Migration patterns of Europeans after Brexit

Candice Baud

Evangelos Paschalidis

Andreas B. Vortisch

Michel Beine

Michel Bierlaire

STRC conference paper 2024 **April 30, 2024**

STRC | **24th Swiss Transport Research Conference**
Monte Verità / Ascona, May 15-17, 2024

Migration patterns of Europeans after Brexit

Candice Baud
Transport and Mobility Laboratory
École Polytechnique Fédérale de Lausanne, Switzerland
candice.baud@epfl.ch

Evangelos Paschalidis
Transport and Mobility Laboratory
École Polytechnique Fédérale de Lausanne, Switzerland
evangelos.paschalidis@epfl.ch

Andreas B. Vortisch
Department of Economics and Management
University of Luxembourg
andreas.vortisch@uni.lu

Michel Beine
Department of Economics and Management
University of Luxembourg
michel.beine@uni.lu

Michel Bierlaire
Transport and Mobility Laboratory
École Polytechnique Fédérale de Lausanne, Switzerland
michel.bierlaire@epfl.ch

April 30, 2024

Abstract

This paper examines how Brexit-induced access restrictions have influenced migration patterns among European Union (EU) residents, particularly their destination choices. We analyze whether the change in migration policies has altered European Union residents' intentions to migrate to the UK and explore how these potential migrants are redirecting their destination choices. Using discrete choice modelling framework, we apply a logit model on the Gallup World Poll data set containing declared migration aspiration of European Union citizens. We show that Brexit has led to decreased migration intentions towards the UK among EU residents, with varying effects observed during the uncertainty period (June 2016 to 2021) and the post-Brexit period (after 2021). During the uncertainty period, access conditions remained unchanged, while post-Brexit measures restricting entry had a substantial impact on migration dynamics.

Keywords

Discrete choice modelling, Migration aspirations, Logit, Nested logit, Cross nested logit

Contents

List of Tables

1 Introduction

Migration represents a significant societal challenge, impacting demographic, economic, and political realms. Debates on border openness and closure have intensified in recent years, notably in the Americas with the election of Donald Trump and in Europe following waves of refugee migration. When a country, previously popular for migration, decides to complicate or even prohibit migrant entry, individuals may either persist in their migration attempts, reconsider their plans, or redirect their destinations.

Brexit, was voted in June 2016 and implemented in 2021, which altered access conditions to the United Kingdom for citizens of European Union member countries, now requiring work visas akin to non-EU nationals. Between the referendum in 2016 and the effective exit of European Union in 2021, uncertainty prevailed regarding the measures to be implemented. Investigating the impact of this uncertainty is crucial to understanding how policy changes affect migration patterns and destination choices. We hypothesize that this uncertainty decreased migration intentions from European Union residents towards the UK, leading potential migrants to consider alternative destinations. Indeed, existing literature indicates that uncertainty reduces migration (Czaika (2012)), with Brexit being a manifestation of this trend (Basile *et al.* (2022); Di Iasio and Wahba (2023); Clifton-Sprigg *et al.* (2021); Auer and Tetlow (2022)). Moreover, as visas become more difficult to obtain, especially for unskilled workers, we expect self-selection among migrants and heterogeneous decreases in migration to the UK based on education level (Basile *et al.* (2022); Belot and Hatton (2012); Mahroum (2008)). In addition to quantifying the Brexit effect during the uncertainty period, we also aim to assess the post-Brexit impact following the official leave on the 1st of January 2021. During the uncertainty period, access conditions to the UK had not yet changed, suggesting that the effect may vary significantly after the implementation of measures that now restrict entry, potentially influencing migration dynamics in distinct ways.

This project goes beyond quantifying migration decreases and examines changes in migrants' intentions towards other countries. Factors influencing choice of residence have been extensively studied (Baláž *et al.* (2014); Jentjens (2021); Czaika and Reinprecht (2022); Borjas (1994)), highlighting economic, cultural, geographic, and accessibility criteria. Consequently, it is plausible that the closure of British borders to EU member states will unevenly redirect migrant flows, as some alternative destinations share characteristics with the UK that make them more attractive as substitutes. Our aim is thus to establish a model reflecting Brexit migration dynamics and quantify substitution effects to understand which countries will be favored by aspiring migrants.

