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Immigration, Growth and Unemployment: Panel VAR Evidence From E.U. Countries

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Abstract
Migration is primarily propelled by economic and security considerations. As of 2021, the European Union (EU) housed 23.7 million non-EU citizens, emphasizing the crucial need to evaluate the economic ramifications of migration within the EU. This research seeks to scrutinize the impact of migration on economic development and unemployment across the 27 EU nations from 1990 to 2020, utilizing a PVAR model. The Pesaran CIPS test (2007) was employed for second-generation unit root testing, while cointegration was examined using the ARDL panel model. The ARDL panel model and error correction model were employed to assess causal relationships and their directions. Initial tests indicated that the fixed effects model was the most suitable, and there existed cross-sectional dependency and heterogeneity among EU countries. Furthermore, second-generation unit root tests indicated that the variables were integrated at order I(0) or I(1). The study's findings demonstrate a significant positive correlation between both GDP per capita and the unemployment rate with the net migration rate to EU countries. Causal effects revealed a bidirectional long-term causal relationship between migration and unemployment, as well as a unidirectional long-term causal relationship between growth and migration, and growth and unemployment. Short-term Granger causality indicated a bidirectional causal relationship among all the variables under examination.

Keywords Immigration · Growth · Unemployment · Panel VAR · Panel ARDL · Panel Granger causality test

JEL Classification C33 · E20 · F22 · J61

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Introduction

Migration is the international movement of people to a destination country of which they are not indigenous, in order to settle as permanent residents. The increasing trend of individuals relocating from their residing countries is driven by a variety of factors, predominantly political and economic. The principal catalyst is the impact of war and political pressures, compelling people to search for more secure living environments. Migrants are driven to relocate from their home countries for various reasons, including limited access to local resources, aspirations for economic success, the pursuit of paid employment to enhance their living standards, or a wish to improve their overall quality of life. Poverty serves as a conventional "push factor," while job opportunities act as a pertinent "pull factor." Consequently, the European Union and notably the USA have emerged as major host countries for immigrants seeking such opportunities.

Climate change serves as a catalyst for migration, as prolonged exposure to extreme weather conditions has enduring impacts on individuals' economic well-being, health, and safety. Consequently, it poses a threat to fundamental human rights such as access to adequate food, health, and housing. Additionally, the repercussions of climate change can exacerbate violent conflicts. Developing countries, especially those significantly affected, grapple with the challenges of climate change with limited resources. Consequently, many individuals in these nations are compelled to migrate in an attempt to escape worsening living conditions. Migration, for those particularly affected by the adverse impacts of global warming, becomes a means of adapting to climate change (Federal Ministry for Economic Cooperation and Development 2023).

In the year 2021 alone, 23.7 million individuals were displaced due to extreme weather conditions. However, it is not solely natural disasters like floods that prompt people to abandon their homes. For instance, when agricultural yields diminish due to gradual environmental changes, such as warming, some individuals choose to embark on migration. The factors influencing migration decisions are often intricate and personal, with economic, political, social, family, and demographic considerations taking center stage, further complicated by environmental and climatic influences. The ongoing impact of climate change on migration hinges on the success of efforts to reduce greenhouse gas emissions. This assistance manifests through various adaptation measures integrated into comprehensive climate risk management (Federal Ministry for Economic Cooperation and Development 2023).

The treatment of migrants in host countries, whether by governmental authorities or the native population, is a subject of discourse and criticism regarding the infringement of migrants' human rights. Although 48 states have ratified the UN Convention on the Protection of the Rights of Migrants, significant countries and regions that receive migrants, such as Western Europe, have yet to ratify the convention, despite hosting the majority of internationally laboring migrants.In the late twentieth century, immigration to Europe experienced a notable upswing. Following World War II, Western European nations witnessed a substantial surge in immigration, resulting in a significant immigrant population of both European and non-European origin in many European countries today. In the context of contemporary globalization, migrations to Europe have escalated swiftly. During the 1990s, a considerable proportion of immigrants to Western European states originated from former Eastern bloc countries, notably in Spain, Greece, Germany, Italy, Portugal, and the UK. In 2004, the EU granted its citizens the freedom of movement and residence within the EU, leading to the categorization of non-EU citizens as "migrants."

The European Union's expansions in 2004 and 2007, along with the growth of the EU's internal market and the introduction of freedom of movement for workers to the new Member States in Central and Eastern Europe, transformed the migration dynamics in Europe. These enlargements removed barriers that had previously impeded East–West migration flows during the Cold War, establishing an internal labor market for a population of approximately half a billion people. This market spanned across Member States with varying levels of economic development, wages, unemployment rates, and labor market institutions. The reception of these new migratory patterns in host countries was not uniformly positive. Migration from Central and Eastern Europe became a focal point in discussions surrounding the UK's decision to exit the European Union, commonly known as "Brexit" (Kahanec and Pytlikova 2017).

Concerning economic ramifications, research indicates that migration yields benefits for both destination and origin countries. Improved development can be observed when the qualifications of migrants surpass those of the local population (Koczan et al., 2021). Additionally, studies suggest that eliminating barriers to migration can enhance global GDP, diminish poverty, and address demographic challenges, particularly in the aging population of the European Union. The freedom of individuals to move and work across European borders has positively impacted the average European's situation without adversely affecting the well-being of low-skilled Europeans. The primary factors influencing the developmental impact of migration are the age and qualification structure of migrants (Dustmann & Preston, 2019). Migrants contribute extra labor to the host country and enhance its economy by offering their services at lower wages and specializing in production. This is likely to result in a net increase in GDP, even if a portion of the production income is received by immigrants. (Aslan & Altinöz, 2020). Conversely, the occurrence of sustained economic growth is linked to the educational attainment of migrants, serving as a factor that contributes to innovation (Hunt & Gauthier-Loiselle, 2010).

The tendency for migration to result in an excess of labor in the host country exerts downward pressure on labor prices. Reduced wages, in turn, spur an upswing in labor demand. One potential outcome is a rise in unemployment and job displacement among native workers. The influence of migrants on both the labor market and overall output indirectly influences the overall price level, with surplus labor leading to cost reductions (Aslan & Altinöz, 2020).

Capital mobility stands out as another crucial determinant of growth, especially with the surge in capital inflows from overseas, facilitated by foreign direct investment. According to economic theory, if the expansion of the labor supply results in a proportional decline in wages, it is anticipated that the cost of capital will rise, subsequently attracting more foreign investment (Samuelson, 1948). Under the condition of high price elasticity of the factors, all else being equal, this phenomenon could potentially drive per capita growth.

The matter of refugee migration has been a central focus of European policy for the past 5 years. Despite the notable rise in migration rates and the substantial influx of migrants into Southeast Europe since 2015, the reactions across the continent have not been consistent. Numerous inquiries have arisen regarding the political and economic repercussions stemming from the recent upswing in refugee migration to Europe. Acknowledging the necessity for a comprehensive examination of migration, numerous scholars have conducted and published studies examining the social, political, demographic, economic, and fiscal impacts of refugee migration in recent years (Manthei, 2021).

Oil market shocks and the financial and economic crisis of 2008 hit migrants hard in most countries of the world (Dagher & Hasanov, 2023). The impact of the economic crisis on unemployment has been more notable for migrants than for native-born individuals in the majority of EU countries. Even more concerning is that the global crisis significantly elevated the risk of marginalization for migrants, particularly those in vulnerable workforce segments such as the low-skilled and young individuals. Between 2008 and 2011, there was a sharp increase in the number of unemployed young migrants. Additionally, new migrants found themselves in part-time and temporary employment more frequently than their adult counterparts in many EU countries. These trends underscore the urgency of implementing effective policies to safeguard the most vulnerable. There is an increased need to prioritize the promotion of education and skill development among young migrants, starting as early as possible.

The global pandemic has had an unprecedented impact on the lives of individuals around the world (Guru et al., 2023). Due to measures implemented by EU governments aimed at "flattening the curve" of infections, the COVID-19 pandemic has significantly impacted mobility and migration. To contain the virus, various travel restrictions have been implemented, including the prohibition of entry for residents from other countries, and some nations have completely closed their borders. In certain countries, labor migration has been temporarily halted, while in others, the processing of migration and assistance to asylum seekers has experienced delays (Guru et al., 2023). Following a decade of consistent progress, the pandemic has adversely affected migrant employment in the EU, reversing the trend of diminishing employment disparities between immigrants and the native-born.

The conflict in Ukraine marks the third asymmetric shock within the last two decades for the EU, following the 2008 financial and economic crisis and the COVID-19 pandemic. An asymmetric shock refers to an abrupt shift in economic conditions that disproportionately affects certain EU countries. The war in Ukraine particularly impacts neighboring countries significantly, primarily due to the influx of refugees and their heightened reliance on Russian gas. The humanitarian crisis in Ukraine is sending shockwaves throughout the European Union. With approximately 5 million refugees already displaced due to the ongoing conflict, this marks the largest exodus in the continent since World War II. Escalating energy and food costs are significantly diminishing household consumption, while economic uncertainty is expected to curb investment and growth projections. The main purpose of the current study is to investigate the effect of migration on growth, and unemployment, in the 27 EU countries over the period 1990–2020. This paper contributes to bibliography on the following ways:

- Utilizing the PVAR method, this study treats all variables as endogenous, employing a panel data technique that accommodates unobserved individual heterogeneity.
- For the cointegration test, the autoregressive distributed lag model (ARDL) is employed, following the proposals of Pesaran and Shin (1999) and Pesaran et al. (2001).
- The asymptotic characteristics of these panel models differ from traditional panels assuming homogeneous slope coefficients in each group.
- Additionally, a dynamic error correction model (ECM) can be derived from the ARDL method through a simple linear transformation (Banerjee et al., 1992). This ECM integrates dynamic short-run dynamics with long-run balance without sacrificing any long-run information
- The estimation procedures utilize the mean group (MG) and the pooled mean group (PMG) estimators as solutions to counteract heterogeneity bias arising from distinct slopes on dynamic panel coefficients (Pesaran et al., 1999).
- Causality testing is executed with an ARDL error correction model, following the recommendation of Mawejje and Odhiambo (2021).

