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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 [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 [2006]. To narrow down the extent of discrimination both basic decomposition possibilities are compared. The economies of Germany and Austria appear structurally very similar. Especially the institutional setting of the labor markets seem to be closely comparable. One would, therefore, expect to find similar levels and structures of wage discrimination. Our findings deviate from this conjecture significantly.

JEL-Classification: J31, J71
Keywords: Wage discrimination, decomposition, quantile-regression

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1 Motivation

From a distance the economies of Germany and Austria appear structurally very similar. Clearly, Austrias economy is highly dependent on trade with its big neighbor, while no comparable reverse dependency exists. Especially the institutional setting of the labor market seems to be closely comparable and therefore one would expect to find levels and structures of wage discrimination in Austria similar to those in Germany.

We will take a closer look at this issue by estimating the extent of wage discrimination for three classical break-ups of the labor force: 1.) by gender, 2.) by sector of employment and 3.) by country of origin. Using the EU-SILC data for both countries, we are able to compare wage discrimination in Germany and Austria straightforwardly. Additionally, we can use very similar models for comparing wage discrimination within countries for the three break-ups.

Existing scholarly literature (see below) 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.

As far as we know analyzing discrimination between public and private employees in Austria by such a decomposition is presented for the first time.

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 section 3.3.

For Austria evidence on the gender gap is more sparse. In Böheim et al. [2005], Böheim et al. [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. [2011] 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. [2011] is the use of matched employer–employee data for over 13000 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 discrimination and explained 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 German socioeconomic panel (GSOEP). He 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.

Evidence for such discrimination in Austria based on comparable approaches is missing.

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 vs. 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.[1] 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, separately for both subgroups:

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

where $\hat{\beta}_k$ denotes the estimated vector of remuneration coefficients for group k. Based on these estimates the mean raw wage difference conditional upon group specific mean values of covariates $\overline{X}_k$ can be defined as

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

[1] 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.

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

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

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:

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

The question of choosing between (1) or (2) will be treated in section 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.[2] Therefore, a natural route to improved decompositions is to use the quantile regressions from Koenker and Bassett Jr. [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.

3.2 The Machado/Mata-approach

Machado and Mata [2005] (hereafter MM) 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.[3] The MM-approach is widely used and more intuitive than alternative decomposition approaches.[4] and can be summarized as follows:

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 $F^{-1}_{W|X}(\tau|x_i) = x_i\beta(\tau)$ for all $\tau \in (0, 1)$ (Koenker and Bassett Jr. [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.[5]

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

[3] 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.

[4] Decomposition alternatives without quantile regressions include the reweighting technique of DiNardo et al. [1996], or RIF-regressions with reweighting by Fortin et al. [2011].

[5] 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.

2. For $s = 1 \dots S$ do:
   (a) Estimate[6] 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.[7] The second two, $\widetilde{W}^c_1 \equiv \{\widetilde{w}^c_{1s}\}_{s=1}^S$ and $\widetilde{W}^c_2 \equiv \{\widetilde{w}^c_{2s}\}_{s=1}^S$, are the counterfactual wage distributions required for decompositions (3) and (4) below.[8]

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.[9] $\widetilde{W}^c_2$ 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:

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

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

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

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.

[6] 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]).

[7] Step 3 (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 (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.

[8] 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].

[9] 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.

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 wright 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 $\widetilde{W}_{1\theta} - \widetilde{W}^c_{1\theta}$. 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 $\widetilde{W}^c_{1\theta} - \widetilde{W}_{2\theta}$ 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 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. [10] 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, immmigrants were less likely to

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

find jobs in the public sector than comparatively qualified natives, this could be considered as part of discrimination. But in the analysis below, the wage effects of such practices would be subsumed under "explained differences".

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 is outside the scope of the present paper.[11] 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 24000 persons, from which, after filtering about 10000 valid observations remained. For Austria the corresponding numbers are 11000 and 4700, respectively. See Tables 1 – 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.[12] 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".

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

[12]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 section 3.5.

