Wage Discrimination Against Immigrants in Austria?

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Abstract. This paper analyses wage discrimination against immigrants in Austria using combined information from the labour force surveys and administrative social security data. We find that immigrants experience a wage penalty of 15 percentage points compared with natives. However, a substantial part of this gap can be explained by differences in human capital endowment and job position. Decomposition methods using quantile regressions indicate larger discrimination in the upper part of the wage distribution.

1. Introduction

In Austria, the share of immigrants in the population amounts to 19 per cent in 2012 and is one of the largest in the OECD. In international comparison, general labour market integration outcomes are not unfavourable (see, e.g., Krause and Liebig, 2011). However, empirical evidence indicates that immigrants face disadvantages with respect to employment, unemployment, job offers, and position in the occupational hierarchy (see, e.g., Huber, 2010; Krause and Liebig, 2011; Titelbach *et al.*, 2013; Weichselbaumer, 2013). Labour market performance and skill levels differ between countries of origin of the immigrant employees. Regarding the share of the different subgroups of the immigrant workers by citizenship,[1] The biggest groups are citizens from EU countries and from former Yugoslavia (40 per cent and 35 per cent on average from 2008 until 2011), followed by citizens of Turkey (10 per cent). Over time, the structure of migrants has changed. Throughout the 1980s and 1990s, the joint share of Turkish and Yugoslav nationals remained steadily above 60 per cent. Since Austria's accession to the European Union in 1995, migration from the EU-15 (in particular from Germany) and Eastern Europe has grown significantly (see, e.g., Liebig and Krause, 2011). Employees from EU countries have higher qualifications compared with native born employees and they are more likely to work in higher skilled job positions. In contrast, employees from former Yugoslavia and in particular from

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We thank the editor Franco Peracchi, Doris Weichselbaumer, Johannes Schweighofer, Thomas Liebig, various referees, and the participants at the 2014 NOeG conference in Vienna for valuable comments; Birgit Wögerbauer and Johannes Schachner for research assistance, and Daniela Gumprecht for help at the SafeCenter of Statistics Austria. Winter-Ebmer and Ahammer gratefully acknowledge financial support from the Christian Doppler Laboratory on Ageing, Health, and the Labour Market.

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DOI: 10.1111/labr.12093

JEL J71, J15

Turkey are hired for mostly low-skilled or unskilled work. This group of workers has a high share of employees with only basic formal qualifications. Second generation migrants are also more often employed in unskilled or low-skilled work than natives (see Titelbach *et al.*, 2013). In this paper, we will analyse wage differentials between immigrants and natives for Austria in a systematic way, using matched data from labour force surveys and administrative social security data.

In general, discrimination can be defined as unequal treatment which penalises immigrants in comparison with natives. The economic literature distinguishes between taste-based and statistical discrimination (see Arrow, 1971; Becker, 1957). While the former relates to unequal treatment due to preferences of economic agents, the latter derives unequal treatment from incomplete knowledge about the true productivity of workers which may lead to stereotyping behaviour. In the following empirical analysis, we will contrast two basic principles of equal treatment: 'equal pay for equal endowments' versus 'equal pay for equal work'. The first principle implements a broader definition of discrimination: wage differentials which cannot be explained by typical (observable) productivity characteristics, such as education and training, are labelled discrimination. The second principle implements a definition of discrimination which is narrower. Holding job characteristics such as industry, occupation, or hierarchical position within the firm constant, only unexplainable wage differentials between natives and immigrants working in the same jobs are defined as discrimination. This definition does not take into account, however, how the workers got their jobs.

With the exception of Grandner and Gstach (2015), almost no research exists on this topic for Austria due to data limitations. In our empirical analysis, we first use Oaxaca-Blinder decomposition techniques to estimate wage differentials at the mean of the distribution. Moreover, we apply quantile decomposition techniques to analyse the heterogeneity of discrimination and human capital effects across the wage distribution.

In other countries, wage discrimination against immigrants has been analysed extensively in recent years (see, e.g., OECD, 2013, for a review). The early wage assimilation hypothesis by Barry Chiswick (1978) for the United States suggests that immigrants will close the initial wage gap to natives within 10–15 years, and then they may overtake due to a very high wage growth. The original results by Chiswick of an overtaking of the immigrants are based on cross-sectional data. Longitudinal data, in which immigrants can be tracked over time, show indeed a catch up, but not an overtaking of immigrants anymore in relation to individuals who were born in the United States (Borjas, 1985).[2]

In European countries, wage differentials between natives and immigrants are less frequently analysed. Peracchi and Depalo (2006) and Jean *et al.* (2010) conduct cross-country analyses on differential labour market outcomes between natives and migrants using data from the European Community Household Panel. Both document lower earnings and employment probabilities for immigrants as compared with natives, even after controlling for observable productivity characteristics. Peracchi and Depalo (2006), however, show that these differences vanish after roughly 20 years of residence in the host country.

For the United Kingdom, Elliot and Lindley (2008) show a wage differential of about 16 per cent among white British men and non-white immigrants, this differential cannot be explained by differences in productivity. Bell (1997) finds no wage disadvantage for white immigrants. However, black immigrants who spent a greater part of their career abroad face wage disadvantages. Dustmann *et al.* (2010) again demonstrate that immigrants from OECD countries have higher wages as natives in the UK.

For Germany, Lehmer and Ludsteck (2011) show that most immigrant groups have 20 per cent lower wages than native Germans. The differences are largest for Poles and smallest for the Spanish. The result of an Oaxaca-Blinder decomposition shows that approximately half of the differential is explained by differences in productivity. Controlling for occupation lowers the unexplained part by 20–30 per cent. Hirsch and Jahn (2012) show that about 14 to 17 percentage points of this 20 percentage point wage differential can be explained by observable productivity characteristics (including occupation). Beblo *et al.* (2012) report a difference in wages between Germans and foreign workers of approximately 15.5 per cent for the period 1996 to 2007. They find strong evidence that foreign workers are employed disproportionately often in low-wage firms. Controlling for these firm effects reduces the wage differential to 10.6 per cent of which about 8 percentage points can be explained by observable productivity characteristics such as education, work experience, and tenure. Moreover, Licht and Steiner (1994) find no evidence for the assimilation hypothesis in Germany.

For Denmark, Nielsen *et al.* (2004) find a higher wage differential between foreigners and natives for men than for women. Males from Turkey, Africa, and Pakistan earn 22 per cent, 23 per cent, and 26 per cent, respectively, less than natives. The wage penalty for female immigrants from these countries amounts to 17 per cent. In an Oaxaca-Blinder decomposition including the standard human capital variables, occupation, and hierarchical job position as productivity measures, nearly the full differential is explained for males. For women, approximately one third of the differential remains unexplained. In the case of Spain, Canal-Domínguez and Rodríguez-Gutiérrez (2008) find wage differentials of nearly 40 per cent of which three quarters can be explained by differences in productivity (including job position).

