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USING CATEGORICAL DATA ANALYSIS TO EVALUATE THE INFLUX OF JOB SEEKERS IN EU15/UK DURING THE CORONAVIRUS PANDEMIC

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ABSTRACT

Numerous articles have been written about the migration of job seekers, and the majority of them have focused on the main causes of high job demands or job loss, which include intense competition, modern skill-biased, technological advancements, and excessive pressure from the economic recession brought on by the coronavirus pandemic. Economists, statisticians, the media, and policymakers undoubtedly continue to place a great deal of importance on evaluating the influx of job seekers; however, a transition from economic theories to economic analysis is necessary to comprehend how the economy functions. The purpose of this study is to draw attention to statistical problems with the influx of job seekers during the coronavirus pandemic in 15 EU nations, including the UK. As a substitute for form methods, the association model will be taken into consideration. To determine the proportion of the data that each model covers, the analysis of association (ANOAS) table is provided. The Column Effects Association Model (C) has the best fit of all the models because it covers 88% of the total data, according to an estimation made to determine which model was acceptable and best fit.

KEYWORDS: Association model, Log-linear and non-linear models, influx of jobseekers, COVID-19 and EU15/UK

1. INTRODUCTION

Following the World Health Organization's (WHO) December 2019 report of the first coronavirus (COVID-19) case, a Public Health Emergency of International Concern was subsequently declared. Statistically, the impact of coronavirus is being felt right across the EU and UK. The spread of COVID-19 and the actions taken by governments had a great impacts on economic, health and social inequalities, and will continue to do so for many years to come. Consequently, the demand for people to be thinking much more and acting flexibly has never been greater than now. As the world we live and work is changing at a rapid pace, public budgets are under more and more strain as a result of the government's responses to the economic crisis, which were intended to stabilise financial markets, preserve jobs, and lessen the effects of unemployment. Tackling major socio-economic challenges within the EU/UK that have surfaced during these difficult times are key insights and opportunities why governments have adopted a strict budgetary austerity policy. Recent developments in the EU/UK, such as wage and employment moderation and, in certain cases, even reductions in public sector wages, salaries, and employment, reflect the reformation needs of the majority of governments.

1.1. EU Background and Brexit

Following Brexit, the EU27 comprises of Belgium, Bulgaria, Czech Republic, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Croatia, Malta, the Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, and Sweden. Prior to Brexit, the EU15 consisted of Belgium, Denmark, Germany, France, Greece, Ireland, Spain, Italy, Luxembourg, the Netherlands, Austria, Portugal, Finland, Sweden, and the United Kingdom. (Eurostat, 2022).

The United Kingdom formally left the European Union on January 31, 2020, a move known as Brexit (British exit). The United Kingdom is the only sovereign nation to have left the European Union, having joined on January 1, 1973. Relevant EU law is retained as domestic law by the European Union Withdrawal Act 2018, which the UK may amend or repeal (Referendum 2016). Eurosceptic organisations had been criticizing the EU and its predecessors during the time that Britain was a member. In a referendum on continued EU membership held in 1975 by the pro-EU government of former Labour Prime Minister Harold Wilson, 67.2% of voters voted to remain in the union. No more referendums were held on the matter, despite the growing political opposition to further European integration aimed at "ever closer union" between 1975 and 2016, particularly from Margaret Thatcher in the late 1980s and 1990s and Conservative Party factions in the 2000s. (Brexit and the Falkland Islands, 2019).

1.2. Growing pressure for a referendum

As a result of much pressure from Eurosceptics in the Conservative Party, the former British Prime Minister David Cameron was induced to take the pledge of a referendum on British membership of the EU if his government is re-elected. Following the general election in 2015, which produced a small but unexpected overall majority for the governing Conservative Party, the promised referendum on whether to continue EU membership was finally held on 23 June 2016. Unarguably, notable supporters of the ‘’Remain Campaign’’ included then-Prime Ministers David Cameron, Theresa May, Liz Truss, John Major, Tony Blair, and Gordon Brown; while notable supporters of the ‘’Leave Campaign’’ included former Prime Ministers Boris Johnson and Rishi Sunak.

All regions of England and Wales (with the exception of London) voted in favour of Brexit (Leave), while Scotland and Northern Ireland voted against (Remain), giving the exit from the European Union a 51.9% vote. As a result, Cameron abruptly resigned, and Theresa May, the Home Secretary at the time, took over. Four years were spent negotiating terms of departure and future relations with the EU.

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

However, this was finished during this time under a Conservative Party government led by Boris Johnson.

