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Decomposing wage discrimination in Germany and Austria with counterfactual densities

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Abstract Using income and other individual data from EU-SILC for Germany and Austria, we analyze wage discrimination for three break-ups: gender, sector of employment, and country of origin. Using the method of Machado and Mata (J Appl Econom 20(4):445–465, 2005) the discrimination over the whole range of the wage distribution is estimated. Significance of results is checked via confidence interval estimates along the lines of Melly (Estimation of counterfactual distributions using quantile regression. Working Paper, SIAW, University of St. Gallen, 2006). The economies of Germany and Austria appear structurally very similar and are highly interconnected. One would, therefore, expect to find similar levels and structures of wage discrimination. Our findings deviate from this conjecture significantly.

Keywords Wage discrimination · Decomposition · Quantile regression

1 Motivation

According to Eurostat, the gender wage gap in unadjusted form in 2010 was 22.3 % in Germany and 24 % in Austria.[1] Within the EU only Estonia has exhibited a higher number with 27.7 %. From this point of view, labor market discrimination seems to be a relevant problem in Germany and Austria. Like in most industrial countries, the

[1] see http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&plugin=0&language=de&pcode=tsdsc340.

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extent of wage inequality was rising in the last decades, as is shown for example in Dustmann et al. (2009) for Germany and Altzinger et al. (2012) for Austria. The German market is not only the most important export market for Austria, there is also massive interaction between both labor markets, due to the common language and major cultural similarities. For that reason it is interesting to study, if levels and structure of wage discrimination are similar in Austria and Germany.

Our concern here is labor market discrimination. This is a very general concept and applies whenever a member of some group A is treated differently from a member of another group B, despite all productivity related characteristics of these persons being the same. Different treatment includes wage discrimination but also different chances of promotion, different access to different economic sectors or to management positions. These basic forms of discrimination are connected but in empirical studies must be dealt with separately.

We concentrate on wage discrimination. This is defined in the usual manner as the difference between the actual wage and a fictitious wage a person would get, if her/his (observable) characteristics were remunerated like those of a member of the other group. Clearly, corresponding estimates depend on what one considers as productivity relevant characteristics, i.e. relevant regressors in the wage equation. Simply adding more and more regressors reduces estimated discrimination figures arbitrarily, as more and more wage differences appear as merely idiosyncratic. This would constitute a case of deliberately downward biased discrimination estimates. Unobserved, yet productivity relevant characteristics give rise to the opposite problem. Because they can not enter as regressors and therefore, can not account for wage differences, the resulting discrimination estimates will tend to be upward biased (unless mastered with some instrumental variable technique). Therefore, discrimination estimates must be studied with care, and so must ours.

We will take a closer look at wage discrimination along three classical break-ups of the labor force: (1) by gender, (2) by sector of employment and (3) by country of origin. The problem of unobservable characteristics is especially relevant for the break-up according to country of origin while self-selection might be an issue in the break-up by sector of employment. We will discuss the latter problem more thoroughly below. Using EU-SILC data for both countries, we, furthermore, compare levels and structure of wage discrimination in Germany and Austria along these break-ups.

Existing scholarly literature (see chapter 2) provides unanimous evidence for the basic direction of wage discrimination for each of these classifications. For levels and explanations of wage discrimination, matters are less clear. Particularly, it must be asked, to which extent observed wage differences arise from discriminatory remuneration of relevant characteristics (education, experience,...) or from different characteristics themselves. Such a decomposition of wage differences can be done with different weighting schemes, depending on what reference group is chosen. Contrary to most of the existing literature, we present both basic decompositions to narrow down the extent of true wage discrimination.

In older papers such decompositions are calculated at the mean of the wage distribution. Applying methods developed in the last decade we present wage discrimination results not only at the mean, but over the whole range of the wage distribution.

The main contribution of the present paper is a decomposition of wage differences for unrestricted samples for Germany and Austria. Most papers covering these countries, instead, restrict the underlying samples and it remains unclear, to which extent corresponding results are driven by specific data filtering. Furthermore, we work with a newer data sample than any of the existing papers. The EU-SILC data base enables a comparative analysis for both countries using a common regression framework. This is not possible with often used country specific data. Finally, to the best of our knowledge, no study so far exists analyzing the immigrants versus natives wage gap for Austria.

2 Literature

Wage discrimination by gender has been extensively studied in the past. For recent international surveys see e.g. Weichselbaumer and Winter-Ebmer (2005) and Arulampalam et al. (2007).

For West Germany relevant results are found eg. in Fitzenberger and Wunderlich (2002) or Fitzenberger and Kunze (2005), but they do not lend themselves for an easy comparison with the analysis here. Fitzenberger and Wunderlich (2002) focuses on the dynamics of the gender pay gap between 1975 and 1995. Fitzenberger and Kunze (2005), also use the approach of Machado and Mata (2005) (hereafter MM) like we do. But they constrain their analysis to young workers with apprenticeships, which clearly is a much more narrow research focus than ours. A comparable study, instead, is the one of Heinze (2010). She also uses the MM-approach but based on matched employer–employee data for 2002. Decomposition of the total gender pay gap in this study is into four parts according to (1) different individual characteristics, (2) different remuneration of these individual characteristics, (3) different establishment characteristics and (4) different remuneration of these establishment characteristics. Starting from the observed total gender pay gap, which decreases from 30 % at the 1st decile to around 20 % for the 8th decile she finds in particular that: (a) contributions of these four components do not vary much across quantiles; (b) differences in the remuneration of establishment characteristics account for the major part (22–16 %) and (c) differences in characteristics (individual and firm specific) only explain a meager 4 % of the overall difference. The EU-SILC data base underlying the present analysis contains no such firm level data (beyond sector and rough firm size) and does not allow distinction into West- and East-Germany. Furthermore, Heinze also restricts attention to full-time employees. Therefore, our results are not strictly comparable to hers. A conceptual problem with the 4-part decomposition is the multitude of potential counterfactual densities that could be used. Because only results for one particular choice are presented, the impact of this specific choice upon results remains unclear. This issue will be discussed in detail in Sect. 3.3.

For Austria evidence on the gender gap is more sparse. In Böheim et al. (2005, 2007) quantile regressions are used but the decomposition is based in traditional manner on conditional densities. As such, the corresponding results strictly speaking are incorrect, because these decompositions of a total difference always leave an unexplained residual of unknown size (see García et al. 2001 or Fortin et al. 2011 for expositions of the problem). Nevertheless, the finding in Böheim et al. (2007) of a decline of pure wage discrimination of women from 17 to 14 % between 1983 and 1997 is noteworthy for comparison. Pointner and Stiglbauer (2010) also use the MM-approach, but their focus is on a decomposition along the time axis comparing the Austrian wage distribution in 2002 with the one in 1996. Only Böheim et al. (2013) is somewhat more comparable to the present analysis. It is based on Melly (2006), an approach comparable to Machado and Mata (2005) and, thus, to the one used in the present paper. A distinguishing feature of Böheim et al. (2013) is the use of matched employer–employee data for over 13,000 workers. These, particularly, include (typically unavailable) firm-level data on work interruptions due to unemployment spells or birth of a child. Concentrating on the private sector, they estimate increasing wage discrimination against women across quantiles, starting at 5 % for the 1st decile and ending at 15 % for the 9th with a rather constant total difference of around 25 %. They interpret the increasing discrimination across quantiles "as evidence that women fare worse in individual bargaining than men as most low paying jobs are covered by (industry-wide) collective bargaining agreements."

Also the decomposition of wage differences between public and private employees into explained and discriminatory parts has become a standard topic in scholarly literature. See e.g. Poterba and Rueben (1995) for the US or Mueller (1998) for Canada. For West Germany recent relevant evidence is found e.g. in Melly (2005b) using data from the 1984–2001 German socioeconomic panel (GSOEP) and in Depalo et al. (2013) relying on EU-SILC 2004–2007 data.

Melly (2005b) also employs the MM-approach but calculates the decomposition separately for men and women. For men wage discrimination in favor of public employees is 5 % at the 1st decile in 2001, declining almost linearly to -17 % at the 9th decile. For women the corresponding estimates show a similarly linear decline, but from 30 down to 7 %. Taking simple averages of Melly (2005b) for comparison with our results, this amounts to a linear decline in discrimination from around 17 % at the 1st decile down to -12 % at the 9th decile. It should be added, that Melly finds only negligible variation of this decomposition results across the time period 1984–2001.

Results from Depalo et al. (2013) cover Germany and Austria (amongst other countries), but are based only on observations for men aged 25+.[2] Furthermore, their analysis is based on the RIF-regression plus reweighting technique by Firpo et al. (2009). For Germany authors report a similarly declining pattern of raw wage gaps across income deciles but a significantly larger average raw wage gap ($\sim$14 %) than we find in our sample ($\sim$8 %), apparently owing to the particular data selection. Estimated discrimination figures for Germany exhibit a markedly falling tendency with sign reversal (+36 % at the 1st decile and -25 % at the 9th). Furthermore, discrimination figures are higher than raw wage gaps for top quantiles, revealing a considerable amount of hidden wage discrimination against public sector employees. For Austria, instead, authors report increasing raw wage gaps

[2] A major rational for this sample restriction is the removal of self-selection bias. But, as our results on self-selection in the "Appendix" will show, filtering along the gender dimension is most likely insufficient for that purpose.

(from 12 % at the 1st decile up to 20 %, the opposite pattern of the one found in our sample), while estimated discriminatory wage differences are consistently positive (8 % at 1st to 4 % at 9th decile) and account for significant portions of the raw gap.

