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## A Cross-Country Comparative Study of Immigrants in 17 Western European Countries

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## A Cross-Country Comparative Study of Immigrants in 17 Western European Countries

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## Abstract

The labor market integration of migrants, focusing on employment and job quality, differs notably across Southern and Continental-Northern European nations, often involving trade-offs. Nonetheless, little is known about whether these diverse migrant inclusion models in European labor markets extend to the combination of employment and overeducation. Additionally, the role of gender in this context remains unclear. While overeducation is more prevalent among immigrants compared to native, its prevalence varies across countries. To fill this gap, we analyzed data from the 2015-2019 European Labor Force Survey in 17 European countries, considering gender and migrant type- Western vs. non-Western. Results show that non-Western migrants and migrant women face more challenges than Western and male counterparts. Among males, a trade-off model predominates, with low employment penalties but high overeducation penalties in Mediterranean countries, and vice versa in Continental and some Nordic nations. For females, those in Southern Europe align with the Mediterranean trade-off model, while those in most Continental and Nordic countries experience a double penalty. In Liberal countries, male migrants tend toward the Mediterranean trade-off model, while female migrants align with the integration model.

**Keywords:** Overeducation, Trade-Offs, Gender, Inclusion Models, European Labor Markets

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## 1. Introduction

Compared to natives, immigrants have been found to suffer from higher levels of educational-occupational mismatch (henceforth EOM), i.e., difficulty in achieving an occupational status that corresponds to their educational level (Chiswick & Miller, 2009, 2010a; Reitz, 2001). The levels of EOM experienced by migrants, as well as the gap between migrants and natives, vary significantly across European countries, depending on a set of characteristics of both the country of origin and the country of destination (Akgüç & Parasnis, 2023; Aleksynska & Tritah, 2013; Nieto et al., 2015).

In addition to EOM, immigrants also encounter penalties in various other dimensions of socioeconomic integration, such as employment opportunities (Reyneri & Fullin, 2011), class attainment (Panichella et al., 2021), and wages (Longhi & Platt, 2008). Even these disadvantages – commonly labeled "ethnic penalties" in migration and labor market studies (Heath & Cheung, 2007) – differ considerably across countries, reflecting each destination country's specific contexts and characteristics. In this respect, a growing number of studies have shed light on the diverse models of labor market inclusion of immigrants in Europe, taking into account the various combinations of ethnic penalties in terms of employment and job quality (Ballarino & Panichella, 2015, 2018; Cantalini et al., 2023). Specifically, migrants in Southern European countries have been found to have similar employment and unemployment rates as the native population but also to be overrepresented in unskilled and nonstandard jobs (Ambrosini, 2018). Conversely, in Continental and Northern Europe, migrants are more strongly penalized regarding unemployment risks, but they face a lower penalization in terms of job quality (Reyneri & Fullin, 2011b).

This study aims to combine these two branches of literature, introducing EOM (specifically, overeducation) in the debate on the models of labor market inclusion of immigrants in Europe. Overeducation serves as a pivotal measure for evaluating the integration process of migrants in the host countries (Aleksynska & Tritah, 2013). The phenomenon of overeducation not only underscores inefficiencies within the labor market and economic inequalities but also accentuates the prospects for social integration among migrants (Chen & Hu, 2023). When migrants' skills go underutilized, it not only diminishes their job satisfaction (Frank & Hou, 2018; McGuinness & Byrne, 2015) and earning capacity (Chiswick & Miller, 2010), but also signifies a wastage of valuable human capital that could otherwise fuel innovation and facilitate economic advancement. Moreover, a vital aspect in investigating overeducation revolves around an individual's educational level, encompassing their official certifications, which often are not recognized in the country of destination and result in migrants' returns to education being lower compared to natives (Cantalini et al., 2023). Our paper thus asks whether the different models of migrants' inclusion found across European labor markets also

apply to the combination of employment and overeducation. Do migrants in Mediterranean countries exhibit smaller penalties in employment and larger penalties in overeducation? Does the opposite occur in Continental and Northern Europe?

In addition, most of the existing studies on EOM focus on male immigrants (Chiswick & Miller, 2009; Green & Kler, 2007) or use pooled samples of men and women (Aleksynska & Tritah, 2013; Cim et al., 2017; McGuinness & Byrne, 2015), ignoring gender-specific aspects that might shape female employment status and occupational attainment. However, recently, a few studies have highlighted the particularities of EOM among migrant women, pointing out their disadvantaged condition (Akgüç & Parasnis, 2023) as well as the underlying mechanisms, such as language use (Birgier & Bar-Haim, 2023b). Moreover, migrant women have often been found to suffer a double disadvantage in the host labor markets, reflecting the combined negative impact of birthplace and sex (Birgier & Bar-Haim, 2023a; Donato et al., 2014; He & Gerber, 2020). Therefore, this study also examines gender differences in the native-to-immigrant gaps in overeducation – in its combination with employment opportunities – across European countries.

## 2. Theoretical background

### *2.1 Cross-country differences in migrants' labor market integration*

Patterns and characteristics of migrants' labor market integration change across European societies, depending on the host country's institutional context, especially its labor market structure and regulation (Kogan, 2006; Lewin-Epstein et al., 2003). Two main models characterize the integration of non-Western migrants in Europe, both characterized by a *trade-off* between employment (or unemployment risk) and job quality (Ballarino & Panichella, 2018; Cantalini et al., 2023; Reyneri & Fullin, 2011b). The first model characterizes Mediterranean countries, where migrants have similar employment and unemployment rates as the natives but essentially find themselves in unskilled and unstable jobs in the secondary labor market (Reyneri & Fullin, 2011b). This trade-off between a low employment penalty and a high job quality penalty mainly stems from the segmentation of the Southern European labor markets, characterized by a relatively high number of small businesses, a widespread informal economy, and a significant demand – not met by the native workforce – for the so-called 3D jobs (dirty, dangerous, and demanding; see (Ambrosini, 2018; Reyneri, 1998)).

The second model regards migrants in Continental and Northern Europe, where they are more strongly penalized in terms of employment and unemployment, but once employed, they face a lower penalty in terms of job quality. In other words, this model is characterized by a trade-off between high employment penalty and a low job quality penalty, as migrants face difficulties in entering

employment, but are less concentrated in the worst occupational position compared to their counterparts in Southern Europe, due to the higher demand for skilled non-manual jobs (Ballarino & Panichella, 2015, 2018; Reyneri & Fullin, 2011b). Immigrants in the United Kingdom and Ireland follow a similar inclusion model, although some peculiarities have led scholars to identify a third ideal type, in-between the Continental and Mediterranean nations (Guetto, 2018). On the one hand, the flexible labor market regulation in these countries, characterized by weak trade unions and lower employment protection (Hall & Soskice, 2001), enhances employment opportunities for immigrants, surpassing those found in central-northern countries. On the other hand, selective migration policies favor the entry of highly educated workers into specific sectors, such as healthcare, reducing the risk of segregation in less skilled occupations (Guetto, 2018).

Besides these two main models of migrants' inclusion in European labor markets, research has suggested the existence of two further ideal-typical models, still resulting from the combination of the ethnic penalty in employment and job quality. The first is characterized by a *double penalty* for migrants, which some scholars associate with the Continental model (Panichella, 2018), given the existence of a relatively high ethnic penalty in both employment and job quality. The second model reflects the full *integration* of immigrants into the receiving labor market due to low ethnic penalties or even an 'ethnic premium' in terms of both employment and job quality. This model applies, for example, to skilled immigrants from Western countries, whose risk of unemployment and occupational status are generally similar, if not better, than those of the native population (Panichella, 2018).

While the patterns of male migrants' inclusion in European labor markets, apart from most Western migrants (see above), largely follow the two main models of (Mediterranean and Continental) trade-off whereby lower employment penalties correspond to higher job quality penalties, and vice versa, the situation is more heterogeneous among migrant women (Cantalini et al., 2022). Although cross-country studies have shown that migrant women also tend to follow trade-off models of labor market inclusion (Ballarino & Panichella, 2018; Guetto, 2018), these models appear less clear compared to men, and some groups of women seem to be more aligned with the double penalty or the integration ones. This considerable heterogeneity may depend on various factors, such as the difference in the female labor market participation levels for both migrant and native women across European societies (Elhorst & Zeilstra, 2007). Moreover, migrant women are generally segregated in specific labor market sectors (e.g., personal care and services), where upward mobility opportunities are scarce (Ballarino & Panichella, 2018). In addition, the gendered nature of migration, with most women being in a subordinate position in family migration decisions and more frequently becoming 'tied movers' (Ballarino & Panichella, 2018), increases the risk for migrant women to experience larger ethnic penalties compared to their male counterparts.

*2.2 Cross-country differences in migrants' EOM*

Literature has primarily shown that immigrants are more likely to experience overeducation compared to the native population (Birgier & Bar-Haim, 2023b; Prokic-Breuer & McManus, 2016; Reitz, 2001; Visintin et al., 2015), especially if they come from non-Western countries (Hardoy & Schøne, 2014). This may occur as immigrants have substantial deficits in country-specific human capital (Chiswick & Miller, 2013), not least because of language barriers (Dustmann & Fabbri, 2003). In other words, the human capital immigrants acquire in their country of origin – both in terms of educational credentials and skills – is not fully transferable to the destination labor market (Chiswick & Miller, 2009). Moreover, employers can place immigrants behind similarly or less qualified natives, as they have less experience with workers educated abroad, or explicitly discriminate against certain immigrant groups, thereby increasing the likelihood of immigrants being overeducated (Rafferty, 2012).

The magnitude of EOM among immigrants also varies substantially across countries (Akgüç & Parasnis, 2023; Aleksynska & Tritah, 2013; Nieto et al., 2015). In this respect, EOM among immigrants depends on a set of characteristics related to the country of origin, such as the level and quality of schooling, and to immigrants' self-selection patterns (Cim et al., 2017; Mattoo et al., 2008; Sanromá et al., 2015). Moreover, it also depends on features related to the country of destination, such as the economic conditions, the labor market institutions, and the immigration policies (Akgüç & Parasnis, 2023; Aleksynska & Tritah, 2013). For instance, host-country labor market institutions employ assignment mechanisms that can either restrict or intensify EOM among all workers, as well as mechanisms that penalize (e.g., legal barriers, licensing rules, etc.) or facilitate immigrant incorporation (e.g., language and employment training). More specifically, studies have shown that immigrants have higher levels of overeducation in countries with higher levels of unemployment and stronger trade unions. Conversely, countries with a higher degree of shadow economy tend to exhibit lower levels of overeducation among immigrants (Aleksynska & Tritah, 2013).

Despite mixed evidence regarding gender differences in overeducation (Addison et al., 2020; Castagnetti et al., 2018; Groot & Maassen Van Den Brink, 2000), the few studies on occupational mismatch among immigrant women have shown that they experience higher levels of EOM compared to both immigrant men and native women (Akgüç & Parasnis, 2023; Birgier & Bar-Haim, 2023). For instance, migrant women with academic degrees are less likely to work in jobs requiring academic education than their male counterparts (Pecoraro, 2011). Concerning cross-country variation in the levels of EOM among migrant women, previous research has shown that while certain factors like levels of female education and employment and attitudes towards women's work in the destination

country are relevant in explaining women's overqualification in general, they do not fully account for the disadvantage experienced by immigrant women. Instead, individual skill levels and household income have been found to play a more substantial role in determining the extent of overqualification among immigrant women (Akgüç & Parasnis, 2023).

## 3. Comparison strategy and expectations

This paper aims to incorporate overeducation in the debate on the models of labor market inclusion of immigrants in Europe. Specifically, it studies whether immigrants' labor market inclusion aligns more closely with a Mediterranean trade-off, a Continental trade-off, a double penalty, or an integration model regarding the combination of employment and overeducation. We propose that the concept of EOM can be effectively incorporated into this framework as an additional measure of job quality, similar to other commonly used indicators in studies on the ethnic penalty, such as occupational status, social class, and income. EOM can be considered an indicator of lower job quality when individuals are employed in positions that do not match their level of education. However, EOM encompasses an additional dimension that is particularly relevant for analyzing the labor market integration of migrants, namely the returns to education. Migrants often experience lower returns to education compared to native workers, primarily due to difficulties in transferring foreign educational credentials (Cebolla-Boado et al., 2019; Panichella et al., 2021), especially in Southern Europe (Cantalini et al., 2023). Consequently, we can assume that EOM is higher among immigrants when their returns to education are lower.

Our analysis focuses on migrants residing in 17 Western European countries, selected based on their labor market regulation and welfare regime. Specifically, the countries included in the study are Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, United Kingdom, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, and Switzerland.[1] Our empirical strategy involves different types of comparisons. Firstly, we compare immigrants to natives to examine whether the former face higher employment penalties and overeducation levels than the latter. In this analysis, we further differentiate immigrants based on their origin, distinguishing between those from Western countries (EU15, North America, and Australia) and non-Western countries (Africa, Asia, Latin America, and Eastern Europe). While existing research on the ethnic penalty and labor market inclusion of migrants often makes this distinction, primarily focusing on migrants from non-Western societies, the literature on migrants' overeducation typically treats all migrants collectively without distinguishing their origin. Secondly, by examining both men and women, we not only compare immigrant men and women to their

[1] The country selection was also guided by data limitations, excluding countries with fewer than 100 migrant men or women and countries where distinguishing between EU15 migrants and other EU migrants was impossible.

native counterparts but also assess whether (potential) ethnic penalties are more pronounced for migrant women or men. This strategy enables us to empirically investigate the notions of double disadvantage (Donato et al., 2014) and intersectionality (Oso & Ribas-Mateos, 2013), which suggest that migrant women experience labor market penalties but also opportunities compared to both male migrants and native-born women.

We generally expect that immigrants, especially those originating from non-Western countries, are likely to face penalties in terms of both employment and overeducation (H1). The specific models of labor market inclusion may vary depending on the destination country. In Mediterranean countries, we expect to observe a trade-off between low employment penalty and high EOM penalty for non-Western migrants (H2). Conversely, Continental, Northern, and Anglo-Saxon countries may exhibit the opposite pattern (H3). Concerning migrants from Western countries, we expect they align with the integration model, experiencing low penalties in both employment and overeducation across the destination countries (H4). In terms of gender-migration intersectionality, we expect to observe that migrant women suffer from larger gaps in both employment and overeducation compared to migrant men (H5). As a result, we anticipate a higher heterogeneity in the models of inclusion of migrant women, particularly for those originating from non-Western countries, with a higher occurrence of the double penalty model (H6).

