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# MIGRATION, INNOVATION AND GROWTH IN THE EUROPEAN UNION

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DOI: 10.2478/tjeb-2021-0010

*In today's globalised world, international migration represents one of the most important topics of the 21st century, with diverse effects on a country's economic, political, and social dimensions. Depending on how well government actors succeed to manage these flows, the positive effects can be further boosted, while the adverse effects can be diminished (for both receiving and sending countries). A great deal of attention must be paid to policy strategies that foster domestic investments and innovation, as they represent a meaningful engine of economic growth, influencing positively and significantly the income in the long run. This research aims to evaluate the influence of human capital (with a focus on foreign human resources), innovation activities and investments (finance and support) on per capita economic growth (proxied by GDP per capita), in the case of all the European Union countries. The timeframe is between 2014 and 2021. For the econometric analysis of the panel data, we used Fixed-Effects regression and System GMM approach (both short-run and long-run estimations). The econometric results emphasise the positive and statistically significant effects (both on short-run and long-run) of foreign PhD students, patent applications, resource productivity, employment in innovative enterprises and tertiary educated people on per capita economic growth. The coefficients of the independent variables were higher in the long run than in the short run. Therefore, in the long run, a one standard deviation improvement in variables: foreign PhD students and patent applications lead to a 0.014-fold, respectively 0.088-fold increase in the logarithm GDP per capita.*

**Keywords:** **PhD foreign students, Innovation, R&D expenditures, European countries**

**JEL Classification:** **J61, O31, O32**

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# 1. Introduction

In today's globalised world, international migration represents one of the most important topics of the 21st century. These movements have diverse effects (positive and negative) on origin and destination countries' economic, political, and social dimensions (Koczan et al., 2021). Depending on how well government actors manage these flows, the positive effects can be further boosted, while the adverse effects can be diminished for both receiving and sending countries (IOM, 2018). Moreover, a great deal of attention must be paid to policy strategies that foster innovation, as it is relevant for per capita economic growth (Maradana et al., 2017). It is well known that the nation's quality of governance and its economic output are highly correlated (Dima et al., 2013; Dima et al., 2017).

Lately, more and more economies are trying to attract and maintain the most talented workers (Boeri et al., 2012; Docquier & Machado, 2016), as they represent crucial resources in enhancing the overall productivity (Peri, 2012), innovation, and therefore competitiveness, and economic and social development (Foresti et al., 2018). For receiving countries, highly skilled foreigners represent a "brain gain", with meaningful implications in technological progress and economic growth (Miguelez & Noumedem Temgoua, 2020). Since these types of migrants have different educational and cultural backgrounds (high levels of diversity), they positively influence productivity at the workplace, provide complementary skills for local co-workers and fill vacancies in diverse fields. Moreover, as skilled immigrants tend to be, on average, younger than the native workers, many countries have implemented specific migration programmes which aim to attract qualified foreign workers and offset the possible downsides of population ageing (Cerna & Czaika, 2016). When it comes to origin countries, migrants may contribute positively to knowledge and technology disseminating from the destination back to the country of origin, send remittances and thus represent an engine for domestic innovation and economic growth (Gelb & Krishnan, 2018). Apart from the significant advantages brought by migrants (both in origin and destination countries), some downsides/ costs may also occur. However, all in all, skilled migration induces welfare gains at the global level because the benefits achieved by some countries surpass the hindrances faced by other countries (Biavaschi et al., 2020).

It is well known that human capital (both foreign and local) makes vital contributions to technological innovation (which is a driver of economic growth), and domestic investments serve as another meaningful engine of economic growth (Dima et al., 2013). Therefore, these topics are worth exploring and analysing further so that all countries (both receiving and sending) can take advantage of human mobility and improve their economic output. Therefore, this research aims to evaluate the influence of human capital (with a focus on foreign human resources), innovation activities and investments (finance and support) on per capita economic growth (proxied by GDP per capita), in the case of all the European Union countries. The timeframe is between 2014 and 2021. For the econometric analysis of the

DOI: 10.2478/tjeb-2021-0010



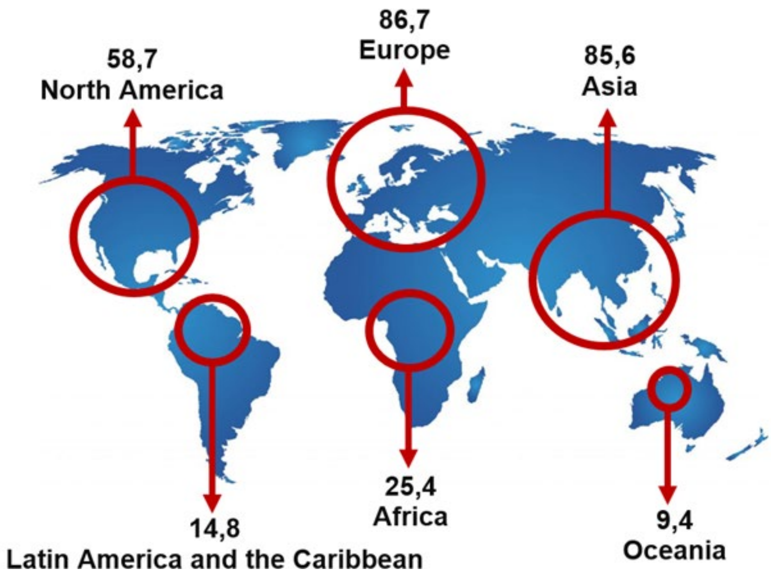
panel data, we used the One-step System GMM approach (both short-run and long-run estimations), and the data was computed using Excel and STATA 14 econometric packages.

