An Analysis of the Economic and Social Factors Affecting Real Convergence in Romania

Otilia Georgiana Floroiu
"Stefan cel Mare" University of Suceava, Romania
otilia.floroiu@yahoo.com

Abstract

It is essential that a high level of real convergence is achieved before joining the euro area, as major differences can lead to difficulties in managing the business cycles, in the absence of an independent monetary policy.

Therefore, each country should ensure a sufficient level of GDP per capita before the accession. But what can be considered sufficient? Looking back, most euro candidates had a GDP per capita level of 70%-80% of the EU level when adopting the euro currency.

Although Romania has made significant progress lately, the following still need to be achieved: labor market reforms, massive infrastructure investments, reducing the regional gaps, increasing innovation investments, and growing budget revenues.

The purpose of this paper is to identify the economic and social factors that influence real convergence in Romania, as we believe that working towards increasing real convergence will create the right framework for improving nominal convergence performance.

Key words: real convergence, GDP per capita, linear regression, innovation, euro confidence.
J.E.L. classification: F15, F36, O4.

1. Introduction

For a country to be allowed to join the euro area, it needs to meet the nominal criteria set out in the Maastricht Treaty, with reference to price stability, government budgetary position, exchange rate and long-term interest rate. However, the same treaty also refers to the sustainability of the degree of convergence, meaning the ability to maintain the criteria necessary for accession in the long term.

Unlike the nominal convergence requirements, there is no guidance procedure regarding the real convergence criteria. But the lessons learned from the eurozone have highlighted the importance of real convergence, without which the transition process cannot be effective. Therefore, it is essential to achieve a high level of income per capita convergence prior to the accession, as major differences can potentially cause disruptions in managing the business cycles, in the absence of an independent monetary policy.

All things considered, in this paper we aim to study the way and the amplitude with which certain economic and social factors influence the value of GDP per capita in Romania. We strongly believe that sustainable efforts towards increasing real convergence will create the right framework for improving the nominal convergence performance and increase our chances to adopt the euro currency in the foreseeable future.

Gross domestic product (GDP) is a macroeconomic indicator used to measure the performance of a country's economy. It tracks the market value of goods and services over a period, and its main components are consumption, investment, net exports, and government spending.

GDP per capita is obtained by dividing the value of the GDP by the number of inhabitants and reflects the relative performance of countries. The European Commission uses the value of this indicator expressed in standard purchasing power (PPS) to eliminate price differences in various countries and to facilitate comparison between states. GDP per capita (PPS) is used as a performance indicator in cross-country comparisons. An increase in its value indicates economic growth and national progress.

The purpose of this study is to analyze the effect of the independent variables on GDP per capita expressed in purchasing power standards in Romania, using data from 2011 to 2020. When choosing the independent variables we considered the conclusions of other studies, and the convergence performance in Romania.

In the model, we used GDP per capita (PPS) as a dependent variable and the following independent variables: tertiary education (X1, percentage of total population), population (X2, millions of citizens), corruption perception index (X3, score), GDP (X4, million euro), at-risk-of-poverty rate (X5, of total population), confidence in euro (X6, %), and total number of registered patents (X7).

The literature abounds with studies that test the interconnection between different independent variables, such as GDP, GDP growth rate, inflation, youth unemployment rate, inflation, surface area of a country, government type and GDP per capita.

2. Theoretical background

Upreti (2015) analyzes the factors influencing GDP growth and demonstrates, using the Least Squares (LS) method, that the exports volume and the production of natural resources have had a significant positive impact on the dependent variable. The same relationship could also be observed in the case of life expectancy and the level of investment.

In his study, Barro (1996) shows that the main factors influencing the growth rate of GDP per capita for one hundred states, analyzed between the 1960-1990 period are: compliance with the law, reduction of government spending, increase of life expectancy and to the number of compulsory education years, lower inflation, and increased trade. However, political freedom was found to have a very little, insignificant influence.

In the case of developing countries, there are other meaningful factors that must be taken into consideration when building a statistical model, in addition to variables such as consumption and exports that indubitably have a high influence on GDP growth. These include but are not limited to rising oil prices, power outages, corruption, political instability, and war (Kira, 2013).

