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Inequality-adjusted gender wage differentials in Germany

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Abstract

This paper exploits data from the German Socio-Economic Panel (SOEP) to re-examine the gender wage gap in Germany on the basis of inequality-adjusted measures of wage differentials which fully account for gender differences in pay distributions. The inequality-adjusted gender pay gap measures are significantly larger than suggested by standard indicators, especially in East Germany. Women appear penalized twice, with both lower mean wages and greater wage inequality. A hypothetical risky investment question collected in 2004 in the SOEP is used to estimate individual risk aversion parameters and benchmark the ranges of inequality-adjusted wage differentials measures.

JEL-Classification: D63; J31; J70

Keywords: gender gap; wage differentials; wage inequality; expected utility; risk aversion; East and West Germany; SOEP; Singh-Maddala distribution; copula-based selection model

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1 Introduction

The gender gap in pay in Germany is often considered as one of the largest in Europe. According to recent IAB InfoPlattform briefing, the average gross hourly earnings of women is 22 percent lower than men, for an EU average of 16 percent.[1] Eurostat's 2011 estimate of Germany's (unadjusted) gender pay gap is third only to Estonia and Austria among 26 european countries.[2]

Factors contributing to the gap are generally sought in career breaks, part-time employment and relative concentration of women in low skill and low pay occupations (Al-Farhan, 2010*a*; Antonczyk et al., 2010; Heinze, 2010). The size of the gender gap is known to differ markedly in Western and Eastern Germany: while mean wages are generally lower in Easter Germany, women face a much smaller penalty relative to men than in Western Germany (see, e.g., Hunt, 2002; Smolny and Kirbach, 2011; Kohn and Antonczyk, 2013). Smolny and Kirbach (2011) observe that the gender wage gap is one of the few statistics for which there is no convergence to Western levels in the period 1990–2008.

At the same time, Germany recently experienced an increase in overall wage inequality; see, e.g., Dustmann et al. (2009); Fuchs-Schündeln et al. (2010); Card et al. (2013). According to Al-Farhan's (2010*b*) analysis of the German Socio-Economic Panel (SOEP) data, the wage distribution in Germany appeared to stabilize at historically high levels of inequality in the recent ten years, while Antonczyk et al. (2010, 2011) still find increasing wage inequality between 2001 and 2006 using Structure of Earnings data. Observing high levels of wage inequality with a large gender gap in pay is consistent with the demonstration by Blau and Kahn (1992, 1996, 1997) that wage inequality is positively associated to the gender pay gap. Al-Farhan (2010*a*) shows indeed that recent trends in the gender pay gap and in wage inequality in Germany are driven by common underlying factors such as changes in potential experience, in workers occupational positions and in firm sizes.

In this context of a high gender pay gap and historically high levels of wage inequality, we undertake a re-examination of the German gender gap using inequality-adjusted measures of wage differentials. A standard measure of the gender gap gives (one minus) "the cents a woman makes on average for every dollar an observationally equivalent man makes on average." Unlike the raw figures mentioned in the opening sentences of this paper, such an indicator controls for gender differences in human capital (and possibly job characteristics) and compares observationally equivalent men and women. However it remains somewhat limited in that it focuses on comparisons of mean wages of men and women. It has long been recognised that a comprehensive assessement of wage differentials should consider the whole wage distributions of men and women –not just the mean–

[1] See `http://infosys.iab.de/infoplattform/dokSelect.asp?pkyDokSelect=71` (accessed August 6, 2013).

[2] See `http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Gender_pay_gap_statistics` (accessed August 6, 2013).

and comparisons be made on the basis of utility functionals defined over such distributions (see,e.g., Dolton and Makepeace, 1985). This is particularly relevant in a context of rising wage inequality if trends in wage dispersion vary by gender.

Using SOEP data on a subsample of individuals aged 25–55 over the period 1999–2008, we estimate upper and lower bounds for indices of wage differentials that incorporate a distributional dimension as proposed in Van Kerm (2013). The range includes a standard wage differential index focused on mean wages as special case. We find that this special case is (close to) the lower bound and that ignoring distributional concerns potentially underestimates the magnitude of the wage gap by up to three-fold in Eastern Germany and up to fifty percent in Western Germany. The much larger impact of accounting for inequality in Eastern Germany challenges current evidence that the gender gap is smaller in the East: taking male-female inequality differences into account very much reduces the contrast between Eastern and Western Germany.

We estimate the measures with and without correction for endogenous labour market participation using a copula-based selection model (Smith, 2003) and provide lower and upper bounds for the inequality-adjusted gender wage gap over a broad range of inequality aversion parameters. Additionally, we take advantage of a special module on risk attitudes collected in the 2004 wave of the survey (Dohmen et al., 2005, 2011) to estimate individual-level coefficients of relative risk aversion which, when plugged in the inequality-adjusted wage gap measure provide benchmark indicators relying on individual-specific risk aversion parameters. These benchmarks turn out to be close to the upper bounds in our range of inequality-adjusted indicators.

The paper proceeds as follows. Section 2 describes the inequality-adjusted measure of wage differentials and estimation methods. Section 3 provides information on the sample and variables of interest and describes construction of the individual measures of risk aversion from answers to the SOEP hypothetical risky investment question. Results are presented in Section 4. Section 5 concludes.

2 Inequality-adjusted measures of wage differentials

As mentioned in the Introduction, a standard indicator of the wage gap gives the "cents a woman makes on average for every dollar an observationally equivalent man makes on average" (see, e.g., Jenkins, 1994):

$$\Delta_1 = \exp\left[\int_{\Xi} \left[\log\left(\mu_x^w\right) - \log\left(\mu_x^m\right)\right] h^w(x)dx\right] \tag{1}$$

where (i) μ_x^w is the average wage of a woman with characteristics x (e.g., education, experience, etc.) and μ_x^m is the average wage of a man with the same characteristics x and (ii) $h^w(x)$ is the (multivariate) probability density function of characteristics x among women. Δ_1 is usually estimated from wage regressions of the form

$$\log(w_i) = x_i\beta^s + u_i, \qquad i = 1, \ldots, N^s \tag{2}$$

for $s \in \{m, w\}$, and then pluging regression coefficients to obtain

$$\begin{aligned} \Delta_1^{\mathsf{OB}} &= \exp\left[\int_{\Xi} x\left(\beta^w - \beta^m\right) h^w(x)dx\right]\theta & (3) \\ &= \exp\left[\bar{x}^w\left(\beta^w - \beta^m\right)\right]\theta & (4) \end{aligned}$$

where $\bar{x}^w$ is the vector of average women characteristics.[3] Δ_1^{OB} is the ubiquitous Oaxaca-Blinder measure of 'unexplained' wage differences (see, e.g., Fortin et al., 2011).[4]