## 4. Data, variables, and methods

### *4.1 Data and sample*

The European Labour Force Survey (EULFS) data for 2015-2019 is used to compare the levels of native-to-migrants differences in employment and overeducation across countries, controlling for individual characteristics. The EULFS serves as the primary data source for labor market information at the household level in the European Union. It offers standardized cross-sectional data encompassing various aspects such as employment status, occupation, income, education, and other sociodemographic characteristics for all members of surveyed households. The sample was restricted to individuals in their prime working ages (25-64). We also restrict our analysis to natives and 'recent' migrants, thus excluding those who moved to the destination countries more than ten years before the survey year. The sample includes over 2.27 million men, of which over 183 thousand are migrants, and over 2.35 million women, of which 212 thousand are migrants. The samples of non-Western migrants by country range from around 750 in Iceland to over 47 thousand men and women in Germany. Appendix Tables 1 and 2 present the sample by migration status and country, for men and women, respectively.

*4.2 Dependent variables*

We measured the labor market inclusion of migrants with simultaneous estimation of the probability of being employed and the probability of being overeducated. The first variable, measured on the entire analytical sample, is a dummy indicating whether individuals are employed or unemployed/inactive. The second variable focuses on vertical EOM and is measured only among the employed individuals. Vertical EOM refers to the extent to which individual education is higher (or lower) than the typical educational level required for the occupation in which the same individual is employed.[2] In this paper, we focus on overeducation, and following Chiswick & Miller (2009), we use the Realized Match approach, which defines overeducation based on the actual educational levels of workers in each occupation.[3] The individual's and occupation's education levels are determined based on ISCED categories, with occupations classified according to the ISCO-08 two-digit scheme. For each occupation in each country, we calculate the mode level of educational attainment among all workers (men and women regardless of their immigration status). Individuals are thus classified as 'overeducated' if their educational level exceeds the mode educational level for their occupation in their specific country.

*4.3 Independent variable*

Our main independent variable is the migrant status, distinguishing migrants from the native population based on their place of birth. Within the migrant category, we further classify individuals into two subgroups: Western migrants (originating from EU15 countries, North America, and Australia), and non-Western migrants (originating from Africa, Asia, Central America, Southern America, and Eastern Europe). We conducted additional analyses using a more detailed categorization of migrant status. This categorization distinguished between Western immigrants from EU15 countries and Western immigrants from North America and Australia, as well as between non-Western immigrants from Eastern Europe and non-Western immigrants from non-European countries. However, due to limited sample sizes in some countries, we opted to use the less detailed categorization in our main analyses. Nonetheless, the analyses with the more detailed categorization confirmed that there were no substantial variations within the broader categories.

[2] Horizontal mismatch refers to the extent to which an individual field of study matches the occupation in which he/she is employed. Unfortunately, the EULFS data do not contain information on the field of study, restricting our ability to focus on both types of occupational mismatch.

[3] There are three main ways to assess over/under education: (1) realized match approach, (2) worker self-assessment, and (3) normative/job analysis (JA) method. Despite some variations in point estimates, past studies show that the overall conclusions regarding comparative levels remain consistent across different measurements (Chiswick & Miller, 2010b; McGuinness, 2006).

*4.4 Controls*

We incorporated controls for various individual-level variables, encompassing age and educational attainment, distinguishing individuals holding a BA, MA, or advanced degrees from others. Additionally, within the overeducation models, we introduced a binary variable to account for part-time employment, aligned with the EULFS definition. Moreover, we controlled for an individual's marital status due to its substantial implications for employment decisions. Lastly, to mitigate potential macro-level shifts over time, we introduced a control variable representing the survey year.

*4.5 Methods*

We use probit models with sample selection (see (Van de Ven & Van Praag, 1981)), estimated separately by country and gender. These models allow us to estimate overeducation while simultaneously accounting for the varying selectivity of both migrants and natives into employment. Considering that overeducation is estimated on a *selected* sample (in our case, employed individuals), it is necessary to employ sample selection models to ensure unbiased, efficient parameter estimates. In this model, there are two dependent variables: a binary variable for overeducation, and another binary variable that indicates whether the individual is observed in the sample, i.e., whether the individual is employed. Both variables are simultaneously modeled through the joint estimation of a probit model for the overeducation equation and a probit model for the selection equation for each country.

The selection equation should include at least one regressor not included in the probit equation, the exclusion restriction, which would affect the probability of being employed, but not the probability of being overeducated. Following previous research on women's labor supply and wages (Heckman 1979) as well as studies on the ethnic wage penalty (Cantalini et al. 2022; 2023), we use marital status as our exclusion restriction. As a robustness check, we also use an additional exclusion restriction: the number of children in the household. As this information is not provided for all countries, we were forced to exclude it from the main analysis. However, we checked the robustness of our results by estimating models with and without this variable when available. Besides the exclusion restriction, the selection equation also includes migrant status, age, academic education (=1), and the survey year. The overeducation equation further includes, alongside the previous variables, also part-time employment (=1).[4]

As stated, the probit models with sample selection were estimated for each country by gender to assess the levels of overeducation correcting for selection into employment (the models by country are

[4] Most previous studies include the levels of education as a control variable in their analysis of overeducation, see, for example (Akgüç & Parasnis, 2023; Birgier & Bar-Haim, 2023b).

presented in Appendix Tables 2 and 3, for men and women, respectively). In the second stage, we predict the probabilities of employment and overeducation for natives and migrants by gender and calculate the gaps in these predicted probabilities relative to natives. This is done to assess the cross-country variation in the extent of the penalties between migrants and natives in overeducation and employment levels.

## 5. Findings

### *5.1 Descriptive overview*

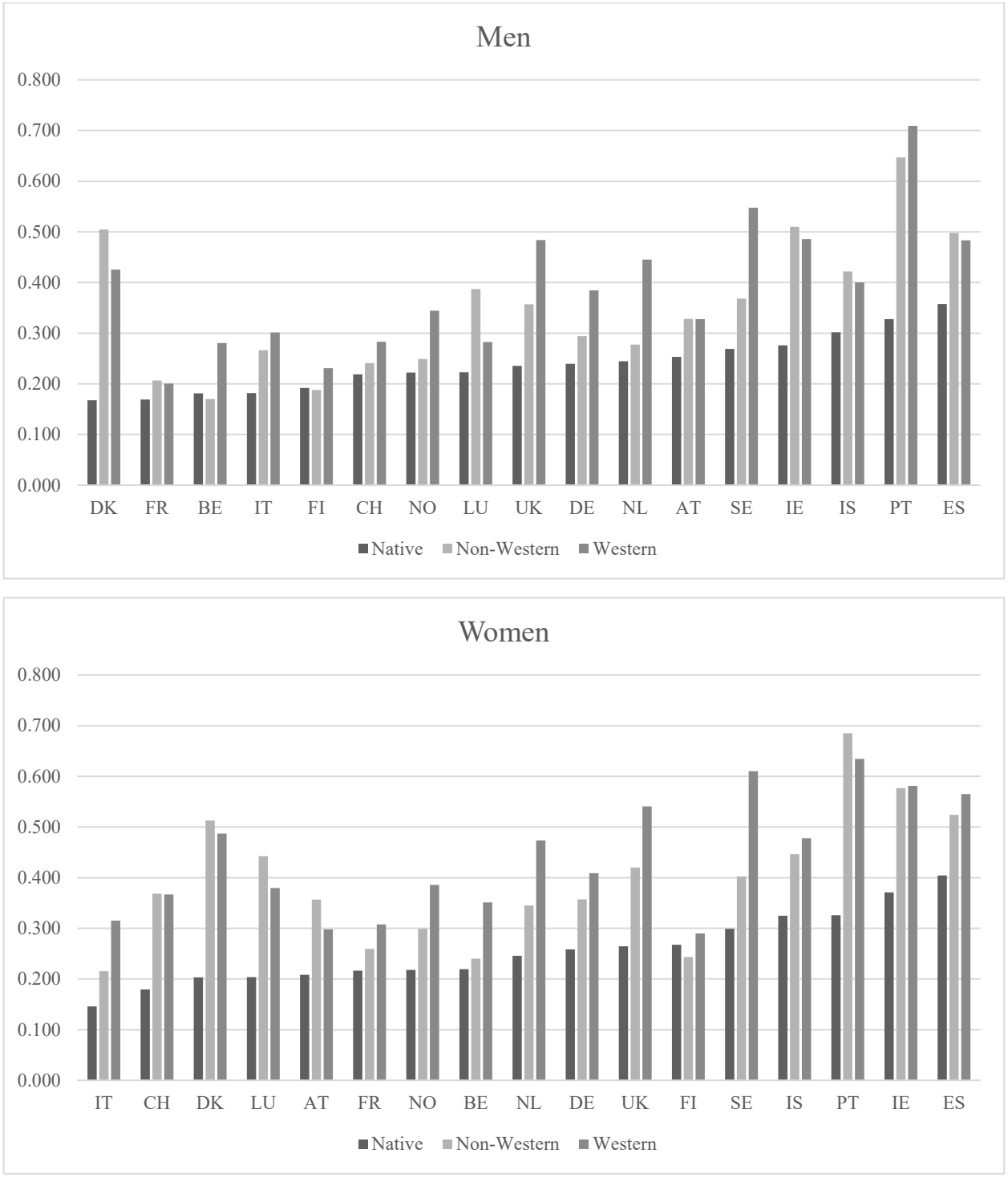
Figure 1 presents the proportion of overeducated individuals by country, migrant status, and gender, sorted by the overeducation levels of native men and women. There is substantial variation in the extent of overeducation across Western European countries for both genders. For instance, some countries, like Denmark, France, Belgium, Italy, and Finland, exhibit less than 20 percent overeducation among native men. In contrast, in other countries, including Southern European ones like Portugal and Spain, natives report over 30 percent overeducation. The same pattern is evident for women, but in some countries, native women exhibit very high levels of overeducation (such as Ireland and Spain).

When looking at the differences in overeducation between migrants and natives, it becomes apparent that in most countries and across genders, migrants experience higher levels of overeducation. The comparison between migrants from Western and non-Western countries does not consistently reveal lower overeducation levels for the former, but rather the opposite. In most cases, Western migrants show considerably higher overeducation levels than non-Western migrants (as in the case of both men and women in Belgium, the UK, Germany, the Netherlands, and Sweden). Often, the differences between these two groups are minor (as seen in the case of men in France, Austria, Iceland, and Spain or women in Switzerland, Ireland, and Denmark). Finally, it is worth noting that, with some exceptions, levels of overeducation tend to be higher among women, both for natives and particularly for migrants.

While potentially startling, these finding merits judicious consideration due to the inherent limitations stemming from the absence of control over individual attributes, notably encompassing variations in employment rates and distinct educational attainments within the analyzed groups. Appendix Tables A5 and A6 delineate the employment rates of both natives and (the two groups of) immigrants, thereby elucidating a significant disparity between them, particularly notable among women, and mainly manifest in the low rates among non-Western immigrants in comparison to native and Western immigrant counterparts, with this disparity varying significantly across countries.

The large variation in both the extent of overeducation of the native population alongside the native to immigrants' gaps in overeducation thus calls for further examination as they are shaped by the levels of employment, the migrants' individual characteristics (mainly, their educational level), and other macro-level characteristics in each country.

**Figure 1: Proportion of Overeducated Individuals, by Gender and Migrant Origin**



*5.2 Employment and overeducation by migrant status and gender*

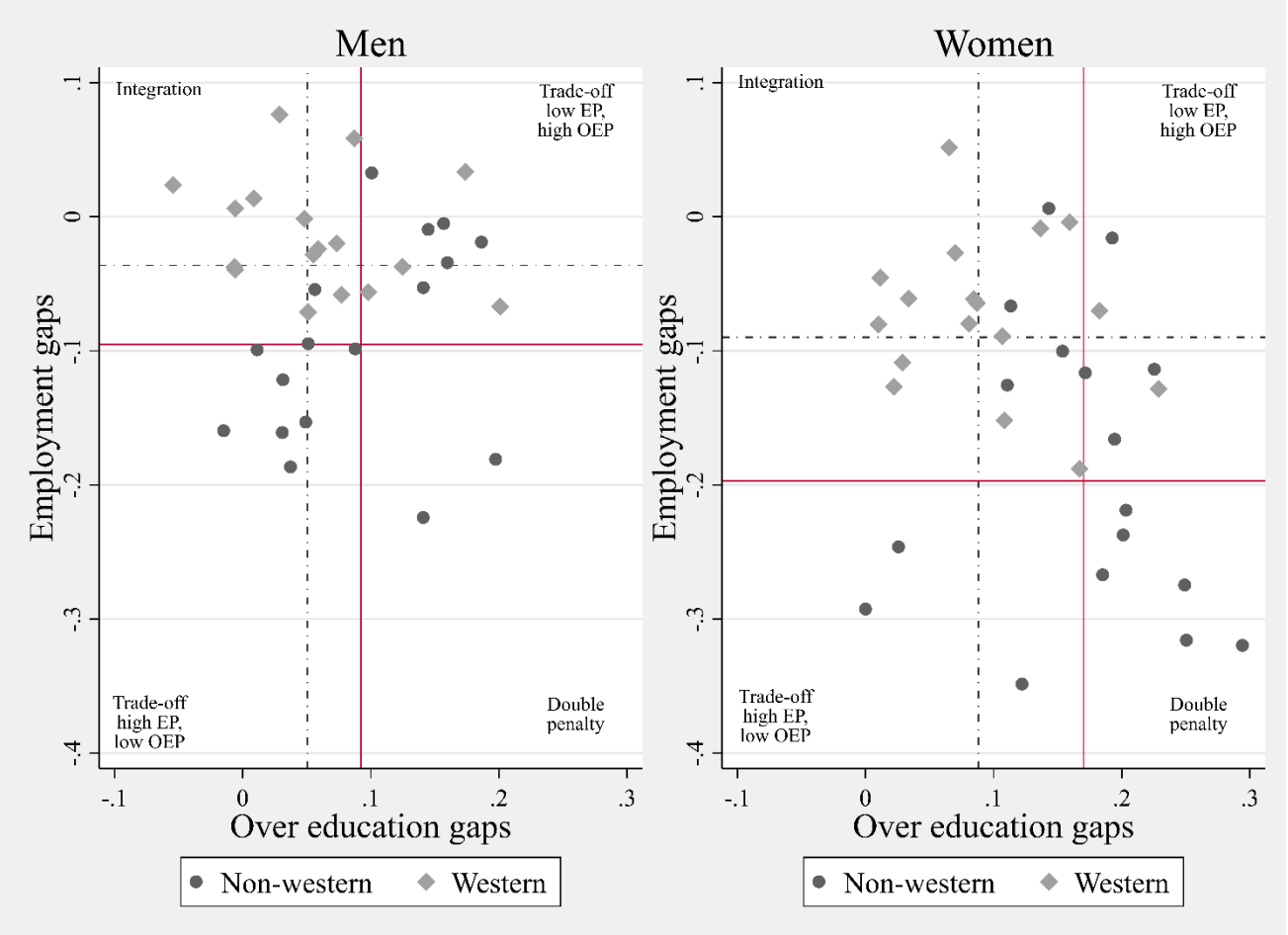
Figure 2 illustrates the results of our probit models with sample selection through a scatterplot for men (left panel) and women (right panel), which displays the combination of the gap in the probability of being employed (y-axis) and overeducated (x-axis) between migrants and natives. Each dot on the plot represents the average gap relative to natives in each respective country, with light grey diamonds indicating Western migrants and dark grey dots referring to non-Western migrants.