2 Data

2.1 Data on migration aspirations

We utilize the Gallup World Poll data spanning from 2012 to 2022, encompassing 99 percent of the global adult population and ensuring national representativeness. Our study specifically focuses on European Union (EU) members, whose access to the UK has been influenced by Brexit. This dataset comprises individuals' responses regarding various societal issues, including business and economics, citizen engagement, technology, education, family, food, politics, health, religion, law, well-being, and work. Although the dataset is not cross-sectional, the annual survey facilitates the consideration of migration aspiration variations over time.

To quantify migration aspirations, we employ the following questions:

- WP1325: *Ideally, if you had the opportunity, would you like to move permanently to another country, or would you prefer to continue living in this country?*
- WP3120: *To which country would you like to move? (Asked only of those who would like to move to another country.)*

Within European Union countries, approximately 17 percent of respondents express a desire to relocate from their country, ranging from a high of 30 percent in Cyprus to a low of 9 percent in Finland. Throughout the entire period, the most favored destinations for EU members include Germany, the United Kingdom, and the United States of America, accounting for 12.2 percent, 10.4 percent, and 9.5 percent of migration intentions respectively. The top 15 selected destinations predominantly comprise European countries, as illustrated in Table 4 in Appendix A.2.

In absolute numbers, the UK hosts significant diaspora communities from diverse origins. Notably, the diaspora from within the European Union primarily comprises mostly nationals from Poland, Ireland, Germany, Romania, Italy and France. Comprehensive tables detailing worldwide (5) and European (6) diaspora populations can be found in Appendix A.2.

2.2 Individual characteristics

Individual characteristics are included in the Gallup World Poll data such as age, educational status, gender, income, and household composition. Educational status has three levels : low skilled (LS, primary education or lower), middle skilled (MS, secondary education completed and up to three years of college education), high skilled (HS, at least 4 years of tertiary education completed). The individual income is calculated using the number of members in the household such that we assign a weight of 1 to the first adult, a weight of 0.7 to the other members aged 15 and more, and a weight of 0.5 for members under 15. Those variables are known to be relevant to model the choices of destination and we follow the same specification as in Beine *et al.* (2022).

2.3 Destination-specific variables

To measure attractiveness of countries of destination, we add destination-specific attributes such as the GDP, the population, and categorical indicators denoting membership in various groups such as the European Union, Europe, OECD, European single market, and English-speaking status. Additionally, we incorporate origin-and-destination-specific attributes like distance between the origin and destination countries (measured between respective capital cities), diaspora presence from the origin country in the destination, language similarity between the two, and a binary indicator for contiguity. To ensure consistency, we align the values of these variables with the survey year. For instance, if a respondent is interviewed in 2015, the attributed values correspond to their status in 2015. A comprehensive list of variables and their sources is available in the annex A.1.

3 Models

3.1 Discrete choice models

Our research operates within the discrete choice modeling framework, where individuals are presented with various alternatives and are tasked with selecting one, as exemplified by the choice of destination country in our study. We construct a choice set for which individual $\mathcal{C}_n$ that delineates the available alternatives, each associated with a utility. This utility comprises both a deterministic component, amalgamating the benefits and costs linked to each destination, and a stochastic component representing unobservable factors, independent from the deterministic aspect. In our case, for each country of destination c and individual n, we can define

$$U_{c,n} = V_{c,n} + \epsilon_{c,n}$$

where $V_{c,n}$ represents the deterministic part of the utility and $\epsilon_{c,n}$ the stochastic component.