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 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.[13] 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).[14]

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 vs. immigrants, because the latter rarely hold such positions (see the numbers given in Table 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:

[13]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.

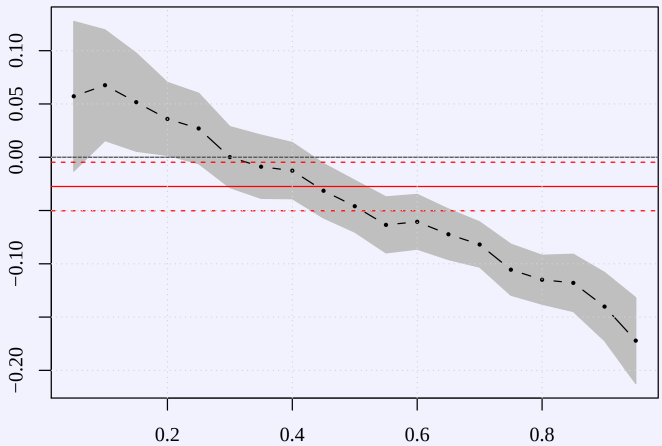
[14] Using "age", "age^2" and "experience" instead of "age", "experience" and "$experience^2$" lead to a worse fit and was formally rejected by corresponding tests.

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

Figure 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.

Regarding experience, it can be calculated from the coefficients displayed in figures 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.[15] 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 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 ($\sim$ 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 Figures 3 – 6. Some of them are remarkably distinct from corresponding OB-decomposition results given in tables 6 – 8. Apart from decomposition, they also draw quite different pictures of overall wage differences between subgroups than the standard quantile regressions.

Each graph in Figures 3 – 6 shows total wage differences[16] 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 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.

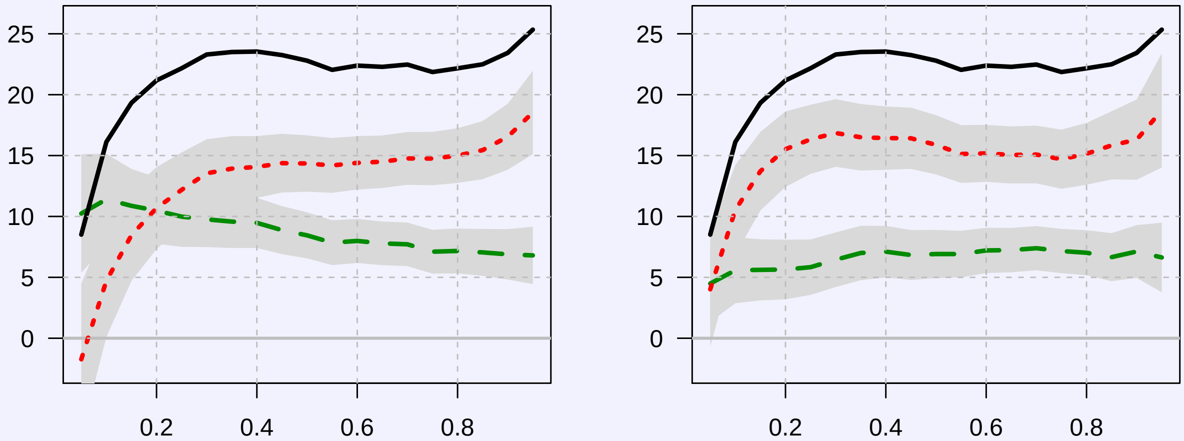
[15] This is a fairly standard result and easy to interpret: Negative values for the bottom percentiles arise naturally, if the lowest incomes are associated with manual labor, which deteriorates in quality with age. Positive values for higher incomes simply reflect widespread seniority pay.

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

6.1 Men vs Women

The main results regarding wage differences by gender in Germany are depicted in Figure 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).

