

Perceived Discrimination in the European Labor Market: Demographic Determinants and Cross-Country Variations

INTRODUCTION

The participation of diverse labour force is crucial for the economic growth and innovation development of a country as a wider range of perspectives, knowledge, skills and experience can be brought into the country. Migrants, who are also part of the labour market, often facing unique challenges in their host countries, including legal barriers, discrimination and language proficiency. According to the international migration stock data (2024), nearly 87 million international migrants lived in Europe. Out of the 87 million migrants, there were around 44 million who were born within Europe, but living elsewhere in the region and around 40 million of non-European migrants resided in European regions (International Organization of Migration, 2020). Despite their significant presence, migrant employees experience sizeable employment gaps compared to the native employees.

The study by Giang Ho and Rima Turk-Ariss on the labour market integration of migrants in Europe (2018) found that employment opportunities for migrants would gradually converge to that of natives, but full coverage has not been observed even after 20 years. The persistent employment gap highlights migration integration complexity and suggests that discrimination, along with other structural barriers, may continue to affect the experience in workplace by the migrants. Another interesting perspective to investigate is the so called “Integration paradox”. The integration paradox suggests that the higher-educated and more integrated migrants reports that they have experienced higher level of discrimination than those who are less integrated (Verkuyten, 2016).

Therefore, this study aims to first examine the demographic and contextual factors influencing the discrimination perception among the labour force participants in Europe, focusing on the role of gender, age, educational attainment and country of birth. Specifically, the study will assess the predictive power of the demographic factors on the likelihood of perceiving discrimination, how perceptions of discrimination vary across different hosting countries and the key factors contributing to the variation, and whether certain groups such as highly skilled migrants are more likely to over-report or under-report their discrimination perception in order to provide further evidence to the integration paradox. By exploring these relationships, the objective of the study is to provide insight into the underlying factors contributing to the perceived discrimination and offer policy implications applicable to certain countries that can potentially help minimize the employment gap.

HYPOTHESES

H1: Female migrants are less likely to perceive discrimination if they have higher education attainment.

H2: Highly educated migrants who have experienced tertiary education are more likely to over-report discrimination compared to migrants who are less educated.

H3: Demographic factors such as educational attainment, country of birth, age, hosting country and gender significantly predict the likelihood of migrants perceiving discrimination in Europe.

H4: There are distinct groups of European countries where the migrants perceive discrimination in a similar way and each demographic factor affects each distinct group differently.

DATA DESCRIPTION

Data

This study will utilize the dataset from Eurostat, which was collected in year 2021 and encompassed 29 countries including both EU members and non-EU members such as Switzerland, Spain, Italy and Austria through the European Union Labour Force Survey (EU LFS). The survey is performed by randomly rotating samples of persons from private households aged between 15 and 74. The dataset provides the number of migrants measured in thousand persons who fall under different combinations of gender, age, country of birth, hosting country, educational attainment and the perception of types of discrimination experienced by the labour force. After excluding the combination without number of migrants, the dataset comprises only 27 countries which include Spain, Italy, Hungary, Netherlands, Austria, Belgium, Switzerland, Greece, Croatia, France, Luxembourg, Cyprus, Czechia, Germany, Portugal, Finland, Estonia, Norway, Slovenia, Sweden, Denmark, Slovakia, Ireland, Lithuania, Malta, Poland, Latvia. There were 79697.9 thousands of respondents who fall under each different combination of the factors.

ANALYSIS APPROACH

Description of response variable

The response variable in this case is the type of discrimination that the respondent perceives, which are categorized as follows:

- “Lack of language skills”

- “None”
- “No suitable job available”
- “Never sought work or never worked”
- “Other”
- “Discrimination due to foreign origin”
- “Lack of recognition of qualifications”
- “Citizenship or residence permit”
- “Language skills, qualifications, citizenship, foreign origin, job and other barriers”