The scatterplots are divided into four quadrants, each corresponding to the four ideal-typical models of migrant labor market inclusion outlined in previous literature (see Panichella 2018; Cantalini et al. 2022), now incorporating the overeducation dimension. The top-right quadrant shows the trade-off characterized by a low employment penalty and a high overeducation penalty, whereas the bottom-left quadrant exhibits the opposite trade-off – high employment penalty and low overeducation penalty. The remaining two quadrants represent the best and worst scenarios for migrants: the top-left quadrant refers to the integration model, characterized by low penalty in both outcomes; the bottom-right quadrant represents the double penalty model, marked by high penalty in both outcomes. These quadrants are defined using two criteria: first, the average native-to-immigrants gap on each outcome considering the entire migrant group, including both Western and non-Western migrants (indicated by grey dashed lines); second, the average native-to-immigrants gap on each outcome considering solely non-Western migrants (indicated by red lines), the subgroup typically studied in literature focusing on ethnic penalty and migrant labor market inclusion. [5]

The figure shows that Western migrants are in a comparatively more advantageous position than their non-Western counterparts, regardless of gender, exhibiting generally lower employment and EOM penalties relative to non-western migrants. When taking the average penalties among all migrants as a reference (the grey dashed lines), although Western migrants in a few countries are situated within the Mediterranean trade-off and double penalty quadrants, a large portion falls within the integration quadrant. This is particularly evident when assessing the average penalties among non-Western migrants (the red lines), where the majority of migrants from EU15, North America, and Oceania align more closely with the integration model of inclusion.

[5] We opted not to use axes origin in the quadrants definition as we are interested in the magnitudes of migrants penalties across European countries. This approach is adopted for two primary reasons: firstly, in the majority of cases, migrants face disadvantages when compared to natives (as evidenced by dots located in the negative values of employment, signifying lower employment levels relative to natives, and positive values of overeducation, indicating higher penalties in EOM). Secondly, our primary interest lies in comparing migrants' penalties across countries.

**Figure 2: Overeducation and Employment Gaps for Migrants Relative to Natives, by Gender and Migrant Origin. Average marginal effects**




Note: estimates based on probit models with sample selection (EULFS 2015-2019). EP = employment penalty; OEP = overeducation penalty. Dashed grey lines correspond to the average EP (y = -0.036 for men; y =-0.090 for women) and the average OEP (x = 0.051 for men; x = 0.088 for women) for all migrants. Solid red lines correspond to the average EP (y =-0.0954 for men; y =-0.197 for women) and the average OEP (x = 0.092 for men; x = 0.170 for women) for non-Western migrants only.

Non-western migrant men predominantly fall within the trade-off quadrants, where higher employment penalties correspond to lower EOM penalties, and vice versa. This pattern holds regardless of the criteria used to define the quadrants, with a particularly pronounced trend when considering the average penalties among non-Western migrants. These findings confirm earlier conclusions about the labor market inclusion of non-Western male migrants in Western Europe (Reyneri and Fullin 2011; Ballarino and Panichella 2015). Conversely, results for women depict a less favorable situation compared to men, irrespective of the migrant group under consideration. Indeed, migrant women in most countries experience more substantial ethnic penalties in employment and overeducation compared to their male counterparts, in line with the argument of double disadvantage. Furthermore, the situation among women appears to be more heterogeneous, especially within the non-

Western migrant group, with fewer countries within the trade-off quadrants and a greater number aligning with the double penalty model. These findings are consistent with prior research using different outcomes, such as wages (Cantalini et al. 2022).

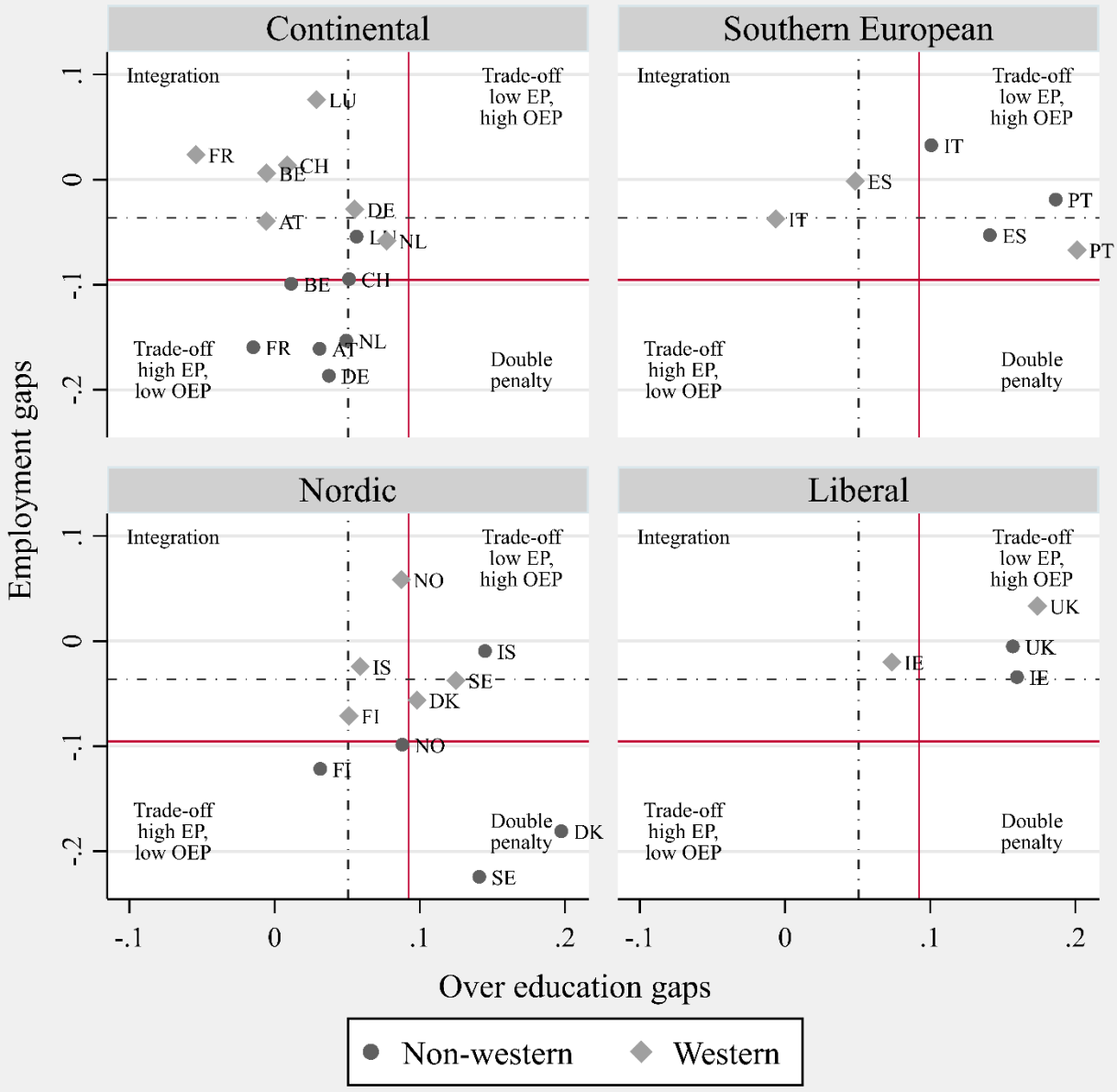
Moreover, upon a gender-based examination of the data, it becomes evident that the disparities in employment and overeducation levels among migrant women are more striking. The average gap for Western migrant women closely corresponds to that observed among all migrant men, reflecting approximately 10-percentage points penalties compared to natives in both employment and overeducation. Notably, when considering that the comparison group within each country comprises native women, the hardships faced by migrant women assume even greater prominence. This observation is of particular significance, as native women often contend with their own set of disadvantages when juxtaposed with native men in various contexts.

### *5.3 Cross-country variation in employment and EOM penalties*

Figures 3 and 4 display the same results as shown in Figure 2; however, countries have been classified based on their labor market regulation and welfare regime types, aiming to more effectively capture whether the typical models of migrants' labor market inclusion observed in Continental, Mediterranean, Nordic and Liberal countries (see section 2.1) are also applicable to the combination between employment and overeducation. The scatterplots' quadrants are still defined based on the average penalty on each outcome among the entire migrant group (dashed grey lines), and on the average penalty on each outcome among solely the non-Western migrant subgroup (red lines).

Starting with men (Figure 3), the results for Continental and Southern European countries mirror the findings of the existing literature on the labor market integration of non-Western migrants. Among Continental countries, they align more closely with a model characterized by a trade-off between high employment penalties and low penalties for EOM. In contrast, non-Western migrants in Mediterranean countries are situated within the quadrant characterized by the opposite trade-off, with low employment penalties but high EOM penalties. The comparison between Western and non-Western migrants in these two groups of countries highlights another notable distinction. In Continental countries, the penalty for overeducation is comparable between Western and non-Western migrants; however, a clear differentiation arises in employment, with the former facing notably lower penalties than the latter. Conversely, in Mediterranean countries like Italy and Spain, while the penalty of the two groups is similar on employment, Western migrants experience a lower penalty for EOM compared to their non-Western counterparts.

**Figure 3: Overeducation and Employment Gaps for Male Migrants Relative to Natives, by Country Cluster and Migrant Origin. Average marginal effects**




Note: estimates based on probit models with sample selection (EULFS 2015-2019). EP = employment penalty; OEP = overeducation penalty. Dashed grey lines correspond to the average EP (y = -0.036) and the average OEP (x = 0.051) for all migrants. Solid red lines correspond to the average EP (y = -0.095) and the average OEP (x = 0.092) for non-Western migrants only.

Non-Western migrants in Nordic countries can be categorized into three distinct groups. Those residing in Norway and Finland face significant employment penalties compared to natives, yet they experience low EOM penalties, aligning them with the Continental trade-off model. Conversely, individuals in Sweden and Denmark appear to conform to the double penalty model of inclusion, facing substantial

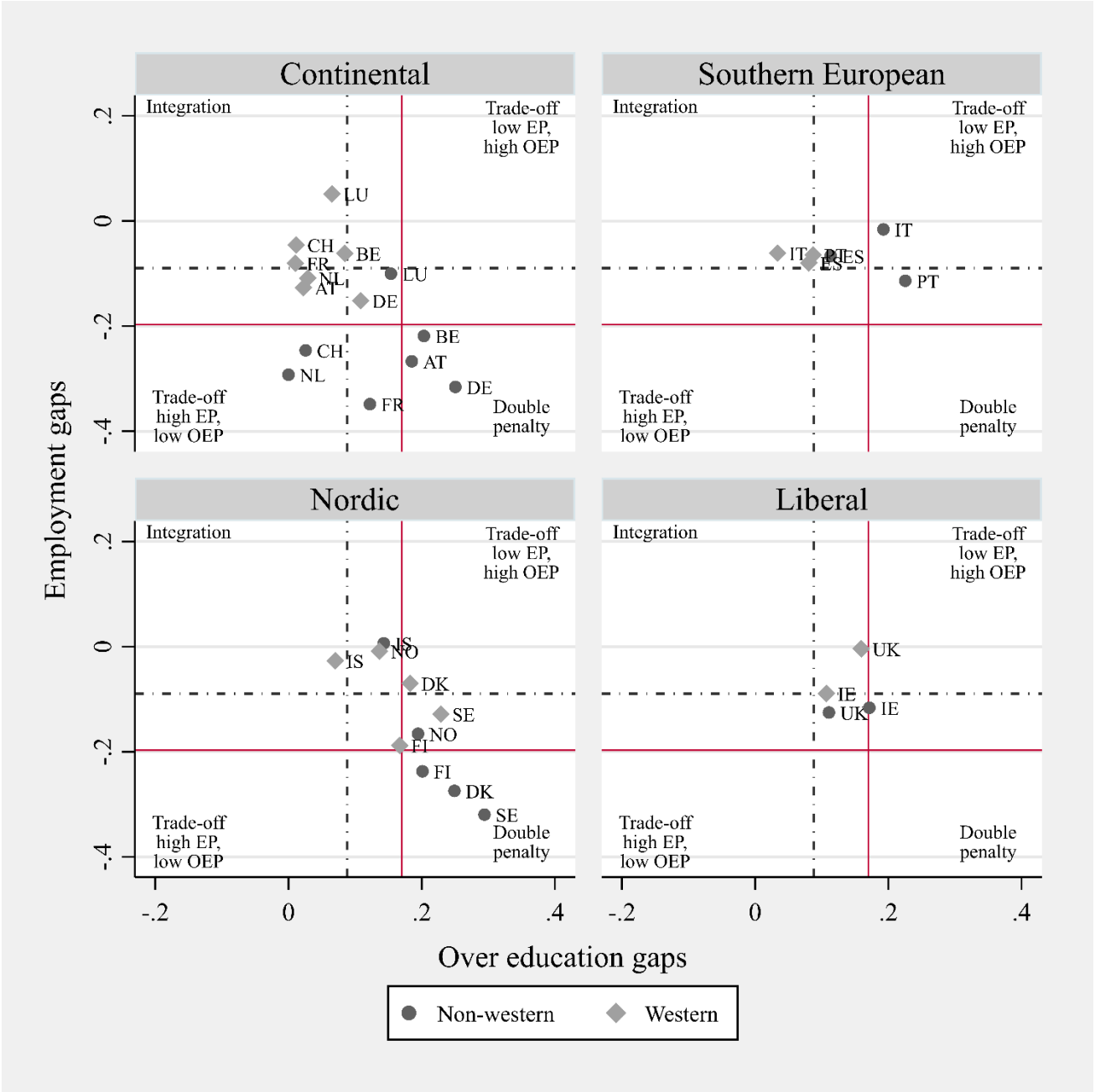
penalties in both employment and overeducation. In Iceland, migrants seem to better correspond with the Mediterranean trade-off model, displaying a low employment penalty alongside a high EOM penalty. Furthermore, except for Iceland, the employment penalty is lower for Western migrants compared to their non-Western counterparts, while the degree of the EOM penalty varies across countries. Norway, Finland, and Sweden exhibit analogous penalties on overeducation for both Western and non-Western migrants, whereas Western migrants encounter notably lesser penalties in Denmark.

The condition of non-Western migrants in the UK and Ireland contrasts with prior findings on migrants' labor market integration. While earlier research positioned these migrants between those moving to Continental and Mediterranean countries, their situation remarkably mirrors the latter when considering overeducation. Another resemblance to Southern Europe is observed when comparing Western and non-Western migrants, at least for Ireland, where analogous employment penalties are coupled with lower EOM penalties for the former group.

