i>0.254</i>	0.117	<i>0.321</i>	0.093	<i>0.290</i>	0.088	<i>0.283</i>
age 25–30	0.145	<i>0.352</i>	0.161	<i>0.368</i>	0.134	<i>0.340</i>	0.152	<i>0.359</i>	0.141	<i>0.348</i>	0.103	<i>0.304</i>
age 30–35	0.180	<i>0.384</i>	0.141	<i>0.348</i>	0.176	<i>0.381</i>	0.150	<i>0.357</i>	0.153	<i>0.360</i>	0.135	<i>0.342</i>
age 35–40	0.158	<i>0.365</i>	0.137	<i>0.344</i>	0.164	<i>0.370</i>	0.143	<i>0.350</i>	0.146	<i>0.354</i>	0.162	<i>0.368</i>
age 40–45	0.132	<i>0.338</i>	0.140	<i>0.347</i>	0.139	<i>0.346</i>	0.137	<i>0.344</i>	0.147	<i>0.355</i>	0.152	<i>0.359</i>
age 45–50	0.113	<i>0.317</i>	0.117	<i>0.322</i>	0.117	<i>0.322</i>	0.120	<i>0.325</i>	0.132	<i>0.338</i>	0.138	<i>0.345</i>
age 50–55	0.091	<i>0.287</i>	0.088	<i>0.283</i>	0.098	<i>0.298</i>	0.093	<i>0.291</i>	0.082	<i>0.275</i>	0.095	<i>0.293</i>
age 55–60	0.074	<i>0.261</i>	0.059	<i>0.236</i>	0.079	<i>0.269</i>	0.063	<i>0.243</i>	0.050	<i>0.217</i>	0.054	<i>0.227</i>
age 60–70	0.018	<i>0.134</i>	0.005	<i>0.067</i>	0.013	<i>0.115</i>	0.004	<i>0.065</i>	0.042	<i>0.200</i>	0.056	<i>0.231</i>
white									0.744	<i>0.436</i>	0.719	<i>0.450</i>
married	0.695	<i>0.461</i>	0.542	<i>0.498</i>								
kids	0.635	<i>0.915</i>	0.260	<i>0.570</i>								
no vocational qualification, no Abi †	0.172	<i>0.377</i>	0.206	<i>0.404</i>	0.136	<i>0.342</i>	0.140	<i>0.347</i>				
no vocational qualification, Abi †	0.076	<i>0.266</i>	0.072	<i>0.259</i>	0.007	<i>0.081</i>	0.008	<i>0.089</i>				
with vocational qualification, no Abi †	0.693	<i>0.461</i>	0.644	<i>0.479</i>	0.722	<i>0.448</i>	0.728	<i>0.445</i>				
with vocational qualification, Abi †	0.059	<i>0.235</i>	0.077	<i>0.267</i>	0.033	<i>0.177</i>	0.055	<i>0.228</i>				
university of applied science degree	0.065	<i>0.246</i>	0.118	<i>0.322</i>	0.046	<i>0.209</i>	0.028	<i>0.164</i>				
university degree	0.097	<i>0.296</i>	0.083	<i>0.276</i>	0.058	<i>0.233</i>	0.042	<i>0.200</i>				
years of education									12.33	<i>2.198</i>	12.691	<i>2.194</i>
unskilled worker	0.215	<i>0.411</i>	0.164	<i>0.371</i>	0.216	<i>0.411</i>	0.151	<i>0.358</i>				
skilled worker	0.360	<i>0.480</i>	0.068	<i>0.253</i>	0.372	<i>0.483</i>	0.064	<i>0.245</i>				
master craftsman	0.038	<i>0.190</i>	0.003	<i>0.058</i>	0.030	<i>0.170</i>	0.002	<i>0.042</i>				
white collar, salaried	0.387	<i>0.487</i>	0.764	<i>0.425</i>	0.383	<i>0.486</i>	0.783	<i>0.412</i>				
tenure	9.570	<i>9.639</i>	8.071	<i>8.234</i>	7.351	<i>7.136</i>	6.273	<i>6.211</i>	7.783	<i>8.391</i>	6.130	<i>7.189</i>
work experience	13.38	<i>9.573</i>	11.37	<i>8.500</i>								
East-Germany	0.252	<i>0.434</i>	0.340	<i>0.474</i>	0.163	<i>0.369</i>	0.219	<i>0.413</i>				
job covered by union									0.282	<i>0.450</i>	0.137	<i>0.344</i>
union member									0.260	<i>0.439</i>	0.116	<i>0.320</i>
work for government	0.150	<i>0.357</i>	0.353	<i>0.478</i>					0.090	<i>0.287</i>	0.244	<i>0.429</i>
size of firm, 1–20 employees	0.214	<i>0.410</i>	0.239	<i>0.426</i>								
size of firm, 20–200	0.317	<i>0.465</i>	0.295	<i>0.456</i>								
size of firm, 200–2000	0.242	<i>0.428</i>	0.264	<i>0.441</i>								
size of firm, more than 2000	0.227	<i>0.419</i>	0.202	<i>0.401</i>								
number of observations	14388		7535		1606783		850964		3837		3730	