Wage differences between natives and immigrants is another typical area for the application of decomposition analysis, although less frequent for Germany or completely missing as for Austria. A comparable study for Germany is Peters (2008), who analyses the wage differences between native and immigrant fulltime employed men in West Germany with the comparable approach of Melly (2006). Based on GSOEP data for 2006 he finds an increasing percentage of discrimination, starting from zero at the lowest wages and reaching 12 % for the top percentiles. Ivanov (2008) instead starts from the selectivity (into certain sectors, types of contract...) approach of Neuman and Oaxaca (2004a), extending it to quantile specific estimates. But he focuses on women only. His major finding is the "predominant importance of the endowment effect in explaining the wage gap".

Comparable studies regarding wages of immigrants versus natives for Austria to the best of our knowledge are missing again. If anything, we find Austria covered only as part of international comparative wage distribution studies, as the one by Fournier and Koske (2012) for example. But none of these comes methodologically near to the present approach.

3 Methodology

3.1 Decomposing wage differences

Observed wage differences between subgroups can be considered as sum of explicable differences and pure discrimination, both unobserved. Thus, the key issue is to quantify the contribution of various explanatory wage-relevant characteristics to this sum. Only the part not explicable by different characteristics of the subgroups can be regarded as (pure) discrimination.[3] To estimate the two components requires an "as if" calculation: What, for example, would the wage distribution of women look like, if they received the same remuneration for each characteristic as men? One might also pose the same question differently: What would the wage distribution of men look like, if they had equal schooling and experience etc. (i.e. characteristics) as women? The phrasing does not matter. The important thing to note is, that, in econometrics terms, this requires the estimation of counterfactual distributions.

In the classical approach by Oaxaca (1973) and Blinder (1973) (OB) the decomposition principle is most easily illustrated, because it involves only expected values and does not require counterfactual distributions. In the first step of the OB-decomposition one would explain individual wages W_i by individual characteristics X_i (=covariates including a constant) via some regression approach calculating the conditional expectation (conditional mean), separately for both subgroups:

[3] In the econometric literature dealing with decomposition this discriminatory part is called structural effect, whereas the part associated with different characteristics is known as composition effect. We will keep using the terms "discrimination" and "explained differences" instead.

$$W_{ik} = \hat{\beta}_k X_{ik} + \epsilon_{ik} \quad \text{for } k = 1, 2$$

where $\hat{\beta}_k$ denotes the estimated vector of remuneration coefficients for group k. By the law of iterated expectations it can be seen that the unconditional mean of the wage is the the same as the conditional mean evaluated at the mean of the covariates. The mean raw wage difference can therefore be calculated by the conditional wages evaluated at group specific mean values of covariates $\overline{X}_k$.

$$\overline{W}_1 - \overline{W}_2 = \hat{\beta}_1 \overline{X}_1 - \hat{\beta}_2 \overline{X}_2$$

The desired decomposition is then derived by a simple manipulation of this equation:

$$\overline{W}_1 - \overline{W}_2 = \underbrace{\hat{\beta}_1 (\overline{X}_1 - \overline{X}_2)}_{explained} + \underbrace{\left(\hat{\beta}_1 - \hat{\beta}_2\right)\overline{X}_2}_{discrimination} \tag{1}$$

The *explained* part involves a counterfactual mean $(\hat{\beta_1}\overline{X}_2)$ and describes the average wage difference caused by different covariates based on the remuneration of group 1. The *discrimination* part cannot be explained by the wage equations. A different question one might ask is: What would the wage distribution of men look like, if they received remuneration for each characteristic like women? This would imply the use of a different counterfactual and would lead to the following, complementary decomposition:

$$\overline{W}_1 - \overline{W}_2 = \hat{\beta}_2 (\overline{X}_1 - \overline{X}_2) + \left(\hat{\beta}_1 - \hat{\beta}_2\right)\overline{X}_1 \tag{2}$$

The question of choosing between (1) or (2) will be treated in Sect. 3.3. Here it should be merely stressed, that both of these decompositions cover only mean wage differences. But, as is well established, mean effects of covariates in wage equations are often not representative for all quantiles of the wage distribution.[4] Therefore, a natural route to improved decompositions is to use the quantile regressions from Koenker and Bassett (1978) to explain wages rather than the simple model for averages as above. This entails a drawback, however, because now the conditioning of expected wage differences upon mean values of covariates is no longer appropriate. The estimation process gives us the quantiles conditioned on covariates, but we have to calculate the unconditional ones.

3.2 The Machado/Mata-approach

Machado and Mata (2005) provide one possible solution to this problem. They augment conditional quantile estimates for the coefficients β_k with corresponding unconditional densities (actual and counterfactual) derived from resampling.[5] The MM-approach is much more widely used than alternatives without (conditional) quantile regressions, including the reweighting technique of DiNardo et al. (1996),

[4] A more thorough discussion of the shortcomings of the OB-decomposition is found e.g. in Fortin et al. (2011).

[5] Similar ideas are found in Gosling et al. (2000), Albrecht et al. (2003) and Melly (2005a). Testing with these approaches only yielded marginally different results relative to those of MM and are not reported here.

or RIF-regressions with reweighting by Fortin et al. (2011).[6] Like MM these alternative techniques have their own virtues and drawbacks due to the underlying particular assumptions. Overall we considered the MM approach more intuitive than these other approaches. The MM approach can be summarized as follows:

We can find the unconditional quantiles by integrating estimated conditional quantile functions over all covariates. In the MM approach this integration is done by resampling. By using covariates from members of the other group, a counterfactual wage distribution can be estimated.

More precisely: Let n_k observations on wages W_k and individual characteristics X_k for two groups $k = 1{,}2$ be given. Assume linearity of conditional quantiles, i.e. that wages are drawn independently from a distribution $F^{-1}_{W|X}(\tau|x_i) = x_{\beta i}(\tau)$ for all $\tau \in (0, 1)$ (Koenker and Bassett (1978)). Thus, quantile regression coefficients $\beta(\tau)$ can be interpreted as remuneration of the different characteristics at the specified quantile of the conditional distribution.

Choose a sufficiently large number S of bootstrap samples to be drawn.[7]

1. Draw a random sample $\{\tilde{\tau}_s\}_{s=1}^S$ of quantiles from the uniform (0,1)-distribution and random samples $\widetilde{X}_1 = \{\widetilde{X}_{1s}\}_{s=1}^S$ and $\widetilde{X}_2 = \{\widetilde{X}_{2s}\}_{s=1}^S$ with replacement from X_1 and X_2, respectively.
2. For $s = 1\ldots S$ do:
   (a) Estimate[8] regression coefficients $\hat{\beta}_1(\tilde{\tau}_s)$ for quantile $\tilde{\tau}_s$ conditional on X_1 and a vector $\hat{\beta}_2(\tilde{\tau}_s)$ conditional on X_2.
   (b) Define wages $\widetilde{w}_{1s} = \widetilde{X}_{1s}\hat{\beta}_1(\tilde{\tau}_s)$ and $\widetilde{w}_{2s} = \widetilde{X}_{2s}\hat{\beta}_2(\tilde{\tau}_s)$ associated with these coefficients for quantile $\tilde{\tau}_s$.
   (c) Construct counterfactual group 1 wages $\widetilde{w}^c_{1s} = \widetilde{X}_{1s}\hat{\beta}_2(\tilde{\tau}_s)$ based on remuneration of characteristics like for group 2, and, analogously $\widetilde{w}^c_{2s} = \widetilde{X}_{2s}\hat{\beta}_1(\tilde{\tau}_s)$.

The above calculations yield four different bootstrap samples: The first two of them, $\widetilde{W}_1 \equiv \{\widetilde{w}_{1s}\}_{s=1}^S$ and $\widetilde{W}_2 \equiv \{\widetilde{w}_{2s}\}_{s=1}^S$, mimic the unconditional wage distributions for the two groups.[9] The second two, $\widetilde{W}^c_1 \equiv \{\widetilde{w}^c_{1s}\}_{s=1}^S$ and $\widetilde{W}^c_2 \equiv \{\widetilde{w}^c_{2s}\}_{s=1}^S$,

[6] Results using RIF-regressions with reweighting were not found qualitatively different from the MM-results. These results are available from the authors upon request.

[7] We found that the number of bootstrap samples S required to get stable results should be a multiple of the total number of observations. For the application we have chosen $S = 40000$ which is roughly four times the $n_1 + n_2$ number of observations in the case of Germany and eight times in the case of Austria. With this number of bootstraps the differences between the MM approach and Melly (2005b) are negligible for practical purposes.

[8] Formulated as a programming problem, quantile regression coefficients $\beta(\tau)$ for quantile τ are estimated as solution to $\min_{\beta(\tau)} (1/n)\sum_i \rho_\tau [w - x_i\beta(\tau)]$ with $\rho_\tau(u) = \tau\, u$ for $u \geq 0$ and $\rho_\tau(u) = (\tau - 1)u$ for $u < 0$. We use the R-package quantreg by Roger Koenker for that purpose (see Koenker 2012).