From the deterministic utility and the stochastic component's distribution, and using the random utility maximization principle, one can compute the probability of an individual selecting each alternative by determining the likelihood of it offering the highest utility. In other words one can compute $P_n(c|\mathcal{C}_n)$, the probability that an individual n chooses option c by

$$P_n(c|\mathcal{C}_n) = P(U_{c,n} > U_{j,n} \forall j \neq c, j \in \mathcal{C}_n)$$

Through the assumption of independent, identically, and extreme value-distributed random terms $EV(\eta, \mu)$, we derive the logit model

$$P_n(c|\mathcal{C}_n) = \frac{e^{\mu V_{c,n}}}{\sum_{j \in \mathcal{C}_n} e^{\mu V_{j,n}}}$$

3.2 Utility specification

For each individual, we are interested in his/her utility associated with each of his/her possible choices. The specification depends on parameters that we estimate via Maximum Likelihood Estimation in the sample. When the parameters are estimated, we can plug their values in the utility and compute the probabilities associated to choosing each alternative. Additionally, we can compute elasticities and cross elasticities to capture the substitution patterns.

Utility to stay : The decision to stay is primarily influenced by individual characteristics rather than destination-specific variables. We denote $U_{stay,n}$ as the utility of staying associated with individual n, represented as a linear combination of various factors. These factors encompass the individual's age, which undergoes a piece-wise linear transformation with a threshold set at 65 years. Additionally, we incorporate variables such as educational level, gender, and income.

$$\begin{aligned}U_{stay} = {} & \beta_{Over65,stay} \cdot \text{Age}_{Over65} + \beta_{Under65,stay} \cdot \text{Age}_{Under65} + \beta_{HS,stay} \cdot 1_{HS} + \beta_{MS,stay} \cdot 1_{MS} \\ & + \beta_{LS,stay} \cdot 1_{LS} + \beta_{income,stay} \cdot \text{Income} + \beta_{Male,stay} \cdot 1_{Male}\end{aligned}$$

Utility to move : The decision to migrate is influenced by a combination of individual attributes and destination-specific factors. We quantify the utility associated with relocating to each destination country c as U_c. Across all countries, a standardized specification is employed, encompassing variables such as distance, GDP, and diaspora, each interacted with education level; but also population size, language proximity, and contiguity. Additionally, countries are categorized into specific groups such as the OECD, Schengen area, and English-speaking nations. Furthermore, in the case of the United Kingdom (UK), we incorporate a baseline educational effect across three educational levels and introduce interactions between Brexit periods and educational level into the utility function. This approach enables to capture both the general factors affecting migration choices and the impact of Brexit on individuals' migration preferences differentiated by period and education status.

$$\begin{aligned}U_{\text{common}} = {} & \beta_{\text{distance}} \cdot \text{distance} + \beta_{\text{gdp,HS}} \cdot \text{GDP} \cdot 1_{\text{HS}} + \beta_{\text{gdp, MS}} \cdot \text{GDP} \cdot 1_{\text{MS}} + \beta_{\text{gdp, LS}} \cdot \text{GDP} \cdot 1_{\text{LS}} \\ & + \beta_{\text{diaspora,HS}} \cdot \text{diaspora} \cdot 1_{\text{HS}} + \beta_{\text{diaspora, MS}} \cdot \text{diaspora} \cdot 1_{\text{MS}} + \beta_{\text{diaspora, LS}} \cdot \text{diaspora} \cdot 1_{\text{LS}} \\ & + \beta_{\text{population}} \cdot \text{population} + \beta_{\text{contigous}} \cdot \text{contiguous} + \beta_{\text{language}} \cdot \text{language} \\ & + \beta_{\text{oecd}} \cdot 1_{\text{OECD}} + \beta_{\text{English}} \cdot 1_{\text{English}} + \beta_{\text{Single market}} \cdot 1_{\text{Single Market}} + \beta_{\text{UE}} \cdot 1_{\text{UE}}\end{aligned}$$