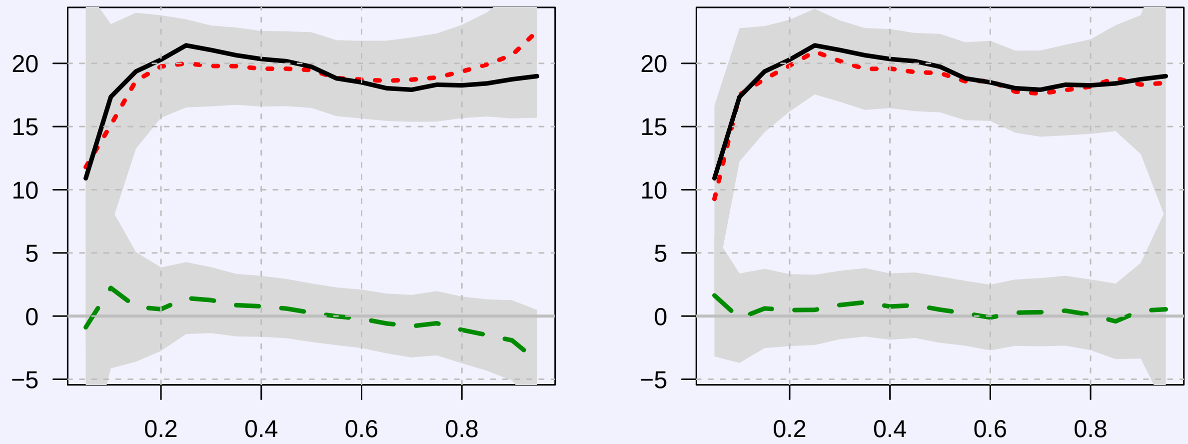
Figure 2: Percentage wage differences between men and women in Germany



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).

The picture for Austria (see Figure 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. [2011], where the explained part is significantly different from zero, leaving only between 5% and 15% of pure discrimination. The restriction of Böheim et al. [2011] to private sector employees can not explain this difference, because inclusion of public sector employees should, if anything, decrease estimated wage discrimination of women.

Figure 3: Percentage wage differences between men and women in Austria

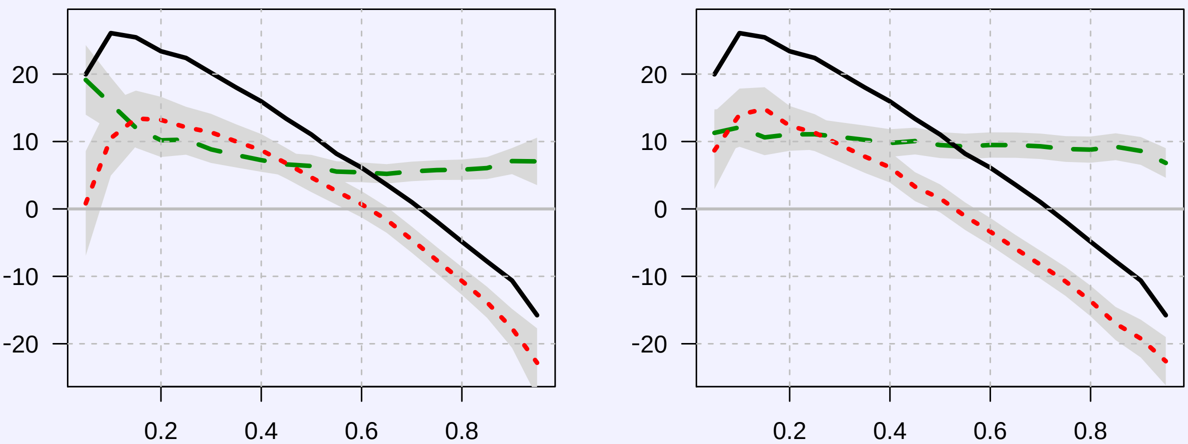


See legend in Figure 2.

