Regional and Country-level Analysis on Migration Choice

Determinants estimation of migration by education and regional strata

地域・国レベルでの移民先の決定要因：

教育レベル・地域性による層化分析

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Abstract

The global migration population was growing recent years. This article aims to investigate determinants of the destination selection made by migrants with different educational levels and their home countries. The data used in this paper is mainly obtained from OECD's Database. We adopt the multilevel linear mixed regression model to cope with intra class reliability of the clusters of countries. Estimation results indicate that the difference in wage and unemployment between migrant's origin and host countries are significant impact on migration. The results also prove that there are random effects of migration decision by their educational level and regions where they belong to.

1. Introduction

The global migration population was growing recent years. According to the *Population Facts* published by United Nations, the number of international migrants is estimated to be 272 million, increase of 51 million in 2015 (UN, 2019).

This article aims to estimate determinants of global migration with various levels of education. We analyze global migration from 173 origin countries to 73 destination countries using OECD's Database on Immigrants in OECD Countries (DIOC) and their extension to include non-OECD countries (DIOC-E) for the year 2010. Figure 1 present stocks of migrants in selected five OECD countries[1] in 2000 through 2017,

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[1] Countries selected in the figure are Canada, France, Germany, UK and USA.

which are consistently increasing in numbers over years.[2] Figure 2 shows migrants inflow into same OECD countries for last ten years.

We firstly review literature examining migration selection and discuss estimation model in the second chapter; then we seize migration selection pattern by educational levels and different regions in the third chapter, the dataset to be used in estimation will be discussed in the fourth section, which is followed by the estimation results of the prepared model in the fifth section. Finally the last section is devoted to the conclusion from our estimates.

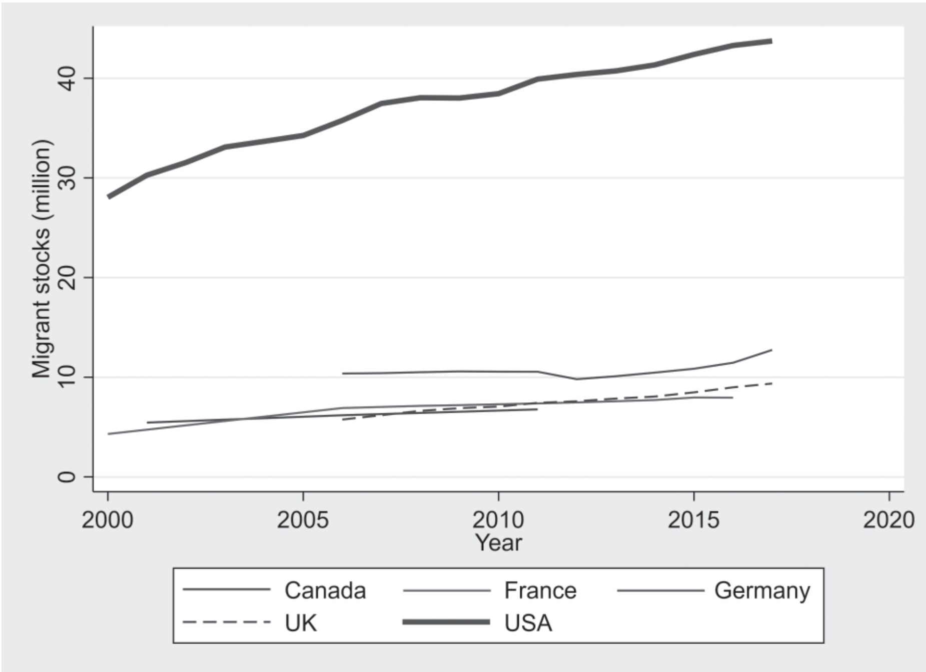

Figure 1　*Migration stock in OECD countries*

[2] The data is retrieved from OECD database "Stocks of foreign-born population in OECD countries." The figure is made by authors.