$$\begin{aligned}U_{\text{UK}} = {} & U_{\text{common}} + \beta_{\text{HS}} \cdot 1_{\text{HS}} + \beta_{\text{MS}} \cdot 1_{\text{MS}} + \beta_{\text{LS}} \cdot 1_{\text{LS}} \\ & + \beta_{\text{Uncertainty, HS}} \cdot 1_{\text{Uncertainty}} \cdot 1_{\text{HS}} + \beta_{\text{Uncertainty, MS}} \cdot 1_{\text{Uncertainty}} \cdot 1_{\text{MS}} \\ & + \beta_{\text{Uncertainty, LS}} \cdot 1_{\text{Uncertainty}} \cdot 1_{\text{LS}} \\ & + \beta_{\text{Post Brexit, HS}} \cdot 1_{\text{PostBrexit}} \cdot 1_{\text{HS}} + \beta_{\text{Post Brexit, MS}} \cdot 1_{\text{PostBrexit}} \cdot 1_{\text{MS}} \\ & + \beta_{\text{Post Brexit, LS}} \cdot 1_{\text{PostBrexit}} \cdot 1_{\text{LS}}\end{aligned}$$

4 Preliminary Results

We estimate all models with the software Biogeme (Bierlaire (2003, 2008)). The sample that we use contains 231,649 observations, among which 34,352 correspond to people who desire to move. We estimate the simple logit on all the data with 203 countries of destination in the choice set. Table 1 presents the parameters estimation of whishing-to-stay-respondents' and 2 corresponds to those wishing to move.

Table 1: Multi-logit model - Stayers

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
$\beta_{\text{Age above 65}}$	0.0556	0.00423	13.1	0
$\beta_{\text{Age above 65}}$	0.0363	0.000493	73.5	0
β_{hs}	15.2	0.236	64.4	0
β_{ms}	15.3	0.205	74.6	0
β_{ls}	15.6	0.315	49.4	0
β_{income}	0.0587	0.00483	12.2	0
β_{male}	-0.156	0.0119	-13.2	0

In the context of each continuous variable, a positive coefficient signifies that an increase in the variable's value corresponds to a higher likelihood of selecting the alternative. Conversely, a negative coefficient indicates that an increase in the variable's value leads to a decreased probability of choosing the alternative. For dummy variables, the coefficient denotes the additional utility gained or lost by being associated with the specific group indicated by the dummy variable. Analyzing Table 2, it is evident that during the period of uncertainty, Brexit had a negative impact across all education levels, with the magnitude of this impact increasing alongside higher levels of education. However, this effect was not statistically different from 0 among respondents with lower skill levels. In the post-Brexit period, a negative effect of Brexit was observed across all education levels, significantly differing from zero. The effects of the remaining destination specific variables were consistent to previous similar literature, for instance Beine *et al.* (2022). The size of diaspora and GDP at destination had a positive impact on utility while distance had a negative effect. Moreover, OECD and English-speaking countries had a higher likelihood to be selected.