Visualization of response variable

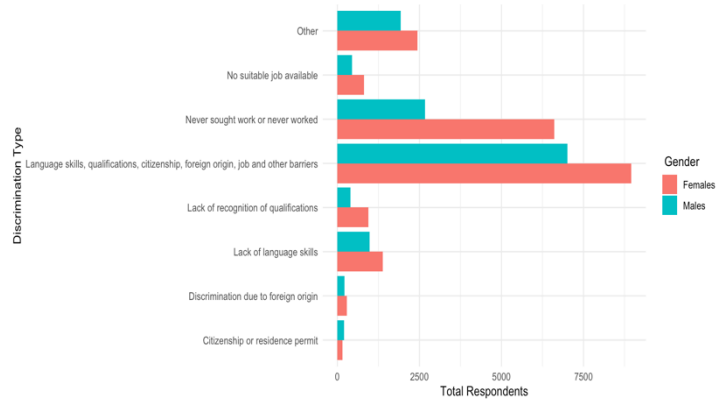
Below shows the visualization of the proportion allocation of the discrimination types among the total respondents and the frequency of respondents under each type of discrimination and level of educational attainment, gender and age interval. As shown in the first plot, there are 55.54% of migrants reported that they have not experienced any discrimination, and 22.43% reported they have experienced only one discrimination and 20.03% reported they have experienced more than one discrimination types. In the plot of total respondents by discrimination type and age interval we can see that majority of the respondents who have responded experiencing discrimination reported that they have experienced multiple discriminations, in particular the age interval between 25 and 54 years who represents the core working population. Younger individuals (15-24 years) are more likely to have never sought work or worked, which is likely due to ongoing education or lack of work experience. Meanwhile, older individuals (55-74 years) appear to face difficulties in finding suitable jobs, possibly due to skill mismatches or age-related employment challenges.

In terms of gender, the plot shows that the proportion of respondents to the survey is approximately the same between males and females and there are more female respondents reported than males under each discrimination type except in the “Citizenship and permanent permit” two gender categories appear to be approximately the same. In addition, females having a significantly higher proportion in barrier “Never sought work or never worked” and also multiple discriminations experienced. This supports our first hypothesis but will investigate further to see if there is any effect caused by other variables. In terms of educational attainment, majority of respondents with secondary and tertiary education reported that they experienced multiple discriminations without specifying the most significant discrimination that they are experiencing while majority of respondents with less than primary and lower secondary reported that they have experienced “Never sought work or never worked”. If the observations who have reported experiencing all types of discriminations are removed, there are only 63737 thousands of observations.

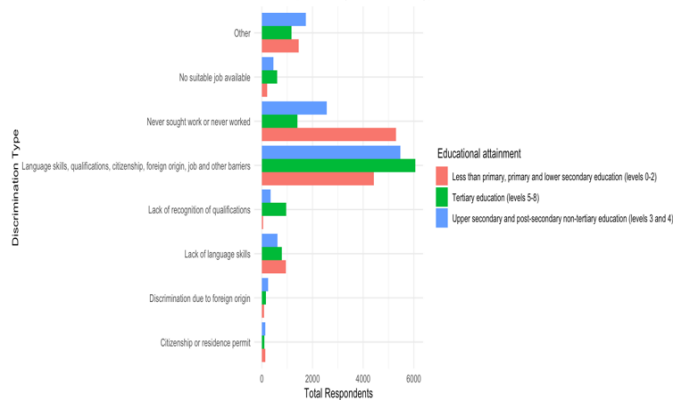
Proportion of Respondents by Discrimination Type



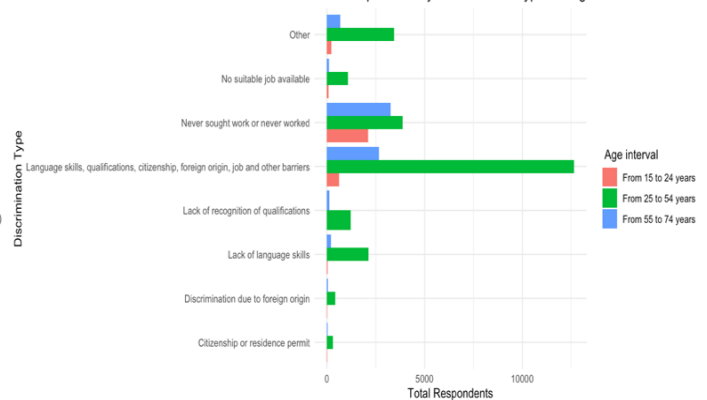
Total Respondents by Discrimination Type and Gender



Total Respondents by Discrimination Type and Educational Attainment



Total Respondents by Discrimination Type and Age Interval



Predictors

In this study, there are five predictors which are the following:

Variables	Type	Definition in the model
Gender	Categorical (Binary)	0=Male, 1=Female
Age	Categorical (Ordinal)	1=15-24 years, 2=25-54 years, 3=55-74 years
Educational attainment	Categorical (Ordinal)	1= Less than primary, primary and lower secondary education (Level 0-2), 2= Upper secondary and post-secondary non-tertiary education (Level 3-4), 3= Tertiary education (Level 5-8)
Country of birth	Categorical (Nominal)	1 = EU27 except reporting country, 2=Non-EU27, 3=Foreign country
Hosting country	Categorical (Nominal)	27 countries are assigned with different numerical numbers