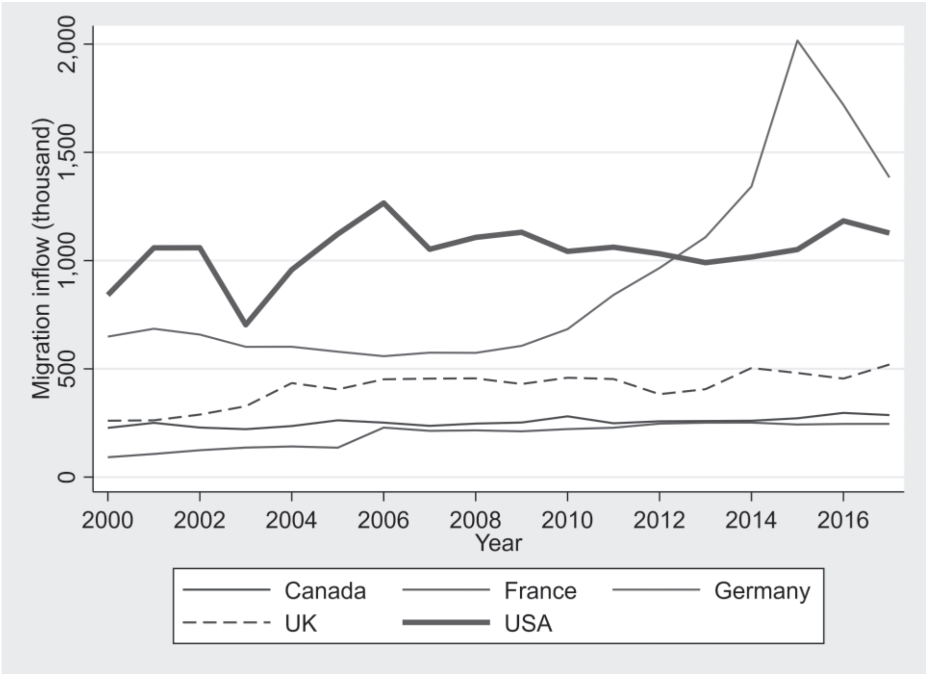

Figure 2 *Inflow of migrant to OECD countries*

2. Leading Literature

This section provides an analysis and an evaluation of the literature studied the high skilled migration and factors affecting its flows. Claus et al. (2010) studied the effect of taxation on migration. Their study proved migrants with tertiary education are more responsible to taxation of destination countries than migrants with other education levels.

Jajri and Ismail (2014) examined the determinants of immigration from the ASEAN-3: Indonesia, Thailand, and the Philippines, to Malaysia. The analysis is based on panel data covering the years around 1990 through 2008 using the autoregressive distributed lag approach. The study explained that the strongest determinant of migration from the ASEAN-3 is the real wage ratio between these countries and Malaysia, and that the impact of this variable is negative.

This summary also investigates the fact that the analyses conducted in existing research have limitations. These literatures studied the factors and determinants affecting skilled migration however, some of the limitations include:

A) To our knowledge, there are no studies reflecting the concept of intra- and inter-regional migration. Most of literatures defined migration as crossing the national borders however, there should be some factors affecting leaving the region where migrants' origin country is located or remain in the regional borders.

B) There is a lack of considering pull factors of the policies implemented by migrants' host country to attract high-skilled workers or students.

3. Model and Method

3.1 Leading model

Claus et al. (2010) studies the effect of taxation on migration by developing a formulating stylized, two-country model to assess the impact of taxation on labor mobility. To investigate the impact of taxation on migration the following equation is estimated by OLS; the dependent variable is the proportion of migrants from individual ASEAN or APEC economy living in each of OECD countries.[3] The non-tax explanatories are the following: distance from the equator of the ASEAN or APEC economy, life expectancy of destination countries, real GDP per capita of destination countries, population of origin country.

$$
\begin{aligned}
y_{i,j} = {} & \textit{distance from ASEAN}_{i,j} + \textit{life expectancy}_{i,j} + \log \textit{GDP per capita}_{i,j} \\
& + \log \textit{population}_{i,j} + \textit{colonize dummy}_{i,j} + \textit{distance from equator}_{i,j} \\
& + \textit{total tax on GDP}_{i,j} + \textit{marginal income tax rate}_{i,j} \\
& + \textit{value added tax rate}_{i,j} + \epsilon_{i,j} \qquad \text{...(1)}
\end{aligned}
$$

where y_{ij} denotes the proportion of migrants from ASEAN or APEC economy i living in OECD country j, and ϵ is the associating disturbance term.

3.2 Empirical model in this study

Each row in our dataset shows the number of people migrated from their origin country to a destination country, with given educational level and labor force status. In this case, there should be relatively large gaps between inter-regional and intra-regional correlation and that could be obstacles for the OLS. We assume that each migrant's origin country has each different intercept and coefficient of migration decision. Therefore, we utilize the multilevel mixed regression model with mac-

[3] Countries which belong to both ASEAN and APEC were omitted from estimation sample.

ro-level data, which considers deviation within and between clusters (Rabe-Hesketh & Skrondal, 2012). The multilevel linear mixed model combines both fixed effects and random effects.

