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The Price of Security: On the Causality and Impact of Lay-off Risks on Wages

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Abstract

We examine the impact of lay-off risks on wages. Portfolio as well as search theoretic modelling predicts higher exogenous lay-off risks to go along with higher wages. But, an impact of wages on lay-off risks (e.g., endogenous job destruction) is also plausible. Using the German BA Employment Panel (2008), we estimate a wage equation with exogenous lay-off risks for the most important industries in West Germany. We address the mutual causality by controlling for endogeneity via an instrumental variable approach. Furthermore, we restrict our analysis to the high skilled to avoid a high impact on tariff commitment. Our findings suggest the presence of risk premiums in three of five industries. The level of impact and its significance depends on the industry and on the gender of the employee.

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1 Motivation

"Life can never give security, it can only promise opportunity."[1] Security is a basic need of the majority of people. This statement is also true for workplace security. Because risk is part of a dynamic economy, the market creates compensating mechanisms when a lack of security is present. Wages often serve as a compensation for risk in the labour market. This competition allows for the opportunity to trade between risk and money.

While negotiating wages, risk factors are important issues for both employers and employees. Therefore, the risks are twofold: health risk and lay-off risk. Numerous studies have investigated the impact of health risks on wages [e.g., Viscusi (1978)]. Literature of the last three decades has examined the tradeoff between lay-off risks and wages [Abowd and Ashenfelter (1981), Villanueva (2007)]. In this paper, we contribute to the literature by identifying the impact of the risk of lay-offs on wages. We extend the existing literature by analysing risk premiums due to lay-off risk for regular employment in the five most important private sector industries in West Germany (construction, manufacturing, wholesale and retail trade, real estate, renting and business activities and transport, storage and communication). West Germany serves as a good example of a Central European labour market. Its institutional framework and the industrial specific shares of employment [Eurostat (2011)] correspond with the European average.[2]

Using the BA-Employment Panel (2008), this is the first study to focus on high skilled employees. We do so for two reasons. First, the scarcity of high skilled workers strengthens their negotiation position. Their stronger negotiation position eases the pricing of risk. Second, the tariff commitment of medium- and low-skilled employees is probably higher.

[1] Chinese proverb.

[2] Furthermore the unemployment rates shows similar cyclicality and therefore comparable fluctuations in the lay-off risk.

Thus, exogenous wage setting may induce lay-offs. To avoid this problem of mutual causality (endogeneity), we concentrate our analysis on the high skilled employee. However, the endogeneity cannot be totally excluded by focusing only on the high skilled employees. Therefore, we address this problem and control for econometric endogeneity in detail.

To identify the lay-off risk premiums, we estimate wage equations for high skilled male and female employees for the five main industries. Our method is in line with the empirical literature that uses exogenous measure of lay-off risk [e.g., Moretti (2000)]. In contrast to the literature that uses wage distribution measures as a proxy for the lay-off risks [e.g., Hartog et al. (2003)], we calculate gender and industry specific drop-out rates because those rates represent the pure risk of losing a job.

The remainder of the paper is organised as follows: In Section 2, we provide a review of the related literature. Section 3 describes our dataset. Section 4 presents the econometric specifications. Our findings are presented in Section 5, and in Section 6, we discuss the problem of endogeneity and mutual causality in detail. In Section 7, we conclude and discuss our findings.

2 Literature

The relationship between (lay-off) risk and wage can be shown by different types of economic models. Basically, it is possible to adapt a portfolio model to the labour market [e.g., Abowd and Ashenfelter (1981)] whereby a worker is faced with two comparable job offers with different lay-off risks. The lay-off risk is exogenous for the worker. In equilibrium, workers want the same expected incomes in both the risk and the nonrisk job. This consideration induces workers to want higher wages for jobs with higher risks. The same is true for risk change over time. If a worker is working continuously in the same job and only the lay-off risks change exogenously, then he adjusts his expected income. If the lay-off risk increases, the wage increases as well.

The result of a positive impact of the lay-off risk on wages can also be derived from search-theoretic models [e.g., Burdett and Mortensen (1998)].[3] The workers' calculus, which is similar to the portfolio model, is extended by the firm's calculus. Both models show that in equilibrium the (reservation) wage depends, among other factors, on the lay-off risk. The derivation of the (reservation) wage with respect to the lay-off risk is positive.[4]

The empirical literature of earning differentials focuses on the question of whether there are wage premiums for workplace disadvantages. Only a portion of the literature focuses on unemployment risk. There are two methods to calculate the wage premiums for unemployment risk. A first approach uses the variance of wages as proxy for the earning risk. A higher variance of wages is considered a higher income risk. For example, Li (1986), McGoldrick (1995) and Hartog et al. (2003) use this method and find a positive wage compensation for higher risks.[5]

The second method is to estimate a wage equation with the unemployment risk as an exogenous variable. The majority of empirical studies use this method to determine the effect of higher unemployment risks on wages. In two studies from the U.S., Abowd and Ashenfelter (1981, 1984) find a negative effect of unemployment (risk) on wages. Two recent examples are Moretti (2000) and Villanueva (2007). Moretti (2000) uses panel data to identify the impact of individual unemployment risks, as well as general unemployment risks, on

[3] A good and widespread description is given by Rodgerson et al. (2005). The extension of losing a job was introduced by Burdett and Mortensen (1980) and Wright (1987).

[4] The sign of the derivation depends on the matching probabilities (on-the-job and out-of-unemployment) as well as the proportion of the marginal productivity of a worker and the unemployment benefit. Our dataset indicates a positive sign.

[5] Moore (1995) finds a general negative impact of unemployment risk on wages, but he focus on union membership. Considering union membership, he finds a positive impact.

wages. He compares permanent workers with seasonal workers and finds a positive risk premium for the seasonal worker. Villanueva (2007) uses the German Socioeconomic Panel to investigate risk premiums for voluntary job changes. Among other factors, he estimates the compensating effect of increased job insecurity; however, he finds little evidence for this effect. Using a unique dataset with information on income expectations, Guiso et al. (2002) analyse the link between future income and unemployment risks in Italy. They use both methods and note that "variations in the perceived probability of unemployment explain a large part of differences in income prospects" [see Guiso el. al. (2002) p. 251]. We follow the second approach and also estimate a wage equation with exogenous lay-off risks.

3 The Dataset

We use the German BA-Employment-Panel (2008) to identify risk premiums. This dataset is a two-percent sample of all socially secured employees in Germany. The BA-Employment-Panel (2008) contains quarterly information from 1998 to 2007. We use the BA-Employment Panel (2008) from the year 2000 because unemployment information is not available until then. In our analysis, we focus on full-time employees; apprentices and part-time employees are not considered. We divide the dataset into East and West Germany. The segmentation is based on the job location, and we focus on those employees who have worked continuously in West Germany. We exclude East Germany because it is in the process of structural transition.

The dataset provides comprehensive information on individual characteristics (e.g., sex, age, wage, employment status, education, type of employment,) as well as on firms' characteristics (e.g., size, rate of old and young employees, industry). A disadvantage of our dataset is that the wages are truncated at the maximum as contributions to the social insurance have to be paid. All higher income information is optional. Higher incomes are, for the most part, reported as the maximum at contributions to the social insurance have to be paid. Therefore, changes in wages beyond this maximum are not observable. Thus, we truncate the dataset one euro below the maximum level at which contribution to the social insurance must be paid.[6] For low wages, we use 650 euro per month as a minimum cut-off level because 650 euro is the average benefit level for the long-term unemployed [Federal Statistical Office Germany (2010)]. All wages below the 650 euro cut-off are most likely supported by top-up benefits. Finally, we build a balanced panel, that is, we include all persons who were observed continuously throughout all 32 quarters. Table 1 presents a summary of our dataset.

