REVISITING IMMIGRATION – UNEMPLOYMENT RELATIONSHIP IN EUROPE

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Abstract

Immigration is a controversial and vital issue that has become an acute problem for countries facing cultural and economic difficulties resulting from it, and unemployment is at the forefront of these difficulties. According to theory, migration causes unemployment; thus, the causality relationship between migration and unemployment is empirically examined in our study. For this purpose, we used a new test known as the Panel Fourier Toda-Yamamoto (PFTY) method for the period 1990–2019, which contributes to the existing literature from a methodological standpoint. This test allows investigating multiple structural breaks, cross-section dependence and country heterogeneity. Our first test results show that when we use the Dumitrescu-Hurlin (2012) test, the causal relationship is confirmed neither for any country nor the entire panel. However, when we employ the PFTY test, we reach causality runs from migration to unemployment for the entire panel and four countries.

Keywords: Migration, unemployment, labour market, Panel Granger causality, Fourier function

JEL Classification*:* C23, E24, F22, J61

1. Introduction

In recent years, although the immigrant population has been rising in both developing and developed counties, the latter have been accommodating a higher percentage of the total immigrant population. The main critical reasons that drive migration are numerous and diverse: poverty, warfare, starvation and repression. In addition, population pressures on finite natural resources, wage or income disparities between rich and poor nations, civil war and lack of human rights are other severe reasons to consider (Martin and Widgren, 2002).

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These factors are classified as "push and pull" factors in the literature and are shown in Table 1.

Today's migrant-receiving (host) countries have various migrant-related economic, social and cultural concerns. Currently, Europe is dealing with one of its most difficult crises in terms of migration, and policymakers encounter new societal problems due to this crisis environment (Esposito *et al.,* 2020). Besides the social factors shown in Table 1, economic reasons appear to be the other main push and pull factors. Severe economic conditions such as higher unemployment would come up as a result of evaluating immigrants as cheap labour. Furthermore, besides an increase in unemployment, the rise in governmental expenditures would be inevitable, especially in health and education, due to adaptation and integration policies.

Table 1: Determinants of migration (push and pull factors)

Push factors	**Pull factors**
ECONOMIC	***ECONOMIC***
High taxes	Demand for labour
High unemployment	High wages
Overpopulation	Generous welfare benefits
Poverty/low wages	Good healthcare and education systems
NON-ECONOMIC	Strong economic growth
Discrimination	Technology
Poor healthcare	Low cost of living
War or oppression	***NON-ECONOMIC***
Corruption	Family and friends/networks
Crime	Rights and freedoms
Compulsory military service	Property rights
Natural disasters	Law and order
Famine	Amenities

Source: Bansak *et al.* (2015)

When the course of migration is examined generally, Europe comes first among the regions where the migration phenomenon is seen the most. The reason migrants are intrigued by Europe is the better economic conditions, especially in terms of education and health, which are the keystones to having a decent life for future generations. However, the mutual relation between natives and migrants displays a comprehensive structure on the labour market. Moreover, this structure changes across countries, even in the European Union, since these countries have their very own labour markets, and their migration policies change widely.

The 2015 European Refugee Crisis (so-called Syrian Refugee Crisis) had a significant short- and long-term impact on the migration and migrant interaction policies of EU countries and paved the way for reforms in the EU asylum law. Additionally, the citizenship status of migrants is an essential factor in reaching the labour market and being subject to the same laws as the natives. Therefore, having citizenship in an EU country or a non-EU country can affect primarily the employment situation of migrants and that of natives consequently. Table 2 provides a detailed description of the non-national population for the ten countries in our data.

Table 2: Non-national population, 2019

Host countries	Total host country citizens (1) (thousands)	EU country citizens except host country (2) (thousands)	Non-EU country citizens (3) (thousands)	Stateless (4) (thousands)	Total non-national population (thousands)	(2)/(1) (%)	(3)/(1) (%)
Denmark	580.6	205.7	311.8	8.3	525.8	35.43	53.70
Germany	83,019.2	4,293.9	5,783.9	11.5	10,089.3	5.17	6.97
Ireland	4,904.2	336.7	275	0.3	612	6.87	5.61
Spain	46,937	1,679.9	3,158.7	1.6	4,840.2	3.58	6.73
Italy	59,816.6	1,554	3,700.7	0.8	5,255.5	2.60	6.19
Luxembourg	613.8	240.3	50.8	0.2	291.3	39.15	8.28
Netherlands	17,282.1	520.4	534.8	12.9	1,068.1	3.01	3.09
Finland	5,517.9	95.1	159.7	1.2	256	1.72	2.89
Sweden	10,230.1	302	598.4	19.8	920.2	2.95	5.85
Switzerland	8,544.5	1,370.4	775.5	0.5	2,146.4	16.04	9.08

Source: Authors' calculations

As the migration-unemployment relation has become an essential subject to tackle in the literature, it has been investigated mainly via traditional panel causality tests. According to the majority of the previous findings in the literature, migration does not cause unemployment. However, our study distinguishes itself from them by employing Yilanci and Gorus's (2020) Panel Fourier Toda-Yamamoto (PFTY) causality test since it has some advantages over other standard panel causality tests. The first advantage is that the PFTY test takes the number, location and form of the breaks and cross-section dependence into account. Secondly, it delivers findings for the Fourier Toda-Yamamoto test on an individual basis. Finally, Fourier functions can replicate the nature of the breaks without knowing the size, dates and number of the breaks.