Popa (2012) analyzes the impact of social influences on GDP per capita, using the following independent variables: population at risk of poverty, unemployment rate, life expectancy, and the average time spent in school. Increased life expectancy and education have shown to positively impact the level of GDP per capita, while unemployment rate and the population at risk of poverty have a negative influence.

Mamo's (2012) uses inflation, investment, population, and the level of initial GDP as independent variables in his study. The conclusion shows that rising inflation is a significant negative factor towards GDP per capita, while growing investments significantly affect GDP per capita in a positive manner. Population was shown to have a positive influence, while the initial level of GDP exhibited a negative influence, however neither of these factors were statistically significant.

GDP per capita and post-secondary education (X_1): Marquez-Ramos and Mourelle (2019) show that both secondary and tertiary education have an impact on economic growth. Barro and Sala-i-Marin (1995) show that higher education has the greatest effect on economic growth compared to the primary and secondary levels of education. According to Krueger and Lindahl (2001), highly educated countries display a negative relationship between education and economic growth. The same conclusion is reached in our study, with a negative relationship between the level of tertiary education and GDP per capita.

GDP per capita and population (X_2): Starting from the formula GDP per capita = (GDP / population), we expect an inversely proportional relationship between the two variables, meaning that an increase in the country's population will lead to a decrease in the value of GDP per capita. The same conclusion was reached in the following studies: Ilter (2017), Kim, Hewings & Nam (2014) and Hong (1994).

GDP per capita and the perceived corruption index (X_3): this independent variable refers to a country's level of institutional transparency through the perceived corruption index. Unsurprisingly, multi-national corporations prefer to invest and expand into countries with a high level of transparency. This implies a fair justice system, freedom of speech, freedom of the press, a system of checks and balances between governing bodies, and low corruption. Grundler & Potrafke (2019), Ugur (2014), Campos et al. all (2010) demonstrate a negative relationship between corruption and economic growth.

According to the 2020 Eurobarometer questionnaire answered by 7,700 companies, out of which 300 were from Romania, 88% of the Romanian participants mentioned corruption as a major problem in the Romanian business environment, the highest percentage in the European Union. Also, 97% consider that acts of corruption are extremely widespread in the country, the majority (51%) being cases of bribery. For most companies, poor infrastructure (93%) and high tax rates (82%) are major issues, along with excessive bureaucracy (89%) and institutional nepotism (84%).

GDP per capita and GDP (X_4): Considering the GDP per capita formula, we anticipate that there will be a positive correlation between the two variables. Ilter (2017) demonstrates the same positive relationship highlighted throughout this study.

GDP per capita and at-risk-of-poverty population rate (X_5): The relationship between GDP per capita and the rate of population close to the poverty line is significant, but contrary to expectations, it is not negative. An increase in GDP per capita does not necessarily result in a decrease in population that is near the poverty line, due to wealth inequality, depending on how the growth is distributed between the poor and the rich.

GDP per capita and confidence in the euro (X_6): To outline an effective strategy for adopting the euro, we have decided to introduce a parameter that summarizes the confidence of the population in the euro currency. The values were extracted from the Flash Eurobarometer reports from 2011-2020. If a statistically significant relationship is found between X_6 and the dependent variable, we can conclude that GDP per capita is indeed influenced by the population's confidence in the euro currency and could possibly represent the starting point for future research.

GDP per capita and total number of patents (X_7): Fagerberg (1987) states that there is a close correlation between the level of economic growth and the level of technological development. This is measured by a country's expenditures towards Research and Development and the number of patents it files for. Bere et al. (2014), considers that investing in Research and Development not only brings economic benefits, by stimulating high productivity and competitiveness, but also has a social impact, through engaging human capital in innovative activities that generate added value over time. Balash et. al (2020) confirms the hypothesis that there is an interdependence between the growth rate of GDP per capita and the increase in the amounts allocated to technological innovations.

3. Research methodology

The research was based on quantitative data, as well as qualitative data. The qualitative data was analyzed and then summarized in the literature review section, while the quantitative data was organized in Excel and uploaded in EViews, where we were able to efficiently manage the data, performed econometric and statistical analysis and produced high quality graphs and tables.

The data was recorded in Romania between 2011 and 2020. When choosing the independent variables, we considered both the existing studies and the variables relevant to the chosen topic. Our chosen dependent variable is GDP per capita (PPS).

