IN SEARCHING FOR GREENER ECONOMIC OUTCOMES; IDENTIFICATION OF FACTORS INFLUENCING GREEN GDP

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Abstract The recent slowdown in CO_2 emission is largely result of three factors; weaker economic growth due to global crisis aftermaths, continual improvements in energy intensity and shifts to lower carbon energy thus higher carbon footprint of energy. Various approaches such as IPAT and/or KAYA identities are used to analyze the input factors of CO_2 emissions, playing a crucial role in the creation of distinct emission forecasts. In addition, Environmental Kuznets curve hypothesizes a positive relation between income and environmental quality. Arguments that came out of the controversies regarding the validity of these identities provided relevant theoretical discussion for the claim that economic growth can be achieved on sustainable and green foundations. Based on a scarce number of papers related to Green GDP – energy intensity – carbon footprint nexus, we want to analyze how major environmental factors (GDP per capita, emissions of CO_2, energy consumption per GDP and carbon intensity per unit energy) affect the so-called green growth perspective. Long-run empirical assessment is founded on a panel cointegration modelling for the period 2007-2019 for the sample of 37 European countries. The results confront some established environmental stances, confirming the negative effect of GDP per capita and CO_2 emissions, and a positive effect of both energy intensity and carbon footprint on the green growth developments.

Keywords:: green GDP, green growth, energy intensity, CO_2, panel cointegration, European countries.

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1 Introduction

As never before, the world is facing new economic, social and environmental challenges. The global pandemic has emphasized the importance of sustainable and socially responsible business, hence the focus on new digital products and services. Unsustainable economic solutions have created a growing socio-economic gap between developed and all other countries, thus resulting in an urgent need for new synergies between economic and environmental solutions in order to achieve a more accurate assessment of true progress and prosperity in the future. At a time when the issue of population growth has become crucial for some countries in addressing the long-term growth challenges, many countries, on the other hand, are developing more intensively without any influence of globally introduced environmental regulations. With drastic changes in the environment, there are fears that economic growth, unsustainable patterns of production, urbanization, consumerism and related lifestyle requirements disrupt the ecological balance, economic stability and even socio-economic security. Green growth became a strategy pointed towards energy saving and carbon emission reductions and is a widely accepted solution to control the improvement of socio-economic life. Green technology is evolving into a process of stimulating green economic growth as many studies confirmed that cleaner technological implementation significantly reduces carbon emissions, whereas green growth has been proclaimed one of the best alternative strategies for sustainable development (Tomić, Đorđević and Grdić, 2022). In this context, green growth could be perceived as a form of green entrepreneurship based on a friendly attitude towards the environment, nature and overall biodiversity, while using the latest technological improvements.

The gross domestic product (GDP) of each country has different production background and is generated in ways that provide distinct effect on human welfare, as environmental degradation is seen as one of the greatest challenges of our time. Considering the importance and future perspective of green growth and shortcomings of standard measures of economic progress, such as GDP and/or GDP per capita growth, there is no reason to doubt the need for more forceful usage of more sustainable concepts such as circular economy or green gross domestic product (Green GDP) measurement. Carbon dioxide (CO_2) emissions are seen as the main cause of climate change and global warming, therefore this indicator is vastly used in clarification of global environmental degradation. The recent slowdown in CO_2 emission is largely result of three factors; weaker economic growth due to global crisis aftermaths, continual improvements in energy intensity and shifts to lower carbon energy, thus higher carbon footprint of energy. Various approaches such as IPAT and/or KAYA identities are used to analyze the input factors of CO_2 emissions, playing a crucial role in the creation of distinct emission forecasts. In addition, Environmental Kuznets curve hypothesizes a positive relation between income and environmental quality. Arguments that came out of the controversies regarding the validity of these identities provided relevant theoretical discussion for the claim that economic growth can be achieved on sustainable and green foundations (Škare, Tomić and Stjepanović, 2020).

Limited empirical background on the green growth – energy intensity – carbon footprint nexus, steered this research towards the question; how major environmental factors (GDP per capita, emissions of CO_2, energy consumption per GDP and carbon intensity per unit energy) affect the green growth prospect? Hence, the main goal is to identify and evaluate the factors influencing the Green GDP within the framework of famous Kaya identity. Long-run empirical assessment is founded on a panel cointegration modelling for the period 2007-2019 for the sample of 37 European countries. The results confront some established environmental stances, confirming the negative effect of GDP per capita and CO_2 emissions, and a positive effect of both energy intensity and carbon footprint on the green growth developments.