In our study, we employed both the conventional panel test and the panel Fourier test to analyse the causal relationship between migration and unemployment and whether these two tests provide different results. According to our findings, whereas the conventional test is consistent with the other findings in the literature and puts forward no causal relationship, the panel Fourier test shows the opposite of these results, which means that migration does cause unemployment.

The first section of the study conducts a literature review on unemployment and migration. The second section describes the data set and econometric method used in our study. The third section provides descriptive statistical information on the data and theoretical explanations for the tests employed in the study. The fourth section incorporates the study's empirical findings. Finally, the conclusion section analyses the empirical data from an economic perspective.

2. Literature Review

In an early study, Shan (1999) used the Toda-Yamamoto Granger causality test to analyse the causal linkage between migration and unemployment for Australia and New Zealand. The study found no causality relationship between the two variables. Later, Feridun (2005) investigated this relationship in Norway using a Granger causality test and found that migration did not affect unemployment.

Islam (2007) examined this relationship for Canada, and the findings of that study indicate no bi-directional causality relationship and no observed increase in aggregate unemployment as a result of migration in the long run. In another study conducted for Canada by Latif (2015), FMOLS (Fully Modified Ordinary Least Square), DOLS (Dynamic Ordinary Least Square), and a panel VECM (Vector Error Correction Model) were used to assess the influence of permanent migration on unemployment. Due to the results, while a considerable positive effect on unemployment was found in the short run, a negative but insignificant impact on unemployment was detected in the long run.

Chletsos and Roupakias (2012) used cointegration and the Granger causality test for Greece to specify the causality direction between migration, GDP per capita and unemployment. According to their findings, the null hypothesis is rejected, and therefore they concluded that migration does not cause unemployment. Another study that aimed to analyse Greece was conducted by Tzougas (2013), where GDP per capita, migration and unemployment were investigated for 1980–2007 annually using the ARDL (Autoregressive Distributed Lags) cointegration method, and findings similarly put forward no causality relation running from migration to unemployment.

Fromentin (2013) analysed this relationship for France using the VECM method. In the long run, the analysis found no evidence of an increase in aggregate unemployment as a result of migration. The same method was employed by Espinosa and Díaz-Emparanza (2021) for Spain and Feridun (2007) for Sweden. Espinosa and Díaz-Emparanza (2021) analysed the relationship over the period 1981–2016 using cointegration and causality analyses based on VECM and found that migration causes unemployment. In Sweden, Feridun (2007) found that migration did not cause unemployment using ARDL and Granger causality based on the VECM model for the period 1980–2004. Chamunorwa and Mlambo (2014) investigated this relationship for South Africa between 1980 and 2010 using the ordinary least squares method and found a positive relationship between these variables.

The migration and unemployment relationship in OECD (Organisation for Economic Co-Operation and Development) countries has been analysed frequently. Jean and Jiménez (2011) investigated this relationship for 18 different OECD countries from 1984 to 2003. The study results show no significant long-run impact on natives' unemployment. On the other hand, as a result of a study conducted by Boubtane *et al.* (2013a) for 22 OECD countries using panel VAR (vector autoregression) over the period 1987–2009, it was found that migration affects unemployment negatively. In a different study by Boubtane *et al.* (2013b), which was conducted on a broader perspective for 22 OECD countries and in which Kónya's (2006) Granger causality test was used based on bootstrap critical values over the period 1980–2005, results showed that migration does not cause unemployment in these countries.

Esposito *et al.* (2020) investigated the relationship between two variables using a panel error correction model in 15 EU countries for the period 1997–2016. According to their long-run results, migration diminishes unemployment in peripheral countries. Dalinayodov (2021) studied the US on data for 1989–2018, analysed the migration impact on unemployment inflation using the VAR method, and found no causal relationship running from migration to unemployment.

Theoretical studies conducted by Johnson (1980), Borjas (1987), Schmid *et al*. (1994), and Greenwood and Hunt (1995) explained the impact of migration on unemployment with respect to being substitutes or complements in production between immigrants and natives. If they are substitutes, migration may cause unemployment due to the fact that natives do not want to work at a lower level of wages. However, if they are complements in production, migration increases productivity and leads to higher wages and employment opportunities.

3. Data and Methodology

In our analysis, we used the most migrant-receiving European countries (Denmark, Germany, Ireland, Spain, Italy, Luxembourg, the Netherlands, Finland, Sweden and Switzerland)[1]. Our sample is limited to the period 1990–2019 since uninterrupted immigration time series data start from 1990, and latest conclusive data are from 2019. Immigration data are taken from Eurostat, and unemployment data are taken from the World Bank Database.

Table 3 provides the statistical explanations of the data used in the study. The data set of the study consists of 300 observations for the period 1990–2019 and 10 countries. The average unemployment rate of these countries is about 8%.