## 2. Overview of International Migration and Innovation

### 2.1. Global Migration Trends and Determinants of International Migration

Over the years, the number of international migrants maintained an upward trend, growing slightly faster than predicted in some years. However, in the actual COVID-19 pandemic context, human mobility was significantly obstructed, with the number of international migrants reaching only 281 million (3,6% of the global population) in 2020 (UN, 2020). If it were not for the COVID-19 pandemic, an increase in international migrants by about 2 million worldwide would have been expected from July 2019 to June 2020.

Figure 1 emphasizes the number of international migrants in 2020 among six regions: Europe, Asia, North America, Africa, Latin America and the Caribbean and Oceania. In 2020, the highest number of international migrants resided in three regions, namely Europe (86,7 million), Asia (85,6 million) and North America (58,7 million). The other three areas hosted a lower number of international migrants, namely Africa (25,4 million), Latin America and the Caribbean (14,8 million) and Oceania (9,4 million) (UN, 2020).




*Source: Own computation using data from UN International Migration 2020 Highlights*

**Figure 1.** International migrants by region (million), 2020

The majority of migrants (182 million) have established in high-income countries (seeking the most meaningful opportunities for themselves and their families), 86 million resided in middle-income countries, and only 12 million lived in low-income countries. Among the most five popular destination countries in 2020 were the United States of America (which hosted 51 million international migrants), Germany (which hosted about 16 million), Saudi Arabia (which hosted 13 million), the Russian Federation (which hosted 12 million) and the UK (hosting 9 million). Among the five major emigration countries were India (18 million), followed by Mexico and the Russian Federation (11 million each), China (10 million), and the Syrian Arab Republic (8 million) (UN, 2020).

In 2020, almost half of all international migrants settled within their region of origin. Usually, when people migrate, they tend to establish in closer or similar places to their former dwellings. Not many are eager to move to remote locations, of which they have limited knowledge (Martin and Zürcher, 2008).

The decision to migrate from one place to another (temporary or permanently) is more or less influenced by five groups of drivers: economic, political, social, demographic, and environmental (Black et al., 2011). These drivers are dynamic forces with strong linkages, which influence/ constrain people to make specific decisions concerning the inception of migration and its perpetuation (Van Hear et al., 2017).

The migration decision is made on both an economic and an emotional basis. While the financial motivations mainly imply economic gains, the emotional reasons imply the relationship with the neighbours in terms of giving and receiving help when needed (known as social capital), attachment to the place (local) and aversion to risk (Clark & Lisowski, 2019).

Bodvarsson & Van den Berg (2013) emphasized that the migration determinants fall into four categories (figure 2):

- Push factors, which are negative stimuli from the origin country that determine individuals abandon their origin country and emigrate;
- Pull factors, which are positive stimuli from the destination country that determine individuals settle in that particular foreign country;
- Stay factors, which are positive stimuli from the origin country that determine individuals remain in their origin country and not to emigrate;
- Stay away factors, which are negative stimuli from a foreign country that determine individuals not to desire to settle there.


*Source: Bodvarsson & Van den Berg (2013), modified*

**Figure 2. Determinants of migration: push, pull, stay, and stay away factors**

The migration determinants/ motivations change over time, depending on the surroundings and life courses. Also, the decision-making process concerning migration may be distinctive among people, depending on one's age, commitments, expectations, or goals. However, some individuals may not have the possibility to migrate, even if they desire, because they are restrained by poverty and economic hardship (IOM, 2016).

## 2.2. Measuring Innovation and Innovation Trends Globally and at the EU Level

It is well known that innovation and technical change are vital components of per capita economic growth (which is one of the features of economic development) (Maradana et al., 2017). Therefore, from all times, economists sought to find appropriate indicators for innovation as a whole (Venturini et al., 2012). During the years, considerable effort has been made to identify the different forms of measuring innovation. However, a generally acknowledged indicator or set of indicators does not exist for measuring innovative performance (Hagedoorn & Cloodt, 2003).

Nevertheless, it is widely acknowledged by many researchers (Griliches et al., 1986; Griliches, 1990; Furman et al., 2002; Bottazzi & Peri, 2003) that patent applications are a valuable and unique indicator for technological and innovative activity, being tightly correlated with firms' R&D activities. Patents are a valuable proxy for the technological effort of the firms and non-firm entities endeavouring to design novel products and processes. Moreover, patents are preferred to other indicators because they do not raise issues in terms of data availability

