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The male immigrant–native employment gap in Sweden: migrant admission categories and human capital

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Abstract

Despite having a celebrated labor market integration policy, the immigrant–native employment gap in Sweden is one of the largest in the OECD. From a cross-country perspective, a key explanation might be migrant admission group composition. In this study we use high-quality detailed Swedish register data to estimate male employment gaps between non-EU/EES labour, family reunification and humanitarian migrants and natives. Moreover, we test if differences in human capital are able to explain rising employment integration heterogeneity. Our results indicate that employment integration is highly correlated with admission category. Interestingly, differences in human capital, demographic and contextual factors seem to explain only a small share of this correlation. Evidence from auxiliary regressions suggests that low transferability of human capital among humanitarian and family migrants might be part of the story. The article highlights the need to understand and account for migrant admission categories when studying employment integration.

Keywords Labour market integration · Sweden · Human capital · Migration categories · Employment gaps

JEL Classification J21 · J24 · J6 · J61

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Introduction

According to the Migrant Integration Policy Index (MIPEX 2015), Sweden is ranked as having the most optimal labour market integration policies of the 38 countries covered in the index. At the same time, Sweden, as a relatively high immigration intake country, has for a long time had great difficulty accommodating these immigrants into the labour market (Bevelander 2011). According to the OECD, the immigrant–native employment gap is one of the largest in the OECD (OECD/European Union 2015).

An increasingly popular explanation that has been highlighted in recent years is the migrant group composition with respect to type of migration or admission category. According to the OECD (2014: 37) this category is the single largest determinant of labour market integration outcomes. They note that humanitarian and family migrants struggle with labour market integration in all countries, and that the different categories into which immigrants are slotted on arrival account for most of the cross-country differences in labour market outcomes.

As a next step, it would then be of great interest to also understand why these performance differences arise. Humanitarian and family migrants tend to have lower average levels of human capital. According to traditional human capital theory (Becker 1992), differences in human capital determine labour market success. However, immigration complicates this relationship due to the difficulties involved in transferring human capital (Chiswick and Miller 2009). Hence, lower average levels of and return to human capital characteristics could be potential explanations for Sweden, whose intake largely consists of family reunification and humanitarian immigrants. Other fruitful explanations include factors related to self-selection, intention to stay, social network and experience.

The article has two research questions:

- To what extent is employment integration correlated with migrant admission categories?
- How important is human capital, operationalized as level, transferability and type of education, in explaining the employment gap between natives and immigrant admission categories?

In order to answer these questions, we employ high quality register data on the population of Swedish immigrants in 2011. In particular, we make use of detailed information regarding origin, socio-demographics, level and type of education, employment and, most notably, the admission category upon arrival. Regression and decomposition analyses highlight substantial admission category heterogeneity with respect to employment integration. Differences in human capital, here defined as type and level of education, do not seem to be the underlying driver. Our results suggest, however, that low transferability of human capital among humanitarian and family migrants might be a factor. This article adds to research on the role of human capital and migrant admission categories for labour market integration in Sweden. In contrast to previous studies, however, we combine these

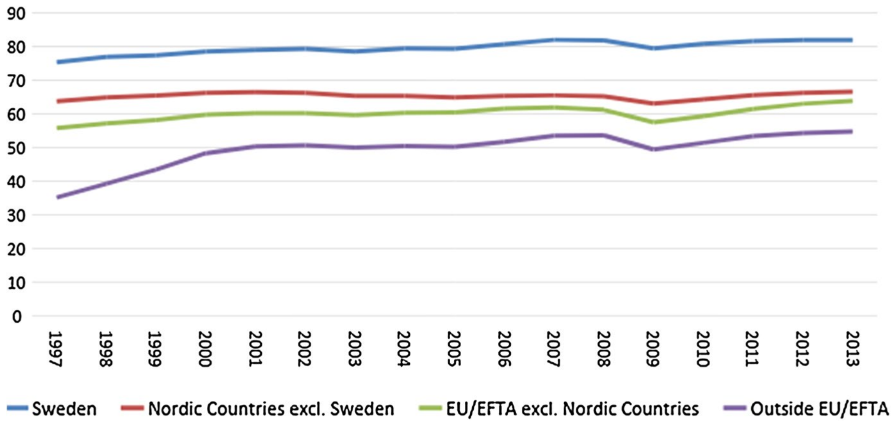

Fig. 1 Employment rate, 20–64 years, by region of birth. *Source*: Statistics Sweden

distinct research strands. By doing this we highlight the issue of human capital transferability in a new and original way.

The structure of this article is as follows. In "Background information", we present the Swedish context of labour market integration and discuss theoretical considerations on migrant-specific employment success and the related literature. "Data and methodology" presents our data and first descriptive statistics. We conduct our methodology and main empirical analysis in the "Results" section and conclude our work in "Concluding discussion".

Background information

Migration and labour market integration: the Swedish context

According to Eurostat (2014), Sweden, compared to other European Union (EU) countries, is characterized by high immigration of humanitarian and family migrants. The country is one of the major destinations for asylum-seekers (Bitoulas 2015) and the absence of income requirements (Borevi 2014) has favoured subsequent family migration. Labour migration from outside the EU was quite small-scale from the beginning of the 1970s up until the 2008 liberalization of Sweden's labour migration policy (Emilsson 2016), which the OECD (2011) deems to be one of the world's most open. Hence, the number of foreign-born people has increased rapidly in Sweden over recent decades. Since 2000, the stock of migrants has increased by almost 60% to over 1.6 million, representing 16.5% of the population in 2014.

Figure 1 shows the employment rates of native-born Swedes and three geographical groups of immigrants over time. Since the early 2000s, the gaps between immigrant groups and natives have been quite stable. Persons born in Nordic countries have an employment rate of about 65% and immigrants from EU/EFTA countries about 5% lower. Immigrants born outside EU/EFTA countries, which represent by far the largest intake group, have an employment rate of approximately 50%. In recent years it has increased slightly and was about 55% in 2013. This study focuses on the latter large but unsuccessful group: immigrants from outside the EU/EFTA.

Theoretical considerations: employment integration and migrant categories

In standard labour market supply studies it is assumed that the probability of working is determined by the level of human capital. This includes formal education, labour market experience and skills acquired at work. One of the challenges of human capital theory when it comes to migration is to take into account the migration-related depreciation of human capital. Skills may not be perfectly transferable across countries. Chiswick et al. (2005) define skills as labour market information, destination-language proficiency, and occupational licenses, certifications or credentials, as well as more narrowly defined task-specific skills. They exemplify the problem of transferability with three types of high-level occupation—economist, medical doctor and lawyer:

> Country-specific skills for the economist may include language and style of practice. The medical doctor has less transferable skills because, in addition to language and style of practice, the practice of medicine requires a license specific to the destination. The skills of lawyers are even less transferable across countries because, in addition to the above, the legal system … varies sharply across countries (2005: 335).

According to their theory, those with the least transferable skills among potential migrants are not likely to become economic migrants. Refugees, on the other hand, base their migration decision, in part, on a different set of intentions. Income differentials are also a factor for refugees, but their decisions are firstly influenced by non-economic factors concerning their safety and security.[1]

Chin and Cortes (2015) use the model of Jasso and Rosenzweig (2009) to discuss the migration decision and selection of non-economic and economic migrants using an income-maximization framework augmented by amenities (living in the same country as your spouse, living in a country with foreign culture, fear of execution). While it is intuitive that the number of emigrants increases in the event of a large refugee-inducing event, the selection with respect to economic gain in the destination country is likely to be smaller. The general sign of selection is ambiguous and depends on the nature of the refugee-producing event and the selection of the “regular” migration (Chin and Cortes 2015). Their model also captures that credit constraints lead to a positive wealth selection, which can be even more pronounced for refugees due to losses of wealth or social networks. Finally, they argue that high migration costs to distant developed countries and a longer list of utility-inducing closer developing countries for refugees result in

[1] The labour market integration of refugees can also be impeded on an individual level through the long reach of traumatic experiences.

distinct destination preferences. Here, it is noteworthy that labour migrants' lists of destination countries are far shorter and targeted towards their human capital. In essence, therefore, refugee streams include a larger proportion of immigrants who are less adapted for labour market integration (Chiswick et al. 2005).

However, Aydemir (2011) stresses that even favourable selection in human capital characteristics does not always translate into better labour market outcomes. This is because many of these characteristics, such as schooling and experience, that are almost always acquired in source countries, have little or no return in the host country labour market and, hence, have very limited power in predicting short-term labour market outcomes (2011: 453–454). He concludes that there are many unobservables which are important to determine the quality and relevance of immigrants' human capital. This may result in skill transferability problems or a mismatch between demand and supply.

We understand this argument as being of significant importance for the Swedish case. The Swedish system of labour migration is employment-driven and all labour migrants must have an offer of employment in order to obtain a work permit. The employment offer itself should be a sign that the migrants' skills are useful and acknowledged by the employer. The majority of high-skilled labour migrants are employed as computer specialists in English-speaking work environments (Emilsson and Magnusson 2015), which implies that their human capital did not decrease due to insufficient knowledge of the host-country language. However, few humanitarian and family migrants have Swedish-language skills before entering the country, which certainly increases the depreciation of their human capital. Thus, in contrast to labour migrants, humanitarian and family migrants could be disadvantaged due to both differences in their education levels and their transferability.