Table 3: Descriptive statistics of variables

Variables	Obs	Mean	Std. dev.	Min	Max	Immigration	Unemployment
Immigration	300	202,766.1	281,904.8	10,027	1,571,047	1.000	0.0537
Unemployment	300	7.9954	4.668968	1.48	26.09	0.0537	1.000

Source: Authors' calculations

3.1. Empirical methodology

In order to test the causal relationship between two variables, first of all, it is necessary to determine the stationarity level of the variables used in the study. For this purpose, cross-section dependencies of the variables are tested for the appropriate unit root test. We consider cross-section dependency using Breusch-Pagan (1980) LM and Pesaran CD tests. The null hypothesis, which is evaluated by comparing statistical values to critical values, implies that there is no cross-sectional dependence. The statistical results for the Breusch-Pagan (1980) LM test are calculated in the manner specified in Equation (1) (Pesaran, 2004).

1 See https://ec.europa.eu/eurostat/web/main/data/database

$$\lambda_{\text{LM}} = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{ij}^2 , \tag{1}$$

where $\hat{p}_{ij}$ denotes the number of correlations between the residuals of *i* and *j* units, which is determined using Equation (2):

$$\hat{p}_{ij} = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_{it} \hat{\varepsilon}_{jt}}{\left(\sum_{t=1}^{T} \hat{\varepsilon}_{it}\right)^{1/2} \left(\sum_{t=1}^{T} \hat{\varepsilon}_{jt}\right)^{1/2}} , \tag{2}$$

where ε indicates the ordinary least squares (OLS) estimation for u_{it}. The degree of freedom of the LM test statistic is d ($d = N(N - 1)/2$). If N (the unit dimension) is less than T (the time dimension), the Breusch-Pagan LM test can be used. However, consistent results may not be obtained when N is greater than T. In other words, the Pesaran CD test is employed instead of the Breusch-Pagan (1980) LM test in order to produce consistent results when N is greater. The Pesaran CD test is calculated as shown in Equation (3).

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{ij} \right). \tag{3}$$

The Multivariate Augmented Dickey-Fuller (MADF) test was preferred for the stationary analysis since it considers cross-sectional dependency. Additionally, the MADF test yields consistent and unbiased results when T exceeds N. Therefore, the MADF test is preferred in our examination. It takes the correlation into account in a unit root analysis as well as the correlation between units in panel data. By creating a time series and estimating the auxiliary regression in the following manner, one can test for a unit root using the following method:

$$q_t = \mu + \sum j = 1k \rho q_{t-j} + u_t , \tag{4}$$

where k is the number of lags and signifies the estimated white noise residual. The condition $\Sigma j = 1^k p_j < 1$ is essential for stationary analysis. Following are the hypotheses for these test statistics:

$\boldsymbol{H_0}$: $1^k p_j = 1$ unit root process

$\boldsymbol{H_1}$: $1^k p_j < 1$ $i = 1, \ldots, N$.

In this sense, if the test statistic value exceeds the critical values, the null hypothesis of a unit root process is rejected.

3.2 Swamy S panel homogeneity test

In a panel causality test, whether the panel data are homogeneous or heterogeneous is essential for the selection of proper estimation methods. The constant and slope coefficients do not change according to the units in homogeneous panel data, while in heterogeneous panels, they vary according to the units. In this context, the homogeneity of the panel is investigated using the Swamy S test. Swamy (1970) developed a slope homogeneity test for panel data models where N is small relative to T. Moreover, this test allows for cross section heteroskedasticity. The null hypothesis tested in the Swamy S test is as follows:

$$H_0 : \beta_i = \beta \, . \tag{5}$$

The null hypothesis states that the parameters do not change from unit to unit. To test the null hypothesis, the test statistic value is calculated as per Equation (6) shown below (Swamy, 1971) .

$$\overline{S} = X^2_{k(N-1)} = \sum_{i=1}^{N} \left(\hat{\beta}_i - \overline{\beta}^* \right)' \hat{V}_i^{-1} \left(\hat{\beta}_i - \overline{\beta}^* \right) . \tag{6}$$

In the equation above, the expression represents the parameter estimates obtained according to the OLS estimation results, the weighted within-group estimator, and the difference between the variances of the OLS and the within-group estimator. Accordingly, if the calculated test statistic values exceed the critical values, the null hypothesis is rejected and it is concluded that the parameters are not homogeneous and vary from unit to unit. In other words, it is determined that the panel data are heterogeneous.

Granger causality relationships between two variables have been widely tested using VAR models. The Wald test, which has an asymptotical chi-square distribution, is utilized to test the null hypothesis. However, a standard asymptotic theory is not suitable to test the null hypothesis if the variables are integrated or cointegrated. Therefore, it is necessary to use a pre-test to determine the integration and cointegration of variables in VAR models. On the other hand, the Granger causality test may be subject to substantial pre-test bias.

Toda and Yamamoto (1995) proposed a new method to overcome this problem. This technique examines causality independent of variable integration or the presence of a cointegration relationship. The only condition required in this test is the maximum order of integration (dmax).

