SKILL MISMATCHES IN THE EU: IMMIGRANTS vs. NATIVES

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Abstract

The situation of immigrants within their host countries' labour markets is generally worse than the situation of natives. We focus our interest in the analysis of the differences in skill mismatches between immigrants and natives in EU countries. We use microdata from the Adult Education Survey (AES) carried out in 2007. This dataset allows us to analyse the incidence of different types of skill mismatches (vertical and horizontal) among native and immigrant workers. We do not find any significant difference in the probability of having horizontal mismatch between natives and immigrants once individual characteristics are controlled for. However, we find that immigrants are more likely to be overeducated than natives, and that this effect is higher for immigrants coming from non-EU countries than for those coming from other EU countries. Nonetheless, the pace of the assimilation process in the host country is faster for the first group. By means of the Yun decomposition, we also find that immigrants from the EU have a higher probability of being overeducated than natives because they have worse observable characteristics which influence positively the probability of overeducation, whereas results for immigrants from non-EU countries suggest the opposite: the gap is explained by differences in the returns to observable characteristics. This result suggests that immigrants from non-UE countries have a limited transferability of their human capital that pushes their situation of overeducation in the host country.

Keywords: Immigration, overeducation, assimilation.

JEL Codes: J61, J24

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1. INTRODUCTION, BACKGROUND AND OBJECTIVES

Human capital is one of the key factors in the determination of most of labour market outcomes (Card, 1999; Psacharopoulos and Patrinos, 2004). Consistent with this perspective, the analysis of the situation of immigrants within their host countries' labour markets has also focused on their human capital. In particular, the two main empirical results from this literature —the presence of a significant initial wage gap relative to native-born workers and the rapid wage growth from the moment of arrival—can basically be explained by their human capital. Further, human capital partially explains most differences between immigrants and natives in terms of participation in labour market or job quality, among others. Thus, the disadvantage experienced by immigrants when they arrive in a new country can generally be attributed to the limited transferability of the human capital they have acquired in their home country. The reason may lie in the lower quality of the educational system there or in the different cultural background. Whatever the case, the relevant fact is that newly arrived immigrants seem to lack human capital adequate to the needs of the host country's labour market (Chiswick, 1978; Chiswick and Miller, 1985, 2009; Friedberg, 2000). Moreover, the explanatory factor behind the rapid growth in immigrant labour market outcomes over time, especially in wages, can be found in the accumulation of different types of human capital in the host country, which is particularly significant in the first years of residence in the host country (i.e., knowledge of the host country language). It is also noteworthy that this rapid growth in labour market outcomes generally leads to assimilation with the native population (Chiswick, 1978; Baker and Benjamin, 1994; Chiswick and Miller, 1995; and Bell, 1997; among others).

Within this literature, recent studies have focused on the role played by educational (or vertical) mismatch and more specifically, on the level of overeducation. Although an extensive body of research has analysed overeducation[1] since the seminal contributions of Freeman (1976) and Duncan and Hoffman (1981), only a few recent

[1] Surveys by Hartog (2000), Rubb (2003) and McGuiness (2006) have summarised the main findings of this literature.

studies have considered differences between natives and immigrants in terms of skill mismatches.[2]

Overeducation is usually defined as the situation where workers have greater educational skills than their jobs require (Rumberger, 1981). The idea underpinning this new literature is thus that the imperfect portability of human capital acquired in origin countries forces immigrants to accept jobs requiring lower qualifications than those acquired in their country, making them formally overeducated workers.[3] The main outcomes of these recent studies can be summed up in two empirical regularities. First, there is evidence of a greater incidence of overeducation among immigrants than among the native population. Second, immigrant workers succeed in reducing the difference in overeducation with respect to the native population as their stay in the new country is prolonged, i.e. the phenomenon of assimilation takes place in overeducation (in a similar way to the one found for earnings assimilation).

The literature on immigrant assimilation started with Chiswick (1978) who explained the lower marginal returns of immigrant human capital in the USA by the limited portability of their human capital. The results obtained for other economies confirm the differences between natives and immigrants in terms of the remuneration of their human capital, and also show the existence of assimilation processes (Chiswick and Miller, 1995, for Australia; Baker and Benjamin, 1994, for Canada; Bell, 1997, for the UK; Schmidt, 1992, and Constant and Massey, 2003, for Germany; and Longva and Raaum, 2003, for Norway). Shields and Wheatley Price (1998) and Friedberg (2000) obtain also interesting results separating the education acquired by immigrants in their country of origin from the education acquired in the country of destination. They find that the human capital imported from culturally distant countries receives a lower remuneration than the one acquired in the country of destination, and this remuneration differs depending on the characteristics of the origin country. Thus, the greater the distance in terms of language, culture, and economic development, the less portable the human capital acquired abroad becomes and the greater the initial inequality in the job market in comparison with members of the native population.

[2] See for instance, Piracha and Vadean (2012); Dustman and Glitz (2011) and Leuven and Oosterbeek (2011)

[3] Possible differences in the quality of the different educational systems limit the comparison between native and immigrants workers. Nevertheless, many other factors (including a partial knowledge of the language, qualifications not being recognised and studies adapted to the new labour market) reduce the expected productivity of immigrants leading them to accept lower-paid jobs.

Nonetheless, Duleep and Regets (1997) find out that those immigrants characterized by a lower portability of their human capital show a higher speed of assimilation.

Other interesting results have been found when overeducation has been explicitly introduced into the analysis of the differences between natives and immigrants. Most of the literature concludes that immigrants have a higher rate of overeducation than natives (Chiswick and Miller, 2010). For instance, using data from Australia, Kler (2006) and Green et al. (2007) point out that the incidence of overeducation is higher among immigrants from non-English-speaking countries, who also show lower returns for overeducation. In the case of the United Kingdom, Lindley and Lenton (2006) find a higher incidence of overeducation not just among immigrants but also for non-white members of the native-born population. Using data from United States, Chiswick and Miller (2008) claim that the educational mismatch explains almost two thirds of the differences in human capital returns between natives and immigrants.

In the analysis of the incidence of overeducation among immigrants, other results related to the degree of transferability of human capital acquired in the origin country and the process of assimilation are also interesting. In particular, Chiswick and Miller (2007) find that the greater the work experience in the country of origin, the greater the probability of overeducation in the United States, which indicates low transferability not only of schooling but also of work experience acquired in origin countries. Sanromá et. al (2008) point out that immigrants living in Spain accumulate knowledge and experience that are perfectly adapted to the local labour market, thus making for an easier assimilation process that reduces the intensity of over-education. However, the pace of assimilation is notably slow -so that around fifteen years of living in Spain would be necessary to eliminate the educational mismatch- and differs depending on the origin country. Using data from New Zealand, Poot and Stillman (2010) also conclude that it is relevant to control for origin heterogeneity when analysing the pace of assimilation of immigrants in terms of overeducation. Last, Nielsen (2007) shows that overeducation in Denmark affects immigrants with education acquired abroad more than it does for natives and immigrants who have acquired their education in Denmark. According to this author, this fact reveals the partial portability of human capital acquired in migrants' origin countries. Furthermore, immigrants with education acquired in their own country reduce their overeducation level as they increase their effective work experience in Denmark. Thus, they successfully assimilate. As for the returns to years of overeducation, Nielsen shows that immigrants who have studied abroad have the lowest returns, followed by immigrants with Danish qualifications, and by the native-born population who enjoy the highest returns

On the other hand, there are some studies that have not found any evidence of a successful assimilation process by immigrants in the host country. Dell'Aringa and Pagani (2010) shows that the "catch-up" by foreigners in Italy seems unachievable, even once they have adapted their skills to the host country's labour market. Comparing data from 25 countries, the OECD (2007) obtains similar results in most of the countries. A similar conclusion is found by Aleksynska and Tritah (2013) when analysing data from the European Social Survey for 22 European countries for the period 2002-2009.