Table 1: Summary Statistics of the Conditioned Dataset (2000-2007)

	West Germany
Total Employees	170 700
Unemployment Quarters	2.69%
Male	73.04%
High Skilled	10.64%
Construction Industry	6.48%
Manufacturing Industry	35.73%
Wholesale and Retail Trade	14.91%
Real estate, Renting and Business Activities	8.21%
Transport, Storage and Communication	5.56%
Small Firm (<50 Employees)	31.59%
Medium Firm	24.18%
Large Firm (>200 Employees)	44.23%

Source: BA-Employment Panel (2008), authors' calculations.

We extend the dataset with additional information. We calculate the industrial and gender-specific share of workers who became unemployed (seasonal adjusted and detrended).[7] The resulting variable is added as a drop-out-rate to proxy the lay-off risk. Moreover, we add the job tenure of each worker in the sample, and we calculate the real wages from the given

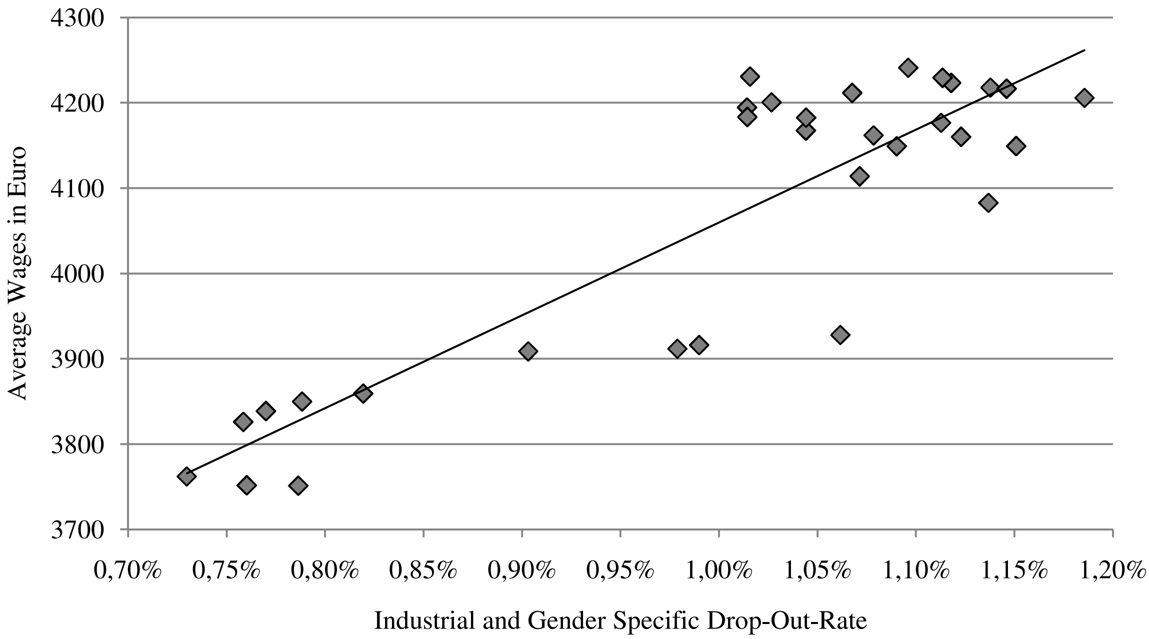
[6] The truncation affects only 1.5% to 3% of all individuals, depending on the industry.

[7] We calculate the moving average to seasonally adjust the data. Furthermore, we use a standard Hodrick-Prescott-Filter with λ=1600 to detrend quarterly data.

nominal values using price level data from the Federal Statistical Office Germany (2011). The classification of industries follows the European national account system [see Federal Statistical Office Germany (2007)].

The extended BA-Employment Panel (2008) allows a primer descriptive illustration of the assumed relation between lay-off risk (drop-out-rate) and wages. We scatter the quarterly drop-out-rates with the corresponding quarterly average wages for high skilled male and female workers. Figure 1 is a representation of the scatter plot for high skilled male employees in the real estate, renting and business activities industry.

Figure 1: Scatter Plot of the Drop-Out-Rate and Wages for High Skilled Male Employees in the Real Estate, Renting and Business Activities Industry



Source: BA-Employment Panel (2008), authors' calculations.

Figure 1 suggests a positive correlation between lay-off risks and wages. This descriptive illustration may give a first impression of a possible relation. Detailed econometric analyses are needed to derive reliable statements about the connectedness of lay-off risk and wages. In the next section, we derive an empirical model, which is later verified with the dataset.

4 The Empirical Model

The related literature suggests the following empirical model to estimate the impact of lay-off risk on wages:

$$\omega_{it} = \beta_0 + \beta_1 \lambda_{jt-1} + controls + u_{it}.$$

The individual's (i) real wage (ω) in period t is explained by a constant, the industry specific (j) lay-off risk (λ) in period $t-1$, control variables and an error term. As control variables, we use age, professional status, firm-size, firm's age structure, job tenure as well as year-and quarter-dummy variables. The quarter-dummy variables capture seasonal effects, and the year-dummy variables capture the general economic development.

To provide evidence for the assumption that risks are compensated by higher wages, we estimate our empirical model with a focus on λ, the industrial and gender specific lay-off risk.[8] We calculate the lay-off risk as industrial and gender specific drop-out-rates. The drop-out-rates are the shares of all employees in a period and industry who switch to unemployment. For the estimation, we use the one period lagged drop-out-rates. Our estimation presents the calculus of rational individuals, which use all available information. In period t, the individual earns a wage that is based on the expected income with respect to the lay-off risk of period $t-1$. The expected incomes are based on information that is available up to the current period.

[8] Another option is to calculate the (individual) lay-off risk (e.g., logit or probit regressions). In the first stage, one has to estimate the lay-off risk using variables that are also important for the wage equation (e.g., sex, origin, experience and skill). In the second stage, those variables have to be excluded from the wage equation. Borjas and Sueyoshi (1994) show that such a two-stage estimator for probit models is unbiased if the exogenous variables of both stages are independent from one another. Because of the loss of variables for the second stage, the wage estimation loses quality.

The drop-out-rates are a proxy for the individual unemployment risk. The advantage is that they are exogenous for each individual. The average drop-out-rates in a certain industry affect the individual wage but not vice versa. The individual takes into account the industrial specific lay-off risk (drop-out-rate), but the individual wage does not affect this drop-out-rate. We restrict our analysis to high skilled employees for two reasons. First, the individual negotiating power increases with skill level. High skilled individuals are scarce, and this scarcity strengthens their bargaining position. In contrast to medium- and low-skilled workers, high skilled individuals are able to achieve risk compensating premiums more easily because their out-side option (to change firms or industries) is more plausible. The second reason is the fact that wages of low- and medium-skilled workers are often determined by collective bargaining. Hence, they are often not able to negotiate individual wages because of their risk. Unfortunately, the skill specific union bargaining is still an open field of empirical economic research.

We estimate the empirical wage equation for different industries to get clear industrially specific evidence.[9] Hence, we focus on the time variation of the wages, which can be explained by the variation of the lay-off risks in different industries. The industrial specific estimation derives reliable results despite the exclusion of inter-industrial mobility of worker. Two reasons support our considerations. First, the existence of the out-side option for high skilled workers is sufficient. Second, we observe only a very small fraction of inter-industrial job changes in our dataset.

If separate industries are analysed, the problem of self-selection of workers may be present. This issue is, for example, addressed by Garen (1987) who shows serious problems by selecting a useful sample because of the possibility of self-selection. Jacobs et al. (2009)

[9] An estimation for the whole economy would be inefficient because the dummy-variables for different industries are correlated with the industrial specific drop-out-rates in each period. Therefore, the standard errors of the estimators increase.

suggest that empirical estimations of risk premiums may be biased through self-selection and that the impact of individual risk may be underestimated, but the direction of the impact between risks and wages do not change.