Several studies analyse the gender wage differential in Austria empirically (see, e.g., Böheim *et al.*, 2013; Winter-Ebmer and Zweimüller, 1994); however, empirical evidence on wage differentials by nationality or migration status is very scarce. In a first study, Grandner and Gstach (2015) use EU-SILC data for the analysis of wage discrimination between immigrants and natives in Austria. They report a wage penalty in the range of 15 to 25 per cent. They use counterfactual densities to decompose the wage differential and report a discrimination component ranging from 5 to 20 percentage points. The discrimination component follows a marked U-shape over the income distribution reaching a maximum at around the 8th decile. While Grandner and Gstach (2015) use comparable EU survey data from a relatively small sample, we can profit from the combination of comprehensive administrative data with high-quality labour force data. We consider wage differentials between natives and immigrants for males and females separately to avoid problems with gender wage differentials. Moreover, we are able to distinguish between first and second generation migrants, and migrants from different countries. In their comparative approach for OECD countries using the European Community Household Panel, Peracchi and Depalo (2006, tables 16 and 17) estimate a raw wage differential in average monthly earnings of 7.3 per cent (2.6 per cent) between male (female) immigrants and Austrians.

The remainder of the paper is organized as follows. The next section presents the methods we use to analyse wage discrimination. Section 3 deals with a description of our data source and presents basic information on differences in characteristics between immigrants and natives. Section 4 discusses the econometric results. The final section concludes.

2. Methods to measure discrimination

In this paper, we analyse wage differentials between natives and immigrants using decomposition methods (see Fortin *et al.*, 2011; for a general overview). First, we use the Oaxaca-Blinder (OB) approach, which decomposes the wage gap of natives and immigrants in a component measuring differences in productivity-related characteristics, and a so-called residual term ('discrimination component').[3] The wage differential estimated by this method, however, is only informative at the mean of the wage distribution. Thus, in a second step, we use a quantile regression framework that allows the wage differential to vary along the wage distribution (Chernozhukov *et al.*, 2013; Koenker, 2005; Machado and Mata, 2005). Reweighting techniques are an alternative approach to eliminate differences in observable population characteristics. Fortin *et al.* (2011) suggest recentred influence function (RIF) regressions with reweighting. This approach relies, however, on local approximations which may not be accurate if the covariate distribution of the groups compared is not sufficiently close to each other. Under correct specification, both approaches are equally valid (Chernozhukov *et al.*, 2013).

2.1 Oaxaca-Blinder decomposition

The Oaxaca-Blinder method (Blinder, 1973; Oaxaca, 1973) is used to decompose the average wage differential between natives (N) and migrants (M) in a productivity-related difference (E) and a so-called discrimination component (U).

The starting point is the so-called Mincerian wage equation which is estimated for each of the two groups separately. The log hourly wage is a linear function of a variety of individual and firm level characteristics, e. g., education, work experience, job tenure, firm size, or industry. The coefficient vector β reflects the price of the individual characteristics, such as the wage effect of an additional year of schooling.

Let $\text{In}(Y_N) = \beta_N X_N + \varepsilon_N$ and $\text{In}(Y_M) = \beta_M X_M + \varepsilon_M$ be the Mincerian wage equations for both of the groups. Then, the average wage gap can be decomposed in the following way:

$$\overline{\text{In}\,Y_N} - \overline{\text{In}\,Y_M} = \overline{X_N} - \overline{X_M})\beta_N + \overline{X_M}(\beta_N - \beta_M), \qquad [1]$$

where the first term $E = (\overline{X_N} - \overline{X_M})\beta_N$ represents the share of the average wage gap which is due to the different endowments of the two groups with productivity-related characteristics, while $U = \overline{X_M}(\beta_N - \beta_M)$ represents the unexplained residual or the discrimination component. It should be noted that this part also includes all unobservable differences between the natives and migrants. The decomposition used requires an estimate of the non-discriminatory wage structure. We assume that the wage structure of the natives is non-discriminatory.[4]

2.2 Estimating counterfactual wage distributions

2.2.1 Objects of interest. In order to extend our decomposition of mean wage differentials to the full distribution, we follow the literature (e.g., Böheim *et al.*, 2013; or Lehmer and Ludsteck, 2011) and use a method proposed by Chernozhukov *et al.* (2013) which suggests using regression methods to estimate counterfactual wage distributions. The idea is to estimate the entire conditional distribution through parametric quantile regressions and then to integrate the conditional distribution over the range of covariates which gives us an estimate for the unconditional wage distribution. Finally, we simulate counterfactual quantiles which we use to decompose the effect of coefficients and the effect of characteristics on the wage distribution.

Formally, let $D_i \in \{N, M\}$ indicate migratory status of individual i. Furthermore, let Y_i (N) be the wage outcome for a native ($d = N$) and Y_i (M) be the wage outcome for a migrant ($d = M$), and denote by $Q_Y(\theta) = F_Y^{-1}(\theta)$, $\theta \in (0,1)$, the θth quantile of Y, where $F_Y(y)$ is the cumulative distribution of Y at y. In order to construct counterfactual wage distributions, we require estimates of the conditional distribution $F_{Y_i(d)|X_i}$ for each population d. Chernozhukov *et al.* (2013) discuss different methods to recover these estimates, most importantly *quantile regressions* (e.g., Koenker, 2005) and *distribution regressions* (e.g., Foresi and Peracchi, 1995). The latter generalize quantile regressions by allowing for a known link function to capture the relationship between the vector of explanatory variables X_i and the conditional distribution of Y_i. This is especially useful when the distribution of Y is discrete or has mass points. Simulation results in Chernozhukov *et al.* (2013) indicate, however, that quantile regression provide a better approximation of the conditional distribution if Y_i has a smooth conditional density. As Y_i is continuous in our empirical specification, we therefore stick to quantile regressions.

2.2.2 Identification and estimation. Going forward, we assume that the conditional quantiles of $Y(d)$ given X_i are linear in X_i:

$$Q_{Y(d)}(\theta|X_i) = X_i\beta_d(\theta), \quad \text{for all } d = N, M \textit{ and } \theta = (0,1). \qquad [2]$$

Necessary assumptions which guarantee identification are discussed in detail in Chernozhukov *et al.* (2013), in particular we require unconfoundedness of our regressors (see also Section 2.3 for a discussion on the validity of this assumption), i.e., $Y(N), Y(M) \perp D|X$, where $\perp$ denotes statistical independence. We proceed by estimating the conditional wage distribution at q by

$$\hat{F}_d(y|X_i) = \int_0^1 \mathbf{1}\{X_i\hat{\beta}_d(\theta) \le y\}d\theta \qquad [3]$$

where $\mathbf{1}\{\bullet\}$ denotes an indicator function, and

$$\hat{\beta}_d(\theta) = \arg\min_{b\in\mathbb{R}^K} \sum_{i:D_i=d} \mathbf{1}\{D_i = d\}\rho_\theta(Y_i - X_i b), \quad d = N, M; \qquad [4]$$

is a consistent estimator for $\beta_d(\theta)$ with $\rho_\theta(z) = z(\theta - \mathbf{1}\{z \le 0\})$ being the so-called check function. Chernozhukov *et al.* (2013) show that $X_i\hat{\beta}_d(\theta)$ is a consistent estimate of the θth conditional quantile of Y_d given X_i. The unconditional distribution of $Y(d)$ is then estimated by integrating over the covariates X_i, that is,

$$\hat{F}_d(y) = \int \hat{F}_d(y|x)d\hat{F}_d(x)), \quad d = N, M; \qquad [5]$$

with $\hat{F}_d(x)$ being the marginal distribution function of the covariates for group d, and the estimator of the θth quantile of the unconditional distribution of y is given by

$$\hat{q}_d(\theta) = \inf\{y : \hat{F}_d(y) \geq \theta\}, \quad d = N, M; \qquad [6]$$

where n_d is the number of observations in subpopulation $d \in \{N, M\}$. Define now the θth counterfactual quantile of the unconditional wage distribution. That is, the quantile of the distribution we would observe if migrants were natives,

$$\hat{q}_c(\theta) = \inf\{y : \int \hat{F}_N(y|x) \quad d\hat{F}_M(x) \geq 0\}. \qquad [7]$$

A decomposition between the θth quantile of the unconditional distribution of migrants and natives can then be expressed as

$$\hat{q}_M(\theta) - \hat{q}_N(\theta) = [\hat{q}_M(\theta) - \hat{q}_c(\theta)] + [\hat{q}_c(\theta) - \hat{q}_N(\theta)] \qquad [8]$$

where the first bracket captures the effect of coefficients and the second captures the effect of characteristics. We approximate the conditional wage distribution with 99 quantile regressions; inference is based on bootstrapped standard errors. Hundred bootstrap replications are used to obtain an estimate of the variance—covariance matrix of the estimators.