The multilevel linear mixed model is a generalization of linear regression allowing the random deviations other than those associated with the overall error term. According to Laird and Ware (1982), the mixed model offers easy specification of random effects. With data being clustered by some key j, it is convenient to organize the mixed model as a series of M independent clusters or groups:

$$y_j = X_j \beta + Z_j u_j + \epsilon_j, \quad j = 1, \dots, M \qquad \text{...(2)}$$

where the jth cluster comprising n_j observations. $X_j\beta$ indicates the fixed effects, and $Z_j u_j$ indicates the random effects associated with the cluster. X_j and Z_j are the design matrices reflecting p and q variables, respectively, and u_j are a column vector of size q that is normally distributed with mean 0. The whole model combining all the equations (2) concerning M clusters can be written with the $n_j \times p$ matrix X_j and the $n_j \times q$ matrix Z_j as follows.

$$y = \begin{bmatrix} y_1 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 \\ \vdots \\ X_M \end{bmatrix} \beta + \begin{bmatrix} Z_1 & 0 & \cdots & 0 \\ 0 & Z_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & Z_M \end{bmatrix} \begin{bmatrix} u_1 \\ \vdots \\ u_M \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_M \end{bmatrix} = X\beta + Zu + \epsilon$$

The basic model in this study is formulated as shown in Equation (3) below, and is estimated with the cross-sectional dataset mainly compiled from DIOC 2010 (OECD).

$$\begin{aligned} PMigrant_{o,h,e,s} = {} & \alpha_1 + \beta_1 GDP_h + \beta_2 Population_o + \beta_3 Wage\ difference_{o,h,e,s} \\ & + \beta_4 Unemployment\ difference_{o,h,e,s} \\ & + \beta_5 Wage\ difference_{o,h,e,s} \times Region\ dummy_{o,h} \\ & + \beta_6 Unemployment\ difference_{o,h,e,s} \times Region\ dummy_{o,h} \\ & + \beta_7 Employed_{o,h,e} + \beta_8 Unemployed_{o,h,e} + \beta_9 Inactive_{o,h,e} \\ & + \beta_{10} Primary\ education_{o,h} + \beta_{11} Secondary\ education_{o,h} \\ & + \beta_{12} Tertiary\ education_{o,h} + \iota_{oe} + \mu_{o,h,e,s} \qquad \text{...(3)} \end{aligned}$$

Our dataset include four dimensions: viz., the origin and host countries of the migrants, their educational levels, and gender. The dependent variable $PMigrant_{o,h,e,s}$ is the proportion of migrants, which is defined as the quotient of $Migrant_{o,h,e,s}$, the number of migrants from origin country o to country h with educational level e and gender s, divided by the total number of migrants from origin country o in the study year. A separate proportion is calculated for each of three groups based on their educational level e; primary or less; secondary; and tertiary or above. GDP_h denotes the GDP in the host country h in 2010 USD, and $Population_o$ denotes the population in country o. $Wage\ difference_{o,h,e,s}$ and $Unemployment\ difference_{o,h,e,s}$ represent the difference of mean wages in USD, and the difference of the mean unemployment rates in percentages, respectively, between origin and host countries, for those belonging to the educational and gender groups, e and s.

Variables representing educational status of migrants are three variables representing proportions of migrants whose educational levels are; $Primary\ education_{o,h}$ (primary education or below), $Secondary\ education_{o,h}$ (secondary education), and $Tertiary\ education_{o,h}$ (tertiary education or above), for each pair of origin and host countries. Likewise, three variables are added to represent the labor force status[4] of the migrants; they indicate the proportions of $Employed_{o,h,e}$ (employed), $Unemployed_{o,h,e}$ (unemployed), and $Inactive_{o,h,e}$ (inactive), respectively. $Region\ dummy_{o,h}$ is a binary dummy variable which takes the value of 1 if the origin and host countries, o and h, belong to the same region.[5] $\iota_{o,e}$ represents the random effect associated with origin country or its region, and $\mu_{o,h,e}$ is an error term.

4. Data

4.1 Data resource and its coverage

Migration data in this study are collected from the DIOC-E. Our dataset obtained information on demographic characteristics, labor market outcomes, educational attainment based on the International Standardized Classification of Education category (ISCED) and the places of birth including both OECD and non-OECD countries from

[4] DIOC-E defines employed population includes paid workers, self-employed and unpaid workers engaged in the production of economic goods. The unemployed are out of work, currently available to work and actively seeking a job. The economically inactive population comprises all those persons neither “employed” nor “unemployed”. For some countries, DIOC-E cannot distinguish between unemployed and inactive and those migrants are classified into not-working. In this study, we combined “inactive” and “not-working” migrant as inactive.