We only take into account industries of the private sector with more than 5% of all fulltime employees in our dataset.[10] These industries cover approximately 86% of all employees in the private sector in our sample. To identify the effect of the lay-off risk, we applied random effect as well as fixed effect panel estimations. Collinearity is a common problem in OLS-regression, causing possible inefficiency and the insignificance of important variables. Testing for pair wise correlations suggests that collinearity of the exogenous variables is not present. For the majority of variables, we do not find strong correlations. We use robust random (OLS-RE) and fixed effect estimation methods (OLS-FE) to avoid heteroscedasticity. To decide whether to use random effect or fixed effect regression, we run a Hausman-test. The Hausman-test suggests fixed effect estimation. Therefore, we run gender specific, fixed effect regressions in every industry. In an aggregated estimation, we would otherwise lose time invariant information such as gender and skill.

Because we focus our analyses on the variation over time, we must also address the possible problem of auto-correlated error terms. Although auto-correlated error terms do not bias the estimators, they change the significance by increasing the standard deviation. Using the test method proposed by Wooldridge (2002), we find auto-correlated error terms for all specifications. Multiple possible sources of auto-correlation exist. Most common are the model misspecifications such as nonlinear impact of exogenous or omitted variables. Furthermore, a time trend of the dependent variable or nonstationarity of the panel may induce auto-correlation. We check for a nonlinear impact of the exogenous variables, we control for the stationarity of the panel, and we detrend the lay-off risk. Unfortunately, these

[10] The public sector is excluded because lay-off risk is largely theoretical in this sector.

measures could not completely remove the auto-correlation, thus an omitted variable bias is still possible. Therefore, we extend our analysis by two regression methods that allow for auto-correlated error terms. The first is the mixed models estimation (MME), and the second is a fixed-effects linear model with an autoregressive disturbance (OLS-AR).[11]

Finally, we control for the problem common to most empirical models: endogeneity. There are two sources of endogeneity in econometrics, correlation between the error term and the independent variable and mutual causality between the endogenous and exogenous variables. Unfortunately, it is not possible to check for the former because the real error terms are not known. We address the second issue by a separate, detailed discussion and an instrumented variable estimation (two-stage least square, TSLS).

5 Empirical Evidence

In this section, we provide empirical evidence for our hypothesis that higher wages are the result of increased lay-off risks. We present the results for high skilled males and females for five industries: construction; manufacturing; wholesale and retail trade; real estate, renting and business activities; and transport, storage and communication. Table 2 and Table 3 present the effect of lay-off risk on wages for these industries for high skilled male and female employees in West Germany. The coefficients for the lay-off risk, the corresponding t- or z-values and the within R-squared are reported. Detailed results of all estimations can be found in the appendix.[12]

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[11] An overview of MME is provided by Demidenko (2004). A MME application with auto-correlated error terms is given by Hedeker and Gibbons (1996). The fixed-effects OLSAR uses the methods derived by Baltagi and Wu (1999).

[12] The detailed tables contain the coefficients of all exogenous variable and their t-values or z-values. Furthermore, the numbers of observations are given.

Table 2: Regression Results for High Skilled Males in West Germany

Model		Manufacturing Industry	Construction Industry	Wholesale and Retail Trade	Real Estate, Renting and Business Activities	Transport, Storage and Communication
OLS-FE	coeff	120381.00***	13694.35***	133256.60***	102785.10***	146532.00**
	t-value	(17.63)	(4.08)	(3.89)	(11.62)	(2.15)
	R^2	0.5202	0.2727	0.3532	0.3031	0.2520
OLS-RE	coeff	120307.50***	13724.15***	137552.20***	104197.90***	144380.70***
	z-value	(31.95)	(6.91)	(6.99)	(21.16)	(3.20)
	R^2	0.5195	0.2703	0.3522	0.3027	0.2487
Log OLS-FE	coeff	0.15***	0.07***	0.23***	0.19***	0.03
	t-value	(24.10)	(3.91)	(7.76)	(13.93)	(-0.38)
	R^2	0.4239	0.2034	0.2414	0.2043	0.1379
MME	coeff	109574.20***	12441.47***	130437.10***	100312.10***	160089.50***
	z-value	(23.60)	(5.42)	(5.41)	(16.42)	(3.35)
Log MME	coeff	0.08***	0.06***	0.19***	0.19***	0.17*
	z-value	(15.63)	(4.06)	(4.17)	(11.60)	(1.64)
OLS-AR	coeff	578679.50***	55296.61***	528687.60***	336563.7***	581476.50***
	t-value	(113.61)	(18.63)	(50.36)	(71.61)	(23.79)
	R^2	0.4614	0.3306	0.4000	0.3222	0.3542
Controls	Age, Professional Status, Firm-size, Firm´s Age Structure, Job Tenure, Year and Quarter Dummy Variables					

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*).

Table 3: Regression Results for High Skilled Females in West Germany

Model		Manufacturing Industry	Construction Industry	Wholesale and Retail Trade	Real Estate, Renting and Business Activities	Transport, Storage and Communication
OLS-FE	coeff	137199.90***	-948.46	81568.78	115700.90***	46146.74
	t-value	(3.95)	(-0.06)	(0.90)	(4.10)	(0.38)
	R^2	0.2197	0.1263	0.0949	0.1002	0.2015
OLS-RE	coeff	138745.40***	841.25	80859.47**	114808.10***	40307.83
	z-value	(7.52)	(0.13)	(2.02)	(5.88)	(0.48)
	R^2	0.2192	0.1200	0.0941	0.0996	0.2006
Log OLS-FE	coeff	0.20***	-0.02	0.43***	0.24***	0.44***
	t-value	(5.25)	(-0.12)	(4.17)	(4.47)	(3.55)
	R^2	0.1409	0.1305	0.0760	0.0551	0.1779
MME	coeff	130791.8***	4274.88	93961.20	113974.50***	202791.20**
	z-value	(5.57)	(0.44)	(1.59)	(5.98)	(2.31)
Log MME	coeff	0.12***	0.03	0.18	0.27***	0.34*
	z-value	(4.07)	(0.40)	(1.30)	(4.50)	(1.87)
OLS-AR	coeff	576119.70***	52579.76***	435907.20***	262670.50***	440539.4***
	t-value	(22.96)	(3.84)	(17.07)	(19.10)	(10.56)
	R^2	0.1859	0.0630	0.1430	0.1221	0.3096
Controls	Age, Professional Status, Firm-size, Firm´s Age Structure, Job Tenure, Year and Quarter Dummy Variables					

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*).

We find a positive and significant effect for male high skilled employees in all industries. The sign is robust in every regression model. Even the significance does not change in the regressions that control for auto-correlated error terms (MME, OLS-AR).[13] In contrast to male employees, the explanatory power of the empirical model is not that good for female high

[13] The MME is specified with an individual random effect and fixed effect for the other exogenous variables. Moreover, an auto-correlated error term is added to the model. A likelihood-ratio test suggests that this specification is better than a pure FE model. To our knowledge, there are no appropriate quality criterion.

skilled employees. The within-R-squared is lower, in general, and for some industries, the risk has no effect on the wage (construction industry and transport, storage and communication). Similar to the male high skilled employee the coefficient is positive and significant in the manufacturing and the wholesale and retail trade industry. The positive relation implies that if the risk increases over time, it induces higher wages. As discussed by Murphy and Topel (1987), results of such estimations must be interpreted with caution. The coefficient in Table 2 is the marginal effect of an increase in the lay-off risk on wages. For example, if the average industrial specific lay-off risk in the manufacturing industry increases from zero to unity, the wage of high skilled male employees increases by € 120 381. This high value is just a theoretical effect. A more practical approach is provided by the fixed effect OLS, respectively, the MME model that uses logarithmic values for the lay-off risk and wage (Log OLS, Log MME). Here, the coefficient can easily be interpreted as an elasticity. To maintain the same example of the manufacturing industry, a 1% increase of the lay-off risk increases the wage approximately 0.15% (Log OLS FE) or 0.08% (Log MME) for the high skilled male employees. We find the highest risk premiums in the wholesale and retail trade and the real estate, renting and business activities industries; this result holds true for both men and women.