2 Theoretical and empirical background

2.1 The theory behind the Kaya identity

Globally, there have been improvements in the energy intensity and carbon intensity in recent years, returning to levels not seen since the 1990's with GDP growth beginning to strengthen again. These three effects combined (slightly lower economic growth, improved energy intensity, improved carbon intensity) have all led to the slower growth in global CO_2 emissions (Peters et al., 2017). Despite the need for energy conservation, energy inputs are necessary in production (given the demands for economic growth, increasing population, heating energy demands, energy prices that have not fully encompassed environmental costs, etc.) and consequently the configuration of the impact of energy cuttings on economic growth remains important. The usage of any alternative GDP measure (sustainable GDP or Green GDP) in place of the traditional GDP in the energy-growth nexus research field will enable comparisons between the effects of energy conservation on welfare (Menegaki, 2021.). Reaching a 'greener objectives' requires a collective agreement in order to push the economy towards a society with more respect of the environment, whilst at the same time aspiring for green economic growth and sustainable development. By revitalising standard relationships with an ecosystem, one technical identity allows us to evaluate collective responsibility in regard to CO_2 emissions related to human actions and economic activity. This identity, a mathematical formula, an artificial equation sets out to find areas to improve efforts to reduce CO_2 emissions and pin-point policies that can be introduced through socio-economic policies on a macro scale. This concept, also known as the Kaya identity defines two global objectives, namely carbon efficiency in energy production and energy efficiency in total production, against the human/economic activity. The Kaya identity formula is the result of the following ratios:

$$CO_2 = Population \times [GDP / Population] \times [Energy / GDP] \times [CO_2 / Energy] \quad (1)$$

as global CO_2 emissions from human activity are a direct consequence of the global population, quality of life, energy intensity and intensity of carbon within the energy mix. Kaya identity closely resembles another multiplicative equation the so-called IPAT identity, written as $I = P \times A \times T$ in fact measures the impact of human activities on the environment as a function of three variables (population, affluence and technology), all of which are additionally inter-related. Both of them are at first used to quantify factors of unsustainability, however, have been reinterpreted to assess the most promising path to sustainability and greener prospect of growth.

Original Kaya identity assumes that it is possible to make an informed projection of future CO_2 as socio-economic variables such as population (rising population means more energy use) and economic production measured by GDP per capita (larger economy results in greater use of energy) have a detrimental part in explaining CO_2 dynamics. The energy intensity term is where technology becomes important too, as new energy technologies or improved efficiency of existing energy technology leads to situations where less energy is needed for the increase in output. On the other side, carbon efficiency suggests that a focus or switch over to renewable energy sources and non-fossil fuel based energy alternatives and improve the carbon efficiency of existing fossil fuel sources we could expect less carbon emitted per unit of energy production (Mann and Gaudet, 2021). Ultimately, technology is seen as the most important factor in the declining emissions trends in higher income countries (Garrett-Peltier, 2018). Though Kaya identity has limitations (it is an accounting equation, assumes unit elasticity within empirical researches, it incorporates key driving forces with parsimony, creates possible illusion of control over the factors included in the equation, does not allow an examination of hidden causalities among the factors, does not take explicit account of geography, nations' culture and institutions, etc.), it really offers just a framework, a starting point for thinking about which policies could be more applicable and have more extensive reach in global context to limit the impact of human behaviour on the environment.

While theoretical and computational issues hinder the development of green growth economic models based on, for example Green GDP measure, they nonetheless provide a source of data that can be used to re-examine the links between GDP and sources of growth commonly used in economic growth models (Talberth and Bohara, 2006). So, the standard growth theory could also argue about green growth if it reveals the nexus between Green GDP and traditional sources of growth such as capital accumulation and technological change. Alternative perspective that Green GDP offers in fact endorses this apparently virtuous model of growth so that economic development can go hand in hand with greater improvement in physical, human as well as natural capital. Therefore, some curious relations could be revealed if the concept of Green GDP is to be observed within the Kaya identity framework.