Most of these papers consider vertical mismatch, i.e. mismatch between worker's educational level and the one required for their job, as an indicator of skill mismatch. However, there are other indicators of skill mismatch that have not been used until now in the analysis of immigrants. In this paper, besides vertical mismatch, we are going to consider horizontal mismatch, which measures the degree of adjustment between the workers' educational field and the one required for their job, as another form of skill mismatch.[4]

With the purpose of analysing the role played by these two kinds of skill mismatches on native and immigrant population, we use a database which allows us to measure both vertical and horizontal mismatches. To the best of our knowledge, there are no previous studies that have analysed both types of skill mismatches separately for natives and immigrants using homogeneous information for a wide group of European Union countries. Taking this into account, the aim of this paper is twofold. First, we examine the determinants of being in a situation of vertical or horizontal mismatch for natives and immigrants from EU countries and from non-EU countries, focusing also on the process of assimilation. Second, we try to identify the explaining factors behind the observed differences in the probability of being mismatched between natives and both types of immigrants.

[4] For instance, Robst (2007) and Wolbers (2003) use this measure as indicator of skill mismatch.

The rest of the paper is organized as follows. Section 2 describes the database and defines the variables of interest. Section 3 shows descriptive evidence of the incidence of vertical and horizontal mismatches for natives and immigrants, focusing also on the analysis of the assimilation process of immigrants. Section 4 explains the applied methodology and shows the results. Last, section 5 summarises the findings of previous sections and point out the main policy conclusions of the analysis.

2. DATA SOURCES AND VARIABLES DEFINITION

2.1. Adult Education Survey

We use microdata from the Adult Education Survey (AES) provided by Eurostat. It is a survey addressed to private households with members between 25 and 64 years old. The survey has been carried out in 29 countries between 2005 and 2008 and the reference year is 2007. The main objective of the survey is to study lifelong learning, i.e., those training and learning activities that the adult population performs with the objective of improving or extending their knowledge, skills and competences from a personal, civil, social or work-related perspective.

This database is particularly appropriate for our analysis because, as far as we know, is the only one that allows us measuring both vertical and horizontal mismatch in a homogeneous way for a wide set of European Union countries and making comparisons between immigrant (from EU countries and from non-EU countries) and native workers.

As we focus our interest on immigrants living in EU countries, we only consider those countries where immigration is a relevant phenomenon (more than 4% of total population). Thus, as shown in Figure 1, we do not consider Bulgaria, Poland, Romania and Slovakia. We also have excluded from the analysis Hungary and the Netherlands because the immigrant population reported in the Adult Education Survey is underrepresented when compared with aggregate data from Eurostat[5].We also exclude Finland, Italy and the United Kingdom from the analysis because in their national surveys some relevant information for our analysis are missing (in particular,

[5]Immigrant population in AES is 4.8% in the Netherlands and 1.6% in Hungary while these percentages correspond in 11.1% and 4.3%, respectively, according to Eurostat data.

immigrants' years of residence in the host country). So, after these restrictions, we finally consider the following 15 European Union countries in the analysis: Austria, Belgium, Cyprus, Czech Republic, Germany, Denmark, Estonia, Spain, France, Greece, Latvia, Lithuania, Portugal, Sweden and Slovenia.

We restrict our analysis to men and women employed (excluding armed forces' employed) at the time of the survey with reliable information about their occupation and level and field of education. We exclude from the analysis individuals below the ISCED3 educational level since the variable "field of education" is only defined for individuals with educational levels higher than ISCED2. The final sample consists of 30,149 native born workers and 2,699 immigrant workers, of which 929 come from European Union countries and 1,770 come from non-European Union countries.

FIGURE 1

The variables used in the analysis are related to personal and job characteristics. As for personal characteristics, we use information related to the country of residence, gender, age, nationality, years of residence in the host country, level and type of education and participation in non-formal education activities during the last 12 months. As for job characteristics, we consider information about the tenure in the firm where they are currently employed, the economic activity of the firm, and the size of the firm. We also consider other variables related to personal and job characteristics such as the number of members of the household, children at home (13 years old or less) and the type and duration of the contract[6]. Descriptive statistics for these variables are shown in Table A.1 of the Annex.

2.2. Measuring skill mismatches

Three different methods have been proposed in the literature to measure vertical mismatch: objective, subjective and statistical method (in terms of the mean and the

[6] The latter information is not available for Denmark, Greece and Slovenia.

mode). Each procedure has its own advantages and weaknesses.[7] As a consequence, the used method usually depends on the nature of the data available.

The objective method is based on "dictionaries" of jobs, compiled by job analysts who determine what level and type of education workers should have in order to perform a certain job. A person is then overeducated if their level of education is higher than the level the analysts define to be ideal for the occupation. The subjective method takes into account the perception of the workers to determine the educational mismatch. Last, the version of the statistical method based on the mean (Verdugo and Verdugo, 1989) considers that workers are overeducated if they have more years of education than the mean of the years of education (plus one standard deviation) of the workers in that occupation. Nevertheless, Kiker et al. (1997) propose the use of the mode instead of the mean; so they consider as overeducated a person who has more years of education than the mode of years of education in the job they perform.

As for horizontal mismatch, most studies have applied similar methods to the ones used to analyse vertical mismatch. In particular, they use similar approaches but substitute the variable "years of education" with the variable "field of education". In this paper, we use the statistical method in terms of the mode for two reasons. First, we cannot use the objective method because, unfortunately, this kind of indicator is not available for most countries, as massive efforts are needed to build these dictionaries, which can easily become obsolete due to occupational change. We can neither use the subjective method because the Adult Education Survey does not provide this information. So, we measure vertical and horizontal mismatch using the statistical method based on the mode. The Adult Education Survey provides the needed information: occupations, educational levels and fields of education. It is worth mentioning that as we are working with immigrants from countries characterized by heterogeneous educational systems, we measure vertical mismatches considering the level of education instead of the years of schooling. With this way of proceeding, we expect to minimize potential measurement errors that can derive from the comparison of very heterogeneous educational systems.

Taking into account these previous considerations, we define both types of mismatches as follows: workers will have vertical mismatch (overeducation) if their

[7] For a discussion, see Hartog (2000).

level of education is higher than the mode of the native workers' level of education within each occupation whereas workers will have horizontal mismatch if their field or type of education is different from the mode of the native workers' field of education within each occupation.