Regression model techniques/Methodology

Since the response variables are categorical, the regression model that is applicable in this case would be the multinomial logistic regression. In order to test the hypotheses that have been set at the beginning of the project, let $X_1 = \text{Gender}$, $X_2 = \text{Age}$, $X_3 =$

Educational attainment, $X_4 = \text{Country of birth}$, $X_5 = \text{Hosting country}$ be the predictors and the response variable with 9 nominal outcomes. The multinomial logistic regression model is presented as follows:

$$\begin{aligned} \text{logit}(Y_j) &= \ln \left[\frac{P(Y = j|X)}{P(Y = J|X)} \right] \\ &= \beta_{j0} + \beta_{j1}X_1 + \beta_{j2}X_2 + \beta_{j3}X_3 + \beta_{j4}X_4 + \beta_{j5}X_5 + \beta_{j6}X_1X_3 + \beta_{j7}X_4X_5 \\ &\quad + \beta_{j8}X_2X_3 + \beta_{j9}X_3X_5 + \beta_{j10}X_1X_4 + \varepsilon_j \end{aligned}$$

and

$$P(Y = j|X) =$$

$$\frac{\exp(\beta_{j0} + \beta_{j1}X_1 + \beta_{j2}X_2 + \beta_{j3}X_3 + \beta_{j4}X_4 + \beta_{j5}X_5 + \beta_{j6}X_1X_3 + \beta_{j7}X_4X_5 + \beta_{j8}X_2X_3 + \beta_{j9}X_3X_5 + \beta_{j10}X_1X_4)}{1 + \sum_{j=1}^{J-1} \exp(\beta_{j0} + \beta_{j1}X_1 + \beta_{j2}X_2 + \beta_{j3}X_3 + \beta_{j4}X_4 + \beta_{j5}X_5 + \beta_{j6}X_1X_3 + \beta_{j7}X_4X_5 + \beta_{j8}X_2X_3 + \beta_{j9}X_3X_5 + \beta_{j10}X_1X_4)}$$

Where $j = 1, 2 \dots J - 1$ and we have set baseline category J as “None”.

- β_{j0} is the intercept for outcome j relative to the baseline category J
- $\beta_{j1}, \beta_{j2} \dots \beta_{j10}$ are the coefficients for the main effect and the interaction terms ($X_1X_3, X_4X_5, X_3X_5, X_1X_4$)
- ε_j represents the error term

Modelling process

1. Building a multinomial logistic regression with interaction term to see the effect of factors such as gender and education on the perceived discrimination by the respondents. The result can be used to test H1, H2 and H3.
2. Visualizing the formation of groups of countries by using multiple correspondence analysis to project the data points to 2D dimension.
3. Using latent class analysis to form different latent classes based on the types of discrimination perceived and the hosting countries to see if there are any clusters of countries with respondents experience similar discrimination types.
4. Use multinomial logistic regression again to see the effect of different demographic factors of the respondents on perceiving the particular type of discrimination on particular country in order to test H4.

RESULTS

After running the regression, we expect to see the predictiveness of each independent variables and if all the variables have contributed to the response obtained. By implementing the dimension reduction techniques such as multiple correspondence analysis and latent class analysis, we can see how the countries can be grouped together so that more personalized policy can be implemented to address the discrimination perception accordingly.

REFERENCES

Giang H. & Rima T., 2018. *The Labour Market Integration in Europe: New Evidence from*

Micro Data. Available:

<https://www.imf.org/en/Publications/WP/Issues/2018/11/01/The-Labor-Market-Integration-of-Migrants-in-Europe-New-Evidence-from-Micro-Data-46296>

[10 March, 2025].

International Organization of Migration, 2020. Chapter 3: Migration and Migrants: Regional

Dimensions and Developments. Available:

<https://worldmigrationreport.iom.int/what-wedo/world-migration-report-2024-chapter-3/europe> [10 March, 2025].

United Nations, 2024. *International Migration Stock 2024*. Available:

<https://www.un.org/development/desa/pd/content/international-migrant-stock> [12

March, 2025]

Verkuyten M., 2016. The Integration Paradox: Empiric Evidence From the Netherlands.

Available: <https://pubmed.ncbi.nlm.nih.gov/27152028/> [12 March, 2025]