Results for non-Western migrant women in Southern European countries are similar to those of men (Figure 4). Apart from Spain, in these countries, migrant women exhibit low employment penalties – akin to those of Western migrant women – together with high EOM penalties. Nevertheless, the situation for women diverges in the other country clusters, highlighting the greater heterogeneity of the labor market inclusion and the higher disadvantage experienced by migrant women relative to both native women and migrant men. For instance, in France, The Netherlands, and Switzerland, non-Western migrants follow a trade-off characterized by a high employment penalty and low EOM penalty, while in Austria, Belgium, and Germany, they face substantial penalties in both outcomes, aligning more with a double penalty model. Non-Western women in Luxembourg stand as exceptions mirroring the case of men, following the integration model of inclusion. With few exceptions, moreover, Western migrants fare much better than non-Western women in terms of both employment and overeducation penalties.

In Nordic countries, non-Western migrant women display various patterns in their employment and EOM outcomes, but in the majority, they face a double penalty, including Sweden, Denmark, and Finland. In Norway, they show a trade-off, with minimal gaps in employment but larger disparities in overeducation, while in Iceland, they even exhibit low penalties in both outcomes, aligning with an integration model. Compared to non-Western migrant women, Western ones have similar penalties in overeducation but lower penalties in employment. Shifting to Liberal countries, non-Western women encounter similar small employment and EOM penalties in Ireland and the United Kingdom, placing them in the integration quadrant. The situation of Western migrant women does not differ significantly from that of non-Western ones, except for slightly lower employment penalties in the United Kingdom.

**Figure 4: Overeducation and Employment Gaps for Female Migrants Relative to Natives, by Country Cluster and Migrant Origin. Average marginal effects**




Note: estimates based on probit models with sample selection (EULFS 2015-2019). EP = employment penalty; OEP = overeducation penalty. Dashed grey lines correspond to the average EP (y = -0.090) and the average OEP (x = 0.088) for all migrants. Solid red lines correspond to the average EP (y = -0.197) and the average OEP (x = 0.170) for non-Western migrants only.

In parallel with the analyses whose results have been presented thus far, based on models with sample selection, we estimated separate logistic regression models for the probability of being employed and overeducated. The aim was to assess whether and to what extent selection into employment matters for the gaps between migrants and natives in overeducation. The comparison between these two model types demonstrates that accounting for selection into employment does not

result in significant differences among men. Figure A1 in the appendix, which shows results from logit models for men, displays highly similar outcomes compared to those derived from the probit models with sample selection presented in Figure 3.[6] On the other hand, accounting for the selection into employment proves to be considerably more important for women, particularly in Continental and Nordic countries (see Figure A2, appendix). Notably, without considering selection into employment, the situation of migrant women in countries like Germany, Belgium, Austria, Sweden, and Finland closely resembles that of men, placing them more in line with a model of inclusion characterized by a trade-off between high employment penalties and low EOM penalties, as shown by existing research. However, correcting for selection into employment makes EOM penalties to emerge more clearly, as those migrant women that manage to access employment in those countries are very few – especially compared to native women – and strongly selected (see also Table A6, appendix).

Unlike Continental countries, the outcomes in most Southern European countries remain relatively consistent between the two models. This might be attributed to the fact that even native women in these countries have a low employment rate (see also Table A6, appendix), and those who are employed are strongly selected. Finally, it is worth noting that among liberal countries, accounting for selection into employment leads to a reduction in the EOM penalty for both groups of migrant women in the UK. This shift alters their classification from a Mediterranean trade-off model to an integration model.

## 6. Discussion and Conclusion

This study investigated immigrants' labor market integration patterns in terms of employment and overeducation across 17 Western European countries, focusing on both men and women. Our primary aim was to incorporate overeducation in the debate on the models of labor market inclusion of immigrants across Europe (Reyneri & Fullin, 2011b, 2011a), while also examining gender differences in the integration of migrants concerning the interplay between overeducation and employment outcomes. Overall, our findings support our primary hypothesis that immigrants generally face disadvantages in terms of employment opportunities and overeducation when compared to native populations (H1 supported). This aligns with the existing body of literature that underscores the challenges immigrants encounter during their integration into the destination labor markets (Ballarino

[6] Of course, only the estimates related to overeducation can potentially vary between the two model types, as models with sample selection adjust for (possible) differences in the selection into employment among natives and migrants. However, due to the different estimation techniques between the two models (probit versus logit), the employment results may not be numerically equivalent.

& Panichella, 2015; Cantalini et al., 2022, 2023; Reyneri & Fullin, 2011b), specifically in terms of overeducation (Akgüç & Parasnis, 2023; Aleksynska & Tritah, 2013; Birgier & Bar-Haim, 2023b; Chiswick & Miller, 2009; Cim et al., 2017; Nieto & Ramos, 2017). However, notable distinctions emerged based on factors such as migrant origin (Western vs. non-Western), gender, and destination country.

Commencing with migrant origin, the analysis uncovered that migrants from Western countries encounter relatively milder disadvantages compared to their non-Western counterparts. Western migrants mostly exhibit an integration model of labor market inclusion, which leads to improved employment prospects and reduced instances of overeducation relative to non-Western migrants (H4 supported). Nevertheless, these discrepancies between groups of migrants appeared to be more conspicuous in Continental and Southern European countries than in Nordic and Liberal ones. This underscores the concept of stratification among migrants and their varying significance across different contexts. While most literature on migrants' EOM focused on international immigrants in general (Akgüç & Parasnis, 2023; Aleksynska & Tritah, 2013; Birgier & Bar-Haim, 2023) and most literature on the ethnic penalty mainly centered on non-Western immigrants (Ballarino & Panichella, 2015; Cantalini et al., 2023), this study stands out by introducing a distinct hierarchy between Western and non-Western migrants. Moreover, it elucidates the ways in which these categories demonstrate disparities within various immigration regimes. Specifically, our paper reveals that differences between migrant groups are more evident in terms of employment levels, with Western migrants exhibiting higher employment rates compared to non-Western migrants. However, the scenario is less clear for overeducation, challenging the notion that the integration of Western immigrants is entirely seamless.

Regarding gender, pronounced disparities are discernible in the magnitude of gaps relative to native populations, encompassing both employment and overeducation. Our findings revealed that migrant women encounter more substantial disadvantages in comparison to migrant men (H5 supported). Women's disadvantage is even more evident considering that the baseline for comparison in all models is not native men but rather native women, which underscores how migrant women experience a "double disadvantage", stemming from their dual condition as both women and migrants (Birgier & Bar-Haim, 2023b; Pecoraro, 2011). Moreover, the findings also highlighted a pronounced diversity in labor market inclusion patterns among migrant women relative to men. While non-Western men are positioned along the diagonal of the two trade-off models, whereby low employment penalties correspond to high EOM penalties, and vice versa, non-Western women align with all four ideal-typical models, with a larger group following the double penalty model (H6 supported). This heightened heterogeneity – coupled with their higher disadvantage – may be attributed to various

factors, such as the difference in the levels of female labor market participation for both migrant and native women across European societies (Elhorst & Zeilstra, 2007), the segregation of migrant women in specific labor market sectors (e.g., personal care and services) and their more frequent status as 'tied movers' (Ballarino & Panichella, 2018). Additionally, it could be attributed to the notion that individual skill levels and household income of migrant women carry more significance in comparison to country-level characteristics, playing a pivotal role in determining the degree of overeducation among immigrant women (Akgüç & Parasnis, 2023). Finally, these variations could also be influenced by our modeling approach, which accounts for the different selectivity of migrants and natives into employment when estimating overeducation. Although this strategy, which is not commonly used in the literature on migrants' labor market inclusion (see for an exception Cantalini et al. 2022; 2023), does not significantly alter the overeducation outcomes among men, it carries significant implications for women, especially in several Continental and Nordic countries where native women exhibit particularly high employment rates and migrant women who are employed are few and presumably highly selected. Interestingly, our modeling strategy does not affect overeducation results for women in Mediterranean countries, where both migrants and natives exhibit low employment rates, and where the selectivity into employment is potentially high for both groups.

Concerning cross-country differences, our results for Mediterranean countries mirror earlier literature for both men and women (Ballarino & Panichella, 2015; Cantalini et al., 2023; Reyneri & Fullin, 2011b, 2011a). Even when considering overeducation, non-Western migrants are not substantially penalized in terms of employment, but they tend to exhibit higher levels of EOM compared to natives and their counterparts in other destination countries (H2 supported). Non-Western migrant men in Continental countries display the opposite trade-off model characterized by high employment penalties and smaller penalties in overeducation, still confirming prior research using other dimensions of job quality. However, the situation among women in these countries is more heterogeneous, and in nations such as Austria, Belgium, and Germany, non-Western migrant women encounter a double penalty scenario, not least because of the possible higher selectivity of migrants entering the labor market, a factor controlled for in our models. Results for Liberal countries, conversely, appeared to deviate from previous research. This discrepancy primarily stems from negligible disparities in migrant employment levels compared to natives, especially when juxtaposed with similar gaps in other countries. Consequently, migrant men in both the UK and Ireland find themselves within the Mediterranean trade-off, while migrant women in these countries tend to align more with the integration model.

The findings from Nordic countries demonstrate diverse patterns for both men and women, lending partial support to hypothesis H3. Among men, certain nations conform to the expected Continental

trade-off, while others lean toward a double penalty model, and a few even exhibit stronger alignment with the Mediterranean trade-off. In the case of women, migrants in the majority of countries follow the double penalty scenario, although some instances place them within the framework of the other three models. The prevalence of the double penalty model among migrant women in Nordic countries can be attributed to three primary factors. Firstly, these nations pose challenges for immigrants in achieving labor market integration at levels comparable to those of native populations, partly due to the notably high employment rates among natives. Secondly, partly related to this, employed migrant women in these countries are likely to be strongly selected, as confirmed by our models with sample selection. Thirdly, even when immigrants succeed in entering the labor market, they often compromise their educational qualifications relative to the occupations they engage in.

Although our study does not explicitly identify which macro-level factors within the Nordic region are accountable for these adverse outcomes, previous research has argued that the extent of labor market rigidity acts as a hurdle for immigrants seeking to enter the workforce in these countries (Bengtsson et al., 2005; Kogan, 2007, 2016). Our finding suggests, in line with other studies (Platt et al., 2021), that the repercussions of labor market rigidity may extend beyond just the initial phase of labor market entry, impacting the quality of employment that immigrants can attain. Recently, Akgüç & Parasnis (2023) suggested that country-level characteristics such as high education levels, female employment levels, and perception towards women's work contribute to diminishing the likelihood of overqualification of migrant women compared to men. However, their study falls short in assessing the impact of these variables on the disparity between migrant and native populations in terms of overqualification. In this regard, we showed that, at least to some extent, in Nordic countries characterized by high levels of female labor force participation, the gaps between migrants and natives in their overeducation levels are more substantial. This leads us to speculate that while higher education and employment rates may contribute positively to the condition of native women, their effects could be less advantageous for their migrant counterparts.

In conclusion, our study contributes to the existing literature by introducing overeducation into the discourse surrounding the ethnic penalty and the labor market inclusion of migrants in Europe. Firstly, it indicates that findings on the models of migrants' labor market inclusion can vary depending on the specific outcomes under consideration. When considering the interplay between education and overeducation, we can clearly confirm results found by previous research for male and female migrants in Mediterranean countries, who are characterized by low employment penalties and high job quality penalties (and limited returns to education), regardless of the job quality measure being applied. However, our analysis reveals nuanced findings for other contexts. For instance, in countries such as

the UK and Ireland, male migrants exhibit a model of labor market inclusion that resembles the Mediterranean trade-off model when examining the combination of employment and overeducation.

Secondly, our paper underscores the importance of the empirical approach chosen when estimating the ethnic penalty on various dimensions of job quality. Specifically, in models that account for the selection into employment, our findings for women unveil higher overeducation penalties in some contexts, due to the higher selectivity of migrant women that succeed to enter the labor market. In other words, in countries such as Austria, Germany, Sweden, and Finland, the overeducation penalty among female migrants is notably high, but this depends, among other things, on the characteristics of the relatively few migrant women who successfully enter these host labor markets, i.e., on the selection processes into employment. Future research should thus explore the intricate dynamics of labor market inclusion among immigrants in a more comprehensive way, focusing on the combination between employment opportunities and different measures of job quality (e.g., class attainment, job stability, overeducation, wage, etc.). Moreover, it should apply statistical techniques that control the different selectivity of migrants and natives into employment, especially when studying the labor market inclusion of migrant women.

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## 7. References


Akgüç, M., & Parasnis, J. (2023). Occupation–Education Mismatch of Immigrant Women in Europe. *Social Indicators Research*. https://doi.org/10.1007/s11205-023-03066-0

Aleksynska, M., & Tritah, A. (2013). Occupation–education mismatch of immigrant workers in Europe: Context and policies. *Economics of Education Review*, *36*, 229–244.

Ambrosini, M. (2018). *Irregular Immigration in Southern Europe*. Springer International Publishing. https://doi.org/10.1007/978-3-319-70518-7

Ballarino, G., & Panichella, N. (2015). The occupational integration of male migrants in Western European countries: Assimilation or persistent disadvantage? *International Migration*, *53*(2). https://doi.org/10.1111/imig.12105

Ballarino, G., & Panichella, N. (2018). The occupational integration of migrant women in Western European labour markets. *Acta Sociologica*, *61*(2), 126–142.

Bengtsson, T., Lundh, C., & Scott, K. (2005). From Boom to Bust: The Economic Integration of Immigrants in Post War Sweden. In K. E. Zimmermann (Ed.), *European migration: What do we know?* (pp. 15–58). Oxford University Press.

Birgier, D. P., & Bar-Haim, E. (2023a). *Language Distance, Language Abilities, and Labour Market Outcome of Migrants by Gender*. Stockholm Research Reports in Demography. https://doi.org/10.17045/sthlmuni.23911089.v1

Birgier, D. P., & Bar-Haim, E. (2023b). Language Used at Home and Educational–Occupational Mismatch of Migrants by Gender. *Social Indicators Research*. https://doi.org/10.1007/s11205-022-03054-w

Cantalini, S., Guetto, R., & Panichella, N. (2022). The ethnic wage penalty in Western European regions: Is the European integration model confirmed when differences within countries are considered? *Demographic Research*, *46*, 681–692. https://doi.org/10.4054/DEMRES.2022.46.23

Cantalini, S., Guetto, R., & Panichella, N. (2023). Ethnic wage penalty and human capital transferability: A comparative study of recent migrants in 11 European countries. *International Migration Review*, *57*(1), 328–356.

Cebolla-Boado, H., Miyar-Busto, M., & Muñoz-Comet, J. (2019). How much can you take with you? The role of education in explaining differences in the risk of unemployment between migrants and natives. *Comparative Migration Studies*, *7*(1). https://doi.org/10.1186/S40878-019-0144-4

Chen, L., & Hu, J. (2023). Overeducation and Social Integration Among Highly Educated Migrant Workers in China. *Social Indicators Research*. https://doi.org/10.1007/s11205-023-03145-2

Chiswick, B., & Miller, P. (2009). The international transferability of immigrants' human capital. *Economics of Education Review*, *28*(2), 162–169.

