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Endowment or Discrimination? An Analysis of Immigrant–Native Earnings Differentials in Switzerland

by

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Endowment or Discrimination? An Analysis of Immigrant–Native Earnings Differentials in Switzerland*

Abstract:

Recent studies have shown that there are significant earnings differentials between immigrants and natives in Switzerland. The goal of this paper is to determine whether these differences can be attributed to diverging socio-economic endowments or to discrimination. We use the well-known econometric technique, developed by Oaxaca (1973) and Blinder (1973), to determine the extent of discrimination. As data on earnings are available only for employed, we adopt a two-stage Heckman procedure to correct for sample-selection bias. Our analysis is based on data from the 1995 wave of the Swiss Labor Force Survey (SLFS). The decomposition of the earnings differential reveals that the discrimination effect plays a more important role in the explanation of the earnings differential than the endowment effect.

Keywords: International Migration, Wage Differentials, Immigrant Workers, Discrimination

JEL classification: F22, J31, J61, J71

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I. Introduction

Over the past 50 years, Switzerland has experienced a substantial inflow of immigrants. Since World War II, the share of foreigners has nearly quadrupled from a mere 5 per cent to almost 20 per cent in 1998. These figures indicate that Switzerland, together with Luxembourg and Australia, has by far the highest share of foreigners in total population among all OECD countries. Issues related to the performance of immigrant workers are therefore interesting not only from an economic, but also from a political point of view.

It is interesting to note that while there are a number of studies focusing on the gender earnings gap for Switzerland (see Kugler 1988, Bonjour 1997, Bonjour and Gerfin 1995, and Diekman and Engelhardt 1995), research on immigrant-native earnings differentials has by and large been neglected, despite the existence of their significance (see Golder and Straubhaar 1998, and Maechler 1993).

The main focus of the present paper is to determine whether these differences can be attributed to diverging individual socio-economic profiles between immigrants and natives or to discrimination. As a starting point, we use a Mincer type earnings function, where logarithmic earnings are linearly related to a number of explanatory variables. A problem involved in this kind of analysis relates to the possibility of a sample-selection bias, which implies that the data used do not constitute a stochastic sample of the total population, as earnings data are only available for employed. To correct for the employment decision, we adopt a two-stage Heckman procedure.

Our analysis of earnings differentials is based on the assumption that in the absence of discrimination, the estimated effects of workers endowments on earnings are identical for immigrants and natives. Discrimination is therefore revealed by differences in the estimated coefficients. To measure the extent of discrimination, we adopt the commonly used earnings difference decomposition approach developed by Oaxaca (1973) and Blinder (1973). This procedure allows a decomposition of the average difference in earnings between immigrants and natives into an endowment and a discrimination component.

The organization of the paper is as follows. In Section II, we provide the theoretical background for the subsequent econometric analysis. The empirical specification for our analysis is discussed in Section III. In Section IV, we present our estimation results and the earnings differential decomposition. In Section V, we finish with some concluding remarks.

II. Theoretical background

In this section we present the theoretical framework used for the analysis of the immigrant-native earnings differentials. Earnings differentials between immigrants and natives can either be attributed to differences in human capital endowments or differences in the rewards to human capital. Following standard human capital theory, the performance of an individual in the labor market is largely dependent on his or her endowment of human capital (see Becker, 1975). Based on the assumption that workers are paid according to their marginal product, differences in socio-economic profiles should explain most of the variation in earnings across people. Nevertheless, earnings differentials between gender and/or nationality can also be due to discrimination, i.e. differences in the rewards for the same endowment. In general, the residual, i.e. the part of the earnings differential that cannot be explained by endowment differences, is used as a proxy for the extent of earnings discrimination.

For a number of reasons it is not unproblematic, however, to equalize this unexplained part of the earnings differential with discrimination. *First*, productivity cannot be fully measured by endowment characteristics, which implies that an under- or overestimation of the discrimination component can occur. *Second*, endowment differences can at least in part be due to pre-market discrimination, e.g. parents promoting more strongly the education of sons than of daughters. *Third*, earnings discrimination is only one possible form of discrimination. Aside from earnings discrimination labor market segmentation is another possible source of discrimination. Despite these problems, analyses that decompose earnings differentials into endowment and discrimination components are important from an academic as well as from an economic policy point of view.

The analysis of earnings discrimination is usually based on the methodology developed by Blinder (1973) and Oaxaca (1973). The absolute earnings difference between two groups, a non-discriminated and a discriminated group, in our case natives and immigrants, is decomposed into a discrimination and an endowment component. As a starting point for the analysis, we use a Mincer type earnings function, which is estimated for the pooled sample of immigrants and natives. The coefficients serve as a basis for the simulation of the labor market outcome, with the extent of discrimination being calculated from the difference in the predicted values of the explanatory variables for the two groups of natives and foreigners. The exogenous variables are valued at their respective mean values (or in case of dummy variables, the respective shares in the sample). These values are then weighted with the estimated coefficients of the earnings function to calculate the projected (logarithmic) earnings.