The anatomy of (1) reveals a double averaging: first by considering the differences in average wage of men and women (conditionally on characteristics x) and, second, by averaging these differences over the characteristics of women. This approach, albeit empirically convenient, has been criticized for putting narrow focus on mean differences and discarding normatively relevant and empirically important distributional differences (Dolton and Makepeace, 1985; Jenkins, 1994; del Río et al., 2011). To address this concern, Van Kerm (2013) proposes an inequality-adjusted measure of wage differentials that is a straightforward extension of (1):

$$\Delta_2(\epsilon) = \exp\left[\int_{\Xi} \left[\log\left(C(F_x^w;\epsilon)\right) - \log\left(C(F_x^m;\epsilon)\right)\right] h^w(x)dx\right] \tag{5}$$

where $C(F_x^s;\epsilon)$ denotes a (conditional) power mean of order $(1-\epsilon)$. The normative significance of $\Delta_2(\epsilon)$ stems from the fact that $C(F_x^s;\epsilon)$ is also the certainty-equivalent for

[3] θ reflects differences in residual variance in the wage regressions for men and women (see Blackburn, 2007; Van Kerm, 2013).

[4] Women are taken as group of interest and men as reference group. The measure captures the disadvantage of women relative to men, what Jenkins (1994) calls 'discrimination against women'. Other choices are obviously available: as Fortin et al. (2011) argue, this question does not have any unambiguous econometric solution.

the uncertain outcome described by the distribution F_x^s and constant relative risk aversion von Neumann-Morgenstern expected utility over the wage distribution:

$$C(F;\epsilon) = \left(\int_0^\infty y^{1-\epsilon} dF(y) \right)^{\frac{1}{1-\epsilon}}$$

for $\epsilon \neq 1$ and $C(F;1) = \exp\left[\int_0^\infty \ln(y) dF(y)\right]$.

$\Delta_2(\epsilon)$ is a simple extension of Δ_1. Both measures are equal for $\epsilon = 0$. Adopting $\epsilon > 0$ leads to $C(F;\epsilon) \leq C(F;0)$: dispersion in the wage distribution is penalized. Adopting $\epsilon < 0$ leads to $C(F;\epsilon) \geq C(F;0)$: dispersion in the wage distribution is rewarded. This simple framework makes it straightforward to incorporate inequality adjustments in the gender wage gap assessment. When women with characteristics x face wage distributions with greater inequality than observationally equivalent men, this will inflate the wage gap index for any index with positive ϵ. On the contrary, lower inequality among women distributions may compensate for lower wages and thereby mitigate standard estimates of the wage gap. By similar arguments, assuming that greater inequality should be positively rewarded and computing wage gap measures with negative ϵ (that is, assuming preference for risk or inequality) higher inequality may mitigate (or worsen) the gender wage gap if there is more (or less) inequality in the wage distributions of women than of observationally equivalent men.

Note that inequality comparisons between men and women are made on conditional wage distributions F_x^w and F_x^m. A related branch of the literature focuses on comparisons of quantiles of the unconditional wage distributions of men and women; see, among others, Juhn et al. (1993); Machado and Mata (2005); Melly (2005); Firpo et al. (2009) on methods and Antonczyk et al. (2010), Heinze (2010) or Al-Farhan (2010*a*) for recent applications to the gender wage gap in Germany. This approach also departs from a narrow focus on mean wages and, by comparing quantiles of the wage distributions, flexibly identifies differences in pay at, say, the bottom or the top of the wage distributions (e.g., to identify 'glass ceiling' effects). The focus is however on understanding and decomposing differences in the *unconditional* wage distribution of men and women (disentangling composition effects from wage structure effects).[5] Our aim instead is to assess the impact and relevance of introducing normative considerations of inequality in aggregate assessments of the gender wage gap and we base this on comparisons of *conditional* wage distributions.

Equation (5) defines a class of wage gap measures indexed by the parameter of inequality aversion. We will report estimates for ϵ in the range $[-4, 10]$ covering a broad range of positions over inequality aversion ($\epsilon > 0$) or preference ($\epsilon < 0$). Variations in the statistic for different ϵ will inform us of the degree to which overall (conditional) wage distribu-

[5] The unconditional wage distribution for women is $F^w(y) = \int F_x^w(y) h_w(x) dx$ and counterfactual unconditional distribution that would be observed if women were paid as men is $F^*(y) = \int F_x^m(y) h_w(x) dx$ which can be inverted to consider unconditional quantiles; see, e.g., Albrecht et al. (2003); Millimet and Wang (2006); Arulampalam et al. (2007); Christofides et al. (2013) for applications to the gender wage gap.

tions differ between women and observationally equivalent men in our sample. We will interpret the maximum and minimum values for $\Delta_2(\epsilon)$ in this range as upper and lower bounds for the inequality-adjusted gender wage gap.

In principle, a distinct ϵ could also be specified for each women in the sample, or for each configuration of characteristics to reflect heterogeneity in individual-level attitudes towards inequality or risk. The SOEP dataset contains individual-level measures of risk attitudes in a special module in the 2004 wave of the survey. Responses to the small set of questions asked were validated in an incentive compatible field experiment with representative subjects (Dohmen et al., 2011). To benchmark our estimation results with constant ϵ for all women, we will exploit individual-level parameter estimates of risk aversion that can be derived from this module under the assumption of constant relative risk aversion utilities. Under the assumption that risk aversion parameters so derived can also reflect individual positions regarding wage inequality, we will estimate $\Delta_2(\epsilon_i)$ with heterogenous, individual-level ϵ_i parameters. This index will benchmark the estimated bounds for the wage gap. The degree to which the gap estimate will differ from indices with constant parameters will depend both on the size of the estimated risk-aversion parameters and on the association between individual-level risk aversion parameters and differences in wage inequality across gender.