3. DESCRIPTIVE EVIDENCE

In this section, we carry out a descriptive analysis on the differences between natives and immigrants regarding horizontal and vertical skill mismatches. The percentage of natives, immigrants from EU countries and immigrants from non-EU countries who show vertical and horizontal mismatch are displayed in figures 2 and 3, respectively. Some interesting insights can be derived from these figures. First, it is worth noting that the percentages of horizontal mismatch are higher than the percentages of vertical mismatch in all groups (39-46 versus 24-35 respectively). Second, figure 2 shows that 24% of natives are overeducated whereas this percentage is 31% for immigrants from EU countries and 35% for immigrants coming from other countries. Nevertheless, in figure 3 we can see that the percentage of horizontal mismatch for natives and immigrants from EU countries is around 40% for both groups whilst for immigrants from countries outside EU is higher, 46%. Although the incidence of horizontal mismatch is higher than the incidence of vertical mismatch for all groups, we observe more differences between natives and immigrants in the incidence of vertical mismatch.

FIGURES 2 and 3

Focusing only on the immigrant population, we can see some interesting differences depending on the years of residence in their host country. Figures 4 and 5 show, respectively, the percentage of immigrant workers with vertical and horizontal mismatch by years of residence in the host country. In figure 5 we see that the incidence of horizontal mismatch decreases for both groups of immigrants as their years of residence increase. This result could be interpreted as evidence of immigrant assimilation. The outcomes are different, however, in relation to vertical mismatch

(Figure 4). In fact, while for immigrants from countries outside the EU, the incidence of overeducation also reduces as the years of residence of these immigrants increase, the same is not valid for immigrants coming from EU countries. In particular, immigrants who reside less than 2 years in the host country present a lower percentage of overeducation than immigrants who reside between 3 to 5 years. In this case, it seems that the assimilation process in the first 5 years in the host country is not as clear for immigrants from EU countries as for the others.

FIGURES 4 and 5

The descriptive analysis carried out in this section does not consider the effect of the characteristics of the individuals on the differences in overeducation. This aspect is considered in the following section.

4. METHODOLOGY AND RESULTS

4.1. Methodology

In order to know whether there are differences in the probability of being overeducated and in the probability of having horizontal mismatch between natives and immigrants after controlling for observable characteristics, we estimate two binomial probit models.

$$prob(V\_MISM) = \Phi(X\beta) \quad (1)$$

$$prob(H\_MISM) = \Phi(X\beta) \quad (2)$$

where prob(V_MISM) and prob(H_MISM) denote the probability of being overeducated and the probability of having horizontal mismatch respectively, Φ is the standard normal cumulative distribution function, X represents the set of observable characteristics and β is the coefficients' vector.

The explanatory variables can be clustered in two groups. The first one is related to personal characteristics of individuals such as gender, age, immigrant condition (also by distinguishing immigrants from EU countries and from non-EU countries), years of residence in the host country, level of education (ISCED3, ISCED4 and ISCED5&6), type or field of education (8 categories[8]) and whether the workers have followed any non-formal education activity in the last 12 months. As we focus our interest on immigrants and their process of assimilation, we also include interactions between the variables related to their different origins (EU and non-EU countries) and their years of residence. The second group of characteristics is related to job characteristics such as tenure in the firm they are currently employed (in years), economic activity of the firm (5 categories[9]) and firm size (small: firms with 10 or less workers; big: firms with more than 10 workers). We also include country fixed-effects and controls for urban size.

To decompose the differences in the probability of having vertical (horizontal) mismatch between immigrants and natives, we then apply Yun's (2004) methodology that is composed by two steps. The first one consists in estimating equation (1) separately for immigrants and natives:[10]

$$prob(V\_MISM)_I = \Phi(X_I \beta_I) \tag{3}$$

$$prob(V\_MISM)_N = \Phi(X_N \beta_N) \tag{4}$$

The second step consists in decomposing the mean difference between immigrants (I) and natives (N) in the probability of having vertical (horizontal) mismatch as:

$$\overline{prob(V\_MISM)_I} - \overline{prob(V\_MISM)_N} = \underbrace{\left[\overline{\Phi(X_I \beta_I)} - \overline{\Phi(X_I \beta_N)}\right]}_{E} + \underbrace{\left[\overline{\Phi(X_I \beta_N)} - \overline{\Phi(X_I \beta_I)}\right]}_{C} \tag{5}$$

[8] Education: Teacher training and education science / Humanities: Humanities, languages and arts; Foreign languages / Social Science: Social Science, business and law / Science: Science, mathematics and computing / Engineering: Engineering, manufacturing and construction. / Agriculture: Agriculture and veterinary. / Health: Health and welfare. / Services: Services.

[9] Industry, agriculture, construction, market services and non-market services.

[10] It is worth mentioning that in this kind of analysis it is not possible to include information on the years of residence as this characteristic is not shared also by natives.

The component labelled *E* refers to the part of the difference in the probability of having a vertical (horizontal) mismatch between immigrants and natives due to differences in the observable characteristics. On the other hand, the *C* component refers to the part of this difference due to differences in coefficients (returns to characteristics). The method also proposes a detailed decomposition that allows understanding the unique contribution of each predictor to each component of the difference. As in the Oaxaca decomposition, Yun (2004) also highlights the need to normalize dummy variables as the results of the decomposition method are not invariant to the choice of the reference category. This correction is used in this paper.

4.2. Results

The marginal effects of the probability of being overeducated (vertical mismatch) are shown in table 1. Columns (1) and (2) only include some personal characteristics as explanatory variables while in columns (3) to (5) additional controls are added sequentially.

TABLE 1

Results from column (1) clearly show that immigrants are more likely to be overeducated than natives after controlling for some personal observable characteristics (the difference is of 44.4 percentage points). However, the negative sign of the variable years of residence indicates that the more are the years in the host country the less is the probability to be overeducated. For each additional year of residence in the host country, the probability of being overeducated is reduced by 2.8 percentage points. So, there seems to be an assimilation process in the host country in terms of overeducation. In column (2) we introduce two different dummies for immigrants in order to distinguish between immigrants coming from EU countries and immigrants coming from non-EU countries. We can see that immigrants from non-EU countries are more likely to be overeducated than immigrants from EU countries. Concerning the process of assimilation of both types of immigrants, the results for the interactions between years of residence and immigrant dummies show that an additional year of residence reduces the probability to be overeducated for immigrants from outside EU countries more than for those coming from EU countries. In particular, the probability to be overeducated for an immigrant from EU country is reduced by 2.3 percentage points for each year of residence in the host country while this reduction is equal to 3.2 percentage points for immigrants from countries outside EU. Therefore, although immigrants from countries outside the EU have a higher probability to be overeducated, their process of assimilation is faster than the one for immigrants from EU countries. These differences between groups hold when additional personal and job controls are included in columns (3) to (5), although the coefficients are slightly reduced as more controls are included. It is important to notice that, as previously explained, column (5) includes some additional control variables that are not available for Denmark, Greece and Slovenia. We show this model just to check whether the inclusion of these variables change the impact of our variables of interest. The inclusion of these additional control variables does not change the main results of the variables related to immigrants.