Chiswick, B., & Miller, P. (2010a). The Effects of Educational-Occupational Mismatch on Immigrant Earnings in Australia, with International Comparisons. *International Migration Review*, *44*(4), 869–898.

Chiswick, B., & Miller, P. W. (2010b). Does the choice of reference levels of education matter in the ORU earnings equation? *Economics of Education Review*, *29*(6), 1076–1085. https://doi.org/10.1016/j.econedurev.2010.06.001

Chiswick, B., & Miller, P. W. (2013). The impact of surplus skills on earnings: Extending the over-education model to language proficiency. *Economics of Education Review*, *36*, 263–275.

Cim, M., Kind, M. S., & Kleibrink, J. (2017). *Occupational mismatch of immigrants in Europe: The role of education and cognitive skills* (687; Ruhr Economic Papers). Essen: RWI - Leibniz-Institut für Wirtschaftsforschung. https://doi.org/10.4419/86788797

Donato, K. M., Piya, B., & Jacobs, A. (2014). The double disadvantage reconsidered: Gender, immigration, marital status, and global labor force participation in the 21st century. *International Migration Review*, *48*(s1), S335–S376. https://doi.org/10.1111/IMRE.12142

Dustmann, C., & Fabbri, F. (2003). Language proficiency and labour market performance of immigrants in the UK. *Economic Journal*, *113*(489), 695–717. https://doi.org/10.1111/1468-0297.t01-1-00151

Elhorst, J. P., & Zeilstra, A. S. (2007). Labour force participation rates at the regional and national levels of the European Union: An integrated analysis. *Papers in Regional Science*, *86*(4), 525–549.

Frank, K., & Hou, F. (2018). Over-education and well-being: How does education-occupation mismatch affect the life satisfaction of university-educated immigrant and non-immigrant workers? *Ethnicity & Health*, *23*(8), 884–901. https://doi.org/10.1080/13557858.2017.1316832

Green, C., & Kler, P. (2007). Immigrant overeducation: Evidence from recent arrivals to Australia. *Economics of Education Review*, *26*(4), 420–432.

Groot, W., & Maassen Van Den Brink, H. (2000). Overeducation in the labor market: A meta-analysis. *Economics of Education Review*, *19*(2), 149–158. https://doi.org/10.1016/S0272-7757(99)00057-6

Guetto, R. (2018). Employment returns to tertiary education for immigrants in Western Europe: Cross-country differences before and after the economic crisis. *Social Inclusion*, *6*(3), 64–77.

Hall, P. A., & Soskice, D. (2001). *Varieties of capitalism: The institutional foundations of comparative advantage*. Oxford University Press.

Hardoy, I., & Schøne, P. (2014). Returns to pre-immigration education for non-western immigrants: Why so low? *Education Economics*, *22*(1), 48–72. https://doi.org/10.1080/09645292.2010.511846

He, Q., & Gerber, T. P. (2020). Origin-Country Culture, Migration Sequencing, and Female Employment: Variations among Immigrant Women in the United States. *International Migration Review*, *54*(1), 233–261. https://doi.org/10.1177/0197918318821651

Heath, A., & Cheung, S. Y. (2007). *Unequal Chances: Ethnic Minorities in Western Labour Markets*. Oxford University Press. https://doi.org/10.5871/bacad/9780197263860.001.0001

Kogan, I. (2006). Labor markets and economic incorporation among recent immigrants in Europe. *Social Forces*, *85*(2), 697–721.

Kogan, I. (2007). *Working through Barriers: Host Country Institutions and Immigrant Labour Market Performance in Europe*. Springer.

Kogan, I. (2016). Integration policies and immigrants' labor market outcomes in Europe. *Sociological Science*, *3*(16), 335–358.

Lewin-Epstein, N., Semyonov, M., Kogan, I., & Wanner, R. A. (2003). Institutional Structure and Immigrant Integration: A Comparative Study of Immigrants' Labor Market Attainment in Canada and Israel1. *International Migration Review*, *37*(2), 389–420. https://doi.org/10.1111/j.1747-7379.2003.tb00142.x

Longhi, S., & Platt, L. (2008). Pay gaps across equalities areas. *Equalities and Human Rights Commission, Manchester*.

Mattoo, A., Neagu, I. C., & Özden, Ç. (2008). Brain waste? Educated immigrants in the US labor market. *Journal of Development Economics*, *87*(2), 255–269.

McGuinness, S. (2006). Overeducation in the labour market. In *Journal of Economic Surveys*. https://doi.org/10.1111/j.0950-0804.2006.00284.x

McGuinness, S., & Byrne, D. (2015). Born abroad and educated here: Examining the impacts of education and skill mismatch among immigrant graduates in Europe. *IZA Journal of Migration*, *4*(1), 17.

Nieto, S., Matano, A., & Ramos, R. (2015). Educational mismatches in the EU: immigrants vs natives. *International Journal of Manpower*, *36*(4), 540–561.

Nieto, S., & Ramos, R. (2017). Overeducation, Skills and Wage Penalty: Evidence for Spain Using PIAAC Data. *Social Indicators Research*, *134*(1). https://doi.org/10.1007/s11205-016-1423-1

Oso, L., & Ribas-Mateos, N. (2013). An introduction to a global and development perspective: A focus on gender, migration and transnationalism. *The International Handbook on Gender, Migration and Transnationalism: Global and Development Perspectives*, 1–41. https://doi.org/10.4337/9781781951477.00007

Panichella, N. (2018). Economic crisis and occupational integration of recent immigrants in Western Europe. *International Sociology*, *33*(1), 64–85. https://doi.org/10.1177/0268580917742002/ASSET/IMAGES/LARGE/10.1177_0268580917742002-FIG2.JPEG

Panichella, N., Avola, M., & Piccitto, G. (2021). Migration, class attainment and social mobility: An analysis of migrants' socioeconomic integration in Italy. *European Sociological Review*, *37*(6), 883–898.

Pecoraro, M. (2011). *Gender, brain waste and job-education mismatch among migrant workers in Switzerland* (11; International Migration Paper).

Platt, L., Polavieja, J., & Radl, J. (2021). Which Integration Policies Work? The Heterogeneous Impact of National Institutions on Immigrants' Labor Market Attainment in Europe: *International Migration Review*. https://doi.org/10.1177/01979183211032677

Prokic-Breuer, T., & McManus, P. A. (2016). Immigrant educational mismatch in Western Europe, apparent or real? *European Sociological Review*, *32*(3), 411–438. https://doi.org/10.1093/esr/jcw005

Rafferty, A. (2012). Ethnic penalties in graduate level over-education, unemployment and wages: Evidence from Britain. *Work, Employment and Society*, *26*(6), 987–1006.

Reitz, J. G. (2001). Immigrant skill utilization in the Canadian labour market: Implications of human capital research. *Journal of International Migration and Integration / Revue de l'integration et de La Migration Internationale*, *2*(3), 347–378.

Reyneri, E. (1998). The role of the underground economy in irregular migration to Italy: Cause or effect? *Journal of Ethnic and Migration Studies*, *24*(2), 313–331. https://doi.org/10.1080/1369183X.1998.9976635

Reyneri, E., & Fullin, G. (2011a). Ethnic penalties in the transition to and from unemployment: A West European perspective. *Https://Doi.Org/10.1177/0020715211412114*, *52*(4), 247–263. https://doi.org/10.1177/0020715211412114

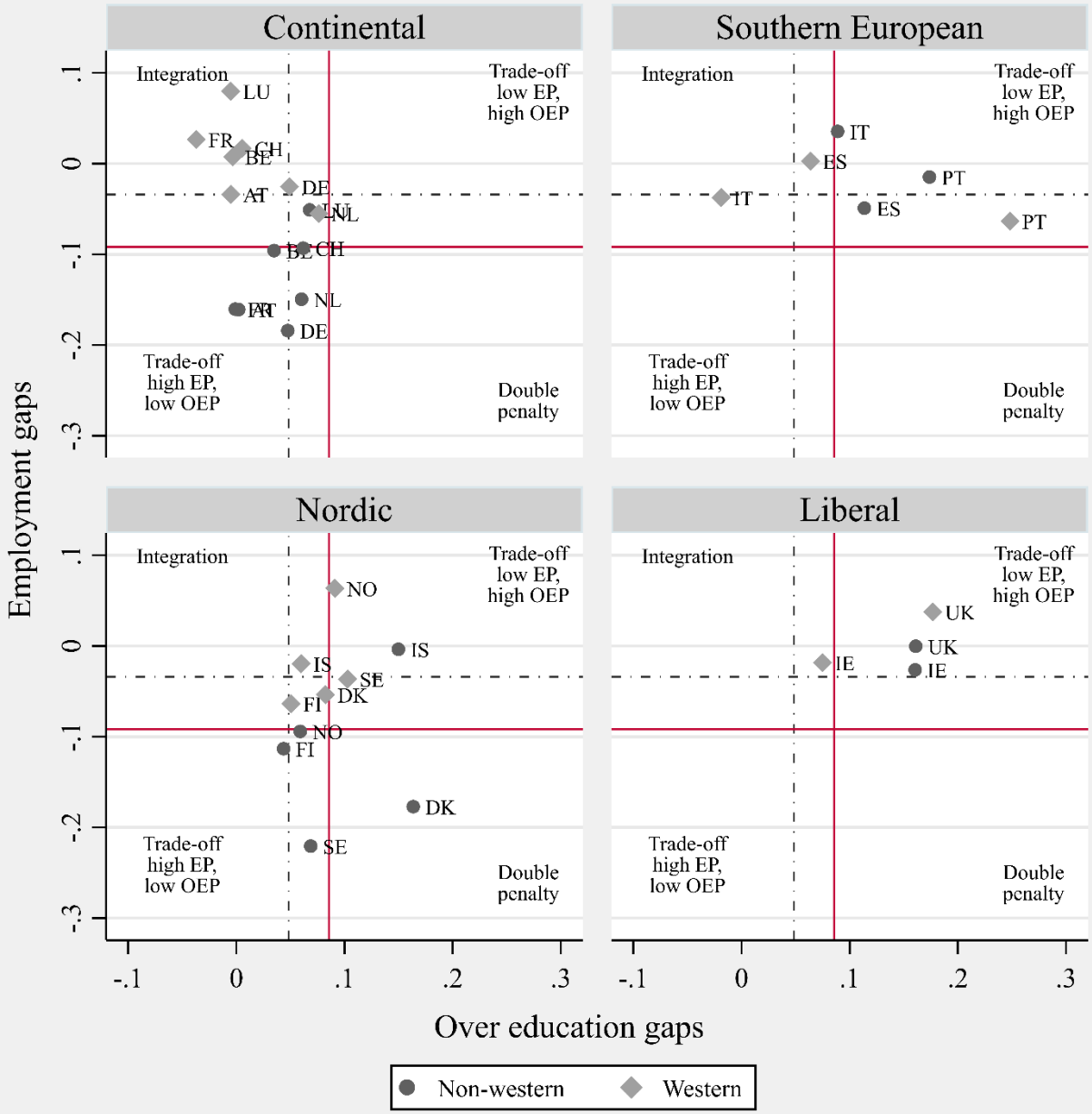
Reyneri, E., & Fullin, G. (2011b). Labour Market Penalties of New Immigrants in New and Old Receiving West European Countries. *International Migration*, *49*(1), 31–57. https://doi.org/10.1111/J.1468-2435.2009.00593.X

Sanromá, E., Ramos, R., & Simón, H. (2015). Portability of Human Capital and Immigrant Overeducation in Spain. *Population Research and Policy Review*, *34*(2), 223–241. https://doi.org/10.1007/S11113-014-9340-Y/TABLES/5

Van de Ven, W. P., & Van Praag, B. M. (1981). The demand for deductibles in private health insurance: A probit model with sample selection. *Journal of Econometrics*, *17*(2), 229–252. https://doi.org/10.1016/0304-4076(81)90028-2

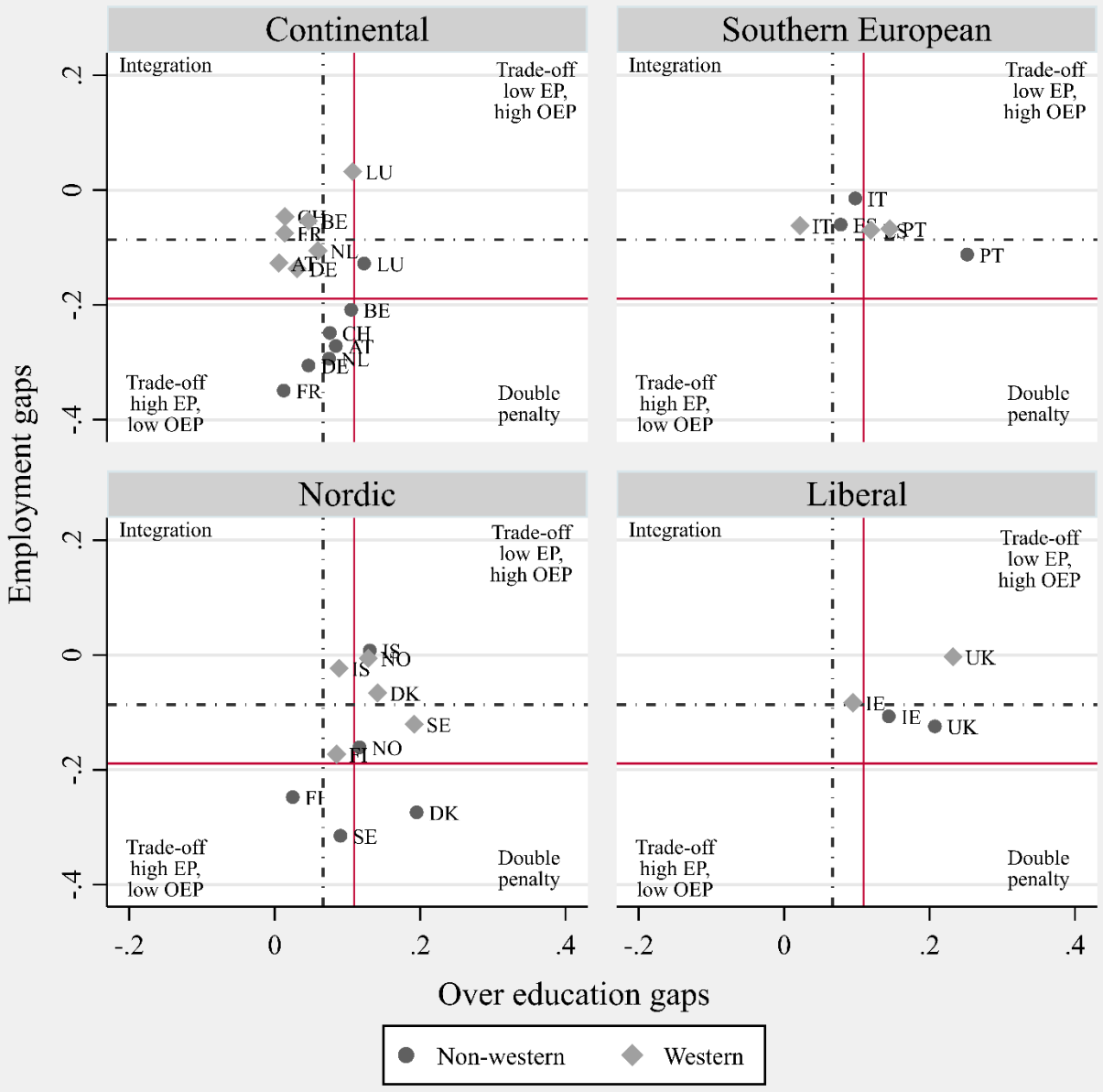
Visintin, S., Tijdens, K., & van Klaveren, M. (2015). Skill mismatch among migrant workers: Evidence from a large multi-country dataset. *IZA Journal of Migration*, *4*(1). https://doi.org/10.1186/s40176-015-0040-0

**Appendix Figure A1: Overeducation and Employment Gaps for Male Migrants Relative to Natives, by Country Cluster and Migrant Origin. Average marginal effects**




Note: estimates based on logit models for employment and overeducation (EULFS 2015-2019). Dashed grey lines correspond to the average EP (y = -0.034) and the average OEP (x = 0.048) for all migrants. Solid red lines correspond to the average EP (y = -0.092) and the average OEP (x = 0.086) for non-Western migrants only.