[5] DIOC-E classifies countries into 6 regions: Africa, Asia, Europe, North America, Oceania and South and Central America and Caribbean.

DIOC-E. In addition, ILO Statistics (ILOSTAT), which accumulates labor-related data from various perspectives, is utilized to obtain unemployment rates and wages by countries and job types. Our dataset is a collection of 16 variables as summarized in Table 1, and includes 177,874 observations.[6]

Table 1 *Variables in dataset*

Variable name	Description
PMigrant	Proportion of migrants to a country with given education level, labor force status and gender to all the migrants from their origin country (2010)
GDP (trillion)	Total GDP of migrants' host country in USD observed in 2010
Population (billion)	Total population of migrants' origin country in 2010
Wage difference (million)	Difference of monthly mean wages between the migrants' origin and host country in USD
Unemployment rate difference	Difference of mean unemployment rate between the migrants' origin and host countries in %
Labor force status of migrant groups	Proportion of migrants whose current labor force status is employed among migrants from o to h with educational level e
	Proportion of migrants whose current labor force status is unemployed among migrants from o to h with educational level e
	Proportion of migrants whose labor force status is inactive among migrants from o to h with educational level e
Education of migrants	Proportion of migrants whose educational level is primary or below among migrants from o to h
	Proportion of migrants whose educational level is secondary among migrants from o to h
	Proportion of migrants whose educational level is tertiary or above among migrants from o to h

4.2 Data cleaning and interpolation

ILOSTAT collects unemployment rate by levels of education and gender, but wage data are categorized by gender and occupation. While the wage data are available in the International Standardized Classification of Occupation (ISCO)[7], unemployment

[6] The number of observations indicates 184,737 patterns of migration arisen by migrants' origin and host countries, sex, educational levels and labor force statuses.

[7] ISCO-08 was adopted through a resolution of a Tripartite Meeting of Experts on Labor Statistics held in December 2007. This resolution was subsequently endorsed by the Governing Body of the ILO in March 2008.

data are available in educational categories; ISCED.[8] Therefore, it is necessary to convert ISCO to ISCED because DIOC-E employs ISCED categories when compiling its data. This can be done by utilizing the ISCO skill levels based on ILO (2012). The correspondence among various classifications are summarized in Table A.1.

Table 2　*Descriptive statistics of variables*

	Mean	Standard deviation	Min.	Max
Proportion of migrants	.0012	0.0084	0.00	1
GDP of host country	1.42 trillion	3.059	0.00	15 trillion
Population of origin country	0.07 billion	0.20	0.00	1.34 billion
Wage difference	638.50	2.32 thousand	-12.32 thousand	12.08 thousand
Unemployment diff.	-0.46	11.71	-68.46	72.35
Labor force of migrants				
Employed	0.0007	0.0069	0	0.55
Unemployed	0.0001	0.0015	0	0.43
Inactive	0.0004	0.0040	0	1
Education				
Primary or below	0.0005	0.005	0	1
Secondary	0.0004	0.004	0	0.55
Tertiary and above	0.0002	0.003	0	0.43
Regional dummy	0.36	0.48	0	1
N	177,874			

There are some missing values of wages and unemployment rates in ILOSTAT for our study year of 2010. We interpolated by taking the average of the values for the nearest two years, such as 2009 and 2011, whenever available. Otherwise the mean value of the region to which the country belongs is used as a proxy. Table 2 summarized the descriptive statistics of the variables in concern, where the means are calcu-

[8] ISCED provides a comprehensive framework for organizing education programs and qualification by applying uniform and internationally agreed definitions to facilitate comparisons of education systems across countries.

lated as shown in the footnote.[9]

5. Analysis

5.1 Estimated coefficients

Our dataset is linked with 4 types of spatial units; viz. migrants' origin and host countries as well as the origin and host regions to which the relevant country belongs, utilizing the regional categorization introduced in DIOC-E. We estimated equation (3) for two separate spatial levels; the country and regional (cluster) levels. Our estimations are based on a linear mixed model with random intercepts and coefficients on migrants' origins by educational levels, considering covariance between intercept and slope. Table 3 reports the fixed parts of estimates for the regional (cluster) level in column 1 and the country level in column 2.