The marginal effects of the probit estimation related to the probability of having horizontal mismatch are shown in table 2. As before, columns (1) and (2) include only some control variables while in columns (3) to (5) additional explanatory variables are included.

TABLE 2

Column (1) shows that the probability of having a horizontal mismatch is 18 percentage points higher for immigrants than for natives. It is also worth noting that the difference in the probability of horizontal mismatch between immigrants and natives is much lower than the difference in the probability of overeducation (which is equal to 44.4 percentage points). Regarding the years of residence in the host country, we can see that the probability of having horizontal mismatch is only reduced by 1 percentage point for each additional year and this effect is also not statistically significant. Results from column (2) show that immigrants from non-UE countries are more likely to have horizontal mismatch than natives (19.5 percentage points of difference). On the other hand the difference in the probability of horizontal mismatch between natives and immigrants from EU countries is not significant. Moreover, the interactions between years of residence and both types of immigrants are not significant. When additional variables are included (columns (3) to (5)), the higher probability of horizontal mismatch of immigrants from non-EU countries is slightly reduced (14.5 percentage points) but remains statistically significant.

Once these differences between natives and immigrants in the probability of overeducation and horizontal mismatch have been detected, we apply the Yun decomposition (Yun, 2004) method in order to explain them. Given that there are no differences statistically significant in the probability of having horizontal mismatch between immigrants from UE and natives, we do not decompose this difference.

This decomposition helps us identifying which factors influence the differences in the probability of being overeducated (or horizontal mismatched) between immigrants and natives. In particular, the method allows us detecting whether the differences in the probability of being overeducated (horizontal mismatched) between natives and immigrants are due to differences in the observable characteristics (worse endowment of human capital or worse job characteristics) or to differences in the returns to these characteristics between the two groups. Table 3 shows the aggregated results of Yun's (2004) decomposition.[11] From this table we can see that the differences in the probability of being overeducated between both types of immigrants and natives are statistically significant and consistent with the differences in the percentages of overeducation between groups observed in figure 2. The same consistency can be observed for the difference in the percentages of horizontal mismatch between immigrants from non-EU countries and natives and the ones observed in figure 3. In particular, we obtain that the difference in the probability of overeducation is of 7 percentage points for immigrants from EU countries, and of 11 percentage points when immigrants from non-EU countries are compared to natives. On the other hand, the horizontal mismatch's probability difference between non-EU countries and natives is of 7 percentage points. In both vertical and horizontal mismatch, immigrants experience a higher probability of being mismatched, but the causes of these differences differ between groups. In fact, in the case of the difference in the probability of being overeducated between immigrants from EU countries and natives, we can see that the 52% of this difference is explained by differences in characteristics. So, immigrants from EU countries have a higher probability of being overeducated partly

[11] The results of the detailed decomposition are shown in Table A.2. in the Annex.

because they have worst observable characteristics than natives. Also, the 48% of this difference is due to differences in coefficients, even if the component is statistically significant only at the 10% level. Therefore, immigrants from EU and natives have a higher probability of being overeducated also because they are not equally remunerated (detailed Yun decomposition shown in table A.2. manifest that each observed variable is significant to explain this difference). Concerning the difference in the probability of being overeducated between immigrants from non-EU countries and natives, the 87% of this difference can be explained by differences in coefficients (is statistically significant). That is, immigrants from non-EU countries are not remunerate at the same way than natives, while differences in characteristics do not play an important role. The detailed decomposition shows that the age of immigrants is very important to explain this difference. In fact, age could be an indicator of general human capital acquired in home country, so it may indicates that the general human capital of immigrants is worse valued than the one of natives. This may indicate a limited transferability of their human capital to the host country.

Finally, the differences in the probability of horizontal mismatch between immigrants from non-EU countries and natives are due to differences in coefficients (90%). Detailed decomposition results show that this difference is highly related to the immigrants' field of education. Immigrants who have coursed humanities or education studies are worse valued than natives who have studied the same fields. In this case, it may be also explain by a limited transferability of their human capital acquired in home country in general field of study (education and human studies).

TABLE 3

5. FINAL REMARKS

In this paper we have analysed differences in skill mismatches between immigrants and natives in EU countries. Using microdata from the Adult Education Survey (AES), we have analysed the incidence of different types of skill mismatches (vertical and horizontal) among native and immigrant workers.

Our results show that immigrants are more likely to be overeducated than natives, and that this effect is higher for immigrants from non-EU countries than for those from other EU countries, although the pace of the assimilation process in the host country is faster for the first group. On the other hand, we do not find such striking evidence in the case of horizontal mismatch. In particular, results show that only immigrants from non-EU countries have a higher probability of horizontal mismatch than natives. However, this effect does not vary when years of residence in host country increase.

Applying Yun's decomposition, we also find that immigrants from the EU have a higher probability of being overeducated than natives because they are characterized by both worse observable characteristics and by a lower remuneration of (return to) the these characteristics, whereas results for immigrants from non-EU countries (also for horizontal mismatch): suggest that the gap is almost entirely explained by differences in the remuneration of observable characteristics. This result points out that immigrants from non-UE countries may have a limited transferability of their human capital that pushes their situation of overeducation and horizontal mismatch in the host country.

To sum up, our results confirm that immigrants experience a higher overeducation penalty than natives due to the imperfect transferability of the human capital acquired in their origin countries. However, immigrants accumulate knowledge and experience in the host country that adapt to the local labour market, thus facilitating an assimilation process that reduces the intensity of overeducation. The pace of assimilation however is notably slow for immigrants. Therefore there is a certain risk that immigrants from outside the European Union remain permanently trapped in bad jobs, regardless of their levels of education. Taking into account the wage consequences of overeducation, this last result implies that the wage gap between native and immigrants will not disappear after several years of residence in the host country. Policy actions should focus on three different aspects: first, incorporating in the migration policy formal criteria related to educational levels and to the match with the current needs in the labour market (i.e., like the Australian points system); second, trying to design a system of assessment and recognition of foreign-acquired educational degrees in order to give an appropriate signal to the labour market and, third, providing publicly-provided informal training to recently arrived immigrants with appropriate skills in order to improve the transferability of their skills to the new labour market.