Two snap elections were held in 2017 and 2019 as a result of the politically difficult and deeply polarising withdrawal negotiation process in the UK. The UK Parliament overwhelmingly rejected the deal, which created a great deal of uncertainty and resulted in the withdrawal date being postponed in order to prevent a no-deal Brexit. Following the passage of a withdrawal agreement by Parliament, the UK finally exited the EU on January 31, 2020. However, during an eleven-month transition period, it remained a member of many EU institutions, such as the customs union and single market, to ensure smooth trade until all post-Brexit details were finalised and put into effect. Within days of the transition period's planned conclusion, trade deal negotiations resumed, and on December 30, 2020, the EU-UK Trade and Cooperation Agreement (TAC) was signed. For all products and services that meet the relevant rules of origin, TAC offers zero tariffs and zero quotas. In the majority of industries, including digital trade, intellectual property, public procurement, aviation and road transportation, energy, fisheries, social security coordination, law enforcement and judicial cooperation in criminal matters, thematic cooperation, and participation in Union programs, it permits EU investors to set up and freely operate their businesses in the United Kingdom. It is supported by clauses that guarantee fair competition and observance of fundamental rights. The cooperation agreement, which was in effect from January 1, 2021, until May 1, 2021, is a factor in determining the consequences of Brexit. (Reuters, 2016).

Table 1. Referendum result

2016 June 23 referendum on UK membership in the European Union
Is it better for the United Kingdom to stay in the European Union or to leave?
Votes for Choice %
Withdraw from the European Union: 17,410,742 (51.89%)
Continue to be a European Union member: 16,141,241 (48.11%)
Votes that are valid: 33,551,983 (99.92%)
Blank or invalid votes: 25,359 (0.08)
Total votes 33,577,342, (100.00)
Turnout/registered voters: 46,500,001 (72.21)

Source: (UK National Electoral Commission, 2019)

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

1.2. Economic Performance

Numerous elements influence a country's economic performance, such as its natural and human resources, capital stock (buildings and machinery), technology, and the individual and collective economic decisions made by its citizens. The government's macroeconomic policies are another crucial element influencing economic performance (Andrew et al., 2016). There are significant variations in the average per capita income throughout the European Union. According to average yearly per capita income, the wealthiest residents are found in the heart of London (€78.000/inhabitant), Luxembourg (€62.500/inhabitant), and Brussels (€52.500/inhabitant); the poorest are found in the northern Romanian provinces (€6.900/inhabitant) and the southern Bulgarian provinces (€6.900-7.200/inhabitant) (Nwaubani et al., 2019).

2. Statistical data and results

The Organisation for Economic Co-operation and Development (OECD) and Eurostat provided the data used in this study, which was computed annually. The influx of job seekers in the UK and EU15 during the coronavirus pandemic is the subject of the introduction and processing of observations (data).

Table 2. Total influx of jobseekers in the EU/UK during Covid19

Geo / Time	Belgium	Denmark	Germany	Greece	Spain	France	Ireland	Italy	Luxemburg	Netherlands	Austria	Portugal	Finland	Sweden	UK
2011	86	93	834	675	1114	1183	244	1522	5	223	201	689	146	93	400
2012	84	90	792	645	1102	1150	232	1463	5	221	197	675	129	90	391
2013	80	88	762	624	1105	1118	232	1397	5	228	189	639	125	88	384
2014	80	86	740	605	1117	1089	214	1356	5	229	184	603	122	85	380
2015	77	82	727	599	1160	1066	209	1297	5	224	180	567	113	81	374
2016	76	78	715	594	1113	1045	192	1222	5	222	179	532	103	77	361
2017	75	76	685	577	1059	1025	172	1197	4	220	172	531	94	77	334
2018	71	77	659	561	1054	1006	167	1199	4	211	168	520	92	76	329
2019	**70**	**72**	**632**	**546**	**1004**	**988**	**158**	**1176**	**4**	**209**	**166**	**511**	**89**	**75**	**314**
2020	**73**	**70**	**610**	**532**	**957**	**971**	**158**	**1138**	**4**	**204**	**163**	**512**	**106**	**74**	**302**
2021	**72**	**68**	**592**	**519**	**938**	**953**	**158**	**1128**	**4**	**200**	**161**	**508**	**103**	**73**	**296**

Source: OECD Employment rate by age group (indicator/Outlook): Labour market statistics

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

The outcomes of data regarding the influx of jobseekers in the EU15/UK during the coronavirus pandemic from 2019–2021, was showcased by implementing the Categorical Data Analysis program (CDAS). The values of the models that are being estimated are shown below. The Likelihood-Ratio Chi-Square G^2 probability ratio and X^2 (Pearson) Chi-Square are the statistics used to compare the association (correlation) of the different models (Clogg, C.C.2000). In addition, the program yields the outcomes shown in table 3 below.

Table 3. Results

Models	X^2 (Pearson) Chi-Square	Likelihood-Ratio Chi-Square G^2	Degreesof Freedom	Index of Dissimilarity	Maximum Deviation
O	87.96704	88.39701	140	0 .01291	0.00000000
U	84.15592	84.58799	139	0.01269	0.00007874
R	77.77402	78.10032	130	0.01211	0.00007628
C	43.05353	42.99297	126	0.00875	0.00001530
R+C	36.56456	36.49701	117	0.00810	0.00007920
RC	23.99647	23.94764	117	0.00645	0.00098955

2.1. Association Model

This study applied the methodology by taking into consideration six of the most popular association models of the categorical data analysis system. These are:

(1) The model of Independence or null association model which is also symbolized by (O) and holds that there is no relationship between the variables. This is the log-linear model: Where log represents the natural logarithm, Fij represents the expected frequencies under the independence model, $\lambda A(i)$ represents the row main effect, and $\lambda B(j)$ represents the column main effect, $\log(F_{ij}) = \lambda+\lambda A(i)+\lambda B(j)$ (Diewert and Erwin, 2007).