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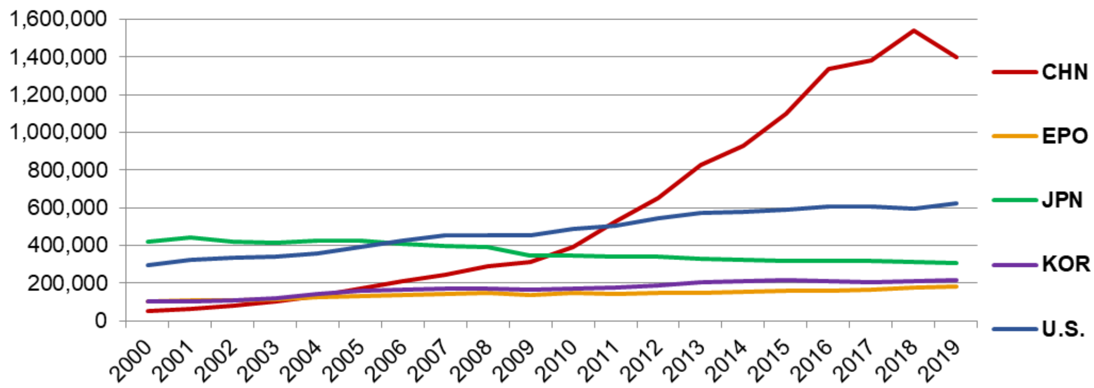
and accessibility (Griliches, 1990). On the other hand, some authors consider studying only the number of patents misleading when analysing the creative output. Firstly, because patents vary in terms of technological and economic value, only a few are remarkably valuable, while many are less valuable (Schankerman & Pakes, 1985). Secondly, various essential innovations are not patented (because of diverse reasons: the invention cannot be patentable or is not considered significant enough to be worth being patented, or the inventor chooses not to patent it) (Fontana et al., 2013).

Figure 3 emphasises the trend in the total patent applications for the top five offices: China (CHN), U.S. (U.S.), Japan (JPN), Republic of Korea (KOR), and European Patent Office (EPO), between 2000 and 2019 (WIPO, 2021).




*Source: Own computation using data from the WIPO statistics database, January 2021*

**Figure 3. Trend in the patent applications for the top five offices, 2000-2019**

From 1980 to 2005, the Patent Office of Japan registered the most patent applications worldwide (with a maximum of 440.248 patents in 2001). From 2006, the U.S. Patent Office held the top position until 2010 (with a maximum of 490.226 patents in 2010), when the Patent Office of China exceeded it. Since then, China has recorded dynamic growth in patents (with a maximum of 1.542.002 in 2018). However, in comparison to 2018, in 2019, the Patent Office of China faced a downward trend, recording 1.400.661 patent applications. Apart from Japan (which had an upward course until 2005 and then suffered a drop) and China (which faced a decrease in 2019), all the other three Patent Offices followed an approximately ascending trend from 1980 to 2019.

In the year 2019, in China (1,243,568 patents vs 157,093 patents), Japan (245,372 patents vs 62,597 patents) and Republic of Korea (171,603 patents vs 47,372 patents), the number of patent applications filed by residents exceeded the number of patent applications filed by non-residents. At the opposite pole, in U.S. (336,340 patents vs 285,113 patents) and EPO

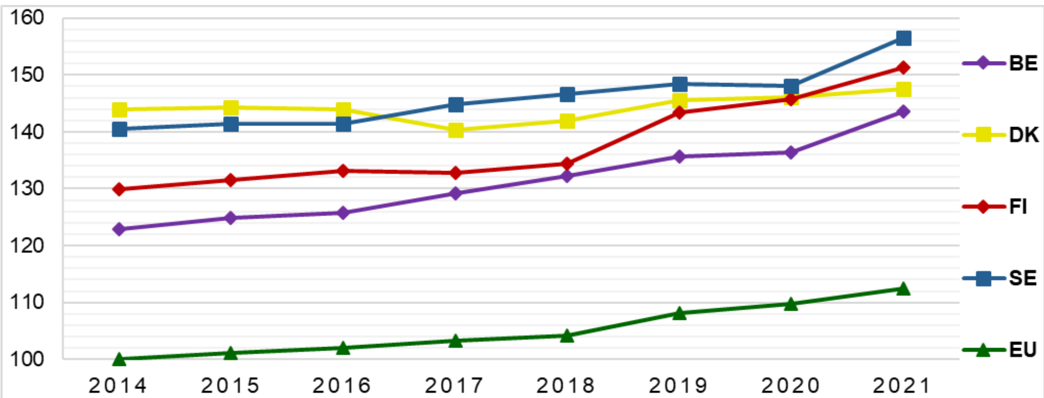
(98,895 patents vs 82,584 patents), non-residents filed more patent applications in comparison to residents.

When it comes to the EU countries, the overall performance of the innovation system is measured through the Summary Innovation Index. For 2021, this indicator is composed of the unweighted average of 32 indicators (European Innovation Scoreboard, 2021). According to their Summary Innovation Index (SII), the EU countries are divided into four categories. In 2021, the countries with SII exceeding 125% of the EU average are considered Innovation Leaders, the countries with SII between 100% and 125% are deemed Strong Innovators, the countries with SII between 70% and 100% are Moderate Innovators, and the countries with SII below 70% are Emerging Innovators.

All EU countries are listed according to their Summary Innovation Index ranking (for 2021):

- Innovation Leaders: Sweden, Finland, Denmark and Belgium;
- Strong Innovators: the Netherlands, Germany, Luxembourg, Austria, Estonia, France and Ireland;
- Moderate Innovators: Italy, Cyprus, Malta, Slovenia, Spain, Czechia, Lithuania, Portugal and Greece;
- Emerging Innovators: Croatia, Hungary, Slovakia, Poland, Latvia, Bulgaria and Romania.