The independent variables that we selected were tertiary education (percentage of total population), population of the country (millions of citizens), corruption perception index (score obtained: maximum 100, minimum 0), GDP (million euros), poverty risk rate (% of the total population), confidence in the euro (%), total number of patents.

For the variables: GDP per capita, tertiary education, population, GDP, at-risk-of-poverty rate, data was obtained using Eurostat. Regarding the total number of patents, the statistics are taken from the website www.epo.org. The Corruption Perceptions Index was obtained using transparency.org, and data on confidence in the euro were extracted from Flash Eurobarometer reports published by the European Commission.

One of the most popular modelling techniques is linear regression, using the least squares method. Through multiple regression (Pearson, 1908), we can highlight the relationship between a dependent variable, also called an endogenous variable, and the chosen independent variables, known as exogenous variables. With the help of linear regression, we can demonstrate the impact of independent variables on the dependent variable.

The general linear model is considered to be the foundation for the multiple regression technique and can be expressed with the following equation:

$$Y = \alpha \times X + \varepsilon$$

Where Y is the dependent variable, X represents the vector of the independent variables, α represents the vector of the coefficients, and ε includes the random events and represents the residue of the regression.

The model in our study can be mathematically rendered using the following equation:

$$Y = C_1 + C_2 \times X_1 + C_3 \times X_2 + C_4 \times X_3 + C_5 \times X_4 + C_6 \times X_5 + C_7 X_6 + C_8 \times X_7 + \varepsilon$$

Where Y = GDP per capita (PPS), X1 = tertiary education, X2 = population, X3 = corruption perception index, X4 = GDP, X5 = Poverty risk rate, X6 = Confidence in the euro, X7 = Total number of patents.

To be able to use the values obtained from statistical modeling in making predictions, a series of hypothesis are required to be tested in advance: H1-The residuals should follow a normal distribution, H2-Multicollinearity, H3-Homoskedasticity, H4-Errors independence, H5-Model validation, H6-Model justification, and H7-Regression coefficients significance.

4. Findings

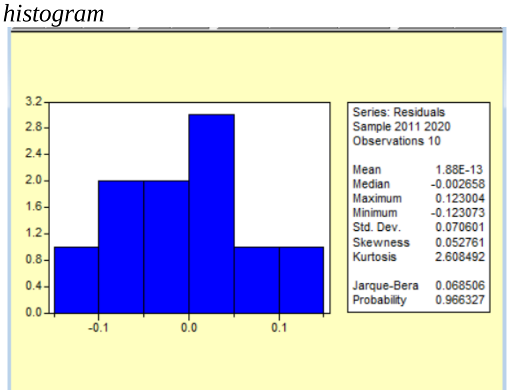
We used EViews to perform econometric and statistical analysis required to test our hypothesis.

- H1: The residuals should follow a normal distribution

If the assumption of normality is violated, the properties of estimators constructed on the basis of the least squares method have only asymptotic properties, i.e., they require large samples or data sets. We can use the following methods to test this hypothesis: analysis of skewness and kurtosis value, apply the Jarque-Bera Test, and analysis of the probability of the Jarque-Bera test for a 5% confidence level.

The Histogram of the Residual can be used to check whether the variance is normally distributed. For the selected data, the histogram is shown below.

Figure no. 1. The residue histogram



Source: (Own computation in EViews)

To check the normality of the errors, the degree of symmetry or asymmetry (skewness) and their flattening (kurtosis) has been analyzed. To have a normal distribution, the skewness must be equal to zero and the kurtosis equal to three.

H_a: skewness = 0 and kurtosis = 3, distribution is normal

H_b: skewness ≠ 0, and kurtosis ≠ 3, distribution is not normal

In our model, the skewness value is close to 0, and the kurtosis value is close to 3, indicating a normal distribution.

With the help of the Jarque–Bera Test, we can assess whether a distribution is normally distributed. This test is based on the simultaneous verification of the asymmetry and vaulting properties of the residue series. The test measures the difference between the asymmetry coefficient and the kurtosis of the analyzed distribution and the normal distribution values.

$$JB=n\left[\frac{S^2}{6}+\frac{(K-3)^2}{24}\right]$$

To determine the value of Jarque Bera, we can either use the previous formula or the value calculated in EViews 0.068506. The critical JB table value, for a probability of 5% and 10 values, is 2,535. The calculated JB value is less than the table value, therefore we do not have enough reasons to reject the null hypothesis $H0$, hence the distribution is normal.