To achieve this objective, the study employs the PVAR model and econometric techniques that consider cross-sectional dependence and heterogeneity among the 27 EU countries, utilizing the econometric software packages Stata 14.0 and Eviews 12.0. The research methodology is grounded in panel cointegration tests, specifically the ARDL approach, and panel error correction-based Granger causality tests. Additionally, two estimation procedures, namely the mean group (MG) and the pooled mean group (PMG), are implemented to address the heterogeneity bias arising from diverse slopes in dynamic panel coefficients. These approaches, recommended by Pesaran Shin and Smith (1999), accommodate a higher level of parameter heterogeneity in growth regressions. The remainder of this paper is structured as follows: "Literature Review" provides a literature review and outlines the main contributions. Data and variables are detailed in "Data." The methodology is expounded upon in "Methodology." Preliminary tests are discussed in "Preliminary Tests," and empirical results are presented in "Empirical Results." "Discussion" delves into the discussion, while "Policy Suggestions" covers policy suggestions. Lastly, "Conclusions and Policy Implications" concludes with a summary and highlights policy implications.

Literature Review

Since the early 1980s, numerous researchers have addressed the influence of immigration on the labor market and the economic advancement of the host country (Greenwood & Hunt, 1995; Schmidt et al., 1994). Theoretical studies indicate that the impact of immigrants on employment hinges on whether immigrants and locals function as substitutes or complements in production. If the work of immigrants and locals is viewed as a substitute, the introduction of immigrants is expected to lower wages while increasing employment. On the contrary, if the work of immigrants and locals is complementary to production, the presence of immigrants will enhance the productivity and wages of local residents (Boubtane et al., 2013). Other theoretical papers used Solow's augmented by human capital development model to investigate the impact of variables on development. Their work concludes that the impact of migrants on economic development depends on migrants' skills and education (Barro & Sala-i-Martin, 1995; Dolado et al., 1994).

Borjas (1995) contends that immigrants contribute to the expansion of the labor supply in host countries, leading to a new internal equilibrium characterized by a reduced national wage, heightened employment, and increased national income. In a paper by Hanson (2008), the effects of migration on well-being are examined under the assumption of worker heterogeneity in terms of skills and perfect substitutability between native and foreign-born workers. Numerous empirical studies suggest that migration flows do not diminish the labor market opportunities for local residents. As an example, Damette and Fromentin (2013) examined the impact of alterations in migration levels on unemployment across 14 OECD countries. Their study utilized data spanning from 1960 to 2003 and employed a trivariate vector error correction model (VECM). The findings of their research indicate that the rise in migrant numbers is likely to boost wages in destination countries both in the short and long term. Additionally, they assert that there is no evidence of negative effects on unemployment attributable to migration. Latif (2015) employed panel data analysis to examine the impact of immigration on unemployment in Canada. In his empirical investigation, he applied panel econometric methods including FMOLS, DOLS, and panel VECM. The outcomes of his study revealed a positive correlation, indicating that immigration had an adverse effect on unemployment.

Kahanec and Pytlikova (2017) explore the consequences of migration from the new EU Member States and Eastern Partnership countries (Armenia, Azerbaijan, Belarus, Georgia, Republic of Moldova, and Ukraine) on the economies of the established EU Member States from 1995 to 2010. Employing an international migration dataset and an empirical model that considers the endogeneity of migration flows, they discovered substantial effects of post-enlargement migration flows from the new EU Member States on the GDP, GDP per capita, and employment rate of the established Member States, along with a negative impact on production per employee. Skuflic and Vuckovic (2018) examined the impact of migration on unemployment in nine European Union Member States: Bulgaria, Estonia, Greece, Croatia, Latvia, Lithuania, Poland, Portugal, and Romania. The panel data analysis, employing a fixed-effects model, spans the period from 2004 to 2015. The findings indicate that migration contributes to an increase in the unemployment rate in countries experiencing migration. This confirms that, alongside the typically anticipated positive effects leading to increased unemployment, migration may also exert a negative influence on the labor markets of these countries. Esposito et al. (2020) employed a panel error correction model to examine the influence of migration on domestic unemployment, both in the short and long run, within a sample of 15 EU countries from 1997 to 2016. The findings from their study indicated that, in the long run, immigration diminishes unemployment solely in peripheral countries. However, in the short run, the research revealed that immigration reduces unemployment across all countries in the sampled dataset.

Aslan and Altinöz (2020) explore the correlation between the immigrant population and the unemployment rate in the USA from 1980 to 2013. To achieve this, they initially estimate the coefficients for both the long-run and short-run relationships using the autoregressive distributed lag (ARDL) methodology, and afterwards they apply the linear and non-linear causality test. The findings of their study reveal a positive long-term impact of immigration in the USA on the unemployment rate. The outcomes of the Bootstrapped Toda-Yamamoto linear causality tests indicate the absence of a causal relationship between immigration and unemployment. Furthermore, there is no discernible non-linear relationship between the immigrant population and the unemployment rate in the USA.

Guzi et al. (2021) investigate the connection between migration, economic growth, and inequality in 25 EU countries during the period 2003–2017. The empirical structure of the study relies on a standard dynamic linear panel model, with income inequality gauged by the Gini index derived from balanced disposable income. The findings from the analysis reveal that migration has played a role in diminishing inequality across the 25 EU countries studied during the specified period.

Iscan and Demirel (2021) investigate the interplay among migration, unemployment, and economic growth across 33 OECD countries from 2000 to 2019. Causality analyses are implemented using the panel autoregressive distributed lag (ARDL) and panel vector error correction model (VECM) to elucidate their relationships and directions. The outcomes unveil a substantial and enduring connection between migration and economic growth, indicating that a 1% rise in migration levels is correlated with a 0.43% increase in GDP.

Gundogmuş and Bayır (2021) conduct an empirical examination of the impact of international immigration on unemployment rates in 27 European countries. Utilizing panel regression for the period 2000–2017, their empirical analysis reveals that international immigration does not exhibit a statistically significant effect on unemployment. Moreover, findings indicate that increases in GDP, public expenditure, education expenditure, and wage levels have a diminishing effect on unemployment rates.

Lanati and Thiele (2021), employing diverse panel data methodologies, expand the exploration of the connection between per capita income and immigration in OECD countries, focusing on three distinct skill groups: low-skilled, medium-skilled, and high-skilled emigrants. Their results unveil a consistent negative correlation between GDP per capita and emigration across all three skill groups. This implies that policymakers need not be overly anxious about potential trade-offs between fostering economic growth and managing emigration, at least within the temporal scope covered by their analysis, both in the short and long term.

In their study, Strzelecki et al. (2021) utilize various official data sources to assess the accurate count of immigrants in four Polish towns. They estimate the effective labor supply of Ukrainian immigrants by considering productivity-adjusted hours worked. The authors discovered that the influx of Ukrainian workers led to an annual 0.8% increase in Poland's labor supply from 2013 to 2018. When incorporating this added labor supply into a growth accounting analysis, they determined that the contribution of Ukrainian workers amounted to an annual 0.5, constituting approximately 13% of Poland's GDP growth.

Ohenewa Bruce-Tagoe (2022) explored the impact of immigration on unemployment and wages in the USA, utilizing balanced data from seven states spanning the years 2007 to 2019. The states of California, New York, Florida, Texas, New Jersey, Illinois, and Massachusetts were chosen due to their having the highest immigrant populations in the USA. By estimating two models for the growth rates of unemployment and wages, the study found that immigration exerts an insignificant effect on the labor market in the USA. The increase in immigrants displayed a positive but statistically insignificant impact on the growth rate of unemployment. Similarly, the results indicated a positive but statistically insignificant effect on the growth rate of wages in the USA. In their 2022 paper, Kwilinski et al. assessed current patterns in international migration and investigated how population movements influence economic, social, political, and ecological factors. The aim of the paper is to analyze the causal relationships between the international immigration and the economic, environmental, and socio-political aspects of the development of EU countries. In their study, the authors employed panel data spanning from 2000 to 2008. They utilized the Pedroni and Kao tests for assessing the cointegration of variables, while the FMOLS and DOLS methods were applied to examine the long-run relationship. Additionally, the Dumitrescu-Harlin procedure was employed to conduct the causal relationship test. The results of their paper revealed a unidirectional causal relationship from the average monthly wages towards immigration, a unidirectional causal relationship from immigration to growth, a unidirectional causal relationship from immigration towards unemployment, as well as a unidirectional causal relationship from CO_2 emissions towards immigration.

Data

In conducting the analysis for this study, we utilized annual data spanning from 1990 to 2020, focusing on the 27 EU countries, which are the primary host nations. The data were sourced from the World Development Indicators and Labour Market Statistics databases. To investigate the interaction among migration, unemployment, and economic activity, we employed the net migration rate, calculated as the total annual arrivals minus the total annual departures (net migration), divided by the total population. The choice of using net migration data is motivated by its fewer comparability issues in contrast to available data on inputs and outputs. Additionally, net migration data offer better coverage for the countries under examination. It is important to highlight that clear immigration data encompass all immigrants without distinguishing between nationals and foreigners. Moreover, the analysis solely considers permanent and long-term movements.