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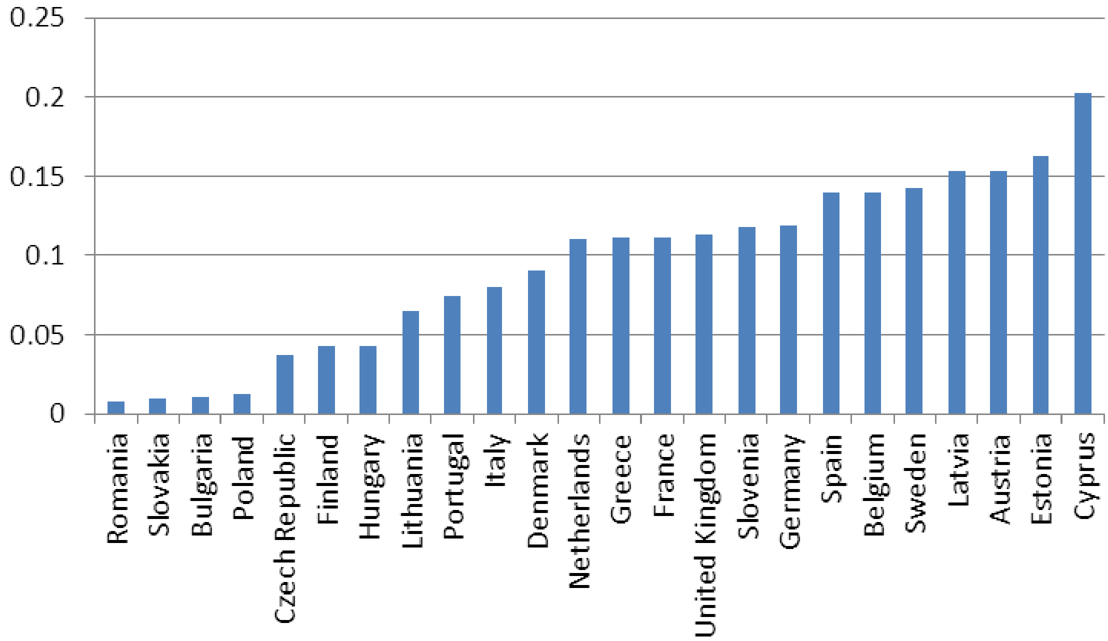
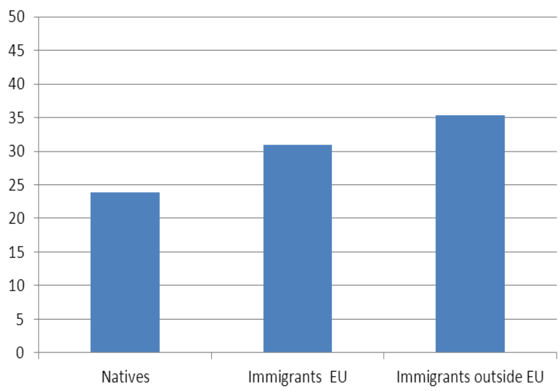
7. FIGURES AND TABLES

Figure 1. Proportion of immigrant' population in total population (average 2009-2011)



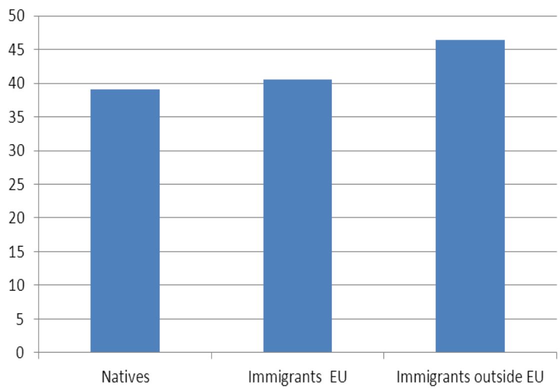
Source: Eurostat.

Figure 2. Percentage of vertical mismatch



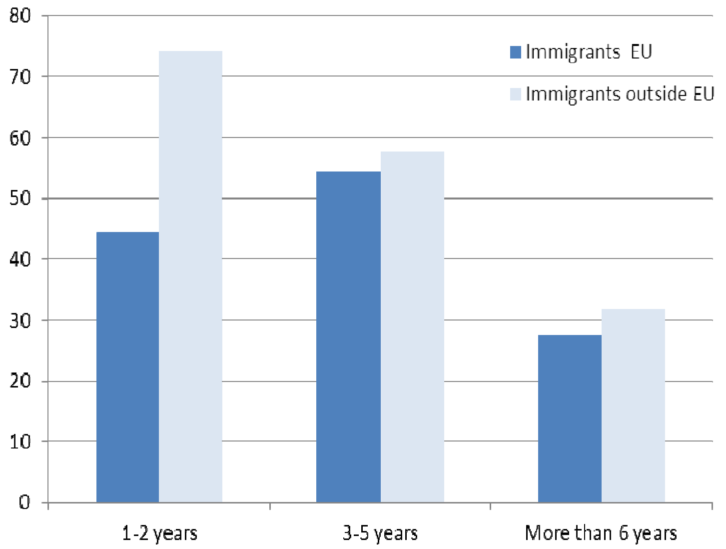
Data: AES 2007

Figure 3. Percentage of horizontal mismatch



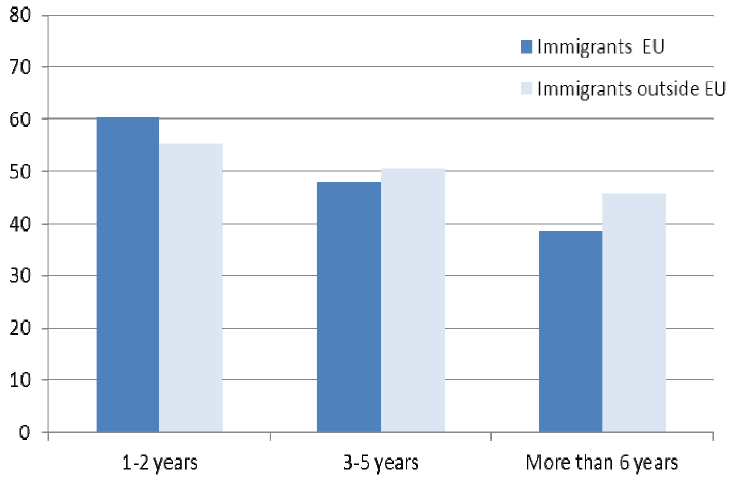
Data: AES 2007

Figure 4. Percentage of immigrants with vertical mismatch by years of residence in the host country



Data: AES 2007

Figure 5. Percentage of immigrants with horizontal mismatch by years of residence in the host country