Note that the procedure described above can easily be generalized by estimating conditional quantile functions fully non-parametrically. In order to increase precision of our estimates, however, we follow recent contributions to the literature on discrimination (Böheim *et al.*, 2013; Lehmer and Ludsteck, 2011) and stick to the more parsimonious parametric framework.

2.3 Validity

The validity of such a decomposition depends crucially upon the selection of explanatory variables in the wage function. If too many control variables are selected, discrimination might be underestimated. This can be illustrated with an example from promotion: If there is a so-called glass ceiling effect and migrants are not promoted to top positions, then a regression including the control variable 'occupational rank' would underestimate discrimination as this variable represents an endogenous variable. If a narrower concept of discrimination is assumed instead, i.e., one considers only wage differentials between persons with the same human capital and similar occupational ranks, then this control variable would be justified. Lehmer and Ludsteck (2011) discuss this problem with respect to occupation dummies. If the selection into occupations or job positions depends only on productive characteristics, which may not be visible to the researcher but are, in fact, observable by the employer (e. g., imperfect transferability of human capital acquired in foreign countries, insufficient language skills, etc.), occupational dummies are justified. In contrast, if assignment to occupations or job positions is governed by discriminatory preferences of employers, the inclusion of such dummies masks discrimination.

As discussed before, unconfoundedness of income with respect to different treatment status (native, foreign) given our control variables is necessary for proper identification of the wage differential. The availability of many control variables in our data set should make this assumption valid, at least if we presume that observables and non-observables are correlated. However, issues like transferability of formal human capital and language skills are prime suspects for violations of the unconfoundedness assumption. If formal human capital accumulated abroad is less valuable in, or transferable to Austria, the discrimination coefficient might be overestimated. The same applies if language skills are missing among the X variables. The overlapping support assumption, which is critically discussed in the gender gap literature, is fulfilled, as we can match every foreign worker with a native who has the same characteristics due to the large sample size. Note, however, that our method rules out the presence of general equilibrium effects.

To take account of these two dangers of under- and overestimating the discrimination coefficient, we use two different specifications of the wage function. Specification I is based on a broader definition of discrimination. In this specification, education, work experience, job tenure, employment days in the Austrian labour market within the last 5 years, firm size, marital status, number of children, level of urbanization, and region are included in the wage equation as explanatory variables. Later, we additionally include dummies for industry, occupation (vertical segregation), hierarchical position (horizontal segregation), and blue-white-collar (specification II). Typically, discrimination measured according to specification II will be lower as compared with specification I. To claim this, we have to assume that in the assignment of occupations and job positions migrants are not positively discriminated against. This is a relatively innocuous assumption as the major unobserved characteristics which might be responsible for this assignment are language skills and access to specific receiving country skills which might be transfer home-country skills — competences, where we can assume that natives have an advantage. The equations are estimated separately for men and women, respectively, using OLS.

These two specifications correspond to two different concepts of discrimination. Specification II is based on the principle of 'equal pay for equal work': here, we want to control for the type of job or the occupational hierarchy. This concept constitutes a comparison between two employees of different nationalities at the same job. It assumes that it does not matter how these two people came into this job. Note however, that the allocation of jobs, career advancement, etc., may already have been characterized by unequal treatment.

The measure of overall discrimination in the labour market could therefore have been underestimated. Specification it defines discrimination as 'equal pay for equal endowments': as only productivity features are used as explanatory factors, but not features of the job. This level of discrimination may represent an overestimation of discrimination because some productivity-relevant characteristics of the workers may not be exactly measured and they could possibly affect wages through job allocation. These two issues of the measurement of discrimination provide a common area of discussion which occurs in similar ways in the gender pay gap discussion. In this field, the glass ceiling with respect to promotions and the choice or assignment of women to typical low-paid women's jobs are major research topics.

3 Data

We combine the Austrian micro-census (labour force survey) with data from social security records. The data set was matched at the individual level. For reasons of data protection, the matching was done by Statistics Austria and the econometric estimations were carried out in the Safe Center of Statistics Austria. The merged data contain human capital variables, such as education and experience, workplace characteristics, and complete working histories since 1988. The sample size corresponds to the number of observations in the micro-census.

The Austrian micro-census is a quarterly panel survey which collects information on private households. It is representative of the Austrian population and contains information of about 80,000 individuals per year. Every quarter, a fifth of the sample is renewed. The micro-census served as the central data source for the study. As valid statements for different migrant groups require an adequate sample size, the micro-censuses of the years 2008 to 2010 were pooled and the data of the second quarter were used. The micro-census was used to obtain information on personal (sex, age, nationality, migration background) and labour market characteristics (occupation, current employment status, working hours, industry, and job position). The indicator for the job position depends on skill requirements and occupation. We differentiate between the following job positions: Elementary occupation, minor skills required, medium skills required, high skills required, advanced skills required, and leading manager in large firms. The data from the micro-census are supplemented with information from the labour market database which is based on social security registers.

The data on income from the Federation of Austrian Social Insurances (available as social security contribution bases) are used for the mean wage gap analysis because information is available for 2008–2010. In addition to the income data, employment days within a year, job tenure, and firm size have been taken from the labour market data base. Furthermore, an indicator of the employment days in Austria within the last five years was constructed. Based on annual income in the respective firm, associated employment days and standard working hours according to the micro-census, as well as gross hourly wages were calculated as an indicator for the salary. The analysis of the effects across the wage distribution is undertaken with income data from the micro-census. The income information of the micro-census 2009 and 2010 is based on wage tax records data (Baierl *et al.*, 2011) and is not censored at the maximum contribution celling.[5] As the dependent variable, we use net hourly wages.