**Appendix Figure A2: Overeducation and Employment Gaps for Female Migrants Relative to Natives, by Country Cluster and Migrant Origin. Average marginal effects**




Note: estimates based on logit models for employment and overeducation (EULFS 2015-2019). Dashed grey lines correspond to the average EP (y = -0.086) and the average OEP (x = 0.066) for all migrants. Solid red lines correspond to the average EP (y = -0.189) and the average OEP (x = 0.109) for non-Western migrants only.

# Appendices:
# Tables

**Appendix A1: Descriptive statistics of variables included in the models, by country and group (native, non-Western, and Western migrants) - MEN**

| country | Group | Over education | Employment | BA+ | Age | SD age | Part time | Married | N of cases | Total N of cases |
|---|---|---|---|---|---|---|---|---|---|---|
| AT Austria | Native | 0.219 | 0.819 | 0.129 | 43.526 | 12.729 | 0.069 | 0.477 | 90,332 | 100,209 |
| | Non-Western | 0.241 | 0.770 | 0.180 | 35.917 | 9.686 | 0.098 | 0.615 | 6,824 | |
| | Western | 0.283 | 0.843 | 0.387 | 38.682 | 11.198 | 0.117 | 0.357 | 3,053 | |
| BE Belgium | Native | 0.181 | 0.725 | 0.332 | 42.419 | 13.222 | 0.068 | 0.421 | 49,197 | 55,352 |
| | Non-Western | 0.170 | 0.644 | 0.242 | 37.960 | 10.112 | 0.076 | 0.566 | 4,386 | |
| | Western | 0.280 | 0.781 | 0.552 | 39.558 | 11.235 | 0.071 | 0.425 | 1,769 | |
| CH Switzerland | Native | 0.253 | 0.888 | 0.473 | 43.871 | 12.912 | 0.154 | 0.553 | 67,275 | 88,340 |
| | Non-Western | 0.328 | 0.835 | 0.487 | 38.502 | 9.381 | 0.110 | 0.715 | 6,166 | |
| | Western | 0.328 | 0.918 | 0.597 | 41.736 | 9.792 | 0.100 | 0.562 | 14,899 | |
| DE Germany | Native | 0.240 | 0.845 | 0.306 | 43.698 | 12.831 | 0.073 | 0.489 | 635,936 | 687,343 |
| | Non-Western | 0.294 | 0.694 | 0.299 | 35.712 | 10.276 | 0.105 | 0.545 | 46,700 | |
| | Western | 0.385 | 0.854 | 0.475 | 38.040 | 11.128 | 0.107 | 0.468 | 4,707 | |
| DK Denmark | Native | 0.168 | 0.822 | 0.270 | 42.929 | 13.537 | 0.102 | 0.463 | 80,583 | 87,047 |
| | Non-Western | 0.505 | 0.721 | 0.557 | 36.015 | 10.475 | 0.148 | 0.501 | 4,811 | |
| | Western | 0.425 | 0.803 | 0.601 | 41.090 | 12.240 | 0.096 | 0.451 | 1,653 | |
| ES Spain | Native | 0.358 | 0.699 | 0.207 | 44.290 | 12.366 | 0.043 | 0.544 | 128,413 | 133,930 |
| | Non-Western | 0.498 | 0.669 | 0.140 | 36.878 | 10.413 | 0.084 | 0.546 | 5,004 | |
| | Western | 0.483 | 0.749 | 0.472 | 41.942 | 10.236 | 0.084 | 0.456 | 513 | |
| FI Finland | Native | 0.192 | 0.767 | 0.254 | 43.530 | 13.055 | 0.064 | 0.460 | 34,008 | 35,171 |
| | Non-Western | 0.188 | 0.716 | 0.223 | 36.564 | 9.498 | 0.098 | 0.517 | 964 | |
| | Western | 0.231 | 0.769 | 0.286 | 38.583 | 9.489 | 0.075 | 0.497 | 199 | |
| FR France | Native | 0.169 | 0.728 | 0.177 | 42.920 | 12.850 | 0.055 | 0.420 | 55,393 | 58,027 |
| | Non-Western | 0.207 | 0.623 | 0.228 | 36.084 | 9.640 | 0.086 | 0.573 | 2,146 | |
| | Western | 0.201 | 0.811 | 0.316 | 39.930 | 11.311 | 0.092 | 0.502 | 488 | |
| IE Ireland | Native | 0.276 | 0.777 | 0.300 | 42.651 | 12.676 | 0.075 | 0.536 | 94,693 | 110,431 |
| | Non-Western | 0.510 | 0.794 | 0.446 | 35.913 | 8.949 | 0.091 | 0.559 | 11,837 | |
| | Western | 0.486 | 0.782 | 0.587 | 38.587 | 11.381 | 0.057 | 0.442 | 3,901 | |
| IS Iceland | Native | 0.302 | 0.888 | 0.281 | 42.406 | 13.169 | 0.078 | 0.444 | 11,101 | 12,139 |
| | Non-Western | 0.422 | 0.888 | 0.178 | 37.463 | 10.636 | 0.036 | 0.490 | 723 | |
| | Western | 0.400 | 0.886 | 0.473 | 37.444 | 11.687 | 0.108 | 0.387 | 315 | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| IT Italy | Native | 0.182 | 0.706 | 0.148 | 44.561 | 12.523 | 0.051 | 0.539 | 406,962 | 432,348 |
| | Non-Western | 0.266 | 0.727 | 0.074 | 36.671 | 9.909 | 0.107 | 0.581 | 24,636 | |
| | Western | 0.301 | 0.691 | 0.411 | 41.580 | 11.632 | 0.069 | 0.479 | 750 | |
| LU Luxembourg | Native | 0.223 | 0.739 | 0.282 | 41.868 | 13.139 | 0.050 | 0.518 | 5,614 | 8,974 |
| | Non-Western | 0.387 | 0.764 | 0.621 | 38.228 | 9.516 | 0.041 | 0.628 | 1,034 | |
| | Western | 0.282 | 0.856 | 0.538 | 39.911 | 10.790 | 0.036 | 0.559 | 2,326 | |
| NL Netherlands | Native | 0.245 | 0.864 | 0.375 | 44.571 | 13.144 | 0.198 | 0.581 | 108,653 | 111,746 |
| | Non-Western | 0.277 | 0.718 | 0.330 | 35.924 | 11.134 | 0.210 | 0.448 | 2,509 | |
| | Western | 0.445 | 0.849 | 0.536 | 38.404 | 10.843 | 0.180 | 0.474 | 584 | |
| NO Norway | Native | 0.222 | 0.842 | 0.236 | 42.346 | 13.032 | 0.099 | 0.410 | 33,404 | 37,701 |
| | Non-Western | 0.249 | 0.781 | 0.151 | 37.263 | 10.070 | 0.147 | 0.565 | 3,382 | |
| | Western | 0.344 | 0.911 | 0.291 | 40.754 | 10.045 | 0.093 | 0.456 | 915 | |
| PT Portugal | Native | 0.328 | 0.737 | 0.153 | 44.083 | 12.663 | 0.049 | 0.543 | 82,237 | 84,232 |
| | Non-Western | 0.647 | 0.751 | 0.182 | 34.681 | 10.567 | 0.049 | 0.447 | 1,744 | |
| | Western | 0.709 | 0.633 | 0.390 | 40.327 | 12.369 | 0.088 | 0.394 | 251 | |
| SE Sweden | Native | 0.269 | 0.854 | 0.219 | 42.299 | 13.019 | 0.103 | 0.374 | 120,878 | 135,319 |
| | Non-Western | 0.368 | 0.674 | 0.258 | 36.832 | 10.462 | 0.128 | 0.565 | 12,563 | |
| | Western | 0.547 | 0.851 | 0.564 | 40.373 | 10.673 | 0.112 | 0.489 | 1,878 | |
| UK United Kingdom | Native | 0.236 | 0.819 | 0.249 | 43.354 | 12.732 | 0.073 | 0.512 | 89,515 | 99,799 |
| | Non-Western | 0.357 | 0.864 | 0.203 | 36.600 | 9.381 | 0.088 | 0.618 | 8,513 | |
| | Western | 0.484 | 0.883 | 0.385 | 36.921 | 9.889 | 0.074 | 0.461 | 1,771 | |

**Appendix A2: Descriptive statistics of variables included in the models, by country and group (native, non-Western, and Western migrants) - WOMEN**

| country | Group | Over education | Employment | BA+ | Age | SD age | Part-time | Married | N of cases | Total N of cases |
|---|---|---|---|---|---|---|---|---|---|---|
| AT Austria | Native | 0.208 | 0.747 | 0.139 | 43.846 | 12.667 | 0.368 | 0.508 | 91,201 | 102,352 |
| | Non-Western | 0.357 | 0.596 | 0.245 | 36.502 | 9.963 | 0.277 | 0.661 | 8,277 | |
| | Western | 0.298 | 0.742 | 0.380 | 37.257 | 11.176 | 0.337 | 0.414 | 2,874 | |
| BE Belgium | Native | 0.220 | 0.661 | 0.421 | 42.845 | 13.118 | 0.280 | 0.459 | 51,991 | 59,039 |
| | Non-Western | 0.240 | 0.433 | 0.300 | 36.940 | 10.073 | 0.196 | 0.617 | 5,207 | |
| | Western | 0.351 | 0.681 | 0.589 | 37.350 | 10.434 | 0.250 | 0.436 | 1,841 | |
| CH Switzerland | Native | 0.179 | 0.818 | 0.334 | 44.091 | 12.671 | 0.570 | 0.551 | 73,287 | 95,948 |
| | Non-Western | 0.369 | 0.614 | 0.483 | 38.107 | 8.877 | 0.335 | 0.776 | 9,522 | |
| | Western | 0.367 | 0.814 | 0.607 | 40.046 | 9.509 | 0.401 | 0.560 | 13,139 | |
| DE Germany | Native | 0.259 | 0.781 | 0.242 | 43.956 | 12.838 | 0.360 | 0.534 | 633,566 | 684,773 |
| | Non-Western | 0.357 | 0.505 | 0.328 | 36.019 | 10.214 | 0.242 | 0.642 | 47,181 | |
| | Western | 0.409 | 0.701 | 0.491 | 36.504 | 10.880 | 0.274 | 0.491 | 4,026 | |
| DK Denmark | Native | 0.203 | 0.772 | 0.390 | 43.406 | 13.304 | 0.245 | 0.498 | 84,096 | 91,426 |
| | Non-Western | 0.513 | 0.586 | 0.580 | 36.493 | 10.221 | 0.216 | 0.603 | 5,736 | |
| | Western | 0.487 | 0.742 | 0.644 | 39.274 | 11.924 | 0.223 | 0.434 | 1,594 | |
| ES Spain | Native | 0.404 | 0.581 | 0.284 | 44.917 | 12.186 | 0.137 | 0.573 | 132,680 | 140,591 |
| | Non-Western | 0.524 | 0.526 | 0.194 | 37.609 | 10.130 | 0.182 | 0.565 | 7,433 | |
| | Western | 0.565 | 0.586 | 0.483 | 40.515 | 11.533 | 0.155 | 0.458 | 478 | |
| FI Finland | Native | 0.268 | 0.755 | 0.342 | 44.015 | 12.946 | 0.132 | 0.499 | 33,633 | 34,913 |
| | Non-Western | 0.243 | 0.524 | 0.274 | 38.021 | 10.270 | 0.131 | 0.619 | 1,180 | |
| | Western | 0.290 | 0.620 | 0.330 | 35.850 | 9.125 | 0.130 | 0.440 | 100 | |
| FR France | Native | 0.217 | 0.678 | 0.203 | 43.340 | 12.725 | 0.195 | 0.426 | 59,116 | 62,760 |
| | Non-Western | 0.260 | 0.349 | 0.238 | 35.582 | 9.426 | 0.155 | 0.599 | 3,134 | |
| | Western | 0.308 | 0.641 | 0.361 | 39.314 | 11.376 | 0.233 | 0.502 | 510 | |
| IE Ireland | Native | 0.371 | 0.666 | 0.345 | 42.864 | 12.479 | 0.205 | 0.542 | 99,953 | 116,954 |
| | Non-Western | 0.577 | 0.630 | 0.498 | 35.498 | 8.907 | 0.174 | 0.562 | 12,981 | |
| | Western | 0.581 | 0.661 | 0.614 | 36.514 | 11.163 | 0.155 | 0.418 | 4,020 | |
| IS Iceland | Native | 0.325 | 0.830 | 0.414 | 43.004 | 12.913 | 0.276 | 0.474 | 11,578 | 12,712 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Non-Western | 0.446 | 0.836 | 0.309 | 39.005 | 10.872 | 0.208 | 0.520 | 793 | |
| | Western | 0.478 | 0.833 | 0.572 | 38.745 | 11.868 | 0.267 | 0.440 | 341 | |
| IT Italy | Native | 0.146 | 0.521 | 0.198 | 45.142 | 12.371 | 0.162 | 0.585 | 421,520 | 460,541 |
| | Non-Western | 0.216 | 0.472 | 0.138 | 38.937 | 10.847 | 0.196 | 0.614 | 37,904 | |
| | Western | 0.315 | 0.514 | 0.430 | 41.423 | 11.286 | 0.160 | 0.532 | 1,117 | |
| LU Luxembourg | Native | 0.204 | 0.666 | 0.310 | 42.530 | 13.206 | 0.242 | 0.541 | 5,992 | 9,361 |
| | Non-Western | 0.443 | 0.629 | 0.650 | 37.567 | 9.030 | 0.144 | 0.664 | 1,367 | |
| | Western | 0.380 | 0.756 | 0.532 | 38.608 | 10.436 | 0.204 | 0.588 | 2,002 | |
| NL Netherlands | Native | 0.246 | 0.773 | 0.365 | 45.102 | 12.768 | 0.605 | 0.611 | 110,455 | 115,100 |
| | Non-Western | 0.345 | 0.554 | 0.389 | 36.794 | 10.502 | 0.359 | 0.570 | 3,912 | |
| | Western | 0.473 | 0.764 | 0.595 | 37.437 | 10.497 | 0.420 | 0.509 | 733 | |
| NO Norway | Native | 0.218 | 0.802 | 0.373 | 42.939 | 12.894 | 0.272 | 0.443 | 32,589 | 36,790 |
| | Non-Western | 0.299 | 0.656 | 0.216 | 37.170 | 9.528 | 0.291 | 0.628 | 3,480 | |
| | Western | 0.386 | 0.829 | 0.448 | 39.254 | 10.200 | 0.219 | 0.454 | 721 | |
| PT Portugal | Native | 0.326 | 0.669 | 0.238 | 44.902 | 12.393 | 0.078 | 0.559 | 89,480 | 92,447 |
| | Non-Western | 0.685 | 0.607 | 0.264 | 37.670 | 10.574 | 0.119 | 0.511 | 2,655 | |
| | Western | 0.635 | 0.612 | 0.423 | 38.026 | 11.823 | 0.074 | 0.397 | 312 | |
| SE Sweden | Native | 0.299 | 0.841 | 0.340 | 43.121 | 12.854 | 0.290 | 0.422 | 116,769 | 131,613 |
| | Non-Western | 0.403 | 0.550 | 0.305 | 37.321 | 9.962 | 0.235 | 0.629 | 13,187 | |
| | Western | 0.610 | 0.791 | 0.639 | 38.053 | 10.750 | 0.252 | 0.480 | 1,657 | |
| UK United Kingdom | Native | 0.265 | 0.736 | 0.275 | 43.325 | 12.641 | 0.296 | 0.503 | 97,586 | 110,190 |
| | Non-Western | 0.420 | 0.634 | 0.201 | 35.986 | 9.294 | 0.210 | 0.616 | 10,499 | |
| | Western | 0.541 | 0.766 | 0.406 | 35.371 | 9.464 | 0.208 | 0.455 | 2,105 | |