[9] Step 2 (b), by the probability integral transformation principle, simulates random sampling from the (estimated) conditional distributions of w_{ki} conditional on X_k, for $k = 1{,}2$. Or, put differently: The w_{ki} consistently estimate the corresponding quantiles of the conditional distribution, see Koenker and Bassett (1978). Repeating these quantile estimates for S random draws of characteristics from the original distributions then amounts to integrating out these characteristics from the corresponding conditional distributions.

are the counterfactual wage distributions required for decompositions (3) and (4) below.[10]

3.3 Dependency of results upon choice of counterfactual

Analogous to the two basic weighting schemes in the OB-approach, the MM decomposition can be based on two alternative, basic counterfactual distributions.[11] $\widetilde{W}_2^c$ defined above, for example, stems from the question, what the wage distribution of women (group 2) would look like, if the remuneration of their characteristics were like that for men (group 1). So the counterpart to the OB-decomposition (1), evaluated at some quantile of interest θ would be:

$$\widetilde{W}_{1\theta} - \widetilde{W}_{2\theta} = \underbrace{\widetilde{W}_{1\theta} - \widetilde{W}_{2\theta}^c}_{explained} + \underbrace{\widetilde{W}_{2\theta}^c - \widetilde{W}_{2\theta}}_{discrimination} \tag{3}$$

In (3) the part explained by different characteristics is evaluated at group 1 payments while the discriminatory part (remuneration differences) is evaluated at group 2 characteristics. The alternative, complementary decomposition, would then be

$$\widetilde{W}_{1\theta} - \widetilde{W}_{2\theta} = \underbrace{\widetilde{W}_{1\theta}^c - \widetilde{W}_{2\theta}}_{explained} + \underbrace{\widetilde{W}_{1\theta} - \widetilde{W}_{1\theta}^c}_{discrimination} \tag{4}$$

which is the counterpart to OB-decomposition (2). In (4) the part explained by different characteristics is evaluated at group 2 payments while the discriminatory part is evaluated at group 1 characteristics.

It should be stressed, that there is no natural choice between the two decompositions, unlike some of the applied literature implicitly suggests by reporting results for only one of them. As Fortin et al. (2011) put it: "There will be no right answer" to the question of choosing a meaningful counterfactual. In a medical experiment, instead, it might make sense to consider the control group (let's say group 2), which received no medication, as natural reference group. In such a controlled setup one would single out decomposition (4) as the relevant one: It captures the item of primary interest, the average treatment effect upon the treated (group 1) as $\widetilde{W}_{1\theta} - \widetilde{W}_{1\theta}^c$. In this context the use of $\widetilde{W}_{1\theta}$ as weighting scheme to calculate the average treatment effect $(\beta_1 - \beta_2)$ arises naturally. The composition effect, as the remaining term $\widetilde{W}_{1\theta}^c - \widetilde{W}_{2\theta}$ in (4) would here be called, could be made arbitrarily small by deliberately choosing individuals with similar characteristics for both the treatment and the control group. This would render the proper choice for weighting the differences in characteristics irrelevant. Furthermore, the application of the treatment to the whole population would not affect prior estimates of the

[10] For more details see Machado and Mata (2005). A formal proof of consistency and asymptotic normality of the derived difference measures is contained in Albrecht et al. (2009).

[11] Numerous non-basic counterfactual distributions can be imagined and found in the literature (see Cahuc and Zylberberg 2004 pp. 280–282 for a short discussion). For example, one based on fictitious non-discriminatory market remuneration coefficients β^m for both groups. Such non-basic counterfactuals are not considered here.

treatment effect, if both groups were chosen representatively in the prior medical experiment.

Unfortunately, such reasoning does not translate to the realm of economics. Here it is quite unclear, what, for example, the abolition of gender wage discrimination (the "treatment") means: In a general equilibrium setup the outcome might be a new wage structure leaning more towards the former wages of men or of those of women. Without formulating a general equilibrium model we simply cannot tell. The upshot of this is that we will refrain from steering results in one or the other direction by a corresponding choice. Instead, we will simply report results for both decompositions. Only if these results are more or less the same, will we draw stronger conclusions about discrimination.

3.4 Asymptotic variance of differences

We will present the decomposition results along with confidence intervals based on Melly (2006), who derives asymptotic standard errors for the relevant differences analytically and proves their consistency.[12] Furthermore, he shows the numerical identity of his own approach and the one in MM, when the number of bootstrap samples drawn in the latter goes to infinity. Consequently, the asymptotic standard errors of Melly (2006) also apply to the MM-calculations. Analytical standard errors, of course, require less computation time than the alternative bootstrapped variant thereof. An additional advantage, as shown in Melly (2006), is that they usually outperform bootstrapped standard errors in finite samples in terms of MSE. For an alternative derivation of analytical standard errors in the MM-framework see Albrecht et al. (2009).

3.5 Selectivity and sample selection bias

A question applying to any such decomposition analysis is whether the distribution of wage-relevant characteristics (limited/unlimited or fulltime/parttime contracts, management positions...) does not already capture part of the discrimination. In the literature this issue is discussed under the heading of "selectivity" (see e.g. Neuman and Oaxaca 2004b). If, for example, immigrants were less likely to find jobs in the public sector than comparatively qualified natives, this could be considered as part of discrimination. In the analysis below, the wage effects of such practices would be subsumed under "explained differences". But we will also report results correcting for such potential selectivity bias in the "Appendix".

A related issue is sample selection bias. It could occur, for example, if low qualified women are more likely to refrain from offering their labor services on the market (and thus would not be part of the sample) than comparably qualified men. In this case the observed wage differences between women and men are likely to understate the true extent of discrimination. Evidence confirming this conjecture can be found for example in Albrecht et al. (2009) and Picchio and Mussida (2010). But, like selectivity, this issue

[12] Melly provides a corresponding R-source code on http://www.econ.brown.edu/fac/Blaise_Melly/code_R_rqdeco3.html.

is outside the scope of the present paper.[13] Therefore, our discrimination estimates should be regarded as conservative. Regarding the gender comparison between the two countries sample selection is no issue because female participation rates are about the same in Germany (25.1 %) and in Austria (24.4 %). Likewise the extent of parttime work is comparable (22.6 % in Germany vs. 19.4 % in Austria).

4 Data description

Our estimates are based on EU-SILC cross-section data for 2008 in revision 3 from March 2011. These data contain a rich variety of economically relevant information about individuals on an internationally comparable basis. For Germany these data cover originally roughly 24,000 persons, from which, after filtering about 10,000 valid observations remained. For Austria the corresponding numbers are 11,000 and 4,700, respectively. See Tables 1, 2, 3, 4 and 5 in the "Appendix" for more details on filtering and resulting group sizes.

Key filter criteria for a valid observation are employee status as well as employment and positive gross labor income during the last year.[14] Additional filter criteria are valid responses on some variables. For Germany the relative size of the relevant subgroups in the overall sample are 46 % women, 28 % public sector employees and 10 % of foreign origin. The corresponding figures for Austria are 44 % women, 24 % public sector employees and 17 % of foreign origin. In Austria additional 47 observations were skipped due to recorded experience (EXP) values of zero, despite values of 1 (indicating valid response) of the corresponding flag variable.

Hourly wages are constructed by dividing gross wages (PY010G) for the reference year by total hours worked. The latter are calculated from months worked fulltime (PL070) plus parttime (PL072) times 4 (weeks per month) times hours worked per week in the main job (PL060) plus in other jobs (PL100).

All estimates are corrected for the different individual weights (PL040) in the EU-SILC data set. The extent of oversampling or undersampling in the various subgroups of the original dataset can be determined from these weights and is reported in the above mentioned tables in columns labeled "%os".

4.1 Regression specification

The choice of explanatory variables is primarily guided by availability in the EU-SILC data set and includes the traditional variables in Mincerian wage equations plus a few, which in later studies have shown to be significant wage drivers. Our dependent variable in all calculations is the logarithm of wages per hour.

Turning to the explanatory variables: To proxy years of schooling (not covered by EU-SILC data) highest education level attained (PE040) is used. Thereby, lower

[13] Relevant approaches are found e.g. in Buchinsky (1998), Albrecht et al. (2004), Neuman and Oaxaca (2004a) or Ivanov (2008).

[14] This latter criterion may potentially introduce another type of sample selection bias, as it ignores different likelihoods of longer unemployment spells for each subgroup considered. See Sect. 3.5.

secondary education and below is coded as EDU2 (and used as reference category), at least upper secondary but no university degree as EDU3 and tertiary education as EDU4.[15] Based on prior specification tests we decided to deploy age (AGE) in linear form, but work experience in years since first job in linear (EXP) and in squared form (EXP^2).[16] The reason for using age and experience simultaneously is twofold: On the one hand age and experience exert very different influences depending on quantiles. On the other hand, with the joint consideration of age and experience we try to capture the degree of continuousness of labor market experience.

Holding a management position (MGR) is captured with an extra dummy, if occupation is of type "Legislators, senior officials and managers" (i.e. PL050 = 11, 12 or 13). Furthermore, firm size is captured via a dummy (BIG), taking value 1 for work in a unit with at least 50 employees. Like in comparable studies, where they repeatedly have proven to affect wages significantly negative, also consensual union status (living alone as opposed to cohabitation = SINGLE) and TEMPJOB (for labor contracts of limited duration as opposed to unlimited ones) are covered by corresponding dummies.

The sector in which someone is employed is classified as either AIC, SERV or PUB based on an aggregate version of the corresponding classification in EU-SILC (variable PL110), the "Statistical Classification Of Economic Activities" according to NACE revision 1.1. Occupation in a service oriented sector (but excluding public administration) is coded as SERV = 1 when PL110 is in ("g", "i", "j", "k", "o + p + q"). Occupation in manufacturing, construction and other non-service oriented sector is coded as AIC = 1 when PL110 is in ("a + b" ,"c + d + e", "f"). And finally employment in the public sector is coded as PUB = 1 when PL110 code is in ("l", "m", "n"). The latter group, apart from explicit public administration jobs ("l") also includes jobs in the education ("m") and the health sector ("n"), because the vast majority of jobs in these sectors is publicly financed in Germany and Austria. We have chosen AIC as reference sector. Thus, coefficients of PUB and SERV indicate wage gains relative to sector AIC. Additional variables include dummies for males (MALE) and for being born abroad (IMM).