Another important difference between economic and refugee immigrants is the option to return to their home country (Cortes 2004). Assuming that humanitarian immigrants have a substantially longer time horizon in the host country, they also face a different set of incentives to invest in host-country specific human capital (Dustmann and Görlach 2016). However, as humanitarian immigrants also enter the host-country labour market at a lower level, in our cross-sectional analysis the resulting implications for our admission groups are ambiguous.

A reason for admission group differences in employment integration could also be kinship networks. Aydemir (2011) argues that family migrants often have access to kinship networks in the host country which can facilitate access to crucial information regarding the labour market and may initiate investments in human capital prior to arrival that are valued in the host-country labour market. These types of network may also help to overcome barriers in the labour market through job contacts or a better knowledge of processes leading to the recognition of credentials.

Finally, differences in access to services could, in theory, be a reason for the observed heterogeneity. In Sweden, however, migrants have access to various services. While all humanitarian migrants have the right to a 24-month introduction program, only families of recent humanitarian migrants have the same right. This program includes language training, civic orientation and labour market services and is administered by the Public Employment Service (Emilsson

2014). Nevertheless, most services are also available to family and labour migrants—for example, free language training.

Related empirical evidence on the importance of migrant categories for employment outcomes

While the influence of formal education on immigrants' employment and earnings has proved positive, especially if some of this education is obtained in Sweden (Nordin 2007), differences in formal education do not completely explain the employment differential between native and foreign-born workers (Eriksson 2010). Szulkin et al. (2013) suggest that it is the composition of the immigrant group in Sweden which is probably the factor that can best explain the native–immigrant employment gap in Sweden compared to other countries.

However, in the Swedish and Canadian contexts, Bevelander (2011) and Bevelander and Pendakur (2014) confirm that human capital characteristics *also* matter for the labour market integration of non-economic migrants. Controlling for personal, contextual and immigrant intake characteristics, Bevelander (2011) finds that family-reunion migrants integrate into the employment market to a larger extent than asylum claimants who, in turn, integrate more quickly than resettled refugees. Thus, the results confirm the importance of admission categories. In particular, our study adds to this literature with an analysis of human capital's role for the Swedish employment integration across admission categories.

Studies from other countries confirm the importance of the admission category for labour market integration, especially in traditional settler countries such as Australia, Canada, New Zealand and the US. The studies show that the points system for labour migrant selection generates a more-highly skilled immigrant flow than those admitted for family reasons (Aydemir 2011; Cobb-Clark 2000; Jasso and Rosenzweig 1995). Several studies from Australia show that refugees have greater difficulty in finding employment than other immigrants (Chiswick and Miller 1992; Wooden 1990). De Silva (1997) and DeVoretz et al. (2004) examine the labour market integration of skilled immigrants in Canada compared both to assisted relatives and to refugees and find that the latter groups have a lower employment success rate. In all studies, the gap gets smaller over time. Connor (2010) studies the US employment gap between refugees and natives and shows a refugee disparity in earnings and occupational attainment. However, employment rates are about the same for refugees as for other migrant categories. In an earlier study, Cortes (2004) shows that even though entry earnings are lower for refugees than for economic immigrants, refugees' higher earnings growth more than offsets the initial disadvantage in the U.S. labour market. In Germany and Denmark, where the context is more similar to Sweden, refugees and those who arrive through family reunification have a weaker position in the labour market compared to labour migrants (Constant and Zimmermann 2005).

Data and methodology

Data and descriptive statistics

We use a cross-section from the STATIV database supplied by Statistics Sweden. It is extracted from the population register for the year 2011. It includes all residents in Sweden and collects data from several different registers—i.e. demographic, education, employment and immigration. Crucial to our analysis, it records the most recent (actual) admission status of immigrants when granted legal status in Sweden. Hence, our identification of migrant groups should be subject to considerably smaller measurement error than alternative classifications through a combination of country-of-origin and year-of-migration or even self-reported migration. Nevertheless, the usual pitfalls of cross-sectional data in research on labour market gaps apply. In particular, we are not able to distinguish the gap upon arrival and its subsequent development without strong assumptions concerning age and year of migration. Instead we compare overall group averages by admission class (irrespective of the assimilation path).

We limit our analysis to the male working age population between 25 and 59 years. Moreover, we only keep natives and the large group of non-EU/EES immigrants who entered between 1990 and 2009 and, thereby, exclude immigrants with less than 2 years of residence. This procedure is important as all labour migrants have a job upon arrival, whereas a large share of humanitarian and family reunification migrants follows introduction programs or other forms of education such as language training throughout their first years in Sweden (Statistics Sweden 2012). This comes at the price of potential outmigration. In particular, outmigration of the unskilled (e.g. due to job search failure) could bias the employment assimilation upwards (Edin et al. 2000). Humanitarian and family reunification migrants tend to have lower outmigration rates and a greater intention to stay compared to temporary labour migrants (Edin et al. 2000; Cortes 2004). We would therefore expect more bias for the labour migrant gap. Assuming a downward bias, estimates should then be treated as lower-bound estimates.

Our dependent variable is employment status. We use the standard EU definition of employment also used by Statistics Sweden. Our human capital measure, educational level, is based upon the Swedish system of education and is comprised of seven levels (see Table 1). From the same source we use field of education. This measure captures nine different fields and an "unknown" category (again, see Table 1). By definition the lower education levels are classified as 'general education'. The key advantage of the STATIV dataset used in this analysis is that the classification includes immigrant arrival categories, i.e. admission status for all immigrants. We distinguish immigrants into three admission categories: labour, family reunion and humanitarian migrants (refugees). Moreover, we have information on age, marital status, number of children, country of residence, area of origin, age at arrival and, consequently, years since immigration. We drop individuals with missing information on dependent or independent variables. Ultimately our sample consists of 1,699,060 natives and 117,049 immigrants.

Table 1 Mean characteristics of the analysis sample

	Native	Immigrant	Immigrant (labour)	Immigrant (family)	Immigrant (humanitar-ian)
Employment					
Employed	0.88	0.63	0.81	0.64	0.62
Education					
Pre-secondary < 9	0.01	0.14	0.04	0.12	0.16
Pre-secondary 9	0.12	0.11	0.03	0.13	0.10
Secondary < 3	0.29	0.21	0.06	0.21	0.21
Secondary 3	0.23	0.18	0.04	0.17	0.19
Post-secondary < 3	0.15	0.15	0.19	0.16	0.15
Post-secondary ≥ 3	0.19	0.20	0.48	0.20	0.18
Scientific	0.01	0.01	0.16	0.02	0.01
Education type					
General	0.19	0.36	0.10	0.36	0.37
Pedagogics	0.03	0.03	0.02	0.02	0.03
Humanities	0.04	0.04	0.04	0.05	0.03
Social sciences	0.14	0.10	0.11	0.11	0.10
Natural sciences	0.03	0.05	0.20	0.06	0.04
Technical	0.42	0.24	0.37	0.21	0.24
Agriculture	0.03	0.01	0.01	0.01	0.01
Health	0.04	0.05	0.06	0.05	0.05
Services	0.06	0.04	0.02	0.04	0.04
Unknown	0.02	0.08	0.07	0.08	0.08
Demographics					
Age	42.26	40.16	35.54	38.67	40.85
Couple	0.39	0.61	0.51	0.55	0.63
Single	0.51	0.24	0.43	0.27	0.23
Divorced	0.09	0.14	0.06	0.18	0.13
Widowed	0.00	0.00	0.00	0.00	0.00
Children	0.96	1.33	0.50	1.20	1.40
County					
Stockholm	0.21	0.29	0.48	0.39	0.25
Gothenburg	0.17	0.18	0.16	0.17	0.19
Skane	0.12	0.16	0.10	0.15	0.17
Immigration					
Years since immigration		11.94	5.71	12.00	12.15
Age at immigration		28.22	29.83	26.66	28.70
Rest of Europe		0.32	0.16	0.24	0.35
Africa		0.14	0.09	0.21	0.12
North America		0.02	0.06	0.07	0.01
South America		0.03	0.03	0.07	0.02
Asia		0.09	0.48	0.12	0.07
Oceania		0.01	0.02	0.02	0.00

Table 1 (continued)

	Native	Immigrant	Immigrant (labour)	Immigrant (family)	Immigrant (humanitarian)
Soviet Union		0.00	0.01	0.00	0.00
Middle East		0.38	0.14	0.27	0.43
Labour		0.03			
Family		0.25			
Humanitarian		0.72			
Observations	1,699,060	117,049	3247	29,193	84,609

All variables except the number of children, age, years since immigration and age at immigration are mean dummy variables and can be interpreted as percentages. The remaining variables are traditional level means. The data is from Statistics Sweden

Table 1 displays the sample characteristics of male Swedish natives and immigrants. The latter we break down with respect to admission category. Column 3 shows that the large majority (72%) of our immigrants entered Sweden via the humanitarian admission category. Another 25% entered the country in the family category and only 3% arrived as labour migrants. Hence, the distribution of migrant groups according to admission type in Sweden is far from uniform. Almost 90% of all Swedish males in our sample are employed. Among the group of immigrants, the highest employment rate is found for the labour admission category (83%). However, only slightly more than 60% of family and humanitarian immigrants are employed. Hence, not accounting for admission category masks substantial heterogeneity.