6.2 Public vs. 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).

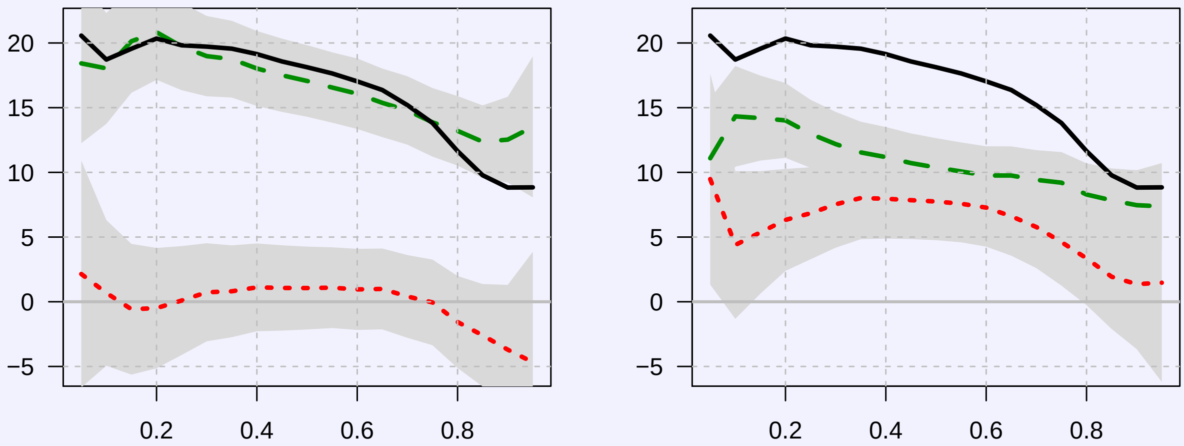
Figure 4: Percentage wage differences between public and private employees in Germany



See legend in Figure 2.

The relevant Austrian case is displayed in Figure 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 vs. 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.

Figure 5: Percentage wage differences between public and private employees in Austria

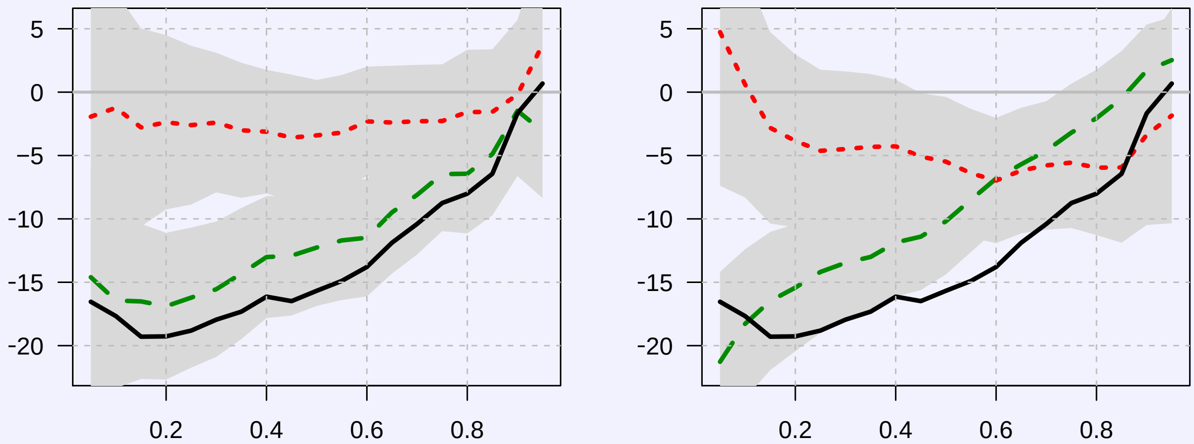


See legend in Figure 2.

6.3 Immigrants vs. 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 Figure 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.