To estimate group-specific densities (underlying the decompositions) the single dummy variable identifying affiliation with one or the other group in any comparison (i.e. MALE or PUB or IMM) is skipped. Management positions (MGR) had to be skipped in comparing natives versus immigrants, because the latter rarely hold such positions (see the numbers given in Tables 2 and 4), leading to failures of the resampling procedure when it came to the calculation of boundary quantiles. Thus, the three regression specifications underlying the three comparisons are:

[15] Unfortunately, the understanding of these education levels has been different in Germany and Austria. This explains the implausible, massive differences in the proportions of these three levels between the two countries (see Tables 2 and 4 in the "Appendix"). This prohibits comparing the estimated standard quantile regression coefficients for these variables between countries. To our knowledge, statistical offices are aware of the corresponding shortcomings and currently work on improved definitions and comparable coding.

[16] Using "age", "age^2" and "experience" instead of "age", "experience" and "$experience^2$" lead to a worse fit and was formally rejected by corresponding tests.

1. Comparison men versus women: log(WAGE/HOUR) ← IMM, PUB, SERV, EDU3, EDU4, EXP, EXP^2, AGE, MGR, BIG, SINGLE, TEMPJOB
2. Comparison public versus private sector employees: log(WAGE/HOUR) ← MALE, IMM, SERV, EDU3, EDU4, EXP, EXP^2, AGE, MGR, BIG, SINGLE, TEMPJOB
3. Comparison natives versus immigrants: log(WAGE/HOUR) ← MALE, PUB, SERV, EDU3, EDU4, EXP, EXP^2, AGE, BIG, SINGLE, TEMPJOB

5 Results from standard quantile regressions

Standard quantile regression results are stated here only briefly for reference. The public sector dummy coefficient in the case of Germany serves as striking example for the potential benefit of quantile regressions over OLS (see Fig. 1). The OLS coefficient (the solid, horizontal line) indicates about a 4 % wage advantage of public sector employees. The quantile regression coefficients (the dash-dotted line), instead, show, that public sector employment for individuals in the lowest 10 percentiles means an advantage of roughly 6 %, while for the individuals in the top 10 percentiles it implies a disadvantage of around 15 % with an almost linear decline in between. Austrian public sector employees (see Fig. 9), instead, earn almost consistently more (between 0 and 6 %) than their private sector counterparts, but without any unique tendency either downward or upward across quantiles. Furthermore, in case of Austria the OLS results do not differ significantly from the quantile regression results.

Regarding experience, it can be calculated from the coefficients displayed in Figs. 8 and 9 (jointly considering the linear and the squared experience term), that the contribution of additional experience to wages vanishes practically completely for the highest income brackets. Furthermore, the impact of experience upon wages comes in U-form: Ceteris paribus the highest expected wages are achieved at a medium experience level, while they are lower with either very low or high experience. With respect to education, we find advantages of education levels 3 and 4 compared to reference level 2 which are significantly higher for the bottom than for the top percentiles. This constrasts sharply with the results in Machado and Mata (2005), who state that “education has a greater effect upon the wages of individuals at the top of the wage distribution than upon wages of individuals at the bottom of that distribution”. Age, on the other hand, has a steadily increasing quantitative impact upon wages if we move up across quantiles. Starting at or below zero for the bottom percentile the corresponding coefficient reaches values between 0.01 and 0.02 for the top percentiles.[17] The latter, evaluated at an age of 40, implies an age premium between 1.5 and 4.4 % per year.

Turning to the coefficients of the other two grouping variables used in the decomposition analysis below we find the following: First wages of German men are roughly 10–15 % higher than those of women with a falling tendency towards higher quantiles. The comparable figures for Austria are not only higher overall (in the

[17] This is a fairly standard result and easy to interpret: Negative values for the bottom percentiles arise naturally, if the lowest incomes are associated with manual labor, which deteriorates in quality with age. Positive values for higher incomes simply reflect widespread seniority pay.

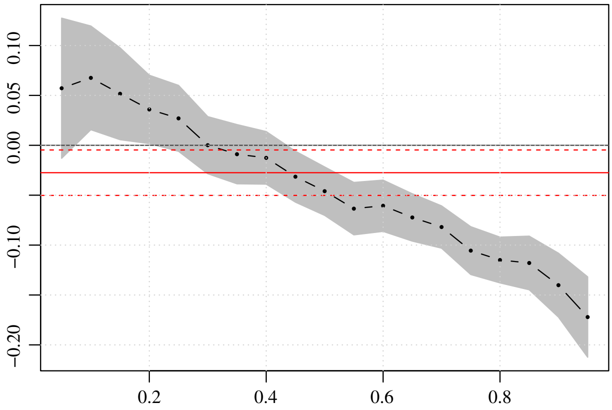

Fig. 1 Public sector employment coefficient, Germany. *Dash dotted line* = quantile regression estimate with 5 and 95 % confidence bounds (the *gray band*, based on bootstrapping). *Horizontal lines* = OLS-estimate along with same confidence bounds

15–20 % range) but also tend to increase towards the top quantiles. For both countries we find that these estimates typically do not differ significantly from the corresponding OLS figures. Second, for persons born abroad (~ immigrants) wages are consistently lower than for their domestically born colleagues in both countries. In Germany the disadvantage hovers about −3 % beyond the 10th percentile, only below it is absolutely higher (but not significantly so). In Austria the disadvantage of immigrants is more than −20 % in the bottom percentiles, then, up to the 70th percentile remaining persistently below −11 % and vanishing only towards the top few percentiles. Again, in both countries these results do not deviate significantly from their OLS counterparts.

6 Decomposition results

At the core of the present analysis is the decomposition of wage differences for each quantile based on unconditional densities, both basic and counterfactual. The corresponding results are graphically depicted in Figs. 2, 3, 4, 5, 6 and 7. Some of them are remarkably distinct from corresponding OB-decomposition results given in Tables 6, 7 and 8. Apart from decomposition, they also draw quite different pictures of overall wage differences between subgroups than the standard quantile regressions.

Each graph in Figs. 2, 3, 4, 5, 6 and 7 shows total wage differences[18] at regularly spaced quantiles (0.05, 0.10,…0.95). In each case the left graph is based on decomposition (3) and the right graph on decomposition (4). Results are visualized by three lines: (a) the total difference (solid line), (b) the difference explicable by characteristics (long-dashed line) and (c) the purely discriminatory part due to payment differences (short-dashed line). By construction, the latter two must sum to the total.

The differences apply to log wages and, therefore, are proxies for percentage differences in the wage levels ("log-point percentages"). As indicated above, all

[18] Synonymously we will speak of overall wage differences or raw discrimination.

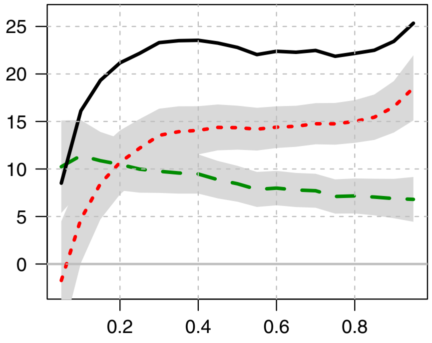

Fig. 2 Percentage wage differences between men and women in Germany. *Left*: decomposition (3). *Right*: decomposition (4). *Solid line* = total difference. *Long-dashed line* = wage differences explained by different individual characteristics. *Short-dashed line* = wage discrimination due to different payment of same characteristics. *Data source* EU-SILC 2008, revision 3 (March 2011)

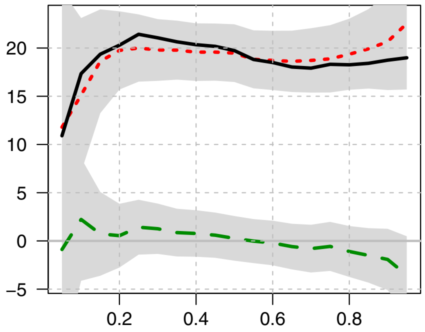

Fig. 3 Percentage wage differences between men and women in Austria. See legend in Fig. 2

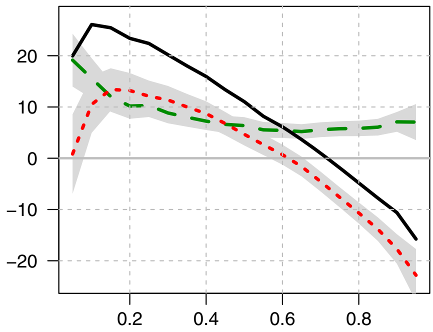

Fig. 4 Percentage wage differences between public and private employees in Germany. See legend in Fig. 2

comparisons are done by calculating group 1 wages minus group 2 wages. Therefore, group 2 wages (women, private sector employees or natives) are the basis of percentage figures.