Our estimation sample consists of full-time employed workers aged 20–55 who were active during the years 2008–2010 in the private sector of the Austrian economy. For the respective employment in the second quarter of each year, the hourly wage was calculated and deflated to prices in 2006. Only workers who were employed at least 270 days in their companies were included.[6]

Migration status is based on the concept of migration background. People with a migration background are defined as persons whose parents were both born abroad. This migrant group can be divided into first generation migrants (country of birth abroad) and second generation migrants (country of birth is Austria). The use of this concept has some advantages compared with a definition by nationality: For example, a change of citizenship does not cause a selection problem, and for second generation immigrants we expect less unobservable characteristics (language capabilities, quality of school education abroad)

In Table 1, summary statistics for natives and immigrants are shown. Hourly wages of immigrants are about 15 per cent lower than those of natives. However, it also becomes apparent that natives and immigrants differ in their productivity-related characteristics. One of the most important determinants of wages is the amount of formal schooling. Immigrants have on average half a year less of education. Also, job tenure is considerably shorter. Immigrants live more often in large cities and in the provinces Vienna and Vorarlberg. With respect to industry, the share of immigrants is above average in manufacturing and in the tourism sector. Significant differences are also apparent in occupation and job

Table 1. Descriptive statistics: natives and immigrants

	Men			Women		
	Natives	**Migrants 1st gen.**	**Migrants 2nd gen.**	**Natives**	**Migrants 1st gen.**	**Migrants 2nd gen.**
Gross hourly wage (in Euros)	11.2	9.6	11.0	9.5	7.9	8.5
Education (in years)	11.8	11.3	11.3	12.1	11.6	11.6
Tenure (in years)	11.1	7.4	9.5	9.8	7.6	7.7
Experience (in years)	20.6	21.6	17.7	19.6	22.9	16.3
Employed in Austria (share of the time in last 5 years)	0.9	0.9	0.9	0.9	0.8	0.8
Married	79.0	85.5	80.7	63.3	73.3	67.6
Single	21.0	14.5	19.3	36.7	26.7	32.4
Blue-collar worker (0,1)	43.1	73.7	47.6	16.6	53.7	27.0
White-collar worker (0,1)	56.9	26.3	52.4	83.4	46.3	73.0
Number of children						
No children	31.5	28.5	31.2	49.4	38.7	36.0
1 child	29.6	21.9	29.7	27.3	26.1	27.9
2 children	29.5	30.9	30.5	17.6	26.3	24.3
3 children +	9.5	18.7	8.6	5.7	9.0	11.7
Firm size						
0–9	13.8	11.6	12.3	18.7	12.6	14.4
10–19	8.1	8.9	7.1	8.3	6.4	9.0
20–49	15.0	16.3	13.8	12.7	14.3	9.0
50–499	40.4	43.4	40.9	34.7	39.5	36.9
500+	22.8	19.7	26.0	25.6	27.2	30.6
Citysize						
0–10,000	70.7	36.0	42.4	61.1	34.3	35.1
10,001–100,000	16.2	28.2	34.6	18.6	23.8	36.9
100,000 +	13.2	35.7	23.0	20.3	41.9	27.9
Federal State						
Burgenland	4.7	1.9	2.2	6.0	2.6	2.7
Carinthia	10.2	6.4	2.6	10.8	5.1	5.4
Lower Austria	11.7	11.7	9.3	10.9	8.5	7.2
Upper Austria	15.7	13.5	8.9	12.0	11.6	16.2
Salzburg	10.9	12.1	8.6	11.0	13.1	9.9
Styria	13.3	6.1	3.7	12.7	4.9	2.7
Tyrol	11.6	10.8	11.9	10.9	10.7	8.1
Vorarlberg	9.8	16.5	34.6	8.9	14.0	27.9
Vienna	12.2	21.0	18.2	16.8	29.6	19.8
Industry						
Primary production[a]	3.4	1.9	1.1	1.5	1.2	0.0
Manufacturing	32.9	34.4	42.4	15.8	24.3	27.0
Construction	14.5	18.5	9.7	3.0	1.1	0.9
Trade	16.2	15.0	18.2	20.6	17.2	30.6
Tourism	1.5	5.7	0.4	5.9	16.1	1.8
Business services	19.8	17.0	21.9	21.4	15.5	15.3
Public services	8.4	4.8	4.5	26.2	19.5	17.1
Other services	3.3	2.8	1.9	5.5	5.1	7.2
Occupation						
Managers	9.0	3.6	9.3	4.7	4.7	3.6
Professionals	6.9	4.6	4.8	5.7	4.0	6.3
Technicians	23.4	8.9	20.4	26.4	13.3	20.7

Table 1. Continued

	Men			Women		
	Natives	**Migrants 1st gen.**	**Migrants 2nd gen.**	**Natives**	**Migrants 1st gen.**	**Migrants 2nd gen.**
Office employees	8.8	3.4	7.4	30.2	9.9	23.4
Clerks	4.4	6.1	4.8	19.7	17.0	24.3
Agricultural worker	0.7	0.8	0.0	0.8	0.4	0.0
Craft workers	27.9	31.8	23.8	2.4	4.1	0.9
Operators	11.0	16.0	14.9	2.1	6.1	4.5
Elementary Occupations	7.8	24.8	14.5	8.0	40.5	16.2
Job Position						
Unskilled	2.9	20.8	8.2	4.3	33.2	15.3
Low-skilled	17.9	35.2	21.2	12.9	25.6	12.6
Medium-skilled	47.0	30.8	42.0	53.8	25.7	55.0
High-skilled	15.8	4.6	13.4	16.4	6.7	8.1
Advanced/leading	16.4	8.7	15.2	12.6	8.9	9.0
N	11,137	1,598	269	5,110	802	111

Source: Micro-census 2008–2010, AMDB.
Note: [a]Primary production includes agriculture, forestry, mining, and the energy sector.

position. On average, immigrants have a higher probability to work in low-wage occupations and less favourable job positions. Three quarters of male and slightly more than half of female immigrants are blue-collar workers. For Austrians, the corresponding proportions are 43 per cent and 17 per cent, respectively. One out of five (three) migrant males (females) work in elementary occupations. For Austrians, this applies only to 3 to 4 per cent. Thus, these data show considerable heterogeneity between natives and immigrants with respect to human capital and job positions.

Figure A1 reports the share of migrants across the wage distribution. As can be seen from the Figure, migrants are concentrated at the lower part of the distribution. While 50 per cent of all female migrants are found in the lowest three deciles, only 5 per cent are located in the top two deciles. For male migrants, a similar picture occurs, however, the concentration in the lower part of the wage distribution is less strong. The number of migrants drops steadily over the wage distribution. In the bottom decile, we find 15 per cent of the migrants, in the top decile the amount drops to 4 per cent.

4 Results

4.1 Wage differentials at the mean

The descriptive evidence revealed marked differences in the endowments of natives and immigrants. We use the Oaxaca-Blinder decomposition to explore the native-migrant wage gap (Tables A1 and A2 in the Appendix present the coefficients of the estimated wage equation.) According to Table 2, the raw wage gap between natives and immigrants amounts to 13.6 log points for men and 17.2 log points for women, respectively. The analysis shows that differences in human capital (education and experience) contribute significantly to the observed wage gap. Differences in human capital alone explain 30 per cent of

Table 2. Oaxaca-Blinder decomposition

	All immigrants	**First generation**	**Second generation**
Men			
Wage gap	−0.136	−0.155	−0.023
p-value	0.000	0.000	0.202
Specification I			
Explained	−0.040	−0.045	−0.018
p-value	0.000	0.000	0.097
Unexplained	−0.095	−0.110	−0.005
p-value	0.000	0.000	0.713
Specification II			
Explained	−0.107	−0.120	−0.034
p-value	0.000	0.000	0.007
Unexplained	−0.029	−0.035	0.011
p-value	0.000	0.000	0.421
#natives	11,140	11,140	11,140
#immigrants	1,867	1,598	269
Women			
Wage gap	−0.172	−0.181	−0.106
p-value	0.000	0.000	0.001
Specification I			
Explained	−0.020	−0.016	−0.049
p-value	0.017	0.074	0.012
Unexplained	−0.152	−0.165	−0.057
p-value	0.000	0.000	0.038
Specification II			
Explained	−0.122	−0.127	−0.083
p-value	0.000	0.000	0.000
Unexplained	−0.050	−0.053	−0.024
p-value	0.000	0.000	0.402
#natives	5,113	5,113	5,113
# migrations	913	802	111