Half of all natives have some secondary education, whereas 34% have continued to higher education. A sizeable 83% of all labour immigrants have pursued their education beyond upper-secondary level. This makes them, on average, more skilled than their native counterparts. Roughly the same relative share of natives, humanitarian and family immigrants have received a higher education. However, in contrast to natives, a larger share attained lower, as opposed to medium-level, education. The education followed by natives is mostly technical (42%), general (19%) or has a social science background (14%). In line with lower average education, general education is far more prevalent for family and humanitarian immigrants. In the same vein, the large share of high-skilled individuals among labour immigrants coincides with the largest share of specialisations such as in the natural sciences.

According to socio-economic factors, the immigrants in our sample are younger, are more likely to cohabit and have more children than their native counterparts. While roughly half of all Swedish natives are single, the same holds true for only about a quarter of humanitarian and family immigrants. Labour immigrants are the most likely to be single and have on average fewer children. A distinct feature of humanitarian immigrants is that they are less clustered within the three big urban counties of Sweden.

Finally, we compare immigrant-specific sample characteristics. On average, our group of immigrants entered the country about 12 years ago at the age of 28. However, compared to humanitarian and family immigrants, labour immigrants arrived more recently and hence acquired only half of the other immigrants' experience in

Sweden. Moreover, they arrived at a slightly older age. Here, it is noteworthy that labour immigrants per se do not arrive in childhood or adolescence. The main regions of origin are the Middle East (38%) and the Rest of Europe (32%), excluding Northern European countries and the EU 27. The bulk of the remaining immigrants originated in Africa or Asia (23%). In contrast to humanitarian immigrants, individuals in the family admission category are more often from Africa, Asia and the Americas (47%). Hence, family immigrants show the widest source-region dispersion. Asian origin, excluding the Middle East, is particularly common among labour immigrants.

Our descriptive analysis documents immigrant–native and immigrant–immigrant differences according to employment and human capital. As lower human capital coincides with lower employment integration, our descriptive results seem to be in line with the potential human capital theory explanation. As there is, however, substantial observed (and probably also unobserved) group heterogeneity, we cannot use this descriptive unconditional analysis as hard evidence. As a first attempt to approach this issue, we now turn to multivariate analysis.

Methodology: determinants of employment and employment gap decomposition

We begin our main analysis by estimating one employment model per population group g. This allows us to compare the determinants of native and immigrant employment. In particular, as employment is binary, we run five multivariate nonlinear probit regressions (Eq. 1). The employment status of individual i, $E_{i,g}$, is a function of the human capital matrix $Educ_{i,g}$ (education level and type), socio-economic characteristics $Dem_{i,g}$ and county fixed effects $Reg_{i,g}$. For each group, $\beta_{educ,g}$ captures the association between human capital and employment status. Our socio-demographic controls age, marital status and number of children as well as regional fixed effects control for differences in lifecycle stage and experience, preferences and local labour market conditions.[2] $\varepsilon_{i,g}$ is the individual group-specific heteroscedasticity-consistent error term. The non-linear relationship is modelled via the cumulative standard normal distribution Φ.

$$Pr(E_{i,g} = 1|X = x) = \Phi\left(\beta_{0,g} + \beta_{Dem,g}Dem_{i,g} + \beta_{Reg,g}Reg_{i,g} + \beta_{Educ,g}Educ_{i,g} + \varepsilon_{i,g}\right). \tag{1}$$

As a next step, we conduct a pooled regression with natives and immigrants and add an immigrant indicator to our set of controls. The latter can be interpreted as the immigrant–native gap. In particular, we can obtain an unconditional gap and get some insight about the underlying drivers through sequentially increasing the set of controls. For instance, if the estimated gap decreases after the inclusion of human capital controls, this suggests that part of the gap could be explained by differences

[2] An anonymous referee made the important point that location choice, and arguably also some of our socio-demographic controls, might be endogenous. For instance, a Stockholm dummy could pick up labour market differences but also transferability and ability through self-selection. This makes a clean interpretation of the county dummy complicated and might also affect our estimates for human capital and transferability. As our study is mainly descriptive, making natives and immigrants comparable with respect to local labour markets is our highest priority.

in human capital. In order to get more qualified evidence concerning admission categories, we replace the immigrant indicator by an admission category indicator.

Naturally, our research strategy also has pitfalls. While, in contrast to ordinary least squares, probit models account for the non-linear nature of the dependent variable, rescaling between nested models can bias the coefficient comparison between nested models (Karlson et al. 2012). The rescaling bias is expected to counteract the effect of including a confounder such as education, so that the role of the latter might be understated. In contrast to this, unobservable differences in ability might bias our education estimate upwards. This omitted variable bias holds true, if we assume that self-selected immigrants are more "able" than the average (randomly selected) Swede. While the sign of the self-selection bias relative to the home and host population is not trivial and, hence, an interesting subject in itself, it is not part of this study. As we study the role of human capital, as opposed to formal education, however, the lack of clear distinction might be less problematic for our research question. Lastly, failing to capture the correct functional form can be an issue. Here, it is noteworthy that we model relationships with a flexible dummy approach for most of our variables.

While a pooled regression accounts for group differences in observed characteristics, it also assumes that group returns are uniform. Consequently, it does not capture that immigrants might experience a different return to education than Swedish natives. There are, however, multiple reasons why this could occur such as differences in quality, limited transferability or even discrimination. In order to account for this possibility, we conduct a generalised non-linear two-way Blinder–Oaxaca decomposition analysis, as suggested by Yun (2004).[3] Crucial to our analysis, it allows us to calculate the gap and the contribution of human capital differences through level or return.

Our average group employment difference between $\overline{E_{img}}$ and $\overline{E_{nat}}$ can be decomposed into endowment ΔX and coefficient effect $\Delta\beta$(see Eq. 2). Endowment effects are based on observable differences in characteristics (Eq. 3). Hence, they are called the 'explained gap', whereas coefficient effects are also called the 'unexplained gap'. The decomposition makes use of the characteristics X_{img} and X_{nat} and estimated coefficients β_{img} and β_{nat} from our group-specific regressions.

$$\overline{E_{nat}} - \overline{E_{img}} = \Delta X + \Delta\beta \tag{2}$$

$$\Delta X = \left[\Phi\left(X_{nat}\beta_{nat}\right) - \Phi\left(X_{img}\beta_{nat}\right)\right] \tag{3}$$

$$\Delta\beta = \left[\Phi\left(X_{img}\beta_{nat}\right) - \Phi\left(X_{img}\beta_{img}\right)\right]. \tag{4}$$

[3] An anonymous referee pointed out that an alternative strategy would be to include an interaction between education and migration admission category into our pooled regression framework. While we agree that this strategy has merit in an ordinary least squares framework, there are two main reasons why we followed the decomposition approach. First, the marginal effect of an interaction in a probit framework is neither equal to the marginal effect of the interaction term nor constant. Second, instead of interacting only education with admission category, our decomposition can be interpreted as a fully interacted model. Hence, while one can question if the additional effort is worthwhile, we chose the comprehensive approach. A discussion on the arising issue of scaling is given in "Methodology: determinants of employment and employment gap decomposition".

As mentioned earlier, we are able to calculate the gap contribution of each variable.[4] Finally, we follow Jann (2008) and include a group dummy in our pooled regression to obtain non-discriminatory coefficients and avoid over- or under-valuation of one of the two groups. As the choice of omitted categories affects the detailed decomposition results of the unexplained gap (Oaxaca and Ransom 1999), we follow Yun (2005) and run a regression for each possible benchmark category and average the resulting estimated coefficients. The estimated contributions to the unexplained gap can be interpreted as deviation from the grand mean.

Again, also non-linear decompositions have their pitfalls. While they account for the limited dependent nature of employment and are commonly used, they are subject to controversial debate as they entail many computational challenges (Fortin et al. 2011). As in the pooled regression framework, for instance, different scaling in group-specific regressions are an issue. Hence, the method might obtain coefficient effects in the absence of "true" differences in returns.

Results

Multivariate regression

Table 2 displays the estimated average marginal effects of human capital on the employment likelihood for each population group. Conditional on socio-economic and regional characteristics, human capital significantly influences the employment likelihood. Higher educational attainment has a positive and significant effect for natives and overall immigrants. Having a 3-year secondary-school qualification, instead of less than 9 years of education, increases the likelihood of employment by 17% points for natives and 22 percentage points for all immigrants. For humanitarian immigrants and, to a much smaller extent, for family reunion migrants, employment returns on increasing educational attainment up to secondary level are greater. However, the return on increasing educational attainment to a post-secondary level is greater for natives, especially compared to family immigrants. Labour immigrants show insignificant returns on increasing educational attainment. There are two reasons for this finding: roughly 73% of labour immigrants have a qualification higher than secondary level, so that there are only few individuals in the lower categories. Second, when conducting a bivariate analysis between employment rates and educational attainment, the educational gradient is flat (see Table 7 in the "Appendix"). For instance, for labour immigrants, fewer than 9 years of education and research education both show an employment rate of 80%. In contrast, humanitarian and family immigrants show a substantially more pronounced education gradient.

Changing education fields from general to technical or agricultural increases the likelihood of being employed by 5 or 6% points. For humanitarian and family immigrants, health or technical education increases the likelihood by up to

[4] The contribution is based on weighing each gap. Therefore all contributions sum to 1. For details on the calculation of weights, see Yun (2004).