6 Endogeneity and Causality

Now, we return to the problem of endogeneity. In our situation, mutual causality may induce endogeneity; however, wages could also have an impact on the lay-off risk. For example, if the wage level increases exogenously (e.g., collective agreement) firms may lay-off employees. Because of that, the lay-off risk may increase if the wages increase. To address the problem of endogeneity, we apply a two-stage least square instrumental variable approach (TSLS). Thus, the lay-off risk is instrumented to exclude endogeneity. The causality of the chosen instruments must be clear. In a first step, we use a time-lagged lay-off risk as an instrument for the lay-off risk. We do so because it is impossible for current wages to affect previous lay-off risks. The time lag induces another problem: auto-correlation. The lay-off risk of the last period mainly explains the current lay-off risk. Hence, the length of the lag should exclude this auto-correlation link. In our situation, a five-quarter lag satisfies this condition. The correlation between the (five-quarter) lagged lay-off risk and the current lay-off risk in the different industries for males and females is between 51% and 86%. The correlation between wages and lagged lay-off risk is 3% to 15%. In the first stage of the TSLS approach, the lay-off risk is estimated by instruments. The F-statistics of the first stage regression for industries and both gender are sufficiently high; thus, the corresponding p-values are very close to zero. This result suggests that the instruments are usable. Table 4 summarises the results of the TSLS estimation.[14] The reported coefficients represent the impact of the instrumented variable in the second stage (lay-off risk). The corresponding z-values are reported in parentheses. The p-value of the first stage F-statistic as well as the partial R-square of the instrument and the total R-square of the second stage also are reported.

[14] More detailed results can be found in the tables in the appendix.

Table 4: Summary of the IV-Regression (TSLS) Results for High Skilled in West Germany

Sex		Manufacturing Industry	Construction Industry	Wholesale and Retail Trade	Real Estate, Renting and Business Activities	Transport, Storage and Communication
Male	coeff	-360381.40***	40323.59***	89270.26	461116.7***	111517.5
	z-value	(-5.79)	(3.46)	(0.16)	(6.06)	(0.11)
	p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000
	Par R^2	0.0132	0.0901	0.0041	0.0143	0.0052
	R^2	0.5067	0.2695	0.3569	0.2931	0.2541
Female	coeff	-787045.6**	57249.33	610714	246279.4	-301992.3
	z-value	(-2.46)	(1.02)	(0.49)	(1.05)	(-0.35)
	p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000
	Par R^2	0.0133	0.0973	0.0062	0.0151	0.0224
	R^2	0.1762	0.1305	0.0896	0.0961	0.1869
Controls	Age, Professional Status, Firm-size, Firm´s Age Structure, Job Tenure, Year and Quarter Dummy Variables					
Instrumented	Lay-off Risk					
Instrument	Lagged lay-off Risk (t-5)					

Source: authors' calculation. Significance-level: 0.01(***), 0.05(**) and 0.1(*).

This TSLS-regression draws an ambiguous picture. Besides the manufacturing industry, this approach confirms the expected positive sign of the coefficients, but, unfortunately, they often become insignificant. A plausible explanation for this result may be the small partial R-square of the instrument. The lagged lay-off risk on its own explains only a small fraction of the current lay-off risk in the first stage regression (1% to 10%).[15] The negative and significant sign of the coefficient in the manufacturing industry indicates possible endogeneity in this industry. Mutual causality of wages and lay-off risk seems to be plausible in this industry. This phenomenon could be due to the strong impact of unions in the manufacturing industry

[15] Weak identification tests suggest that our specification is not weakly identified, but the low partial R-square implies that the lag instrument is not the best solution.

in Germany.[16] Thus, the wages become exogenous for the firms as well as for the individuals, and a wage increase may, therefore, induce lay-offs.

In addition to the weak partial R-square, another point limits the use of lagged variables as instruments: the rationality of individuals. If individuals form rational expectations, endogeneity cannot be completely excluded by using time-lagged variables. Therefore, we run a TSLS regression with an alternative instrument: sickness absence rate.[17] The sickness absence rate shows a high correlation with the lay-off risk in many industries. Moreover, the correlation between the wages and the sickness absence rate is between 0% and 8%. Table 5 shows the correlations for males and females in the five industries.

Table 5: Correlation Coefficient between Sickness Absence Rate and Lay-off Risk

	Manufacturing Industry	Construction Industry	Wholesale and Retail Trade	Real Estate, Renting and Business Activities	Transport, Storage and Communication
Male	0.1735	0.5760	-0.9950	-0.9603	-0.9851
Female	0.0897	0.5291	-0.9851	-0.9787	-0.9956

Source: authors' calculation.

For three industries (wholesale and retail trade, real estate, renting and business activities and transport, storage and communication), the correlation is very strong and shows the expected negative sign. In times with a low lay-off risk, the sickness absence rate can be expected to be higher because of higher absenteeism if employees do not fear a potential lay-off. The positive signs in the manufacturing and construction industries are not intuitive. Nevertheless, the high correlation in the construction industry allows us to use this instrument. Because of the weak correlation, the results for the manufacturing industry should be viewed with

[16] The union (IG Metall) in the manufacturing industry is one of the biggest in Germany. Furthermore, the tariff commitment in this industry is the strongest in the private sector economy.

[17] The sickness absence rate is the share of sick employees to all public health insured employees [Federal Ministry of Health (2010)]. The rate is detrended and seasonal adjusted.

caution. Table 6 summarises the results of the TSLS with the sickness absence rate as an instrument for the lay-off risk.

Table 6 Summary of the IV-Regression (TSLS) Results for High Skilled in West Germany with Sickness Absence Rate

Sex		Manufacturing Industry	Construction Industry	Wholesale and Retail Trade	Real Estate, Renting and Business Activities	Transport, Storage and Communication
Male	coeff	165223.8***	3626.802	-243534.7**	134090.3***	257369.7*
	z-value	(8.88)	(0.44)	(-2.40)	(4.34)	(1.64)
	p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000
	Par R^2	0.3930	0.4252	0.8692	0.2486	0.5325
	R^2	0.0851	0.0840	0.0551	0.0413	0.0657
Female	coeff	219797.4***	10978.67	-974916.6**	211205.4***	390582.1*
	z-value	(3.42)	(0.40)	(-2.52)	(3.81)	1.88)
	p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000
	Par R^2	0.9603	0.9767	0.3402	0.8764	0.9909
	R^2	0.0266	0.1961	0.0238	0.0144	0.0817

Controls	Age, Professional Status, Firm-size, Firm´s Age Structure, Job Tenure, Year and Quarter Dummy Variables
Instrumented	Lay-off Risk
Instrument	Sickness Absence Rate

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*).

Using the sickness absence rate as an instrument for the lay-off risk, the positive sign of the coefficient can be confirmed for four industries (manufacturing, constructing, real estate, renting and business activities and transport, storage and communication). However, the coefficient in the construction industry becomes insignificant while for the wholesale and retail trade industry the coefficient is significant and negative. The partial R-square of the instrument in the first stage is very high. This result indicates that the instrument is good.[18] The p-value of the F-statistic supports the sickness absence rate as a valid instrument. Unfortunately, the overall R-square of the second stage decreases. A possible explanation for this result is the loss of periods for regression. The sickness absence rate is only available since 2003. The shorter the observation period, the smaller the within variation is and, therefore, the smaller the R-square. As our set-up is designed to measure the within variation, a loss of observation periods is unfortunate.