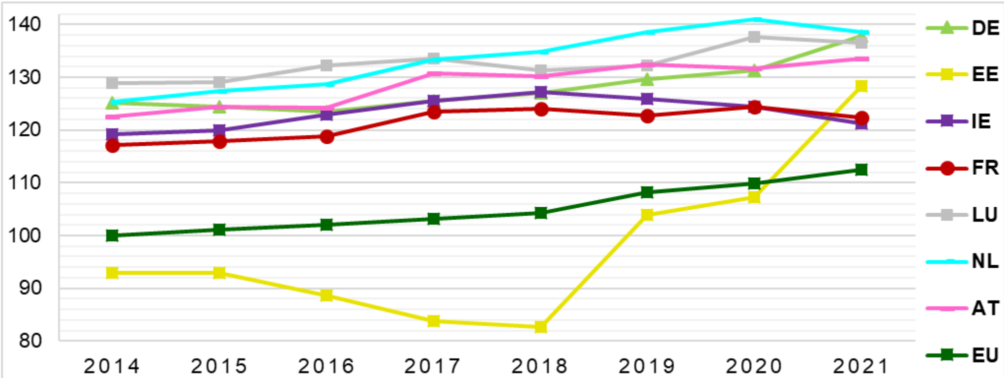
Figure 4 and 5 highlights the Innovation Index performance trends for Innovation Leaders and Strong Innovators (from 2014 to 2021), compared to the EU Innovation Index performance in 2014 (2014 is the reference year). EU Innovation Index in 2014 = 100 points.




*Source: Authors' own computation on the dataset in Excel*

**Figure 4.** **Innovation Index trends relative to EU performance in 2014 (for Innovation Leaders), 2014-2021**

As shown in figure 4, all four countries have an ascending trend in terms of the Innovation Index, in all eight years being above the EU performance in 2014. In 2021, the highest Innovation Index score is registered in SE (156,45 points), followed by FI (151,38 points), DK (147,51 points) and BE (143,52 points).




*Source: Authors' own computation on the dataset in Excel*

**Figure 5. Innovation Index trends relative to EU performance in 2014 (for Strong Innovators), 2014-2021**

Figure 5 shows that in all eight years, apart from EE, all countries have the Innovation Index above the EU performance in 2014. However, during 2018 (82,68 points) and 2021 (128,29 points), the Innovation Index of EE had a visible ascending trend. In 2021, the highest Innovation Index score for Strong Innovators is registered in NL (138,5 points), followed by DE (137,92 points), LU (136,53 points), AT (133,62 points), EE (128,29 points), FR (122,3 points) and IE (121,27 points).

## 3. Literature Review (Implications of Migration in Recipient and Origin Countries)

In the globalised world, highly skilled immigrants' mobility has widely increased. For destination countries, this fact positively affects human capital accumulation, which plays a significant role in economic development.

It is well known that the composition of the workforce is by far more meaningful than the size of it (quality vs quantity) (Romer, 1990). Therefore, many developed economies compete to attract the best and brightest immigrants, as they represent an essential engine of overall productivity and boost global science and economic growth in the long term (Peri, 2016). Consequently, an increasing number of countries have implemented labour migration policies to lure and select skilled and highly skilled foreigners (Docquier & Machado, 2016).

Investigating the role of skilled immigrants on the product and process innovation activity at the firm level in Britain, Gagliardi (2014) found that innovation accomplishment depends on two types of factors: internal (R&D expenditures and skilled local labour) and external (skilled immigrant labour). Therefore, countries should take advantage of both internal and external resources on their way to economic development.

In a similar vein, other studies highlight that along with R&D investments, highly skilled employees (defined as workforce with tertiary-education or doctoral studies) facilitate the performance at the firm and industry level, being indispensable factors in boosting creativity and technological innovations (Leiponen, 2005; Mohnen & Roller, 2005). For instance, in the U.S., it is unquestionable that highly educated immigrants (students and workers), especially from origin countries like China and India, represent influential factors for the U.S. technology development, with deep positive spills-over on the U.S. productivity and competitiveness (Chellaraj et al., 2006).

When it comes to the increased diversity of the workforce, it may induce both positive and negative effects, depending on various aspects (Bove & Elia, 2017). Ferrucci & Lissoni (2019) found that the diversity of highly skilled foreigners plays an essential role in boosting creativity and technological innovations at the team level. In a similar vein, Hong & Page (2004) reveal that the demographic, cultural, ethnic, and expertise diversity of a team contribute positively to decision making and problem-solving at the workplace. Overall, the immigrants' diversity in skills and education is positively correlated with their performance in the workplace. This is a case when the downsides/ costs generated by foreigners (for example, communications barriers) are surpassed by the gains induced by foreigners (for example, immigrants provide complementary skills to local peers, the diversity of a team is essential in better decision-making and problem-solving) (Lazear, 1999).

Following Alesina et al. (2016), the size and diversity of foreign workers (diversity measured through birthplace diversity) are positively correlated with measures of economic prosperity (mainly for skilled foreigners originating from more prosperous economies). Moreover, skilled immigrants provide local workers with complementary skills, magnifying income per capita by raising total factor productivity (TFP) (Boubtane et al., 2016).