Dumitrescu and Hurlin (2012) designed an extension version of the Granger (1969) to detect causality in panel data models. The underlying regression is shown as in Equation (7). The test gives efficient and consistent results in heterogeneous panels. In this test, coefficients are allowed to differ across individuals, and the panel must be balanced (Lopez and Weber, 2017).

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_{ik} y_{i,t-k} + \sum_{k=1}^{K} \beta_{ik} x_{i,t-k} + \varepsilon_{i,t} \;\; with\, i = 1, \ldots, N \;\; and\, t = 1, \ldots, T, \tag{7}$$

where x_{it} and y_{it} are the two stationary variables. The null and alternative hypotheses of the DH test are shown in Equations (8) and (9), respectively. K is the lag order.

$$H_0 = \beta_i 1 = \ldots = \beta_i K = 0\,. \tag{8}$$

The null hypothesis, as stated mathematically in Equation (8), denotes the absence of causality for all individuals in the panel. The alternative hypothesis of the DH test, which assumes probability of causality for some individuals but not necessarily for all, is shown in Equation (9).

$$H_1 = \beta_i 1 = \ldots = \beta_i K = 0\,. \tag{9}$$

To test the null hypothesis of the DH test, the Wald test is used as shown in Equation (10):

$$W_{N,T}^{HNC} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T}\,, \tag{10}$$

where $W_{i,T}$ is the individual average Wald statistic for each cross-section unit. However, when T is small, Dumitrescu and Hurlin (2012) proposed the asymptotic standardized statistic (Z_N^{HNC}) and approximated standardized statistic ($Z_N^{\sim HNC}$) since the average Wald statistic does not follow the standard chi-square distribution.

$$Z_N^{HNC} = \frac{\sqrt{N}\left[W_{N,T}^{HNC} - N^{-1}\sum_{i=1}^{N} E\left(W_{i,T}\right)\right]}{\sqrt{N^{-1\sum_{i=1}^{N} Var\left(W_{i,T}\right)}}} \rightarrow N(0,1)\,. \tag{11}$$

The approximated standardized statistic ($Z_N^{\sim HNC}$) is calculated as follow.

$$Z_N^{\sim HNC} = \frac{\sqrt{N}\left[W_{N,T}^{HNC} - N^{-1}\sum_{i=1}^{N} E\left(W_{i,T}\right)\right]}{\sqrt{N^{-1\sum_{i=1}^{N} Var\left(W_{i,T}\right)}}} \rightarrow N(0,1)\,. \tag{12}$$

If the value of Z_N^{HNC}) and $Z_N^{\sim HNC}$) is superiour to the normal critical value, the null hypothesis is rejected. This means that there is a causality relationship between variables. However, structural breaks may affect both the unit root and cointegration results. Moreover, they affect the causality analysis. Enders and Jones (2016) demonstrated that VAR models cause misspecification errors and false rejections of the true null hypothesis without taking structural breaks into account. They also stated that Granger causality tests have a tendency to reject the null hypothesis if the breaks are not taken into account. This evidence emphasizes both the significance of accounting for structural breaks and the importance of how breaks are captured.

Breaks are divided into two categories: additive outliers (AO) and innovational outliers (IO). The difference between these two breaks is that shifts occur immediately in an AO model, whereas they spread over time in an IO model. It is an econometric question how to capture the breaks when the number and form of the breaks are not known in advance (Enders and Jones, 2015). To overcome this problem, the Fourier function has been used recently; it is shown below:

$$d_{it} = a_{i0} + \sum_{k=1}^{n} a_{ik} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} b_{ik} \cos\left(\frac{2\pi kt}{T}\right). \tag{13}$$

where $d_{i,t}$ is smooth function of time, $\pi = 3.1416$; T, and t denote sample size and trend terms, respectively.

There are several advantages to using the Fourier technique. Firstly, the Fourier function may simulate the nature of the breaks even when the size, dates and number of the breaks are not known. Secondly, controlling for breaks turns into determining the appropriate frequency for the model. Thirdly, the variables $a_{i,k}$ and $b_{i,k}$ have a multivariate normal distribution, as shown in Equation (7). As a result, a standard t-test or an F-test can be used to test for non-linearity in the data. The trigonometric frequencies, on the other hand, form an orthogonal basis in the sense that sin ($2\pi kt$ / T) and cos ($2\pi kt$ / T) are orthogonal to each other for all integer values of the constant k. Thus, evaluating whether all of the $a_{i,k}$ or $b_{i,k}$ in Equation (13) jointly equal zero is straightforward since the regressors do not have any correlation with one another. Finally, the Fourier approximation is effective regardless whether the variables are in the IO or AO range of values (Enders and Jones, 2016).

