INVESTIGATING THE NEXUS BETWEEN FUEL ETHANOL AND CO$_2$ EMISSIONS. A PANEL SMOOTH TRANSITION REGRESSION APPROACH

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Abstract. In this paper, we fill the gap in the literature by identifying a negative relationship between fuel ethanol consumption and CO$_2$ emissions, building on a sample of 17 European countries covering seven years, from 2010 to 2016. Based on a Panel Smooth Transition Regression approach we show that countries with high levels of income inequality have difficulties in avoiding environmental degradation by promoting policies and regulations for more intense use of biofuels. Furthermore, we bring strong empirical evidence suggesting that biofuels could be an alternative in the future to reducing CO$_2$ emissions. In our opinion, this non-linear analysis could provide the scientific basis for authorities, especially the European Commission to promote environmental policies to a specific country with different levels of carbon emissions rather than to the entire group.

Keywords: CO$_2$ emissions, biofuels, EKC, threshold effects, GINI Index, GDP growth.

JEL Classification: C5, F1, Q1, Q3.

Introduction

Energy is an essential driver of economic development, regardless of whether we are talking about industrialized or transition countries (Destek & Sinha, 2020). Most energy production involves the consumption of traditional sources like oil, coal, and gas, however, which creates an enormous amount of CO$_2$. As a result, over the past few decades, global greenhouse gas emissions have almost doubled. According to Hübler (2017) the level of CO$_2$ emissions increased spectacularly from a 1.0% yearly average during the 90s to a 2.4% yearly average during 2000–2014. These emissions are now leading to noticeable climate-change effects and global warming. Consequently, more and more governments have set mandatory emission

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reduction targets through the utilization of clean energy sources, such as hydropower, solar power, wind power, and geothermal power, to sustain continued economic growth.

Traditional fuels remain a practical solution, however, especially in transition economies, due to their price and accessibility in comparison to the aforementioned clean sources. For this reason, during the last two decades, governments and environmental authorities have perceived other less expensive renewable-energy sources, such as fuel ethanol, as promising alternatives to fossil fuel consumption. According to Ohia et al. (2020, p. 21), "increasing the use of bio-fuels for energy generation purposes is of particular interest nowadays because they not only allow mitigation of greenhouse gases but provide means of energy independence and even offer new employment possibilities".

Nonetheless, fuel ethanol production involves distilling a series of sugar-based feedstock, such as sugarcane or corn, which requires energy consumption and creates additional CO_2 emissions. This has led to doubts about the effectiveness of this method (Hill et al., 2006). Brazil was the first country to run a large-scale program to mitigate CO_2 emissions using ethanol as fuel (Dias de Oliveira et al., 2005).

The current literature covers all relevant aspects regarding how demography and economic development amplify environmental degradation. However, the literature lacks a comprehensive analysis of the ecological effects of ethanol fuel used as an alternative to gasoline. Although several papers have describe the advantages and disadvantages of using ethanol as fuel (e.g. Hill et al., 2006; Balat & Balat, 2009; Ohia et al., 2020), such investigations are limited to a biochemical perspective. Furthermore, no statistical techniques were used to validate their hypotheses.

For this reason, several questions on this topic remain unanswered. The first question refers to whether bioethanol usage has a statistically significant impact on the reduction of CO_2 emissions across European countries. The second question relates to the impact of bio-fuel production on CO_2 emissions given the level of economic inequality. The third question refers to the feasibility of countries' adoption of an environmental ethanol-based strategy by producing it from cellulose waste.

In this paper, we address all these questions by performing a panel analysis across 17 European countries covering seven years from 2010 to 2016, which represents the longest period with available data. To ensure homogeneity, we include in the sample EU member states that manufacture ethanol alongside other countries, such as the Russian Federation, Turkey, and Ukraine, given their strong commercial relationships with EU states. In this way, we have ensured that the sample includes only countries that play by similar environmental rules.

The contribution to the literature is threefold. First, we present strong empirical evidence indicating that bioethanol production is beneficial to CO_2 emission mitigation under specific circumstances, which is a novel result. Second, we show that high-income countries are likely to exhibit difficulties in avoiding environmental degradation through the promotion of policies and regulations for more intense use of biofuels. Finally, a case study of Romania's agriculture sector reveals some unexplored channels that could be considered to increase the production of bioethanol.

The remainder of the paper is structured as follows. Section 1 presents a literature review, while the data and the panel smooth transition regression (PSTR) model are discussed in Section 2. Section 3 presents the results and offers a discussion and the policy implications are explained in Section 4. Last Section concludes the paper.

1. Literature review

In recent decades, scholars and practitioners have extensively debated the key determinants of CO_2 emissions, both in developing and developed countries, and many studies have investigated the factors amplifying CO_2 emissions from different angles. Although the literature is comprehensive, however, it has some significant limitations, especially when it comes to CO_2 emissions across European countries.