Table 2 Probability model of employment

	Native	Immigrant	Immigrant (labour)	Immigrant (family)	Immigrant (humanitarian)
Education					
Pre-secondary 9	0.09***	0.09***	− 0.07	0.08***	0.09***
	(0.00)	(0.01)	(0.05)	(0.01)	(0.01)
Secondary < 3	0.11***	0.15***	− 0.06	0.12***	0.16***
	(0.00)	(0.01)	(0.05)	(0.01)	(0.01)
Secondary 3	0.17***	0.22***	− 0.06	0.18***	0.23***
	(0.00)	(0.01)	(0.05)	(0.01)	(0.01)
Post-secondary < 3	0.15***	0.11***	0.01	0.09***	0.11***
	(0.00)	(0.01)	(0.05)	(0.02)	(0.01)
Post-secondary ≥ 3	0.18***	0.17***	− 0.02	0.15***	0.17***
	(0.00)	(0.01)	(0.05)	(0.01)	(0.01)
Scientific	0.19***	0.21***	− 0.04	0.17***	0.18***
	(0.00)	(0.01)	(0.06)	(0.02)	(0.02)
Type					
Pedagogics	0.04***	0.06***	0.00	0.06**	0.07***
	(0.00)	(0.01)	(0.08)	(0.02)	(0.01)
Humanities	− 0.04***	− 0.03**	0.03	− 0.00	− 0.04***
	(0.00)	(0.01)	(0.06)	(0.02)	(0.01)
Social sciences	0.01***	0.04***	− 0.03	0.03*	0.05***
	(0.00)	(0.01)	(0.05)	(0.01)	(0.01)
Natural sciences	− 0.00	0.05***	0.03	0.05***	0.04***
	(0.00)	(0.01)	(0.05)	(0.02)	(0.01)
Technical	0.05***	0.10***	0.09	0.09***	0.10***
	(0.00)	(0.01)	(0.05)	(0.01)	(0.01)
Agriculture	0.06***	0.06***	0.05	0.07**	0.07***
	(0.00)	(0.01)	(0.08)	(0.03)	(0.02)
Health	0.02***	0.14***	− 0.04	0.09***	0.17***
	(0.00)	(0.01)	(0.06)	(0.02)	(0.01)
Services	0.04***	0.07***	− 0.05	0.06***	0.07***
	(0.00)	(0.01)	(0.07)	(0.02)	(0.01)
Unknown	0.01***	0.04***	− 0.06	0.01	0.05***
	(0.00)	(0.01)	(0.05)	(0.01)	(0.01)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,699,060	117,049	3247	29,193	84,609
Pseudo R^2	0.094	0.050	0.068	0.047	0.054
Log-lik.	− 557,372.61	− 73,414.58	− 1480.64	− 18,192.87	− 53,324.91
χ^2	93,367.48	7504.29	200.60	1694.84	5830.17

Average marginal effects reported. Robust standard errors in parentheses

The Data is from Statistics Sweden

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

17% points. In general, all specialisations except the humanities result in a positive effect on employment. This makes intuitive sense, as specialisation is by definition strongly correlated with higher educational attainment. For labour immigrants, the only educational field that comes close to a significant increase in employment likelihood is technical education.

Our estimated controls for the above analysis are listed in Table 6 in the “Appendix”. Again, we find differences in returns. Among others, being in the oldest age group—between 50 and 59 years old—has a strong negative effect on all immigrant groups, while for natives it increases their employment likelihood. The effects of being single, the number of children and living in any county other than Stockholm have uniform signs but different amplitudes for native and immigrant populations. For instance, being single has a larger effect for natives, whereas living outside the county of Stockholm, particularly, lowers the employment likelihood of humanitarian and family immigrants.

Pooled multivariate regression

Column 2 of Table 3 shows our unconditional immigrant–native employment gap from the pooled estimation. In column 3 we replace this indicator by a more informative admission category indicator. After that we sequentially extend our set of controls. In line with our descriptive results, the breakdown into admission categories suggests that an aggregate group masks employment integration heterogeneity. For each gap, especially for family and humanitarian immigrants, controlling for socio-demographic and county differences increases the employment gap. Consequently, immigrants seem to have on average more employment-favourable characteristics than natives with respect to socio-demographics and residence. An alternative explanation, however, would be that we simply observe a rescaling between the “full” and “reduced” model. Adding educational attainment and type in columns 4 and 5 decreases the difference for all but labour migrants, where, potentially due to their favourable educational characteristics, the gap increases slightly. Here, it is noteworthy that, even if we underestimate the role of education due to rescaling, our estimates seem to be at least unlikely to be a key driver. All regressions have in common that, after accounting for educational attainment, educational type contributes very little to the gap. For labour migrants, none of the considered factors seem to contribute to the resulting gap. Here, different unobserved factors seem to be at play. Finally, even conditional on human capital, socio-demographics and county fixed effects differences by admission categories remain substantial.

Results: non-linear decomposition analysis

The above analysis is based on the assumption that returns on characteristics are identical for all groups (Abdulloev et al. 2014). This assumption is, however, violated if there are origin-specific returns to human capital (Friedberg 2000). In order to allow for group-specific returns to characteristics, we run a decomposition analysis for each immigrant group-native employment gap. Following decomposition

Table 3 Probability model of employment—pooled

All					
All immigrants	– 0.26***				
	(0.00)				
Labour immigrants		– 0.07***	– 0.09***	– 0.10***	– 0.10***
		(0.01)	(0.01)	(0.01)	(0.01)
Family immigrants		– 0.24***	– 0.29***	– 0.26***	– 0.24***
		(0.00)	(0.00)	(0.00)	(0.00)
Humanitarian immigrants		– 0.27***	– 0.34***	– 0.30***	– 0.29***
		(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,816,109	1,816,109	1,816,109	1,816,109	1,816,109
Pseudo R^2	0.032	0.033	0.086	0.106	0.112
Log-lik.	– 692,343.36	– 692,061.20	– 653,954.18	– 639,206.09	– 634,990.51
χ^2	47,989.48	48,539.85	112,926.44	132,655.49	139,294.19
Controls					
Category	No	Yes	Yes	Yes	Yes
Demographic and county FE	No	No	Yes	Yes	Yes
Education	No	No	No	Yes	Yes
Education type	No	No	No	No	Yes

Average marginal effects reported. Robust standard errors in parentheses

Data from Statistics Sweden

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

logic, a large unexplained employment gap between any immigrant group and the native group indicates that the underlying gap is not driven by differences in observed characteristics but by either differences in returns or the intercepts. The latter, then, refers to other unobserved factors confounding the employment differential between natives and admission category.

Table 4 lists the results of our gap decompositions. Each column refers to a different employment gap. The first panel includes information on the employment gap and its decomposition into explained and unexplained components. The second and third panels break down each component into individual contributions of educational attainment, educational type and the remaining control variables.

First, the predicted employment gaps closely resemble our pooled regression estimates and, hence, again underline the need to account for intake information. For each gap, a substantial share cannot be explained by differences in observable group characteristics, including human capital and socio-demographics. Instead, differential returns to characteristics (coefficients) and (unobserved factors related to) sheer group membership (intercept) seem to be the main gap contributors. Only for family immigrants do comparatively less-favourable group characteristics seem to explain a significant share of the employment gap (column 4). However, their contribution to the overall employment difference amounts to only 4% (0.01/0.24). In fact, the human capital and socio-demographic characteristics of humanitarian and labour immigrants tend to narrow, in contrast to drive, the employment gap with natives.

Table 4 Non-linear decomposition analysis

	Immigrant–native	Labour immigrant–native	Family immigrant–native	Humanitarian immigrant–native
Panel 1: overall				
Native	0.88***	0.88***	0.88***	0.88***
	(0.00)	(0.00)	(0.00)	(0.00)
Immigrant	0.63***	0.81***	0.64***	0.62***
	(0.00)	(0.01)	(0.00)	(0.00)
Difference	0.26***	0.07***	0.24***	0.27***
	(0.00)	(0.01)	(0.00)	(0.00)
Explained	− 0.00**	− 0.01***	0.01***	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Unexplained	0.26***	0.08***	0.24***	0.27***
	(0.00)	(0.01)	(0.00)	(0.00)
Panel 2: explained				
Controls	− 0.01**	0.00**	− 0.38	− 0.01***
	(0.00)	(0.00)	(0.66)	(0.00)
Education	0.00***	− 0.01***	0.18	0.00***
	(0.00)	(0.00)	(0.31)	(0.00)
Education type	0.00***	0.00***	0.21	0.00***
	(0.00)	(0.00)	(0.35)	(0.00)
Panel 3: unexplained				
Controls	0.03***	0.01	0.00	0.04***
	(0.00)	(0.02)	(0.01)	(0.01)
Education	− 0.00*	0.02*	− 0.00	− 0.01***
	(0.00)	(0.01)	(0.00)	(0.00)
Education type	0.00	− 0.02**	0.00	0.00
	(0.00)	(0.01)	(0.00)	(0.00)
Constant	0.23***	0.07**	0.23***	0.24***
	(0.01)	(0.03)	(0.01)	(0.01)
N	1,816,109	1,702,307	1,728,253	1,783,669

Robust standard errors in parentheses

Data from Statistics Sweden

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

In order to understand which specific mean differences contribute to this small explained gap, we turn to the detailed decomposition in Panel 2 of Table 4. Group differences in educational attainment and type increase the employment gap for family and humanitarian immigrants. Put differently, assimilation with the native distribution of educational attainment would decrease the underlying employment gaps. A closer look at the contribution of each level of educational attainment or type indicates a crucial role for the smaller share of 3-year secondary and technical education among immigrants (see Table 10 in "Appendix"). Instead, this seems to be offset by a higher share of pre-secondary educational attainment (< 9 years) and unknown education type (Table 10 in "Appendix"). As labour immigrants have by far the largest share of at least post-secondary educational attainment, differences with native educational characteristics do not drive but shrink the employment gap (− 0.01). However, the economic magnitude for educational attainment and type is small and counteracted by regional and socio-demographic characteristics subsumed in the 'control' group. The larger share of married individuals and Stockholm-county residents, together with the greater number of children of family and humanitarian immigrants compared to natives, shrink the employment gap and offset human capital differences (Table 10). Also for labour immigrants the impact of socio-demographics reverses the trend. In particular, their younger average age and fewer children drives our gap of interest and offsets part of their more favourable human capital characteristics (Table 10). Altogether, by definition, these factors add up to the earlier-mentioned small net contribution of the differences in characteristics (explained gap).