- H2: Multicollinearity

The higher the intensity of the link between the vectors, the higher the degree of collinearity (of the values recorded for the explanatory variables). If two or more explanatory variables used in the multiple regression model are perfectly correlated, then the parameter estimators will not be able to be estimated using the LS method (least squares method) (Jula, 2015).

The existence of a linear relationship between two or more exogenous variables chosen for the regression model (i.e., the existence of multicollinearity) leads to the impossibility of correctly estimating the regression parameters, to larger confidence intervals and a high risk of null acceptance of the null hypothesis.

The multicollinearity hypothesis can be verified using the Klein criterion. From the correlation matrix, we select the largest $r_{x/x_{ji}}$ and if $R^2 < r_{x/x_{ji}}$, then we can detect collinearity. In our study, the most powerful correlation exists between the variables X2 and X4 (0.979916). The R^2 value we got by appying the OLS method is 0.999896 and is higher than the one previously mentioned. Therefore, the hypothesis is confirmed, the multicollinearity does not affect the estimates in this case.

Table no. 1 Variables correlation

	X1	X2	X3	X4	X5	X6	X7
X1	1.000000	-0.960153	0.653675	0.947730	0.369941	0.376395	0.755986
X2	-0.960153	1.000000	-0.548301	-0.979916	-0.125334	-0.296718	-0.845240
X3	0.653675	-0.548301	1.000000	0.460299	0.556668	0.700038	0.583569
X4	0.947730	-0.979916	0.460299	1.000000	0.110474	0.187030	0.784874
X5	0.369941	-0.125334	0.556668	0.110474	1.000000	0.598117	-0.137401
X6	0.376395	-0.296718	0.700038	0.187030	0.598117	1.000000	0.323801
X7	0.755986	-0.845240	0.583569	0.784874	-0.137401	0.323801	1.000000

Source: (Own computation in EViews)

- H3: Homoskedasticity

Homoscedasticity assumes that there is a constant variance of errors calculated based on conditional distributions. Errors are homoscedastic if their variances are equal and constant. The homoscedasticity hypothesis assumes that the variance of the errors is constant. If the hypothesis of homoskedasticity is violated, the efficiency of estimating the parameters of the regression model will decrease. For OLS predictions to be effective, residues need to be tested for homoscedasticity. The Breusch – Pagan - Godfrey test hypotheses are:

H_0:V(ε_i)=σ^2, the errors are homoscedastic

H_1:V(ε_i)≠σ^2, the errors are heteroskedastic

Figure no. 2 Breusch – Pagan – Godfrey test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	14.91191	Prob. F(7,2)	0.0643
Obs*R-squared	9.812001	Prob. Chi-Square(7)	0.1995
Scaled explained SS	0.315651	Prob. Chi-Square(7)	0.9999

Source: (Own computation in EViews)

We can observe that all the probabilities have higher values than the chosen significance level (the alpha level), therefore we did not find enough reasons to reject the null hypothesis (homoscedasticity).

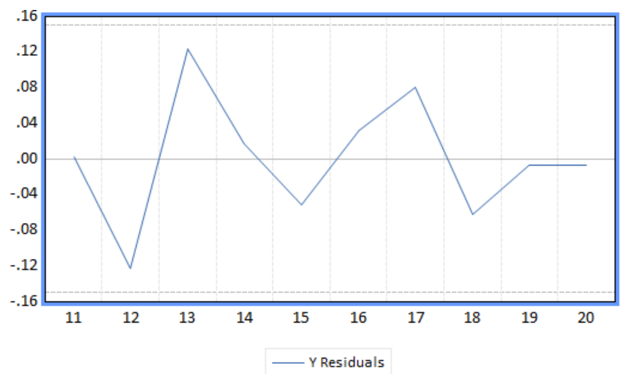
- H4: Errors independence hypothesis

One of the four classical assumptions of the linear regression model is that elements of the disturbance vector are considered uncorrelated. Several statistical procedures can be used to detect the autocorrelation of residuals variables, including: the graphical method, the Durbin Watson test and the Breusch Godfrey test. The presence of autocorrelation may occur due to the failure to include one or more important explanatory variables in the regression model or if the regression model is not correctly specified.