Figure 6: Percentage wage differences between natives and immigrants in Germany

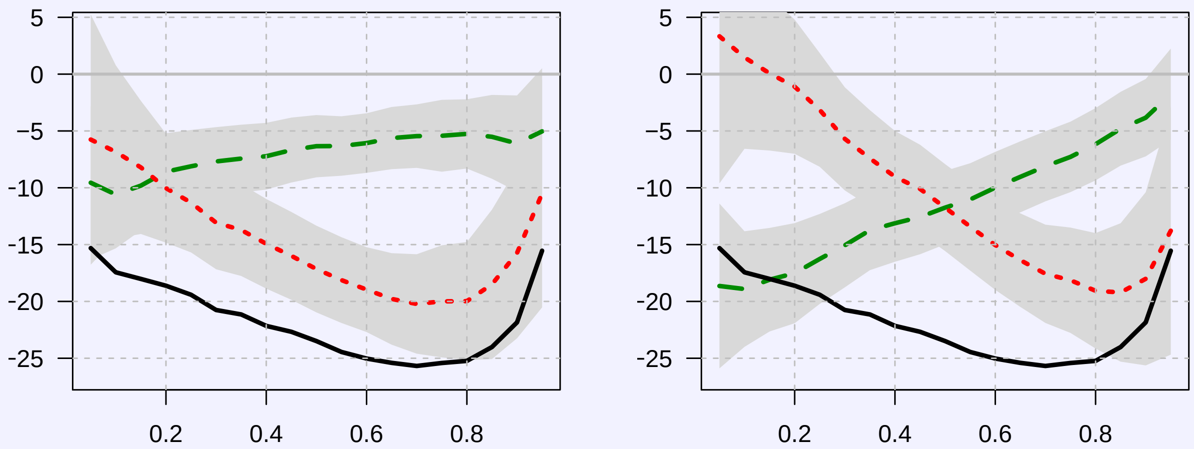


See legend in Figure 2.

The case of Austria is very different again (see Figure 7). There immigrants earn between 15% and 25% less than their native colleagues.[17] 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 to 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.

[17] Fournier and Koske [2012] report a difference of 25% at the median (Figure 13) 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.

Figure 7: Percentage wage differences between natives and immigrants in Austria



See legend in Figure 2.

7 Summary

This paper analyses wage differences between subgroups of the population in Germany and Austria: Men vs. women, public employees vs. private employees and natives vs. 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 – 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. [2011].

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.

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Appendix

Data filtering

Table 1: Filtering of observations

	Germany	Austria
Total Observations before filtering	24336	10955
Employees	12656	8614
Grossincome > 0	12363	5856
Typical weekly hours in main job > 0	12633	5944
Months worked (full- plus parttime) > 0	12422	6304
Firmsize known or <= 10	24336	10954
Response occupation (ISCO-88)	22376	9844
Response industry (NACE 1.1)	12595	5691
Response firmsize	12526	5334
Response experience	22143	9844
Remaining Observations after filtering	10280	4661

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

Final data for Germany 2008 (after filtering)

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

	n	%os	%WOM	%IMM	%PUB	mean	median
ALL	10280		51.4	95.0	33.0	16.8	15.6
MEN	5282	-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	4540	-14.3	49.2	3.8	24.6	14.4	13.7
EDU4	4934	38.4	47.4	5.2	34.6	20.2	18.8
SINGLE	2895	-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	5968	1.9	41.1	5.2	35.3	19.0	17.7
SERV	4123	-7.5	51.6	5.2	0.0	16.0	14.1
PUBL	3390	19.8	65.3	3.7	100.0	16.9	16.3

Legend: 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	2158	-5.5	24.1	10.8	19.2	17.9
CONSTR	479	-15.8	13.5	12.6	13.8	13.2
TRADE	1413	-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
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	1297	13.5	45.8	3.3	17.8	17.1
EDUC	796	49.3	66.1	7.3	19.1	18.1
HEALTH	1297	12.4	78.9	8.8	14.5	13.9

Legend: 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

Final data for Austria 2008 (after filtering)

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

	n	%os	%WOM	%IMM	%PUB	mean	median
ALL	4661		54.6	85.6	25.5	16.7	14.3
MEN	2545	-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	2561	0.7	42.3	11.9	19.4	15.3	13.7
EDU4	1494	4.0	48.4	12.5	35.1	21.9	18.7
SINGLE	1610	-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	1868	0.4	36.3	14.3	27.3	18.1	16.0
SERV	2084	-0.3	51.3	15.6	0.0	16.2	13.3
PUB	1188	4.6	63.4	9.1	100.0	18.3	16.2