Calculation of $\Delta_2(\epsilon)$ requires estimates of conditional wage distributions F_x^m and F_x^w for all x observed in the sample. Several alternative estimators can be chosen from, such as quantile regression, non-parametric kernel estimation, 'distribution regression'; see, e.g., Hall et al. (1999) for non-parametric approaches or Rothe (2010) and Chernozhukov et al. (2012) for recent general discussions. We follow Biewen and Jenkins (2005) and Van Kerm (2013) and adopt a fully parametric approach. Wages are specified as Singh-Maddala distributed conditionally on covariates, with the three parameters of the distribution allowed to vary log-linearly with covariates:

$$F_x^s(y) = 1 - \left[1 + \left(\frac{y}{b^s(x)}\right)^{a^s(x)}\right]^{-q^s(x)} \tag{6}$$

where $b^s(x) = \exp(x\theta_b^s)$ is a scale parameter, $a^s(x) = \exp(x\theta_a^s)$ is a shape parameter modifying both tails and $q^s(x) = \exp(x\theta_q^s)$ is a shape parameter modifying the upper tail (Singh and Maddala, 1976). Power means for the Singh-Maddala distribution have convenient closed-form expressions. This makes estimation of $\Delta_2(\epsilon)$ easy from coefficient estimates of model (6):

$$C(\hat{F}_x^s;\epsilon) = \hat{b}^s(x)\left(\frac{\Gamma\left(1+(1-\epsilon)/\hat{a}^s(x)\right)\Gamma\left(\hat{q}^s(x)-(1-\epsilon)/\hat{a}^s(x)\right)}{\Gamma\left(\hat{q}^s(x)\right)}\right)^{\frac{1}{1-\epsilon}} \tag{7}$$

where $\Gamma(\cdot)$ is the Gamma function and $(\hat{\theta}_a^s, \hat{\theta}_b^s, \hat{\theta}_q^s)$ are (say, maximum likelihood) estimates of the Singh-Maddala parameters (Kleiber and Kotz, 2003). Such a specification, albeit parametric, is flexible and allows for broad variations in degrees of skewness and kurtosis of the wage distributions. It can also deal with the heavy tail typical of earnings data.

A key advantage of the parametric approach over quantile regression or non-parametric procedures is that it can be adapted to handle endogenous labour market participation.[6] As is well-known, endogenous selection may lead to an over-estimation of the wage distributions when estimated only from observed wages. A differential effect of sample selection between women and men might appear, as the former group is more likely to include workers with lower earnings potential and/or higher reservation wages. See Hunt (2002) for a discussion of this in the context of East Germany.

Van Kerm (2013) shows that a Singh-Maddala distribution for wages can be combined with the standard Heckman-selection-type normality assumption (Heckman, 1979) to correct for endogenous participation using a copula-based selection model (Smith, 2003). Say z denotes participation for a given agent with wage y observed if $z = 1$. Let z^* be a latent propensity to participate in the labour market with $z = 1$ if $z^* > 0$ and $z = 0$ otherwise. Assuming the pair (y, z^*) is jointly distributed with cumulative distribution H_x and expressing H_x using its copula, the marginal Singh-Maddala distribution for y and an assumed distribution for the latent z^* (denoted G_x) leads to

$$H^s(y, z^*) = \Psi^s x(F_x^s(y), G_x^s(z^*)) \tag{8}$$

As in standard selectivity-corrected regression models, G_x^s can be assumed normal with mean $x\delta^s$ and unit variance. Following Van Kerm (2013), we take Ψ^s to be a Clayton copula:

$$\Psi(u, v; \theta_C^s) = \left(u^{-\theta_C^s} + v^{-\theta_C^s} - 1\right)^{-1/\theta_C^s} \tag{9}$$

where θ_C^s is an association parameter to be estimated. Joint estimation of θ_a^s, θ_b^s, θ_q^s, δ^s and θ_C^s, for example via maximum likelihood, leads to estimates of the Singh-Maddala distribution appropriately corrected for endogenous labour market participation. See Christofides et al. (2013) for a recent application of this model.

For inference on estimates of $\Delta_2(\epsilon)$, we assess sampling variability on the basis of bootstrap resampling. We implement the repeated half-sample bootstrap algorithm of Saigo et al. (2001) with a resampling that takes into account the repetition of individuals in the pooled longitudinal dataset as well as the sampling dependence between observations implied by the survey design (stratification and clustering).

[6] See Huber and Melly (2011) on issues with quantile regression with sample selection.

3 Data

3.1 Sample definition and labour market variables

The German Socio-Economic Panel (SOEP) is a nationally representative longitudinal survey on living conditions in Germany collected annually by the Deutsches Institut fur Wirtschaftsforschung (DIW, Berlin). Multiple topics are covered and include, e.g., income and employment, housing, health, educational achievements (see Wagner et al., 1993, 2007). SOEP data are available yearly since 1984 (since 1990 for East Germany). For our analysis we pool ten waves of data covering the period 1999–2008.

To limit the influence on wages of transitions into and out of the labour market, we restrict our analysis to respondents aged between 25 and 55. We consider the wages of individuals working in the private or public sector at least 15 hours per week in a regular (full-time or part-time) job. This excludes workers on vocational training, in sheltered workshops, or reporting marginal or irregular part-time employment. Self-employed workers are excluded as their wage rate is ill-defined. We exclude workers in the agricultural sector. Individuals with hourly wage below €4 are considered as out of regular employment. Cross-section sample weights are used throughout the analysis to correct for unequal sampling probabilities in the SOEP sampling design.

Gross hourly wage in the main job is calculated as gross earnings received in the month preceding interview divided by 4.32 and then by average weekly hours worked. Gross monthly earnings exclude additional payments such as holiday money or back-pay, while include money earned for overtime. Hours of work include information on average hours worked normally during a week, including overtime. We inflate all wages to 2008 prices using the national consumer price index.[7] To prevent outlying data from driving our estimates, abnormally large wages are excluded: observations with hourly wages above €70 are discarded. We also recode as missing any hourly wage from a person reported as normally working more than 65 hours per week.