If the figure has certain regularities, then we can say that at the level of the series the phenomenon of collinearity is manifested.

By graphical representation, the correlation is not obvious. Therefore, we will also apply the two tests previously mentioned.

Figure no. 3 Durbin Watson statistic



Source: (Own computation in EViews)

The Durbin Watson Test tracks the serial correlation of errors and can only be applied if the regression model has a free term, and the explanatory variables are not random. If the errors are not correlated, the value of DW will be around 2. If the value DW = 0, then there is a maximum positive autocorrelation of the errors, and if the value DW = 4, then there is a maximum negative autocorrelation of the errors. This test applies only to the identification of first-order autocorrelation. The main disadvantage of this test is that it cannot identify the seasonality phenomenon.

The DW test values generated by EViews tell us directly which hypothesis will be accepted. Note that the value returned by EViews (2.79) is close to the value 2, for which ρ=0. Thus, we can accept the lack of first-order autocorrelation of errors.

We will also test the non-correlation hypothesis by applying the Breusch-Godfrey test:

Figure no. 4 Breusch-Godfrey test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 1 lag

F-statistic	83.10527	Prob. F(1,1)	0.0696
Obs*R-squared	9.881101	Prob. Chi-Square(1)	0.0017

Source: (Own computation in EViews)

The most important section of the test output is the first part, which presents the F-Statistic test and the probability associated with it. The null hypothesis is that there is no serial correlation of the regression equation errors. If the associated probability is lower than the alpha level chosen (5%), then the null hypothesis is rejected, so the non-existence of the serial correlation is rejected. Otherwise, the null hypothesis is accepted, (there is no serial correlation). According to the results obtained from the data of this regression, the probability (0.0696) is higher than the relevance level, meaning there is no serial correlation of the errors.

- H5: Model validation testing. The Fisher exact test

The Fisher test is a test of statistical significance, used mainly for small samples. The test hypotheses are:

H_a: all parameters corresponding to the explanatory variables are null. Under this assumption no explanatory variable can explain the evolution of the endogenous variable.

H_b: there is at least one explanatory variable that can explain the variation of the explained variable.

Using the formula:

$$F= \frac{R^2}{1-R^2} \times \frac{n-k-1}{k},$$

We can determine the calculated F value, or we can use the value returned by EViews in the LS method. The statistical value of F returned by EViews is 2753,678, with a probability of 0.000363. The table value for F resulted using the FINV function in Excel is Ftab = 8.94.

Comparing the calculated F value (F-statistically) with table value for F, we observe that Fcalculated> Ftab, so we accept the H1 hypothesis: there is at least one explanatory variable that can explain the variation of the endogenous variable. The Prob (F-statistic) = 0.000363, lower than the chosen significance level of 0.05, therefore the constructed regression model is valid with a probability of at most 99.99% (100-0,000363=99.999637) and can be further used to analyze the dependence between the specified variables.

- H6: Model justification

We observe that the connection between the variables is strong (Pearson's coefficient), and to demonstrate the extent to which the regression model explains the dependence between the variables, we calculate the R-squared coefficient of determination.

The coefficient of determination R^2 (0.999896) measures the success of the regression in predicting the values of the dependent variable.

$$R^2 = 1 - \frac{\sum_{t=1}^{n} u_t^2}{\sum_{t=1}^{n}(Y_t - \overline{Y})^2}$$

R-squared shows that 99.9896% of GDP per capita is explained by the influence of the 7 factors, the difference of 0.01% being explained by other factors that were not included in the model.

Corrected coefficient R_{adj}^2 ($\bar{R}^2$) (0.999533): while the R-squared indicator never decreases with the introduction of additional independent variables, the adjusted R-squared indicator penalizes the introduction of new variables that do not have the power to explain the model.

$$\bar{R}^2 = 1 - \frac{n-1}{n-k-1}(1-R^2)$$

If Adjusted R-squared (0.999533) had been significantly smaller than R-squared, we could have concluded that important explanatory variables are missing, and the dependent variable cannot be fully measured in their absence, but in our case the difference is very small.