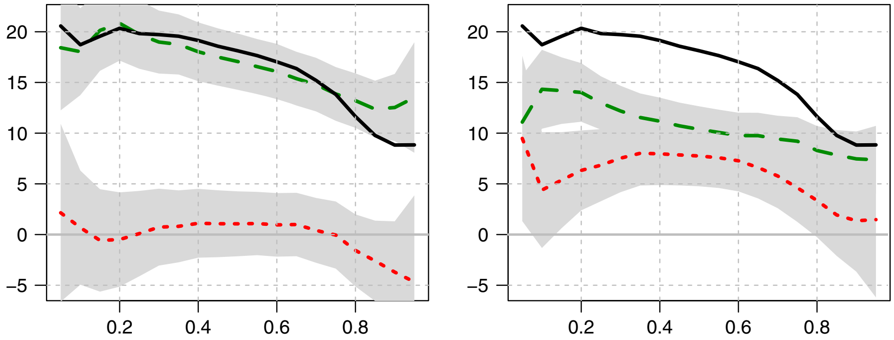

Fig. 5 Percentage wage differences between public and private employees in Austria. See legend in Fig. 2

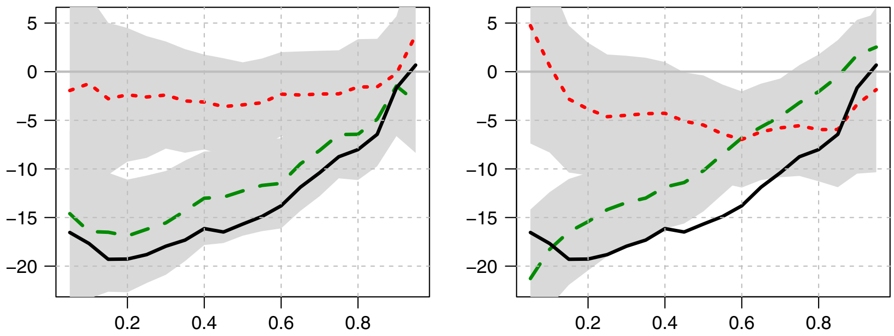

Fig. 6 Percentage wage differences between immigrants and natives in Germany. See legend in Fig. 2

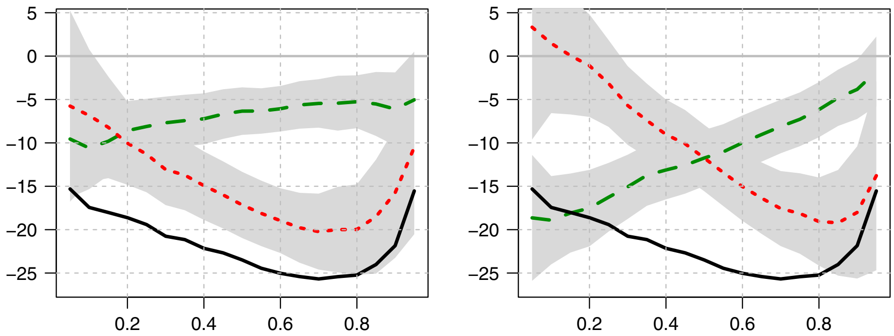

Fig. 7 Percentage wage differences between immigrants and natives in Austria. See legend in Fig. 2

6.1 Men versus women

The main results regarding wage differences by gender in Germany are depicted in Fig. 2. As can be seen, the overall differences beyond the 2nd decile are roughly constant around 23 %. Only towards the lower percentiles they fall and reach an overall low of 10 % in the bottom percentile. These figures are considerably lower than those of Heinze (2010), but it is unclear to which degree this comes from our inclusion of parttime employees ($\sim$22.6 % in the sample). To reconcile the findings one would have to assume, that the raw wage difference amongst parttime employees (concentrated in the lower income brackets) is considerably lower than for fulltime employees. However, roughly a third of our estimated differences (or 8 percentage points) can be attributed to different characteristics of women and men (in Heinze it is only around a sixth). This leaves a pure discrimination of around 15 % (compared to the 20 % found by Heinze).

The picture for Austria (see Fig. 3) is rather different and striking, because nearly all wage differences are due to pure discrimination against women at a rather stable margin of 20 % across all income groups. Consequently, wage differentials explicable by different characteristics are nowhere significantly different from zero, indicating no such differences in characteristics. Comparing the left and the right corresponding graphs also makes clear: This result does not depend on the weighting scheme used for the decomposition. Whether using variant (3) or variant (4), the picture remains the same. This contrasts strongly with results from Böheim et al. (2013), where the explained part is significantly different from zero, leaving only between 5 and 15 % of pure discrimination. The restriction of Böheim et al. (2013) to private sector employees can not explain this difference, because inclusion of public sector employees should, if anything, decrease estimated wage discrimination of women. Instead, the high explained proportion of wage gaps could be due simply to the large number of regressors used in Böheim et al. (2013).

6.2 Public versus private sector

For Germany the very pronounced falling tendency and sign reversal of wage differences between public and private sector across quantiles has already been indicated by the simple quantile regressions above. Figure 4 sheds more light on this finding: Obviously, differences in qualification do not exhibit this falling tendency at all. Rather, the characteristics of public sector employees have persistently higher earning potential compared to those of their private sector colleagues, and would justify roughly 8–10 % higher wages. By the same token, the true discrimination is roughly 10 percentage points lower than the observed total wage differentials. So it is the remuneration factor (the discriminatory part), which accounts for this falling tendency in the overall difference. Thus, the situation of German public sector employees can be described as significantly advantageous (at most 12 % at the 2nd decile) for incomes below the 60th percentile and as significantly disadvantageous above (reaching −20 % for the top percentiles).

The relevant Austrian case is displayed in Fig. 5. It shows a more or less constant earnings advantage of public sector employees of slightly above 20 % up to the 4th decile. Then the advantage declines steadily to around 8 % for the 95 percentile. But, unlike in Germany, the differences in characteristics of public sector employees versus their private sector colleagues follow this overall wage discrimination pattern more or less closely. Put differently, differences in characteristics can explain at least around three quarters of the overall wage difference. This leaves a purely discriminatory income advantage of public sector employees of between 0 and 5 %, depending on quantile and decomposition type.

The bias induced by self-selection to work in either the private or the public sector does not affect the substantial results given above. This is shown in detail in the "Appendix". Particularly, as Table 11 reveals, explained and unexplained portions of total wage gaps do conform very well to the results without bias correction. In case of Germany, we again find the same extent of typical payment discrimination versus public sector employees and again regardless of the specific counterfactual used. In case of Austria, the high explanatory power of different characteristics is confirmed while the influence of different counterfactuals is reduced to 85–93 %, as opposed to 66–99 % above.

It might be argued, that the public sector in any case is a big employer and, therefore, also private sector employment, for comparison, should be restricted to big firms. We found that this restriction to big firms of the private sector indeed would have considerable overall impact upon the public/private wage gap analysis. But for a number of reasons we doubt these results to be relevant. The first and most important is, that the very idea of counterfactual distributions is to create the desired comparability anyway, without need for extra sample restrictions. On the other hand it is unclear, whether wage structures offered by big private firms (intimately tied to non-wage characteristics of employment at the local unit) are truly comparable with those of hundreds of municipal offices with often less than 10 employees.

Then, the EU-SILC variable (PL130) refers to establishment size rather than to firm size.

6.3 Immigrants versus natives

The last comparison is between immigrants (more exactly, those being born in a foreign country) and natives. The standard OB-decomposition in Table 8 indicates, that we should expect an overall earnings disadvantage of immigrants relative to natives of around 12 % in Germany and 21 % in Austria. Furthermore, it suggests, that pure discrimination accounts for only a very little fraction of overall differences in Germany and for a highly variable proportion in Austria, depending on quantile. Results from the MM-approach applied to Germany are depicted in Fig. 6. As can be seen, overall wage differentials between immigrants and natives are almost continuously declining in absolute value, starting at around −18 % in the 10th percentile and monotonically approaching zero towards the top end. Despite some discrepancies between the two possible weighting schemes, the MM-decomposition reveals differences in characteristics as major explanatory factors of this finding. In the lower half of the wage distribution these differences in characteristics account for between 60 and 90 % of the observed differences, leaving a pure discrimination between 0 and 5 %. In the top half of the distribution the decomposition depends more on perspective, but there discrimination is far less of an issue anyway with pure discrimination nowhere exceeding −6 %. These findings are roughly in line with Ivanov (2008), although he focuses on women only. This suggests, that discrimination of immigrants is not a matter of gender. Contrastingly, in Peters (2008) an increasing discrimination of immigrants across quantiles is reported, reaching a maximum of around −12 % for the top percentiles, where we find, instead, discrimination to be negligible. Given our results and those of Ivanov, it is hardly possible, that the restriction of analysis to male workers in Peters can account for this difference. It is also questionable, whether Peter's further restriction to West German full time employees can explain this divergence.

The case of Austria is very different again (see Fig. 7). There immigrants earn between 15 and 25 % less than their native colleagues.[19] These differences follow a marked U-shape reaching a maximum discrimination at around the 8th decile. This implies markedly stronger wage discrimination against foreign professionals than against foreign blue collar. Higher earning potential of the characteristics of natives can account only for 5–10 percentage points of the overall difference in variant (3), whereas it displays high variability when using variant (4). Only for the top 2 deciles we get a unanimous picture of pure discrimination as significantly dominating explanation for observed wage differences.