2.2 The empirics behind the Kaya identity

In this part we will present just some of the interesting studies that have focused on different theoretical and/or methodological aspects of the Kaya identity. Duro and Padilla (2006) proposed applying the Theil index to decompose international inequalities in per capita CO_2 emissions into equation factors with two interaction terms and found that the international inequality in per capita CO_2 emissions can be attributed to inequality in per capita income levels. Hwang et al. (2020) evaluated causal relationships by conducting a parallel multiple mediation analysis. They used the fossil fuel CO_2 flux based on the Open-Source Data Inventory of Anthropogenic CO_2 emissions and found out that the indirect effects of the decomposed variables on the CO_2 flux are significant, however, that the Kaya identity factors show neither strong nor even significant mediating effects. Khusna and Kusumawardani (2021) calculated the Kaya relationship in eight ASEAN countries (Indonesia, Malaysia, Singapore, Thailand, Philippines, Vietnam, Myanmar and Brunei Darussalam) from 1990 to 2017 by using the Logarithmic Mean Division Index. They found that the effect of energy intensity causes CO_2 emissions in lower-middle income countries to decrease, while in upper-middle and high-income countries, it increases carbon emissions. In contrast to the effect of carbon intensity, that actually makes CO_2 emissions increase in lower-middle income countries and reduces carbon emissions in upper-middle and high-income countries. Same authors pointed that Kaya identity decomposition studies are also often used to compare CO_2 emissions in the same region or countries with very different CO_2 emissions levels, suggesting several authors for further insight into the topic. (Moutinho, 2015; Robalino López et al., 2016; Román Collado & Morales Carrión; 2018; Rüstemoglu & Andres, 2016). Even though the Kaya identity has been extensively scrutinized, there are no papers, to our knowledge, that deal with the Green GDP – Kaya identity factors nexus.

3 The scope of the research

3.1 Methodology

In order to comprehend the imperative of greener economic outputs in regard to CO_2 emission, population, economic activity and energy within the most general perception of a sustainable relationship between humanity and nature, we introduced adjusted formula that has its background in Kaya identity. Since the Kaya equation is derived from the IPAT equation in order to specifically determine various driving forces behind CO_2 emissions, we followed the logic from Tomić, Stjepanović and Učkar (2021) who alternatively evaluated IPAT identity for China by replacing environmental variable *I* with green gap variable to capture pure environmental impact of featured socio-economic variables. For that purpose, we have transformed standard Kaya formula as to reflect changes that Kaya factors have on green growth opportunity, i.e. Green GDP. Our formulation can be expressed as:

$$\textit{Green gap} = \textit{GDPpc} \times CO_2\ \textit{emissions} \times \textit{Energy intensity} \times \textit{Carbon intensity} \qquad (2)$$

so that the *Green gap* variable reflects green growth dynamics (standard GDP minus Green GDP) in respect to change in *GDPpc* (amalgamation of human and economic activity), trends in *CO_2 emissions* and technological aspect through ratios of Energy/GDP and CO_2/Energy i.e. *Energy intensity* and *Carbon intensity*. When observing data on these variables (*Figure 1.*) we can notice an increase in total population, GDPpc and CO2 emissions on a global level, however, we can also track the general decrease in energy intensity and carbon intensity over the last half of the century. In order to meet general standards of green growth and sustainable development, having in mind expectation of further growth of population and quality of life, the only way to bridge the gap is to further rationalise the use of energy and reduce the CO_2 emissions in the production of energy, particularly through the promotion of energies low in carbon. But, these actions are feasible only if the relations between the factors from the equation (*2*) display causalities explained within the equation (*1*).

Since the focus of our empirical research are European countries who are highly diverse in respect to population density, economic growth, industry, energy consumption and carbon footprint, as well as many other factors, we find them suitable for exploring the green growth perspective. Namely, Europe is taking a leading role in implementing active climate change policy, as all countries jointly decided to reduce CO_2 emissions by 40% until 2030 and by even 55% until 2050 (Hwang et al., 2020).