A comparison of all regression coefficients between this TSLS model with the original models suggest that endogeneity is not a problem for at least three industries (constructing, real estate, renting and business activities and transport, storage and communication).[19] However, the results for the manufacturing industry must be considered with caution. Here, the sickness absence rate appears not to be a perfect instrument because of the very low correlation with the lay-off risk. In combination with the lagged TSLS approach, endogeneity cannot be excluded for this industry. For the wholesale and retail trade industry, endogeneity might be a serious problem. The first TSLS approach leads to insignificant coefficients, and the second TSLS approach with a strong and valid instrument leads to negative and high significant coefficients. The change of sign of the coefficient in the second TSLS, compared to the initial OLS-estimation, points at possible mutual causality between wages and lay-off risks for this industry. A possible explanation is, again, an exogenous wage setting, even though the all over tariff commitment in this industry is not very high. A different tariff commitment for different skill levels is conceivable. High skilled employees may have a

[18] Different tests for weak identification suggest strong instruments; our specification is not weakly identified.

[19] Detailed results for the TSLS approach with sickness absence rate can be found in the appendix. We run a Hausman-test to compare the OLS and TSLS coefficients for the period between 2003 and 2007. Unfortunately, the test statistic becomes most of the times negative. It is not possible to interpret negative test statistics with the Hausman test. In cases of positive and, therefore, interpretable test statistics, the Hausman-test indicates equivalent coefficients.

lower commitment. Unfortunately, however, there are no data or current research on this topic available in Germany.

7 Conclusions

We found evidence that high skilled fulltime employees use the opportunities of lay-off risk in the labour market. In three of five main industries (constructing, real estate, renting and business activities and transport, storage and communication) in West Germany, risk premiums are present. The check for endogeneity shows that in two industries (manufacturing and wholesale and retail trade), mutual causality may be problem. A 1% increase of the lay-off risk leads to an increase in wages between 0.06% and 0.34%. The impact depends on the industry and the gender. For females, we find less significant results compared with males. This result may be related to a smaller sample size for high skilled females as their fulltime labour market participation is significantly smaller than it is for males [Fitzenberger et al. (2004)].

Because of the possible mutual causality between lay-off risk and wages, we checked for econometric endogeneity. Using TSLS estimation with two different instruments, we back up our findings. The instruments are the lagged lay-off risk and the sickness absence rate. For three industries, the results of the original estimations are definitely supported by both TSLS estimations

Our research findings suggest that more unsecure (flexible) labour market conditions are internalised in wages. The employees are aware of higher lay-off risks and, therefore, claim higher wages in several industries. In general, employees are interested in achieving the right balance between greater job security (lower risk) and higher wages. Employees pay a price for secure jobs whereas employers pay a price for unsecure jobs. The existence of a lay-off risk premium probably attracts more high skilled employees to temporary employment. Hence, the potential for flexible high skilled jobs could be increased, and therefore, firms may benefit from this flexible labour supply.

Our study introduces several areas for future research. First, endogenous job destruction should be linked with the examination of lay-off risk premiums. Such a link eases the analysis for all skill levels and the potential effects of exogenous wage increases on the lay-off risk. A second research area is connected with the first one: investigating skill-specific tariff commitments. A third research area should focus on intra-industrial job changes.

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Appendix

Table 7: Male High Skilled in the Manufacturing Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	OLS-AR	TSLS time	TSLS sick
Age	-1.29	12.19***	0.01***	5.48***	0.00***	20.42***	-1.16	0.09
	(-0.82)	(16.59)	(19.59)	(10.74)	(9.16)	(37.24)	(-0.73)	(0.05)
Worker	-285.36***	-396.03***	-0.12***	-298.72***	-0.10***	-234.96***	-261.43***	-261.87***
	(-21.62)	(-5.72)	(-31.60)	(-22.00)	(-26.01)	(-16.32)	(-18.89)	(-15.47)
Technician	-178.41***	-250.49***	-0.07***	-231.08***	-0.07***	-173.94***	-174.47***	-214.06***
	(-20.48)	(-5.31)	(-29.30)	(-22.32)	(-24.99)	(-15.93)	(-19.02)	(-17.22)
Foreman	-6.28	-42.96	-0.01	-60.61***	-0.02***	-21.96***	6.11	52.71***
	(-0.49)	(-0.76)	(-1.42)	(-4.06)	(-3.63)	(-1.39)	(0.46)	(2.94)
Small Company	-74.95***	-85.63***	-0.02***	-43.38***	-0.01***	-32.54***	-72.92***	-42.13***
	(-19.82)	(-5.10)	(-21.76)	(-11.91)	(-12.94)	(-8.57)	(-18.62)	(-8.90)
Large Company	49.96***	63.25***	0.01***	18.84***	0.01***	17.85***	48.86***	37.42***
	(18.40)	(6.18)	(18.97)	(6.60)	(7.55)	(5.98)	(17.38)	(10.83)
Under 20	-229.38***	-291.71	-0.07***	-116.11***	-0.03***	-25.57	-245.33***	-179.43***
	(-6.82)	(-2.19)	(-6.91)	(-3.80)	(-3.96)	(-0.80)	(-6.94)	(-4.41)
Over55	-119.35***	-126.19**	-0.04***	-55.94***	-0.02***	-18.94	-123.44***	1.22
	(-8.13)	(-1.89)	(-8.91)	(-3.35)	(-3.67)	(-1.09)	(-8.07)	(0.07)
Lay-off risk	120381.00***	120307.50***	0.15***	109574.20***	0.08***	578679.50***	-360381.40***	165223.80***
	(17.63)	(31.95)	(24.10)	(23.60)	(15.63)	(113.61)	(-5.79)	(8.88)
Job tenure	0.55***	0.65***	0.00***	-1.17***	0.00***	-2.46***	0.52***	-0.39***
	(5.06)	(1.58)	(5.19)	(-8.10)	(-8.48)	(-16.91)	(4.68)	(-3.31)
Constant	3698.07***	3147.21***	8.97***	3460.28***	8.69***	828.04***		
	(57.39)	(89.69)	(198.78)	(131.86)	(296.17)	(273.76)		
Obs.	173557	173557	173557	173557	173557	166679	167406	110876

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 8: Female High Skilled in the Manufacturing Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	OLS-AR	TSLS time	TSLS sick
Age	0.46	17.17***	0.01***	8.36***	0.00***	15.20***	-0.35	3.51
	(0.06)	(4.78)	(3.85)	(3.29)	(2.94)	(5.34)	(-0.04)	(0.39)
Worker	-764.21***	-835.48***	-0.31***	-823.92***	-0.41***	-677.73***	-682.96***	-800.69***
	(-13.17)	(-2.75)	(-15.78)	(-11.52)	(-17.25)	(-8.87)	(-11.16)	(-10.09)
Technician	-382.21***	-442.93**	-0.16***	-362.88***	-0.15***	-304.44***	-376.43***	
	(-4.71)	(-2.29)	(-5.86)	(-5.32)	(-6.47)	(-4.28)	(-4.16)	
Foreman		612.37***		725.92	0.21			-185.19**
		(9.17)		(0.93)	(0.84)			(-1.98)
Small Company	-176.11***	-186.05***	-0.06***	-95.41***	-0.03***	-96.99***	-180.86***	-197.99***
	(-9.24)	(-3.04)	(-9.12)	(-5.74)	(-5.76)	(-5.50)	(-8.97)	(-7.82)
Large Company	67.00***	93.47	0.02***	61.72***	0.02***	38.45***	59.10**	15.79
	(4.99)	(2.48)	(3.85)	(4.74)	(4.26)	(2.82)	(4.16)	(0.85)
Under 20	-46.72	-216.32	0.09	-302.90**	-0.11**	-197.36	-15.33	-17.79
	(-0.27)	(-0.46)	(1.63)	(-2.24)	(-2.46)	(-1.38)	(-0.09)	(-0.08)
Over55	-141.05*	-173.86	-0.04*	166.65***	0.05*	202.82**	-139.81*	-264.95***
	(-1.89)	(-0.55)	(-1.69)	(2.01)	(1.91)	(2.36)	(-1.79)	(-2.61)
Lay-off risk	137199.90***	138745.40***	0.20***	130791.80***	0.12***	576119.70***	-787045.60**	219797.40***
	(3.95)	(7.52)	(5.25)	(5.57)	(4.07)	(22.96)	(-2.46)	(3.42)
Job tenure	-1.58***	-1.62	0.00***	-3.28***	0.00***	-4.13***	-1.33**	0.63
	(-2.75)	(-0.80)	(-2.76)	(-4.31)	(-4.74)	(-5.38)	(-2.22)	(0.95)
Constant	3096.58***	2406.37***	9.08***	2717.21***	8.73***	585.40***		
	(10.01)	(16.27)	(33.70)	(21.56)	(49.97)	(39.36)		
Obs.	16634	16634	16634	16634	16634	15896	16010	10527