Feyrer (2008) and Parsons (2015) claim that changes in the workforce age structure strongly impact the productivity of innovative activity. It is well known that the ageing of the population has adverse effects on regional competitiveness and growth, whereas immigrants (mainly entrepreneurs and highly skilled) intensify innovation, productivity, and entrepreneurship (significant predictors of competitiveness). Therefore, since skilled foreign workers tend to be, on average, younger than the native workers, many countries seek to attract immigrants to counteract the eventual downsides of population ageing (Poot, 2008; Cerna & Czaika, 2016).

At the opposite pole, apart from immigrants' unquestionable advantages, there may be some disadvantages. There are cases when immigrants may substitute the local workers (resulting in increased unemployment of locals) or diminish the productivity of native peers at the workplace (Borjas, 2003). Sometimes, because of their large diversity, foreigners may hamper the cohesion of the destination country's society and, at last, reliance and competitiveness (Poot, 2008). Also, depending on the type of immigrants, they may increase public expenditures and threaten national security.

When it comes to the origin countries, the emigration of human capital has tremendous implications, both positive and negative. Firstly, labour emigration contributes positively to disseminating knowledge and technology from the destination back to the origin country, representing an engine for domestic innovation and implicit spurting economic growth and living standards (Gelb & Krishnan, 2018). Also, diaspora groups make further vital investments in their homeland through remittance transfers and physical return of migrants who have achieved various skills and expertise abroad or set up new businesses.

However, there is an optimal level of highly skilled emigration, neither too much nor too little (known as "beneficial brain drain"), from which countries of origin can indeed benefit. Nevertheless, if the emigration flow is too high, sending countries face a loss of the most skilful individuals (known as "brain drain"), which has harmful implications over the overall productivity and economic growth (Djiofack et al., 2013).

## 4. Research Methodology

### 4.1. Aim of Research and Research Hypotheses

This research aims to evaluate the influence of human capital (with a focus on foreign human resources), innovation activities and investments (finance and support) on per capita economic growth (proxied by GDP per capita) in the case of the EU countries. The period taken into consideration is between 2014 and 2021.

For this research, the following main hypotheses are tested based on the previous studies concerning the process of economic growth (Cinnirella & Streb, 2017; Diebolt & Hippe, 2018):

*H1*: Human capital accumulation (with focus on PhD international students) plays a crucial role in the economic growth intensification;

*H2*: Finance and support for R&D and technological change are meaningful drivers of economic growth.

### 4.2. Data and Indicators

The econometric analysis of the panel data was performed using multifactorial econometric models. The data was collected from European Innovation Scoreboard 2021 (EIS 2021) and

Eurostat and was computed using Excel and STATA 14 econometric package. All indicators' values are at the country level and are lagged with one year.

The dependent variable is represented by the GDP per capita, a proxy for economic growth. The independent variables are represented by the following variables:

Human capital proxied by Foreign doctorate students as a % of all doctorate students and Population with tertiary education;

- Employment proxied by Employment in innovative enterprises;
- Intellectual assets proxied by PCT patent applications per billion GDP (in PPS);
- Finance and support proxied by R&D expenditure in the public sector as a % of GDP (universities and government research organisations);
- Resource productivity.

## 4.3. Research Equation

We did not specify a theoretical model but rather opted for an empirical one (we "let the data speak for itself"). For the econometric research, we have generated a linear multifactorial model, with the following empirical form of the stochastic equation:

$$Y = f(X_1, X_2, \ldots, X_n) + \varepsilon \qquad (1)$$

Where,

- *Y* is the dependent variable;
- $X_1, X_2, \ldots, X_n$ are the independent variables (*n* is the number of the independent variables);
- $\varepsilon$ is the residual term (error term).

In this study case, we deal with dynamic panel data, where:

- the dependent variable depends on its own past levels;
- some independent variables are not strictly exogenous, they are correlated with past and possibly current error terms (potential endogeneity); therefore, there are simultaneous systems of equations;
- it exists heteroscedasticity, as the variance of the errors is not constant.

Therefore, following Arellano & Bond (1991), Arellano & Bover (1995) and Roodman (2009), we used the Generalized Method of Moments (GMM) approach to obtain unbiased estimators and to improve the efficiency of the model. Rewriting the above equation, we have obtained the following form:

$$Y_{i,t} = \beta_0 + \beta_1 Y_{i,t-1} + \beta_2 X_{i,t} + \beta_3 Z_{i,t} + a_i + u_{it} \quad (2)$$

Where,

- $Y_{i,t}$ is the dependent variable;
- $Y_{i,t-1}$ is the previous value of the dependent variable (lagged dependent variable is also a regressor);
- $X_{i,t}$ represents the vector of explanatory variables (not strictly exogenous variables);
- $Z_{i,t}$ represents the control variables (exogenous variables);
- $\beta_0$ is the estimated intercept coefficient, while $\beta_1, \beta_2, \beta_3$ are the estimated slope coefficients of the variables;
- $\varepsilon_{it} = a_i + u_{it}$ is the error term, including both fixed effects and idiosyncratic shocks;
- *i* represents the country, and *t* represents the year.