Legend: 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
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

Legend: 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

Standard Oaxaca-Blinder decompositions

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

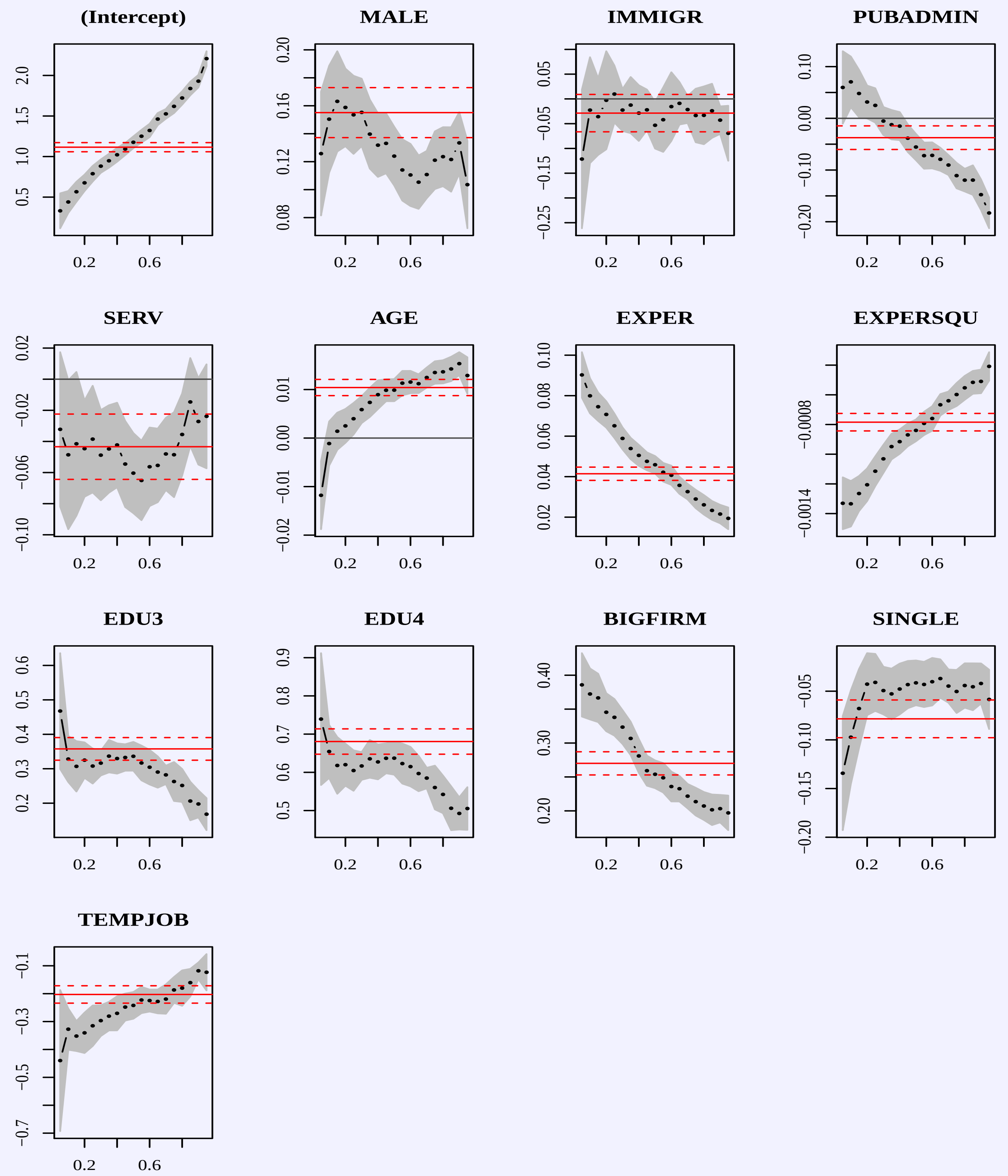
Table 8: Log wage differences between natives and immigrants