Panel 3 displays the detailed decomposition of the unexplained gap. We find higher returns to educational attainment for humanitarian and family immigrants to shrink the employment gap (e.g. − 0.01). Again, for labour immigrants the contribution is reversed. In fact, 25% (0.02/0.08) of their unexplained employment gap can be attributed to lower returns to educational attainment. Here, it is noteworthy that this does not necessarily imply a limited transferability of human capital. As argued earlier, the results are probably driven by the relatively flat education–employment gradient. However, while the latter is offset by the similar gap-shrinking effect of education type, this pattern is not found for the remaining intake categories. Finally, particularly for the humanitarian immigrant–native gap, lower returns on socio-demographics seem to explain a large share (0.04 of 0.27). Again the driving forces seem to be lower returns for being married and number of children (Table 10 in "Appendix"). Overall, it is striking that the intercept, i.e. group membership, is the single largest gap contributor to the unexplained gap. It ranges from 87.5% (0.07/0.08) to 96% (0.23/0.24). This means that neither differences in levels nor in returns are the main gap drivers. While we cannot rule out a bias due to scaling, it is unlikely to explain our finding that human capital does not seem explain the difference to a meaningful extent. Our results therefore highlight the need to account for admission categories when estimating employment integration and research for other explanations for admission category employment heterogeneity.[5]

Does country-of-origin explain our finding?

Results from pooled regression and decomposition analysis suggest that the employment integration of immigrants varies depending on the underlying intake category. Moreover, this heterogeneity cannot be explained by differences in human capital.

[5] We also conducted a range of technical robustness checks for decomposition analysis. Our results are robust to a non-pooled framework with either native or immigrant-specific coefficients. Moreover, switching the reference group or accounting for differences in the relative group size produces similar results. However, the contribution of human capital then lies between the Blinder–Oaxaca and Probit results.

A potential omitted and confounding factor of this could be source region as it is correlated both with employment integration and admission category. Hence, our admission-specific gaps could simply capture differences in the country-of-origin composition.

We rerun the decomposition analysis for the subsamples ‘Rest of Europe’, consisting of non-EU and non-Northern European countries, ‘Africa’, Asia without the Middle East (from now on ‘Asia’), the ‘Middle East’ and, for completeness, the smallest groups of immigrants from the ‘Rest of the World’, including the Americas, Oceania and the former Soviet Union. The results are listed in the “Appendix” (Tables 11, 12, 13, 14).

While the employment gap level is region-specific,[6] they have in common that the large majority of the gap remains unexplained. Moreover, human capital contributes very little to the explained and unexplained gaps. The greatest impact of differences in human capital is found for immigrants from Africa.

The relative gap sizes and the pattern of large unexplained gaps with little human capital contribution also hold for each separate intake category across different source regions. There are, however, larger contributions for immigrants from source regions with larger employment gaps, such as family and humanitarian immigrants from Africa (35 and 25%) and family immigrants from the Middle East (23%). Note, however, that some of this evidence is based on small subsamples of labour migrants.

Even though this empirical evidence might be limited, it seems to suggest that results are unlikely to be driven by unobserved heterogeneity related to source regions. Africa aside, human capital endowment and returns explain only a small share of employment differences for all admission categories. Again, other factors seem to be at play.

Does country-specific human capital explain our finding?

While we tried to capture the effect of foreign human capital through our benchmark Blinder–Oaxaca decomposition, different returns to human capital also depend on several other reasons such as occupational background or discrimination. In order to focus on country-specific human capital more closely, we decompose the employment gap within a specific admission category, yet between different ages at immigration. We can then artificially distinguish individuals with almost-certain Swedish human capital, education and language skills, and their counterparts who pursued most of their education abroad and have uncertain host-country language skills. In particular, we compare immigrants who arrived before the age of ten with their complement. In order to control for differences in experience, we include a measure for years since migration. Due to the early arrival age, we have to limit our analysis to family and humanitarian immigrants. Table 5 shows the results of this immigrant–immigrant decomposition. Again, each column refers to a different

[6] The employment rate of immigrants from the Middle East and Africa is 34 percentage points lower than for their native counterparts. For European immigrants the gap is only 14 percentage points.

employment gap and Panel 1 displays the decomposition into an explained and an unexplained gap. In line with our benchmark decomposition in Table 4, Panels 2 and 3 deliver the detailed decomposition for the explained and unexplained gaps, respectively.

As expected, Panel 1 reports a higher employment rate for early-life immigrants. In line with theory, important drivers of the gap are not only their higher endowment but particularly their returns to human capital attainment. In column 2 of the second panel we find differences in educational attainment which explain roughly 25% (0.02/0.08) of the respective employment gap and its related lower returns to amount to 50% (0.04/0.08) of the raw gap. In particular, the latter result indicates that the lack of country-specific human capital could explain parts of the large employment gap across intake categories. Moreover, it explains the low impact of human capital characteristics and its return. Humanitarian and family immigrants at later ages seem to have a lower educational attainment and a less-favourable specialisation. Remarkably, both findings hold true even though we control for their difference in the number of years since migration. Interestingly, columns 3 and 4 indicate that most of the higher country-specific human capital returns stem from humanitarian immigrants, as the difference between young and old immigrants is not significantly different for family migrants.

Concluding discussion

In this article we study to what extent employment integration is correlated with migrant admission categories in Sweden. Moreover, we test if human capital, operationalized as level and type of education, is able to explain the employment gap between natives and immigrant categories? Using high-quality register data for the year 2011, we add to the empirical evidence on the roles of both human capital and admission category for labour market integration in Sweden.

Our results highlight substantial differences with respect to employment integration across admission categories. While the overall employment gap between immigrants and natives is roughly 25% points, ignoring admission category masks considerable heterogeneity. In particular, whereas labour migrants face a gap of 7% points, family reunification and humanitarian immigrants' differential is around 25%. On a micro-level this seems to be in line with earlier work highlighting the importance of factors related to migrant type and motivation, i.e. selection through admission category (Aydemir 2011; Bevelander 2011; Borjas 1994; Chiswick et al. 2005). On the macro-level the composition of Swedish immigrants might therefore account for some of the cross-country differences.

Interestingly, while human capital is found to be an important determinant of employment (e.g. Bevelander 2011; Dahlstedt and Bevelander 2010; Chiswick and Miller 2009), differences in the level of human capital do not seem to be a gap driver. Conditional on demographic and contextual factors, human capital explains a modest 17 and 15% respectively of the family and humanitarian employment gap, relative to natives. Ultimately, we find that the remaining gap

Table 5 Non-linear decomposition: age at immigration ≤ 10

	Immigrant	Family	Humanitarian
Panel 1: overall			
Immigrant (≤ 10)	0.70***	0.64***	0.72***
	(0.01)	(0.01)	(0.01)
Immigrant (> 10)	0.62***	0.64***	0.61***
	(0.00)	(0.00)	(0.00)
Difference	0.08***	0.00	0.12***
	(0.01)	(0.01)	(0.01)
Explained	0.13***	0.09***	0.14***
	(0.00)	(0.01)	(0.00)
Unexplained	− 0.04***	− 0.09***	− 0.03***
	(0.01)	(0.01)	(0.01)
Panel 2: explained			
Controls	− 0.03***	− 0.04***	− 0.03***
	(0.00)	(0.00)	(0.00)
Education	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
Education type	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Years since migration	0.10***	0.12***	0.10***
	(0.00)	(0.00)	(0.00)
Source	0.02***	− 0.01***	0.04***
	(0.00)	(0.00)	(0.00)
Panel 3: unexplained			
Controls	− 0.05*	− 0.05	− 0.07
	(0.02)	(0.04)	(0.04)
Education	0.04***	0.02	0.06**
	(0.01)	(0.01)	(0.02)
Education type	0.02	0.00	0.03*
	(0.01)	(0.02)	(0.02)
Years since migration	− 0.09	0.14	− 0.30
	(0.12)	(0.18)	(0.22)
Source	0.09*	0.04	0.05
	(0.04)	(0.04)	(0.03)
Constant	− 0.05	− 0.24	0.20
	(0.14)	(0.19)	(0.23)
Observations	113,497	28,222	82,518

Robust standard errors in parentheses

The data is from Statistics Sweden

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

is smallest for labour migrants (10%), and substantially larger for family (24%) and humanitarian (29%) migrants. This is in line with earlier studies for Sweden (Bevelander 2011) and Canada (Aydemir 2011). Overall, these results hold in probit and non-linear decomposition frameworks. Other drivers contribute to the labour migrant–native gap. These are differences in level and return to marital status, number of children, and residency in the county of Stockholm. Lower returns to socio-demographics also explain 17% of the humanitarian gap.