Note: *p*-values for a test of the null hypothesis that the coefficient is not different from zero are presented in parentheses. Specification I includes education, tenure and experience squared, employment in last years, marital status, children, firm size, city size, regional indicators; specification II includes additionally industry, occupation, and job position.

the wage gap for males, for women the share is slightly above 11 per cent (specification I). A detailed decomposition reveals that the unexplained gap is mainly related to lower returns to schooling and especially work experience of immigrants. Controlling for occupation and in particular job position (specification II) reduces the unexplained wage gap even further. The discrimination component falls to 3 (5) log points for males (females).[7]

We find very different results for first and second generation immigrants. For the first generation, the raw wage differential amounts to approximately 17 log points. The raw wage differential for the immigrants of the second generation is considerably smaller (males 2, females 11 log points). First generation immigrants are endowed with less human capital (schooling, tenure). These differences explain approximately one quarter of the raw wage differential of males, for females the share is only one tenth. Differences in occupation and in particular job position are even more important as human capital variables. According to specification II, the unexplained part of the wage gap falls to 3.5 (males) and 5.3 log points (females), respectively.

For male immigrants of second generation, we only find a very small raw wage differential, which is not statistically significant. This small gap can be explained by the less favourable human capital endowment. Overall, there is no evidence for discrimination of male immigrants of second generation. The situation for female immigrants of second generation is different: their raw wage gap amounts to 10.6 log points. Approximately, one half of the raw wage differential can be explained by differences in human capital endowment (schooling, experience). Controlling for occupation and job position reduces the unexplained wage gap to 2.4 log points. Note that the discrimination component is not statistically significant, which may also be due to the small sample size for migrants. The very low returns to experience for female second generation immigrants are striking.

A comparison of the returns to schooling between the first and second generation is interesting. The returns are comparatively low for the first generation immigrants. In contrast, male second generation immigrants earn the same returns as natives. The returns among women of the second generation remain slightly behind natives. This evidence indicates problems in the transferability of human capital which was acquired abroad.

Looking at migrants at large may conceal specific disadvantages for certain nationalities. We define four country groups with respect to nationality to obtain a minimum number of employees for each country group.[8] (Former) Yugoslavia (Y) and Turkey (T) are the traditional ‘guest worker’ countries for Austria. Then, we consider migrants from the European Union (EU). All other migrants form the ‘Other country group’ (OC). We find considerable wage differences compared with natives with respect to these four groups. The highest raw wage differentials for females are found for migrants from Turkey (34 percentage points), followed by workers from Yugoslavia (28), and from OC (17). For males, the raw wage differentials for OC (23), Turkey (21) and Yugoslavia (19) are relatively similar. The raw wage differential is much smaller for migrants from the European Union (3 percentage points for males and females). We also find considerable differences in education and job position between country groups. The education level is relatively low for workers from Turkey and Yugoslavia. Especially, workers from Turkey hold the lowest job positions. These differences drive our results with respect to discrimination. According to specification I, we find the largest discrimination component for OC migrants (21 and 15 percentage points for females and males, respectively) and for migrants from (former) Yugoslavia (17 and 11 percentage points). For workers from Turkey, the discrimination components amount to 13 and 10 percentage points, respectively. By far the lowest discrimination is found for migrants from countries of the European Union (6 and 3 percentage points). In line with our previous results, controlling for occupation and job position reduces the discrimination component considerably. We find a sizeable discrimination component only for migrants from OC (8 percentage points for females and 5, but insignificant, for males) and for migrants from Yugoslavia (4 percentage points).

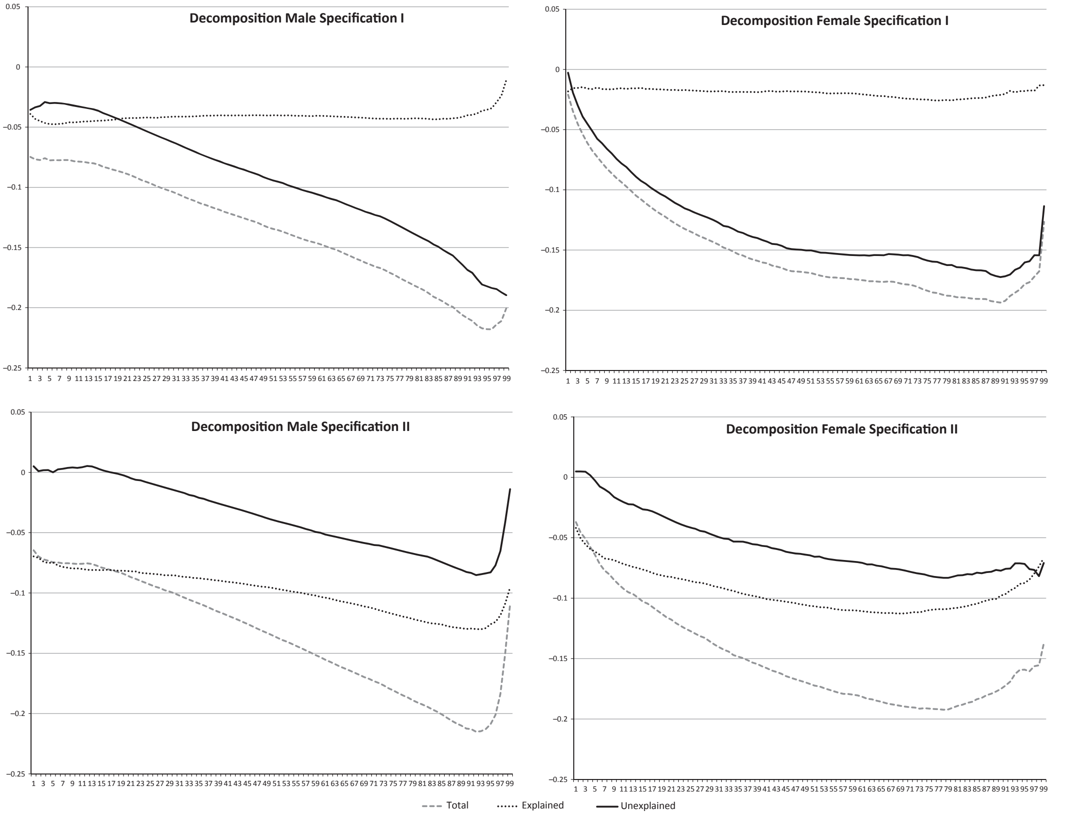
4.2 Decompositions for the entire wage distribution

The Oaxaca-Blinder approach splits up the wage gap at the average level. As unequal treatment may happen differently at different job or wage levels, we now turn to decompositions along the entire wage distribution using quantile regressions. We use net hourly wages as dependent variable and restrict the estimation period to 2009 and 2010. Due to the small number of cases, a splitting up of the group of immigrants into first and second generation is not possible.

Figure 1 shows the decomposition of wage differentials measured in log points, whereas Figure 2 concentrates on the discrimination components only. The discrimination component is shown here as share of total wage differential at the respective quantile of the distribution. Ninety-nine quantile regressions were estimated, separately for each quantile of the wage distribution. It turns out that the wage disadvantage of immigrants increases with the wage level (see the graph 'total' in Figure 1).[9] At the bottom of the wage distribution, it amounts to 8 log points for males and then rises steadily to almost 22 log points. Only in the top decile, it falls slightly. The increase in the wage gap is even steeper for females. For the 25th percentile, it amounts to 13 log points and then rises up to 19 percentage points for the 90th percentile. In the highest income range, the wage gap is slightly smaller. Overall, we find a considerable wage disadvantage for immigrants, in particular in the middle and upper part of the wage distribution.