Data: AES 2007

Table 1: Determinants of overeducation

Probit marginal effects	(1)	(2)	(3)	(4)	(5)
Immigrant	0.444***				
	[0.0728]				
Immig. UE		0.357***	0.350***	0.309***	0.285***
		[0.102]	[0.105]	[0.0960]	[0.0963]
Immig. No-UE		0.508***	0.508***	0.473***	0.459***
		[0.0569]	[0.0579]	[0.0561]	[0.0616]
Male	0.0113	0.0112	-0.00487	-0.00717	-0.00143
	[0.0356]	[0.0356]	[0.0205]	[0.0214]	[0.0254]
Age	-0.00425**	-0.00425**	-0.00400*	-0.00207	-0.00260
	[0.00207]	[0.00207]	[0.00205]	[0.00157]	[0.00180]
Years of residence	-0.0278***				
	[0.00532]				
Years of residence x immig. UE		-0.0226***	-0.0227***	-0.0208***	-0.0186***
		[0.00708]	[0.00732]	[0.00655]	[0.00659]
Years of residence x immig. No-UE		-0.0317***	-0.0317***	-0.0300***	-0.0297***
		[0.00447]	[0.00441]	[0.00453]	[0.00506]
Educational level (ref. ISCED3) - ISCED4	0.698***	0.698***	0.705***	0.708***	0.726***
	[0.130]	[0.130]	[0.129]	[0.130]	[0.118]
Educational level (ref. ISCED3) - ISCED5&6	0.153	0.154	0.175	0.183	0.186
	[0.167]	[0.167]	[0.178]	[0.181]	[0.190]
Non formal education	-0.0347***	-0.0343***	-0.0273***	-0.0151	-0.0138
	[0.0117]	[0.0115]	[0.0105]	[0.00964]	[0.0107]
Field of education (ref. Education) - Humanities			0.257***	0.225***	0.217***
			[0.0465]	[0.0479]	[0.0500]
Field of education (ref. Education) - Social science			0.207***	0.161***	0.153***
			[0.0395]	[0.0408]	[0.0414]
Field of education (ref. Education) - Science			0.162***	0.122***	0.112***
			[0.0327]	[0.0333]	[0.0335]
Field of education (ref. Education) - Engineering			0.199***	0.144***	0.136**
			[0.0560]	[0.0534]	[0.0576]
Field of Education (ref. Education) - Agriculture			0.296***	0.230***	0.216***
			[0.0801]	[0.0742]	[0.0812]
Field of Education (ref. Education) - Health			0.128*	0.128*	0.129*
			[0.0727]	[0.0718]	[0.0785]
Field of Education (ref. Education) - Services			0.276***	0.230***	0.214***
			[0.0729]	[0.0708]	[0.0785]
Economic activity (ref. industry)- Agriculture				0.0232	0.0207
				[0.0379]	[0.0392]
Economic activity (ref. industry) - Construction				0.00142	-5.19e-05
				[0.0123]	[0.00808]
Economic activity (ref. industry) - Services				-0.0180*	-0.0166*
				[0.00927]	[0.00917]
Economic activity (ref. industry)- No sale services				-0.0811***	-0.0779***
				[0.0123]	[0.0132]
Tenure				-0.00272***	-0.00229***
				[0.000947]	[0.000744]
Big company (more than 10 workers)				-0.0420**	-0.0424*
				[0.0207]	[0.0217]
Household size (nº people at home)					0.00670
					[0.00485]
Children at home (ref: no children)					-0.00582
					[0.00660]
Fulltime job (ref: part-time)					-0.0273
					[0.0174]
Temporary contract (ref: permanent)					0.0314**
					[0.0149]
Observations	32848	32848	32848	32848	29335

Robust standard errors clustered on the destination country are reported between brackets. All models are estimated using survey weights and include country fixed-effects and controls for urban size (3 categories). Model (5) does not include GR, DK and SI as data is not available for some control variables * p-value<10% ** p-value<5% *** p-value<1% .

Table 2: Determinants of horizontal mismatch

Probit marginal effects	(1)	(2)	(3)	(4)	(5)
Immigrant	0.180**				
	[0.0805]				
Immig. UE		0.150	0.0735	0.0724	0.0643
		[0.0918]	[0.0785]	[0.0843]	[0.0903]
Immig. No-UE		0.195**	0.173**	0.148*	0.138*
		[0.0764]	[0.0769]	[0.0777]	[0.0715]
Male	-0.0555*	-0.0557*	-0.0473**	-0.0176	-0.0198
	[0.0293]	[0.0293]	[0.0224]	[0.0175]	[0.0206]
Age	0.00106***	0.00108***	0.00184***	0.00500***	0.00467***
	[0.000265]	[0.000262]	[0.000234]	[0.000813]	[0.000594]
Years of residence	-0.0123				
	[0.00906]				
Years of residence x immig. UE		-0.0134	-0.00898	-0.0101	-0.0103
		[0.0103]	[0.00791]	[0.00723]	[0.00795]
Years of residence x immig. No-UE		-0.0116	-0.0101	-0.00912	-0.00997
		[0.00874]	[0.00820]	[0.00756]	[0.00791]
Educational level (ref. ISCED3) - ISCED4	-0.00931	-0.00934	-0.0309***	-0.0423***	-0.0444***
	[0.0115]	[0.0116]	[0.0107]	[0.0142]	[0.0132]
Educational level (ref. ISCED3) - ISCED5&6	0.0176	0.0178	-0.0295	-0.0436**	-0.0418**
	[0.0178]	[0.0178]	[0.0205]	[0.0195]	[0.0205]
Non formal education	0.0226*	0.0233*	0.0228	0.0190	0.0180
	[0.0131]	[0.0134]	[0.0145]	[0.0135]	[0.0121]
Field of education (ref. Education) - Humanities			0.600***	0.607***	0.603***
			[0.0201]	[0.0197]	[0.0219]
Field of education (ref. Education) - Social science			-0.197**	-0.203***	-0.222***
			[0.0947]	[0.0782]	[0.0822]
Field of education (ref. Education) - Science			0.625***	0.630***	0.628***
			[0.0154]	[0.0147]	[0.0167]
Field of education (ref. Education) - Engineering			-0.0823*	-0.0533	-0.0594
			[0.0467]	[0.0352]	[0.0392]
Field of Education (ref. Education) - Agriculture			0.489***	0.500***	0.493***
			[0.0395]	[0.0347]	[0.0392]
Field of Education (ref. Education) - Health			0.0697	0.0600	0.0574
			[0.0439]	[0.0398]	[0.0423]
Field of Education (ref. Education) - Services			0.433***	0.420***	0.423***
			[0.0342]	[0.0431]	[0.0453]
Economic activity (ref. industry)- Agriculture				0.0265	0.0375
				[0.0414]	[0.0463]
Economic activity (ref. industry) - Construction				-0.186***	-0.189***
				[0.0284]	[0.0296]
Economic activity (ref. industry) - Services				0.108***	0.108***
				[0.0174]	[0.0172]
Economic activity (ref. industry)- No sale services				0.102***	0.104***
				[0.0224]	[0.0232]
Tenure				-0.00624***	-0.00628***
				[0.00138]	[0.00150]
Big company (more than 10 workers)				0.000202	0.00575
				[0.00704]	[0.00595]
Household size (nº people at home)					0.00547
					[0.00915]
Children at home (ref: no children)					-0.00937
					[0.0180]
Fulltime job (ref: part-time)					-0.00348
					[0.0170]
Temporary contract (ref: permanent)					0.0127
					[0.0203]
Observations	32848	32848	32848	32848	29335

Robust standard errors clustered on the destination country are reported between brackets. All models are estimated using survey weights and include country fixed-effects and controls for urban size (3 categories). Model (5) does not include GR, DK and SI as data is not available for some control variables * p-value<10% ** p-value<5% *** p-value<1% .