In evaluating the economic status of the host countries, we employ real GDP per capita (adjusted to 2017 Purchasing Power Parities) for the entire working-age population as an indicator of economic activity. The real GDP data are sourced from the World Development Indicators (WDI), and the unemployment rates data are obtained from Labor Market Statistics. Any gaps in the data were addressed by applying a straightforward average or trend-based approach for filling missing observations. Figures 2, 3 and 4 in Appendix 1 show the changes in net migration rates over time in the 27 EU countries over the period 1990–2020. The diagrams show that the net migration rate is heterogeneous between EU countries (very small for some countries) such as Bulgaria (BGR), Estonia (EST), Croatia (HRV), Ireland (IRL), Lithuania (LTU), Latvia (LVA), Poland (POL), and Romania (ROU) (countries with the lowest per capita GDP of EU) and very large for others such as Cyprus (CYP), Germany (DEU), Greece (GRC), Luxembourg (LUX), and Sweden (SWE) (countries with the highest per capita GDP or countries close to EU borders with Africa and Asia). The statistical packages Stata 14.0 and Eviews 12.0 were used in the econometric analysis of the study. Table 1 provides information on the variables, including their symbols, measurements, and sources.

Table 2 provides comprehensive descriptive statistics for the variables under examination.

The average net migration rate of the 27 EU countries is 1453 with a standard deviation of 4825. The estimate of the standard deviation shows that the average net migration rate is more variable than the unemployment rate. In all variables, there is a positive asymmetry (right-skewed), indicating that the distribution is right-skewed with the largest observations to the right. Also, all variables are up-spread peaks (>3) indicating that the distribution is leptokyrtic with most observations being in the middle of the distribution. Finally, all the results of the analysis show that the variables do not follow the normal distribution according to Jarque and Bera (1987).

Methodology

In the study, the order of econometric method is formed as follows:

- Multicollinearity tests
- Hausman (1978) (Random Effects vs. Fixed Effects Estimation)
- Breusch and Pagan (1980), Pesaran (2004), Pesaran (2004), and Baltagi et al., (2011) tests for cross-sectional dependence
- Hsiao (2014) homogeneity-heterogeneity test for testing the homogeneity of slope coefficients

Table 1 Description of the variables and data sources

Variables	Symbols	Measurement	Sources
Net migration rate	MIG	The net migration rate per 1000 population,	World Development Indicators
GDP per capita	GDP	PPP (constant 2017 international $)	World Development Indicators
Unemployment rate	UNER	Unemployment rate Total, % of labour force	Labour: Labour market statistics

Source: Authors' compilation

Table 2 Descriptive statistics

Variables	MIG	GDP	UNER
Mean	1.453	35,291.37	8.815
Std.Deviation	4.825	18,528.29	4.324
Maximum	18.129	120,647.8	27.49
Minimum	– 14.925	7128.92	1.02
Skewness	0.218	1.873	1.128
Kurtosis	4.400	8.703	4.578
Jarque–Bera	75.003	1624.28	264.35
Probability	0.000	0.000	0.000
Observations	837	837	837

Source: author's calculations

- Pesaran, (2007) CADF panel the second-generation unit root test that takes into account both interlayer dependence and heterogeneous loading factors for residuals
- To test for cointegration, the autoregressive distributed lag model (ARDL) used, as proposed by Pesaran and Shin (1999), and Pesaran et al. (2001)
- The dynamic error correction model (ECM) integrates dynamic short-run with long-run balance
- The estimation procedures are performed with the mean group (MG) and the pooled mean group (PMG) estimators, as solutions to heterogeneity bias caused by heterogeneous gradients in dynamic panel coefficients
- The causality check is performed with an ARDL error correction template

To explore the interaction among migration, unemployment, and economic activity, we employ a panel vector autoregression model (PVAR model) introduced by Holtz-Eakin et al. (1988) and extended by Love and Zicchino (2006). This PVAR model integrates the conventional VAR methodology, treating all variables as endogenous, with a panel data technique that accommodates unobserved individual heterogeneity. (Belaid et al., 2021; Grossmann et al., 2014).

A simple form of the PVAR template is as follows:

$$Y_{it} = \Gamma(L)Y_{it} + u_i + e_{it} \tag{1}$$

where

Y_{it} is a vector of stationary variables
$\Gamma(L)$ is a polynomial matrix in the lag operator with

$$\Gamma(L) = \Gamma_1 L^1 + \Gamma_2 L^2 + \ldots + \Gamma_p L^p$$

u_i is one effect vector per country
e_{it} is a vector of idiosyncratic errors

To examine the link between migration, unemployment, and economic activity, Love and Zicchino (2006)'s vector autoregressive model (PVAR) for panel data was employed. The PVAR model with k endogenous variables and lag class p can be defined as follows:

$$Y_{it} = \mathrm{A}_1 Y_{it-1} + \mathrm{A}_2 Y_{it-2} + \ldots + \mathrm{A}_p Y_{it-p} + \mathrm{B}X_{it} + u_i + d_t + e_{it} \tag{2}$$

where $i = 1, \ldots N$ represented the country and $t = 1, 2, \ldots T$ is the time period.

Y_{it}	is a vector of endogenous dimensional variables $1 \times k$
X_{it}	is a vector of exogenous dimensional variables $1 \times m$
u_i	represents the country-effects variable that captures unobservable individual heterogeneity
d_t	is a dimensional pseudo variable $1 \times N$ which captures shocks effecting countries in time t
e_{it}	are the idiosyncratic errors, which are both dimensions $1 \times k$
$\mathrm{A}_1, \mathrm{A}_2, \ldots, \mathrm{A}_p$	are parameters to be estimated dimensions $k \times k$
B	are parameters to be estimated dimensions $m \times k$

Finally, we assume that they $\mathrm{E}(e_{it}) = 0$,$\mathrm{E}(e_{it}, e_{it}) = \Sigma$ and $\mathrm{E}(e_{it}, e_{is}) = 0 \quad \forall t > s$ apply.

In a dynamic panel model, it is acknowledged that the constant effect estimator lacks consistency due to its correlation with the lags of the dependent variables. In such instances, forward mean differencing or orthogonal deviations may be employed (Helmert, Helmert procedure) (see Love and Zicchino, (2006), Love and Turk, (2014), Grossmann et al., (2014), and Belaid et al., 2021)).

To eliminate constant effects, we convert all model variables into deviations by subtracting the forward means, representing the average of all future observations for each country-year. This transformation involves maintaining the rectangularity of the deviations between variables and using the backward reciprocators as instruments. The coefficients are then estimated using the generalized method of moments (GMM) as proposed by Arellano and Bover (1995). Additionally, it is worth noting that in dynamic panel models (PVAR), supposedly exogenous variables can be incorporated.

To eliminate fixed effects, we convert all model variables into forward deviations from the mean value, as outlined below.:

$\overline{y}_{it}^{m} = \frac{\sum_{s=t+1}^{T} y_{is}^{m}}{T_i - t}$ are the means generated from the future values of y_{it}^{m} on the vector $Y_{it} = \left(y_{it}^{1}, y_{it}^{2}, \ldots, y_{it}^{M}\right)'$ where T_i is the last period of available data for a given number of countries.

Similarly, $\overline{e}_{it}^{m}$ are the means generated from the future values of e_{it}^{m} on the vector $e_{it} = \left(e_{it}^{1}, e_{it}^{2}, \ldots, e_{it}^{M}\right)'$. So, we get the transformed values as follows:

$\widetilde{y}_{it}^{m} = \delta_{it}\left(y_{it}^{m} - \overline{y}_{it}^{m}\right)$ and $e_{it}^{m} = \delta_{it}\left(e_{it}^{m} - \overline{e}_{it}^{m}\right)$.

where

$$\delta_{it} = \sqrt{\frac{(T_i - t)}{(T_i - t + 1)}}$$

According to the above, model (1) takes the form below:

$$\widetilde{Y}_{it} = \Gamma(L)\widetilde{Y}_{it} + \widetilde{e}_{it} \tag{3}$$

where.

$$\widetilde{Y}_{it} = \left(\widetilde{y}_{it}^{1}, \widetilde{y}_{it}^{2}, \ldots, \widetilde{y}_{it}^{M}\right)' \text{ and } \widetilde{e}_{it} = \left(\widetilde{e}_{it}^{1}, \widetilde{e}_{it}^{2}, \ldots, \widetilde{e}_{it}^{M}\right)'$$

For the last year of the data, this transformation cannot be calculated because there are no future values.

When the variables exhibit stationarity in the first differences, an alternative to the first-difference procedure is employed, known as forward mean differencing. This transformation involves expressing each observation as a deviation from mean future observations, forming a rectangular deviation. Each observation is weighted to standardize the variance. If the original errors are uncorrelated and possess constant variance, the transformed errors should exhibit similar properties. Consequently, this transformation maintains homoscedasticity and avoids introducing serial correlation (Arellano & Bover, 1995). It is worth noting that this technique enables the utilization of missing variables as instruments and facilitates coefficient estimation through the generalized method of moments (GMM).