As earnings data are available only for employed, we augment the earnings function by a model for the earnings probability, to avoid biased estimations of the regression coefficients as a result of a sample-selection bias. A selection bias can be expected, if unobserved characteristics that have an influence on the employment probability are correlated with the level of market earnings. Following Heckman (1974, 1976, 1979), the influence of the employment decision is usually accounted for with the inclusion of a selection correction variable λ, the so called Heckman-correction. While λ could be incorporated as an additional regressor in the earnings function, as suggested by Dolton and Makepeace (1986), this approach neglects that diverging coefficient values for immigrants and natives do not reveal earnings discrimination but rather differences in preferences. An alternative approach, devised by Reimers (1983), which is used in this paper, suggests that average immigrant and native earnings levels should be corrected with the average selection bias.

As the value of λ decreases with increasing employment probability, the selection correction variable is important mainly for individuals with a relatively low employment probability. The coefficient of λ in the earnings regressions indicates the direction of the selection bias. If the coefficient is negative, the observed earnings imply an underestimation of the potential market based earnings and vice versa.

Despite its advantages in the analysis of earnings differentials, there are a number of shortcomings involved in the use of the Heckman-correction that have to be borne in mind. In a recent survey, Puhani (1997:13) concludes that theoretical considerations as well as the results of various Monte Carlo studies "... cast doubt on the omnipotence implicitly ascribed by many applied researchers to Heckman's (1976, 1979) two-step estimator". One of the main criticisms is related to multicollinearity between the variables of the two regression equations that can lead to inefficient estimators. As emphasized by Puhani, the use of the Heckit-procedure is most needed when there is a high correlation between the error term of the selection and the main equation, and when there is a high degree of censoring in the data. Exactly in these cases, however, the Heckman-estimator is especially inefficient, and ML-estimations allow more robust estimations.

After the discussion of the earnings function and the Heckman-correction, we now turn to the earnings difference decomposition approach, as outlined by Oaxaca (1973) and Blinder (1973). In a first step, the earnings functions for immigrants and natives are estimated separately. The two equations can be written as follows:

$$\ln Y_{ni} = X_{ni}\beta_{ni} + \lambda_{ni}\gamma_{ni} + \varepsilon_{ni} \tag{1}$$

$$\ln Y_{fi} = X_{fi}\beta_{fi} + \lambda_{fi}\gamma_{fi} + Z_{fi}\alpha_{fi} + \varepsilon_{fi} \tag{2}$$

with *ni = native male (nm) and female (nf)*

fi = foreign male (fm) and female (ff)

with β_{ni} and β_{fi} representing the respective coefficient vectors that are identical for immigrants and natives. α_{fi} corresponds to the coefficient vector for the immigrant specific variables and γ_{ni} and γ_{fi} respectively stand for the coefficients of the selection correction variables. As we use OLS to estimate these coefficients, the estimated regression line passes through the mean values. Equation (1) and (2) can therefore be rewritten as follows:

$$\ln \overline{Y}_{ni} = \overline{X}_{ni}\hat{\beta}_{ni} + \overline{\lambda}_{ni}\hat{\gamma}_{ni} \tag{3}$$

$$\ln \overline{Y}_{fi} = \overline{X}_{fi}\hat{\beta}_{fi} + \overline{\lambda}_{fi}\hat{\gamma}_{fi} + \overline{Z}_{fi}\hat{\alpha}_{fi}, \tag{4}$$

with $\hat{\beta}_{ni}$, $\hat{\beta}_{fi}$, $\hat{\alpha}_{fi}$, $\hat{\gamma}_{ni}$, and $\hat{\gamma}_{fi}$ representing the vectors of the estimated OLS-coefficients. The difference in the mean values of the logarithmic earnings between the two groups can then be written as follows

$$\ln \overline{Y}_{ni} - \ln \overline{Y}_{fi} = \left(\overline{X}_{ni}\hat{\beta}_{ni} - \overline{X}_{fi}\hat{\beta}_{fi}\right) + \left(\overline{\lambda}_{ni}\hat{\gamma}_{ni} - \overline{\lambda}_{fi}\hat{\gamma}_{fi}\right) - \overline{Z}_{fi}\hat{\alpha}_{fi}\,. \tag{5}$$