Table 3: General decomposition of the differences in the probability of overeducation and horizontal mismatch between immigrants and natives

	Prob. overeducation		Prob. Horizonal mismatch
	Immigrants from EU vs. Natives	Immigrants from non-EU vs. Natives	Immigrants from non-EU vs. Natives
Diff. in characteristics	0.0364***	0.0138	0.00666
	(52%)	(13%)	(10%)
Diff. in coefficients	0.0342*	0.0979***	0.0574**
	(48%)	(87%)	(90%)
Total	0.0705***	0.112***	0.0641***
	(100%)	(100%)	(100%)

All models are estimated using survey weights .Percentages of the contribution are reported between parentheses. * p-value<10% ** p-value<5% *** p-value<1%

8. Annex

Table A.1. Weighted descriptive statistics (continues)

	Natives		Immigrant from EU		Immigrant from outside EU	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Vertical mismatch	0.238	0.426	0.310	0.463	0.353	0.478
Horizontal mismatch	0.390	0.488	0.405	0.491	0.464	0.499
Male	0.517	0.500	0.577	0.494	0.604	0.489
Female	0.483	0.500	0.423	0.494	0.396	0.489
Age	41.449	9.685	41.430	9.412	40.639	9.140
Years of residence	0.000	0.000	9.507	2.869	9.495	2.646
Education level ISCED3	0.528	0.499	0.528	0.499	0.563	0.496
Education level ISCED4	0.076	0.265	0.051	0.221	0.063	0.243
Education level ISCED5&6	0.395	0.489	0.420	0.494	0.374	0.484
Non-formal education (NFE)	0.541	0.498	0.522	0.500	0.378	0.485
No NFE	0.459	0.498	0.478	0.500	0.622	0.485
Field of education:						
Education	0.057	0.232	0.037	0.189	0.033	0.180
Humanities	0.057	0.232	0.097	0.297	0.060	0.237
Social science	0.290	0.454	0.188	0.391	0.228	0.420
Science	0.052	0.223	0.059	0.236	0.074	0.262
Engineering	0.337	0.473	0.462	0.499	0.409	0.492
Agriculture	0.026	0.160	0.018	0.132	0.024	0.153
Health	0.109	0.311	0.069	0.254	0.077	0.267
Services	0.071	0.258	0.069	0.254	0.095	0.293
Economic activity:	0.012	0.110	0.005	0.072	0.009	0.097
Agriculture	0.230	0.421	0.220	0.415	0.264	0.441
Industry	0.061	0.240	0.101	0.302	0.090	0.286
Construction	0.321	0.467	0.410	0.492	0.370	0.483
Market services	0.375	0.484	0.263	0.441	0.267	0.443
Non-market services	12.423	10.016	9.315	8.118	7.995	7.746
Tenure	0.012	0.110	0.005	0.072	0.009	0.097
Firm size:						
Big company	0.787	0.409	0.772	0.420	0.742	0.438
Small company	0.213	0.409	0.228	0.420	0.258	0.438

Table A.1. Weighted descriptive statistics (continuation)

	Natives		Immigrant from EU		Immigrant from outside EU	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Urban size:						
High degree urb.	0.447	0.497	0.593	0.491	0.641	0.480
Medium degree urb.	0.327	0.469	0.208	0.406	0.257	0.437
Small degree urb.	0.226	0.418	0.198	0.399	0.102	0.302
Countries:						
AT	0.036	0.187	0.046	0.209	0.041	0.199
BE	0.027	0.163	0.040	0.197	0.013	0.114
CY	0.003	0.058	0.005	0.073	0.003	0.058
CZ	0.062	0.241	0.030	0.170	0.005	0.068
DE	0.355	0.479	0.413	0.493	0.447	0.497
DK	0.023	0.149	0.047	0.211	0.003	0.055
EE	0.005	0.073	0.001	0.038	0.017	0.130
ES	0.115	0.319	0.134	0.341	0.150	0.358
FR	0.266	0.442	0.177	0.382	0.200	0.400
GR	0.026	0.159	0.015	0.123	0.024	0.153
LT	0.016	0.125	0.002	0.044	0.015	0.122
LV	0.009	0.093	0.006	0.075	0.015	0.123
PT	0.012	0.109	0.024	0.152	0.019	0.136
SE	0.040	0.197	0.059	0.235	0.039	0.195
SI	0.004	0.065	0.001	0.038	0.008	0.090
Observations	30149		929		1770	

Table A.2. Detailed Yun decomposition of the probability of overeducation and horizontal mismatch between immigrants and natives (continues)

	Overeducation				Horizontal mismatch	
	Immigrants from EU countries vs. natives		Immigrants from non-EU countries vs. natives		Immigrants from non-EU countries vs. natives	
VARIABLES	E	C	E	C	E	C
Total dif. Between groups	0.0705***		0.112***		0.0641***	
	[0.0187]		[0.0135]		[0.0200]	
Total	0.0364***	0.0342*	0.0138	0.0979***	0.00666	0.0574**
	[0.0113]	[0.0183]	[0.0130]	[0.0170]	[0.0167]	[0.0245]
Male	-0.00441***	-0.172	-0.00542	-0.0279**	0.000160	-0.000526
	[0.00147]	[0.420]	[0.00429]	[0.0119]	[0.00119]	[0.0133]
Female	-0.00441***	0.160	-0.00542	0.0260**	0.000160	0.000491
	[0.00147]	[0.392]	[0.00429]	[0.0111]	[0.00119]	[0.0124]
Age	-0.000117**	1.616	-0.00415	0.325***	-0.00219	0.0587
	[4.76e-05]	[3.834]	[0.00303]	[0.105]	[0.00266]	[0.0966]
Level of education:						
Isced3	3.25e-05***	-0.0565	-0.0214	-0.107***	0.000339	-0.00947
	[5.44e-06]	[0.160]	[0.0133]	[0.0218]	[0.000790]	[0.0199]
Isced4	-0.00975***	0.0236	-0.0113	0.0223***	-1.34e-05	-0.000274
	[0.00170]	[0.0609]	[0.00722]	[0.00490]	[0.000398]	[0.00458]
Isced5_6	-0.00326***	-0.0801	0.00515	-0.0355**	0.000232	0.00851
	[0.00100]	[0.207]	[0.00358]	[0.0159]	[0.000479]	[0.0154]
NFE	-1.52e-05	0.0207	0.00307	-0.00271	0.00170	-0.0147
	[0.000377]	[0.0625]	[0.00421]	[0.0116]	[0.00318]	[0.0144]
No NFE	-1.52e-05	-0.0175	0.00307	0.00229	0.00170	0.0124
	[0.000377]	[0.0529]	[0.00421]	[0.00982]	[0.00318]	[0.0122]
Field of education:						
Education	0.00245	0.00153	0.00382	0.00205	-0.00317	0.0100***
	[0.00179]	[0.0231]	[0.00303]	[0.00448]	[0.00342]	[0.00372]
Humanities	0.00306	0.00648	0.000136	-0.00119		
	[0.00260]	[0.0222]	[0.000182]	[0.00327]		
Social Science	0.00659	-0.101	-0.00237	0.00351	0.00973	0.0368**
	[0.00476]	[0.261]	[0.00352]	[0.0121]	[0.0102]	[0.0176]
Science	0.000215	0.0146	0.00219	0.00653*	0.00595	-0.00675
	[0.000591]	[0.0378]	[0.00208]	[0.00356]	[0.00609]	[0.00708]
Engineering	-0.00994	-0.126	-0.00328	-0.0151	-0.0153	-0.0365**
	[0.00633]	[0.297]	[0.00428]	[0.0140]	[0.0159]	[0.0163]
Agriculture	-0.00183*	0.0187	-0.000452	0.00257		
	[0.000948]	[0.0471]	[0.000375]	[0.00226]		
Health	0.00381*	-0.0392	0.00724	-0.0185**	0.00322	-0.00386
	[0.00221]	[0.0959]	[0.00503]	[0.00767]	[0.00331]	[0.00641]
Services	-0.000102	-0.00302	0.00123	-0.00240	0.00143	-0.00216
	[0.000110]	[0.0178]	[0.00208]	[0.00511]	[0.00173]	[0.00526]
Economic activity:						
Agriculture	-0.00149*	0.00926	-3.49e-05	-0.000470	-0.000761	0.00537***
	[0.000835]	[0.0229]	[0.000344]	[0.00123]	[0.000807]	[0.00131]
Industry	-0.000168	0.00393	0.00106	0.00167	-0.00220	-0.0277**
	[0.000460]	[0.0501]	[0.00189]	[0.0107]	[0.00251]	[0.0115]
Construction	0.00556**	0.0374	0.00358	0.00631**	-0.00305	-0.000709
	[0.00244]	[0.0903]	[0.00286]	[0.00315]	[0.00331]	[0.00317]
Market services	-0.00889**	-0.143	0.000418	0.00165	-0.00196	-0.0507***
	[0.00379]	[0.337]	[0.00220]	[0.0124]	[0.00211]	[0.0170]
Non-market services	0.0296***	-0.350	0.0190	-0.0290	0.00558	-0.0547***
	[0.00598]	[0.843]	[0.0135]	[0.0189]	[0.00665]	[0.0186]
Tenure	0.0192**	-0.224	0.0513**	-0.0843**	0.0159	-0.0166
	[0.00795]	[0.583]	[0.0257]	[0.0385]	[0.0204]	[0.0365]