	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

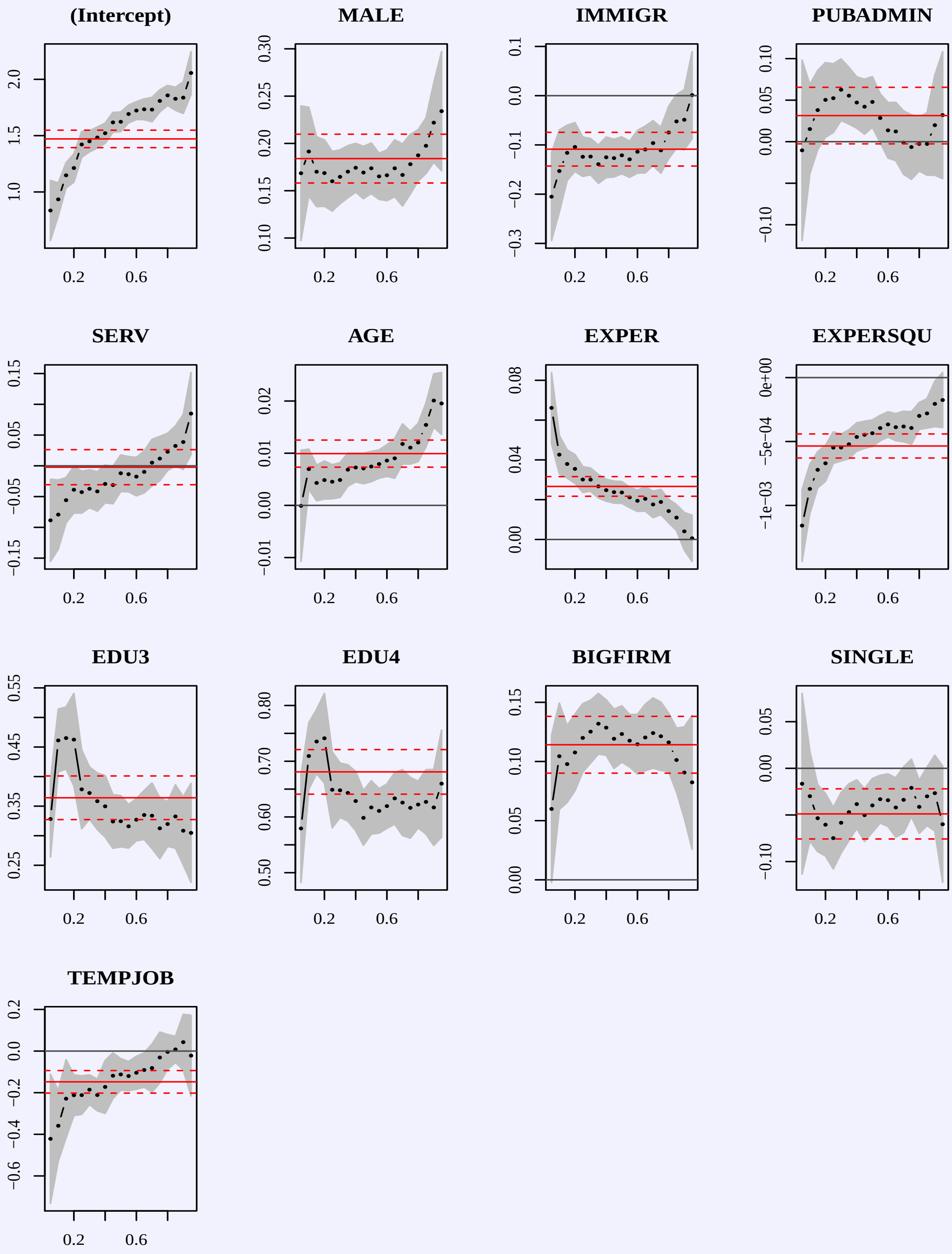
Standard quantile regression results

Figure 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.

Figure 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.