## 4.3. Descriptive Statistics

Table 1 comprises the summary statistics of the sample. It emphasises the mean, median, minimum and maximum values, standard deviation, kurtosis and skewness, and each variable's number of observations. All indicators' values are at the country level.

**Table 1.** Descriptive statistics of the variables

| | ln_GDP_pc | Foreign_PhD | Tert_edu | Patent_app | R&D_public | Empl_innov | Resource_W |
|---|---|---|---|---|---|---|---|
| Mean | 10,23 | 18,92 | 40,27 | 2,56 | 0,60 | 52,83 | 1,84 |
| Median | 10,16 | 12,29 | 40,65 | 1,44 | 0,57 | 56,11 | 1,62 |
| Minimum | 8,86 | 0,20 | 24,20 | 0,16 | 0,20 | 10,93 | 0,62 |
| Maximum | 11,69 | 86,99 | 60,30 | 9,88 | 1,11 | 79,87 | 4,55 |
| Std. Dev. | 0,62 | 17,99 | 8,61 | 2,60 | 0,24 | 14,11 | 0,81 |
| Kurtosis | -0,56 | 4,25 | -0,75 | 0,62 | -0,98 | -0,11 | 0,28 |
| Skewness | 0,16 | 1,87 | 0,10 | 1,30 | 0,19 | -0,67 | 0,85 |
| Obs. | 216 | 216 | 216 | 216 | 216 | 216 | 216 |

*Source*: Authors' own computation on the dataset in Excel

The values of standard deviation are relatively high, showing that, on average, the values for each indicator are not close to the mean value of that indicator. The skewness and kurtosis values for almost all variables show a non-normal distribution (the normal distribution values are 0 for skewness and, respectively, 3 for kurtosis). Therefore, the values of standard deviation and the non-normal values of the distribution parameters indicate the presence of heterogeneity in the data.

DOI: 10.2478/tjeb-2021-0010



# 5. Results and Comments

## 5.1. Tests for Multicollinearity and Heteroscedasticity

In Table 2, we tested the existence of multicollinearity between independent variables.

**Table 2.** Matrix of correlations (test for multicollinearity)

| | Foreign_PhD | Tert_edu_pop | Patent_app | R&D_public | Empl_innov | Resource_W |
|---|---|---|---|---|---|---|
| Foreign_PhD | 1 | | | | | |
| Tert_edu_pop | 0,4599 | 1 | | | | |
| Patent_app | 0,3718 | 0,1701 | 1 | | | |
| R&D_public | 0,3468 | 0,1530 | 0,7742 | 1 | | |
| Empl_innov | 0,4945 | 0,3101 | 0,5322 | 0,6036 | 1 | |
| Resource_W | 0,5851 | 0,1718 | 0,1535 | 0,1178 | 0,4527 | 1 |

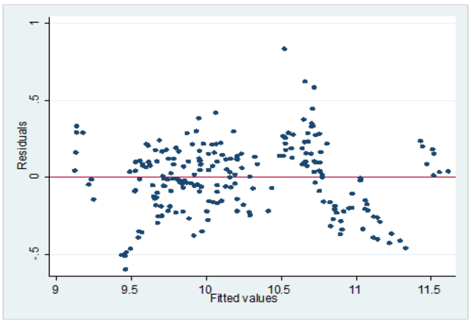
*Source: Authors' own computation on the dataset in Excel*

As observed, the variables are not highly correlated with each other (just a few values are above 0.5). Therefore, overall, we do not deal with multicollinearity issues. Further on, we test the existence heteroscedasticity by applying White's test (Table 3). Because the chi-square statistic is 0, the null hypothesis of homoscedasticity will be rejected at a 1% level of significance. Therefore, we deal with heteroscedasticity issues. Figure 6 highlights the heteroscedasticity of the panel graphically.

**Table 3.** White's test for heteroscedasticity

| Source | chi2 | df | p |
|---|---|---|---|
| Heteroskedasticity | 101.47 | 27 | 0.0000 |
| Skewness | 17.62 | 6 | 0.0073 |
| Kurtosis | 0.67 | 1 | 0.4134 |
| Total | 119.76 | 34 | 0.0000 |

*Source: Authors' own computation on the dataset in STATA 14*




*Source: Authors' own computation on the dataset in STATA 14*

**Figure 6.** Heteroscedasticity graphically

## 5.2. Models Applied and Results

Firstly, we run a preliminary baseline Fixed Effects regression between GDP per capita (dependent variable) and the six independent variables + one lag of the dependent variable (Table 4) in order to obtain an initial estimation of the importance of human capital, investments and innovation activities for economic growth.

**Table 4.** Preliminary baseline estimation: Fixed Effects regression

| | |
|---|---|
| L.ln_GDP_pc | 0.505*** |
| | (0.06) |
| Foreign_PhD | 0.006** |
| | (0.00) |
| Tert_edu_pop | 0.001 |
| | (0.00) |
| Patent_app | -0.016 |
| | (0.01) |
| R&D_public | -0.410*** |
| | (0.08) |
| Empl_innov | 0.000 |
| | (0.00) |
| Resource_W | 0.032 |
| | (0.03) |
| Constant | 5.108*** |
| | (0.59) |
| R-squared (within) | 0.534 |
| F-statistic | 30.006 |
| | (p=0.00) |

*Notes: ***, **, and * represent statistical significance at 1%, 5%, and 10% level. The values in brackets represent the robust standard errors.*
*Source: Authors' own computation on the dataset in STATA 14*

The estimations imply that a percentage change in GDP per capita from the last period is associated with 0.505% increase in the GDP per capita from the current period (at a 1% significance level); a percentage change in foreign PhD students is associated with 0.006% increase in the GDP per capita (at a 5% significance level), while a percentage change in R&D public expenditure is associated with 0.410% decrease in the GDP per capita (at a 1% significance level).