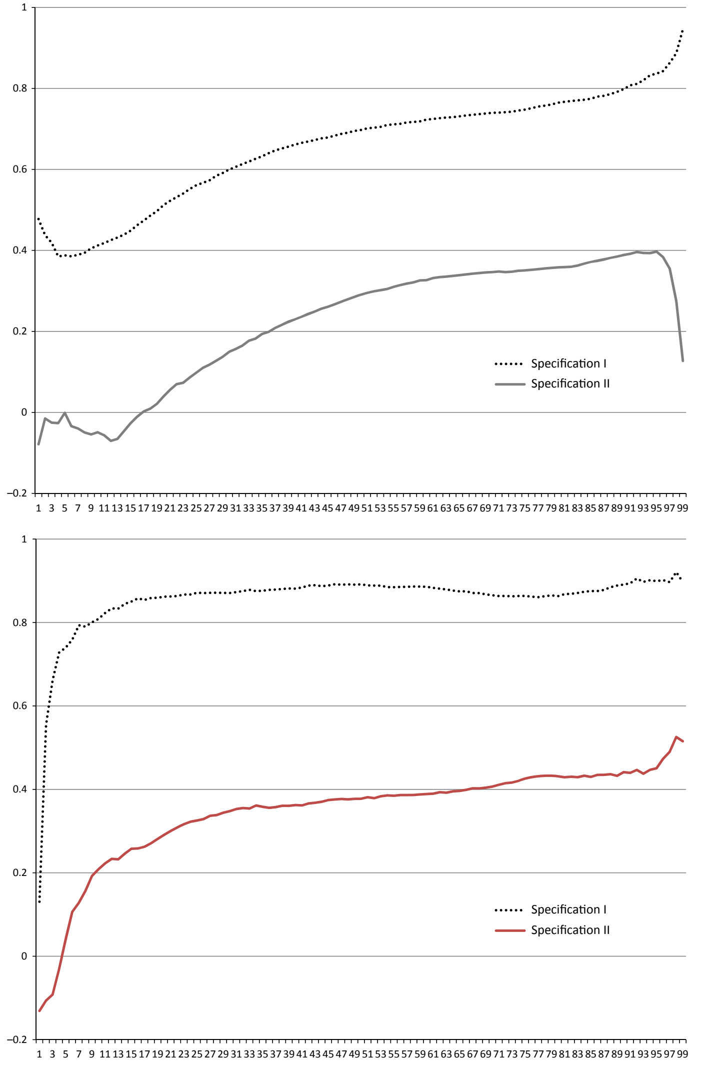
For men, the discrimination component increases with income (see Figure 2). Accordingly, 40 per cent of the wage gap can be explained by productivity-related characteristics at the 10th percentile of the wage distribution (specification I). The discrimination share climbs up to around 90 per cent at the 90th percentile. In the top decile, the endowment

Figure 1. Decomposition of the wage differential



Note: Foreign-native wage differential in percentage points is on the *Y* axes. Decompositions are shown along the earnings quintiles — using male or female coefficients for the decomposition and using specification I or II.

Figure 2. Discrimination component. (a) Decomposition of the wage differentials for men: share discrimination component. (b) Decomposition of the wage differentials for women: share discrimination component



Note: The share of discrimination in terms of the total foreign-native wage differential is shown on the *Y* axes — using specifications I and II for the wage equations.

differences in the productivity-related characteristics are smaller, so that almost the total wage differential must be attributed to discrimination. According to specification II, no discrimination can be found at the bottom of the wage distribution (up to the 20th percentile), then the discrimination proportion rises to 40 per cent (95th percentile). This increase in discrimination is much lower in specification II, which is possibly due to the generically lower amount of discrimination there. The situation is similar for females. To what extent could this measured discrimination pattern be biased because of some discrimination in the 'choice' of industry, occupation or job position? Pre-wage discrimination could, in principle, explain this pattern, if discrimination in job access, promotion, etc. is more prevalent in higher wage jobs. While this may seem a reasonable assumption, there are no empirical studies on this for Austria.

For females, we find a somewhat different picture (specification I). Only at the very bottom of the wage distribution, the unexplained wage gap is small, but then it rises steeply and is already around 85 per cent at the 20th percentile. Afterwards, the discrimination share remains constant. Specification II results in a very similar picture, however with a smaller discrimination component. In the lower third of the wage distribution, the discrimination component increases markedly, than it flattens out.

Figure A2 in the appendix presents confidence bands for the discrimination components. As we can see, in specification I there is a significant discrimination component all over the wage distribution. With respect to specification II, the discrimination component is not significant in the bottom two (females) and three (females) deciles.

Overall, the migrant wage gap increases over the wage distribution. However, the unexplained wage gap differs across the wage distribution with respect to gender. For both groups and in the lowest part of the wage distribution, discrimination against immigrants is very low or even absent. For females, the unexplained wage gap increases strongly with the wage. For men, the discrimination component rises continuously but the level remains below that of women until the fourth quintile of the wage distribution.

5 Discussion

Our paper offers a detailed analysis of wage discrimination against immigrants in Austria. We match data from the micro-census with administrative social security records to provide new evidence for Austria. We find a raw wage gap of immigrants of approximately 15 log points. Results from Oaxaca/Blinder decomposition show that 10 to 30 per cent of this wage gap can be explained by differences in endowment of human capital. Controlling for occupation and in particular for job position reduces the discrimination component considerably. In this case, the unexplained part of the wage gap amounts to 3 to 5 log points only. Overall, the unexplained wage gap of immigrants is small, according to the principle `equal pay for equal work′. However, one should note that controlling for occupation and job position is justified only if this selection depends on productivity-relevant characteristics only (e.g., transferability of human capital acquired abroad, language skills). Otherwise, the degree of discrimination is clearly underestimated. Looking across nationalities, it turns out that measured discrimination is largest against migrants from Non-European countries, typically migrants from Africa or Asia.

Overall, our results for Austria are in line with evidence from other European countries, e.g., Germany. Empirical evidence concerning wage gaps between natives and immigrants over the whole range of the wage distribution is very scarce for Austria. Grandner and Gstach (2015) use survey data from a relatively small sample (EU-SILC) and focus on wage differentials between natives and immigrants for the males and females together. They consider very few control variables [gender, industry (manufacturing, service sector, public sector), education (lower secondary, upper secondary, university degree), work experience (linear, squared), age, firm size (up to 50, at least 50 employees), material status (single, cohabitation), type of contract (temporary, unlimited)]. We extend their analysis in various aspects. We use a comprehensive administrative data with high-quality labour force data. Survey data for wages are always prone to measurement errors. We consider wage differentials between natives and immigrants for males and females separately to avoid problems of mixing gender wage differentials with differentials between natives and immigrants. Neglecting observable differences between natives and foreigners with respect to human capital and job characteristics could bias discrimination results.

We find a lower raw wage differential for Austria as Grandner and Gstach (2015), in particular in the lower part of the income distribution. According to our results, wage discrimination against immigrants is somewhat lower, in particular when we control for job characteristics. In accordance with Grandner and Gstach (2015), we find stronger discrimination in the upper part of the wage distribution. The difference in the results may be due to different indicators for wages and in particular to our extended set of control variables.