(2) The log-linear representation of the Uniform association model, denoted by (U), is $\log(F_{ij}) =\lambda+\lambda A(i)+ \lambda B(j)+\varphi\chi_i y_j$, where φ is a single interaction parameter and χ_i, y_j are the scores for the row and column variables ($i =1,\ldots,I$, $j =1,\ldots,J$) respectively.

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

(3) Log (F_{ij}) = λ+λA(i)+λB(j)+φμIyj is the linear-by-linear interaction-based row effects model (R) where yj are fixed scores for the column variable (j = 1,…, J) and μI are unknown scores for the row variable (i =1,…, I) (Goodman, 1979a).

(4) With a change in subscripts, the column effects model (C) is identical to the R model: Log (F_{ij}) = λ+λA(i)+λB(j)+φνjxI, where νj are unknown scores for the column variable (j =1,…,J) and xI are fixed scores for the row variable (j =1,…,I).

(5) The R+C model is the one that permits both row and column effects in additive form (Goodman, 1979b). The above model's log-frequency variant is: log(F_{ij}) = $\lambda+\lambda_{A(i)}+$ $\lambda_{B(j)}+$ $\sum_{\kappa=1}^{I-1}\beta_\kappa y_j Z_{A(\kappa)} + \sum_{\kappa=1}^{J-1}\gamma_\kappa \chi_i Z_{B(\kappa)}$, where the variables (dummy variables) for the row and column levels are indicated by $Z_{A(i)}$, $Z_{B(j)}$ respectively, and χ_i, y_j, which are the scores (as previously defined).

(6) The R*C model, also known as model II, has multiplicative effects on the local odds ratios rather than additive row and column effects (Goodman, 1981a). Log (F_{ij}) = $\lambda+\lambda_{A(i)}+\lambda_{B(j)}+\varphi\mu_I\nu_j$ is the log-multiplicative model, in which the row score parameters μI and column score parameters νj are estimated from the data but not known.

Moreover, the goal is to identify or determine which of the six models being studied fits the data the best. Because of this, a consideration will be given to the Index of Dissimilarity (L2), which indicates that the lower the number, the better our model will fit the data in our investigation. With the aid of the statistical program for categorical data analysis, the six association models mentioned above will be evaluated (Clogg, 2000). Additionally, the index of dissimilarity will also be used, which is equivalent to:

$$D = \sum_{ij}\left| f_{ij}/n - F_{ij}/n \right| / 2$$ …………………………………..………………………. *Equation (1)*

Where:

f_{ij} are the observed frequencies, and

F_{ij} are the expected frequencies (under the model)

Furthermore, as the table below illustrates, we have the following outcomes:

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

Table 4. Index of Dissimilarity

Model of Dissimilarity Index (D)
1. Model (O) of Null Association-Independence 0.01291
2. Model of Uniform Association (U) 0.01269
3. Association Model of Row-Effects (R) 0.01211
4. Association Model of Column-Effects (C) 0.00875
5. Association Mode of Row+Columns Effects (R+C) 0.00810
6. Association Model of Row Column Effects (R*C) 0.00645

At first glance, table 4 above appears to show that the Row Column Effects of the Association Model (R*C) had the lowest index of dissimilarity (D = 0.00645) and better adjusted to the percentage of the total data for the influx of jobseekers in the EU15/UK prior to and during the COVID-19 between 2011 and 2021.

Given that table 4 contains models with comparable lower ratios, the Index BIC (Bayesian Information Criterion) was computed to support the model that best fits both countries and years. The Bayesian information criterion, also known as the Schwarz criterion, is a criterion used in statistics to choose a model from a limited number of models; the model with the lowest BIC is the one that is favoured. The likelihood function serves as one of its foundations. Adding parameters during model fitting can increase the likelihood, but this could lead to over-fitting. In order to address this issue, BIC introduces a penalty term for the model's parameter count and provides the optimal solution (Schwarz and Gideon, 2003).

The formula for this calculation is:

$BIC = G^2 - (D.F.) \log (n)$ ……………………………………………………………………………….*Equation (2)*

In this case,

G^2 is the likelihood ratio Chi-squared data

D.F. = the models' degrees of freedom

n is the sample size (72161). Log(n) = Log (72161) = 11.186655

The model with the lowest BIC index is assumed to be the best when comparing several models. Out of the six models, the ones with the lowest Index of Dissimilarity and the closest striking similarity were select. Specifically, the fourth, fifth, and sixth models will be examined afterwards.