7 Summary

This paper analyses wage differences between subgroups of the population in Germany and Austria: Men versus women, public employees versus private employees and natives versus immigrants. The amount explicable by different characteristics and the amount due to pure discrimination is determined using the approach of Machado and Mata (2005). Estimation is based on the EU-SILC data base for 2008 with roughly 10000 useful observations in Germany and 5000 in Austria. The results are augmented with confidence intervals from Melly (2006). These together with a comparison of the two basic decomposition possiblities allow to draw some firm conclusions:

Gender For Germany we find persistent overall wage differences of 20–25 % for men and women. 15 percentage points thereof come in the form of pure discrimination against women above the second dezil. From there towards the lowest percentiles discrimination vanishes monotonically. Different characteristics, on the other hand, can explain only between 5 and 10 percentage points. This explained part is somewhat higher than that reported in Heinze (2010) for 2002, indicating, if anything, an increase of the gender pay gap. For Austria a rather constant overall advantage of male wages of around 20 % above the second dezil is estimated with a similar decline towards the bottom end as in Germany. But unlike in Germany, these differences can not be explained at all by different characteristics of men and women. Instead, it appears exclusively as a matter of discrimination. This result is very different from Böheim et al. (2013).

[19] Fournier and Koske (2012) report a difference of 25 % at the median (Fig. 7) where we find 20 %. One reason for this difference might be that we classify all persons born abroad as immigrants, while Fournier and Koske count only those born outside the EU. Furthermore, their underlying regression specification is not quite clear. The basic data set instead is the very same as used here.

Employment sector The public/private sector overall wage gap in Germany follows a very particular pattern: While at the bottom end of the income distribution public sector employees enjoy an advantage of 25 % this turns almost linearly into a 15 % disadvantage at the top end. The pure discrimination part of this exhibits the very same pattern 10 percentage points below. Thus, roughly speaking, pure discrimination turns from 15 to −25 %. These results are comparable to Melly (2005b) based on 2001 data. Corresponding results for Austria, instead, point towards a persistently positive overall wage advantage of public sector employees, from 20 % at the bottom down to 10 % at the top of the wage distribution. Regarding pure discrimination matters are less clear with figures ranging between 0 and 10 %, depending on the decomposition used. The latter highlights the importance of reporting results for both decompositions. In both countries the explained part of overall differences is significantly positive for all quantiles.

Country of origin Overall wage differences between immigrants and natives in Germany follow a rather regular upward pattern, starting from −20 % at the bottom and reaching practically zero at the top. But pure discrimination against immigrants accounts for only 0–5 percentage points thereof and appears not to be statistically significant at usual confidence levels. By the same token, thus, the largest part of observed overall differences can be attributed to different characteristics of natives and immigrants. Overall figures for Austria, instead, follow a pronounced U-shape accross quantiles reaching an absolute maximum of −25 % at around the 7th decile with roughly −15 % at both ends of the wage distribution. The pattern of pure discrimination looks much alike and reaches −20 % at around the 8th decile. For wages above the third decile this pure discrimination is statistically significant and can be interpreted as effective deterrence of potential immigrant professionals.

8 Appendix

8.1 Data filtering

See Table 1.

Table 1 Filtering of observations

	Germany	Austria
Total observations before filtering	24,336	10,955
Employees	12,656	8,614
Grossincome >0	12,363	5,856
Typical weekly hours in main job >0	12,633	5,944
Months worked (full- plus parttime) >0	12,422	6,304
Firmsize known or ≤10	24,336	10,954

Table 1 continued

	Germany	Austria
Response occupation (ISCO-88)	22,376	9,844
Response industry (NACE 1.1)	12,595	5,691
Response firmsize	12,526	5,334
Response experience	22,143	9,844
Remaining observations after filtering	10,280	4,661

Data source EU-SILC, cross-section 2008, revision 3, March 2011

8.2 Final data for Germany 2008 (after filtering)

See Tables 2 and 3.

Table 2 Group size and hourly gross wages across subgroups in Germany

	n	%os	%WOM	%IMM	%PUB	Mean	Median
ALL	10,280		51.4	5.0	33.0	16.8	15.6
MEN	5,282	−5.5	0.0	5.0	22.3	18.9	17.5
IMMIGR	514	−49.0	48.8	100.0	24.5	16.1	13.9
EDU2	806	−43.1	52.9	10.7	21.5	9.6	7.3
EDU3	4,540	−14.3	49.2	3.8	24.6	14.4	13.7
EDU4	4,934	38.4	47.4	5.2	34.6	20.2	18.8
SINGLE	2,895	−15.3	55.9	3.6	34.4	14.1	13.2
TEMPJOB	798	−10.3	58.8	7.8	34.6	12.0	10.0
MGR	521	16.6	26.5	3.8	17.1	25.0	21.9
BIG	5,968	1.9	41.1	5.2	35.3	19.0	17.7
SERV	4,123	−7.5	51.6	5.2	0.0	16.0	14.1
PUBL	3,390	19.8	65.3	3.7	100.0	16.9	16.3

n number of observations in original sample, *%os* percentage oversampling in original sample relative to correct figure, *Data source* EU-SILC, cross-section 2008, revision 3, March 2011

Table 3 Group size and hourly gross wages across sectors in Germany

	n	%os	%WOM	%IMM	Mean	Median
AGRIC	130	−7.8	23.5	7.5	10.4	9.4
MANUF	2,158	−5.5	24.1	10.8	19.2	17.9
CONSTR	479	−15.8	13.5	12.6	13.8	13.2
TRADE	1,413	−9.1	52.7	8.3	13.8	12.3
GASTRO	176	−28.7	64.5	31.4	9.4	7.3
TRANSP	591	−11.9	29.1	11.6	17.0	15.0
FINAN	540	−0.4	50.5	4.4	22.6	20.9

Table 3 continued

	n	%os	%WOM	%IMM	Mean	Median
ESTATE	796	−4.1	52.9	14.7	17.1	14.5
OSERV	607	−0.8	58.9	11.6	14.8	13.9
PUBADM	1,297	13.5	45.8	3.3	17.8	17.1
EDUC	796	49.3	66.1	7.3	19.1	18.1
HEALTH	1,297	12.4	78.9	8.8	14.5	13.9

n number of observations in original sample, *%os* percentage oversampling in original sample relative to correct figure, *Data source* EU-SILC, cross-section 2008, revision 3, March 2011

8.3 Final data for Austria 2008 (after filtering)

See Tables 4 and 5.

Table 4 Group size and hourly gross wages across subgroups in Austria

	n	%os	%WOM	%IMM	%PUB	Mean	Median
ALL	4,661		54.6	14.4	25.5	16.7	14.3
MEN	2,545	−2.5	0.0	15.4	17.1	18.0	15.7
IMMIGR	672	−16.9	41.7	100.0	16.1	13.9	11.8
EDU2	606	−10.9	51.2	29.5	14.7	9.5	9.3
EDU3	2,561	0.7	42.3	11.9	19.4	15.3	13.7
EDU4	1,494	4.0	48.4	12.5	35.1	21.9	18.7
SINGLE	1,610	−8.7	48.1	10.6	23.5	14.4	12.8
TEMPJOB	225	−10.2	55.1	19.1	35.1	14.6	12.2
MGR	224	8.7	19.6	8.0	21.4	27.2	21.1
BIG	1,868	0.4	36.3	14.3	27.3	18.1	16.0
SERV	2,084	−0.3	51.3	15.6	0.0	16.2	13.3
PUB	1,188	4.6	63.4	9.1	100.0	18.3	16.2

n number of observations in original sample, *%os* percentage oversampling in original sample relative to correct figure, *Data source* EU-SILC, cross-section 2008, revision 3, March 2011

Table 5 Group size and hourly gross wages across sectors in Austria

	n	%os	%WOM	%IMM	Mean	Median
AGRIC	42	−12.5	41.9	20.0	10.5	10.3
MANUF	955	−0.6	23.6	18.0	16.5	14.6
CONSTR	392	−8.2	11.0	28.4	15.2	13.9
TRADE	785	0.6	52.3	15.2	15.9	12.3
GASTRO	229	−11.2	63.1	40.0	11.9	9.8
TRANSP	289	0.0	31.1	13.9	15.8	14.8
FINAN	188	10.6	45.3	3.6	21.9	20.4

Table 5 continued

	n	%os	%WOM	%IMM	Mean	Median
ESTATE	415	2.2	52.5	19.6	17.9	14.9
OSERV	178	−4.3	53.4	20.3	14.2	12.7
PUBADM	401	3.4	41.4	3.7	18.5	16.7
EDUC	342	4.3	68.9	11.6	21.2	18.4
HEALTH	445	6.0	76.3	16.1	15.8	14.6

n number of observations in original sample, *%os* percentage oversampling in original sample relative to correct figure, *Data source* EU-SILC, cross-section 2008, revision 3, March 2011

8.4 Standard Oaxaca-Blinder decompositions

see Tables 6, 7 and 8.

Table 6 Log wage differences between men and women

	Variant	Δtotal	Δchar	Δpay
Germany	(1)	0.207	0.058	0.149
	(2)	0.207	0.067	0.140
Austria	(1)	0.183	0.022	0.161
	(2)	0.183	−0.005	0.188

Δtotal = total difference; Δchar = difference due to different characteristics Δpay = difference due to different remuneration of same characteristics

Table 7 Log wage differences between public and private sector

	Variant	Δtotal	Δchar	Δpay
Germany	(1)	0.079	0.093	−0.015
	(2)	0.079	0.094	−0.016
Austria	(1)	0.167	0.166	0.001
	(2)	0.167	0.111	0.056

See legend in Table 6

Table 8 Log wage differences between immigrants and natives

	Variant	Δtotal	Δchar	Δpay
Germany	(1)	−0.116	−0.103	−0.014
	(2)	−0.116	−0.091	−0.026
Austria	(1)	−0.211	−0.067	−0.143
	(2)	−0.211	−0.121	−0.090

See legend in Table 6

8.5 Standard quantile regression results

See Figs. 8 and 9.