Our final samples consist of 24,036 male observations and 17,371 female observations for Western Germany (with mean real hourly wages of €17.01 and €13.35, respectively), and of 7,060 male observations and 6,852 female observations for Eastern Germany (with mean wages of €11.69 and €10.81 euros, respectively). Descriptive statistics on wages percentiles and means by gender and region along with sample sizes are presented in Table 1. Note the regional contrast in differences between men and women in both wages and labour market participation.

The vector of individual characteristics we condition upon when computing our gender gap index contains age (in quadratic form), educational attainment (recorded as five categories from general elementary (or less) to higher, post-secondary education), years of potential labour market experience (computed as age minus years normally required

[7] Data on CPI are taken from the website of the Germany Federal Statistical Office, `http://www.destatis.de`.

to complete attained education minus three and classified in four groups: below 6, 6–10, 11–20 and 20 or more), and whether respondent was born in Germany. Because we pool data over multiple waves we also include a set of year dummies.[8] We adopt a parsimonious specification to avoid including variables that are potentially strongly gender-determined (such as actual years of labour market experience, working hours and occupation or job characteristics). So we look at a total effect of gender on wages and not the partial effect after controlling for all possibly confounding variables (Neal and Johnson, 1996).

Table 1: Mean wage and selected percentiles (by gender and region)

	Western Germany		Eastern Germany	
	Men	Women	Men	Women
Mean	17.01	3.35	11.69	10.81
10th percentile	10.03	7.87	6.73	5.49
25th percentile	12.73	9.84	8.23	6.94
50th percentile	15.60	12.79	10.42	9.84
75th percentile	19.84	15.78	14.00	13.89
90th percentile	25.46	19.20	18.23	17.09
Observations with non-missing wage	24029	17330	7047	6831
Sample size	31801	35082	10893	11450

Notes: Pooled sample of respondents aged 25–55 over survey years 1999–2008. See text for definition of hourly wage.

In models controlling for endogenous labour market participation, we take into account family structure in the equation for $x\delta^s$ (whether living with a partner and the education-level of the partner, the number of children in the household in various age ranges) and θ^s_C is allowed to vary according to the foreign-born status (in the Western Germany samples only).

Means of all covariates are reported in Table 2 by region and gender and within the full sample and for the subsample of observations with non-missing wage. Mean age is about 41 in all samples. The main contrasts between men and women is in educational achievements and years of potential experience (in particular in Eastern Germany). Employed women also have less children (in particular in Western Germany) which signals selective labour market participation.

[8] In particular, equations for $b^s(x)$ include all controls (age minus 25 and its square, education dummies, potential redicted wage experience in years, wave dummies). Equations for $a^s(x)$ include the dummy for not being born in Germany, age and age squared and wage dummies. Equations for $q^s(x)$ only include waves dummies (aggregated in three sub-periods).

Table 2: Covariate means for observations with non-missing wage (1) and in the full sample (2) (by gender and region)

	Western Germany				Eastern Germany			
	Men		Women		Men		Women	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Age	41.59	40.63	41.03	40.24	41.01	41.00	41.71	40.59
Foreign born	0.17	0.18	0.16	0.19	0.01	0.01	0.00	0.02
Education:								
General Elementary	0.10	0.11	0.10	0.16	0.04	0.06	0.03	0.06
Middle Vocational	0.51	0.51	0.51	0.53	0.62	0.62	0.53	0.56
Vocational Plus Abitur	0.07	0.08	0.13	0.09	0.06	0.04	0.05	0.04
Higher Vocational	0.10	0.10	0.06	0.08	0.10	0.11	0.11	0.07
Higher Education	0.22	0.20	0.19	0.15	0.19	0.18	0.28	0.27
Potential experience:								
0–10 years	0.03	0.04	0.04	0.04	0.06	0.03	0.03	0.06
11–20 years	0.22	0.27	0.28	0.27	0.26	0.24	0.20	0.26
21–30 years	0.36	0.35	0.32	0.34	0.31	0.36	0.36	0.33
31 years or more	0.34	0.31	0.33	0.31	0.32	0.31	0.36	0.31
Education of partner:								
No partner	0.30	0.31	0.41	0.29	0.37	0.35	0.28	0.28
General Elementary	0.10	0.12	0.05	0.09	0.03	0.03	0.02	0.03
Middle Vocational	0.35	0.36	0.30	0.35	0.38	0.38	0.43	0.42
Vocational Plus Abitur	0.08	0.06	0.05	0.04	0.03	0.02	0.03	0.02
Higher Vocational	0.05	0.06	0.07	0.08	0.05	0.04	0.10	0.09
Higher Education	0.11	0.09	0.12	0.14	0.15	0.18	0.14	0.16
Number of children in agerange:								
0–1	0.03	0.05	0.01	0.05	0.04	0.04	0.01	0.04
2–4	0.12	0.13	0.06	0.14	0.07	0.09	0.08	0.11
5–7	0.13	0.14	0.09	0.16	0.10	0.08	0.13	0.11
8–10	0.13	0.14	0.12	0.16	0.07	0.08	0.10	0.10
11–12	0.10	0.10	0.08	0.10	0.05	0.07	0.04	0.08
13–15	0.12	0.14	0.10	0.16	0.05	0.13	0.07	0.16
16–18	0.09	0.10	0.09	0.12	0.08	0.13	0.09	0.16

Notes: Pooled sample of respondents aged 25–55 over survey years 1999–2008. See text for definition of hourly wage.

3.2 Individual measures of risk aversion

The SOEP dataset contains individual-level measures of risk attitudes in a special module collected in the 2004 wave of the survey. One particular question allows us to approximate an individual-level risk aversion parameter ϵ_i under the assumption of CRRA utilities. Individual-level parameters can then be used in (5) to compute a measure of wage differentials that incorporates heterogeneous individual-level attitudes towards risk, instead of a constant parameter.

After a range of questions on their personal willingness to take risks (in general and in a number of specific contexts), survey respondents were presented an hypothetical investment opportunity. They were asked to report how much of a windfall gain of €100,000 they would be willing to invest in a risky asset. With equal probability, they would lose half of the value of their investment or they would double their investment. Respondents were asked to select a value for the amount invested $k \in \{€0, €20000, €40000, €60000, €80000, €100000\}$. The expected gain after investment of an amount k in the lottery is $G(k) = (100000 - k) + \frac{1}{2}(\frac{k}{2} + 2k) = 100000 + \frac{k}{4}$. We follow Dohmen et al. (2005, 2011) and combine each respondent's investment choice with measures of initial endowments taken from the data to infer values for individual CRRA coefficients.