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

The following is the calculation:

4th model: BIC = G^2 – (D.F) log(n) = 42.99297 – (126* 11.186655) = -1366.5256

5th model: BIC = G^2 – (D.F) log(n) = 36.49701 – (117* 11.186655) = -1272.3416

6th model: BIC = G^2 – (D.F) log(n) = 23.94764 – (117* 11.186655) = -1284.891

Given that this number (-1366.5256) has the smallest BIC index, it is evident from the calculations above that the fourth model (Column-Effects Association Model (C)) ultimately explains the best fit from the data.

2.1. Examination of the Association Model

To further determine each model's accuracy, quality, or satisfactory fit, the association model is put through a number of tests. The Pearson chi-squared (X^2) distribution and the likelihood-ratio chi-square (G^2) statistics are used for the tests. The Statgraph program is helpful in the case of the X^2 distribution.

First, it is evident that the Independence model (O) has 140 degrees of freedom and the likelihood-ratio chi-square statistic is G^2=88.39701. In addition, 168.853 is the 95% reference point chi-square distribution. Because the X^2 distribution is significantly larger than the likelihood-ratio chi-square statistic G^2, it has an acceptable fit.

The Uniform association model (U) then has 139 degrees of freedom and G^2=84.58799. The chi-square distribution with a 95% reference point is 167.75. Since the X^2 distribution is significantly larger than the likelihood-ratio chi-square statistic G^2, it is evident that this statistic is acceptable and fits the data satisfactorily.

Furthermore, with 130 degrees of freedom, the statistic G^2 for the Row model (R) drastically drops to 78.10032. Also, 157.809 is the 95% reference point chi-square distribution. Because the X^2 distribution is significantly larger than the likelihood-ratio chi-square statistic G^2, the row model is also accepted.

Column model (C) has 126 degrees of freedom and G2=42.99297. Since it can be seen that the X^2 distribution is significantly larger than the likelihood-ratio chi-square statistic G^2, the 95% reference point chi-square distribution is 153.382, indicating an even better fit.

With 117 degrees of freedom, the model R+C's statistics, which account for the effects for both Countries and Years in additive form, are G^2=36.49701. Given that the X^2 distribution is significantly larger than the likelihood-ratio chi-square statistic G^2, the 95% reference point chi-square distribution has an acceptable fit which is 143.483.

Lastly, the model RC, which is log multiplicative but not log-linear, has 117 degrees of freedom and a G^2 statistic of 23.94764. The chi-square distribution with a 95% reference point is 128.98. Unarguably, they have the same degrees of freedom and drastically reduced statistics as the previous model.

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

Additionally, the X^2 distribution is significantly larger than the likelihood-ratio chi-square statistic G^2, indicating that this model fits the data very well. The models with the best fit according to the models' index of dissimilarity are R+C and RC. Therefore, the degree or level of effects on each model should be ascertained but, the Analysis of Association (ANOAS) table should first be created in order to verify this.

2.2. Analysis of Association Table (ANOAS)

The source of the ANOAS table was Goodman, L.A. (1981b). The G^2 (0) statistics for the base (zero) independence model, which calculates the total deviation of the variables are used to divide the X^2 in table 5 below so that it can be used as a two-factor analysis of variance. On the other hand, the proportion of the baseline chi-squared X^2 distribution that affects each of our models could be determined for the phenomenon under study.

Table 5. ANOAS

Models	Likelihood-G^2	Degrees of Freedom	Index of Dissimilarity
O	88.39701	140	**0.01291**
U	84.58799	139	**0.01269**
R	78.10032	130	**0.01211**
C	42.99297	126	**0.00875**
R+C	36.49701	117	**0.00810**
RC	**23.94764**	**117**	**0.00645**

The following model differences are present in the association table analysis below: O-U stands for overall or total effects of the models, U-C for column effects, and C-CR for column effects, which provide residuals of the models and the effects of the column RC.

Table 6. Uniformity Model ANOAS

	G^2 values	D.F.	Percentage
1.General (O-U)	3.80902	1	4%
2. Rows (U-C)	41.59502	13	47%
3. Column-effects which gives the Row-effects (C-RC)	6.49596	9	7%
4. Residual (RC)	36.49701	117	41%
Total (O)	88.39701	140	≈ 100.00%

According to the ANOAS table, the uniform association model (U), as displayed in table 6 above, only accounts for 4% of the baseline chi-squared X2 distribution. The Row model (U-C) accounts for 47% of the total, while the Column-effects which provides the Row-effects (C-RC) only accounts for 7%. Lastly, the RC model explains 41% of the baseline chi-squared value, indicating that the row column

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

effects (Residuals) are strong. Therefore, it could be seen that the variation that is ascribed to null independence has been measured from the RC model at a rate of 41%.

According to data from Eurostat, the corresponding percentage of the influx of jobseekers in the EU15/UK during the coronavirus pandemic in Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland, Sweden, and the United Kingdom had a negative effect on the association of both the countries and the years under study (2011 - 2021). This rate is quite unsatisfactory.