Based on the Toda-Yamamoto causality test, Emirmahmutoglu and Kose (2011) suggested a novel panel causality test that has robust integration and cointegration features of variables. The panel VAR model with two variables is shown in Equations (14) and (15):

$$y_{i,t} = \mu_i + \sum_{j=1}^{k_i + d_{max_i}} A_{11} y_{i,t-j} + \sum_{j=1}^{k_i + d_{max_i}} A_{12} x_{i,t-j} + \mu_{i,t} \tag{14}$$

$$x_{i,t} = \mu_i + \sum_{j=1}^{k_i + d_{max_i}} A_{21} y_{i,t-j} + \sum_{j=1}^{k_i + d_{max_i}} A_{22} x_{i,t-j} + \mu_{i,t}\,, \tag{15}$$

where t and i denote time and units, respectively, d_{max_i} denotes the maximal order of integration and k_i implies the optimal lag order selected by model selection criteria. In order to calculate the test statistics, EK suggests the Fischer test statistics as shown in Equation (16):

$$EK = -\,2\sum_{i=1}^{N} \ln(p_i)\,, \tag{16}$$

where p_i denotes the probability value of the Wald statistic for the i^{th} individual.

Enders and Jones (2016) propose a new causality test in the VAR models with a Fourier function that takes structural breaks into account. Since a small number of low-frequency components can capture structural changes, there is no need to pre-determine the number, dates or forms of the breaks with this test. Nazlıoğlu *et al*. (2016) created a test that added a Fourier function to the Toda-Yamamoto test (FTY). Recently, Yilanci and Gorus (2020) have proposed using a panel version of the FTY to assess the causality relationship. The following two panel VAR models are estimated:

$$y_{i,t} = \mu_i + \sum_{j=1}^{k_i + d_{max_i}} A_{11} y_{i,t-j} + \sum_{j=1}^{k_i + d_{max_i}} A_{12} x_{i,t-j} + A_{13} \sin\left(\frac{2\pi t f_i}{T}\right) + A_{14} \cos\left(\frac{2\pi t f_i}{T}\right) + \mu_{i,t} \quad (17)$$

$$x_{i,t} = \mu_i + \sum_{j=1}^{k_i + d_{max_i}} A_{21} y_{i,t-j} + \sum_{j=1}^{k_i + d_{max_i}} A_{22} x_{i,t-j} + A_{23} \sin\left(\frac{2\pi t f_i}{T}\right) + A_{24} \cos\left(\frac{2\pi t f_i}{T}\right) + \mu_{i,t}, \quad (18)$$

where $\pi = 3.1416$, T and t denote sample size and trend terms, respectively.

Equations (17) and (18) are individually estimated for each country to test the null hypothesis of no causality and the test statistics of FTY causality are obtained as shown below:

$$FTYP = -2\sum_{i=1}^{N} \ln(p_i^*), \quad (19)$$

where p_i^* is the boostrap *p*-values. As mentioned by Yilanci and Gorus (2020), the Fisher test statistic limit distribution may not be valid if a cross-section occurs. Therefore, we follow EK and utilize the critical bootstrap *p*-values to assess causality in cross-sectional panels[2]. There are certain advantages to the FTY test proposed by Yilanci and Gorus (2020). Firstly, the number, location and form of the breaks are determined endogenously. Secondly, FTY test results can be acquired individually. Finally, the units' cross-section dependence is considered.

4. Empirical Results

The empirical results begin with the unit root analysis results. A cross-sectional dependency analysis of the variables is performed to identify the proper unit root test. Table 4 shows the findings of the cross-sectional dependency analysis of the variables. According to the Pesaran CD and Breusch-Pagan test probability values, the null hypothesis of no cross-section dependence is rejected.

2 For more details, see Emirmahmutoglu and Kose (2011).

Table 4: Cross-section dependence results

Variables	Pesaran CD test	Breusch-Pagan
Immigration	14.91 (0.000)	415.59 (0.000)
Unemployment	7.91 (0.000)	239.95 (0.000)

Note: The values in parentheses denote the probability of the tests.
Source: Authors' calculations

As stated before, the MADF test is preferred in this investigation due to both $T > N$ and having cross-section dependency. Table 5 shows the results of the MADF test.

Table 5: Unit root test results

Variables	MADF unit root test	
	Test statistic	**5% critical value**
Unemployment	77.447	27.491
Immigration	36.575	27.491

Source: Authors' calculations

Following the unit root analysis of the variables, it is determined whether the study panel is heterogeneous or homogeneous. Because the tests performed in the study are effective in heterogeneous panels, the panel must be heterogeneous. In this context, the Swamy S test is used to assess the panel heterogeneity. Table 6 displays the test results.

Table 6: Swamy S panel parameter constancy results

Dependent variable: Unemployment	χ^2 test statistic	*p*-value
Immigration	983.36	0.0000

Source: Authors' calculations

As seen in Table 6, the null hypothesis, which asserts that the panel parameters are constant, is rejected. This signifies that the panel parameters are heterogeneous and vary from unit to unit. First, the standard Dumitrescu-Hurlin test is employed in the following step of our investigation, which produces effective results in heterogeneous panels, and appears to be similar to the studies in the literature. Later on, the panel Fourier causality test, a more advanced one, is used in order to double-check our initial results.