Under the assumed CRRA utility function, expected utility of respondent i with initial wealth endowments w_i^0 investing an amount k of the windfall €100000 gain (denoted W) is

$$\bar{u}(w_i^0, k; \epsilon_i) = \frac{1}{2(1-\epsilon_i)} \left(\left(w_i^0 + W - \frac{k}{2} \right)^{1-\epsilon_i} + (w_i^0 + W + 2k)^{1-\epsilon_i} \right) \tag{10}$$

where ϵ_i is the respondent's CRRA. ϵ_i is unknown but we assume that the investment level k_i selected by the respondent leads to a higher expected utility than any other possible investment k_{-i}:

$$\bar{u}(w_i^0, k_i; \epsilon_i) \geq \bar{u}(w_i^0, k_{-i}; \epsilon_i). \tag{11}$$

Plausible estimates of risk aversion coefficients for respondent i are given by the range of values of ϵ_i for which inequality (11) is satisfied.[9] Note that the ordinal nature of the set of possible investment choices implies that we are only able to estimate *ranges* of coefficients of risk aversion. We will therefore construct different values for (5) based on lower bounds and upper bounds for individual risk aversion coefficients. Note also that the range of investment options does not allow us to capture any negative risk aversion: the lower bound for risk aversion is set to 0. For plausibility, we also impose a maximum value for ϵ_i of 10.

Table 3 shows estimates of the individual measures of risk aversion obtained in our sample with three alternative measures of initial endowments w_i^0: the net worth of household wealth (total household assets minus debts), annual household disposable income, and neglect of initial endowments altogether ($w_i^0 = 0$).[10] Using annual disposable income as a level of initial endowments seems to lead to a more credible distribution of CRRA coefficients (which mostly range within the limits of zero and 10) than using net worth. Using data on wealth as endowment leads to more extreme estimates of risk aversion. Like us, Dohmen et al. (2005) find estimated parameters of risk aversion up to 20 and suggest such extreme values to be potentially explained by measurement error in wealth. Disposable household income has the double advantage in this respect of being generally

[9] In our application, we solve this problem numerically on a grid of 21 potential values for $\epsilon_i \in \{0, 0.5, 1, \ldots, 10\}$.

[10] Estimates in Table 3 differ from those of Dohmen et al. (2005) because of our sample restrictions (e.g., to working-age individuals). When computed on the whole set of respondents estimates are similar. Estimates of household net worth are taken from the 2002 and 2007 SOEP wealth modules (averaged over the two years for respondents with both values available).

more precisely measured than wealth and of being available in SOEP in 2004 when the investment question was asked (wealth data are recorded in 2002 and 2007). It also has the advantage of being a strictly financial measure which can be compared to a windfall gain of € 100,000, whereas net worth data combine non-financial assets and debts that may not be relevant amounts for initial endowments in the present context.

Table 3: Means of estimated individual-level risk aversion parameters for observations with non-missing wage (1) and in the full sample (2) (by gender and region)

	Western Germany				Eastern Germany			
	Men		Women		Men		Women	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Initial endowment at net worth:								
Lower bound	5.86	5.90	5.92	6.30	5.55	5.59	6.12	6.02
Upper bound	7.96	7.92	8.18	8.41	7.69	7.87	8.59	8.44
Average	6.91	6.91	7.05	7.36	6.62	6.73	7.35	7.23
Initial endowment at annual household income:								
Lower bound	4.53	4.56	4.85	5.00	4.54	4.63	5.19	5.01
Upper bound	7.27	7.23	7.64	7.82	7.44	7.52	8.14	8.03
Average	5.90	5.90	6.25	6.41	5.99	6.07	6.66	6.52
No initial endowment:								
Lower bound	3.37	3.36	3.57	3.66	3.47	3.58	3.88	3.81
Upper bound	6.71	6.67	7.14	7.31	6.94	7.14	7.76	7.62
Average	5.04	5.01	5.36	5.49	5.20	5.36	5.82	5.71

Notes: Individual-level coefficients of risk aversion calculated from an hypothetical investment question (see text for details). Pooled sample of respondents aged 25–55 over survey years 1999–2008 which responded to 2004 module on willingness to take risks and for which initial endowments can be estimated. Net worth is estimated from SOEP wealth modules of 2002 and 2007.

As suggested in Section 2, individual-level CRRA measures can be directly plugged into (5) to benchmark the range of gender gap indices with constant $\epsilon \in [-4, 10]$ against a measure of wage differentials based on expressed risk aversion among women.