Akaike informational criterion: (-0.968916) is often used for model selection. The lower the AIC value, the better the model. Schwartz criterion: (-0.726848) comes as an alternative to AIC and sanctions the introduction of new coefficients.

$$AIC = \frac{1}{n}\left(\frac{\sum u_t^2}{n}\right) + \frac{2(k+1)}{n};\ SC = \frac{1}{n}\left(\sum_{t=1}^{n} u_t^2\right)\ln(n)^{\frac{2(k+1)}{n}}$$

Low values of the Akaike and Schwartz criteria show a good specification of the model.

- H7: Significance of the regression coefficients

Using the EViews program, we can obtain a statistical image, with the help of which we can observe the connections between the variables. For the equation:

$$Y = C_1 + C_2 \times X_1 + C_3 \times X_2 + C_4 \times X_3 + C_5 \times X_4 + C_6 \times X_5 + C_7 X_6 + C_8 \times X_7 + \varepsilon$$

We got the following E-views output:

Figure no. 5 LS method output

Dependent Variable: Y
Method: Least Squares
Date: 02/28/22 Time: 17:24
Sample: 2011 2020
Included observations: 10

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	768.2368	43.25640	17.76007	0.0032
X1	-6.064080	0.592832	-10.22900	0.0094
X2	-34.44324	1.999518	-17.22577	0.0034
X3	-0.253172	0.033456	-7.567285	0.0170
X4	5.72E-05	1.04E-05	5.477880	0.0317
X5	2.801335	0.240069	11.66889	0.0073
X6	-0.181396	0.014565	-12.45465	0.0064
X7	0.227592	0.017329	13.13329	0.0057

R-squared	0.999896	Mean dependent var	60.40000
Adjusted R-squared	0.999533	S.D. dependent var	6.931410
S.E. of regression	0.149767	Akaike info criterion	-0.968916
Sum squared resid	0.044860	Schwarz criterion	-0.726848
Log likelihood	12.84458	Hannan-Quinn criter.	-1.234464
F-statistic	2753.678	Durbin-Watson stat	2.795696
Prob(F-statistic)	0.000363		

Source: (Own computation in EViews)

The Prob column in the figure below shows the probabilities calculated by EViews for the model coefficients:

Table no. 2 Variables coefficients and probabilities

Variable	Coefficient	t-Statistic	Prob.	Significance test result
C	768.23	17.76	0.0032	Statistically significant
X1	-6.06	-10.22	0.0094	Statistically significant
X2	-34.44	-17.22	0.0034	Statistically significant
X3	-0.25	-7.56	0.0170	Statistically significant
X4	$5{,}72 x 10^{-5}$	5.47	0.0317	Statistically significant
X5	2.8	11.66	0.0073	Statistically significant
X6	-0.18	-12.45	0.0064	Statistically significant
X7	0.22	13.13	0.0057	Statistically significant

Source: (Own computation in EViews)

To test the significance of the parameters, we analyzed the values of the t test for each coefficient, and the associated probability value.

The hypotheses are:

$$\begin{cases} H_0: C(i) = 0 \\ H_1: C(i) \neq 0 \end{cases}, \text{ where } i = 1{,}8$$

Then we set a significance level α = 0.05 for which t-Table = 3.182 is determined, using the TINV function in Excel.

Decision for bilateral test:

- for t-Statistic ϵ (-3,182, 3,182), we accept the null hypothesis, the parameter does not differ significantly from 0.
- for t-Statistic ϵ (-∞; -3.182) U (3.182; + ∞), we reject the null hypothesis and accept the alternative hypothesis, which means that the parameter is statistically significant.

Since all coefficients significantly differ from 0, we can move on to the interpretation of how the dependent variables influence the dependent variable.

5. Conclusions

Based on t-Statistic values, we can see that the variables that influence GDP per capita in Romania the most, between 2011-2020, are: X2 (population), X7 (total number of patents), X6 (confidence in the euro), X5 (at-risk-of-poverty rate), X1 (tertiary education), X3 (Corruption Perceptions Index), X4 (GDP).

The free term C (1) has the value of 768.22368 and is significant at an alpha level of 5%. However, it has no economic significance and cannot be interpreted correctly from this point of view.