A long-term equilibrium relationship exists between innovation (and implicit its components) and per capita economic growth in terms of the incidence of cointegration (Maradana et al., 2017). Therefore, we must consider the presence of a two-way causal relationship between the dependent variable (GDP per capita) and the explanatory variables. Also, we may face potential unobserved country-specific effects that may be correlated with the explanatory variables. In this case, different estimation methods, like ordinary least squares (OLS), will produce biased results. Last but not least, in OLS or Fixed Effects regressions, the orthogonality condition between the error term and variables is not likely to be fulfilled. Therefore, we may have inconsistent estimates using OLS, Within Groups and GLS estimators (Nickell, 1981).

Bearing in mind these things, we followed Arellano & Bond (1991), Arellano & Bover (1995) and Roodman (2009) researches and used the Generalized Method of Moments (GMM) approach to obtain unbiased estimators and to improve the efficiency of the model. This research has analysed all 27 member states (*N*) of the EU over eight years (*T*), resulting in strongly balanced panel data. Following Roodman (2009), we first estimated the dynamic model through pooled OLS and the Fixed-Effects (within) regressions. Then, One-step and Two-step Difference Generalized Method of Moments (GMM) models were generated. The coefficients of the lagged dependent variable (GDP per capita) are presented below (Table 5).

**Table 5. Coefficients of the lagged dependent variable (logarithm GDP per capita)**

| Estimators | Coefficients |
|---|---|
| Pooled OLS (upper-bound estimate) | 0,952722 |
| Fixed Effects (lower-bound estimate) | 0,504813 |
| One-step Difference GMM | 0,315939 |
| Two-step Difference GMM | 0,308463 |

*Source: Authors' own computation on the dataset in STATA 14*

As observed, for both One-step and Two-step Difference GMM coefficients of the lagged dependent variable are below the fixed-effects coefficient (and implicit, below pooled OLS coefficient). Therefore, it is more beneficial to run the System GMM (a better way to reduce the bias) that can identify both short-run and long-run effects. Therefore, firstly we have developed both One-step and Two-step System GMM for the short run. We opted for One-step System GMM (Table 6) because the results were more meaningful statistically for the One-step than for the Two-step System GMM. Then, we developed a One-step System GMM for the long run only with those variables that had significant levels of p-values in the short-run (Table 7). For the short-run model, it was applied the Arellano-Bond test (to test the autocorrelation of residuals) and the Sargan-Hansen test (for over-identifying restrictions in the statistical model).

**Table 6.** Dynamic panel-data estimation, One-step System GMM (short-run)

| ln_GDP_pc | Coef. | St.Err. | t-value | p-value | Significance |
|---|---|---|---|---|---|
| L.ln_GDP_pc | 0.405 | 0.155 | 2.62 | 0.015 | ** |
| Foreign_PhD | 0.008 | 0.003 | 2.97 | 0.006 | *** |
| Resource_w | 0.076 | 0.044 | 1.73 | 0.096 | * |
| Empl_innov | 0.006 | 0.002 | 2.84 | 0.009 | *** |
| Tert_edu_pop | 0.007 | 0.003 | 2.70 | 0.012 | ** |
| Patent_app | 0.053 | 0.013 | 4.05 | 0.000 | *** |
| R&D_public | -0.123 | 0.208 | -0.59 | 0.560 | |
| Constant | 5.125 | 1.388 | 3.69 | 0.001 | *** |
| 1st order autocorrelation (AR 1) *$H_0$: no autocorrelation* | 0.265 | | | | |
| 2nd order autocorrelation (AR 2) *$H_0$: no autocorrelation* | 0.148 | | | | |
| Sargan test | 0.000 | | | | |
| Hansen test | 0.000 | | | | |
| F-test | 38530.43 (p=0.00) | | | | |
| Number of obs. | 189 | | | | |

*Notes: ***, **, and * represent statistical significance at 1%, 5%, and 10% level.*
*Source: Authors' own computation on the dataset in STATA 14*

In the short run, apart from R&D public expenditures, all variables seem to be relevant to economic growth (proxied by GDP per capita), with a positive influence and being statistically significant at 1%, 5%, or 10% levels. It is emphasized the importance of resource productivity, technological change (innovation) and human capital (both foreign and local) on per capita economic growth. The GDP per capita from the last period seems to have the highest coefficient magnitude on the GDP per capita from the current period, at a 5% significance level. Apart from the lagged dependent variable, resource productivity and patent applications have greater coefficients than other variables, being significant at 10% and respectively, at 1% level. An improvement of one standard deviation at the level of resource productivity produces a 0.076-fold increase in the logarithm GDP per capita. An improvement of one standard deviation at the level of patent applications produces a 0.053-fold increase in the logarithm GDP per capita. When it comes to the foreign PhD students, an improvement of one standard deviation at their level produces a 0.008-fold increase in the logarithm GDP per capita, being statistically significant at a 1% level. Therefore, both hypotheses H1 and H2 (Human capital accumulation (with focus on PhD international students) plays a crucial role in the economic growth intensification; Technological changes are meaningful drivers of economic growth.) are fulfilled.