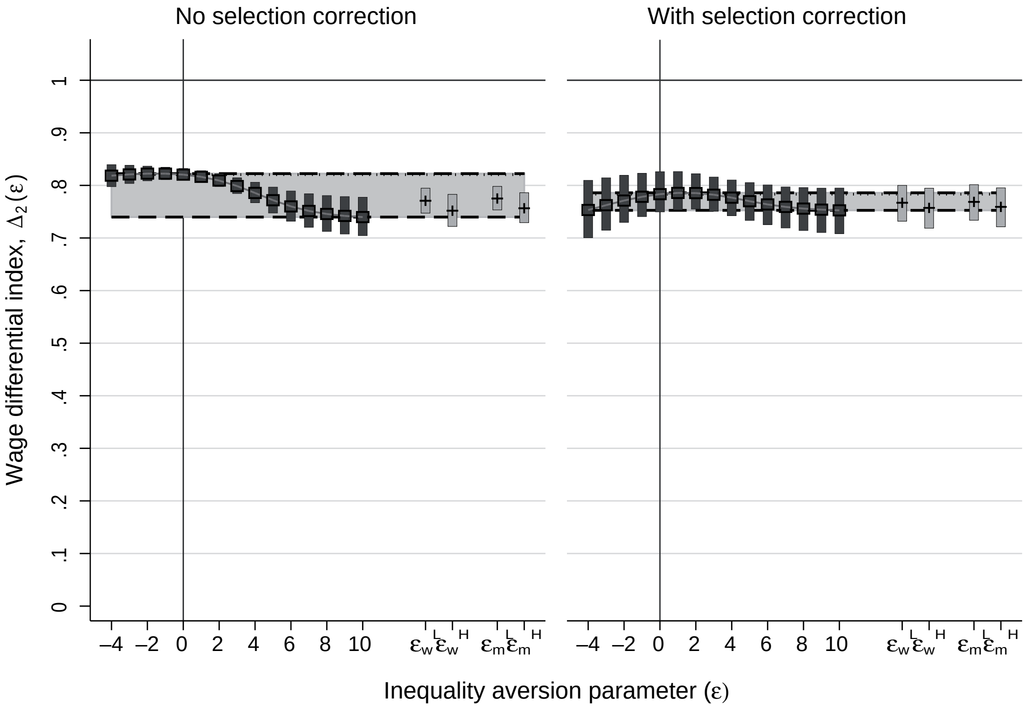
The question that may follow is whether the estimated differential would be different if women had expressed different risk preferences, and in particular if they expressed similar preferences to those of men. As Dohmen et al. (2011), we find that women tend to invest less in the risky asset than men in the hypothetical investment question. This is consistent with their responses to a self-assessment of their general ‘willingness to take risks’ (also available in the SOEP data in 2004), and this leads to higher average individual-level CRRA indices among women than among men.

To address this question, we estimate counterfactual individual-level CRRA coefficients in our sample of women as if they had responded to the hypotethcial investment question in the same way as men (as a function of observed characteristics). We conduct this simulation as follows. We first fit standard ordered probit models for the responses to the investment question on its original six-points scale. The model is fitted separately among men and among women with the following independent variables: all human capital covariates from the wage distribution model, the two variables exploited as exclusion restriction in the model with endogenous participation, as well as the variable on annual household income which is used in the construction of the CRRA indices. Using estimated coefficients from the ordered probit model, we can compute predicted probabilities of each lottery choice conditionally on covariates X_i and gender s:

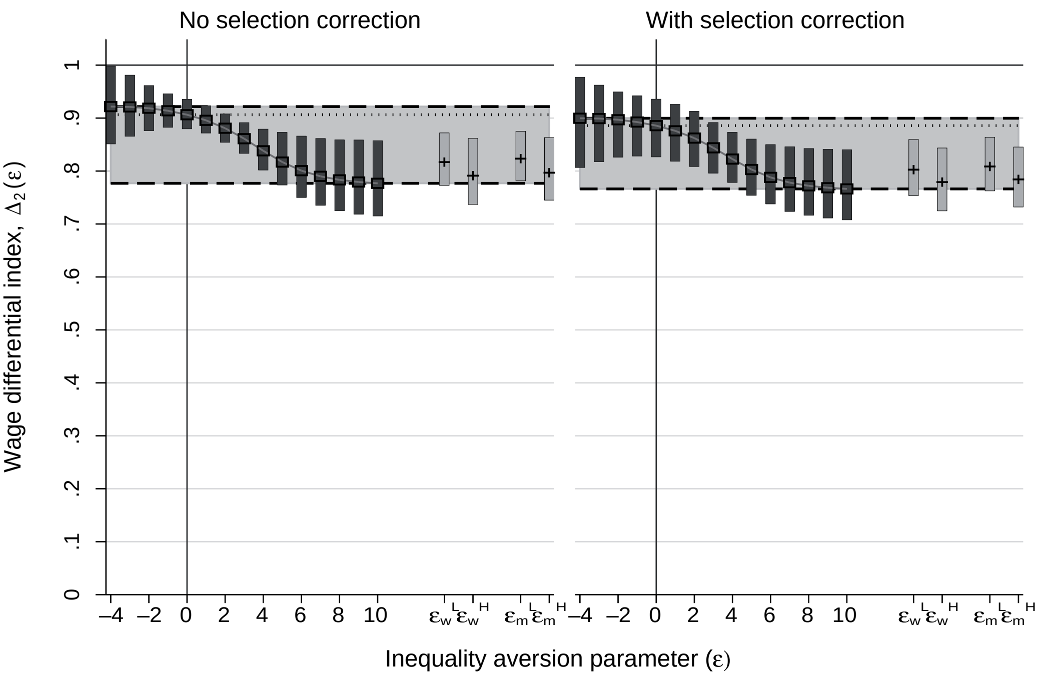
$$\Pr[k_i = k | X_i, s] = \Phi(X_i \hat{\beta}^s + \hat{\kappa}_z^s) - \Phi(X_i \hat{\beta}^s + \hat{\kappa}_{z-1}^s) \tag{12}$$

where $\hat{\beta}^s$ and $\hat{\kappa_2}^s, \ldots, \hat{\kappa_6}^s$ are estimated coefficients and $\hat{\kappa_0}^s$ and $\hat{\kappa}_1^s$ are set to $-\infty$ and 0 respectively. From predictions according to the male sample coefficients in the probit model, we simulate counterfactual values for the lottery choice k_i^* of our female sample, that is how a woman would respond if she had men's preferences (as picked up by the coefficients on the ordered probit model). We use these counterfactual lottery responses to compute a set of counterfactual risk aversion coefficients for women.[11] These counterfactual individual risk aversion parameters then can be adopted for estimation of $\Delta_2(\epsilon_i)$ on our sample of women to assess how the index would vary if women had the risk aversion of men (see Figure 1).

[11] The counterfactual lottery response is obtained as follows. We estimate for each women a relative 'rank' in the underlying latent variable that is consistent with her observed choice (women with identical answer k_i are randomly ranked) and take as counterfactual value the outcome k_i^* which corresponds to this rank from predictions of the model for men.



(a) Western Germany



(b) Eastern Germany

Note: Vertical bars show 90 percent percentile-based bootstrap variability bands (based on 500 repeated half-sample bootstrap replications). The grayed areas show the range of variation of $\Delta_2(\epsilon)$ $\epsilon \in [-4,10]$.The dotted line identifies $\Delta_2(0)$.

Figure 1: Inequality-adjusted gender wage gaps, $\Delta_2(\epsilon)$, (i) for $\epsilon \in [-4, 10]$ and (ii) for individual-specific risk aversion parameters (actual and counterfactual).