If we define the difference in the coefficient vectors for non-immigrant specific variables as follows

$$\Delta\hat{\beta} = \hat{\beta}_n - \hat{\beta}_f \text{, so that } \hat{\beta}_f = \hat{\beta}_n - \Delta\hat{\beta}, \tag{6}$$

then by substituting in (5) and some rearrangements, we get

$$\begin{aligned}\ln \overline{Y}_{ni} - \ln \overline{Y}_{fi} = \left(\hat{\beta}_{0ni} - \hat{\beta}_{0fi}\right) + \sum \left\{\overline{X}_{fi}\left(\hat{\beta}_{ni} - \hat{\beta}_{fi}\right)\right\} - \overline{Z}_{fi}\hat{\alpha}_{fi} \\ + \sum \left\{\hat{\beta}_{ni}\left(\overline{X}_{ni} - \overline{X}_{fi}\right)\right\} + \left(\overline{\lambda}_{ni}\hat{\gamma}_{ni} - \overline{\lambda}_{fi}\hat{\gamma}_{fi}\right)\end{aligned} . \qquad (7)$$

Based on (7), the earnings differential between immigrants and natives can be decomposed as follows.[1] The first decomposition component, the so called group effect, is given by the difference of the constant terms, the share of the earnings differential that is due to diverging coefficients, and the immigrant specific variables. Based on the seminal contribution by Becker (1971), we assume that prejudices by a majority group, in our case natives, vis-à-vis immigrants, lead to a loss in utility for the former, which have to be compensated by wage reductions for the latter. In the terminology of Blinder, this group effect is equal to the hypothetical earnings increase that immigrants could achieve, if they would exhibit the same earnings structure as natives, ceteris paribus. The group effect can thus be interpreted as the discrimination effect which indicates the share of the earnings differential that is due to discrimination.

The endowment effect is composed of the last two terms in (7). The first part reflects the hypothetical additional earnings immigrants could achieve, if they had identical endowments as natives. The second part comprises the sample-selection bias correction variable. This component is included in the endowment effect as we assume that the participation decision of employable males and females is voluntary and unrestricted. If we would, instead, assume that males and females willing to work would be restricted in their participation decision by discriminating employers, we would have to include this component in the discrimination effect.

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1 As the decomposition of the earnings differential is based on logarithmic and not absolute earnings, by taking antilogs, we get geometric mean values. The earnings differential is thus decomposed for the geometric mean values. The endowment and the discrimination effect can then approximately be interpreted as the percentage increase or decrease in the geometric group mean values. In case of larger logarithmic differences, however, this leads only to a rough approximation.

As can be seen from (7), endowment differences are weighted with the estimated coefficients of the non-discriminated group, while the difference in the estimated coefficients is weighted with the average characteristics of the discriminated group. If we would alternatively substitute for $\hat{\beta}_n$, and not for $\hat{\beta}_f$ in (5), we would get the following alternative formulation of the earnings difference decomposition after some rearrangements

$$\begin{aligned}\ln \overline{Y}_{ni} - \ln \overline{Y}_{fi} &= \left(\hat{\beta}_{0ni} - \hat{\beta}_{0fi}\right) + \sum \left\{\overline{X}_{ni}\left(\hat{\beta}_{ni} - \hat{\beta}_{fi}\right)\right\} - \overline{Z}_{fi}\hat{\alpha}_{fi} \\ &+ \sum \left\{\hat{\beta}_{fi}\left(\overline{X}_{ni} - \overline{X}_{fi}\right)\right\} + \left(\overline{\lambda}_{ni}\hat{\gamma}_{ni} - \overline{\lambda}_{fi}\hat{\gamma}_{fi}\right)\end{aligned} \quad . \qquad (8)$$

In this case, the average endowment differences are weighted with the estimated coefficients of the discriminated group and the difference in the coefficients is weighted with the average characteristics of the non-discriminated group. The choice between (7) and (8) for the analysis of the extent of earnings discrimination represents a classical index number problem that involves a decision on which weights to employ.[2] In practice, both equations are usually employed, as it is assumed that they bracket the estimated effects of discrimination on earnings.

Before turning to the empirical results, two remarks have to be made. First, we cannot exclude the possibility of an over- or underestimation of the extent of discrimination, as indicated by the unexplained part of the earnings differential. An overestimation occurs if productivity related characteristics are not fully accounted for and the group with lower earnings exhibits a more unfavorable endowment of non-observable characteristics. If this group, in contrast, exhibits a more favorable endowment of non-observable characteristics, then we get an underestimation of the extent of discrimination.

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2 See Berndt (1996).