Panel ARDL Cointegration Test

- To examine cointegration, we employ the autoregressive distributed lag model (ARDL), as introduced by Pesaran and Shin (1999), along with the framework proposed by Pesaran et al. (2001). The asymptotic characteristics of these panel models differ from traditional panels that assume homogeneous slope coefficients within each group. Additionally, Pesaran et al. (2001) devised the pooled mean group (PMG) estimator, incorporating both pooling and averaging of coefficients. Consequently, the intercept, slope coefficients, and error–correction variances may vary between groups. To determine the optimal lag length in ARDL results, the Akaike (1974) is utilized. ARDL models are evaluated with both a constant and linear trend. It is important to note that if all variables are not stationary in the first differences, the generalized method of moments (GMM) cannot be employed for model estimation. The ARDL model boasts several advantages over other cointegration methods, as highlighted by Dritsaki and Dritsaki (2023). This method proves more efficient than other approaches when dealing with a limited number of observations (Pesaran and Shin 1999).
- It appears to be adaptable regarding variable stationarity, meaning it can be applied irrespective of the variables' order of integration, i.e., whether it is order I(0) or I(1).
- The effectiveness of the ARDL model is enhanced by incorporating an adequate number of time lags. The optimal length of regression lags is determined by select-

ing the minimum values of the Akaike (AIC), Schwarz (SBC), and Hannan-Quinn (HQC) criteria.

- Unlike other cointegration methods, the ARDL approach has the capability to identify and address issues arising between dependent and independent variables, including concerns like autocorrelation and endogeneity.
- Moreover, the ARDL method provides unbiased estimates in long-run models (Harris & Sollis, 2003).
- Furthermore, a dynamic error correction model (ECM) can be derived from the ARDL method through a straightforward linear transformation, as suggested by Banerjee et al. (1992). This dynamic ECM seamlessly combines short-run dynamics with long-run equilibrium, preserving all long-run information.

The panel ARDL equation is represented as follows:

$$\Delta MIG_{it} = \beta_i + \delta_1 MIG_{i,t-1} + \delta_2 GDP_{i,t-1} + \delta_3 UNER_{i,t-1} + \sum_{i=1}^{p} \alpha_{1i} \Delta MIG_{i,t-i} + \sum_{i=0}^{q_1} \alpha_{2i} \Delta GDP_{i,t-i} + \sum_{i=0}^{q_2} \alpha_{3i} \Delta UNER_{i,t-i} + \varepsilon_{it} \tag{4}$$

where $i = 1,2,3,\ldots N$ and $t = 1,2,3,\ldots T$, β_i represents the fixed effects, $\delta_1, \delta_2, \delta_3$ are the long-run coefficients, while the short-run coefficients are $\alpha_{1i}, \alpha_{2i}, \alpha_{3i}$ and ε_{it} is the error term which is assumed to be white noise and varies across countries and time.

Before evaluating the cointegration model, it is essential to confirm the existence of cointegration among variables. Pesaran et al. (2001) suggest using Wald's distribution F for assessing the integration of variables. This distribution represents an asymptotic distribution indicating the collective significance of the coefficients of variables at their levels. The null hypothesis of non-integration between the variables in Eq. (4) is as follows:

$H_0 : \delta_1 = \delta_2 = \delta_3 = 0$ (no integration-long-run relationship)

versus the alternative hypothesis for cointegration

$H_1 : \delta_1 \neq \delta_2 \neq \delta_3 \neq 0$

If cointegration is established, i.e., a long-run relationship is established between the variables, Eq. (4) can be expressed as a model of error correction.

Model (4) can be reworded as a VECM system as follows:

$$\Delta MIG_{it} = \beta_i + \sum_{i=1}^{p} \alpha_{1i} \Delta MIG_{i,t-i} + \sum_{i=0}^{q_1} \alpha_{2i} \Delta GDP_{i,t-i} + \sum_{i=0}^{q_2} \alpha_{3i} \Delta UNER_{i,t-i} + \vartheta_i ECM_{i,t-1} \quad \varepsilon_{it} \tag{5}$$

where $ECM_{i,t-1}$ is the error correction part, and ϑ_i is the speed of adjustment from the short run dynamics to the long-run equilibrium. The coefficient, ϑ_i, is expected to be negative and significant for long-run equilibrium to exist between net migration rate and the explanatory variables. The optimal lag length of the $ECM_{i,t-1}$ model is determined through the Akaike's lag selection criteria and a maximum lag.

Panel Causality Test

To examine Granger causality in panel data, we adopt the two-step approach proposed by Engle and Granger (1987). In the initial step, the long-run model is estimated at the variable levels to produce the estimated residuals, as per the following function:

$$MIG_{it} = \alpha_0 + \alpha_{1i}GDP_{it} + \alpha_{2t}UNER_{it} + \varepsilon_{it} \tag{6}$$

In the subsequent step, the residuals with a time lag from the aforementioned function are employed as an error correction term in an ARDL panel system, facilitating the examination of both short-run and long-run multivariate Granger causality. This system is represented by the following equations:

$$\begin{aligned} \Delta MIG_{it} = \beta_i + \sum_{j=1}^{p} \alpha_{11,ij}\Delta MIG_{i,t-j} + \sum_{j=0}^{q_1} \alpha_{12,ij}\Delta GDP_{i,t-j} \\ + \sum_{i=0}^{q_2} \alpha_{13,ij}\Delta UNER_{i,t-i} + \vartheta_{1i}ECM_{i,t-1} \;\; \varepsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} \Delta GDP_{it} = \beta_i + \sum_{j=1}^{p} \alpha_{21,ij}\Delta GDP_{i,t-j} + \sum_{j=0}^{q_1} \alpha_{22,ij}\Delta MIG_{i,t-j} \\ + \sum_{i=0}^{q_2} \alpha_{23,ij}\Delta UNER_{i,t-i} + \vartheta_{2i}ECM_{i,t-1} \;\; \varepsilon_{it} \end{aligned} \tag{8}$$

$$\begin{aligned} \Delta UNER_{it} = \beta_i + \sum_{j=1}^{p} \alpha_{31,ij}\Delta UNER_{i,t-j} + \sum_{j=0}^{q_1} \alpha_{32,ij}\Delta MIG_{i,t-j} \\ + \sum_{i=0}^{q_2} \alpha_{33,ij}\Delta GDP_{i,t-i} + \vartheta_{3i}ECM_{i,t-1} \;\; \varepsilon_{it} \end{aligned} \tag{9}$$

The short-run Granger causality is jointly tested for the limited coefficients with the F Wald distribution, while the long-run causality is tested by the significance of the ϑ_i coefficient of the error–correction term.

Preliminary Tests

This section presents preliminary tests to assess the suitability of the panel data model to be employed.

Multicollinearity Tests

For the multicollinearity test, we use the variable correlation matrix, the variance inflation factor (variance inflation factor, VIF) $VIF = \frac{1}{1-R^2}$ showing the speed of increase in the variance of an estimator when the problem of multi-linearity exists, as well as the tolerability estimator (tolerance index, TOL). It is obvious that the higher the value of the VIF, the greater the problem of multicolinearity. No critical price to compare the price the VIF estimator gets. A rule of thumb is that when its value is greater than 10, then we say that the corresponding variable creates the problem of multi-collinearity. The tolerability estimator TOL is the inverse of the fluctuation bulge estimator and is defined as follows: $TOL = \frac{1}{VIF}$. If the TOL estimator is zero, then we say that there is complete multi-collinearity, while if it is one there is no multi-collinearity (see Dritsaki & Dritsaki, 2020). Table 3 shows the correlation matrix of variables.

The correlation matrix of variables reveals the existence of multicollinearity. While correlation pertains to bivariate linear relationships and multicollinearity involves multivariate relationships, the correlation matrix can serve as an indicator of multicollinearity, prompting a need for additional investigation. Based on the absolute value of the correlation coefficient, which is less than 0.7, and the variance inflation factor, which is $VIF = \frac{1}{1-R^2} = 1.996$ at the variables level and 1.048 at the first differences (less than 10) and the variance inflation factor $TOL = \frac{1}{VIF} = 0.501$ and 0.954 in the levels and first differences respectively, we can conclude the absence of multi-collinearity.

Hausman Test (Random Effects vs. Fixed Effects Estimation)

Econometric panel data modelling typically applies two basic approaches, constant and random effects. The function for the constant effect model is as follows:

$$\mathrm{A}^g(L)g_t = M^g(L)e_t^g \tag{10}$$

where Y_{it} is the dependent variable, X_{it} are the independent variables, α_i is the constant that incorporates all the time-varying and unobserved factors influencing theY_{it}, β is the column vector of the slope coefficients for the cross-sectional units, and u_{it} is the error term that asymptotically follows the normal distribution.

Table 3 Correlation matrix

Variables	MIG	GDP	UNER
MIG	1.000		
t-statistic			
Probability			
GDP	0.657	1.000	
t-statistic	25.223		
Probability	0.000		
UNER	−0.359	−0.364	1.000
t-statistic	−11.127	-11.297	
Probability	0.000	0.000	

Source: author’s calculations

The function for the random effect model is as follows:

$$Y_{it} = a_0 + \beta_{RE}X_{it} + \mu_{it}\mu\varepsilon\mu_{it} = a_1 = e_{it} \tag{11}$$

where u_{it} is the composite error (idiosyncratic error) consisting of two random components. The constant effect estimator β_{FE} is more accurate than the random effect estimator β_{RE}, but less efficient (greater variance). On the other hand, the random effect estimator β_{FE} is more efficient compared to the fixed effect estimatorβ_{FE}, but it could be biased.