†Abi is the highest schooling degree in Germany which qualify the entrance at university.

equations are used:

$$\ln Y_{i,men} = \beta_{men} * X_i + \varepsilon \quad (1)$$

$$\ln Y_{i,women} = \beta_{women} * X_i + \varepsilon \quad (2)$$

X is a vector of productivity related variables and ε 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.

$$\overline{\ln Y_M} = \beta_M * \overline{X_M} \quad (3)$$

$$\overline{\ln Y_F} = \beta_F * \overline{X_F} \quad (4)$$

The difference of the logarithmic wages becomes:

$$\overline{\ln Y_M} - \overline{\ln Y_F} = \beta_M * \overline{X_M} - \beta_F * \overline{X_F} \quad (5)$$

$$= \underbrace{\beta_M * (\overline{X_M} - \overline{X_F})}_{\substack{\text{diff.} \\ \text{capacities}}} + \underbrace{\overline{X_F} * (\beta_M - \beta_F)}_{\substack{\text{unexplained} \\ \text{rest}}} \quad (6)$$

Equation 6 results from addition and subtraction of $\beta_m \overline{X_F}$. The first part of the wage equation $\beta_M * (\overline{X_M} - \overline{X_F})$ 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 5 addition and subtraction of $\beta_F \overline{X_M}$ 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 displayed here. This assumption is commonly used and sets the male wage as reference wage.

Considering the endowment differences between men and women, the corrected wage gap is the difference in wages if men and women have an identical endowment of all exogenous variables. The difference is again expressed in relation to the male wage.

$$D_c = 1 - \frac{1}{\exp(\overline{X}_W(\beta_M - \beta_W))} \quad (7)$$

3 Results

The results of the pooled regressions are displayed in table 3. The estimated coefficients show the expected signs: 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. Looking at Germany only, the results indicate that East German workers earn less than their West German counterparts. The coefficient for the fatal injury risk is positive with high significance, except for women in the GSOEP dataset. The table only presents the pooled regression results by using the annual injury risk as explanatory variable. The summary of results of applying the decomposition method are displayed in table 4. For all three data sets pooled regressions with the different risk measures and without any risk measure were done separately for male and female workers. The estimated coefficients were used to calculate the unexplained part of the gender pay gap as described in the previous chapter. In the GSOEP and the PSID samples the gender pay gap can obviously be reduced without using the fatality risk as explanatory variable. Adding the fatality risk, however, leads to a further reduction of the unexplained gap. In contrast to these results, the Blinder-Oaxaca-Decomposition of the pay gap in the IABS sample leads to an increase of the gender pay gap.

The corresponding summary of results for the fixed-effect regressions is described in