Second, the model presented here for the analysis of discrimination can be augmented in several ways. First, (7) and (8) could be generalized by the inclusion of weighting factors. By means of a matrix W, we could determine how the differences between the coefficients of the discrimination effect and the mean values of the endowment effects could be weighted.[3] Second, we could use the complete earnings distribution as a basis for the analysis of earnings discrimination, instead of only using the mean earnings differentials.[4]

III. Empirical Methodology and Data

As wage and earnings data are usually characterized by skewed distributions, with median earnings being smaller than mean earnings, we use the natural log of monthly gross earnings as the endogenous variable *(LNINCGM)*. Four remarks have to be made in this context. First, as the Swiss Labor Force Survey (SLFS) is a voluntary sample survey, answers to certain questions can be rejected. As a result, the no-answer rate is rather high for earnings, with almost 20 per cent in the total sample. Second, for those providing information on earnings, these can take the form of hourly, monthly or annual data. To minimize the potential bias arising from recalculations, monthly data are used in our analysis, as almost 90 per cent of all answers are available on a monthly basis. Third, to avoid earnings differences resulting from diverging weekly working hours, only full-time employed persons are considered, i.e. persons with an employment level of 90 to 100 per cent. Finally, we use only information on persons aged 16 to 64, who are working in the civil sector.

The econometric literature on earnings determination is usually based on a semi-logarithmic regression equation of the form

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3 See Blinder (1973), Oaxaca (1973), Reimers (1983) and Velling (1995). Several authors have criticized the exclusion of a weighting matrix (see Cotton, 1988 and Neumark, 1988).

4 Jenkins (1994: 82) argues in this context that the extent of discrimination as measured by the Oaxaca/Blinder decomposition "... may be consistent with very different distributions of discrimination experience".

$$\ln y_i = f(x_i) + u_i \qquad i = 1,\ldots,n \tag{9}$$

with $\ln y_i$ being the natural log of earnings, x_i a number of exogenous, explanatory variables and u_i a stochastic error term, for which the usual assumption $u_i \approx N(0,\sigma^2)$ applies. Following Mincer (1974), we use the educational attainment and years of experience *(EXPE)* as the main explanatory variables. Educational attainment is captured by three dummy variables, with *SCH1* indicating a low, *SCH2* indicating an intermediate, and *SCH3* indicating a high educational level. Experience is calculated as the difference between age, years of schooling and 6.5, which approximates the age of school entry. Following human capital theory, we assume the usual concave shape of earnings over the life cycle. These considerations imply that the earnings function should be expanded by a quadratic term *(EXPSQ)* to account for the decreasing return to labor market experience.

In addition to these individual-specific variables we include the unemployment rates at the state (cantonal) level *(UNPL)* as a macroeconomic indicator for the influence of the prevailing economic conditions on earnings. With regard to the earnings performance of immigrants, we take into account the effect arising from the accumulation of host country specific human capital. This assimilation effect is usually measured by the number of years since migration *(YSM)*. Finally, we include a dummy-variable for immigrants from Northern Europe and other industrial countries *(NTHEU_IC)* and one for immigrants from Southern Europe *(STHEU)*, with immigrants from Non-European countries used as the base category, to account for country-of-origin differences in the earnings performance.

The Heckman-correction proceeds in two steps. First, a probit model is estimated for the employment probability, to calculate the sample-selection variable λ. Second, this variable is used for the correction of the earnings functions. In line with labor market theory, we use the following specification for the probit model. As endogenous variable, we use the employment probability *(EMPL)*, i.e. a dichotomous variable that assumes a value of 1 if the person considered is employed and a value of 0 else.

With respect to the explanatory variables we distinguish two categories of variables. In the first category, variables that determine the market wage are considered, i.e. mainly those variables already included in the earnings function. More specifically, we use schooling *(SCH2, SCH3)* and experience *(EXPE, EXPSQ)*, the state level unemployment rates *(UNPL)*, as well as the immigrant specific nationality group variables *(NTHEU_IC, STHEU)*. The second category comprises those variables that determine the reservation wage. As a first variable, we use the log of monthly household residual earnings *(LN_HHINC)*, which can be derived from the difference of total monthly earnings and monthly gross labor earnings of the target person. Furthermore, we assume that the existence of children bears an influence on the employment probability of the parents. We therefore include three different variables classified by age groups, namely the number of children aged 6 years or less *(KID_6)*, the number of children aged 7 to 14 *(KID7_14)*, and the number of children aged 15 to 25 *(KID15_25)*. As a result of these considerations, the employment decision is assumed to be the result of a comparison between market and reservation wages and not due to discriminatory hiring practices of employers, an issue which is important for the decomposition of the earnings differentials.

Finally, the data used in this paper are taken from the Swiss Labour Force Survey (SLFS), a sample survey which is carried out annually since 1991. The SLFS provides important internationally comparable information on employment in Switzerland. Approximately 18'000 randomly selected persons from the official telephone register are interviewed every year. For the 1995 wave of the SLFS, on which the analysis of this paper is based on, an additional 14'000 persons were interviewed to allow for a more disaggregated analysis. The SLFS comprises a total of 500 questions, with each person asked around 100 questions on labor market related topics as well as on their socio-demographic profiles (e.g. profession, employment status, tenure, job mobility, job search, education, earnings).[5] The survey is restricted to the resident population aged at least 15 years, i.e. Swiss and immigrants holding a residence or an annual permit. To avoid heterogeneity problems, we restrict our analysis to first generation immigrants, i.e. immigrants who were born abroad and at least aged 16 when they came to Switzerland.