To choose between the most suitable between fixed and random effects estimators, we use the Hausman (1978). Hausman basically compares the parameter estimates between the two models. The null hypothesis is as follows:

$$H_0 : \beta_{FE} = \beta_{RE}$$

This implies that the fixed and random effect estimators exhibit no divergence. In such instances, it is worthwhile to examine whether the random effects estimator demonstrates greater efficiency. Conversely, if there is a contrast, the fixed effect estimator is preferred for its enhanced consistency.

When analysing panel data, Hausman (1978) helps to choose between a fixed-effects or a random-effects model. The null hypothesis suggests that the preferred model is the random effects one, while the alternative hypothesis shows the fixed-effects one to be the preferred one. The table below shows the results of the Hausman (1978) Table 4.

The results of the above table reject the null hypothesis, so we can say that the fixed-effects model is the most appropriate.

Cross-Sectional Dependence

To employ panel unit root tests, it is essential to assess the presence of cross-sectional dependency (correlation) in panel data. If there is no cross-sectional dependence, first-generation unit root tests can be applied. However, if cross-sectional dependence is present in panel data, first-generation unit root tests are not applicable. In such instances, second-generation unit root tests (SURADF, CADF, and CIPS) are utilized, considering the influence of cross-sectional dependence.

Cross-sectional dependence would be explained by the following model.

$$Y_{it} = \alpha_i + \beta X_{it} + u_{it} \tag{14}$$

According to the null hypothesis, u_{it} is regarded as (i.i.d.) independent and identically distributed (i.i.d.) over periods and for all cross-sectional units. The null hypothesis (H_0) suggests there are no relationships between cross-sections.

Table 4 Hausman test

Test summary	Chi-sq. statistic	Chi-sq. d.f	Prob
Cross-section random	11.703	2	0.0029

Source: Author's calculations

$Ho: \hat{\rho}_{ij} = \hat{\rho}_{ij} = Corr\left(u_{it'}u_{jt}\right) = 0 \ \ for \ i \neq j$ (no cross-sectional dependence)

For the controls of cross-sectional dependence (correlation) between residuals, we use the tests of Breusch and Pagan (1980), Pesaran (2004), Pesaran (2004), and Baltagi et al., (2011) bias-corrected scaled LM. The results of these tests are shown on Table 5.

The results presented in the table above indicate the rejection of the null hypothesis of no cross-sectional dependence, even at the 1% significance level. Consequently, it is imperative to continue with tests and assessment techniques capable of accommodating cross-sectional dependence.

Homogeneity–Heterogenety Test

When dealing with panel data samples, it becomes crucial to assess the homogeneity or heterogeneity of the cross-sections in the specification generator data process. As per Hsiao (2014), the control of overall homogeneity-heterogeneity is outlined as follows:

Suppose we have the following function:

$$y_{it} = \alpha_i + \beta_i x_{it} + e_{it} \tag{13}$$

From estimating the function (13), we test the following hypotheses:

$$H_0^1 : \alpha_i = \alpha \text{ and } \beta_i = \beta \ \forall i \in [1, N]$$

$$H_0^1 : \alpha_i \neq \alpha_j \ \acute{\eta} \ \beta_i \neq \beta_j \ \exists (i,j) \in [1, N]$$

If we accept the null hypothesis, there is a general homogeneity among the cross-sections individuals. If we reject the null hypothesis, then we can say that there is a generic heterogeneity among cross-sections. In order to test for a whole (total) homogeneity, we use the F distributions with $\nu_1 = (N\text{-}1)(K+1)$ and $\nu_2 = \text{NT-}N(K+1)$ degrees of freedom where K represents the number of independent variables and N the number of cross-sections.

Hsiao's (2014) tests for homogeneity-heterogeneity of cross-sections in panel data are presented in Table 6.

In Table 6, the test statistics and their corresponding p-values in the first row suggest the rejection of the null hypothesis of general homogeneity, indicating evidence of heterogeneity. Examining the second row of the table, we observe the rejection of the

Table 5 Cross-sectional dependence and homogeneity test results

Cross-sectional dependence test (H_0: no cross-sectional dependence)		
Test	Statistic	p-value
Breusch-Pagan LM	2558.824	0.000
Pesaran scaled LM_s	83.32896	0.000
Bias-corrected scaled LM_p	82.87896	0.000
Pesaran CD_{BC}	5.028298	0.000

Source: Author's calculations

Table 6 Specification tests of Hsiao

Hypotheses	F-stat	P-value
H1	51.05197	7.8E-251
H2	22.32769	2.7E-119
H3	45.73115	1.7E-139

Source: Author's calculations

null hypothesis, indicating heterogeneity in the slopes. Similarly, in the third row, the null hypothesis is rejected, signifying heterogeneity in the constants. In summary, there is evidence of heterogeneity in both the slopes and the cross-section constants (countries). Hence, it can be asserted that first-generation unit root tests likely yield ineffective results. Consequently, for second-generation unit root testing, we employ the Pesaran (2007), which considers both cross-sectional dependence and heterogeneity.

Empirical Results

Panel Unit Root Tests

For assessing the second-generation unit root, we employ Pesaran's (2007) single-factor CIPS test, considering both cross-sectional dependence and heterogeneous loading factors for residuals, in conjunction with Phillips and Sul (2003). However, in contrast to relying on deviations from the estimated common factors for unit root controls, our approach involves augmenting the standard DF or ADF regressions with the cross-section average of lagged levels and the first differences of individual series, following the methodology outlined by Hurlin and Mignon (2007). Additionally, the Pesaran test is employed in instances where heteroscedasticity is observed in the unobserved common factor of time series data (Hashiguchi & Hamori, 2010). The results of Pesaran's second-generation unit root test are presented in the table below Table 7.

Table 7 Pesaran CADF panel unit root test

	Pesaran-CIPS			
	Intercept		Intercept and trend	
Variable	t-stat	Prob	t-stat	Prob
MIG	– 2.886	< 0.01	– 3.251	< 0.01
GDP	– 1.482	> 0.10	– 1.812	> 0.10
UNER	– 2.183	< 0.01	– 3.082	< 0.01
ΔMIG	– 2.944	< 0.01	– 3.313	< 0.01
ΔGDP	– 3.489	< 0.01	– 3.751	< 0.01
ΔUNER	– 3.471	< 0.01	– 3.103	< 0.01

Critical values: – 2.32, – 2.17, – 2.08 (intercept), and – 2.83, – 2.68, – 2.60 (intercept and trend). *, **, and ***Indicate 1%, 5%, and 10% level of significance respectively, Δ is first difference, The lag lengths from cross-sections were selected using Akaike information criterion (AIC)

Panel ARDL Cointegration Test

As indicated in the presented table, the variables exhibit integration at both order I(0) and order I(1). Hence, for cointegration testing, the autoregressive distributed lag model (ARDL) is employed. It is essential to establish the existence of cointegration between the variables before evaluating the cointegration model. The *F* Wald's distribution is utilized for testing the integration of variables. The results of the cointegration test are presented in Table 8.

If cointegration is established, i.e., a long-run relationship between the variables is established, then we could create the error correction model.

The outcomes presented in Table 8 indicate the rejection of the null hypothesis of non-integration. The graph below displays the number of time lags for model (8) based on the Akaike (1974).

As depicted in the above figure, the most suitable model is determined to be ARDL (2,1,1) (Fig. 1). In light of the established cointegration, both the long-run and short-run outcomes of the ARDL panel model (2,1,1) are presented in Tables 9 and 10, respectively. The optimal lag lengths are determined using the Akaike information criterion. The estimation of the ARDL (2,1,1) model proves satisfactory, with optimally distributed lags. Prioritized consideration is given to the lower (more recent) lags due to their significant impact on the dependent variable, as emphasized by Koyck (1958). Additionally, larger lags can result in a loss of degrees of freedom, information, and lead to over-parameterization of the ARDL models.

The long-run outcomes presented in Table 9 reveal a significant positive correlation between GDP per capita and the unemployment rate with the net migration

Table 8 Wald test

Test statistics	Value	df	Prob
F-statistic	17.842	(3.748)	0.000
Chi-square	53.527	3	0.000

Source: Author's calculations

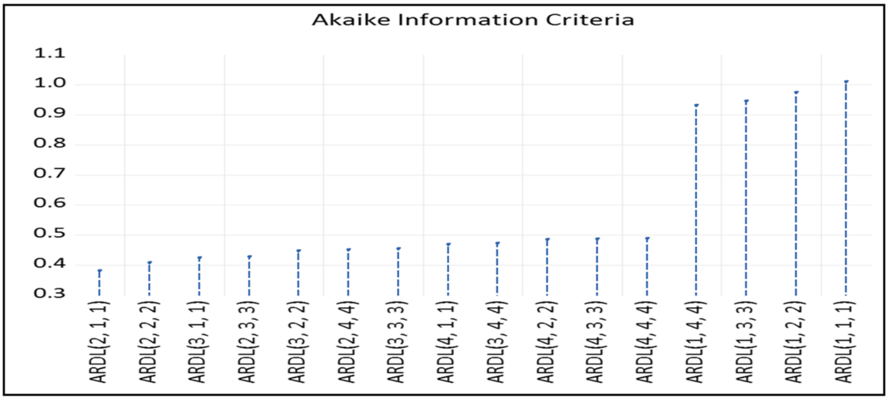

Fig. 1 Akaike Information criteria

Table 9 Long-run results of the panel ARDL (PMG)

ARDL(2,1,1)				
Dependent variable: MIG				
Variable	Coefficient	Std error	*t*-statistic	*p*-value
GDP	0.00054*	5.57E-05	9.694	0.000
UNER	0.15632*	0.0314	4.977	0.000

*Indicates the level of significance at 1%

Table 10 Short-run results of the panel ARDL (PMG)

ARDL(2,1,1)				
Dependent variable: MIG				
Variable	Coefficient	Std error	*t*-statistic	*p*-value
ECM (− 1)	− 0.158*	0.026	− 5.922	0.000
DMIG (− 1)	0.625*	0.050	12.494	0.000
DGDP	− 6.91E − 05*	2.34E − 05	− 2.951	0.003
DUNER	− 0.043	0.027	− 1.599	0.110
C	− 1.901*	0.317	− 5.995	0.000
Trend	− 0.052*	0.010	− 5.263	0.000

*Indicates the level of significance at 1%

rate in EU countries. The findings indicate that a 1% increase in GDP per capita corresponds to a 0.00054% rise in the migration rate. Conversely, a 1% increase in the unemployment rate is associated with an approximately 0.15% increase in the immigration rate. These long-run results align with the findings of Latif (2015), Skuflic and Vuckovic (2018), as well as Iscan and Demirel (2021).