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 9: Male High Skilled in the Construction Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	OLS-AR	TSLS time	TSLS sick
Age	3.12	29.59***	0.00***	15.81***	0.00***	44.82***	3.73	1.44
	(0.44)	(9.60)	(3.46)	(6.67)	(6.38)	(20.99)	(0.52)	(0.18)
Worker	-89.74*	-253.70*	-0.02	-199.48***	-0.05***	-104.17*	-11.59	67.77
	(-1.85)	(-1.66)	(-1.29)	(-3.58)	(-2.89)	(-1.79)	(-0.22)	(1.26)
Technician	-245.01***	-364.66***	-0.09***	-306.23***	-0.10***	-252.05***	-205.74***	-257.40***
	(-7.94)	(-3.81)	(-10.02)	(-7.78)	(-8.60)	(-5.89)	(-6.19)	(-5.37)
Foreman	-62.13*	-151.72	-0.01	-213.83***	-0.07***	-144.81***	-23.60	13.19
	(-1.82)	(-0.95)	(-1.19)	(-5.79)	(-6.53)	(-3.55)	(-0.65)	(0.30)
Small Company	8.72	-5.75	0.00	-20.54**	-0.01***	-11.72	14.09	23.62*
	(0.91)	(-0.23)	(0.91)	(-2.36)	(-2.60)	(-1.28)	(1.45)	(1.92)
Large Company	-16.10*	-6.15	-0.01**	25.84***	0.01*	28.96***	-16.61*	17.45
	(-1.69)	(-0.19)	(-2.06)	(2.64)	(1.90)	(2.80)	(-1.69)	(1.44)
Under 20	-44.66	-81.45	-0.03	-166.10***	-0.05***	-132.25**	-68.71	-189.96**
	(-0.63)	(-0.35)	(-1.27)	(-3.09)	(-3.23)	(-2.34)	(-0.95)	(-2.24)
Over55	-225.74***	-193.18*	-0.06***	-1.94	0.00	24.14	-195.77***	-59.16
	(-5.99)	(-1.70)	(-5.20)	(-0.05)	(0.01)	(0.60)	(-5.04)	(-1.30)
Lay-off risk	13694.35***	13724.15***	0.07***	12441.47***	0.06***	55296.61***	40323.59***	3626.80
	(4.08)	(6.91)	(3.91)	(5.42)	(4.06)	(18.63)	(3.46)	(0.44)
Job tenure	1.97***	1.95	0.00***	1.83***	0.00**	0.33	1.60***	1.31***
	(4.34)	(1.21)	(4.10)	(3.05)	(2.04)	(0.55)	(3.44)	(2.58)
Constant	3483.40***	2416.64***	8.39***	2918.38***	8.25***	783.99***		
	(12.65)	(18.36)	(77.35)	(28.59)	(132.04)	(65.37)		
Obs.	12000	12000	12000	12000	12000	11391	11441	7365

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 10: Female High Skilled in the Construction Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	OLS-AR	TSLS time	TSLS sick
Age	-11.98	-9.13	0.00	-22.19**	-0.01***	-21.82**	-23.33	-16.09
	(-0.34)	(-0.52)	(-0.51)	(-2.47)	(-2.84)	(-2.15)	(-0.66)	(-0.42)
Worker								
Technician	-85.04	-285.15	-0.06	-38.82	-0.02	2.31	-54.86	
	(-0.32)	(-1.08)	(-0.53)	(-0.23)	(-0.33)	(0.01)	(-0.15)	
Foreman	419.00**	294.39*	0.15**	348.85	0.21**	464.70*	435.21**	
	(2.47)	(2.39)	(1.97)	(1.49)	(2.13)	(1.77)	(2.39)	
Small Company	226.84***	139.76	0.08***	5.88	0.00	27.53	230.16***	215.34***
	(4.50)	(1.14)	(3.42)	(0.16)	(-0.18)	(0.69)	(4.45)	(2.94)
Large Company	-494.12***	-286.28	-0.19***	-34.24	-0.01	-114.97**	-547.17***	-707.19***
	(-5.98)	(-1.09)	(-4.93)	(-0.65)	(-0.37)	(-2.09)	(-6.48)	(-7.68)
Under 20	457.14**	393.15	0.26***	-34.27	-0.01	-13.64	393.44**	103.63
	(2.34)	(1.14)	(2.84)	(-0.23)	(-0.09)	(-0.09)	(1.99)	(0.36)
Over 55	-161.11	-136.51	-0.09*	112.65	0.03	52.37	-203.62	-23.02
	(-1.30)	(-0.70)	(-1.66)	(1.03)	(0.78)	(0.47)	(-1.61)	(-0.17)
Lay-off risk	-948.46	841.25	-0.02	4274.88	0.03	52579.76***	57249.33	10978.67
	(-0.06)	(0.13)	(-0.12)	(0.44)	(0.40)	(3.84)	(1.01)	(0.40)
Job tenure	-10.75***	-11.29	0.00***	-5.89	0.00	-8.80**	-11.12***	-14.92***
	(-3.55)	(-1.58)	(-3.18)	(-1.54)	(-1.39)	(-2.17)	(-3.58)	(-3.80)
Constant	3149.82**	3060.37***	7.90***	3442.37***	8.34***	1856.35***		
	(2.38)	(4.62)	(9.26)	(8.85)	(23.04)	(46.06)		
Obs.	1459	1459	1459	1459	1459	1382	1396	949