IV. Estimation Results

In the context of the empirical analysis of earnings differentials, two principal questions have to be answered. First, how much do immigrants earn compared to natives and are there differences between nationality groups? Second, are these differences due to diverging individual characteristics of immigrants or due to the fact that these individuals are immigrants?

The analysis in this section is based on the Mincer type earnings function as depicted in (9). Before we turn to the estimation results, we provide some descriptive statistics for the variables used in the earnings functions. In Table 1, the descriptive statistics for the Heckman-correction are shown. As can be seen, there are significant nationality and gender specific differences not only in the dependent, but also in the explanatory variables. While there are no significant differences in the employment probability between native and immigrant males, as indicated by the t-test statistics on the equality of means, the opposite holds for native and immigrant females and for gender differences.

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5 For more details see Swiss Federal Statistical Office (1996).

Turning to the descriptive statistics of the earnings function in Table 2, it can be seen that natives on average achieve higher labor earnings compared to immigrants, although there are significant gender specific differences. Natives on average are also better educated than immigrants. Accordingly, work experience is significantly longer for immigrants than for natives. Finally, the test statistics indicate that foreigners are on average living in states with an inferior macroeconomic environment compared to natives. The discussion of the estimation results of earnings function for immigrants and natives proceeds in two steps. In a first step, the results of the ML-estimation for the male and female employment probabilities are displayed. In a second step, the results of the OLS-estimation of the earnings function, augmented by the selection correction variable, are shown. The individual regressions are based on the pooled sample of immigrants and natives, with interaction effects being employed to account for possible differences between immigrants and natives.

In Table 3, the ML-estimation results of the Heckit procedure for the pooled sample of native and immigrant males are shown. As can be seen, the effect of education on the employment probability is only significant for natives. In contrast, the effect of experience on the employment probability has the typically concave shape, with the relationship being less pronounced for natives compared to immigrants. The prevailing economic conditions have a similar and significant influence on the employment probability of natives and immigrants. As regards the determinants of the reservation wage, the negative effect of household residual earnings can be explained by increased opportunity costs of labor on the one hand and reduced search costs on the other hand. The positive sign on the children dummies for natives and immigrants is interesting, especially if compared to the negative sign for females in Table 4, which implies that while the existence of children reduces female employment probability and that of males. These findings therefore provide evidence on the proliferation of traditional household structures. Finally, native males have a significantly lower employment probability than immigrants, with Northern European immigrants having the highest and Non-European immigrants having the lowest employment probability.

Turning to the ML-estimation results for females, Table 4 shows that only in the case of high-skilled natives a significantly positive effect on the employment probability can be observed. This result can be explained by the fact that the positive association between the education level and the employment probability is weakened through a substitution effect arising from the positive relation between education and earnings. The incomplete transferability of human capital could also provide an explanation for the insignificant education variable for immigrant females. With respect to work experience we can again observe a concave employment probability profile. As can be seen from the coefficients of the interacted experience variables, the shape of the curve employment-experience is flatter for native females. Furthermore, the macroeconomic condition indicator variable is only significant for native females, although only at the 10 per cent level for both natives and immigrants.

Turning to the determinants of the reservation wage, we can observe a clear and significant relationship between these variables and the employment probability. The negative effect of household residual earnings can be explained by increased opportunity costs of labor on the one hand and reduced search costs on the other hand. The negative effect of the children dummies, which decreases with the age of the children, can also be attributed to opportunity costs of labor. These effects are significantly stronger for native females. Table 4 also shows that female immigrants from Northern Europe exhibit a significantly lower employment probability compared to female immigrants from Southern and Non-European countries. This result is due to the relatively high share of Northern Europeans that are employed only part-time, a fact that is especially true compared to the base category of Non-Europeans.

After the discussion of the Heckman-correction, the estimation results for the earnings function, including the selection correction variable *(LAMBDA)* are shown in Table 5. The comparison between the male and female earnings function reveals a close qualitative correspondence in the estimated coefficients. The major divergence is given by the opposite effect of the macroeconomic conditions on earnings. An interesting variable in Table 5 is the selection correction variable. As can be seen, the effect is significantly negative for males as well as for females. Based on the above considerations, we can therefore conclude that the error term of the market and the reservation wage equations are positively correlated. This implies that, based on the assumption of identical observable characteristics, individuals with higher potential earnings exhibit a higher reservation wage and are accordingly rather underrepresented in the labor market. Therefore, the observable earnings of those being employed underestimate the earnings of those being employable.