Our results could suggest that humanitarian and family migrants face difficulties trying to utilize their educational human capital on the Swedish labour market. Reasons for this could include differences in the quality of education or weaker transferability of qualifications due to missing language proficiency or (internationally-transferable) certificates. This should particularly hold true for humanitarian migrants who are subject to long asylum processes as well as larger transaction costs in procedures to translate credentials. Moreover, humanitarian and family reunification migrants might be subject to pronounced discrimination. A decomposition of the employment gap between young and old humanitarian migrants, in fact, suggests that the return to human capital obtained in Sweden is substantially higher. While this evidence rests on strong assumptions, it is in line with the suggested explanations.

As we have mentioned earlier, there might be explanations other than human capital for the strong correlation between employment integration and admission category such as unobservables related to self-selection, intention-to-stay, social network and traumatic experience. Labour migrants are favourably self-selected and enter a work-related network. While in contrast to humanitarian migrants, family reunification migrants have the benefit of a social network upon arrival, they are both less likely to be self-selected with respect to labour market success. Each non-labour migrant is also more likely to be traumatized by some refugee-inducing event in their home country. Due to a more widespread intention-to-stay, humanitarian and family reunification migrants have a larger incentive to invest in host country human capital. Here, it is important to note, however, that this investment can be considerably disrupted by prolonged asylum processes and uncertainty (Dustmann et al. 2017). While we are not able to test these hypotheses with our data at hand, they are likely to contribute to the gap.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Tables 6, 7, 8, 9, 10, 11, 12, 13 and 14.

Table 6 Probit model of employment

	Native	Immigrant	Immigrant (labour)	Immigrant (family)	Immigrant (humanitarian)
Employed					
Age 30–39	0.33***	− 0.01	− 0.21**	0.03	− 0.02
	(0.00)	(0.01)	(0.07)	(0.02)	(0.01)
Age 40–49	0.34***	− 0.07***	− 0.44***	0.08***	− 0.11***
	(0.00)	(0.01)	(0.09)	(0.02)	(0.02)
Age 50–59	0.20***	− 0.30***	− 0.59***	− 0.25***	− 0.30***
	(0.00)	(0.01)	(0.11)	(0.03)	(0.02)
Single	− 0.52***	− 0.20***	− 0.15*	− 0.22***	− 0.20***
	(0.00)	(0.01)	(0.07)	(0.02)	(0.01)
Divorced	− 0.42***	− 0.23***	0.29*	− 0.24***	− 0.23***
	(0.00)	(0.01)	(0.12)	(0.02)	(0.01)
Widowed	− 0.33***	− 0.34***	0.17	− 0.47***	− 0.31***
	(0.02)	(0.06)	(0.44)	(0.14)	(0.07)
Children	0.14***	0.02***	0.24***	0.05***	0.01***
	(0.00)	(0.00)	(0.04)	(0.01)	(0.00)
County03	− 0.05***	− 0.20***	− 0.02	− 0.12**	− 0.23***
	(0.01)	(0.02)	(0.14)	(0.04)	(0.03)
County04	− 0.04***	− 0.39***	0.46	− 0.38***	− 0.38***
	(0.01)	(0.02)	(0.28)	(0.05)	(0.03)
County05	− 0.10***	− 0.35***	− 0.07	− 0.33***	− 0.34***
	(0.01)	(0.02)	(0.15)	(0.04)	(0.02)
County06	0.11***	0.07***	0.16	0.06	0.09***
	(0.01)	(0.02)	(0.28)	(0.05)	(0.02)
County07	0.11***	− 0.17***	0.20	− 0.21**	− 0.16***
	(0.01)	(0.03)	(0.28)	(0.07)	(0.03)
County08	− 0.03***	− 0.07*	− 0.35	0.05	− 0.08*
	(0.01)	(0.03)	(0.30)	(0.08)	(0.04)
County09	− 0.11***	− 0.43***	− 1.13	− 0.29	− 0.51***
	(0.02)	(0.11)	(0.85)	(0.16)	(0.15)
County10	− 0.08***	− 0.38***	− 0.32	− 0.44***	− 0.36***
	(0.01)	(0.04)	(0.24)	(0.09)	(0.04)
County12	− 0.19***	− 0.35***	− 0.21*	− 0.41***	− 0.32***
	(0.00)	(0.01)	(0.09)	(0.02)	(0.01)
County13	0.06***	0.04	− 0.40	− 0.06	0.09**
	(0.01)	(0.03)	(0.22)	(0.06)	(0.03)
County14	− 0.07***	− 0.20***	− 0.01	− 0.21***	− 0.19***
	(0.00)	(0.01)	(0.08)	(0.02)	(0.01)
County17	− 0.26***	− 0.26***	− 0.18	− 0.38***	− 0.21***
	(0.01)	(0.03)	(0.24)	(0.07)	(0.04)
County18	− 0.06***	− 0.22***	0.14	− 0.20***	− 0.21***
	(0.01)	(0.02)	(0.31)	(0.05)	(0.03)
County19	− 0.07***	− 0.18***	0.76**	− 0.21***	− 0.17***

Table 6 (continued)

	Native	Immigrant	Immigrant (labour)	Immigrant (family)	Immigrant (humanitarian)
	(0.01)	(0.02)	(0.24)	(0.05)	(0.03)
County20	− 0.08***	− 0.36***	0.32	− 0.40***	− 0.36***
	(0.01)	(0.03)	(0.20)	(0.07)	(0.04)
County21	− 0.06***	− 0.46***	0.15	− 0.33***	− 0.49***
	(0.01)	(0.03)	(0.24)	(0.06)	(0.03)
County22	− 0.09***	− 0.40***	0.17	− 0.33***	− 0.43***
	(0.01)	(0.04)	(0.27)	(0.08)	(0.04)
County23	− 0.11***	− 0.41***	− 0.02	− 0.16	− 0.51***
	(0.01)	(0.06)	(0.31)	(0.13)	(0.07)
County24	− 0.11***	− 0.33***	− 0.22	− 0.12	− 0.39***
	(0.01)	(0.04)	(0.18)	(0.07)	(0.04)
County25	− 0.09***	− 0.22***	0.12	− 0.25**	− 0.22***
	(0.01)	(0.05)	(0.24)	(0.09)	(0.06)
Pre-sec. 9	0.34***	0.23***	− 0.25	0.22***	0.23***
	(0.01)	(0.01)	(0.19)	(0.03)	(0.02)
Secondary < 3	0.43***	0.40***	− 0.24	0.32***	0.43***
	(0.01)	(0.02)	(0.20)	(0.03)	(0.02)
Secondary 3	0.78***	0.60***	− 0.25	0.50***	0.63***
	(0.01)	(0.02)	(0.21)	(0.03)	(0.02)
Post-sec. < 3	0.62***	0.30***	0.06	0.23***	0.30***
	(0.01)	(0.02)	(0.23)	(0.04)	(0.02)
Post-sec. ≥ 3	0.83***	0.45***	− 0.09	0.40***	0.44***
	(0.01)	(0.02)	(0.22)	(0.04)	(0.02)
Scientific	0.92***	0.55***	− 0.17	0.47***	0.48***
	(0.02)	(0.04)	(0.23)	(0.07)	(0.06)
Pedagogics	0.20***	0.16***	0.01	0.17**	0.18***
	(0.01)	(0.03)	(0.26)	(0.06)	(0.03)
Humanities	− 0.18***	− 0.07**	0.10	− 0.00	− 0.11***
	(0.01)	(0.02)	(0.21)	(0.04)	(0.03)
Social sciences	0.06***	0.11***	− 0.09	0.08*	0.14***
	(0.01)	(0.02)	(0.19)	(0.04)	(0.02)
Natural sciences	− 0.02*	0.14***	0.13	0.15***	0.11***
	(0.01)	(0.02)	(0.18)	(0.04)	(0.03)
Technical	0.26***	0.29***	0.38*	0.27***	0.29***
	(0.01)	(0.01)	(0.18)	(0.03)	(0.02)
Agriculture	0.35***	0.17***	0.20	0.21**	0.18***
	(0.01)	(0.04)	(0.33)	(0.08)	(0.04)
Health	0.09***	0.39***	− 0.14	0.26***	0.48***
	(0.01)	(0.02)	(0.20)	(0.04)	(0.03)
Services	0.21***	0.19***	− 0.18	0.17***	0.20***
	(0.01)	(0.02)	(0.22)	(0.04)	(0.03)

Table 6 (continued)

	Native	Immigrant	Immigrant (labour)	Immigrant (family)	Immigrant (humanitarian)
Type unknown	0.06***	0.11***	− 0.20	0.04	0.15***
	(0.01)	(0.02)	(0.18)	(0.04)	(0.02)
Constant	0.54***	0.17***	1.04***	0.17***	0.15***
	(0.01)	(0.02)	(0.15)	(0.03)	(0.02)
Observations	1,699,060	117,049	3247	29,193	84,609
Pseudo R^2	0.094	0.050	0.068	0.047	0.054
Log-lik.	− 557,372.61	− 73,414.58	− 1480.64	− 18,192.87	− 53,324.91
χ^2	93,367.48	7504.29	200.60	1694.84	5830.17