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 11: Male High Skilled in the Wholesale and Retail Trade Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	OLS-AR	TSLS time	TSLS sick
Age	3.26	18.21***	0.00*	6.31***	0.00***	-0.83	4.00	2.35
	(0.84)	(8.91)	(1.65)	(4.51)	(3.67)	(-0.50)	(1.04)	(0.58)
Worker	-142.81***	-278.50**	-0.07***	-306.02***	-0.11***	-263.22***	-103.92***	-108.89***
	(-3.73)	(-2.55)	(-5.72)	(-7.68)	(-8.99)	(-6.15)	(-2.58)	(-2.74)
Technician	-68.54***	-138.04	-0.05***	-224.16***	-0.09***	-168.65**	-49.23**	-36.77
	(-3.34)	(-1.34)	(-8.40)	(-8.06)	(-10.16)	(-5.91)	(-2.37)	(-1.40)
Foreman	-116.43***	-178.56	-0.05***	-242.60***	-0.08***	-233.75***	-133.31***	-146.74***
	(-3.78)	(-1.30)	(-4.97)	(-7.24)	(-7.96)	(-6.65)	(-4.25)	(-4.16)
Small Company	-57.81***	-71.54***	-0.01***	-40.18***	-0.01***	-30.03**	-54.68***	-59.16***
	(-8.90)	(-3.47)	(-7.10)	(-6.49)	(-6.12)	(-4.63)	(-8.23)	(-7.23)
Large Company	21.75***	32.70	0.01***	29.24***	0.01***	22.42***	21.75***	12.02
	(3.20)	(1.59)	(3.53)	(4.28)	(3.40)	(3.15)	(3.16)	(1.47)
Under 20	78.53*	8.21	0.00	8.39	0.00	45.07	83.70*	-14.42
	(1.79)	(0.06)	(-0.02)	(0.22)	(-0.39)	(1.16)	(1.88)	(-0.27)
Over 55	-145.37***	-157.33*	-0.04***	-7.93	0.00	-13.04	-129.29***	-45.31*
	(-6.49)	(-1.76)	(-5.97)	(-0.34)	(-0.37)	(-0.55)	(-5.70)	(-1.76)
Lay-off risk	133256.60***	137552.20***	0.23***	130437.10***	0.19***	528687.60***	89270.26	-243534.70**
	(3.89)	(6.99)	(7.76)	(5.41)	(4.17)	(50.36)	(0.16)	(-2.40)
Job tenure	1.07***	0.99	0.00*	0.83*	0.00	0.63	1.04***	0.53
	(3.27)	(0.77)	(1.82)	(1.82)	(0.94)	(1.37)	(3.15)	(1.50)
Constant	2895.40***	2278.16***	9.35***	2754.25***	9.12***	388.85***		
	(11.14)	(15.59)	(48.67)	(17.08)	(39.34)	(54.17)		
Obs	32017	32017	32017	32017	32017	30171	30663	19705

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 12: Female High Skilled in the Wholesale and Retail Trade Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	OLS-AR	TSLS time	TSLS sick
Age	-8.10	6.91	0.00	-0.13	0.00	-8.74**	-9.76	-8.36
	(-0.75)	(1.39)	(-0.16)	(-0.04)	(-0.71)	(-2.14)	(-0.89)	(-0.83)
Worker	167.89**	104.26	0.03	-68.49	-0.08**	24.00	188.41***	-2.16
	(2.43)	(0.53)	(0.99)	(-0.77)	(-2.31)	(0.27)	(2.62)	(-0.03)
Technician	657.53***	605.04	0.35***	180.47***	0.09***	221.43***	640.99***	-844.12***
	(11.35)	(1.12)	(15.84)	(2.74)	(3.63)	(3.21)	(10.64)	(-6.27)
Foreman	487.65***	471.44***	0.21***	48.71	0.01	111.01	513.07***	547.28***
	(6.18)	(3.67)	(6.86)	(0.59)	(0.41)	(1.31)	(6.36)	(4.41)
Small Company	-43.94**	-67.96	-0.02**	-31.73**	-0.01**	-16.00	-49.84***	-1.84
	(-2.41)	(-1.41)	(-2.47)	(-2.28)	(-2.18)	(-1.11)	(-2.65)	(-0.09)
Large Company	43.73**	58.97	0.02***	36.95**	0.01*	31.86*	53.55***	27.30
	(2.42)	(1.13)	(3.14)	(2.19)	(1.95)	(1.81)	(2.87)	(1.42)
Under 20	-182.50**	-234.74	-0.06**	-139.25**	-0.06**	-99.51	-134.27*	-199.14**
	(-2.33)	(-1.11)	(-2.14)	(-2.34)	(-2.48)	(-1.61)	(-1.66)	(-2.19)
Over 55	-74.94*	-93.78	0.01	-3.05	0.00	5.95	-67.11	-46.69
	(-1.65)	(-0.51)	(0.32)	(-0.07)	(0.18)	(0.12)	(-1.43)	(-1.03)
Lay-off risk	81568.78	80859.47**	0.43***	93961.20	0.18	435907.20***	610714.00	-974916.60**
	(0.90)	(2.02)	(4.17)	(1.59)	(1.30)	(17.07)	(0.49)	(-2.52)
Job tenure	-4.33***	-4.54	0.00***	-2.53**	0.00***	-3.58***	-4.94***	-6.26***
	(-5.55)	(-1.41)	(-7.28)	(-2.41)	(-2.62)	(-3.33)	(-6.22)	(-7.79)
Constant	2862.15	2357.51***	10.15***	2507.58***	8.91***	501.03***		
	(4.19)	(7.60)	(15.64)	(6.38)	(12.80)	(31.45)		
Obs.	9588	9588	9588	9588	9588	9099	9172	6097

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 13: Male High Skilled in the Real Estate, Renting and Business Activities Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	TSLS time	TSLS time	TSLS sick
Age	7.98***	18.29***	0.00***	8.02***	0.00***	7.51	7.51	4.04
	(2.90)	(10.79)	(5.33)	(8.89)	(8.25)	(2.73)	(2.73)	(1.48)
Worker	-488.31***	-602.27***	-0.19***	-444.07***	-0.20***	-484.19***	-484.19***	-350.90***
	(-17.54)	(-4.38)	(-21.78)	(-15.37)	(-22.07)	(-16.67)	(-16.67)	(-11.80)
Technician	-275.73***	-342.35***	-0.10***	-171.82***	-0.07***	-269.20***	-269.20***	-40.70*
	(-12.66)	(-3.22)	(-15.03)	(-6.84)	(-8.25)	(-11.75)	(-11.75)	(-1.73)
Foreman	-162.48***	-179.44	-0.04***	-199.03***	-0.06***	-158.23***	-158.23***	-74.09**
	(-4.79)	(-1.48)	(-3.62)	(-5.32)	(-4.78)	(-4.56)	(-4.56)	(-2.02)
Small Company	-46.10***	-54.45***	-0.01***	-42.23***	-0.01***	-46.16***	-46.16***	-49.42***
	(-11.58)	(-4.04)	(-11.61)	(-11.32)	(-10.91)	(-11.32)	(-11.32)	(-10.57)
Large Company	17.48***	26.58**	0.01***	18.64***	0.01***	12.83***	12.83***	21.68***
	(4.25)	(2.18)	(4.12)	(4.46)	(5.34)	(3.06)	(3.06)	(4.48)
Under 20	-38.57	-81.50	-0.01	-48.03	-0.01	-18.46	-18.46	10.35
	(-0.99)	(-0.61)	(-0.80)	(-1.52)	(-1.37)	(-0.46)	(-0.46)	(0.24)
Over 55	-151.91***	-151.11***	-0.04***	-16.91	-0.01	-138.92***	-138.92***	-76.98***
	(-9.32)	(-3.01)	(-7.04)	(-0.97)	(-1.27)	(-8.39)	(-8.39)	(-4.16)
Lay-off risk	102785.10***	104197.90***	0.19***	100312.10***	0.19***	461116.70***	461116.70***	134090.30***
	(11.62)	(21.16)	(13.93)	(16.42)	(11.60)	(6.06)	(6.06)	(4.34)
Job tenure	-2.27***	-2.18***	0.00***	-2.35***	0.00***	-2.47***	-2.47***	-1.93***
	(-11.89)	(-3.09)	(-11.32)	(-9.35)	(-8.93)	(-12.80)	(-12.80)	(-9.81)
Constant	2769.01***	2318.60***	9.03***	2710.78***	9.03***			
	(22.40)	(30.36)	(97.53)	(45.29)	(114.77)			
Obs.	92197	92197	92197	92197	92197	88458	88458	58930