4 Results

Our key estimation results are compactly reported in Figure 1. The left part of each of the four panels shows estimates of $\Delta_2(\epsilon)$ for inequality aversion parameters ϵ ranging from –4 to 10 (point estimates are bracketed by 90 percent percentile bootstrap variability bands). Since $\Delta_2(\epsilon)$ represents the '(inequality-adjusted) cents a women makes for every (inequality-adjusted) euros a man makes', the relevant reference is the horizontal line at 1. The larger the distance of the estimated indices to 1, the greater the disadvantage of women. The grayed areas show the range of variation of $\Delta_2(\epsilon)$: they give upper and lower bounds in the gender gap index once gender differences in inequality are taken into account. Realize that the bounds need not be attained for identical ϵ in all cases: the upper bound in the gap is attained at the corner $\epsilon = 10$ in the four cases, but the lower bound is attained at $\epsilon = -4$ in Eastern Germany and at $\epsilon = -2$ or $\epsilon = 1$ in Western Germany if selection corrections are made or not. Note also that $\Delta_2(\epsilon)$ needs not be monotonically related to ϵ.

The classic gender gap index with $\epsilon = 0$ (identified in Figure 1 by an horizontal dotted line) turns out to be close to the lower bound of the inequality-adjusted index, in particular in Western Germany. $\Delta_2(0)$ evaluates to 0.82 and 0.91 for Western and Eastern Germany respectively if endogenous selection is ignored and to 0.78 and 0.89 respectively if self-selection is taken into account. The upper bound for the inequality-adjusted index evaluates to 0.74 and 0.78 for Western and Eastern Germany without selection correction and 0.75 and 0.77 after selection correction. The difference from the upper bound to the classic index is therefore 8, 13, 3 and 12 cents per euro respectively for Western and Eastern Germany and with and without selection correction. Women tend to face wage distributions which are unfavourable compared to the distribution of men, with a disadvantage going beyond facing lower means. Although there is no one-to-one connection between our inequality-adjusted indices (which focus on gender differences in conditional distributions) and estimates of gender gaps at different quantiles of the unconditional wage distribution, our findings are coherent with evidence on the latter. For example, Arulampalam et al. (2007); Heinze (2010); Christofides et al. (2013) generally find larger gender differences at low wages in Germany –with more women being low paid.

In all cases, the gender gap turns out to be smaller in Eastern Germany than in Western Germany. This is consistent with earlier research (see Maier, 2007). But the impact of adjusting the estimates for inequality differences between men and women is much larger in Eastern Germany. East-West differences in the upper bounds of inequality-adjusted gender gap estimates are much smaller than appears when looking at the classic, 'inequality-neutral' gap estimate. This result is fully consistent with recent findings by Kohn and Antonczyk (2013) showing that wage inequality had been rising in East Germany in the aftermath of the German reunification and that this particularly affected women in the lower part of the wage distribution (primarily through changes in industry-specific remuneration patterns). Our results confirm that this resulted in markedly increased wage inequality in the female pay distribution as compared to the male distribution.

Unsurprizingly, accounting for endogenous selection generally leads to larger gender gap estimates. This is true in both regions, but the impact is stronger in Western Germany. Note that the effect of accounting for selection in Western Germany not only appears to affect the male-female difference in the levels of wage (which would translate in a general shift in all estimates of $\Delta_2(\epsilon)$). It also affects the estimates of the overall shape of the conditional wage distributions, and in fact appears to reduce gender differences in wage distributions: the bounds of $\Delta_2(\epsilon)$ are much tightened, although at levels much higher than what would be indicated by $\Delta_2(0)$ with no selection correction.

The second set of measures presented in the right part of Figure 1 contains the inequality-adjusted index $\Delta_2(\epsilon_i)$ based on estimated individual-level CRRA coefficients estimates as explained in sub-section 3.2.

Each plot contains four such estimates: ϵ_f^L and ϵ_f^H are estimates based on the lower and upper bound estimates of individual risk aversion parameters among women, ϵ_m^L and ϵ_m^H are estimates based on the lower and upper bound estimates based on counterfactual individual risk aversion parameters among women as if they had revealed risk aversion similar to men's in lottery question answers.

Our risk aversion parameter estimates tend to be relatively large and the gender pay gap is indeed substantially larger when individual risk aversion is taken into account, compared to the benchmark of $\epsilon = 0$. $\Delta_2(\epsilon_i)$ estimates tend to be relatively close to the upper bounds of $\Delta_2(\epsilon)$ and, compared $\Delta_2(\epsilon_i)$, the gap increases by approximately 20 percent in Western Germany while it more than doubles in Eastern Germany. Gender gap indices for Eastern Germany are now much closer to the levels observed in Western Germany.

Note that estimates based CRRA parameters constructed on actual responses by women to the lottery question are close to estimates based on counterfactual responses as of men. Gender differences in risk aversion do not influence the assessment of the wage gap.

Finally, Table 4 presents some gender gap estimates for a set of specific subgroups of women and for three values of the ϵ parameter. The estimates presented in the table are simple averages among women of each of the subgroups of their 'individual inequality-adjusted gap' relative to a man of identical characteristics. In other words, it is the average over the $i \in \{1.., N^s\}$ women in each subgroup s of $\big[\log\big(C(F^w_{x_i};\epsilon)\big) - \log\big(C(F^m_{x_i};\epsilon)\big)\big]$.[12]

Partitioning by education level leads to contrasted results between Western and Eastern Germany. In Western Germany, the gender gap is larger for more highly educated women, while the opposite is observed in Eastern Germany. For $\epsilon = 4$, the gap is not even statistically significant for highly educated women in Eastern Germany. The partition into

[12] Note that, for each partition into subgroups, $\Delta_2(\epsilon)$ can be expressed as the average of the subgroup indices weighted by the subgroup shares.

age groups reveals an inverted-U shape with a lower gaps observed among middle-aged women. Finally, comparing estimates from the sample observations observed in 2000 and in 2008 show an interesting contrast for different ϵ: the gap has narrowed over time according to $\epsilon = -4$ (especially in Eastern Germany), has remained stable (in the West) or increased moderately (in the East) for $\epsilon = 0$, but it has increased for $\epsilon = 4$ (especially so in the East). This pattern signals an increase in the difference in (conditional) wage inequality between men and women over time, with inequality becoming higher among women.