3.2 Data

Annual data, covering the period 2007-2019 for the sample of 37 European countries, are taken from the Eurostat and World Bank database. The data for Green GDP are based on the paper Stjepanović, Tomić and Škare (2019) following their alternative approach to sustainability and green growth (Stjepanović, Tomić and Škare, 2017).

Data are expressed in logarithms and presented as: *lnGAP* as the logarithm of the gap from Green GDP to standard GDP measure in current U.S. dollars, *lnGDPpc* as the logarithm of gross domestic product per capita measures in current U.S. dollars, *$lnCO_2$* as the logarithm of annual CO_2 emission in tonnes, *lnEINT* or energy intensity as the logarithm of energy consumption per GDP in kwh per U.S. dollar and *lnCINT* or carbon intensity as the logarithm of an annual CO_2 emissions per unit energy in kg per kwh.

In order to demonstrate a possible causal relationship between the variables, correlation coefficients were extracted. Correlation matrix (*Table 1*) depicts a medium positive correlation for the green gap variable to *lnGDPpc* and *$lnCO_2$* variables), suggesting that there could exist a long-term nexus. On the other side, green gap variable renders questionable, but as expected negative, relation to both energy and carbon intensity.

Table 1: Correlation matrix

Source: Authors' calculations

Correlations	lnGAP	lnGDPpc	$lnCO_2$	lnEINT	lnCINT
lnGAP	1.00	0.50	0.82	-0.17	-0.14
lnGDPpc	0.50	1.00	0.35	-0.36	-0.24
$lnCO_2$	0.82	0.35	1.00	-0.13	0.12
lnEINT	-0.17	-0.36	-0.13	1.00	-0.05
lnCINT	-0.14	-0.24	0.12	-0.05	1.00

Due to a large volume of data on a cross-country scale and possible homogeneity among the European countries, it can be anticipated that cointegration between included variables may exist. For that purpose, we will consider modelling through cointegration method with panel data. In order to proceed with panel analysis, variables must first meet the standard of non-stationarity. If the variables are non-stationary and integrated of the same order, the analysis can continue with testing for the panel cointegration. Following the results of several panel unit root tests (*Table 2*), namely LLC test (Levin, Lin and Chu, 2002), Breitung test (Breitung, 2000), IPS test (Im, Pesaran and Shin, 2003) and Fisher-type tests using the ADF (Maddala and Wu, 1999), we came to conclusion that all variables are indeed integrated I(1), meaning they are stationary in their first differences, which is an important property for our modelling.

Table 2: Panel unit root tests
Source: Authors' calculations.

Variable and test	*Level*		*First difference*	
	Intercept	*Intercept and trend*	*Intercept*	*Intercept and trend*
*Levin, Lin and Chu t**	*Prob.***			
lnGDPpc	0.77	0.00	0.00	0.00
$lnCO_2$	0.09	0.00	0.00	0.00
lnCINT	0.92	0.10	0.00	0.00
lnEINT	0.87	0.00	0.00	0.00
lnGAP	0.32	0.66	0.00	0.00
Breitung t-stat	*Prob.***			
lnGDPpc	-	0.64	-	0.00
$lnCO_2$	-	0.11	-	0.00
lnCINT	-	0.78	-	0.00
lnEINT	-	0.90	-	0.00
lnGAP	-	0.99	-	1.00
Im, Pesaran and Shin W-stat	*Prob.***			
lnGDPpc	0.98	0.49	0.00	0.00
$lnCO_2$	0.82	0.14	0.00	0.00
lnCINT	0.77	0.06	0.00	0.00
lnEINT	0.87	0.41	0.00	0.01
lnGAP	0.90	0.86	0.00	0.00
ADF - Fisher Chi-square	*Prob.****			
lnGDPpc	0.81	0.22	0.00	0.00
$lnCO_2$	0.98	0.27	0.00	0.00
lnCINT	0.13	0.03	0.00	0.00
lnEINT	0.81	0.27	0.00	0.00
lnGAP	0.83	0.57	0.00	0.00

*Notes: * Heteroscedastic Consistent. ** Probabilities are computed assuming asymptotic normality. *** Probabilities are computed using an asymptotic Chi-square distribution. All tests are evaluated by different lags.*