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 14: Female High Skilled in the Real Estate, Renting and Business Activities Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	TSLS time	TSLS sick	OLS-AR
Age	-4.69	16.32***	0.00	5.71**	0.00	-5.26	3.84	-2.88
	(-0.53)	(3.98)	(-0.87)	(2.03)	(1.54)	(-0.60)	(0.42)	(-0.89)
Worker	-119.70**	-189.25	-0.07***	-338.19***	-0.19***	-108.74*	-69.40	-290.12***
	(-1.98)	(-1.29)	(-2.96)	(-6.89)	(-10.41)	(-1.79)	(-1.17)	(-5.73)
Technician	-88.48	-118.11	-0.01	25.30	0.02	-188.75**	53.39	-28.17
	(-1.06)	(-1.18)	(-0.26)	(0.32)	(0.57)	(-2.08)	(0.62)	(-0.35)
Foreman		-208.07***		-20.05	0.05			
		(-4.00)		(-0.02)	(0.15)			
Small Company	-33.48***	-46.85	-0.01***	-46.80***	-0.02***	19:86	-55.59***	-37.20***
	(-2.64)	(-0.98)	(-2.84)	(-4.25)	(-4.29)	(-1.53)	(-3.51)	(-3.22)
Large Company	43.50***	56.97	0.02***	54.12***	0.02***	29.98**	51.19***	39.37***
	(3.50)	(1.50)	(3.87)	(4.67)	(4.95)	(2.37)	(3.38)	(3.24)
Under 20	-171.23*	-204.40	-0.07*	-35.84	-0.02	-160.45*	-181.96	-29.73
	(-1.89)	(-0.67)	(-1.91)	(-0.51)	(-0.79)	(-1.71)	(-1.48)	(-0.40)
Over 55	-88.11*	-83.22	-0.01	-74.32	-0.02	-109.74**	-76.57	-74.01
	(-1.75)	(-0.74)	(-0.46)	(-1.49)	(-0.92)	(-2.16)	(-1.32)	(-1.44)
Lay-off risk	115700.90***	114808.10***	0.24***	113974.50***	0.27***	246279.40	211205.40***	262670.50***
	(4.10)	(5.88)	(4.47)	(5.98)	(4.50)	(1.05)	(3.81)	(19.10)
Job tenure	0.12	0.34	0.00	-1.84**	0.00	-0.82	0.91	-2.78***
	(0.21)	(0.16)	(0.48)	(-2.47)	(-0.69)	(-1.38)	(1.43)	(-3.63)
Constant	2477.58***	1710.90***	9.27***	2083.09***	9.25***			1044.91***
	(6.60)	(8.18)	(26.24)	(11.39)	(31.96)			(88.70)
Obs.	16878	16878	16878	16878	16878	16094	10699	15998

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 15: Male High Skilled in the Transport, Storage and Communication Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	TSLS time	TSLS sick	OLS-AR
Age	-0.49	12.47***	0.00	8.32**	0.00**	0.01	-3.50	0.09
	(-0.05)	(2.57)	(-0.39)	(2.51)	(2.26)	(0.00)	(-0.33)	(0.02)
Worker	-66.30	-337.17**	-0.05**	-253.38***	-0.11***	-59.85	-136.94*	-129.40**
	(-1.13)	(-2.26)	(-2.48)	(-4.38)	(-5.54)	(-0.98)	(-1.79)	(-2.05)
Technician	64.82	-124.25	0.01	-311.67***	-0.14***	95.89*	-140.10**	-308.37***
	(1.24)	(-0.82)	(0.27)	(-5.78)	(-7.67)	(1.76)	(-2.23)	(-5.62)
Foreman		-789.97***		-744.49	-0.20			
		(-11.75)		(-0.94)	(-0.77)			
Small Company	-19.16	-40.11	0.00	-32.88**	-0.01*	-17.10	17.05	-17.62
	(-1.30)	(-0.97)	(0.33)	(-2.36)	(-1.94)	(-1.13)	(0.91)	(-1.21)
Large Company	2.86	16.48	0.01	24.41	0.01*	5.74	41.75**	12.84
	(0.20)	(0.44)	(1.23)	(1.64)	(1.82)	(0.38)	(2.43)	(0.82)
Under 20	72.45	-41.79	-0.04	-167.95	-0.07*	73.95	-571.70***	-134.37
	(0.50)	(-0.10)	(-0.80)	(-1.36)	(-1.65)	(0.49)	(-2.79)	(-1.02)
Over 55	470.40***	378.58	0.24***	246.08***	0.11***	523.28***	658.44***	362.67***
	(6.18)	(0.77)	(8.83)	(3.38)	(4.29)	(6.61)	(7.06)	(4.75)
Lay-off risk	146532.00**	144380.70***	0.03	160089.50***	0.17*	111517.50	257369.70*	581476.50***
	(2.15)	(3.20)	(0.38)	(3.35)	(1.64)	(0.11)	(1.64)	(23.79)
Job tenure	4.05***	3.93	0.00***	2.69**	0.00***	4.31***	6.40***	3.18***
	(5.23)	(0.85)	(8.10)	(2.52)	(3.74)	(5.42)	(6.71)	(2.86)
Constant	2850.59***	2433.39***	8.36***	2474.33***	8.96***			-76.81***
	(5.06)	(7.05)	(17.59)	(7.64)	(17.37)			(-4.42)
Obs.	7573	7573	7573	7573	7573	7282	5071	7110

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

Table 16: Female High Skilled in the Transport, Storage and Communication Industry in West Germany

	OLS FE	OLS-RE	Log OLS-FE	MME	Log MME	TSLS time	TSLS sick	OLS-AR
Age	2.61	25.41**	0.01	11.47*	0.00*	2.75	-4.32	10.08
	(0.15)	(2.48)	(0.91)	(1.89)	(1.66)	(0.16)	(-0.23)	(1.42)
Worker								
Technician	-304.08***	-285.27***	-0.23***	-281.24*	-0.18***	-294.95**		-276.87*
	(-2.56)	(-2.80)	(-5.34)	(-1.89)	(-3.62)	(-2.24)		(-1.70)
Foreman								
Small Company	64.67**	45.69	0.02*	25.13	0.01	61.47**	91.18**	39.87
	(2.15)	(0.59)	(1.93)	(0.95)	(1.52)	(1.97)	(2.41)	(1.42)
Large Company	40.90	56.66	0.02**	55.46**	0.02**	45.23	99.75***	42.57
	(1.36)	(0.74)	(2.16)	(2.11)	(2.27)	(1.46)	(3.01)	(1.54)
Under 20	-938.31***	-968.50	-0.41***	-208.81	-0.14*	-1035.76***	-771.35**	-314.61
	(-3.49)	(-1.17)	(-4.23)	(-0.96)	(-1.93)	(-3.79)	(-2.25)	(-1.39)
Over 55	-1138.04***	-1127.73	-0.38***	-178.06	-0.08	-1057.55***	-624.57***	-138.43
	(-7.71)	(-1.54)	(-7.09)	(-1.23)	(-1.58)	(-7.04)	(-3.47)	(-0.92)
Lay-off risk	46146.74	40307.83	0.44***	202791.20**	0.34*	-301992.30	390582.10*	440539.40***
	(0.38)	(0.48)	(3.55)	(2.31)	(1.87)	(-0.35)	(1.88)	(10.56)
Job tenure	-6.41***	-6.77	0.00***	-13.70***	-0.01***	-6.14***	-10.07***	-12.39***
	(-4.85)	(-1.27)	(-7.90)	(-8.22)	(-10.11)	(-4.60)	(-6.93)	(-7.47)
Constant	2829.69***	2134.64***	10.09***	1508.85***	9.62***			-86.43***
	(2.97)	(3.08)	(12.22)	(2.59)	(10.33)			(-3.17)
Obs.	2413	2413	2413	2413	2413	2315	1567	2276

Source: authors' calculations. Significance-level: 0.01(***), 0.05(**) and 0.1(*). T-values or z-values are reported in parentheses below the coefficients. The models were all estimated with quarter and year dummy variables. In order to ensure a clear representation these variables were omitted from the table

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