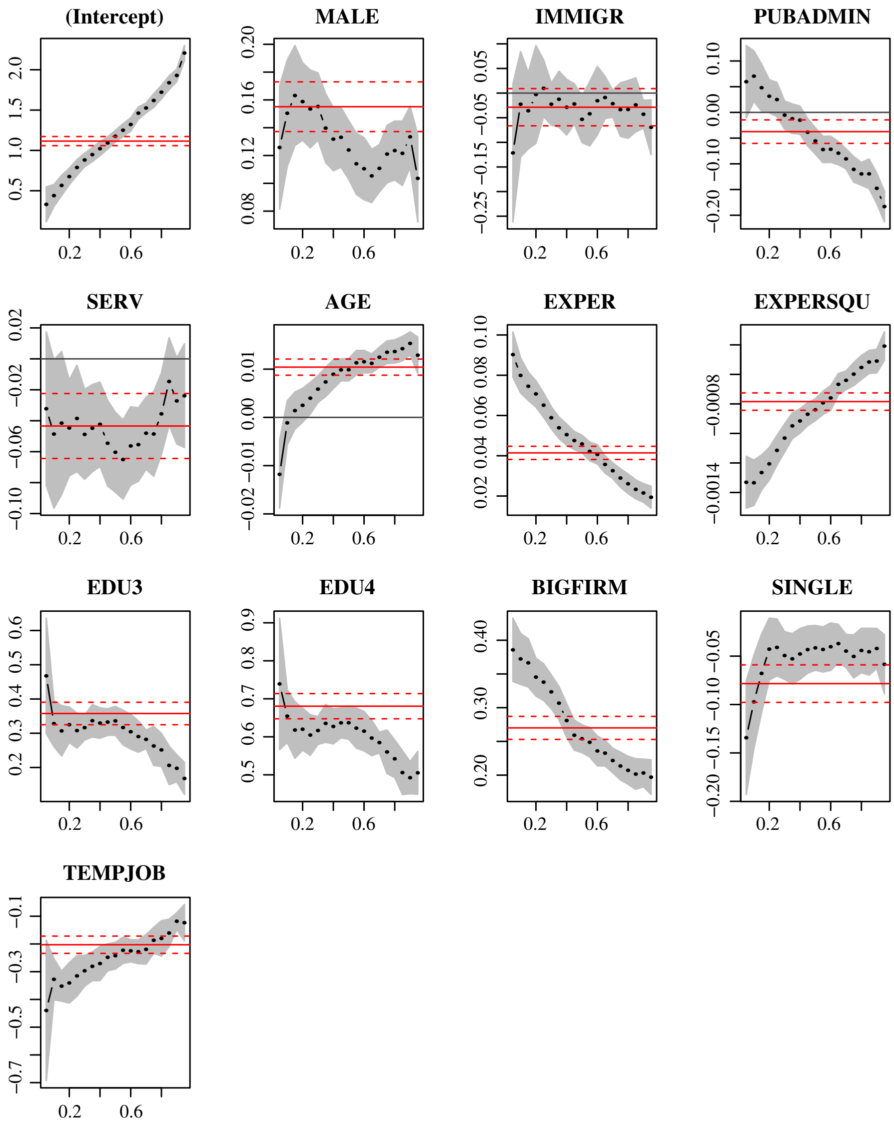

Fig. 8 Estimation of log hourly wages, pooled sample, Germany 2008. *Dash dotted line* = quantile regression estimate with 5 and 95 % confidence bounds (the *gray band*, based on bootstrapping). *Horizontal lines* = OLS-estimate along with same confidence bounds

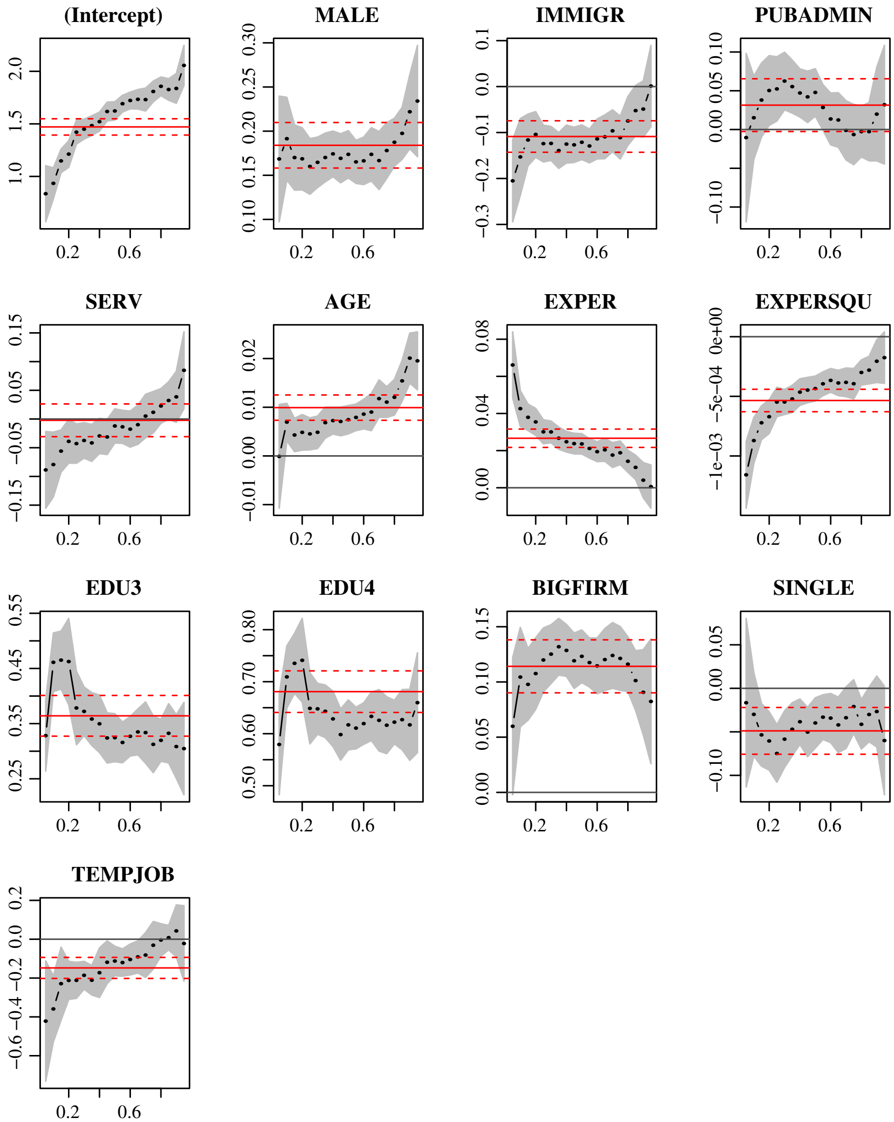

Fig. 9 Estimation of log hourly wages, pooled sample, Austria 2008. *Dash dotted line* = quantile regression estimate with 5 and 95 % confidence bounds (the *gray band*, based on bootstrapping). *Horizontal lines* = OLS-estimate along with same confidence bounds

8.6 Self-selection bias in estimating private/public sector wages

In case of self-selection to work in either the private or the public sector, the above decomposition results might be misleading. To check this possibility, we also calculated Heckman corrected versions of the corresponding OLS-estimates. That

Table 9 ML-Probit estimates for selection into sectors

	Germany				Austria			
	Private		Public		Private		Public	
	Coeff	*p* value	Coeff	*p* value	Coeff	*p* value	Coeff	*p* value
MALE	0.66	0.00	−0.65	0.00	0.57	0.00	−0.55	0.00
IMMIGR	0.39	0.00	−0.35	0.00	0.43	0.00	−0.42	0.00
AGE	−0.01	0.00	0.01	0.00	−0.02	0.00	0.01	0.00
EDU3	−0.07	0.20	0.01	0.88	−0.15	0.05	0.16	0.03
EDU4	−0.49	0.00	0.36	0.00	−0.60	0.00	0.58	0.00
KIDS13	0.01	0.53	0.01	0.61	−0.01	0.59	0.02	0.45
THINPOP	−0.02	0.53	−0.01	0.74	0.06	0.16	−0.06	0.11
RENTER	0.05	0.08	−0.05	0.02	0.11	0.04	−0.09	0.05
AFJ	−0.04	0.00	0.04	0.00	−0.04	0.00	0.04	0.00

is, we performed ML-estimation of a system consisting of the original wage equation plus an additional selection equation.

While not necessary (selection and wage equation might both use the same set of regressors), exclusion restrictions could help to overcome the usually poor identification of such models when based purely on non-linearity of the inverse Mills ratio (used as additional regressor in the conditional wage equation). We found “age at first regular job” (AFJ) and, to a lesser extent, “type of tenancy” (RENTER) to be useful variables in this regard, i.e. significant in the selection equations while excluded due to irrelevance in the wage equations (see Table 9). “Population density” (THINPOP) was also added but did not improve matters.

The resulting Heckit-ML estimates of (log) wage equations correcting for self-selection bias are presented in Table 10.[20] These equations include the inverse Mill’s ratio (IMR) as additional regressor and read

$$\log(w_i) = \beta_0 + \beta_1 \mathrm{MALE}_i + \cdots + \beta_{11} \mathrm{TEMPJOB}_i + \sigma_y \rho \, \mathrm{IMR}_i + \varepsilon_i$$

So the relevant coefficient for IMR is the product $\sigma_y \ \rho$. The coefficient ρ, the correlation between the error terms of selection and wage equation, is highly significant in all estimates. This indicates a relevant self-selection bias regarding coefficient estimates. But it is not clear to which extent this bias translates into a changing decomposition of wage gaps, the ultimately relevant issue here.