Table 7: DH and PFTY test results

Country/Tests	DH test		PFTY test[1]		
	Lags	*p*-value	Test statistic	Frequency	*p*-value
Denmark	8	0.629	3.763	1	0.179
Germany	8	0.649	0.889	3	0.344
Ireland	8	0.439	1.066	1	0.602
Spain	8	0.477	14.155	1	*0.006****
Italy	8	0.702	0.023	2	0.883
Luxembourg	8	0.775	8.408	3	*0.008****
Netherlands	8	0.776	8.597	1	*0.031***
Finland	8	0.969	0.022	1	0.988
Sweden	8	0.538	9.683	1	*0.019***
Switzerland	8	0.455	4.662	1	0.124
Panel	**8**	**0.6343**	**45.306**		**0.001*** **

Note: Lag length in the DH test was selected based on the Akaike Information Criterion (AIC).
Source: Authors' calculation[3]

Table 7 comparatively shows the results of the DH and PFTY tests. The null hypothesis that we tested with both the DH and PFTY tests is that immigration does not cause unemployment for each country and the entire panel. The probability value of each country indicates that the null hypothesis cannot be rejected for any of them, which means immigration does not cause unemployment in these countries. The result is the same for the entire panel. However, when we apply the PFTY test, the results change for some countries and the entire panel. For six countries (Denmark, Germany, Ireland, Italy, Finland, and Switzerland), both the DH and the PFTY tests yield the same results, meaning that the main hypothesis cannot be rejected. However, unlike the DH test, the PFTY test finds that immigration causes unemployment in four countries (Spain, Luxembourg, the Netherlands and Sweden) and in the entire panel.

The impact of immigration on unemployment can be positive or negative, depending on the degree of substitution/complementarity between native and immigrant workers (Esposito *et al.*, 2020). In aging societies such as Germany and Finland, immigration

3 The critical bootstrap values were obtained using the GAUSS codes of the authors who developed the test.

boosts the working-age population and restrains the labour shortages stemming from the aging labour force. In that sense, our results support the complementary role of immigration that does not cause unemployment. In Switzerland, just like Germany and Finland, structural labour shortages accompanied by a high level of economic activity require immigrant workers and could be the reason for not having migrant-related unemployment. In Italy, illegal immigration is a great concern and this can be why immigration does not cause unemployment. Many non-EU immigrants on the labour market are employed in the underground economy and do not have a legal form of work. On the other hand, Ireland and Denmark have different immigration integration strategies which are designed to attract only highly skilled immigrants to change the composition of the immigrant population on the labour market and to make reunification of families harder (Floros and Jørgensen, 2020). Strict work permission rules and related adjustments on the labour market support our findings for these two countries.

On the other hand, in Spain, immigrants are highly supported by natives, which affects the nature of the immigration policies that allow them to have the same rights (Arango, 2013). Together with the generous unemployment benefits provided to unemployed Spaniards, who are not so willing to work in poor working conditions, immigrants take advantage of being supplementary on the labour market, which can end up in increased unemployment. In the Netherlands, the numbers of follow-up migrants[4] are greater than those of worker migrants and generous unemployment benefits provided by the Dutch government pull in low-skilled migrants who mostly have temporary contracts and are likely to create unemployment (Stockmeijer *et al.*, 2020). In Sweden, as the lion share of migrants shifted to non-EU foreigners who are low-skilled and unskilled workers, the labour market structure has changed. Moreover, when unemployment started to be reported separately for natives and other nationalities, it has come to the light that the unemployment rate gap between natives and immigrants has been widening. For this reason, as our test results show that immigration causes unemployment, it might point out the immigrant unemployment, as it reached a critical level (15.5%) in Sweden (OECD, 2020). Luxembourg has an atypical position in that nationals from other EU member states are the vast majority of the foreign population. EU workers can benefit from generous social rights which are already entitled to them regardless of their nationality and residency, while non-EU nationals require a residence permit (Kerschen, 2019). Therefore, as EU-born immigrants are engaged more on the labour market, they are likely to be a substitute for natives and lead to unemployment in line with our PFTY results.

4 Migrants who arrive in the host country via family reunification.

5. Conclusion

This study aimed to investigate the bi-directional causal relationship between immigration and unemployment in ten European countries from 1990 to 2019. For this reason, we used Yilanci and Gorus's (2020) Panel Fourier Toda-Yamamoto (PFTY) causality test as it comes with some advantages compared to other standard panel causality tests. The first advantage is that the PFTY test considers the number, location and form of breaks and cross-section dependence. Secondly, it delivers findings for the Fourier Toda-Yamamoto test on an individual basis.

A two-step study was conducted to determine whether the standard panel test results differentiate from the PFTY causality test results for the same data set. Thereby, we first examined the causal relationship using the Dumitrescu-Hurlin (DH) panel causality test, which revealed that there is no causality relation between immigration and unemployment. However, when we employed the PFTY test, the results indicated the reverse of the DH findings: a causal relationship runs from immigration to unemployment in the entire panel. Moreover, we identified this causal relationship individually in Spain, Luxembourg, the Netherlands and Sweden. Yet, no causal relationship was found in the remaining countries.

Our analysis investigated the impact of migration on unemployment with respect to being substitutes or complements in production between immigrants and natives. If they are substitutes, migration may cause unemployment due to the fact that natives do not want to work at a lower level of wages. However, if they are complements in production, migration increases productivity and leads to higher wages and employment opportunities.