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

	GSOEP		IABS		PSID	
	male workers	female workers	male workers	female workers	male workers	female workers
fatal injury risk $\times 10^3$	0.459 (3.55)	-0.573 (0.94)	0.088 (20.18)	0.066 (3.26)	0.005 (2.44)	0.005 (2.05)
white					0.098 (6.59)	0.009 (0.55)
married	0.070 (6.54)	-0.032 (2.41)				
number of children	0.012 (2.32)	-0.004 (0.39)				
<i>age</i> (Referenz: 15–20–aged)						
20–25	0.190 (2.78)	0.120 (2.49)	0.134 (42.19)	0.149 (38.04)	0.057 (0.96)	0.023 (0.47)
25–30	0.215 (3.09)	0.224 (4.60)	0.243 (78.37)	0.247 (62.88)	0.139 (2.32)	0.186 (3.83)
30–35	0.301 (4.47)	0.288 (5.87)	0.312 (100.85)	0.259 (65.27)	0.216 (3.65)	0.239 (4.98)
35–40	0.290 (4.29)	0.279 (5.53)	0.340 (109.68)	0.251 (62.66)	0.277 (4.66)	0.253 (5.29)
40–45	0.292 (4.31)	0.310 (6.19)	0.349 (112.23)	0.264 (65.95)	0.285 (4.81)	0.261 (5.35)
45–50	0.296 (4.33)	0.277 (5.32)	0.355 (113.51)	0.270 (66.88)	0.256 (4.34)	0.221 (4.66)
50–55	0.279 (4.07)	0.275 (5.09)	0.357 (113.27)	0.260 (63.19)	0.266 (4.34)	0.236 (4.75)
55–60	0.265 (3.85)	0.275 (4.80)	0.329 (102.48)	0.220 (51.09)	0.289 (4.68)	0.176 (3.41)
60–70	0.306 (4.14)	0.367 (2.71)	0.291 (70.73)	0.175 (19.33)	0.263 (3.81)	0.049 (0.93)
<i>highest educational achievement</i> (Ref.: no vocational qualification, no Abi†)						
no vocational qualification, Abi†	0.085 (3.23)	0.174 (4.10)	0.042 (8.27)	0.062 (8.57)		
vocational qualification, no Abi†	0.057 (4.96)	0.061 (3.46)	0.075 (89.45)	0.053 (32.33)		
vocational qualification, Abi†	0.095 (4.26)	0.155 (5.52)	0.152 (89.81)	0.202 (82.22)		
university of applied science degree	0.242 (12.30)	0.207 (8.89)	0.249 (177.66)	0.316 (112.70)		
university degree	0.245 (10.22)	0.217 (5.31)	0.316 (229.39)	0.422 (163.47)		
years of education					0.036 (9.03)	0.054 (12.18)
<i>occupational status</i> (Ref.: unskilled worker)						
skilled worker	0.108 (11.22)	0.169 (6.01)	0.063 (87.76)	0.020 (9.14)		
master craftsman	0.287 (15.69)	0.595 (7.38)	0.286 (178.84)	0.224 (15.82)		
white collar, salaried	0.313 (20.79)	0.296 (12.36)	0.313 (357.69)	0.266 (158.53)		
job tenure	0.005 (2.86)	0.004 (1.42)	0.022 (184.66)	0.022 (99.88)	0.010 (3.81)	0.017 (5.83)
job tenure ² $\times 10^{-1}$	-0.000 (0.37)	-0.000 (0.59)	-0.001 (121.30)	-0.001 (54.07)	-0.000 (1.41)	-0.000 (1.10)
East-Germany	-0.308 (33.12)	-0.228 (19.42)	-0.268 (173.99)	-0.151 (66.96)		
job covered by union					0.140 (3.37)	0.028 (0.68)
belonging to union					0.171 (4.02)	0.149 (3.39)
work for government					0.054 (2.25)	-0.013 (0.78)
firmsize dummies	+	+				
industry dummies	+	+	+	+		
occupation dummies					+	+
year dummies	+	+	+	+	+	+
region dummies			+	+	+	+
number of observations	22,049	11,312	1,606,783	850,964	3730	3837

†Abi is the highest schooling degree in Germany which qualify robust t-statistics in parentheses

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

gender wage gap	<i>dataset</i>		
	GSOEP	IABS	PSID
uncorrected	22.91%	21.64%	20.85%
corrected without the fatal injury risk	19.95%	23.22%	15.28%
corrected with the fatal injury risk	19.05%	23.11%	15.21%
corrected with the 7-year fatal injury risk	19.03%	23.12%	
corrected with the 3-year fatal injury risk	18.99%	23.14%	

Table 5: Blinder-Oaxaca-Decomposition of the different fixed-effect regressions with and without taking into account the fatal injury risk

gender wage gap	<i>dataset</i>		
	GSOEP	IABS	PSID
uncorrected	23.06%	21.64%	20.85%
corrected without the fatal injury risk	19.49%	22.02%	20.44%
corrected with the fatal injury risk	19.18%	21.86%	20.27%
corrected with the 7-year fatal injury risk	19.88%		
corrected with the 3-year fatal injury risk	19.34%	21.19%	

table 5. The uncorrected gender pay gap of about 23% in the GSOEP dataset can be reduced to below 20 percent by adjusting for sociodemographic factors. Taking into account the fatal injury risk leads to further reductions of the gender pay gap. The results are similar to those of the pooled regressions. The corrected unexplained part of the gap in the PSID sample is bigger after the fixed-effect regressions relative to the pooled regressions, but still the raw differential is reduced by only less than 1 percentage points. Including the occupational fatality risk, however, does not strongly reduce the unexplained part in this case. The decomposition in the IABS data again leads to an increase in the gender pay gap. This implies that the gender pay gap would be bigger if the female workers and their occupations in the dataset had the same properties as the male workers. A likely reason for this unexpected result could be the omission of essential variables. For example, the marital status variable appears unreliable in this dataset and

cannot be used for the regressions. Also, firm size is missing in this part of the IABS.

4 Conclusions

In this study we examine male-female wage differentials in Germany and the US. One panel data set for the US (PSID) and two panel data sets for Germany (GSOEP and IABS) are used, containing data on individual sociodemographic attributes and job characteristics. We complement these data by information on the occupational fatality risk. In the data we find a substantial "raw" gender wage gap of about 20.8 to 22.9 percent. This gap is decomposed using the Blinder-Oaxaca method after pooled and panel regressions. Standard corrections for socioeconomic factors reduce the gap. Most importantly, including the occupational injury risk reduces the gap by up to 1 percentage point. While this may not seem a huge effect at first glance, it does seem of relevance relative to the fact that including the set of socioeconomic factors brings about an average reduction of 3 percentage points. 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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