3.3 Modelling

Resulting from the conceptual framework of the equation (*2*) and the characteristic of the data, our model can be presented as:

$$lnGAP_t = \beta_0 + \beta_1\ lnGDPpc_t + \beta_2\ lnCO_{2t} + \beta_3\ lnEINT_t + \beta_4\ lnCINT_t + \varepsilon_t \qquad (3)$$

which can, consequently, be considered for panel cointegration modelling. Following the research logic from Tomić, Šimurina and Jovanov (2020), panel cointegration tests were evaluated according to Pedroni (1999, 2004) and Kao (1999). Pedroni and Kao extend the two-step Engle-Granger framework to tests involving panel data. Pedroni proposes several tests for cointegration that allow for heterogeneous intercepts and trend coefficients across cross-sections with two alternative hypotheses: the homogenous vs. heterogeneous alternative. The Kao test follows the same approach as the Pedroni tests, but specifies cross-section specific intercepts and homogeneous coefficients within the first-stage regressors.

Table 3: Cointegration tests

Source: Authors' calculations

Variables: lnGAP, lnGDPpc, lnCO$_2$, lnEINT, lnCINT								
Pedroni residual cointegration test	*Intercept*				*Intercept and trend*			
	Statistic	*Prob.*	*Weighted Statistic*	*Prob.*	*Statistic*	*Prob.*	*Weighted Statistic*	*Prob.*
Panel v	-1.06	0.85	-2.53	0.99	-1.34	0.91	-4.11	1.00
Panel rho	4.55	1.00	4.19	1.00	6.00	1.00	5.88	1.00
Panel PP	-0.74	0.23	-5.56	0.00	-3.83	0.00	-9.60	0.00
Panel ADF	-0.78	0.22	-4.75	0.00	-3.19	0.00	-6.74	0.00
Group rho	7.09	1.00			8.55	1.00		
Group PP	-8.06	0.00			-11.54	0.00		
Group ADF	-4.05	0.00			-4.82	0.00		
Kao residual cointegration test	*t-Statistic*				*Prob.*			
ADF	-1.31				0.09			

From Pedroni's panel cointegration tests (*Table 3*) we found out that when only intercept is included and again when intercept and trend are included, most of the Pedroni's statistics reject the null hypothesis of no cointegration between variables indicating the existence of long-run panel cointegration relationship between the variables with at least one cointegrating vector. Kao's panel cointegration test strongly rejects the null hypothesis of no cointegration between variables indicating the existence of long-run panel cointegration relationship between the variables. According to two residual cointegration tests, a convincing evidence of a long-term cointegration between the variables for both equations is found. Since Johansen Fisher panel cointegration results may vary according to the number of lags used and due to other specifications, and in addition this method provided us with indecisive outcomes, we opted not to use this type of cointegration test.

3.4 The results

The long-run cointegration is estimated using the pooled Panel Fully Modified Least Squares (FMOLS), pooled Panel Dynamic Least Squares (DOLS) and Pooled Mean Group/AR Distributed Lag (PMG/ARDL) estimation methods. Since FMOLS and DOLS provide only long-run estimates, for the short-run estimation PMG/ARDL is also applied. FMOLS and DOLS estimation methods for panel settings allow the estimation of the panel cointegrating regression equation for non-stationary data by correcting the standard pooled OLS for serial correlation and endogeneity of regressors that are usually present in long-run relationships. In addition, the DOLS allows augmenting the panel cointegrating regression equation with cross-section specific lags and leads to eliminate the endogenity and serial correlation. The PMG/ARDL (Pesaran, Shin and Smith, 1999) takes the cointegration form of the simple ARDL model and adapts it for a panel setting by allowing the intercepts, short-run coefficients and cointegrating terms to differ across cross-sections. Hence, the main advantage over the FMOLS and DOLS is that it can allow the short-run dynamic specification to differ across cross-sections while the long-run coefficients are constrained to be invariant.

For FMOLS and DOLS the default (homogenous variances) coefficient covariance matrix computations use an estimator of the long-run variance computed using a Bartlett kernel and fixed Newey-West bandwidth. So, within DOLS approach, lags and leads are specified using the automatic lag length selection based on the Schwarz information criterion. Finally, for PMG/ARDL, the automatic lag length selection of dependent variable and dynamic regressors is set as a maximum lag of 2 based on a Schwarz criterion with (Škare, Benazić and Tomić, 2016).