It is clear that the percentage of (88.39701–23.94764) / 88.39701= 0.88% of the data is evaluated by the column effects model (on the local odds ratios in a multiplicative way), thus, giving it a satisfactory fit and acceptable due to better adjustment as was found earlier in this study, i.e. the value of the Pearson chi-squared X2 distribution for the 95% reference point are much larger for the model (RC).

3. Evaluation of the models

Table 7. Evaluation of the best model - column-effects model (C)

Years	Countries	Data	Value of (0) Model (f_{ij}^{1})	Value of (C) Model (F_{ij}^{2})
ROW	COLUMN	DATA	OBSERVED	EXPECTED
1	1	0.17544	0.17562	0.17431
1	2	0.18292	0.18309	0.18119
1	3	1.61057	1.61174	1.59465
1	4	1.34636	1.34713	1.33625
1	5	2.43684	2.43782	2.42221
1	6	2.41003	2.41058	2.39360
1	7	0.44401	0.44403	0.43634
1	8	2.92991	2.92953	2.90266
1	9	0.01039	0.01039	0.01030
1	10	0.49701	0.49676	0.49440
1	11	0.40742	0.40714	0.40452
1	12	1.30687	1.30570	1.29335
1	13	0.25402	0.25374	0.25079
1	14	0.18480	0.18455	0.18336

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

1	15	0.80341	0.80219	0.79571

From table 7 above, it could be seen that the values (prices) of the Column-effects model (C) fully fitted to the data under study.

f_{ij}^1: Expected frequencies of the independence model

F_{ij}^2: Expected frequencies of the model C

4. The Column-effects (C) Association Model's logarithms

Table 8. Column-effects Association Model (C)

Belgium: $\hat{\tau}_1 = \ln(0.98543) = -0.01468$	**Denmark:** $\hat{\tau}_2 = \ln(0.97361) = -0.02674$
Germany: $\hat{\tau}_3 = \ln(0.97243) = -0.02796$	**Greece**: $\hat{\tau}_4 = \ln(0.98061) = -0.01958$
Spain: $\hat{\tau}_5 = \ln(0.98785) = -0.01222$	**France:** $\hat{\tau}_6 = \ln(0.98364) = -0.0165$
Ireland: $\hat{\tau}_7 = \ln(0.9551) = -0.04594$	**Italy:** $\hat{\tau}_8 = \ln(0.97423) = -0.02611$
Luxembourg: $\hat{\tau}_9 = \ln(0.97505) = -0.02527$	**Netherlands**: $\hat{\tau}_{10} = \ln(0.99306) = -0.00696$
Austria: $\hat{\tau}_{11} = \ln(0.98221) = -0.01795$	**Portugal**: $\hat{\tau}_{12} = \ln(0.97106) = -0.02937$
Finland: $\hat{\tau}_{13} = \ln(0.96488) = -0.03575$	**Sweden:** $\hat{\tau}_{14} = \ln(0.97965) = -0.02056$
United Kingdom: $\hat{\tau}_{15} = \ln(0.97332) = -0.02704$	

5. COMPARISON

Identifying any variations in the number of job seekers between the UK and the 15 EU member states is the aim of comparison tests.

They are employed to examine how the mean value of certain other variables is impacted by the categorical data. For instance, we compared two Mediterranean countries, i.e. Italy and Spain, it was

International Journal of Education and Social Science Research

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

found out that $\hat{\tau}_8 - \hat{\tau}_5 = 0.00428$, exp (0.01389) = -4.3%. It indicates that Spain had more percentage influx of jobseekers than Italy during the coronavirus pandemic.

Between two Scandinavian nations like Sweden and Finland, the differentiation is $\hat{\tau}_{14} - \hat{\tau}_{13} =$ 0.07687, exp (0.07687) = -2.6%. This means Sweden had lower rate of influx of jobseekers compared to Finland during the coronavirus pandemic.

In the case Greece and Italy $\hat{\tau}_4 - \hat{\tau}_8 = 0.00653$, exp (0.00653) = -5%, the difference in the rate of influx of jobseekers during the coronavirus pandemic in Italy was higher than Greece.

There are differences in the number even among Europe's more developed nations. Specifically, between Luxembourg and Sweden $\hat{\tau}_9 - \hat{\tau}_{14} = 0.01585$, exp (0.01585) = -2.9%, it is clear that Luxembourg had lower rate of influx of jobseekers compared with Sweden during the coronavirus pandemic.

Furthermore, by comparing the Nederlands and Austria, it shows that: $\hat{\tau}_{10} - \hat{\tau}_{11} = 0.01099$, exp (0.01099) = -4.5%. The Nederlands had less influx of jobseekers compared with Austria during the Covid-19 pandemic.

Additionally, the comparison between France and Ireland are: $\hat{\tau}_6 - \hat{\tau}_7 = 0.02944$, exp (0.02944) = -3.5%, this means Ireland had more influx of jobseekers than France during the Covid-19 pandemic.