While our data are so far the best available in Austria for such a purpose, some caveats remain: We have no information on language skills which could be an important factor for the success on the labour market.

In our view, the most remarkable fact is the almost-absence of measured discrimination in terms of 'equal pay for equal work'. With the exception of migrants from Non-European countries, migrants get the same wage as native born workers, once they occupy the same jobs. This conclusion remains valid, even if one calls a fair allocation of these jobs into question. This observation is the more remarkable, as we only control for simple occupation dummies and job hierarchy levels. This finding contrasts strongly with evidence for women in Austria (Böheim *et al.*, 2013) where unequal treatment remains in — seemingly — equal jobs. On the other hand, this observation and the observation of large general wage differentials between natives and migrants point towards the importance of access to jobs, the self-selection into particular jobs and the possibilities of professional advancement. Future studies should take these issues — in the form of correspondence testing (Weichselbaumer, 2013) or other panel-approaches — into account.

Notes

[1] information on country of birth (parents) is available only since 2008.

[2] See Butcher and Card (1991) for an early reference on the impact of migration on wages.

[3] See Weichselbaumer and Winter-Ebmer (2005) for the rhetoric in the use of 'discrimination' or 'unexplained residual' in gender research.

[4] Due to the relatively small number of immigrants, it is less sensible to assume the foreigner's wage structure to be the non-discriminatory one; therefore, the usual index number problem in decomposition analysis does not apply here.

[5] Only in the highest 1 per cent of income, the actual values are replaced by the median of these groups (Baierl *et al.*, 2011).

[6] Following Böheim *et al.* (2013), this limitation was used to eliminate short-term employment or seasonal employment episodes. Foreigners are found with a higher probability in less stable or in seasonal jobs. We redid the analysis with a minimum employment period of 60 days: approximately the same results arise.

[7] In the following section, we use net hourly wage as income variables, which is not available in 2008. We estimate the Oaxaca-Blinder decomposition for the net hourly wage and find qualitatively very similar results. The raw wage differential for males (females) amounts to 14.4 (16.8) log points. We find a discrimination component of 8.7 (12.0) and 2.7 (3.9) log points, respectively. Detailed results are available upon request.

[8] For this analysis, we use data from 2006 to 2010 and define migration status by citizenship ('Staatsbürgerschaft').

[9] At the edge of the distribution (at the 1st, 2nd, or at the 98th, 99th percentile), the results should not be interpreted, because typically there is only a low number of observations.

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Appendix

Table A1. Wage equation men and women: natives versus immigrants, specification I

	Men		Women	
	Natives	**Immigrants**	**Natives**	**Immigrants**
Education	0.05414	0.04572	0.06728	0.05218
	(42.41)	*(17.63)*	*(37.62)*	*(13.96)*
Tenure	0.00661	0.01167	0.00659	0.00956
	(7.68)	*(4.74)*	*(4.68)*	*(2.57)*
Tenure^2	0.00001	−0.00009	0.00007	0.00002
	(0.56)	*(1.03)*	*(1.55)*	*(0.19)*
Experience	0.01588	0.01143	0.01872	0.00542
	(14.01)	*(3.99)*	*(12.72)*	*(1.44)*
Experience^2	−0.00030	−0.00032	−0.00037	−0.00017
	(11.03)	*(4.74)*	*(10.02)*	*(1.90)*
Employment in Austria (5 years)	0.27396	0.18850	0.22563	0.09942
	(15.76)	*(5.54)*	*(10.77)*	*(2.24)*
Single	−0.04594	−0.00356	0.00393	0.03131
	(7.38)	*(0.19)*	*(0.54)*	*(1.60)*
Firm size (Reference group: 0–9)				
10–19	0.04341	0.03353	0.07920	0.01813
	(4.41)	*(1.37)*	*(5.63)*	*(0.45)*
20–49	0.06868	0.03426	0.09196	0.02204
	(8.27)	*(1.61)*	*(7.51)*	*(0.68)*
50–499	0.12060	0.08934	0.12824	0.04526
	(17.30)	*(4.90)*	*(13.24)*	*(1.67)*

Table A1. Continued

500+	0.17347	0.12141	0.15717	0.11071
	(22.44)	*(5.99)*	*(15.03)*	*(3.87)*
City size (Reference: 0–10,000 inh.)				
10,001–100,000	0.00488	−0.00622	0.00685	0.03591
	(0.75)	*(0.44)*	*(0.71)*	*(1.53)*
100.000 +	0.00087	−0.04191	0.02012	−0.00688
	(0.11)	*(2.65)*	*(1.96)*	*(0.28)*
Fed. state (Reference: Burgenland)				
Carinthia	0.04491	0.02498	0.00786	0.04371
	(3.58)	*(0.54)*	*(0.44)*	*(0.68)*
Lower Austria	0.05664	0.04301	0.05920	0.10444
	(4.64)	*(1.00)*	*(3.43)*	*(1.76)*
Upper Austria	0.09363	0.07282	0.05379	0.09711
	(7.94)	*(1.70)*	*(3.14)*	*(1.68)*
Salzburg	0.08832	0.05653	0.07420	0.11297
	(7.15)	*(1.31)*	*(4.27)*	*(1.95)*
Styria	0.04886	0.03274	0.01198	0.09672
	(4.07)	*(0.71)*	*(0.71)*	*(1.49)*
Tyrol	0.06470	0.06337	0.07012	0.13454
	(5.30)	*(1.47)*	*(4.04)*	*(2.32)*
Vorarlberg	0.17770	0.14051	0.12591	0.17796
	(13.91)	*(3.32)*	*(6.87)*	*(3.12)*
Vienna	0.11074	0.07329	0.13770	0.15822
	(8.74)	*(1.69)*	*(7.92)*	*(2.74)*
Number of children (Reference: zero)				
1 child	−0.00757	−0.00824	−0.02336	−0.05371
	(1.23)	*(0.48)*	*(2.85)*	*(2.49)*
2 children	0.00748	0.00011	−0.04012	−0.07486
	(1.16)	*(0.01)*	*(4.11)*	*(3.32)*
3 children +	−0.00990	−0.04431	−0.04810	−0.10883
	(1.12)	*(2.32)*	*(3.10)*	*(3.38)*
Constant	1.10463	1.32826	0.81913	1.14359
	(45.00)	*(21.79)*	*(24.08)*	*(12.94)*
Adjusted R^2	0.3617	0.2924	0.42650	0.30330
	11,140	1,869	5,113	913

Note: Dependent variable: gross hourly wage (log, italic numbers in brackets *t-statistics).*