Table 4: Panel cointegration results– lnGAP (dependent variable)

Source: Authors' calculations

Panel Fully Modified Least Squares (FMOLS) – (lags-leads; 1,1) – pooled estimation								
Variable	*No constant and no trend*				*Constant*			
	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
lnGDPpc	0.33	0.07	5.46	0.00	0.05	0.11	0.46	0.65
$lnCO_2$	0.70	0.05	15.75	0.00	1.43	0.45	5.79	0.00
lnEINT	-0.03	0.14	-0.25	0.80	-0.30	0.18	-1.69	0.09
lnCINT	-0.97	0.22	-4.48	0.00	-0.10	0.27	-0.38	0.71
Panel Dynamic Least Squares (DOLS) – (lags-leads; 0,0)- grouped estimation								
	No constant and no trend				*Constant*			
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
lnGDPpc	0.25	0.07	3.65	0.00	0.13	0.16	0.83	0.41
$lnCO_2$	0.74	0.05	16.06	0.00	2.64	0.68	3.87	0.00
lnEINT	0.16	0.14	1.14	0.26	-1.35	0.59	-2.28	0.03
lnCINT	-1.23	0.25	-4.88	0.00	-1.32	0.66	-2.01	0.05
PMG/ARDL (Pooled Mean Group/AR Distributed Lag) – ARDL (1,1)								
	No constant no trend				*Restricted constant*			
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
	Long Run Equation							
lnGDPpc	-0.61	0.01	-60.06	0.00	0.33	0.05	6.61	0.00
$lnCO_2$	0.99	0.00	306.03	0.00	1.83	0.07	26.11	0.00
lnEINT	-1.71	0.02	-88.49	0.00	-2.22	0.12	-17.74	0.00
lnCINT	-1.86	0.06	-28.99	0.00	-2.76	0.10	-26.96	0.00
	Short Run Equation							
COINTEQ01	-0.21	0.05	-4.32	0.00	-0.35	0.06	-5.83	0.00
D(lnGDPpc)	-0.24	0.55	-0.44	0.66	-0.59	0.62	-0.95	0.35
$D(lnCO_2)$	1.84	0.68	2.70	0.01	1.28	0.66	1.96	0.05
D(lnEINT)	-1.67	0.64	-2.63	0.01	-1.77	0.61	-2.91	0.00
D(lnCINT)	-1.22	0.79	-1.55	0.12	0.49	0.99	0.49	0.63
C					-13.64	2.35	-5-79	0.00

The results across almost all estimation methods display statistically significant long-run coefficients with a direction that is theoretically expected and consistent with the empirical dynamics. Zero restrictions on the long-run parameters are tested using the Wald test (available upon request), confirming their statistical significance. First, GDPpc coefficients are positive and strongly significant varying from 0.25 to 0.33

in the case with no constant, and from 0.05 to 0.33 in the case for constant with no trend (except the coefficient obtained from the PMG/ARDL method with no constant and no trend, which is statistically significant, but negative). Next, CO_2 coefficients are also positive and significant varying from 0.70 to 0.90 in cases with no constant and no trend, and from 1.43 to 2.64 in cases with constant and no trend, across all three estimation methods. Accordingly, it can be concluded that a rise in human welfare, thus production and consumption that creates CO_2 emissions, leads to an increase in the gap between the standard and Green GDP measure. On the other hand, energy intensity coefficients, display statistically significant negative relationship, varying from -0.30 to -2.22 in cases with constant and no trend, and from -1.36 to -2.77 in cases with constant and trend, across all three estimation methods (with some inconclusive results coming from the cases with no constant and no trend). Similarly, carbon intensity coefficients tend to be negative and strongly significant varying from -0.97 to -1.86 in the cases with no constant and no trend, and from -0.10 to -2.76 in the cases for constant with no trend for all three estimation methods. Thereby, the rise in both, energy and carbon intensity, has a positive environmental effect as it leads to a decrease in a green gap variable. Individual short-run cross section results obtained from the PMG/ARDL model estimations (available upon request) suggest similar results to a long-run dynamic, though the signs (direction of impact) differ across the countries in the panel.