Table 4: Inequality-adjusted gender wage gaps for selected population subgroups

	No selection correction			With selection correction		
	$\epsilon = -4$	$\epsilon = 0$	$\epsilon = 4$	$\epsilon = -4$	$\epsilon = 0$	$\epsilon = 4$
Western Germany						
All	0.82	0.82	0.79	0.75	0.78	0.78
	[0.80,0.84]	[0.81,0.83]	[0.77,0.81]	[0.70,0.81]	[0.75,0.83]	[0.74,0.81]
General elementary ed.	0.86	0.88	0.86	0.78	0.82	0.84
	[0.83,0.89]	[0.86,0.90]	[0.83,0.89]	[0.72,0.84]	[0.79,0.87]	[0.80,0.88]
Middle vocational ed.	0.82	0.81	0.76	0.77	0.78	0.75
	[0.80,0.85]	[0.79,0.83]	[0.73,0.78]	[0.72,0.83]	[0.75,0.82]	[0.72,0.79]
Higher education	0.78	0.79	0.76	0.71	0.75	0.75
	[0.75,0.81]	[0.78,0.81]	[0.74,0.79	[0.65,0.78]	[0.71,0.80]	[0.72,0.79]
Aged 25–34	0.75	0.75	0.72	0.70	0.73	0.73
	[0.72,0.78]	[0.73,0.78]	[0.69,0.75]	[0.63,0.76]	[0.68,0.78]	[0.68,0.77]
Aged 35–44	0.86	0.86	0.83	0.77	0.80	0.80
	[0.82,0.90]	[0.82,0.90]	[0.79,0.87]	[0.71,0.84]	[0.75,0.86]	[0.75,0.85]
Aged 45–55	0.81	0.81	0.78	0.74	0.77	0.77
	[0.78,0.84]	[0.79,0.84]	[0.75,0.81]	[0.69,0.80]	[0.73,0.81]	[0.73,0.80]
Year 2000	0.79	0.81	0.78	0.72	0.78	0.77
	[0.76,0.83]	[0.79,0.83]	[0.75,0.81]	[0.65,0.79]	[0.74,0.81]	[0.74,0.81]
Year 2008	0.82	0.81	0.77	0.76	0.78	0.76
	[0.78,0.85]	[0.79,0.83]	[0.74,0.80]	[0.71,0.82]	[0.74,0.82]	[0.72,0.80]
Eastern Germany						
All	0.92	0.91	0.84	0.90	0.89	0.82
	[0.85,1.00]	[0.88,0.94]	[0.80,0.88]	[0.81,0.98]	[0.83,0.94]	[0.78,0.87]
General elementary ed.	0.86	0.87	0.84	0.84	0.85	0.82
	[0.78,0.94]	[0.83,0.91]	[0.78,0.91]	[0.74,0.92]	[0.78,0.90]	[0.76,0.89]
Middle vocational ed.	0.89	0.88	0.83	0.87	0.86	0.81
	[0.81,0.97]	[0.85,0.92]	[0.78,0.88]	[0.77,0.95]	[0.80,0.92]	[0.76,0.87]
Higher education	1.00	0.96	0.85	0.98	0.93	0.83
	[0.91,1.10]	[0.91,1.00]	[0.79,0.91]	[0.86,1.08]	[0.86,1.00]	[0.77,0.90]
Aged 25–34	0.88	0.87	0.81	0.86	0.85	0.79
	[0.75,1.06]	[0.76,1.01]	[0.69,0.95]	[0.71,1.03]	[0.73,1.00]	[0.68,0.94]
Aged 35–44	0.91	0.91	0.86	0.89	0.89	0.84
	[0.80,1.06]	[0.81,1.02]	[0.75,0.98]	[0.76,1.02]	[0.78,0.99]	[0.74,0.96]
Aged 45–55	0.91	0.89	0.82	0.89	0.87	0.81
	[0.83,1.02]	[0.84,0.95]	[0.76,0.89]	[0.79,0.99]	[0.81,0.94]	[0.75,0.88]
Year 2000	0.90	0.93	0.88	0.88	0.91	0.87
	[0.82,0.99]	[0.89,0.96]	[0.84,0.93]	[0.76,0.97]	[0.84,0.95]	[0.82,0.92]
Year 2008	0.96	0.90	0.78	0.95	0.88	0.77
	[0.87,1.08]	[0.86,0.94]	[0.72,0.85]	[0.84,1.06]	[0.81,0.94]	[0.70,0.84]

Notes: Figures in brackets are 90% percentile boostrap confidence intervals based on 500 repeated half-sample bootstrap replications.

5 Summary and conclusion

Our analysis re-examines the gender wage gap in Germany by providing lower and upper bounds for gender gap indicators that fully incorporate conditional wage distribution differences between men and women. We find that the situation of women generally appears worse than suggested by classic indicators focused on mean wage differences: they tend to be penalized twice with lower mean wages and mostly unfavourable configurations of higher moments too. An argument that women's lower average wages could be compensated by favourable differences in higher moments is not supported by our results, even under extreme preferences with regard to inequality. The impact of accounting for inequality is particularly striking in Eastern Germany. The gender pay gap is larger in Western Germany than in Eastern Germany. However, the inequality-related penalty is much larger in Eastern Germany than in Western Germany. Ignoring full male-female differences in conditional wage distributions potentially strongly under-estimates the gender gap in Eastern Germany.

The analysis incorporates adjustments for endogenous labour market participation. Reassuringly, the overall picture remains unaffected once selectivity is taken into account, albeit –unsurprizingly– with generally larger gender gap estimates.

The sources of wage distribution differences and of the higher wage inequality among women conditional on human capital characteristics are likely to be sought in the greater prevalence of low paid part-time employment, strong variations in years of actual experience (conditional on age), and possibly greater dispersion of occupational choices (especially towards low-paid jobs). Our findings suggest that policies that attempt to reduce female wage inequality –in particular by 'raising the floor' for low paid women– would also be beneficial towards reducing the overall gender gap in pay according to generalized, inequality-adjusted indicators.

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