The coefficient C (2), i.e., the coefficient of tertiary education, has a significant negative relationship (p value is 0.0094), with the value of -6.064080, which means that, as the percentage of tertiary education increases by one unit, the value of GDP per capita will decreased by 6.06 units. This relationship can indicate that economic growth is not only influenced by the number of years of schooling, but also by the quality of the education system.

The coefficient C (3), i.e., the population coefficient, has a significant negative relationship (p value 0.0034), with the value of -34.44324, which means that, as the population grows by one unit (million people), the value of GDP per capita will decrease by 34.44 units. Given the GDP per capita formula, this relationship was one that could have been easily anticipated.

The coefficient C (4), i.e., the coefficient of the corruption perception index, has a significant negative relation (p value 0,017) with the value of -0,253127, which means that, when the score of the corruption perception index increases by one unit, the value of GDP per capita decreases by 0.25 units.

The C (5) coefficient, i.e., the GDP coefficient, has a significant positive impact (p value 0,0317) with a value of 0,0000572, which means that as GDP grows by one unit, the value of GDP per capita increases by $5{,}72*10^{-5}$ units.

The coefficient C (6), i.e., the coefficient of the at-risk-of-poverty rate, has a significant positive ratio (p value 0.0073) and a value of 2.801335, meaning that when the at-risk-of-poverty rate increases by one unit, the value of GDP per capita increases by 2.80 units.

Coefficient C (7), i.e., the confidence ratio in euro, has a significant negative ratio (p value 0.0064) with the value of -0.181396, which means that, at a 1% increase in the percentage of the population wishing to adopt the euro, the GDP per capita decreases by 0.18 units.

The coefficient C (8), i.e., the innovation coefficient, expressed by the total number of patent applications, has a significant positive relationship (p value 0.0057), with a value of 0.227592, meaning that when the total number of patents increases by one unit, GDP per capita increases by 0.22 units.

The limitations of the chosen model may be related to the lack of a larger number of observations (for GDP per capita we could have chosen quarterly values, but for most independent parameters the values are annual) and the subjectivity of choosing the number of independent variables. In the case of corruption, public confidence in the euro and the level of innovation potential, we have chosen a representative indicator, but there is a variety of variables one can choose from.

The adoption of the euro currency by a country with a rigid, unreformed economy could lead to more disadvantages than advantages. Joining the European Union does not automatically imply we are entitled to join the euro area, we must earn it first. The euro does not bring stability and growth alone, the candidate countries must sustainably fulfill the Maastricht criteria, and this often translates to the need to ensure a high level of real convergence. This can be obtained by improving the economic performance, but also by investigating what other factors are of great influence and focusing efforts on them.

6. References

- Balash, V., Balash, O., Faizliev, A., Cristopolskaya, E., 2020. Economic Growth Patterns: Spacial Econometric Analysis for Russian Regions. *Information*, 11, 289, Available at: <https://www.mdpi.com/2078-2489/11/6/289/pdf> [Accessed 22 February 2022].
- Barro, R. J., 1996. Determinants of Economic Growth: A Cross- Country Empirical Study. *NBER Working Paper*, 5698, Available at: <https://www.nber.org/papers/w5698> [Accessed 20 February 2022].