4 The discussion

Over the last few years we witnessed nearly no growth in CO_2 emissions from fossil fuels and industry on a global level. Pandemic restrictions of the last two years even more emphasized the slowdown in global emissions growth, mostly due to lower economic growth rates that dates to global financial crisis. But continual improvements in energy and carbon intensity have had its role in the recent stagnation in CO_2 emissions. The European Union has been constantly reducing emissions over the last decades as carbon intensity has improved due to an increased share of renewables, but a slight shift back to less efficient use of fossil fuels has tempered those gains, for CO_2 emissions from fossil fuels are now 20% below 1990 levels, well on the way to 40% in 2030 (Peters et al., 2017). But how those positive trends affect the green growth perspective? As Tawiah, Zakari and Adedoyin (2021) pointed, although green growth may appear synonymous with CO_2, these concepts are quite different for CO_2 emission measures the environmental footprint, while green growth measures the action a country is taken to achieve environmentally and economically sustainable growth and development. In other words, green growth directly involves reducing environmental footprint. As many projections suggest that economic development, population and electricity intensity is and will remain the main contributors to the increase in CO_2 emissions, it is important to expose its influence on the green growth.

The results of our analysis suggest that, indeed, economic activity (combining the impact of welfare improvements and CO_2 dynamics) affects negatively green aspirations. In explanation, higher output growth rates and thus, individual well-being, requires a large amount of energy consumption, whereas high energy consumption is associated with low environmental quality, hence a decrease in green growth, or in our terms this amplifies the gap between the standard and Green GDP measure. Considering inevitable aspirations for further economic development and low, but persistent population growth, there is no prospect of achieving greener paths by limiting economic activity effect in Europe. At the other end, even though output growth has an upward push on emissions and therefore negative influence on the green gap variable, it seems that this effect is offset by improvements in energy efficiency and decarbonization of the energy supply, as we revealed relatively strong and positive influence of both, energy and carbon efficiency, on the decrease in the green gap variable. It means that if European countries are committed to the their social and environmental goal, they could move closer to them by reaching policy decisions in favour of energy efficiency and decarbonization of energy mix. Furthermore, it means that renewable energy and electricity as the dominant factors that influence CO_2 emissions present a good ground to promote green growth. Renewable energy sources make efficient and effective use of natural assets in production and consumption than any other energy source. Despite general energy consumption deters green growth, to the domination of renewable energy in the energy mix could contribute to green and sustainable economic outcomes. There has been a growth in solar and wind models for electricity production, but we have to be aware that without stronger limitations in carbon capture and storage, we cannot expect distinctive results.

Though, European countries, in comparison to other parts of the world, showed very low Green GDP bias (Stjepanović, Tomić and Škare, 2019), our results do not confirm itself optimistic opinion that economic progress will, *per se*, lead to greener and sustainable socio-economic progress, however, advanced countries *de facto* and *de jure*, support a more sustainable economic behaviour and lifestyle, even though in total they 'consume more environment' than many other developing and undeveloped countries.

5 Concluding remarks

Considering traditional economic growth theories that identify sources of economic growth, which are paralysed with various technical assumptions, it is not easy to evaluate direct or indirect contributions of environmental protection to economic growth, and *vice versa*. Growth theory can help in explaining green growth if we can find a nexus reasonable between environmental policies and environmental degradation on the hand, and sources of economic growth and the rates of return on the investments and innovations in the green economy, on the other hand (Smulders, Toman and Withagen, 2014).

In this paper, we have extended Kaya identity for 37 European countries to reveal how driving forces of CO_2 emissions in regard to anthropogenic activities reflect to a pathway to continued economic growth even in the face of persistent environmental pressure. Our results indicate that economic activity, representing economic well-being and CO_2 emissions, affects negatively green aspirations, however, that this effect is alleviated by improvements in energy efficiency and decarbonization of the energy mix, as we revealed positive impact of both, energy and carbon efficiency, on the decrease in the green gap variable. *Ditto*, if European countries ought to committed to the their social and environmental goal, they could move closer to them by reaching policy decisions in favour of energy efficiency and decarbonization of energy supply. This research offers confined contributions to environmental economics and has important policy implications, however, reaching greener economic outcomes requires a collective agreement about a society which is more respectful of the environment, whilst at the same time pushing towards economic growth.

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