To study this question, we repeated the O/B-decomposition analysis with the above estimated wage equations, i.e. with bias corrected coefficients and an additional regressor as compared to the equations in the main body of text. This yielded the results reported in Table 11. As can be seen from comparison with Table 7, the changes in both countries resulting from bias-correction in this decomposition perspective are negligible: For Germany the use of bias corrected

[20] These results are unweighted and, thus, are not strictly comparable to the OLS results from above. But, as the comparison of total wage gaps reported in Tables 7 and 11 shows, the differences are quantitatively negligible.

Table 10 Heckit-ML wage estimates correcting for self-selection bias

	Germany						Austria					
	Private			Public			Private			Public		
	OLS	H-ML	p value	OLS	H-ML	p value	OLS	H-ML	p value	OLS	H-ML	p value
MALE	0.17	0.21	0.00	0.13	0.39	0.00	0.19	0.22	0.00	0.13	0.33	0.00
IMMIGR	0.00	0.02	0.39	−0.09	0.08	0.11	−0.10	−0.08	0.00	−0.16	−0.02	0.71
AGE	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.08
EXPER	0.05	0.05	0.00	0.03	0.04	0.00	0.03	0.03	0.00	0.02	0.02	0.00
EXPERSQU	−0.00	−0.00	0.00	−0.00	−0.00	0.00	−0.00	−0.00	0.00	−0.00	−0.00	0.00
EDU3	0.32	0.31	0.00	0.45	0.37	0.00	0.38	0.37	0.00	0.27	0.20	0.00
EDU4	0.65	0.61	0.00	0.71	0.42	0.00	0.65	0.61	0.00	0.64	0.35	0.00
MANAGER	0.26	0.26	0.00	0.09	0.06	0.19	0.26	0.26	0.00	0.03	0.00	0.95
BIGFIRM	0.34	0.34	0.00	0.13	0.10	0.00	0.12	0.12	0.00	0.12	0.10	0.00
SINGLE	−0.08	−0.08	0.00	−0.06	−0.05	0.00	−0.06	−0.06	0.00	−0.01	−0.00	0.92
TEMPJOB	−0.24	−0.24	0.00	−0.14	−0.08	0.00	−0.12	−0.12	0.00	−0.21	−0.16	0.00
IMR σ_y		0.52	0.00		0.63	0.00		0.49	0.00		0.61	0.00
ρ		0.28	0.00		−0.87	0.00		0.24	0.00		−0.80	0.00

H-ML = Heckit Maximum Likelihood estimates of wage equations including variable IMR (inverse Mill's ratio) as additional regressor (intercept not shown). The OLS-results are only for comparison with uncorrected estimates

Table 11 O/B-decomposition with Heckit bias correction

	Variant	Δtotal	Δchar	Δpay
Germany	(1)	0.077	0.093	−0.015
	(2)	0.077	0.099	−0.022
Austria	(1)	0.167	0.156	0.011
	(2)	0.167	0.142	0.024

Variant (1) with $\bar{X}_1 - \bar{X}_2|P_1$, variant (2) with $\bar{X}_1|P_2 - \bar{X}_2$

wage estimates confirms the former results of hidden payment discrimination against public sector employees, while, in case of Austria, they confirm the almost complete explanation of public sector wage advantages through higher values of relevant characteristics.

References

Albrecht J, Björklund A, Vroman S (2003) Is there a glass ceiling in Sweden? J Labor Econ 21(1):145–177

Albrecht J, van Vuuren A, Vroman S (2009) Counterfactual distributions with sample selection adjustments: econometric theory and an application to the Netherlands. Labour Econ 16(4):383–396

Albrecht JW, van Vuuren Aico, Vroman S (2004) Decomposing the gender wage gap in the netherlands with sample selection adjustments. IZA Discussion Paper No. 1400, Institute for the Study of Labor, Bonn, November 2004

Altzinger W, Berka C, Humer S, Moser M (2012) Die langfristige Entwicklung der Einkommenskonzentration in Österreich 1957–2009. Teil 2: Methodik und Ergebnisse. Wirtschaft und Gesellschaft 38(1):77–102

Arulampalam W, Booth AL, Bryan ML (2007) Is there a glass ceiling over Europe? Exploring the gender pay gap across the wages distribution. Ind Labor Relat Rev 60(2):163–186

Blinder AS (1973) Wage discrimination: reduced form and structural estimates. J Hum Resour 8(4):436–455

Böheim R, Hofer H, Zulehner C (2005) Wage differences between men and women in Austria: evidence from 1983 and 1997. IZA Discussion Papaer No. 1554, Institute for the Study of Labor, Bonn, April 2005

Böheim R, Hofer H, Zulehner C (2007) Wage differences between Austrian men and women: semper idem?. Empirica 34(3):213–229

Böheim R, Himpele K, Mahringer H, Zulehner C (2013) The distribution of the gender wage gap in Austria: evidence from matched employer-employee data and tax records. J Labour Mark Res, 46(1):19–34. ISSN 1614-3485. doi:10.1007/s12651-012-0113-y

Buchinsky M (1998) The dynamics of changes in the female wage distribution in the USA: a quantile regression approach. J Appl Econom 13(1):1–30

Cahuc P, Zylberberg A (2004) Labor economics. The MIT Press, Cambridge

Depalo D, Giordano R, Papapetrou E (2013) Public-private wage differentials in euro area countries: evidence from quantile decomposition analysis. Temi di discussione (Economic working papers) 907, Bank of Italy, Economic Research and International Relations Area, April 2013

DiNardo J, Fortin N, Lemieux T (1996) Labor market institutions and the distribution of wages, 1973–1992: a semi parametric approach. Econometrica 64(5):1001–1044

Dustmann C, Ludsteck J, Schönberg U (2009) Revisiting the german wage structure. Q J Econ 124:843–881

Firpo S, Fortin N, Lemieux T (2009) Unconditional quantile regressions. Econometrica 77(3):953–973

Fitzenberger B, Kunze A (2005) Vocational training and gender: wages and occupational mobility among young workers. Oxf Rev Econ Policy 21(3):392–415

Fitzenberger B, Wunderlich G (2002) Gender wage differences in West Germany: a cohort analysis. Ger Econ Rev 3(4):379–414

Fortin NM, Lemieux T, Firpo S (2011) Decomposition methods in economics. In: Ashenfelter O, Card D (eds) Handbook of labor economics, vol. 4A. North-Holland Elsevier, Amsterdam, pp 1–102

Fournier J-M, Koske I (2012) Less income inequality and more growth—are they compatible?: part 7. The drivers of labour earnings inequality—an analysis based on conditional and unconditional quantile regressions. Economics Department Working Papers, No. 930, OECD

García J, Hernández PJ, López-Nicolás A (2001) How wide is the gap? An investigation of gender wage differences using quantile regression. Empir Econ 26(1):149–167

Gosling A, Machin S, Meghir C (2000) The changing distribution of male wages in the UK. Rev Econ Stud 7(4):635–666

Heinze A (2010) Beyond the mean gender wage gap: decomposition of differences in wage distributions using quantile regression. ZEW Discussion Papers, No. 10-043, Zentrum für Europäische Wirtschaftsforschung

Ivanov AV (2008) Immigrant discrimination in Germany? Quantile regression decomposition of the wage gap. CDSE Discussion Paper No. 41, Center for Doctoral Studies in Economics, University of Mannheim

Koenker R (2012) Quantreg: quantile regression. http://CRAN.R-project.org/package=quantreg. R package version 4.81

Koenker R, Bassett Jr G (1978) Regression quantiles. Econometrica 46(1):33–50

Machado JAF, Mata J (2005) Counterfactual decomposition of changes in wage distributions using quantile regression. J Appl Econom 20(4):445–465

Melly B (2005a) Decomposition of differences in distribution using quantile regression. Labour Econ 12(4):577–590

Melly B (2005b) Public-private sector wage differentials in Germany: evidence from quantile regression. Empir Econ 30:505–520

Melly B (2006) Estimation of counterfactual distributions using quantile regression. Working Paper, SIAW, University of St. Gallen, 2006

Mueller RE (1998) Public-private sector wage differentials in Canada: evidence from quantile regressions. Econ Lett 60(2):229–235

Neuman S, Oaxaca RL (2004a) Wage decompositions with selectivity corrected wage equations: a methodological note. J Econ Inequal 2:3–10

Neuman S, Oaxaca RL (2004b) Wage differentials in the 1990s in Israel: endowments, discrimination, and selectivity. IZA Discussion Paper No. 1362, Institute for the Study of Labor, Bonn

Oaxaca R (1973) Male-female wage differentials in urban labor markets. Int Econ Rev 14(3):693–709

Peters H (2008) Development of wage inequality for natives and immigrants in Germany—evidence from quantile regression and decomposition. SOEPpapers on multidisciplinary panel data research 113, Deutsches Institut für Wirtschaftsforschung, Berlin, June 2008

Picchio M, Mussida C (2010) Gender wage gap: a semi-parametric approach with sample selection correction. CentER discussion paper series 2010-16, Tilburg University

Pointner W, Stiglbauer A (2010) Changes in the Austrian structure of wages, 1996–2002: evidence from linked employer-employee data. Empirica 37(2):105–125

Poterba JM, Rueben KS (1995) The distribution of public sector wage premia: new evidence using quantile regression methods. Working paper nr. 4734, NBER

Weichselbaumer D, Winter-Ebmer RR (2005) A meta-analysis of the international gender wage gap. J Econ Surv 19(3):479–511