Since the labor and educational force statuses are essentially dummy variables, one status is considered as the reference point for each of these variables. They are "employed" for the labor status and "primary" for the educational status. Since coefficients for both unemployed and inactive statuses are negative and significant, those who have migrated are likely to be employed. Concerning education, coefficients for both secondary and tertiary education are negative and significant. This implies that even though most governments welcome highly skilled immigrants, people with lower education levels tend to migrate more easily than those with higher education.

The coefficients of wage difference between the migrants' host and origin countries, $Wage_o - Wage_h$, is significantly negative. It is natural to consider that the motive to migrate will decline if the wage in the origin is higher. The similar explanation will apply to the difference in unemployment rates, $Unemployed_o - Unemployed_h$, which is significantly positive. Such a result implies that the potential migrants will be encouraged if the unemployment rate in the origin is higher.

[9] The mean of variables are defined as follows with # indicating cardinality:

Migrant	$E(Migrant) = \Sigma\ Migrants_{o,h,e,s} / (\#o \times \#h \times \#e \times \#s)$
GDP	$E(GDP) = \Sigma\ GDP_h / \#h$
Population	$E(Population) = \Sigma\ Population_o / \#o$
Wage difference	$E(Wage\ difference) = \Sigma\ Wage\ difference_{o,h,e,s} / (\#o \times \#h \times \#e \times \#s)$
Unemployment difference	$E(Unemployment\ difference)$ $= \Sigma\ Unemployment\ difference_{o,h,e,s} / (\#o \times \#h \times \#e \times \#s)$
Employed	$E(Employed) = \Sigma\ Employed_{o,h,e} / (\#o \times \#h \times \#e)$
Unemployed	$E(Unemployed) = \Sigma\ Unemployed_{o,h,e} / (\#o \times \#h \times \#e)$
Inactive	$E(Inactive) = \Sigma\ Inactive_{o,h,e} / (\#o \times \#h \times \#e)$
Primary Education	$E(Primary) = \Sigma\ Primary_{o,h} / (\#o \times \#h)$
Secondary Education	$E(Secondary) = \Sigma\ Secondary_{o,h} / (\#o \times \#h)$
Tertiary Education	$E(Tertiary) = \Sigma\ Tertiary_{o,h} / (\#o \times \#h)$
Regional dummy	$E(Regional\ dummy) = \Sigma\ Regional\ dummy_{o,h} / (\#o \times \#h)$

The fact that the coefficient for the GDP in the host country is significantly positive indicates that the pull power of the countries with large economies is dominant, and that for population in the origin country is significantly negative indicates that the rate of out-migration is lower in big countries. It must be noted that these results are remarkably robust even when we change the level of spatial clustering.

To assess whether geographical or social distances between origin and host countries affects migration decisions, the cross-effect terms are included regarding the two differences in wages and unemployment rates. In practice, a regional dummy, which takes the value of 1 when both origin and host countries belong to the same region (cluster), is multiplied to each of those differences. The results are summarized in Table 4, where the cross-term for wage difference is significantly negative, and that for unemployment rates is significantly positive. These results essentially magnify the coefficients associated to the difference terms, not considering regional dummies, shown in Table 3. However, it must be noted that multicollinearity between simple differences and cross-effect terms is plausible so that the coefficients associated to the simple difference terms in Table 4 turn insignificant.

Table 3　*Results of multilevel mixed model*

	Regional level		Country level	
Coefficients				
GDP of host country	0.2731***	[0.006]	0.2733***	[0.006]
Population of origin country	-0.8026***	[0.090]	-0.8002***	[0.090]
Wage difference	-37.9104***	[8.015]	-38.6124***	[8.017]
Unemployment difference	5.8831***	[1.565]	5.8139***	[1.596]
Labor force status				
Unemployed	-0.00141***	[0.000]	-0.00141***	[0.000]
Inactive	-0.00069***	[0.000]	-0.00069***	[0.000]
Education status of migrants				
Secondary	-0.00033***	[0.000]	-0.00034***	[0.000]
Tertiary and above	-0.00073***	[0.000]	-0.00073****	[0.000]
Constant	0.00180***	[0.000]	0.00180***	[0.000]
Number of observations	177,874		177,874	
Log likelihood	612,905		612,895	

* represents p < 0.1, ** represents p < 0.05 and *** represents p < 0.001 respectively.
Standard errors are in brackets.