For six of the countries, we found that migration does not cause unemployment; reasons change due to how immigrants are engaged on the labour market. While the majority of the immigrants in Italy are employed illegally, it is the other way around in Denmark and Ireland, such that they have rigid rules to employ migrants. In Germany, Finland and Switzerland, immigration plays a complementary role on the labour market since these countries face labour shortages. For the countries where we found migration does cause unemployment, the common case is providing generous social rights and allowing follow-up migration. These cases are valid for Spain, the Netherlands and Luxembourg, albeit from different standpoints. In Luxembourg, EU-born migrants are the majority of the foreigners and are subject to the same laws as natives, which paves the way for them to be a substitute on the labour market. However, in Sweden, the unemployment of immigrants has reached a critical level of 15.5%, and the unemployment gap between natives and migrants has been widening. Therefore, our results may point out the increasing immigrant unemployment among the unemployed population.

Since immigration does cause unemployment in Spain, Luxembourg, the Netherlands and Sweden, these countries may adopt fiscal policies to mitigate the negative impact of immigration on unemployment and maximize the benefits of migration. Furthermore, since numerous aspects play a role, those aspects can be considered: gender, improving migrant education, human rights discourse, determination of appropriate sectors and subsectors for migrant workers, and tackling illegal immigrants. Therefore, government investment expenditures can be directed to these issues, and as improvements take place, they can consequently serve economic growth, and an adjusted labour market would come up with migrants' contributions to the tax system that could be higher than their individual benefits. Moreover, comprehensive and successful immigrant integration into society would upgrade skills and transfer professional qualifications to current and future generations.

References

Arango, J. (2013). *Exceptional in Europe? Spain's Experience with Immigration and Integration*. Washington, D.C.: Migration Policy Institute. Available at: https://www.migrationpolicy.org/pubs/TCM-Spaincasestudy.pdf

Bansak, C., Simpson, N., Zavodny, M. (2015). *The Economics of Immigration*. Oxford: Routledge. ISBN 9780367416164.

Borjas, G. J. (1987). Immigrants, Minorities, and Labor Market Competition. *Industrial & Labor Relations Review*, 40(3), 382–392, https://doi.org/10.2307/2523494

Boubtane, E., Coulibaly, D., Rault, C. (2013a). Immigration, Growth, and Unemployment: Panel VAR Evidence from OECD Countries. *Labour*, 27(4), 399–420, https://doi.org/10.1111/labr.12017

Boubtane, E., Coulibaly, D., Rault, C. (2013b). Immigration, Unemployment and GDP in the Host Country: Bootstrap Panel Granger Causality Analysis on OECD Countries. *Economic Modelling*, 33, 261–269, https://doi.org/10.1016/j.econmod.2013.04.017

Breusch, T. S., Pagan, A. R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies*, 47(1), 239–253, https://doi.org/10.2307/2297111

Chamunorwa, W., Mlambo, C. (2014). The Unemployment Impact of Immigration in South Africa. *Mediterranean Journal of Social Sciences*, 5(20), 2631–2631, https://doi.org/10.5901/mjss.2014.v5n20p2631

Chletsos, M., Roupakias, S. (2012). *Immigration, Unemployment and Growth: Empirical Evidence from Greece.* MPRA Paper No. 39927. Available at: https://mpra.ub.uni-muenchen.de/39927/

Dalinayodo, V. (2021). *The Impact of Immigration and Inflation of Unemployment in United States of America from 1989 to 2018: a VAR Approach*. Bachelor project. Kuala Lumpur: Tunku Abdul Rahman University College.

Dickey, D. A., Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74(366), 427–431, https://doi.org/10.2307/2286348

Dumitrescu, E.-I., Hurlin, C. (2012). Testing for Granger Non-Causality in Heterogeneous Panels. *Economic Modelling*, 29(4), 1450–1460, https://doi.org/10.1016/j.econmod.2012.02.014

Emirmahmutoglu, F., Kose, N. (2011). Testing for Granger Causality in Heterogeneous Mixed Panels. *Economic Modelling*, 28(3), 870–876, https://doi.org/10.1016/j.econmod.2010.10.018

Enders, W., Jones, P. (2016). Grain Prices, Oil Prices, and Multiple Smooth Breaks in a VAR. *Studies in Nonlinear Dynamics & Econometrics*, *20*(4), 399–419, https://doi.org/10.1515/snde-2014-0101

Espinosa, A. M., Díaz-Emparanza, I. (2021). The Long-term Relationship Between International Labour Migration and Unemployment in Spain. *Journal of International Migration and Integration*, 22(1), 145–166, https://doi.org/10.1007/s12134-019-00716-6

Esposito, P., Collignon, S., Scicchitano, S. (2020). The effect of immigration on unemployment in Europe: Does the core-periphery dualism matter? *Economic Modelling*, 84, 249–258, https://doi.org/10.1016/j.econmod.2019.04.014

Feridun, M. (2005). Investigating the Economic Impact of Immigration on the Host Country: The Case of Norway. *Prague Economic Papers*, 14(4), 350–362, https://doi.org/10.18267/j.pep.270