Table A.2. Detailed Yun decomposition of the probability of overeducation and horizontal mismatch between immigrants and natives (continuation)

	Overeducation				Horizontal mismatch	
	Immigrants from EU countries vs. natives		Immigrants from non-EU countries vs. natives		Immigrants from non-EU countries vs. natives	
VARIABLES	E	C	E	C	E	C
Firm size:						
Big company	0.000580	-0.0672	-7.56e-05	0.0205	-0.00138	0.0516***
	[0.000384]	[0.172]	[0.00131]	[0.0191]	[0.00155]	[0.0195]
Small company	0.000580	0.0182	-7.56e-05	-0.00555	-0.00138	-0.0140***
	[0.000384]	[0.0465]	[0.00131]	[0.00517]	[0.00155]	[0.00527]
Urban size:						
High degree urb.	-0.00102	0.00722	-0.00705	-0.00702	0.000112	-0.00237
	[0.00412]	[0.0604]	[0.00904]	[0.0125]	[0.00339]	[0.0149]
Medium degree urb.	0.00298	-0.0373	0.00416	-0.0163	-0.000652	0.00707
	[0.00345]	[0.102]	[0.00395]	[0.0113]	[0.00167]	[0.0134]
Small degree urb.	-0.000889	0.0221	-0.0119	0.0148*	0.00123	-0.00369
	[0.000943]	[0.0620]	[0.0107]	[0.00887]	[0.00329]	[0.00907]
Countries:						
AT	-0.000755	-0.0104	0.000753	0.00482**	0.000248	0.00252
	[0.000604]	[0.0265]	[0.000581]	[0.00193]	[0.000287]	[0.00189]
BE	0.000107	0.00455	-0.00132	0.00315	-6.66e-05	-0.00173
	[0.000912]	[0.0150]	[0.00193]	[0.00266]	[0.000628]	[0.00234]
CY	0.000252***	0.000952	1.04e-05	0.000275	1.02e-06	0.000107
	[9.74e-05]	[0.00250]	[7.41e-06]	[0.000201]	[1.93e-06]	[0.000210]
CZ	0.000829	-0.0142	-0.00957	0.00630	-0.00594	0.0140**
	[0.00186]	[0.0368]	[0.0104]	[0.00638]	[0.00567]	[0.00594]
DE	-0.00227	-0.0767	-0.0164	-0.0568***	-0.00350	-0.0175
	[0.00305]	[0.216]	[0.0124]	[0.0194]	[0.00387]	[0.0181]
DK	-0.000573	-0.00893	-0.00226	0.000176	0.00359	-0.00587
	[0.00128]	[0.0207]	[0.00527]	[0.00462]	[0.00437]	[0.00473]
EE	0.000632*	-0.00240	-0.00173	-0.000242	-0.000237	-0.000326
	[0.000384]	[0.00601]	[0.00121]	[0.000255]	[0.000349]	[0.000228]
ES	0.00533***	0.104	0.0130	0.0238***	0.000241	-0.00480
	[0.00104]	[0.246]	[0.00829]	[0.00605]	[0.000872]	[0.00507]
FR	-0.000790	-0.00705	0.00188	-0.0113	-0.00248	0.000817
	[0.00422]	[0.0592]	[0.00354]	[0.0115]	[0.00259]	[0.0112]
GR	-0.000875	0.0143	-0.000977	0.0118***	-0.000241	0.00591***
	[0.000865]	[0.0346]	[0.000658]	[0.00222]	[0.000256]	[0.00226]
LT	0.00253	0.00282	0.000826	-0.00929***	2.57e-05	-0.00154
	[0.00320]	[0.0164]	[0.000543]	[0.00208]	[3.33e-05]	[0.00109]
LV	0.000692	-0.00413	-0.00351	-0.00252***	-7.87e-05	0.000228
	[0.000667]	[0.0133]	[0.00242]	[0.000850]	[0.000235]	[0.000634]
PT	0.00168**	0.00482	0.000453	-0.000146	-0.000176	-0.000640
	[0.000770]	[0.0126]	[0.000591]	[0.000839]	[0.000281]	[0.000839]
SE	0.00129	-0.00724	-0.000207	0.00211	-1.38e-06	0.00154
	[0.00128]	[0.0200]	[0.000137]	[0.00280]	[2.90e-05]	[0.00265]
SI	-3.00e-05	-0.00105	0.000278	-0.000127	-0.000123	-6.62e-06
	[0.000432]	[0.00364]	[0.000302]	[0.000266]	[0.000153]	[0.000269]
Constant		-0.510		0.0436		0.118
		[1.316]		[0.0999]		[0.0973]
Observations	31078	31078	31919	31919	31919	31919

All models are estimated using survey weights. Standard errors are reported between brackets.
* p-value<10% ** p-value<5% *** p-value<1%