Average marginal effects reported. Robust standard errors in parentheses

Data from Statistics Sweden

* $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 7 Employment rate by educational attainment

Educational attainment	Native	Immigrant	Immigrant (labour)	Immigrant (family)	Immigrant (humanitarian)
Pre-secondary < 9	65.50	44.64	81.62	49.20	43.10
Pre-secondary 9	78.34	53.86	73.33	56.84	52.33
Secondary < 3	87.79	65.33	74.03	65.46	65.19
Secondary 3	90.34	71.96	71.43	71.25	72.18
Post-secondary < 3	89.21	62.96	85.53	62.85	61.84
Post-secondary ≥ 3	92.54	68.55	81.64	69.51	66.88
Scientific	95.16	73.63	78.09	73.70	69.67

Data from Statistics Sweden

Table 8 Employment rate by education type

Education type	Native	Immigrant	Immigrant (labour)	Immigrant (family)	Immigrant (humanitarian)
General	80.34	53.06	76.76	56.66	51.61
Pedagogics	92.68	65.01	76.00	67.52	64.09
Humanities	81.39	58.31	78.15	61.86	55.82
Social sciences	89.65	65.01	76.37	65.17	64.45
Natural sciences	88.16	66.78	80.66	68.09	63.77
Technical	91.05	71.63	87.78	71.63	70.65
Agriculture	92.41	66.56	80.00	69.77	65.24
Health	89.75	74.99	71.81	71.58	76.33
Services	89.86	67.68	73.42	67.44	67.64
Unknown	88.18	64.72	69.46	64.01	64.79

Data from Statistics Sweden

Table 9 Probit model of employment: pooled by intake category

All				
Labour immigrants	− 0.07***	− 0.09***	− 0.10***	− 0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
Family immigrants	− 0.24***	− 0.29***	− 0.26***	− 0.24***
	(0.00)	(0.00)	(0.00)	(0.00)
Humanitarian immigrants	− 0.27***	− 0.34***	− 0.30***	− 0.29***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,816,109	1,816,109	1,816,109	1,816,109
Pseudo R^2	0.033	0.086	0.106	0.112
Log-lik.	− 692,061.20	− 653,954.18	− 639,206.09	− 634,990.51
χ^2	48,539.85	112,926.44	132,655.49	139,294.19
Immigrant (labour)				
Labour immigrants	− 0.07***	− 0.09***	− 0.10***	− 0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1,702,307	1,702,307	1,702,307	1,702,307
Pseudo R^2	0.000	0.066	0.087	0.093
Log-lik.	− 616,630.74	− 576,201.65	− 562,950.19	− 559,096.08
χ^2	157.05	67,804.56	87,981.84	93,554.03
Immigrant (family)				
Family immigrants	− 0.24***	− 0.30***	− 0.26***	− 0.24***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,728,253	1,728,253	1,728,253	1,728,253
Pseudo R^2	0.009	0.072	0.093	0.099
Log-lik.	− 634,125.92	− 593,890.90	− 580,460.03	− 576,533.35
χ^2	11,900.31	78,943.41	98,271.55	104,176.51
Immigrant (humanitarian)				
Humanitarian immigrant	− 0.27***	− 0.34***	− 0.30***	− 0.29***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,783,669	1,783,669	1,783,669	1,783,669
Pseudo R^2	0.027	0.082	0.103	0.109
Log-lik.	− 671,388.09	− 633,132.69	− 618,493.86	− 614,392.23
χ^2	38,394.64	102,446.91	122,197.67	128,637.50
Controls				
Demographic	No	Yes	Yes	Yes
Education	No	No	Yes	Yes
Education type	No	No	No	Yes

Average marginal effects reported. Robust standard errors in parentheses

Data from Statistics Sweden

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 10 Non-linear decomposition analysis: detail

	Immigrant–native	Labour immigrant–native	Family immigrant–native	Humanitarian immigrant–native
Overall				
Native	0.88***	0.88***	0.88***	0.88***
	(0.00)	(0.00)	(0.00)	(0.00)
Immigrant	0.63***	0.81***	0.64***	0.62***
	(0.00)	(0.01)	(0.00)	(0.00)
Difference	0.26***	0.07***	0.24***	0.27***
	(0.00)	(0.01)	(0.00)	(0.00)
Explained	− 0.00**	− 0.01***	0.01***	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Unexplained	0.26***	0.08***	0.24***	0.27***
	(0.00)	(0.01)	(0.00)	(0.00)
Explained				
Age 20–29	0.00***	0.00***	0.06	0.00***
	(0.00)	(0.00)	(0.10)	(0.00)
Age 30–39	− 0.00**	− 0.00***	− 0.01	− 0.00***
	(0.00)	(0.00)	(0.02)	(0.00)
Age 40–49	− 0.00**	0.00***	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Age 50–59	− 0.00**	− 0.00***	− 0.01	− 0.00***
	(0.00)	(0.00)	(0.02)	(0.00)
Couple	− 0.00**	− 0.00***	− 0.15	− 0.00***
	(0.00)	(0.00)	(0.26)	(0.00)
Single	− 0.00**	− 0.00***	− 0.16	− 0.00***
	(0.00)	(0.00)	(0.27)	(0.00)
Divorced	0.00***	− 0.00***	0.03	0.00***
	(0.00)	(0.00)	(0.05)	(0.00)
Widowed	0.00	0.00	− 0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Children	− 0.00**	0.01***	− 0.10	− 0.00***
	(0.00)	(0.00)	(0.18)	(0.00)
County01	− 0.00**	− 0.00***	− 0.04	− 0.00***
	(0.00)	(0.00)	(0.07)	(0.00)
County03	0.00	− 0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
County04	0.00	0.00**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
County05	0.00	− 0.00***	− 0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County06	− 0.00**	0.00***	0.00	− 0.00***
	(0.00)	(0.00)	(0.01)	(0.00)
County07	− 0.00**	0.00***	0.00	− 0.00***
	(0.00)	(0.00)	(0.01)	(0.00)

Table 10 (continued)

	Immigrant–native	Labour immigrant–native	Family immigrant–native	Humanitarian immigrant–native
County08	0.00**	0.00***	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County09	− 0.00*	− 0.00**	− 0.00	− 0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
County10	− 0.00*	− 0.00	− 0.00	− 0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
County12	0.00***	− 0.00***	0.01	0.00***
	(0.00)	(0.00)	(0.02)	(0.00)
County13	0.00**	0.00***	0.01	0.00***
	(0.00)	(0.00)	(0.01)	(0.00)
County14	0.00	− 0.00	− 0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
County17	− 0.00**	− 0.00***	− 0.01	− 0.00***
	(0.00)	(0.00)	(0.02)	(0.00)
County18	− 0.00	0.00	0.00	− 0.00
	(0.00)	(0.00)	(0.00)	(0.00)
County19	0.00	0.00	− 0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
County20	− 0.00*	− 0.00	− 0.00	− 0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
County21	− 0.00	0.00	− 0.00	− 0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
County22	− 0.00*	− 0.00**	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County23	− 0.00**	− 0.00***	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County24	− 0.00**	− 0.00***	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County25	− 0.00*	− 0.00***	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Pre-sec. < 9	0.00***	0.00***	0.18	0.00***
	(0.00)	(0.00)	(0.31)	(0.00)
Pre-sec. 9	− 0.00**	− 0.00***	0.01	− 0.00***
	(0.00)	(0.00)	(0.01)	(0.00)
Secondary < 3	− 0.00**	− 0.00***	− 0.03	− 0.00***
	(0.00)	(0.00)	(0.05)	(0.00)
Secondary 3	0.00***	0.01***	0.04	0.00***
	(0.00)	(0.00)	(0.07)	(0.00)
Post-sec. < 3	− 0.00	− 0.00***	− 0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Post-sec. ≥ 3	− 0.00*	− 0.01***	− 0.00	0.00***
	(0.00)	(0.00)	(0.01)	(0.00)

Table 10 (continued)

	Immigrant–native	Labour immigrant–native	Family immigrant–native	Humanitarian immigrant–native
Scientific	– 0.00**	– 0.01***	– 0.01	0.00***
	(0.00)	(0.00)	(0.01)	(0.00)
General	0.00***	– 0.00***	0.05	0.00***
	(0.00)	(0.00)	(0.09)	(0.00)
Pedagogics	0.00**	0.00***	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Humanities	0.00*	0.00	0.01	– 0.00
	(0.00)	(0.00)	(0.02)	(0.00)
Social sciences	– 0.00**	– 0.00***	– 0.00	– 0.00***
	(0.00)	(0.00)	(0.01)	(0.00)
Natural sciences	0.00**	0.00***	0.01	0.00***
	(0.00)	(0.00)	(0.01)	(0.00)
Technical	0.00***	0.00***	0.11	0.00***
	(0.00)	(0.00)	(0.18)	(0.00)
Agriculture	0.00***	0.00***	0.01	0.00***
	(0.00)	(0.00)	(0.02)	(0.00)
Health	– 0.00*	0.00*	0.00	– 0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Services	0.00***	0.00***	0.01	0.00***
	(0.00)	(0.00)	(0.01)	(0.00)
Type unknown	0.00***	0.00***	0.01	0.00***
	(0.00)	(0.00)	(0.02)	(0.00)
Unexplained				
Age 20–29	– 0.01***	– 0.03***	– 0.01***	– 0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Age 30–39	0.00***	0.00	0.00***	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Age 40–49	0.01***	0.01***	0.00	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Age 50–59	0.01***	0.00***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Couple	0.02***	0.04***	0.01*	0.02***
	(0.00)	(0.01)	(0.01)	(0.00)
Single	– 0.01***	0.00	– 0.01***	– 0.01***
	(0.00)	(0.01)	(0.00)	(0.00)
Divorced	– 0.00***	– 0.00*	– 0.00**	– 0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Widowed	0.00**	– 0.00	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
Children	0.04***	– 0.01*	0.03***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)