Concerning the short-run findings outlined in Table 10, it is observed that a 1% increase in GDP per capita in EU countries results in a 0.000069% decrease in the immigration rate. In contrast, a 1% increase in the unemployment rate leads to a 0.043% reduction in the immigration rate, reaching a materiality level of 1%. The error correction variable, indicative of the speed of adjustment from the short-run to long-run equilibrium, exhibits a negative and statistically significant value at the 1% level. However, the adjustment speed, approximately 0.16%, is deemed relatively slow for achieving long-run equilibrium. The long-run impact highlights a direct association between the migration rate and the GDP per capita and unemployment rate in EU countries. On the other hand, the short-run effect suggests a potential indirect connection between these variables in the short term, with a subsequent adjustment back to equilibrium driven by the long-run effect.

Appendix 2 presents the short-run outcomes of the ARDL panel models for each EU country, employing dynamic panel coefficients, specifically pooled mean group (PMG). These coefficients accommodate a higher level of heterogeneity in the parameters for the regressions of each EU country. The findings in Appendix 2 reveal that the growth in GDP per capita enhances migration to Bulgaria, the Czech Republic, Denmark, Ireland, Luxembourg, the Slovak Republic, Slovenia, and Sweden, while decreasing migration to the remaining EU countries.

Additionally, the results indicate that an increase in the unemployment rate reduces immigration to Austria, Belgium, Cyprus, the Czech Republic, Germany, Spain, Estonia, France, Greece, Croatia, Ireland, Lithuania, Latvia, the Netherlands, Poland, Portugal, and the Slovak Republic, while increasing immigration to the rest of the EU countries. The error correction variable, indicative of the speed of adjustment from the short-run to long-run equilibrium, is consistently negative and statistically significant at the 1% level in all EU countries. Notably, the most substantial adjustment is observed in the Czech Republic, followed closely by the Slovak Republic, with values of 0.68 and 0.37, respectively.

Panel Causality Test

Empirical research examining the causal relationships among migration rates, GDP per capita, and unemployment rates is limited, and existing studies present inconsistent results that vary across different countries and time periods. The causal dynamics between these variables can be traced back to Granger's work in 1969, where he developed a bivariate test for causality based on time-series data. Granger's causality test requires the precondition of cointegration between the two time series. Subsequently, Dumitrescu and Hurlin (2012) devised a method for conducting pairwise Granger causality tests on panel data. However, this causality test has faced criticism for overlooking short-run adjustment mechanisms. To address this, incorporating error correction terms with lags is suggested, provided that the variables are cointegrated. Additionally, the Granger multivariate causality test allows the inclusion of differentiated lagged values of all variables as additional control variables in an error-correcting autoregressive distributed lag (ARDL) model (Mawejje & Odhiambo, 2021).

The joint test for short-run Granger causality examines the limited coefficients using the *F* Wald distribution, while the long-run causality is assessed through the significance of the error–correction term coefficient. The following table presents the outcomes of both short-run and long-run Granger causality tests Table 11.

The outcomes presented in the above table reveal a bidirectional long-term causal association between the migration rate and unemployment, while a

Table 11 Multivariate Granger causality test results

	Short-run				Long-run
Variable	ΔMIG	ΔGDP	ΔUNER	$F(3.778)$	ECM_{t-1}
ΔMIG	--	2.79E-05*** (0.061)	−0.028** (0.030)	289.32* (0.000)	−0.036* (0.000)
ΔGDP	128.2** (0.027)	--	−312.56 (0.000)	82.88* (0.000)	−0.392 (0.420)
ΔUNER	−0.187* (0.000)	−0.0004* (0.000)	--	148.15* (0.000)	−0.025** (0.042)

*, **, and ***Indicate the level of significance at 1%, 5%, and 10%, *p*-values are shown in parentheses

Source: Author's calculation

unidirectional long-term causal link exists between growth and migration, as well as between growth and unemployment. The short-term Granger causality dynamics demonstrate a bidirectional causal relationship among all the variables under investigation. A summary of the causality directions can be found in Table 12, which consolidates the results of the multivariate panel Granger causality tests.

Discussion

The main purpose of this paper is to investigate the impact of migration on economic growth and unemployment in the 27 EU countries for the period 1990–2020. Observing the descriptive statistics of the data, we note that the mean rat of immigrants in the EU is 1.4 per 1000 inhabitants, the average GDP per capita is 35,291 PPP in US dollars and constant prices of 2017, and the average unemployment rate is 8.8%. Then, the analysis of the panel data with Hausman (1978) helped us to choose the most appropriate fixed-effects model. In addition, the results of the four dependency tests led to the rejection of the null hypotheses related to cross-sectional independence and slope homogeneity. Pesaran's second-generation unit root test, (2007) CIPS that considers cross-sectional dependence and heterogeneity showed that the variables are integrated order I(0) and order I(1). Therefore, to test integration, we use the ARDL model, as proposed by Pesaran et al. (2001). The outcomes of the integration analysis indicate the rejection of the null hypothesis of non-integration. With the confirmation of cointegration, we have presented the long-run and short-run results of the ARDL panel model (2,1,1) employing the optimal lag length determined by the Akaike information criterion. In the long-term analysis, it was observed that a 1% rise in GDP per capita corresponds to a 0.00054% increase in the migration rate. Conversely, a 1% increase in the unemployment rate is associated with an approximately 0.15% rise in the immigration rate. These long-term findings align with the outcomes reported in the studies conducted by Latif (2015), Skuflic and Vuckovic (2018), as well as Iscan and Demirel (2021).

In terms of the short-run outcomes, our findings indicate that a 1% increase in GDP per capita in EU countries leads to a 0.000069% decrease in the immigration rate. Conversely, a 1% rise in the unemployment rate results in a 0.043% reduction in the immigration rate, with a significance level of 11%. The error

Table 12 Direction of short-run and long-run causality

Null hypothesis	Short-run	Long-run
GDP does not Granger cause MIG	GDP → MIG	GDP → MIG
MIG does not Granger cause GDP	MIG → GDP	MIG ≠ GDP
UNER does not Granger cause MIG	UNER → MIG	UNER → MIG
MIG does not Granger cause UNER	MIG → UNER	MIG → UNER
UNER does not Granger cause GDP	UNER → GDP	UNER ≠ GDP
GDP does not Granger cause UNER	GDP → UNER	GDP → UNER

Causality relationships: denotes causality in indicated direction, and ≠ denotes absence of causality correction variable, denoting the pace of adjustment from the short-run to the long-run equilibrium, is negative and statistically significant at a 1% level. However, the adjustment speed, around 0.16%, is deemed relatively slow for achieving long-run equilibrium.

The long-term impact reveals a direct association between the migration rate and both GDP per capita and the unemployment rate in EU countries. On the other hand, the short-term effect suggests a potential indirect relationship between these variables in the short run, yet they are expected to adjust back to equilibrium primarily through the long-term effect.

The causality analyses conducted by the VECM panel validate a reciprocal long-term causal connection between migration and unemployment. Simultaneously, a one-way long-term causal link is observed between growth and migration, as well as between growth and unemployment. In the short run, Granger causality dynamics reveal a bidirectional causal relationship among all the variables under examination. The findings of this study indicate that, in the 27 EU countries, GDP growth contributes to both migration and unemployment over the long term. Given that GDP growth promotes migration and migration, in turn, leads to increased unemployment, it is imperative for future studies to empirically investigate the nature and volume of individuals migrating to the EU to formulate appropriate policies.

Policy Suggestions

EU countries should adopt effective immigration policies to attract a highly qualified labor force, serving as a primary driver for achieving sustainable growth objectives. The phenomenon of international immigration, when compared to mortality and fertility, is considerably intricate, representing a multidimensional occurrence influenced by various factors, both economic and non-economic. Immigrants tend to select countries with stable political, economic, and social growth, along with favorable ecological conditions. Conversely, nations experiencing political, economic, and social imbalances become sources of migration to developed countries. In the long run, this dynamic may impede developing countries from ensuring the realization of sustainable growth goals, potentially widening inequality gaps between developing and developed nations Irrespective of the choices made regarding immigration policies, it is crucial to uphold principles of justice, acknowledging the rights of refugees and ensuring equitable treatment in immigration processes. Additionally, due consideration should be given to the ecological constraints to ensure the prudent utilization of planetary boundaries, which are currently facing significant infringements (O'Neill et al., 2018).