Table 4　*Results of multilevel mixed model with cross-effects*

	Regional level		Country level	
Coefficients				
GDP of host country	0.2741***	[0.006]	0.2744***	[0.006]
Population of origin country	-0.7921***	[0.090]	-0.7906***	[0.090]
Wage difference	17.0109	[13.698]	16.0976	[13.687]
Unemployment difference	1.6251	[2.698]	1.7929	[2.700]
Labor force status				
Unemployed	-0.00141***	[0.000]	-0.00141***	[0.000]
Inactive	-0.00069***	[0.000]	-0.00069***	[0.000]
Education status of migrants				
Secondary	-0.00034***	[0.000]	-0.00034***	[0.000]
Tertiary and above	-0.00073***	[0.000]	-0.00073***	[0.000]
Wage difference × regional dummy	-81.4594***	[16.546]	-81.2504***	[16.538]
Unemployment difference × regional dummy	6.0816*	[3.340]	5.7180*	[3.339]
Constant	0.00180***	[0.000]	0.00180***	[0.000]
Number of observations	177,874		177,874	
Log likelihood	612,918		612,908	

* represents $p < 0.1$, ** represents $p < 0.05$ and *** represents $p < 0.001$ respectively. Standard errors are in brackets.

5.2 Random slopes by regions and education level

In section 3.2, we suppose that each of migrants' origin regions have random effects of its own on migration decision. Figures 3 and 4 show the slopes concerning the number of migrants to the differences in wages and unemployment rates, respectively, by migrants' regions of origin.[10] Both positive and negative slopes are found in these figures, and each slope is accompanied by its own intercept. The slopes illustrate the differences in coefficients by six regions of origin and three educational levels.

In Figures 5 and 6, the regional slopes are analyzed more closely to distinguish the effects of educational levels. These figures demonstrate that migrants from a region has different tendency to migrate depending on their educational level. For example, only Europe has a positive slope in Figure 3, and this feature is maintained in Figure 5 even when a separate slope is drawn for each educational level. Further, the result

[10] The names of the regions are displayed as abbreviation in legends: AFRI: Africa, ASIA: Asia, EURO: Europe, NOAM: North America, OCEA: Oceania and SCAC: South and Central America and Caribbean.

that those with only primary education has the highest tendency to migrate followed by those with secondary education is consistent with the fixed part results summarized in Tables 3 and 4. Although the regional differences in slopes regarding the unemployment rates are more complicated, the figures are consistent in that those with lower education have stronger tendency to migrate.