Comparing Germany with Portugal, there are: $\hat{\tau}_3 - \hat{\tau}_{12} = 0.00141$, exp (0.97106) = -6.6%. The difference in the rate of influx of jobseekers during the coronavirus pandemic in Germany was lower than Portugal.

Lastly, contrasting the rate of job seekers' arrival during the coronavirus in the UK and Denmark during the coronavirus pandemic, it could be seen that $\hat{\tau}_{15} - \hat{\tau}_2 = 0.03322$, exp (0.03322) = -3.4%. It indicates that during the coronavirus pandemic, the UK saw a lower influx of job seekers than Denmark.

6. RESEARCH FINDINGS

(a) Migration

Generally speaking, the United Kingdom has seen higher levels of international migration in recent years than other EU nations.

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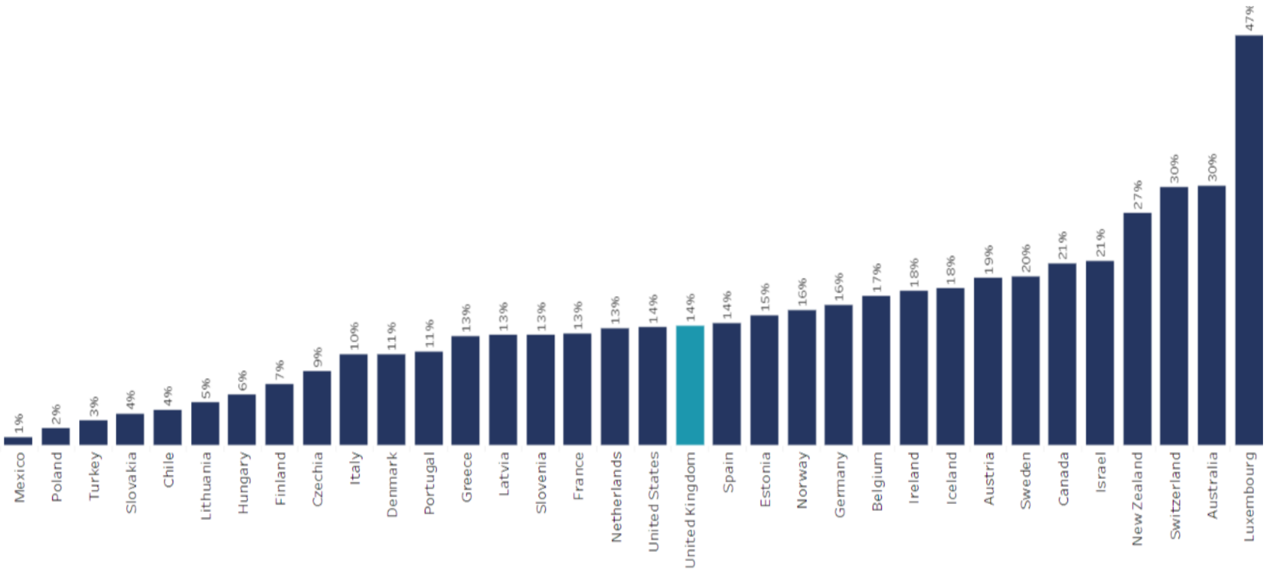

Figure 1……Levels of migration

Source: Migration Observatory analysis of OECD, International Migration Database.

Although the level of migration to a nation may have some economic effects, researchers uphold that the makeup of migration matters more than its quantity. According to MAC (2018), one of the fundamental elements that contributes to the economic impact of migration is whether migrants are employed, as well as the skills and qualifications they contribute.

Following the COVID-19 pandemic, net migration in Europe and the UK in particular is extremely high. This is mainly due to a huge influx of foreign students seeking employment in the healthcare and education sectors. A common way to gauge the total amount of migration in a nation is to look at net migration. The calculation takes into account both individuals entering and departing a country.

Beyond the effects of the COVID-19 pandemic, stricter immigration laws implemented by EU member states after Brexit had a significant impact; however, other EU nations did not experience the same dramatic drop in interest among job seekers as the UK. Company owners have cautioned that a shortage of foreign workers would probably cause the EU and UK's economic recovery from COVID-19 to a growth or even go into recession. This could lead to inflation as a result of having to pay high wages to recruit new employees. Commonwealth nations like Hong Kong, India and Nigeria were leading the increase in jobseeker interest from non-EU countries, but it was not sufficient to counteract the decline in EU interest.

The pandemic caused non-EU net migration to gradually decline in 2020, but by the end of June 2023, the number of non-EU migrants entering the United Kingdom had sharply increased to 768,000.

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According to the Office for National Statistics (2023), there were 968,000 non-EU long-term arrivals in the year ending June 2023 - more than 2.5 times as many as there were in 2019.