Table 10 (continued)

	Immigrant–native	Labour immigrant–native	Family immigrant–native	Humanitarian immigrant–native
County01	− 0.01***	0.00	− 0.02***	− 0.01***
	(0.00)	(0.01)	(0.00)	(0.00)
County03	− 0.00	0.00	− 0.00*	− 0.00
	(0.00)	(0.00)	(0.00)	(0.00)
County04	0.00***	− 0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County05	0.00**	0.00	0.00	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
County06	− 0.00***	− 0.00	− 0.00*	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County07	0.00***	− 0.00	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
County08	− 0.00***	0.00	− 0.00**	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County09	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
County10	0.00**	0.00	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
County12	− 0.00*	0.00	0.00*	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County13	− 0.00***	0.00*	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County14	− 0.00***	− 0.00	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County17	− 0.00***	− 0.00	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County18	− 0.00	− 0.00	− 0.00	− 0.00
	(0.00)	(0.00)	(0.00)	(0.00)
County19	− 0.00***	− 0.00**	− 0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County20	0.00**	− 0.00	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
County21	0.00***	− 0.00	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County22	0.00***	− 0.00	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
County23	0.00	− 0.00	− 0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
County24	0.00	0.00	− 0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
County25	− 0.00	− 0.00	− 0.00	− 0.00
	(0.00)	(0.00)	(0.00)	(0.00)

Table 10 (continued)

	Immigrant–native	Labour immigrant–native	Family immigrant–native	Humanitarian immigrant–native
Pre-sec. < 9	− 0.01***	− 0.01***	− 0.01***	− 0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Pre-sec. 9	− 0.00***	− 0.00	− 0.00***	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Post-sec. < 3	− 0.01***	− 0.00	− 0.01***	− 0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Secondary 3	− 0.00	0.00**	0.00	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Post-sec. < 3	0.00***	− 0.00	0.01***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Post-sec. ≥ 3	0.01***	0.02**	0.01***	0.01***
	(0.00)	(0.01)	(0.00)	(0.00)
Scientific	0.00***	0.01***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
General	0.00***	− 0.00	0.00	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Pedagogics	0.00***	0.00	0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Humanities	− 0.00***	− 0.00**	− 0.00***	− 0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Social sciences	− 0.00	0.00	0.00	− 0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Natural sciences	− 0.00***	− 0.01**	− 0.00***	− 0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Technical	0.00	− 0.01**	0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Agriculture	0.00***	0.00	0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Health	− 0.00***	0.00	− 0.00***	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Services	0.00***	0.00*	0.00*	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Type unknown	− 0.00**	0.00	0.00	− 0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.23***	0.07**	0.23***	0.24***
	(0.01)	(0.03)	(0.01)	(0.01)
Observations	1,816,109	1,702,307	1,728,253	1,783,669

Robust standard errors in parentheses

Data from Statistics Sweden

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 11 Immigrant–native employment gap by source region: all men

	All	Rest of Europe	Africa	Asia w/o Middle East	Middle East	Rest of the World
Overall						
Native	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Immigrant	0.63***	0.74***	0.54***	0.65***	0.55***	0.71***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Difference	0.26***	0.14***	0.34***	0.23***	0.34***	0.18***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Explained	− 0.00**	− 0.01***	0.01***	0.01***	− 0.00***	− 0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unexplained	0.26***	0.15***	0.33***	0.22***	0.34***	0.18***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Explained						
Controls	− 0.01**	− 0.02***	− 0.10***	0.07	− 0.01***	− 0.01***
	(0.00)	(0.00)	(0.01)	(0.05)	(0.00)	(0.00)
Education	0.00***	0.01***	0.07***	− 0.03	0.00***	− 0.00***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)
Educ. type	0.00***	0.00***	0.04***	− 0.04	0.00***	0.01***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)
Unexplained						
Controls	0.03***	0.03***	− 0.01	0.01	0.04***	− 0.02
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Education	− 0.00*	− 0.01***	− 0.00	− 0.00*	0.00	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Educ. type	0.00	− 0.00	0.00	− 0.00	0.01*	− 0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.23***	0.13***	0.34***	0.22***	0.29***	0.19***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Observations	1,816,109	1,736,463	1,715,252	1,710,071	1,744,115	1,706,448

Robust standard errors in parentheses

Data from Statistics Sweden

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 12 Immigrant–native employment gap by source region: male labour immigrants

	All	Rest of Europe	Africa	Asia w/o Middle East	Middle East	Rest of the World
Overall						
Native	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Immigrant	0.81***	0.81***	0.78***	0.81***	0.83***	0.75***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Difference	0.07***	0.07***	0.10***	0.07***	0.05**	0.13***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Explained	− 0.01***	− 0.01***	− 0.03***	− 0.02***	0.01*	− 0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unexplained	0.09***	0.08***	0.13***	0.09***	0.05*	0.15***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Explained						
Controls	− 0.00	− 0.01**	− 0.01***	− 0.00	0.01*	− 0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education	− 0.02***	− 0.01***	− 0.02***	− 0.02***	− 0.00	− 0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Educ. type	0.01***	0.01***	0.01***	0.00***	0.00***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unexplained						
Controls	0.02	0.04	− 0.08	− 0.01	− 0.05	− 0.03
	(0.03)	(0.03)	(0.09)	(0.06)	(0.04)	(0.05)
Education	0.02	− 0.00	− 0.05	0.07	0.00	− 0.04
	(0.01)	(0.02)	(0.09)	(0.04)	(0.02)	(0.07)
Educ. type	− 0.02**	− 0.02	− 0.01	− 0.04**	− 0.04	− 0.04
	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)	(0.03)
Constant	0.08*	0.07	0.27*	0.08	0.14*	0.25**
	(0.03)	(0.04)	(0.12)	(0.07)	(0.06)	(0.09)
Observations	1,702,307	1,424,651	1,463,124	1,573,605	1,374,971	1,425,677

Robust standard errors in parentheses

Data from Statistics Sweden

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 13 Immigrant–native employment gap by source region: male family immigrants

	All	Rest of Europe	Africa	Asia w/o Middle East	Middle East	Rest of the World
Overall						
Native	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Immigrant	0.64***	0.71***	0.57***	0.66***	0.59***	0.69***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Difference	0.24***	0.17***	0.31***	0.22***	0.30***	0.19***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Explained	0.01***	– 0.00*	0.01***	0.02***	0.02***	– 0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unexplained	0.24***	0.18***	0.30***	0.20***	0.28***	0.20***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Explained						
Controls	– 0.38	– 0.01***	– 0.07***	– 0.02***	– 0.05***	– 0.01***
	(0.66)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)
Education	0.18	0.01***	0.04***	0.01***	0.04***	– 0.00***
	(0.31)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Educ. type	0.21	0.00***	0.04***	0.02***	0.03***	0.01***
	(0.35)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Unexplained						
Controls	0.00	0.01	– 0.02	0.01	– 0.00	– 0.05*
	(0.01)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)
Education	– 0.00	– 0.01	– 0.00	– 0.00	– 0.01	0.01*
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Educ. type	0.00	0.00	– 0.01	– 0.00	– 0.00	– 0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Constant	0.23***	0.18***	0.33***	0.19***	0.29***	0.24***
	(0.01)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)
Observations	1,728,253	1,705,958	1,705,201	1,702,663	1,706,904	1,703,767

Robust standard errors in parentheses

Data from Statistics Sweden

*$p<0.05$; **$p<0.01$; ***$p<0.001$

Table 14 Immigrant–native employment gap by source region: male humanitarian immigrants

	All	Rest of Europe	Africa	Asia w/o Middle East	Middle East	Rest of the World
Overall						
Native	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Immigrant	0.62***	0.74***	0.51***	0.61***	0.53***	0.73***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Difference	0.27***	0.14***	0.37***	0.28***	0.35***	0.15***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Explained	− 0.00***	− 0.01***	0.02***	0.00**	− 0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unexplained	0.27***	0.15***	0.36***	0.27***	0.35***	0.15***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Explained						
Controls	− 0.01***	− 0.02***	− 0.11***	0.03	− 0.02***	0.02
	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.05)
Education	0.00***	0.01***	0.08***	− 0.02	0.01***	0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Educ. type	0.00***	0.00***	0.05***	− 0.01	0.01***	− 0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.04)
Unexplained						
Controls	0.04***	0.04***	0.00	0.03*	0.05***	− 0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Education	− 0.01***	− 0.01	− 0.01	− 0.02***	− 0.00	0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Educ. type	0.00	− 0.00	0.01	0.01	0.01**	0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Constant	0.24***	0.12***	0.36***	0.25***	0.30***	0.14***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Observations	1,783,669	1,729,042	1,708,810	1,693,600	1,735,803	1,684,963

Robust standard errors in parentheses

Data from Statistics Sweden

*$p<0.05$; **$p<0.01$; ***$p<0.001$

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