Table A2. Wage equation: natives versus immigrants, specification II

	Men		Women	
	Natives	**Immigrants**	**Natives**	**Immigrants**
Education	0.02553	0.01358	0.03522	0.01957
	(16.02)	*(4.46)*	*(17.01)*	*(4.94)*
Tenure	0.00607	0.01023	0.00520	0.00700
	(7.77)	*(4.66)*	*(4.17)*	*(2.21)*
Tenure^2	−0.00003	−0.00011	0.00005	0.00003
	(1.12)	*(1.34)*	*(1.29)*	*(0.31)*
Experience	0.01495	0.01206	0.01743	0.01473
	(14.43)	*(4.72)*	*(13.28)*	*(4.49)*
Experience^2	−0.00025	−0.00029	−0.00031	−0.00032
	(10.25)	*(4.96)*	*(9.67)*	*(4.32)*
Employment in Austria (5 years)	0.24261	0.14989	0.19260	0.05560
	(15.26)	*(4.92)*	*(10.33)*	*(1.45)*
Single	−0.03492	−0.00256	0.01203	0.02450
	(6.18)	*(0.16)*	*(1.86)*	*(1.47)*
White-collar worker	0.08140	0.03687	0.06313	0.04269
	(12.35)	*(2.16)*	*(4.93)*	*(1.49)*
Number of children (Reference: zero)				
1 child	−0.00471	−0.00859	−0.02005	−0.05827
	(0.85)	*(0.56)*	*(2.76)*	*(3.15)*
2 children	0.00981	0.00917	−0.03438	−0.04816
	(1.68)	*(0.62)*	*(3.97)*	*(2.50)*
3 children +	0.00246	−0.02810	−0.04515	−0.06661
	(0.31)	*(1.65)*	*(3.27)*	*(2.41)*
Firm size (Reference: 0–9)				
10–19	0.04408	0.05160	0.05748	0.02728
	(4.94)	*(2.38)*	*(4.59)*	*(0.80)*
20–49	0.06918	0.05024	0.07558	0.02590
	(9.17)	*(2.66)*	*(6.92)*	*(0.92)*
50–499	0.11542	0.08954	0.11278	0.00522
	(18.01)	*(5.47)*	*(12.74)*	*(0.22)*
500+	0.16940	0.11799	0.13957	0.04652
	(23.51)	*(6.39)*	*(14.36)*	*(1.81)*
City size (Reference: 0–10,000 inh.)				
10,001–100,000	−0.00318	−0.00299	−0.01108	0.03646
	(0.54)	*(0.24)*	*(1.29)*	*(1.82)*
100,000 +	−0.00314	−0.02656	0.01118	0.00090
	(0.45)	*(1.88)*	*(1.23)*	*(0.04)*
Fed. state (Reference: Burgenland)				
Carinthia	0.03742	−0.00229	0.00678	0.04640
	(3.29)	*(0.06)*	*(0.43)*	*(0.84)*
Lower Austria	0.04508	0.01383	0.03835	0.06342
	(4.07)	*(0.36)*	*(2.51)*	*(1.25)*
Upper Austria	0.07315	0.03924	0.04423	0.07671
	(6.82)	*(1.03)*	*(2.91)*	*(1.55)*
Salzburg	0.06212	0.04863	0.04263	0.12149
	(5.53)	*(1.27)*	*(2.76)*	*(2.45)*
Styria	0.03822	0.00542	0.00991	0.08237
	(3.50)	*(0.13)*	*(0.66)*	*(1.47)*
Tyrol	0.05529	0.04758	0.06286	0.13941
	(4.99)	*(1.25)*	*(4.09)*	*(2.80)*

Table A2. Continued

Vorarlberg	0.12668	0.09671	0.09975	0.12287
	(10.88)	*(2.57)*	*(6.13)*	*(2.51)*
Vienna	0.08052	0.05017	0.09367	0.13627
	(6.99)	*(1.30)*	*(6.05)*	*(2.76)*
Industry (Ref.: Primary production[a])				
Manufacturing	−0.03934	0.05116	−0.00927	−0.17417
	(3.28)	*(1.27)*	*(0.35)*	*(2.49)*
Construction	−0.05075	0.03412	0.01345	−0.15780
	(3.96)	*(0.83)*	*(0.44)*	*(1.63)*
Trade	−0.12675	−0.02020	−0.09150	−0.27534
	(10.07)	*(0.49)*	*(3.50)*	*(3.90)*
Tourism	−0.22954	−0.19078	−0.15895	−0.39809
	(10.85)	*(4.00)*	*(5.54)*	*(5.58)*
Business services	−0.10755	−0.01502	−0.01729	−0.27059
	(8.65)	*(0.37)*	*(0.66)*	*(3.81)*
Public services	−0.17216	−0.03301	−0.05689	−0.20884
	(12.81)	*(0.73)*	*(2.18)*	*(2.94)*
Other services	−0.12201	−0.10399	−0.09764	−0.31609
	(7.65)	*(2.11)*	*(3.43)*	*(4.21)*
Occupation (Reference: Managers)				
Professionals	0.01049	0.02440	−0.02454	−0.09519
	(0.93)	*(0.73)*	*(1.23)*	*(1.88)*
Technicians	−0.01054	−0.02839	−0.01826	−0.09541
	(1.26)	*(0.97)*	*(1.16)*	*(2.36)*
Clerks	−0.03647	−0.06242	−0.03716	−0.11518
	(3.58)	*(1.72)*	*(2.33)*	*(2.73)*
Service workers	−0.13618	−0.17061	−0.15395	−0.25005
	(10.44)	*(4.52)*	*(9.13)*	*(6.00)*
Agricultural workers	−0.20143	−0.11444	−0.21728	−0.57883
	(7.81)	*(1.56)*	*(5.52)*	*(4.32)*
Craft	−0.05788	−0.07156	−0.17320	−0.24624
	(5.93)	*(2.21)*	*(6.73)*	*(4.48)*
Operators	−0.10047	−0.09245	−0.09841	−0.15717
	(8.95)	*(2.75)*	*(3.56)*	*(3.05)*
Elementary occupations	−0.09745	−0.08751	−0.12981	−0.20684
	(7.82)	*(2.63)*	*(5.96)*	*(4.70)*
Job position (Ref.:Un-skilled)				
Low-skilled	0.04218	0.05306	0.04762	0.05859
	(3.21)	*(3.57)*	*(2.80)*	*(2.76)*
Medium-skilled	0.10797	0.11341	0.12726	0.13085
	(7.89)	*(6.17)*	*(6.97)*	*(4.04)*
High-skilled	0.17371	0.24236	0.20058	0.21630
	(11.71)	*(8.59)*	*(10.12)*	*(4.99)*
Advanced/leading	0.17971	0.27524	0.25385	0.25491
	(11.60)	*(8.99)*	*(12.16)*	*(5.75)*
Constant	1.46964	1.68554	1.21028	1.81860
	(45.29)	*(21.67)*	*(24.73)*	*(15.85)*
Adjusted R^2	0.47710	0.44850	0.55250	0.50550
N	11,137	1,867	5,110	913

Note: Dependent variable: gross hourly wage (log), italic numbers in brackets: *t-statistics*.
[a]Primary production = agriculture, forestry, mining and the energy sector.

Figure A1. Share of migrants in the wage distribution

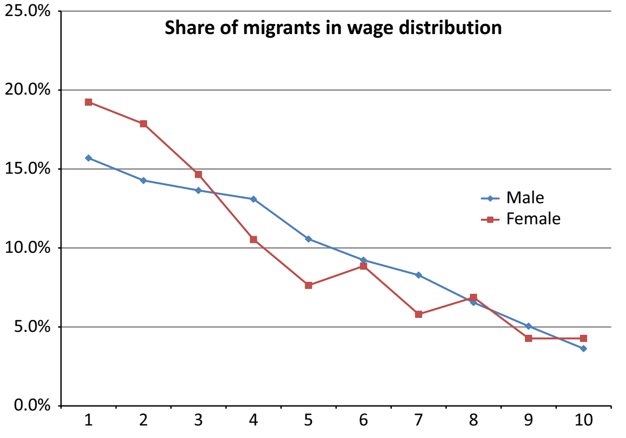

Figure A2. Statistical significance of discrimination components
Note: Foreign-native wage differential in percentage points is on the *Y* axes.