Both Arellano-Bond tests, AR(1) and AR(2), have pretty high values, meaning we cannot reject the null hypothesis ($H_0$: no autocorrelation). Therefore, the residuals in the first differences are serially correlated. Also, the values of Sargan and Hansen tests of over-identifying restrictions in the statistical model are too low.

Table 7 emphasises the One-step System GMM for the long run, only with those variables that had significant levels of p-value in the short run.

**Table 7. Dynamic panel-data estimation, One-step System GMM (long-run)**

| ln_GDP_pc | Coef. | St.Err. | z-value | p-value | Sig |
|---|---|---|---|---|---|
| Foreign_PhD | 0.014 | 0.002 | 6.15 | 0.000 | *** |
| Resource_w | 0.128 | 0.071 | 1.79 | 0.073 | * |
| Empl_innov | 0.010 | 0.004 | 2.77 | 0.006 | *** |
| Tert_edu_pop | 0.012 | 0.005 | 2.16 | 0.031 | ** |
| Patent_app | 0.088 | 0.021 | 4.19 | 0.000 | *** |

*Notes: ***, **, and * represent statistical significance at 1%, 5%, and 10% level.*
*Source: Authors' own computation on the dataset in STATA 14*

All considered variables are statistically significant at 1%, 5%, or 10% levels in the long run. Also, in the long run, all indicators have more significant values of coefficients than in the short-run model. It seems that again, the highest values of coefficients are registered for resource productivity and patent applications, being significant at 10% and, respectively, at a 1% level. An improvement of one standard deviation at the level of resource productivity produces a 0.128-fold increase in the logarithm GDP per capita, while an improvement of one standard deviation at the level of patent applications produces a 0.088-fold increase in the logarithm GDP per capita. For foreign PhD students, the magnitude of the coefficient has doubled in the long run (coef.=0.014) compared to the short-run (coef.=0.008) with a statistical significance of 1%. An improvement of one standard deviation at the level of tertiary educated people produces a 0.012-fold increase in the logarithm GDP per capita, being significant at a 5% level. Last but not least, an improvement of one standard deviation at the level of employment in innovative enterprises produces a 0.010-fold increase in the logarithm GDP per capita, at a significance level of 1%.

## 5. Conclusion

In the nowadays globalised world, the mobility of highly skilled immigrants has widely increased, representing one of the most important topics of the 21st century as it generates diverse effects on a country's economic, political, and social dimensions (Koczan et al., 2021). Depending on how well government actors manage these flows, the positive effects can be further boosted, while the adverse effects can be diminished for both receiving and sending countries (IOM, 2018). Nowadays, more and more economies are trying to attract and maintain the most talented workers (human capital), representing significant factors in technology development, with deep positive spill-over on the country's productivity, competitiveness, economic and social development. Moreover, a great deal of attention must be paid to policy strategies that foster innovation, as it is relevant for per capita economic growth (Maradana et al., 2017). Apart from human capital and technical change, domestic investments serve as another meaningful engine of economic growth, influencing positively and significantly the income in the long run (Dima et al., 2013).

This research aims to evaluate the influence of human capital (with a focus on foreign human resources), innovation activities and investments (finance and support) on per capita economic growth (proxied by GDP per capita), in the case of all the European Union countries. The timeframe is between 2014 and 2021. For the econometric analysis of the panel data, we used the Fixed-Effects regression and System GMM approach (both short-run and long-run estimations), and the data was computed using Excel and STATA 14 econometric packages. The econometric results emphasise the positive and statistically significant effects (both on short-run and long-run) of foreign PhD students, patent applications, resource productivity, employment in innovative enterprises and tertiary educated people on per capita economic growth. As observed, the coefficients of the independent variables were higher in the long run than in the short run. Therefore, in the long run, a one standard deviation improvement in variables: foreign PhD students and patent applications lead to a 0.014-fold, respectively 0.088-fold increase in the logarithm GDP per capita. The higher coefficient value remains for resource productivity, a one standard deviation improvement in this indicator leading to a 0.128-fold increase in the logarithm per capita economic growth. In conclusion, the main two hypotheses have been validated:

> H1: Human capital accumulation (with focus on PhD international students) plays a crucial role in the economic growth intensification;
>
> H2: Technological changes are meaningful drivers of economic growth.

As a general conclusion, it is well known that the nation's quality of governance and its economic output are highly correlated (Dima et al., 2013; Dima et al., 2017). Therefore, the more efforts and investments are dedicated to human capital development, technological change and R&D processes, the more predictable the overall economic growth is (which is a driver of economic development) (Gelb & Krishnan, 2018).

The limit of this research is the lack of data availability in terms of foreign skilled/ educated workforce. This study used only foreign PhD students as a proxy for foreign human capital because data about highly-educated immigrants employed in key innovation sectors was not available on EIS 2021 database. Also, for the following study, it would be interesting to extend the research to many other countries, not only for UE countries. This could be a subject of future research.

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