Conclusions and Policy Implications

The globalization of the labor market distinguishes itself from the globalization of other markets. It involves the cross-border movement of labor, impacting not only the labor supply and demographic makeup of the host country but also influencing conditions in the sending country. Migration plays a crucial role in economic growth, influencing unemployment rates and income dynamics in host countries. Similar to trade, immigration involves the movement of individuals from low-income and low-productivity nations to those with higher productivity and, consequently, higher income levels. Migration facilitates individuals in effectively responding to both short-term and long-term job opportunities. (Newbold, 2019).

Inflows of migration have an impact on each country's ability to accept foreign labour (reflected by GDP per capita growth) and overall unemployment rates can be explained by the following reasons:

- A migration decision is related to the job opportunities and the probability of employment in the host country.
- Better economic conditions in host countries increase migrants' incentives to emigrate.
- Governments adapt their migration policies to changing labour market needs.
- In times of elevated unemployment, the majority of host countries may limit the issuance of permanent residence permits through government restrictions.
- Countries with high unemployment rates are less attractive to migrants and are willing to pursue more restrictive immigration policies.

Immigration to Europe experienced a significant surge towards the close of the twentieth century. Western European nations witnessed a substantial uptick in immigration post-World War II, leading to a noteworthy immigrant presence in many European states today, originating from both European and non-European backgrounds. Amidst contemporary globalization, migration to Europe has intensified, and in recent decades, there has been a rise in negative sentiments toward immigration. Various factors influence attitudes toward migration, including individual characteristics, the unique attributes of each country, and considerations related to climate change, extreme weather events, and environmental degradation. Since February 2022, the European Union (EU) has demonstrated unprecedented solidarity in response to a substantial influx of Ukrainian refugees. Following Russia's invasion of Ukraine, approximately 4.3 million people have fled the country, with many seeking refuge in neighboring countries and a considerable number continuing their migration westward.

The UN Agenda 2030 for sustainable development identifies the reduction of inequalities and enhancement of the well-being of the labor force as pivotal dimensions for future progress. Despite the economic growth observed in EU countries, certain nations such as Bulgaria, Poland, and Romania are experiencing population decline. A majority of EU countries exhibit negative birth rates and positive death rates, posing potential obstacles to achieving sustainable development goals. The swift economic growth has positively impacted the quality of life, household income, educational levels, and access to education knowledge. This increased prosperity has contributed to the reduction of corruption and mortality rates, particularly among children, and has spurred the implementation of environmentally friendly initiatives. Consequently, this has resulted in a rapid increase in birth rates, forming the foundation for a country's economic growth (Kwilinski et al., 2022). Employing a qualitative approach to assess the advantages and disadvantages of migration, this study quantifies migration trends in European Union (EU) countries and evaluates their impact on economic growth and unemployment. The primary objective is to analyze how migration influences the economic development and labor market dynamics of host countries. The research reveals that the influx of migrants positively contributes to the economic well-being of host nations, underscoring the elevated skill levels of migrants in recent decades. Notably, the positive impact on economic development is more pronounced when immigrants possess higher levels of education. Furthermore, considering the challenge of an aging population in the EU, migration emerges as a potential solution to counterbalance labor shortages in several EU countries. Consequently, EU nations can tailor their migration policies to align with the demands of the labor market.

In alignment with the environmental pledges of the European Union (EU), a direct policy approach could involve minimizing high migration rates in specific European nations like Germany and Spain. Conversely, countries with a steady or declining population, such as Poland, Hungary, and the Netherlands, may choose to embrace rather than resist these demographic shifts. Another option for EU countries is to reconsider their existing environmental commitments, potentially increasing immigration and welcoming more densely populated areas. While sustainability is not the sole objective of policy-making, it is unquestionably a crucial goal essential for long-term societal prosperity (Cafaro & Gotmark, 2019).

The limitations of the paper are the following:

- Index calculations covered the period 1990–2021 according to the model. To accept or reject the results, it is necessary to expand the study period.
- On a larger sample, structural breaks panel unit root and cointegration test could be applied on one or more structural breaks.
- A linear regression model was used in order to model direct linear relationships, while it is necessary to create other type of models among data.

In a subsequent study, it is advisable to explore additional variables beyond those considered in this paper, such as environmental, climatic, and natural disasters. The outcomes derived from such an investigation would facilitate the development of EU strategies for assessing and managing the desirability of migration in various countries and regions. Specific recommendations can then be formulated based on distinct groups of factors, encompassing economic, sociodemographic, political security, language, cultural, and ecological natural aspects.

Appendix 1

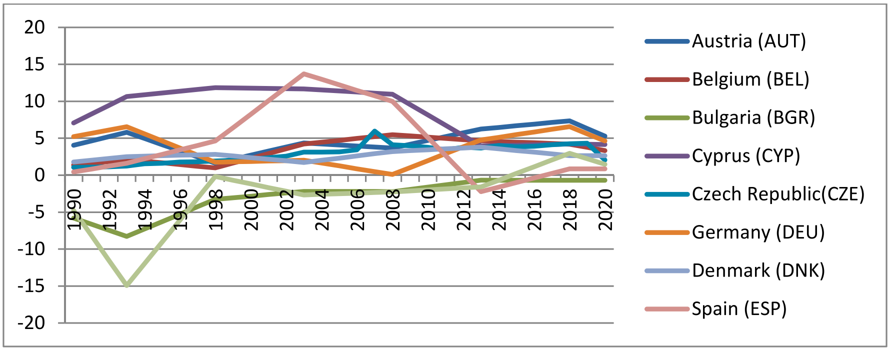

Fig. 2 Net migration rate in E.U countries (per 1000 inhabitants)

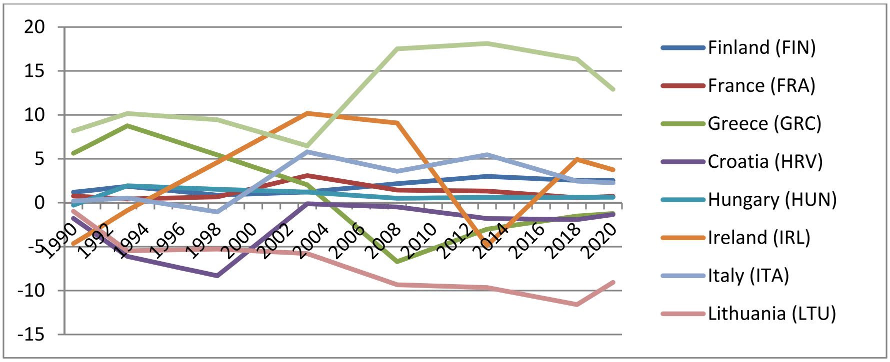

Fig. 3 Net migration rate in E.U countries (per 1000 inhabitants)

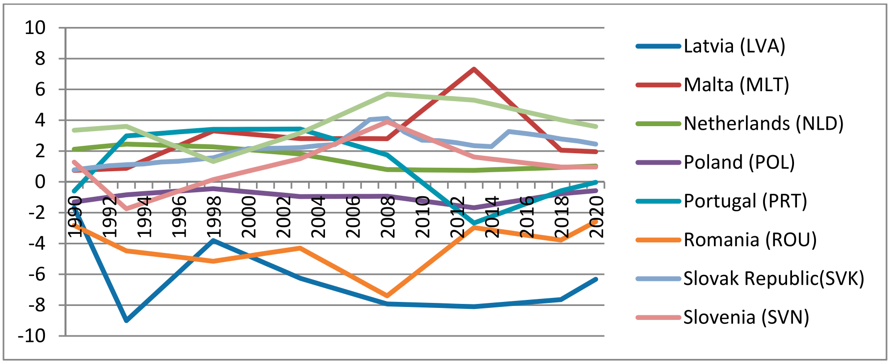

Fig. 4 Net migration rate in E.U countries (per 1000 inhabitants)

Appendix 2

Table 13 Cross-section short-run coefficient

Austria

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.127242	0.001428	-89.11735	0.0000
D(MIG(-1))	0.761198	0.017047	44.65226	0.0000
D(GDP)	-0.000207	1.10E-08	-18715.44	0.0000
D(UNER)	-0.266395	0.040173	-6.631175	0.0070
C	-2.110294	0.541485	-3.897232	0.0300
@TREND	-0.040789	0.000198	-206.1551	0.0000

Belgium

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.151893	0.003695	-41.10287	0.0000
D(MIG(-1))	0.741290	0.012199	60.76752	0.0000
D(GDP)	-4.89E-05	2.18E-09	-22453.29	0.0000
D(UNER)	-0.037590	0.004084	-9.203727	0.0027
C	-2.840443	1.578476	-1.799484	0.1698
@TREND	-0.030341	0.000120	-251.9849	0.0000

Bulgaria

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.127727	0.002016	-63.34421	0.0000
D(MIG(-1))	0.744080	0.013987	53.19704	0.0000
D(GDP)	6.83E-05	7.50E-09	9105.327	0.0000
D(UNER)	0.002832	0.001079	2.624011	0.0787
C	-1.499249	0.400553	-3.742944	0.0333
@TREND	-0.007635	5.30E-05	-143.9285	0.0000

Table 13 (continued)

Cyprus

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.195425	0.002768	-70.59169	0.0000
D(MIG(-1))	0.325862	0.015811	20.61020	0.0002
D(GDP)	-7.71E-05	4.52E-09	-17055.01	0.0000
D(UNER)	-0.222103	0.004751	-46.74809	0.0000
C	0.147797	0.135239	1.092861	0.3544
@TREND	-0.143048	0.001322	-108.1692	0.0000