After the derivation of the regression coefficients in the earnings functions we now turn to the discussion of the results on the earnings difference decomposition displayed in Table 6 and 7. In both tables the results of (7) and (8) are displayed. Three main results can be derived from the earnings difference decomposition for immigrant and native males in Table 6. First, the discrimination effect bears a larger weight than the endowment effect in the explanation of the 15.5 per cent earnings differential. If the constant would be neglected, the regression would imply an even larger earnings differential in favor of natives.

Second, the earnings differential between native and immigrant males is driven by the individual-specific variables. The large discrimination effect implies that the rate of return on education and experience is lower for immigrants than for natives. This result can, however, also be attributed to the incomplete transferability of human capital and experience acquired in the home country.

Third, turning to the effects of the immigrant specific variables, it can be seen that they contribute to the reduction of the discrimination effect, as all three effects have a negative sign. The signs of the two dummy variables for the nationality groups, however, hinge on the selection of the reference group.[6] If Northern European immigrants would have been used as the base category instead of Non-Europeans, the signs for the two dummy variables would have been positive. The sample-selection correction variable shows that there is a positive endowment effect in favor of immigrant females.

Table 7 shows the decomposition of the 13.2 per cent earnings advantage of native females over immigrant females. An interesting result is that, ignoring the constant, the regression actually accounts for only a slight 2 per cent differential in favor of immigrant females. This implies that if immigrant females would keep their characteristics, and given the same earnings equation with the shift coefficient of native females, they would earn only 2 per cent less than natives. As a result of its magnitude, the shift coefficient bears a large impact on the discrimination effect. Foremost among the factors contributing to the native earnings advantage is education. The breakdown shows that this effect can be attributed to the higher rates of return that are realized by natives rather than to higher levels of education. Experience as a second important factor shows that while the endowment effect clearly favors immigrants, natives again achieve higher returns on a given level of experience. As regards the immigrant specific variables, while being Northern European reduces the earnings differential, being Southern European increases the earnings gap. The duration

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6 See Oaxaca and Ransom (1997) and Nielsen (1998).

of stay also reduces the earnings gap slightly. Finally, the sample-selection correction variable shows that there is a small positive endowment effect in favor of immigrant females.

V. Concluding Remarks

The aim of this paper was to analyze whether earnings differentials between immigrants and natives are due to differences in endowments or to discrimination. Following the approach developed by Blinder (1973) and Oaxaca (1973), we decompose the earnings differential between immigrant and natives into an endowment and a discrimination component. The procedure is as follows. In a first step, we estimate separate earnings regressions for the two groups by gender. To correct for sample-selection bias, arising from the endogeneity of the employment decision, we use a two-stage Heckman procedure. In a second step, the mean values of the endowment differences are weighted with the estimated coefficients from the earnings function of the non-discriminated group and the differences in the estimated coefficients are weighted with the average characteristics of the discriminated group.

The decomposition of the earnings differentials reveals that the discrimination effect plays a more important role than the endowment effect for males as well as for females. For males and females schooling and experience explain most of the earnings differential, although the shift coefficient bears a large effect in the earnings decomposition. Furthermore, the analysis reveals that the nationality group specific variables reduce the discrimination effect for males and females, although not for females from Southern Europe. Finally, the sample-selection correction variable used to correct the female earnings functions leads to a positive endowment effect in favor of natives.

Appendix

Table 1 – Descriptive Statistics: Heckmann-correction

Variables	*Native males*	*Native females*	*Immigrant males*	*Immigrant females*
Sample size	5552	6652	888	802
EMPL	0.85	0.38†††	0.85	0.47***/†††
	(0.35)	(0.48)	(0.35)	(0.50)
SCH	10.94	10.17†††	10.39***	9.85***/†††
	(2.68)	(2.09)	(3.14)	(2.85)
EXPE	21.85	23.40†††	25.34***	23.64†††
	(12.26)	(12.65)	(11.22)	(11.48)
EXPSQ	6.28	7.08†††	7.68***	6.90†††
	(6.18)	(6.66)	(6.04)	(6.12)
UNPL	4.05	4.12†	4.75***	4.84***
	(1.81)	(1.85)	(1.92)	(1.97)
NTHEU_IC			0.29	0.33†
			(0.45)	(0.47)
STHEU			0.48	0.46
			(0.50)	(0.50)
LN_HHINC	4.46	6.30†††	4.86***	6.03**/†††
	(3.96)	(3.74)	(3.81)	(3.71)
KID_6	0.28	0.32†††	0.39***	0.29†††
	(0.65)	(0.68)	(0.68)	(0.58)
KID7_14	0.27	0.33†††	0.32**	0.37
	(0.66)	(0.72)	(0.65)	(0.69)
KID15_25	0.13	0.17†††	0.21***	0.26***/†
	(0.45)	(0.49)	(0.52)	(0.62)