**Appendix table A3: Probit models with sample selection for the probability of overeducation, by country (EULFS data 2015-2019). Beta coefficients and robust standard errors in parentheses - MEN**

| Variables | AT | BE | CH | DE | DK | ES | FI | FR | IE |
|---|---|---|---|---|---|---|---|---|---|
| Non-Western | 0.094** | 0.058 | 0.274** | 0.142** | 0.792** | 0.390** | 0.122* | -0.064 | 0.511** |
| | (0.023) | (0.037) | (0.039) | (0.011) | (0.025) | (0.027) | (0.055) | (0.052) | (0.016) |
| Western | -0.018 | -0.030 | 0.047* | 0.205** | 0.438** | 0.141 | 0.195 | -0.259** | 0.245** |
| | (0.032) | (0.053) | (0.022) | (0.022) | (0.038) | (0.076) | (0.118) | (0.083) | (0.027) |
| BA+ | 0.492** | 1.481** | 2.860** | 1.303** | 1.401** | 0.308** | 1.052** | 0.842** | 1.200** |
| | (0.019) | (0.061) | (0.042) | (0.008) | (0.021) | (0.015) | (0.052) | (0.034) | (0.016) |
| Age | 0.002** | -0.006** | 0.001 | -0.004** | 0.002** | -0.011** | 0.017** | -0.016** | -0.004** |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) |
| Part time | 0.057** | 0.086** | -0.117** | -0.023** | 0.177** | 0.063** | -0.034 | 0.133** | 0.114** |
| | (0.019) | (0.032) | (0.020) | (0.007) | (0.017) | (0.022) | (0.035) | (0.033) | (0.017) |
| 2016 | -0.040* | -0.102** | -0.097** | 0.020** | 0.050* | -0.028 | 0.037 | 0.017 | -0.074** |
| | (0.018) | (0.032) | (0.025) | (0.007) | (0.020) | (0.018) | (0.030) | (0.028) | (0.016) |
| 2017 | -0.020 | -0.068* | -0.050* | 0.032** | 0.102** | -0.012 | 0.061* | 0.024 | -0.028 |
| | (0.018) | (0.032) | (0.024) | (0.006) | (0.020) | (0.017) | (0.030) | (0.028) | (0.015) |
| 2018 | 0.014 | -0.050 | -0.075** | 0.044** | 0.054** | 0.001 | -0.073* | 0.008 | -0.185** |
| | (0.018) | (0.034) | (0.024) | (0.007) | (0.020) | (0.017) | (0.032) | (0.030) | (0.017) |
| 2019 | -0.007 | -0.136** | -0.077** | 0.010 | 0.066** | -0.006 | -0.048 | 0.058* | -0.178** |
| | (0.018) | (0.033) | (0.024) | (0.007) | (0.020) | (0.018) | (0.032) | (0.028) | (0.017) |
| Constant | -0.791** | -1.393** | -2.829** | -1.059** | -1.734** | -0.177** | -1.897** | -0.547** | -0.859** |
| | (0.027) | (0.106) | (0.056) | (0.014) | (0.046) | (0.036) | (0.083) | (0.056) | (0.032) |
| **Selection** | | | | | | | | | |
| Non-Western | -0.520** | -0.302** | -0.406** | -0.643** | -0.587** | -0.159** | -0.381** | -0.465** | -0.125** |
| | (0.021) | (0.027) | (0.030) | (0.007) | (0.023) | (0.024) | (0.049) | (0.037) | (0.016) |
| Western | -0.145** | 0.020 | 0.076** | -0.119** | -0.205** | -0.005 | -0.231* | 0.080 | -0.074** |
| | (0.035) | (0.043) | (0.023) | (0.024) | (0.040) | (0.086) | (0.111) | (0.082) | (0.026) |
| BA+ | 0.456** | 0.564** | 0.402** | 0.449** | 0.368** | 0.515** | 0.530** | 0.477** | 0.483** |
| | (0.019) | (0.016) | (0.015) | (0.005) | (0.013) | (0.013) | (0.021) | (0.019) | (0.011) |
| Age | -0.020** | -0.011** | -0.007** | -0.011** | -0.007** | -0.011** | -0.015** | -0.014** | -0.015** |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) |
| 2016 | 0.035* | 0.059** | 0.005 | 0.012* | 0.013 | 0.066** | 0.047 | 0.019 | 0.058** |
| | (0.017) | (0.021) | (0.023) | (0.006) | (0.018) | (0.015) | (0.024) | (0.021) | (0.014) |
| 2017 | 0.050** | 0.212** | 0.027 | 0.012 | 0.037* | 0.121** | 0.088** | 0.020 | 0.123** |
| | (0.017) | (0.020) | (0.023) | (0.006) | (0.017) | (0.015) | (0.025) | (0.021) | (0.014) |
| 2018 | 0.080** | 0.241** | 0.030 | 0.083** | 0.080** | 0.164** | 0.169** | 0.066** | 0.170** |
| | (0.017) | (0.021) | (0.023) | (0.006) | (0.017) | (0.015) | (0.025) | (0.022) | (0.015) |
| 2019 | 0.131** | 0.276** | 0.058* | 0.118** | 0.107** | 0.187** | 0.178** | 0.036 | 0.195** |
| | (0.018) | (0.020) | (0.023) | (0.006) | (0.017) | (0.015) | (0.025) | (0.021) | (0.015) |
| Married | 0.526** | 0.453** | 0.463** | 0.535** | 0.656** | 0.609** | 0.585** | 0.404** | 0.699** |
| | (0.012) | (0.015) | (0.016) | (0.004) | (0.012) | (0.011) | (0.017) | (0.014) | (0.011) |
| athrho | -0.348** | -0.185 | 0.174 | -0.106** | -0.186** | 0.210** | -0.259* | -0.025 | -0.113* |
| | (0.054) | (0.142) | (0.126) | (0.030) | (0.064) | (0.047) | (0.132) | (0.126) | (0.046) |
| Constant | 1.386** | 0.583** | 1.099** | 1.114** | 0.789** | 0.561** | 0.918** | 1.023** | 0.841** |
| | (0.024) | (0.028) | (0.031) | (0.008) | (0.022) | (0.020) | (0.034) | (0.030) | (0.020) |
| *N* | 100,209 | 55,352 | 88,340 | 687,273 | 87,047 | 133,930 | 35,171 | 58,027 | 110,431 |

**Appendix table A3- Continued**

| VARIABLES | IS | IT | LU | NL | NO | PT | SE | UK |
|---|---|---|---|---|---|---|---|---|
| Non-Western | 0.395** | 0.343** | 0.200** | 0.281** | 0.291** | 0.545** | 0.429** | 0.576** |
| | (0.055) | (0.013) | (0.060) | (0.048) | (0.029) | (0.042) | (0.019) | (0.019) |
| Western | 0.166* | -0.025 | 0.106* | 0.433** | 0.289** | 0.585** | 0.383** | 0.631** |
| | (0.077) | (0.071) | (0.050) | (0.076) | (0.051) | (0.129) | (0.038) | (0.040) |
| BA+ | 0.577** | 0.863** | 0.529** | 2.242** | 1.104** | 0.067** | 1.208** | 1.510** |
| | (0.053) | (0.009) | (0.045) | (0.020) | (0.036) | (0.018) | (0.021) | (0.014) |
| Age | 0.004** | -0.020** | 0.001 | -0.001 | -0.001 | -0.030** | -0.002** | 0.001 |
| | (0.001) | (0.000) | (0.002) | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) |
| Part time | 0.092* | -0.073** | 0.098 | 0.047** | 0.096** | -0.031 | 0.210** | 0.152** |
| | (0.044) | (0.012) | (0.069) | (0.016) | (0.026) | (0.027) | (0.014) | (0.020) |
| 2016 | -0.020 | -0.012 | 0.103* | -0.037 | -0.017 | 0.035 | -0.024 | -0.046* |
| | (0.041) | (0.010) | (0.052) | (0.022) | (0.028) | (0.020) | (0.013) | (0.018) |
| 2017 | 0.092* | -0.034** | 0.152** | -0.003 | 0.043 | 0.035 | -0.026* | -0.063** |
| | (0.042) | (0.010) | (0.054) | (0.022) | (0.028) | (0.020) | (0.013) | (0.018) |
| 2018 | 0.006 | -0.027** | -0.084 | 0.062** | -0.008 | -0.008 | -0.013 | -0.083** |
| | (0.040) | (0.010) | (0.053) | (0.022) | (0.027) | (0.021) | (0.014) | (0.018) |
| 2019 | 0.059 | -0.019 | -0.057 | 0.043 | -0.034 | -0.001 | -0.032* | -0.079** |
| | (0.041) | (0.010) | (0.051) | (0.022) | (0.027) | (0.021) | (0.016) | (0.018) |
| Constant | -0.841** | -0.130** | -1.195** | -2.023** | -0.966** | 0.535** | -0.756** | -1.248** |
| | (0.102) | (0.025) | (0.096) | (0.044) | (0.059) | (0.040) | (0.036) | (0.028) |
| **Selection** | | | | | | | | |
| Non-Western | -0.051 | 0.104** | -0.176** | -0.559** | -0.345** | -0.063 | -0.770** | -0.021 |
| | (0.067) | (0.011) | (0.051) | (0.034) | (0.029) | (0.040) | (0.015) | (0.020) |
| Western | -0.126 | -0.112 | 0.292** | -0.240** | 0.265** | -0.213* | -0.163** | 0.151** |
| | (0.099) | (0.058) | (0.041) | (0.087) | (0.069) | (0.102) | (0.041) | (0.046) |
| BA+ | 0.454** | 0.489** | 0.417** | 0.401** | 0.553** | 0.335** | 0.367** | 0.316** |
| | (0.041) | (0.007) | (0.038) | (0.014) | (0.025) | (0.016) | (0.013) | (0.013) |
| Age | -0.003 | -0.000 | -0.014** | -0.014** | -0.005** | -0.016** | 0.002** | -0.017** |
| | (0.002) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) |
| 2016 | 0.097 | 0.030** | -0.019 | 0.028 | -0.041 | 0.049** | 0.039** | 0.017 |
| | (0.049) | (0.008) | (0.048) | (0.019) | (0.028) | (0.017) | (0.013) | (0.016) |
| 2017 | 0.074 | 0.053** | -0.063 | 0.072** | -0.037 | 0.162** | 0.054** | 0.038* |
| | (0.050) | (0.008) | (0.048) | (0.019) | (0.028) | (0.017) | (0.013) | (0.016) |
| 2018 | 0.029 | 0.076** | 0.011 | 0.099** | 0.054* | 0.245** | 0.099** | 0.057** |
| | (0.047) | (0.008) | (0.047) | (0.019) | (0.028) | (0.017) | (0.014) | (0.016) |
| 2019 | -0.031 | 0.089** | -0.016 | 0.129** | 0.035 | 0.281** | 0.105** | 0.060** |
| | (0.049) | (0.008) | (0.047) | (0.020) | (0.027) | (0.018) | (0.017) | (0.016) |
| Married | 0.571** | 0.535** | 0.504** | 0.681** | 0.481** | 0.663** | 0.464** | 0.626** |
| | (0.040) | (0.005) | (0.032) | (0.013) | (0.020) | (0.012) | (0.011) | (0.010) |
| athrho | -0.713** | 0.117** | 0.480 | 0.043 | -0.380** | 0.207** | -0.599** | -0.039 |
| | (0.235) | (0.028) | (0.430) | (0.116) | (0.090) | (0.061) | (0.061) | (0.053) |
| Constant | 1.007** | 0.199** | 0.877** | 1.174** | 0.851** | 0.860** | 0.748** | 1.298** |
| | (0.065) | (0.010) | (0.066) | (0.026) | (0.036) | (0.024) | (0.020) | (0.023) |
| *N* | 12,139 | 432,348 | 8,974 | 111,746 | 37,701 | 84,232 | 135,319 | 99,799 |