Table 2: Multi-logit model - Movers

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
$\beta_{brexit\_hs\_after}$	-0.235	0.0928	-2.53	0.0113
$\beta_{brexit\_hs\_uncertainty}$	-0.284	0.0834	-3.41	0.000652
$\beta_{brexit\_ms\_after}$	-0.412	0.0691	-5.96	2.51×10^{-09}
$\beta_{brexit\_ms\_uncertainty}$	-0.16	0.0519	-3.09	0.00199
$\beta_{brexit\_ls\_after}$	-0.395	0.169	-2.34	0.0191
$\beta_{brexit\_ls\_uncertainty}$	-0.0217	0.107	-0.204	0.838
$\beta_{diaspora\_hs}$	0.0122	0.00376	3.23	0.00122
$\beta_{diaspora\_ms}$	0.015	0.00223	6.75	1.50×10^{-11}
$\beta_{diaspora\_ls}$	0.0199	0.00496	4.01	6.16×10^{-05}
β_{gdp_hs}	0.865	0.0159	54.3	0
β_{gdp_ms}	0.871	0.0115	75.9	0
β_{gdp_ls}	0.902	0.0253	35.7	0
β_{hs_UK}	0.251	0.0908	2.76	0.00573
β_{ms_UK}	0.22	0.0839	2.62	0.00884
β_{ls_UK}	0.235	0.0973	2.42	0.0156
$\beta_{distance}$	-0.377	0.0155	-24.2	0
$\beta_{language}$	-0.0062	0.0533	-0.116	0.907
$\beta_{population}$	0.451	0.00536	84.3	0
$\beta_{contiguous}$	0.0424	0.0231	1.84	0.066
β_{oecd}	0.924	0.0191	48.4	0
$\beta_{schengen}$	0.629	0.0292	21.5	0
$\beta_{english}$	0.934	0.0169	55.4	0
constant_{AUT}	-1.65	0.22	-7.51	5.82×10^{-14}
constant_{BEL}	-1.49	0.172	-8.69	0
constant_{BGR}	0.395	0.112	3.52	0.000435
constant_{CYP}	1.75	0.0922	19	0
constant_{CZE}	-0.361	0.128	-2.81	0.00496
constant_{DEU}	-1.61	0.186	-8.64	0
constant_{DNK}	-1.17	0.175	-6.67	2.59×10^{-11}
constant_{ESP}	-0.169	0.117	-1.44	0.149
constant_{FIN}	-0.979	0.184	-5.32	1.06×10^{-07}
constant_{FRA}	-1.4	0.159	-8.84	0
constant_{GRC}	0.553	0.105	5.29	1.22×10^{-07}
constant_{HRV}	-0.744	0.14	-5.31	1.11×10^{-07}
constant_{HUN}	0.29	0.111	2.61	0.00897
constant_{IRL}	-0.652	0.128	-5.11	3.25×10^{-07}
constant_{ITA}	0.374	0.107	3.49	0.00048
constant_{LTU}	1	0.0927	10.8	0
constant_{LUX}	-1.48	0.187	-7.89	2.89×10^{-15}
constant_{LVA}	0.527	0.103	5.12	3.03×10^{-07}
constant_{MLT}	1.62	0.0899	18.1	0
constant_{NLD}	-1.51	0.174	-8.68	0
constant_{POL}	0.58	0.102	5.7	1.2×10^{-08}
constant_{PRT}	0.207	0.112	1.86	0.0635
constant_{ROU}	0.706	0.102	6.93	4.23×10^{-12}
constant_{SVK}	-0.179	0.12	-1.49	0.137
constant_{SVN}	-0.732	0.153	-4.8	1.6×10^{-06}
constant_{SWE}	-0.922	0.171	-5.41	6.42×10^{-08}

5 Conclusion and next steps

This paper presents preliminary findings from discrete choice models applied to migration intensity modeling. The initial results obtained using a logit model indicate that Brexit had a negative impact on migration intentions towards the UK across all skill levels, with varying intensities observed during different periods (uncertainty period vs. post-Brexit period). Consistent with existing literature, we observe that uncertainty surrounding Brexit led to a decline in the attractiveness of the UK for potential migrants, particularly affecting skilled workers. In the post-Brexit period, characterized by implemented measures, this decline in attractiveness was more pronounced among low-skilled and middle-skilled workers, who were among the most impacted by policy changes.

The logit model however presents limitations due to the assumption that the random terms are independently and identically distributed (iid). Therefore, the logit model satisfies the IIA property which implies that the relative probabilities of choosing between two alternatives remain unaffected by the presence or absence of other alternatives in the choice set. However, in migration decision-making, this assumption often oversimplifies the dynamics, as destinations may not be independent choices; their attractiveness can be influenced by the characteristics and availability of other alternatives. To address these limitations, we will consider more sophisticated models, namely nested logit and cross-nested logit models. These models relax the IIA assumption by allowing for correlated choices within defined groups or nests of alternatives. The nested logit model groups individuals in exclusive nests, based on shared unobserved characteristics. The cross-nested logit model extends this capability further by allowing for overlaps between groups of countries.

Thus, we plan to explore nested logit and cross-nested logit models, which should better account for correlations between destination choices. A potential approach involves implementing a nested logit model that groups intended movers separately from intended stayers, recognizing their distinct decision-making dynamics. Additionally, we intend to explore a cross-nested logit model inspired by Beine *et al.* (2022), employing nests corresponding to OECD countries, Schengen countries, and English-speaking countries.

6 References

Auer, D. and D. Tetlow (2022) Brexit, uncertainty, and migration decisions.