Czech Republic

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.686297	0.072963	-9.406062	0.0025
D(MIG(-1))	-0.373045	0.042905	-8.694722	0.0032
D(GDP)	0.000131	2.41E-08	5438.899	0.0000
D(UNER)	-0.150061	0.018454	-8.131709	0.0039
C	-6.485458	7.133584	-0.909144	0.4303
@TREND	-0.204663	0.004779	-42.82227	0.0000

Germany

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.093791	0.001362	-68.86160	0.0000
D(MIG(-1))	0.933154	0.017258	54.07151	0.0000
D(GDP)	-0.000282	9.47E-09	-29799.67	0.0000
D(UNER)	-0.241560	0.023450	-10.30098	0.0020
C	-1.439307	0.591376	-2.433828	0.0930
@TREND	-0.037005	0.000187	-198.3562	0.0000

Denmark

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.053602	0.000474	-113.1227	0.0000
D(MIG(-1))	0.797866	0.015082	52.90315	0.0000
D(GDP)	2.24E-05	1.56E-09	14347.38	0.0000
D(UNER)	0.030323	0.001704	17.79504	0.0004
C	-1.155791	0.215544	-5.362215	0.0127
@TREND	-0.012518	3.44E-05	-363.6220	0.0000

Table 13 (continued)

Spain

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.059047	0.000744	-79.41615	0.0000
D(MIG(-1))	0.638882	0.010718	59.60674	0.0000
D(GDP)	-9.80E-05	2.21E-08	-4429.700	0.0000
D(UNER)	-0.226037	0.006958	-32.48506	0.0001
C	-0.219944	0.229210	-0.959572	0.4081
@TREND	-0.047234	0.000350	-135.0335	0.0000

Estonia

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.306819	0.005354	-57.31182	0.0000
D(MIG(-1))	0.720402	0.011499	62.64848	0.0000
D(GDP)	-4.89E-05	4.60E-08	-1063.220	0.0000
D(UNER)	-0.065161	0.015907	-4.096348	0.0263
C	-4.217279	1.772181	-2.379710	0.0976
@TREND	-0.056533	0.000786	-71.97029	0.0000

Finland

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.067799	0.000143	-473.4360	0.0000
D(MIG(-1))	0.212892	0.014036	15.16811	0.0006
D(GDP)	-8.30E-07	1.78E-10	-4660.098	0.0000
D(UNER)	0.063830	0.000211	301.8801	0.0000
C	-1.257560	0.044509	-28.25426	0.0001
@TREND	-0.013964	9.89E-06	-1411.372	0.0000

France

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.244790	0.003205	-76.37208	0.0000
D(MIG(-1))	0.795628	0.012581	63.24124	0.0000
D(GDP)	-0.000122	1.39E-09	-87589.70	0.0000
D(UNER)	-0.019377	0.002107	-9.198540	0.0027
C	-4.585784	1.622432	-2.826488	0.0664
@TREND	-0.050200	0.000160	-313.7122	0.0000

Table 13 (continued)

Greece

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.011687	0.000980	-11.92082	0.0013
D(MIG(-1))	0.642679	0.018075	35.55568	0.0000
D(GDP)	-0.000275	1.14E-08	-24052.31	0.0000
D(UNER)	-0.036541	0.005002	-7.304713	0.0053
C	-0.200096	0.077165	-2.593099	0.0809
@TREND	-0.005490	0.000664	-8.271070	0.0037

Croatia

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.198220	0.002522	-78.60618	0.0000
D(MIG(-1))	0.705616	0.008497	83.03909	0.0000
D(GDP)	-0.000112	1.66E-08	-6779.750	0.0000
D(UNER)	-0.026626	0.005142	-5.178250	0.0140
C	-2.888365	0.654754	-4.411375	0.0216
@TREND	-0.020653	0.000182	-113.7597	0.0000

Hungary

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.017998	0.001741	-10.33801	0.0019
D(MIG(-1))	0.637136	0.010668	59.72565	0.0000
D(GDP)	-2.69E-05	1.22E-09	-22003.71	0.0000
D(UNER)	0.033552	0.000984	34.11179	0.0001
C	-0.151880	0.095542	-1.589670	0.2101
@TREND	-0.004427	0.000205	-21.55426	0.0002

Ireland

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.065132	0.002418	-26.93533	0.0001
D(MIG(-1))	0.511459	0.013831	36.98002	0.0000
D(GDP)	5.07E-05	5.61E-09	9031.582	0.0000
D(UNER)	-0.249761	0.016723	-14.93510	0.0007
C	-0.444579	0.356596	-1.246727	0.3010
@TREND	-0.088164	0.002846	-30.98135	0.0001

Table 13 (continued)

Italy

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.224649	0.002910	-77.20109	0.0000
D(MIG(-1))	0.736013	0.012186	60.40037	0.0000
D(GDP)	-0.000126	6.78E-09	-18625.82	0.0000
D(UNER)	0.084283	0.012210	6.902588	0.0062
C	-5.003175	1.857220	-2.693905	0.0742
@TREND	0.016311	0.000156	104.8670	0.0000

Lithuania

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.193955	0.004804	-40.37506	0.0000
D(MIG(-1))	0.640814	0.018769	34.14169	0.0001
D(GDP)	-0.000133	5.76E-09	-23045.91	0.0000
D(UNER)	-0.030659	0.000700	-43.80351	0.0000
C	-1.567637	0.299660	-5.231392	0.0136
@TREND	-0.149312	0.003393	-44.00839	0.0000

Luxembourg

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.059073	0.000813	-72.64273	0.0000
D(MIG(-1))	0.742099	0.014554	50.98937	0.0000
D(GDP)	4.26E-05	2.70E-09	15749.69	0.0000
D(UNER)	0.271004	0.061291	4.421572	0.0215
C	-2.157818	0.938440	-2.299367	0.1050
@TREND	-0.034804	0.000485	-71.72202	0.0000

Latvia

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.207687	0.002903	-71.54975	0.0000
D(MIG(-1))	0.439863	0.016808	26.16920	0.0001
D(GDP)	-0.000307	1.62E-08	-18947.03	0.0000
D(UNER)	-0.140905	0.002469	-57.07386	0.0000
C	-1.971196	0.391564	-5.034158	0.0151
@TREND	-0.110886	0.000939	-118.1242	0.0000

Table 13 (continued)

Malta

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.168916	0.005949	-28.39269	0.0001
D(MIG(-1))	0.952900	0.035655	26.72582	0.0001
D(GDP)	-1.33E-05	4.17E-09	-3183.820	0.0000
D(UNER)	0.236757	0.046416	5.100719	0.0146
C	-1.348411	0.547534	-2.462701	0.0906
@TREND	-0.061717	0.000775	-79.67581	0.0000

Netherlands

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.004963	0.000203	-24.48684	0.0001
D(MIG(-1))	0.844530	0.021414	39.43790	0.0000
D(GDP)	-3.89E-05	1.19E-10	-327713.2	0.0000
D(UNER)	-0.025862	0.000119	-217.7890	0.0000
C	-0.079159	0.067655	-1.170044	0.3265
@TREND	-0.002155	3.94E-05	-54.76502	0.0000

Poland

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.066343	0.001052	-63.08429	0.0000
D(MIG(-1))	0.782340	0.011826	66.15197	0.0000
D(GDP)	-2.77E-05	7.90E-10	-35092.23	0.0000
D(UNER)	-0.025003	6.19E-05	-403.6597	0.0000
C	-0.515034	0.060333	-8.536512	0.0034
@TREND	-0.025008	0.000162	-154.5610	0.0000

Portugal

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.085746	0.001305	-65.70242	0.0000
D(MIG(-1))	0.617932	0.005943	103.9815	0.0000
D(GDP)	-0.000204	3.91E-09	-52018.97	0.0000
D(UNER)	-0.256572	0.002174	-117.9998	0.0000
C	-0.579637	0.176564	-3.282879	0.0463
@TREND	-0.048151	0.000216	-223.0470	0.0000

Table 13 (continued)

Romania

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.115993	0.002024	-57.31728	0.0000
D(MIG(-1))	0.610601	0.016073	37.98997	0.0000
D(GDP)	-0.000224	4.66E-09	-47927.20	0.0000
D(UNER)	0.068022	0.005894	11.54040	0.0014
C	-1.272664	0.207141	-6.143961	0.0087
@TREND	-0.022343	0.000339	-65.92901	0.0000

Slovak Republic

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.369765	0.013327	-27.74453	0.0001
D(MIG(-1))	0.439572	0.021705	20.25166	0.0003
D(GDP)	0.000124	7.13E-09	17445.56	0.0000
D(UNER)	-0.023261	0.001604	-14.50042	0.0007
C	-2.356301	0.611618	-3.852568	0.0309
@TREND	-0.118708	0.001425	-83.28368	0.0000

Slovenia

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.235489	0.006311	-37.31616	0.0000
D(MIG(-1))	0.637109	0.007384	86.28482	0.0000
D(GDP)	6.26E-05	2.94E-09	21303.75	0.0000
D(UNER)	0.048100	0.007480	6.430453	0.0076
C	-2.800565	1.120315	-2.499801	0.0877
@TREND	-0.062370	0.000485	-128.5423	0.0000

Sweden

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.145211	0.001195	-121.5263	0.0000
D(MIG(-1))	0.661766	0.009571	69.14099	0.0000
D(GDP)	3.19E-06	1.61E-09	1984.339	0.0000
D(UNER)	0.038251	0.001741	21.96671	0.0002
C	-2.350860	0.399853	-5.879317	0.0098
@TREND	-0.045712	0.000166	-275.7294	0.0000

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