** p<0.01, * p<0.05

**Appendix table A4: Probit models with sample selection for the probability of overeducation, by country (EULFS data 2015-2019). Beta coefficients and robust standard errors in parentheses - WOMEN**

| VARIABLES | AT | BE | CH | DE | DK | ES | FI | FR | IE |
|---|---|---|---|---|---|---|---|---|---|
| Non Western | 0.517** | 0.523** | 0.165** | 0.653** | 0.838** | 0.317** | 0.516** | 0.340** | 0.467** |
| | (0.062) | (0.030) | (0.059) | (0.007) | (0.029) | (0.020) | (0.040) | (0.092) | (0.016) |
| Western | 0.069 | 0.217** | 0.075** | 0.277** | 0.640** | 0.223** | 0.425** | 0.030 | 0.283** |
| | (0.048) | (0.041) | (0.024) | (0.020) | (0.038) | (0.072) | (0.127) | (0.084) | (0.025) |
| BA+ | 0.483** | 0.328* | 2.617** | 0.360** | 1.088** | -0.355** | 0.163** | 0.609** | 0.422** |
| | (0.053) | (0.140) | (0.038) | (0.004) | (0.034) | (0.010) | (0.015) | (0.087) | (0.054) |
| Age | -0.008** | 0.001 | 0.004** | -0.001** | -0.003** | -0.008** | 0.006** | -0.018** | -0.000 |
| | (0.002) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) | (0.002) | (0.001) |
| Part time | 0.048** | 0.039 | -0.066** | -0.058** | 0.016 | 0.012 | -0.042** | -0.042* | 0.060** |
| | (0.013) | (0.021) | (0.017) | (0.002) | (0.013) | (0.008) | (0.009) | (0.017) | (0.012) |
| 2016 | -0.002 | 0.005 | -0.192** | -0.005 | 0.022 | -0.036* | 0.040 | 0.022 | -0.022 |
| | (0.018) | (0.023) | (0.027) | (0.005) | (0.019) | (0.014) | (0.021) | (0.025) | (0.014) |
| 2017 | -0.029 | -0.103** | -0.217** | -0.009 | 0.075** | -0.043** | 0.020 | 0.017 | -0.163** |
| | (0.019) | (0.021) | (0.026) | (0.005) | (0.019) | (0.014) | (0.021) | (0.026) | (0.013) |
| 2018 | -0.097** | -0.115** | -0.244** | -0.016** | 0.042* | -0.048** | -0.038 | 0.026 | -0.202** |
| | (0.018) | (0.023) | (0.026) | (0.005) | (0.019) | (0.014) | (0.022) | (0.027) | (0.014) |
| 2019 | -0.106** | -0.159** | -0.222** | -0.028** | 0.035 | -0.098** | -0.066** | 0.015 | -0.329** |
| | (0.019) | (0.021) | (0.026) | (0.005) | (0.019) | (0.014) | (0.022) | (0.027) | (0.015) |
| Constant | -0.389** | -0.333* | -2.718** | -0.198** | -1.331** | 0.763** | -0.454** | 0.141 | 0.058 |
| | (0.029) | (0.135) | (0.048) | (0.007) | (0.058) | (0.021) | (0.030) | (0.074) | (0.037) |
| **Selection** | | | | | | | | | |
| Non-Western | -0.757** | -0.613** | -0.754** | -0.884** | -0.767** | -0.177** | -0.659** | -0.934** | -0.334** |
| | (0.018) | (0.023) | (0.020) | (0.006) | (0.020) | (0.019) | (0.039) | (0.030) | (0.015) |
| Western | -0.381** | -0.180** | -0.168** | -0.458** | -0.217** | -0.214** | -0.531** | -0.226** | -0.258** |
| | (0.033) | (0.038) | (0.020) | (0.021) | (0.038) | (0.073) | (0.128) | (0.065) | (0.023) |
| BA+ | 0.406** | 0.773** | 0.348** | 0.447** | 0.452** | 0.701** | 0.517** | 0.557** | 0.675** |
| | (0.016) | (0.014) | (0.012) | (0.004) | (0.010) | (0.010) | (0.017) | (0.017) | (0.009) |
| Age | -0.023** | -0.008** | -0.009** | -0.006** | -0.006** | -0.006** | 0.004** | -0.005** | -0.012** |
| | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) |
| 2016 | 0.026 | 0.002 | 0.034 | 0.030** | 0.011 | 0.042** | 0.036 | 0.017 | 0.044** |
| | (0.016) | (0.019) | (0.018) | (0.005) | (0.016) | (0.014) | (0.023) | (0.020) | (0.013) |
| 2017 | 0.048** | 0.099** | 0.021 | 0.050** | 0.032* | 0.075** | -0.014 | 0.033 | 0.094** |
| | (0.016) | (0.018) | (0.018) | (0.005) | (0.016) | (0.014) | (0.022) | (0.020) | (0.012) |
| 2018 | 0.046** | 0.147** | 0.026 | 0.077** | 0.060** | 0.098** | 0.057* | 0.060** | 0.126** |
| | (0.016) | (0.020) | (0.018) | (0.005) | (0.016) | (0.014) | (0.023) | (0.020) | (0.013) |
| 2019 | 0.079** | 0.186** | 0.055** | 0.111** | 0.082** | 0.133** | 0.102** | 0.089** | 0.138** |
| | (0.016) | (0.019) | (0.018) | (0.005) | (0.016) | (0.014) | (0.023) | (0.020) | (0.013) |
| Married | 0.161** | 0.111** | -0.165** | 0.005 | 0.304** | -0.012 | 0.089** | 0.104** | 0.039** |
| | (0.012) | (0.026) | (0.012) | (0.003) | (0.011) | (0.007) | (0.011) | (0.013) | (0.008) |
| athrho | -0.356 | -1.957** | 0.634** | -2.676** | -0.319** | -3.991** | -4.346** | -0.662** | -1.169** |
| | (0.204) | (0.399) | (0.149) | (0.030) | (0.077) | (0.045) | (0.247) | (0.198) | (0.164) |
| Constant | 1.471** | 0.362** | 1.265** | 0.885** | 0.616** | 0.269** | 0.248** | 0.530** | 0.632** |
| | (0.024) | (0.027) | (0.026) | (0.008) | (0.021) | (0.019) | (0.031) | (0.028) | (0.018) |
| Observations | 102,352 | 59,039 | 95,948 | 684,773 | 91,426 | 140,591 | 34,913 | 62,760 | 116,954 |

**Appendix table A4- Continued**

| VARIABLES | IS | IT | LU | NL | NO | PT | SE | UK |
|---|---|---|---|---|---|---|---|---|
| Non-Western | 0.472* | 0.688** | 0.392** | 0.000 | 0.552** | 0.649** | 0.785** | 0.416** |
| | (0.194) | (0.013) | (0.040) | (0.031) | (0.030) | (0.045) | (0.014) | (0.018) |
| Western | 0.244 | 0.143* | 0.165** | 0.150* | 0.398** | 0.270* | 0.598** | 0.573** |
| | (0.265) | (0.070) | (0.034) | (0.059) | (0.056) | (0.112) | (0.036) | (0.034) |
| BA+ | 1.047** | 1.169** | 0.004 | 1.853** | 0.548** | 0.143** | 0.407** | 1.223** |
| | (0.088) | (0.019) | (0.029) | (0.013) | (0.055) | (0.035) | (0.009) | (0.011) |
| Age | -0.007** | -0.015** | 0.008** | -0.005** | -0.009** | -0.025** | -0.009** | -0.003** |
| | (0.002) | (0.000) | (0.001) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) |
| Part time | 0.005 | 0.153** | 0.135** | -0.083** | -0.082** | 0.072** | -0.002 | 0.071** |
| | (0.033) | (0.008) | (0.023) | (0.013) | (0.018) | (0.021) | (0.007) | (0.010) |
| 2016 | -0.180 | -0.025* | 0.135** | -0.114** | 0.036 | 0.032 | -0.046** | -0.050** |
| | (0.134) | (0.012) | (0.042) | (0.019) | (0.028) | (0.020) | (0.011) | (0.015) |
| 2017 | -0.032 | -0.120** | 0.069 | -0.041* | 0.073** | -0.092** | -0.045** | -0.011 |
| | (0.062) | (0.012) | (0.042) | (0.019) | (0.028) | (0.022) | (0.011) | (0.015) |
| 2018 | -0.164** | -0.116** | -0.106* | 0.027 | 0.105** | -0.058* | -0.033** | -0.025 |
| | (0.059) | (0.012) | (0.042) | (0.019) | (0.027) | (0.023) | (0.012) | (0.015) |
| 2019 | -0.223* | -0.117** | 0.021 | -0.010 | 0.045 | -0.027 | -0.010 | -0.008 |
| | (0.089) | (0.012) | (0.040) | (0.019) | (0.027) | (0.024) | (0.014) | (0.015) |
| Constant | -0.832 | -0.557** | -0.489** | -1.596** | -0.522** | 0.327** | 0.025 | -1.182** |
| | (0.720) | (0.035) | (0.060) | (0.027) | (0.067) | (0.068) | (0.017) | (0.022) |
| **Selection** | | | | | | | | |
| Non-Western | 0.026 | -0.042** | -0.282** | -0.839** | -0.519** | -0.318** | -0.983** | -0.367** |
| | (0.064) | (0.009) | (0.041) | (0.025) | (0.026) | (0.031) | (0.014) | (0.015) |
| Western | -0.106 | -0.160** | 0.160** | -0.339** | -0.031 | -0.184* | -0.453** | -0.013 |
| | (0.087) | (0.045) | (0.037) | (0.064) | (0.064) | (0.089) | (0.040) | (0.034) |
| BA+ | 0.539** | 0.761** | 0.520** | 0.539** | 0.740** | 0.533** | 0.619** | 0.493** |
| | (0.031) | (0.006) | (0.031) | (0.012) | (0.019) | (0.013) | (0.011) | (0.011) |
| Age | -0.005** | 0.006** | -0.010** | -0.018** | -0.006** | -0.012** | 0.004** | -0.009** |
| | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) |
| 2016 | 0.050 | 0.022** | -0.029 | 0.008 | 0.013 | 0.044** | 0.035** | 0.024 |
| | (0.050) | (0.007) | (0.043) | (0.016) | (0.027) | (0.015) | (0.012) | (0.013) |
| 2017 | 0.033 | 0.033** | -0.016 | 0.035* | -0.019 | 0.111** | 0.051** | 0.063** |
| | (0.050) | (0.007) | (0.043) | (0.016) | (0.026) | (0.016) | (0.013) | (0.014) |
| 2018 | -0.029 | 0.040** | 0.084* | 0.084** | 0.015 | 0.177** | 0.070** | 0.076** |
| | (0.053) | (0.007) | (0.043) | (0.016) | (0.026) | (0.016) | (0.014) | (0.014) |
| 2019 | -0.022 | 0.054** | 0.049 | 0.108** | 0.019 | 0.204** | 0.051** | 0.093** |
| | (0.053) | (0.007) | (0.041) | (0.017) | (0.026) | (0.016) | (0.016) | (0.014) |
| Married | 0.234** | -0.112** | 0.017 | 0.197** | 0.206** | 0.233** | 0.092** | 0.091** |
| | (0.048) | (0.005) | (0.020) | (0.011) | (0.018) | (0.011) | (0.009) | (0.009) |
| athrho | 0.501 | -0.195** | -2.647** | 1.775** | -0.540** | 0.055 | -2.184** | 1.911** |
| | (4.717) | (0.029) | (0.196) | (0.227) | (0.116) | (0.134) | (0.092) | (0.603) |
| Constant | 0.875** | -0.341** | 0.681** | 1.163** | 0.731** | 0.658** | 0.572** | 0.826** |
| | (0.069) | (0.010) | (0.062) | (0.023) | (0.034) | (0.023) | (0.019) | (0.019) |
| Observations | 12,712 | 460,541 | 9,361 | 115,100 | 36,790 | 92,447 | 131,613 | 110,190 |

** p<0.01, * p<0.05

**Appendix table A5: Natives' and immigrants' employment rate, and gaps relative to natives - MEN**

| | Native | Non-Western | Gap relative to native | Western | Gap relative to native |
|---|---|---|---|---|---|
| ES Spain | 0.699 | 0.669 | -0.030 | 0.749 | 0.049 |
| IT Italy | 0.706 | 0.727 | 0.021 | 0.691 | -0.016 |
| BE Belgium | 0.725 | 0.644 | -0.080 | 0.781 | 0.057 |
| FR France | 0.728 | 0.623 | -0.105 | 0.811 | 0.083 |
| PT Portugal | 0.737 | 0.751 | 0.014 | 0.633 | -0.104 |
| LU Luxembourg | 0.739 | 0.764 | 0.026 | 0.856 | 0.117 |
| FI Finland | 0.767 | 0.716 | -0.051 | 0.769 | 0.002 |
| IE Ireland | 0.777 | 0.794 | 0.017 | 0.782 | 0.004 |
| AT Austria | 0.819 | 0.770 | -0.049 | 0.843 | 0.024 |
| UK United Kingdom | 0.819 | 0.864 | 0.044 | 0.883 | 0.064 |
| DK Denmark | 0.822 | 0.721 | -0.101 | 0.803 | -0.019 |
| NO Norway | 0.842 | 0.781 | -0.062 | 0.911 | 0.069 |
| DE Germany | 0.845 | 0.694 | -0.151 | 0.854 | 0.009 |
| SE Sweden | 0.854 | 0.674 | -0.181 | 0.851 | -0.003 |
| NL Netherlands | 0.864 | 0.718 | -0.146 | 0.849 | -0.015 |
| IS Iceland | 0.888 | 0.888 | 0.000 | 0.886 | -0.003 |
| CH Switzerland | 0.888 | 0.835 | -0.053 | 0.918 | 0.030 |
| **average** | **0.795** | **0.743** | **-0.052** | **0.816** | **0.021** |

**Appendix table A6: Natives' and immigrants' employment rate, and gaps relative to native - WOMEN**

| | Native | Non-Western | Gap relative to native | Western | Gap relative to native |
|---|---|---|---|---|---|
| IT Italy | 0.521 | 0.472 | -0.049 | 0.514 | -0.007 |
| ES Spain | 0.581 | 0.526 | -0.054 | 0.586 | 0.005 |
| BE Belgium | 0.661 | 0.433 | -0.227 | 0.681 | 0.020 |
| IE Ireland | 0.666 | 0.630 | -0.036 | 0.661 | -0.005 |
| LU Luxembourg | 0.666 | 0.629 | -0.037 | 0.756 | 0.090 |
| PT Portugal | 0.669 | 0.607 | -0.062 | 0.612 | -0.057 |
| FR France | 0.678 | 0.349 | -0.329 | 0.641 | -0.037 |
| UK United Kingdom | 0.736 | 0.634 | -0.103 | 0.766 | 0.030 |
| AT Austria | 0.747 | 0.596 | -0.151 | 0.742 | -0.005 |
| FI Finland | 0.755 | 0.524 | -0.231 | 0.620 | -0.135 |
| DK Denmark | 0.772 | 0.586 | -0.186 | 0.742 | -0.031 |
| NL Netherlands | 0.773 | 0.554 | -0.219 | 0.764 | -0.009 |
| DE Germany | 0.781 | 0.505 | -0.276 | 0.701 | -0.080 |
| NO Norway | 0.802 | 0.656 | -0.146 | 0.829 | 0.027 |
| CH Switzerland | 0.818 | 0.614 | -0.205 | 0.814 | -0.004 |
| IS Iceland | 0.830 | 0.836 | 0.006 | 0.833 | 0.002 |
| SE Sweden | 0.841 | 0.550 | -0.291 | 0.791 | -0.050 |
| **Average** | **0.635** | **0.521** | **-0.114** | **0.636** | **0.001** |

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