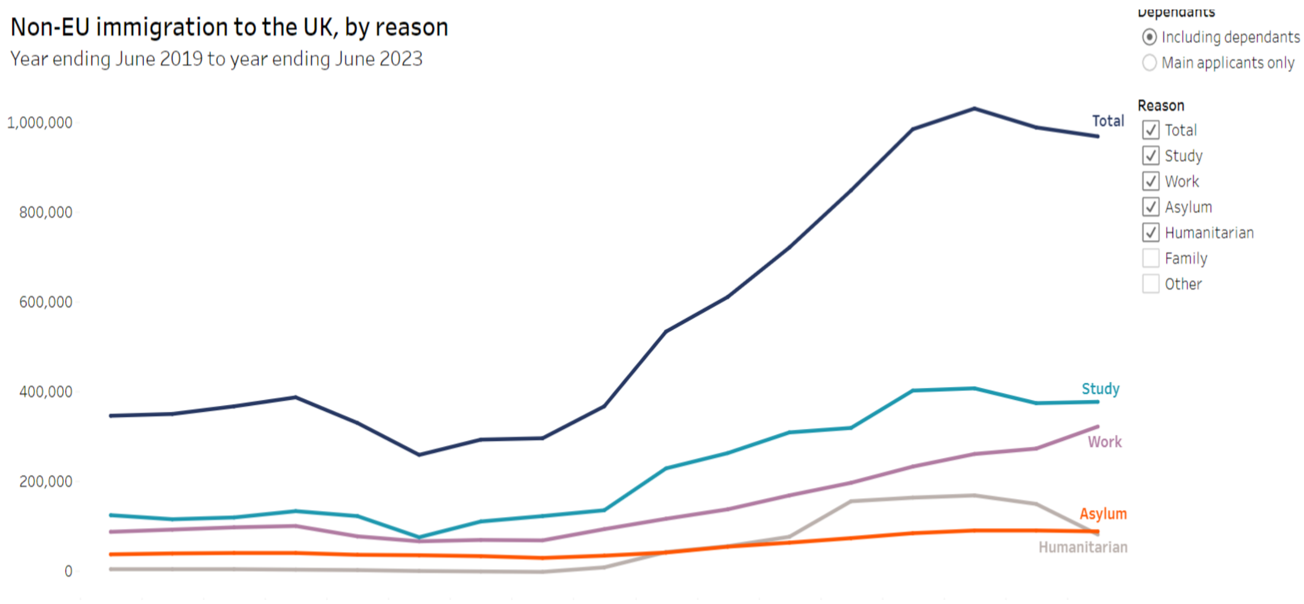

Figure 2. Net migration

Source: ONS, Long-term international migration

(b) Education: Students from other countries. From January 2019 to June 2023, international students and their dependents accounted for 43% of the increase, making them the largest single group responsible for the increase. The UK is a prime example of a strategy for expanding and diversifying the recruitment of international students. It's also possible that the reinstatement of post-Brexit post-study work rights has increased the UK's appeal to international students seeking higher education.

(c) Skilled workers: Those coming for work, especially skilled workers and their dependents, accounted for 37% of the increase in long-term immigration from 2019 to the year ending June 2023. The growth was primarily driven by the health and care sector, which included care workers who were granted access to the immigration system in February 2022. Additionally, there has been an increase in demand for certain workers, like nurses and doctors, who were previously eligible for visas under the previous system.

(d) Share of non-EU students switching to other visa categories within two years of arrival

The future of immigration, particularly in the UK, is unavoidably uncertain because the EU governments have announced a number of measures aimed at reducing migration, especially by family members of international students and care workers. It is reasonable to assume that a large number of international students will eventually depart the United Kingdom. But, given that recent cohorts are

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ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

more likely to be from nations like Nigeria and India, which have historically had higher rates of permanent stay in the UK and Europe, it's possible that jobseekers who travel overseas (using a student visa pattern) will be different and higher.

According to preliminary data from the Office for National Statistics (ONS), recent student cohorts have been staying longer than their predecessors. This is most likely because of the graduate route, as the graph below illustrates. The number of students who will continue to stay in the EU15/UK permanently is uncertain, for as many of them will try to switch over to long-term skilled work visas.