- Barro, R. J., Sala-i-Martin, X., 1995. Economic Growth. *Cambridge MA: MIT Press,* Available at: <https://ideas.repec.org/a/eee/dyncon/v21y1997i4-5p895-898.html> [Accessed 22 February 2022].
- Bere, C. M., Otoiu, A., Bucerzan, I., 2014. Determinants of economic growth in cities acting as growth poles in regions from Romania. *Procedia Economics and Finance*, 10 (2014) 357-365, Available at: <https://www.sciencedirect.com/science/article/pii/S2212567114004158/pdf?md5=a08a024e7b8b67 d78985 3588752a2619&pid=1-s2.0-S2212567114004158-main.pdf. > [Accessed 20 February 2022].
- Campos, N.F., Dimova, R. and A. Saleh (2010). Whither corruption? A quantitative survey of the literature on corruption and growth. *IZA Discussion Papers No 5334*, Available at: https://www.researchgate.net/publication/324661693_Corruption_in_International_Business [Accessed 20 February 2022].
- Fagerberg, J., 1987. A technology gap approach to why growth rated differ. *Research Policy*, 16 (2-4), 87-99, Available at: <https://www.sv.uio.no/tik/InnoWP/archive/wpno002-1987.pdf> [Accessed 25 February 2022].
- Grundler, K., Potrafke, N., 2019. Corruption and economic growth; New empirical evidence. *Ifo Working paper,* no 309, Available at: <https://www.econstor.eu/bitstream/10419/213586/1/167566210X.pdf> [Accessed 25 February 2022].
- Hong, Y., 1994. The quality of economic growth and the effect of population. *Chin J Popul Sci*, 6(1):13-8. PMID: 12288174, Available at: < https://pubmed.ncbi.nlm.nih.gov/12288174/> [Accessed 25 February 2022].
- Ilter, C., 2017. What Economic and Social Factors Affect GDP per Capita? A Study on 40 Countries. *Journal of Global Strategic Management,* V. 11, N. 2, Available at: < http://isma.info/uploads/files/051-what-economic-and-social-factors-affect-gdp-per-capita-a-study-on-40-countries.pdf> [Accessed 21 February 2021].
- Jula, D., 2015. Metode și tehnici performante de testare a ipotezelor în economie. *READ,* Fondul Social European, Available at: < http://mone.acad.ro/wp-content/uploads/2014/12/Jula-Testarea-ipotezelor.pdf> [Accessed 21 February 2022].
- Kim, E., Hewings, G. J. D., Nam, K-M., 2014. Optimal Urban Population Size: National vs Local Economic Efficiency. *Urban Studies*, 51(2):428-445, Available at: <https://www.researchgate.net/publication /237050986_Optimal_Urban_Population_Size_National_vs_Local_Economic_Efficiency> [Accessed 21 February 2022].
- Kira, A., 2013. The Factors Affecting Gross Domestic Product (GDP) in Developing Countries: The Case of Tanzania. *European Journal of Business and Management*, Vol. 5, No. 4, Available at: < https://www.researchgate.net/publication/313168253_The_Factors_Affecting_Gross_Domestic_Product_GDP_in_Developing_Countries_The_Case_of_Tanzania> [Accessed 21 February 2022].
- Krueger, A. B., Lindhal, M., 2001. Education for Growth: Why and For Whom?. *Journal of Economic Literature*, Vol. XXXIX, pp. 1101-1136, Available at: <https://www.unibg.it/dati/corsi/91015/49249-JEL%202000_kruegerlindahl.pdf> [Accessed 18 February 2022].
- Mamo, F. T., 2012.Economic Growth and Inflation – A panel data analysis, *Sodertorn University Department of Social Sciences Thesis,* Available at: < http://sh.diva-portal.org/smash/record.jsf?pid=diva2:576024> [Accessed 20 February 2022].
- Marquez-Ramos, L., Mourelle, E., 2019. Education and economic growth: an empirical analysis of nonlinearities. *Applied Economic Analysis*, Volume 27, Issue 79, Available at: < https://www.emerald.com/insight/content/doi/10.1108/AEA-06-2019-0005/full/html> [Accessed 22 February 2022].
- Pearson, K., Lee, A., 1908. On the Generalized Probable Error in Multiple Normal Correlation. *Biometrika*, Vol. 6, No. 1, pp. 59-68, Available at: <https://www.jstor.org/stable/2331556> [Accessed 18 February 2022].
- Popa, A-M., 2012. The Impact of Social Factors on Economic Growth: Empirical Evidence for Romania and European Union Countries. *Romanian Journal of Fiscal Policy I,* Volume 3, Issue 2, pp. 1-16, Available at: https://www.econstor.eu/bitstream/10419/107942/1/771108060.pdf>, [Accessed 18 February 2022].
- Ugur, M. (2014): Corruption's direct effects on per-capita income growth: A meta-analysis, *Journal of Economic Surveys* 28, 472-490, Available at: https://onlinelibrary.wiley.com/doi/full/10.1111/joes.12035 [Accessed 18 February 2022].
- Upreti, P., 2015. Factors affecting Economic Growth in Developing Countries. *Major Themes in* Economics, Volume 17, Article 5, Available at: <https://scholarworks.uni.edu/cgi/viewcontent. cgi?article=1114&context=mtie> [Accessed 20 February 2022].