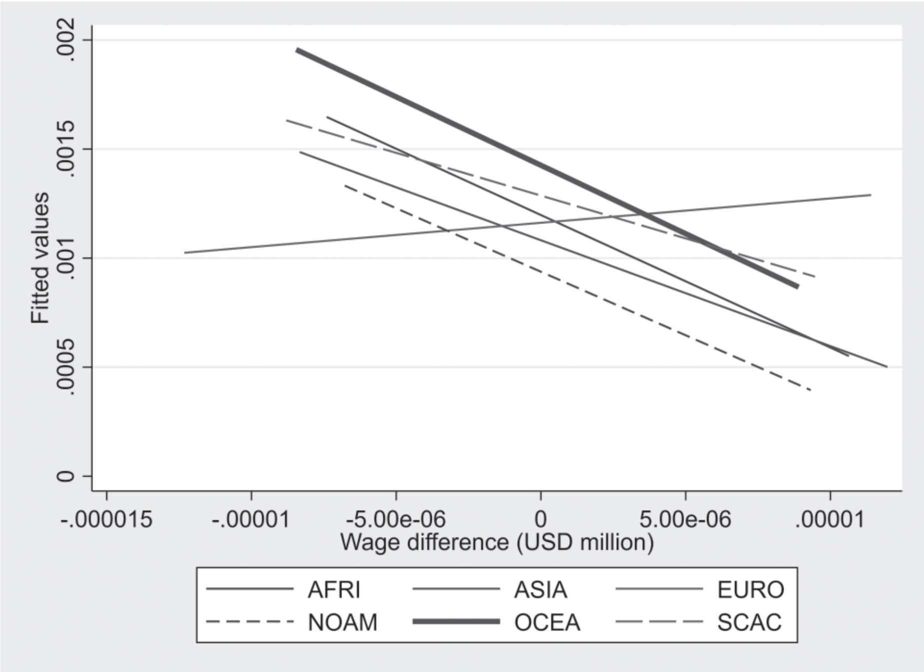

Figure 3　*Slopes of wage difference by regions*

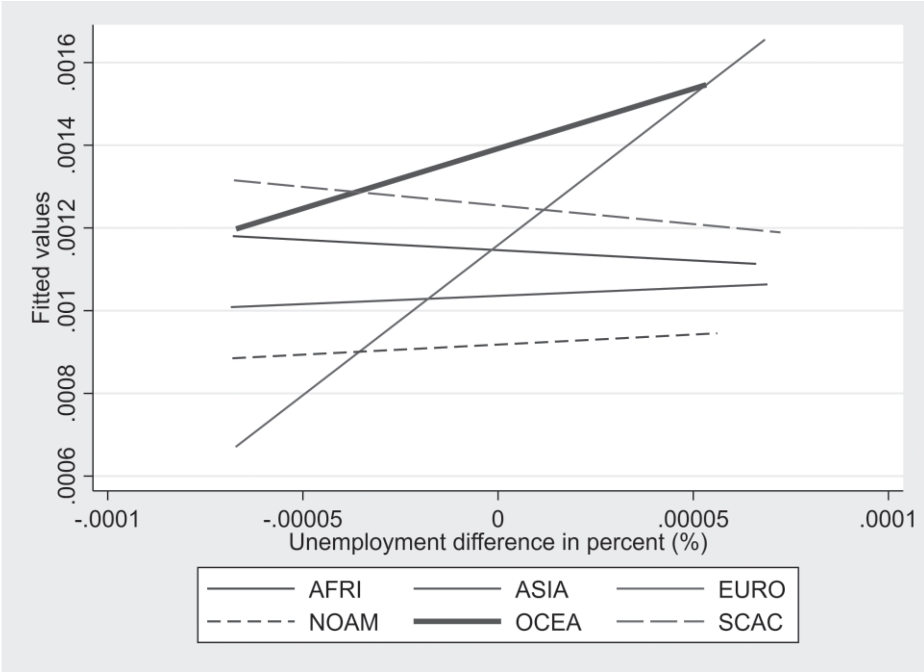

Figure 4 *Slopes of difference in unemployment rates by regions*

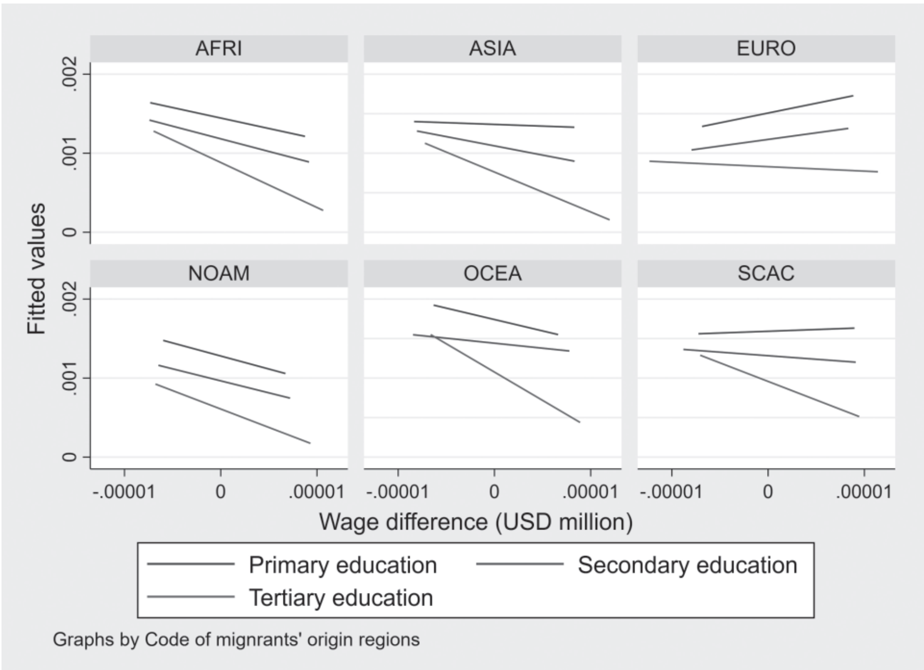

Figure 5 *Slopes of wage difference by regions and education*

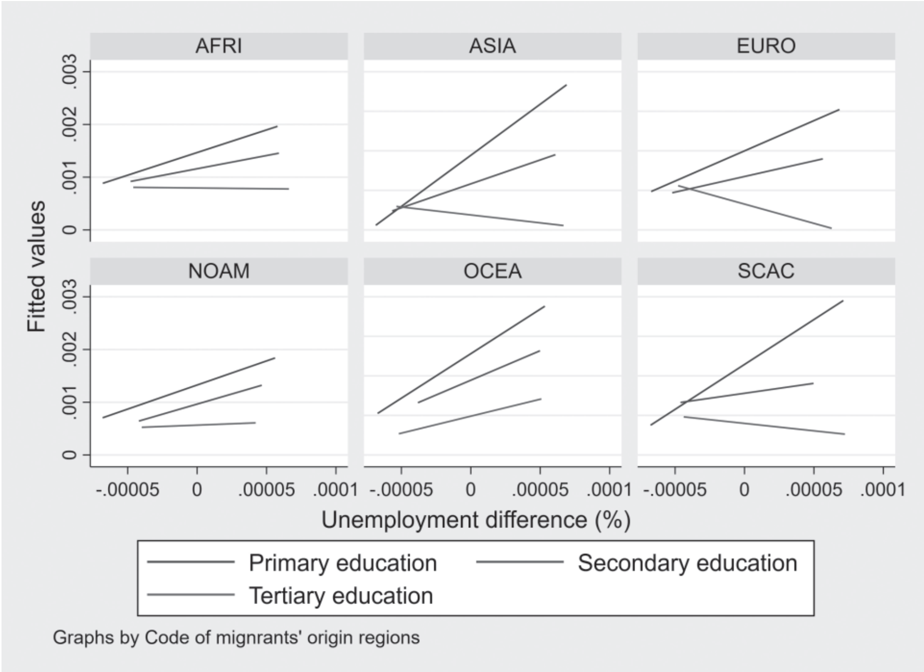

Figure 6　*Slopes of difference in unemployment rates by regions and education*

6. Concluding Remarks

This article aims to assess determinants of migration on the ground of migrants' educational levels. The results of multilevel linear mixed model presented in previous chapters proved that the difference in unemployment rates between the migrants' origin and host countries has positive effect on the number of migration, whereas the difference in the mean wages presents significantly negative impact on migration. Regarding educational status of migrants, attaining higher education significantly reduces migration statistically.

Our second model, which includes cross-effect terms of wage and unemployment disparities multiplied by regional dummies, reached essentially the same results as the first model mentioned above. It is reasonable to see that the higher wage in the destination or lower wage in the home seems to encourage migration, and the higher unemployment in the destination or lower unemployment in the home seems to discourage the same. The migration cost and geographic distance certainly affect most of economic effects amongst explanatory variables involved.

It is worth mentioning that the regional category used in our study is a little different from conventional definition of "regions" in that it does not distinguish Middle