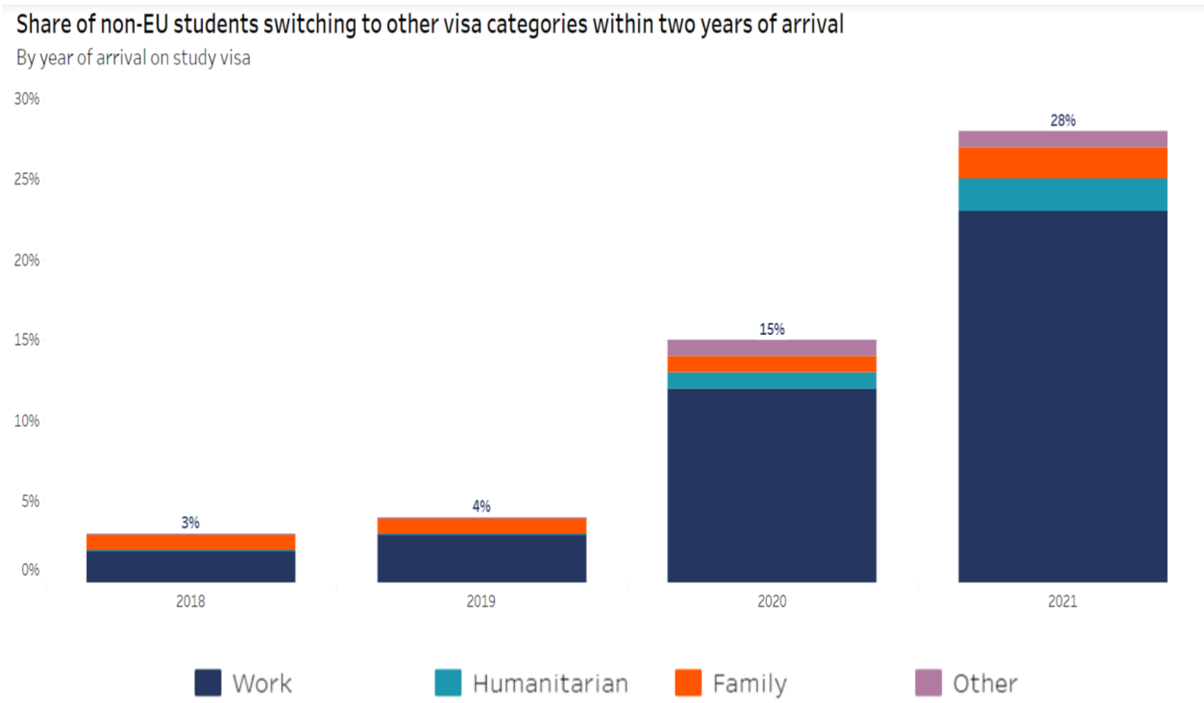

Figure 3. Non-EU Students switching to long-term skilled work visas.

Source: ONS, Underlying data for Long-term international student migration, provisional: 2018 to 2023,

Note: Study visas include those who arrive on study dependant visas. Work dependant visas and graduate visas are included in the work visa category.

7. SUMMARY

Our data evaluation indicates that the association model fits the data well and is acceptable. However, because it covers nearly all of the data, the Column Effects Association Model (C) provided the best fit out of all of them and proved to be much better and fully fitted to the data. More specifically, though, a number of factors might have contributed to the surge of job seekers in EU15/UK during the coronavirus pandemic in 2019–2021. These might be the consequence of:

ISSN 2581-5148

Vol. 7, Issue.6, Nov-Dec 2024, p no. 78-96

1. A country's capital stock (buildings and machinery), technology, human and natural resources, and the economic decisions made by its people, both individually and collectively (Sloman et al., 2018)
2. The policies and procedures of a nation during the coronavirus pandemic.
3. Every nation's level of living standards are determined by how well its workforce is utilised, which is directly correlated with how productive its citizens are (the amount of goods and services a worker can produce for every hour of work). According to Fairbanks and Michael (2000), a nation can thrive if its people are productive and do not engage in many anti-growth behaviours like corruption and a poor work ethic.
4. Experience-weighted measures are likely to access into consideration differences in work characteristics such as working hours, and job search behaviour for example, duration of unemployment between nations and years.
5. A number of additional variables that are challenging to be ascertained in every nation.

8. CONCLUSION

To sum up, it could be observed that Θ which is from the uniform association model is 0.99933, or roughly equal to 1, indicates that the variables are independent of one another. We use the second model's θ (the uniform association model, symbolised by U) to calculate the degree of association (correlation) between these nations and years. In log-linear form, the innate correlation index is exactly equal to $\log(F_{ij}) = \lambda + \lambda_{A(i)} + \lambda_{B(j)} + \varphi_{\chi iyj}$, where φ is a single interaction parameter (Nwaubani and Haritou, 2008 and 2010).

The interaction parameter $\varphi = \log\theta = \log(0.99933)$

$$\Phi = \ln((0.99933) = -0.00067$$

$$|\varphi 1/2| = -\sqrt{0.00067} = 0.02588 \text{ and}$$

$$\varphi 1/2 = -\sqrt{0.02588} = 0.16089$$

An analysis of the 15 member states that made up the EU15 between 1951 and 1995 -Belgium, Germany, France, Italy, Luxemburg, Holland, Denmark, Ireland, the United Kingdom, Greece, Spain, Portugal, Austria, Finland, and Sweden reveals that during the coronavirus pandemic, the rate of job seekers entering the EU15/UK fell by 72% between 2019 and 2021. Temporary employment as a percentage of total employment grew steadily, rising from 2.5 percent to 11.9 percent. In contrast, the EU15/UK saw a sharp decline in the number of hours actually worked each week. Consequently, we could arrive at the conclusion that the EU15/UK countries and the years examined under study had a negative correlation. It will be interesting to know that the definitions of job seeking or job searching are simple and clear as it enhances cross-temporal and cross-spatial phenomenon, while comparability will be captivating and puzzling.

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