Source: SLFS (1995), own calculations

*Notes: Standard errors in parentheses — Test for equality of means between natives and immigrants: * 10 % level of significance, ** 5 % level of significance, *** 1 % level of significance; Test for equality of means between males and females: † 10 % level of significance, †† 5 % level of significance, ††† 1 % level of significance*

Table 2 – Descriptive Statistics: Earnings function

Variables	***Native males***	***Native females***	***Immigrant males***	***Immigrant females***
Sample size	4733	2500	757	378
LNINCGM	8.66	8.33†††	8.51***	8.20***/†††
	(0.37)	(0.35)	(0.37)	(0.38)
SCH	10.94	10.46†††	10.34***	10.07***
	(2.61)	(2.25)	(3.09)	(2.90)
EXPE	21.40	18.95†††	24.57***	21.71***/†††
	(11.15)	(11.52)	(10.65)	(9.82)
EXPSQ	5.82	4.92†††	7.17***	5.67***/†††
	(5.50)	(5.26)	(5.59)	(4.66)
UNPL	3.98	4.17†††	4.66***	4.77***
	(1.79)	(1.84)	(1.92)	(2.03)
YSM			17.51	14.59†††
			(10.70)	(9.65)
NTHEU_IC			0.30	0.34
			(0.46)	(0.47)
STHEU			0.48	0.44
			(0.50)	(0.50)

Source: SLFS (1995), own calculations

*Notes: Standard errors in parentheses — Test for equality of means between natives and immigrants: * 10 % level of significance, ** 5 % level of significance, *** 1 % level of significance; Test for equality of means between males and females: † 10 % level of significance, †† 5 % level of significance, ††† 1 % level of significance*

Table 3 – ML-estimation results of male employment

Variables	***Pooled Sample of Natives and Immigrants*** *Slope b (abs. t values)*	*Marginal effects*	***Variables***	***Pooled Sample of Natives and Immigrants*** *Slope b (abs. t values)*	*Marginal effects*
Sample size	6440		***Sample size***	6440	
CONSTANT	1.621*** (4.38)	0.271	***SWISS* SCH_2***	0.611*** (3.93)	0.102
SCH_2	–0.090 (0.66)	–0.015	***SWISS* SCH_3***	0.632*** (3.21)	0.105
SCH_3	–0.178 (1.00)	–0.030	***SWISS* EXPE***	0.053** (2.04)	0.009
EXPE	0.067*** (2.74)	–0.011	***SWISS* EXPSQ***	–0.082* (1.72)	–0.014
EXPSQ	–0.177*** (3.94)	–0.029	***SWISS* UNPL***	0.027 (0.79)	0.004
UNPL	–0.115*** (3.65)	–0.019	***SWISS* LN_HHINC***	0.010 (0.52)	0.002
LN_HHINC	–0.122*** (6.94)	–0.020	***SWISS* KID_6***	0.088 (0.72)	0.015
KID_6	0.174 (1.61)	0.029	***SWISS* KID7_14***	–0.049 (0.44)	–0.008
KID7_14	0.161 (1.58)	0.027	***SWISS* KID15_25***	–0.033 (0.23)	–0.005
KID15_25	0.321** (2.50)	0.054	***NTHEU_IC***	0.465*** (2.78)	0.078
SWISS	–1.036*** (2.67)	–0.173	***STHEU***	0.383** (2.47)	0.064
Log–L	–2043.389				
Pseudo–R^2	0.478				

Source: SLFS (1995), own calculations

*Notes: * 10 per cent level of significance, ** 5 per cent level of significance, *** 1 per cent level of significance*