Feridun, M. (2007). Immigration, Income and Unemployment: An Application of the Bounds Testing Approach to Cointegration. *The Journal of Developing Areas*, 41(1), 37–49, https://doi.org/10.1353/jda.2008.0014

Floros, K., Jørgensen, B. M. (2020). Tracing the future of migrants' labour relations. Experiences of institutionalised migrant precarity in Denmark and Greece. *Political Geography*, 77, 102120, https://doi.org/10.1016/j.polgeo.2019.102120

Fromentin, V. (2013). The Relationship Between Immigration and Unemployment: The Case of France. *Economic Analysis and Policy*, 43(1), 51–66, https://doi.org/10.1016/S0313-5926(13)50003-8

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 37(3), 424–438. https://doi.org/10.2307/1912791

Greenwood, M. J., Hunt, G. L. (1995). Economic Effects of Immigrants on Native and Foreign--Born Workers: Complementarity, Substitutability, and Other Channels of Influence. *Southern Economic Journal*, 61(4), 1076–1097, https://doi.org/10.2307/1060742

Islam, A. (2007). Immigration Unemployment Relationship: The Evidence from Canada. *Australian Economic Papers*, 46(1), 52–66, https://doi.org/10.1111/j.1467-8454.2007.00305.x

Jean, S., Jiménez, M. (2011). The Unemployment Impact of Immigration in OECD Countries. *European Journal of Political Economy*, 27(2), 241–256, https://doi.org/10.1016/j.ejpoleco.2010.11.006

Johnson, G. E. (1980). The Labor Market Effects of Immigration. *ILR Review*, 33(3), 331–341, https://doi.org/10.1177/001979398003300304

Kerschen, N. (2019). Changes in Luxembourg's welfare system (1998–2018): Coalition governments and Europeanisation as major driving forces. In: Blum, S., Kuhlmann, J., Schubert, K. *Routledge Handbook of European Welfare Systems*. 2nd edition, 327–347. London: Routledge. ISBN: 9780429290510.

Kónya, L. (2006). Exports and growth: Granger causality analysis on OECD Countries with a panel data approach. *Economic Modelling*, 23(6), 978–992, https://doi.org/10.1016/j.econmod.2006.04.008

Latif, E. (2015). The Relationship Between Immigration and Unemployment: Panel Data Evidence from Canada. *Economic Modelling*, 50, 162–167, https://doi.org/10.1016/j.econmod.2015.06.013

Lopez, L., Weber, S. (2017). Testing for Granger causality in panel data. *The Stata Journal*, 17(4), 972–984, https://doi.org/10.1177/1536867X1801700412

Martin, P., Widgren, J. (2002). International Migration: Facing the Challenge. *Population Bulletin*, 57(1).

Nazlioglu, S., Gormus, N. A., Soytas, U. (2016). Oil Prices and Real Estate Investment Trusts (REITs): Gradual-Shift Causality and Volatility Transmission Analysis. *Energy Economics*, 60, 168–175, https://doi.org/10.1016/j.eneco.2016.09.009

OECD (2020). *International Migration Outlook 2020*. Paris: OECD. ISBN: 9789264854765, https://doi.org/10.1787/1999124x

Pesaran, M. H. (2004). *General Diagnostic Tests for Cross Section Dependence in Panels* IZA Discussion Paper No. 1240. Available at: https://docs.iza.org/dp1240.pdf

Schmidt, C. M., Stilz, A., Zimmermann, K. F. (1994). Mass Migration, Unions, and Government Intervention. *Journal of Public Economics*, 55(2), 185–201, https://doi.org/10.1016/0047-2727(94)90051-5

Shan, J. (1999). Immigration and Unemployment: New Evidence from Australia and New Zealand. *International Review of Applied Economics*, 13(2), 253–260, https://doi.org/10.1080/026921799101698

Stockmeijer, A., de Beer, P., Dagevos, J. (2020). Explaining Differences in Unemployment Benefit Takeup Between Labour Migrants and Dutch Native Workers. *International Social Security Review,* 73(2), 75–99, https://doi.org/10.1111/issr.12235

Swamy, P. A. V. B. (1970). Efficient Inference in a Random Coefficient Regression Model. *Econometrica: Journal of the Econometric Society*, 311–323, https://doi.org/10.2307/1913012

Toda, H. Y., Yamamoto, T. (1995). Statistical Inference in Vector Autoregressions with Possibly Integrated Processes. *Journal of Econometrics*, 66(1–2), 225–250, https://doi.org/10.1016/0304-4076(94)01616-8

Tzougas, J. (2013). *Immigration, Economic Growth and Unemployment in Greece: An Application of the ARDL Bounds Testing Approach to Cointegration*. Piraeus: Hellenic Statistical Authority, https://doi.org/10.2139/ssrn.2297466

Yilanci, V., Gorus, M. S. (2020). Does Economic Globalization Have Predictive Power for Ecological Footprint in MENA Counties? A Panel Causality Test with a Fourier Function. *Environmental Science and Pollution Research*, 27(32), 40552–40562,