East and North Africa (MENA) and Central Asia from Asia and Africa. Furthermore, our dataset does not include variables reflecting past colonization, while some literature indicates that there exist certain ties between former colonies and its suzerainty. In particular, Acemoglu et al. (2001) suggests that migration estimation should include the suzerain-colony relationship.

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Appendix

Table A1　*Correspondence of education and job categories between DIOC and ILOSTAT*

DIOC classifi-cation	DIOC description	ISCED 97 classifi-cation	ISCED description	ISCO skill level	ISCO classifi-cation	ISCO description
3	High education	6	Second stage of tertiary education	4	1+2	1:Managers, 2:Professionals
3	High education	5a	First stage of tertiary education (medium duration)	4	1+2	1:Managers, 2:Professionals
3	High education	5b	First stage of tertiary education (short duration)	3	3+1	1:Managers, 3:Technicians and associate professionals
2	Middle education	4	Post-secondary, non-tertiary education	2	4	Clerical support workers
2	Middle education	3	Upper secondary education	2	4	Clerical support workers
1	Low education	2	Lower secondary education	2	4	Clerical support workers
1	Low education	1	Primary level of education	1	9	Elementary occupations
1	Low education	0	Early childhood education	NA	NA	NA

Table A.2 *Table of variable correlation*

	Propor-tion of migrants	GDP of host country	Pop. of origin country	Labor force status of migrants	Wage differ.	Unemploy-ment rate differ.	Education of migrants	Region. dummy
Proportion of migrants	1							
GDP of host country	0.1035	1						
Pop. of origin country	-0.0244	-0.0328	1					
Labor force status of migrant	-0.037	-0.0067	-0.0066	1				
Wage difference	-0.0094	0.0436	-0.0238	-0.0024	1			
Unemployment rate difference	0.0033	0.004	-0.0299	-0.0079	0.1452	1		
Education of migrants	-0.0352	0.0063	0.0009	-0.0461	0.0966	0.1394	1	
Regional dummy	-0.0509	0.1891	0.1086	0.0053	0.0798	-0.0414	0.028	1