Baláž, V., A. M. Williams and E. Fifeková (2014) Migration decision making as complex choice: Eliciting decision weights under conditions of imperfect and complex information through experimental methods.

Basile, R., F. Licari, C. Reynaud and E. Tucci (2022) Brexit and migration diversion : Evidence from italy.

Beine, M. A. R., M. Bierlaire and F. Docquier (2022) New york, abu dhabi, london or stay at home? using a cross-nested logit model to identify complex substitution patterns in migration, *SSRN*, March 2022. Available at SSRN: `https://ssrn.com/abstract=4092328` or `http://dx.doi.org/10.2139/ssrn.4092328`.

Belot, M. V. K. and T. J. Hatton (2012) Immigrant selection in the oecd.

Bierlaire, M. (2003) BIOGEME: A free package for the estimation of discrete choice models., paper presented at the *3rd Swiss Transportation Research Conference*, Ascona, Switzerland.

Bierlaire, M. (2008) *An Introduction to BIOGEME Version 1.6*.

Borjas, G. J. (1994) The economics of immigration, *Journal of Economic Literature*, **32** (4) 1667–1717.

Clifton-Sprigg, J., I. Homburg, J. James and S. Vujic (2021) A bad break-up? assessing the effects of the 2016 brexit referendum on migration, *IZA Discussion Paper*, (16468). Available at SSRN: `https://ssrn.com/abstract=4580845` or `http://dx.doi.org/10.2139/ssrn.4580845`.

Czaika, M. (2012) Migration in times of uncertainty: On the role of economic prospects, *Working Paper*, **52**, International Migration Institute, University of Oxford, Oxford.

Czaika, M. and C. Reinprecht (2022) Migration drivers: why do people migrate, in *Introduction to Migration Studies: An Interactive Guide to the Literatures on Migration and Diversity*, 49–82, Springer International Publishing, June 2022.

Di Iasio, V. and J. Wahba (2023) Expecting brexit and uk migration: Should i go?, *European Economic Review.*

Jentjens, S. (2021) Je ne parle pas français—so what? the impact of language on skilled german migrant women's employment in france, **21** (1).

Mahroum, S. (2008) Europe and the immigration of highly skilled labour.

A Appendix - Data

A.1 Variables

Table 3: Description of Variables

Variable	**Source**	**Type**
Age	GWP	Numeric
Individual income	GWP and processing	Numeric
Education	GWP	3 levels
Gender	GWP	2 levels
Language proximity	CEPII	Numeric
Population	United Nations	Numeric
Diaspora	United Nations	Numeric
GDP	World Bank	Numeric
Distance	Computed	Numeric
Contiguity	Added manually	Dummy
OECD	Added manually	Dummy
English speaking	Added manually	Dummy
European Union	Added manually	Dummy
Single Market	Added manually	Dummy

A.2 Descriptive statistics

Table 4: Share of migration intentions by country

Country Name	**Share of migration intentions (%)**
Germany	12.2
United Kingdom	10.4
United States of America	9.5
Australia	6.6
Spain	6.5
Canada	4.9
Switzerland	4.7
France	4.5
Italy	3.9
Austria	3.8
Sweden	3.5
Norway	3.2
Netherlands	2.4
Denmark	1.6
Ireland	1.5

Table 5: Absolute diaspora in the UK - World Top 15

Country Name	**Absolute diaspora**
India	718853
Poland	626612
Pakistan	477379
Ireland	404995
Germany	293791
Bangladesh	209194
South Africa	207866
Romania	195311
United States	178160
China	177461
Nigeria	170529
Italy	158151
France	140606
Jamaica	139227
Kenya	135593

Table 6: Absolute diaspora in the UK - European Union

Country Name	**Absolute diaspora**
Poland	626612
Ireland	404995
Germany	293791
Romania	195311
Italy	158151
France	140606
Lithuania	130288
Portugal	114927
Spain	101041
Latvia	62973
Netherlands	61771
Bulgaria	54918
Slovakia	53173
Malta	28354
Sweden	27333
Belgium	25390
Denmark	23078
Austria	19710
Finland	14842
Croatia	7281
Slovenia	2592
Luxembourg	2072