Table 4 – ML-estimation results of female employment

Variables	***Pooled Sample of Natives and Immigrants***		***Variables***	***Pooled Sample of Natives and Immigrants***	
	Slope b (abs. t values)	*Marginal effects*		*Slope b (abs. t values)*	*Marginal effects*
Sample size	7454		***Sample size***	7454	
CONSTANT	0.572* (1.86)	0.204	***SWISS* SCH_2***	0.013 (0.10)	0.005
SCH_2	0.104 (0.89)	0.037	***SWISS* SCH_3***	0.331* (1.73)	0.118
SCH_3	–0.100 (0.57)	–0.036	***SWISS* EXPE***	–0.061 (2.67)***	–0.022
EXPE	0.101*** (4.65)	0.036	***SWISS* EXPSQ***	0.098** (2.18)	0.035
EXPSQ	–0.265*** (6.21)	–0.094	***SWISS* UNPL***	0.045* (1.63)	0.016
UNPL	–0.038 (1.52)	–0.014	***SWISS* LN_HHINC***	–0.019 (1.25)	–0.007
LN_HHINC	–0.099*** (6.97)	–0.035	***SWISS* KID_6***	–0.645*** (6.06)	–0.230
KID_6	–0.558*** (5.90)	–0.199	***SWISS* KID7_14***	–0.266*** (2.95)	0.0950
KID7_14	–0.451*** (5.45)	–0.161	***SWISS* KID15_25***	–0.025 (0.26)	–0.091
KID15_25	–0.366*** (4.10)	–0.130	***NTHEU_IC***	–0.267* (1.84)	–0.095
SWISS	0.451 (0.96)	0.161	***STHEU***	0.090 (0.67)	0.032
Log–L	–3200.576				
Pseudo–R^2	0.640				

Source: SLFS (1995), own calculations

*Notes: * 10 per cent level of significance, ** 5 per cent level of significance, *** 1 per cent level of significance*

Table 5 – OLS-estimation results of the male and female earnings function (with Heckman-correction)

Variables	***Pooled Sample of Male Natives and Immigrants***	***Pooled Sample of Female***
Sample size	5490	2878
CONSTANT	7.920***	7.694***
	(105.31)	(69.76)
SCH_2	0.056**	0.112***
	(2.06)	(2.87)
SCH_3	0.401***	0.408***
	(10.67)	(7.24)
EXPE	0.025***	0.029***
	(4.38)	(3.68)
EXPSQ	–0.043***	–0.058***
	(3.84)	(3.44)
UNPL	0.002	0.017**
	(0.25)	(2.10)
SWISS	–0.097	0.110
	(1.17)	(0.96)
SWISS*SCH_2	0.189***	0.173***
	(5.59)	(3.98)
SWISS*SCH_3	0.164***	0.139**
	(3.79)	(2.26)
SWISS*EXPE	0.016***	–0.002
	(2.61)	(0.19)
SWISS*EXPSQ	–0.017	0.014
	(1.38)	(0.79)
SWISS*UNPL	0.001	–0.012
	(0.15)	(1.36)
YSM	0.006***	0.004
	(2.71)	(1.28)
NTHEU_IC	0.287***	0.221***
	(8.17)	(4.60)
STHEU	0.068**	–0.063
	(2.06)	(1.41)
LAMBDA	–0.167**	–0.131**
	(2.08)	(2.56)
SWISS*LAMBDA	0.114	–0.001
	(1.32)	(0.01)
Adj.–R^2	0.349	0.303

Source: SLFS (1995), own calculations

Notes: absolute t-values in parentheses are corrected for heteroskedasticity [see White (1980)]

** 10 per cent level of significance, ** 5 per cent level of significance, *** 1 per cent level of significance*

Table 6 – Earnings difference decomposition for native and immigrant males

Variables	***Endowment effect (7)***	***(8)***	***Discrimination effect (7)***	***(8)***	***Earnings difference***
CONSTANT			–0.097	–0.097	*–0.097*
SCH_2	0.062	0.014	0.077	0.125	*0.139*
SCH_3	0.044	0.031	0.033	0.046	*0.077*
EXPE	–0.129	–0.078	0.290	0.340	*0.262*
EXPSQ	0.081	0.058	–0.121	–0.098	*–0.040*
UNPL	–0.002	–0.001	0.005	0.004	*0.003*
NTHEU_IC			–0.085	–0.085	*–0.085*
STHEU			–0.033	–0.033	*–0.055*
YSM			–0.096	–0.096	*–0.096*
LAMBDA	0.026	0.026			*0.026*
Total effect	***0.082***	***0.050***	***0.073***	***0.105***	***0.155***

Source: SLFS (1995), own calculations

Table 7 – Earnings difference decomposition for native and immigrant females

Variables	***Endowment effect (7)***	***(8)***	***Discrimination effect (7)***	***(8)***	***Earnings difference***
CONSTANT			0.110	0.110	*0.110*
SCH_2	0.098	0.039	0.067	0.126	*0.165*
SCH_3	–0.011	–0.008	0.021	0.018	*0.010*
EXPE	–0.077	–0.081	–0.033	–0.029	*–0.110*
EXPSQ	0.033	0.044	0.078	0.068	*0.110*
UNPL	–0.003	–0.010	–0.058	–0.050	*–0.061*
NTHEU_IC			–0.075	–0.075	*–0.075*
STHEU			0.028	0.028	*0.028*
YSM			–0.053	–0.053	*–0.053*
LAMBDA	0.008	0.008			*0.008*
Total effect	***0.048***	***–0.009***	***0.084***	***0.141***	***0.132***

Source: SLFS (1995), own calculations

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