1.1. Environmental Kuznets curve

The first strand of research tests the validity of the environmental Kuznets curve (EKC) hypothesis described by Grossman and Krueger (1991). In the primary stage of economic development, countries burn fossil fuels to fulfill their energy requirements, releasing large amounts of carbon dioxide. When economic expansion reaches a certain development level, governments become more interested in reducing CO_2 emissions by forcing high-polluting companies to use cleaner technologies.

In recent years, the validity of the EKC hypothesis has been tested using different samples and econometric approaches, with inconclusive findings. For example, several cross-country analyses (Cole, 2005; Galeotti et al., 2006; Kasman & Duman, 2015) have provided strong empirical evidence to support the validity of the EKC hypothesis. In contrast, other researchers, such as Al-mulali et al. (2016) and Stern and Common (2001), did not find statistically significant estimates to relate economic developments to CO_2 emissions, regardless of their sample selection or the econometric approach used. More recently, Sarkodie and Strezov (2019) have reported mixed results indicating the validity of the EKC hypothesis. Table 1 presents details of the results described above.

Table 1. The validity of EKC hypothesis

Authors	Method	Sample	Findings
Sarkodie and Strezov (2019)	Panel Quantile Regression	China, India, Iran, Indonesia and South Africa / 1982–2016	EKC hyopothesis is valid only for China and Indonesia.
Kasman and Duman (2015)	Fully modified OLS	EU member and candidate countries / 1992–2010	EKC hyopothesis is valid.
Al-mulali et al. (2013)	Canonical Cointegrating Regression	Latin American and Caribbean countries / 1980–2008	No relationship between growth and CO_2 emissions for 41% of the countries.
Galeotti et al. (2006)	Polynomial Regressiom	Non-OECD / 1971–1998 And OECD / 1960–1998	EKC hyopothesis is valid in OECD countries but not in non-OECD countries.
Cole (2005)	Random effect panel model	110 countries / 1984–2000	EKC hyopothesis is valid.
Stern and Common (2001)	Panel random-effects and fixed-effects models	74 countries / 1960–1990	EKC is inadequate and the estimates of the EKC are biased.

1.2. Financial development and CO_2 emissions

Another research area has been devoted to investigating the connection between financial development and CO_2 emissions. Some recent studies (e.g. Ahmad et al., 2018; Rahman et al., 2019a) have revealed that the annual domestic credit given to the private sector exerts a significant positive effect on CO_2 emissions, both in the long and short run. In addition, Xie et al. (2020), Nasir et al. (2019), Rahman et al. (2019b), Liu et al. (2017), and Lan (2012) investigated the Foreign Direct Investments (FDI) – CO_2 emission nexus and confirmed that FDI inflows amplify environmental pollution. Moreover, Ahmad et al. (2019a) and Rahman et al. (2019a) found evidence indicating that remittances exert a positive influence on CO_2 emissions. Table 2 presents details of these results.

Table 2. Financial development–CO_2 emissions nexus

Authors	Method	Sample	Findings
Xie et al. (2020)	Panel Smooth Transition Regression	8 high polluting countries (2005–2014)	The influence of FDI on environmental pollution has significant regional heterogeneity and reveals a "W+V– shaped" temporal characteristics.
Ahmad et al. (2019a)	Nonlinear auto regressive distributed lag model	China (1980–2014)	A positive shock in remittances causes an increase in CO_2 emissions.
Nasir et al. (2019)	Dynamic and Fully Modified Least Squares	ASEAN-5 economies (1982–2014)	Financial development, as well as FDI, has a statistically long-run relationship with CO_2 emissions.
Rahman et al. (2019a)	Auto regressive distributed lag model	Top six Asian nations (1982–2014)	The influence of FDI on environmental pollution has a significant effect in Sri Lanka, Pakistan, the Philippines, and Bangladesh and is non-significant in India and China.
Rahman et al. (2019b)	Nonlinear auto regressive distributed lag model	Pakistan (1975–2016)	There is a symmetric association between FDI inflows and CO_2 emissions the short and long run.
Ahmad et al. (2018)	Nonlinear auto regressive distributed lag model	China (1980–2014)	Thre is a long-term and positive relationship among CO_2 emissions and financial development.
Liu et al. (2017)	Simultaneous equations model	112 Chinese cities (2002–2015)	The total effects of FDI on pollutant emissions are negative.
Lan (2012)	Panel random-effects and fixed-effects models	China (1997–2007)	The impact of FDI on pollution emissions is highly dependent on the level of human capital.

1.3. Socio-demographic characteristics and CO_2 emissions

In the last two decades, many empirical studies have investigated the roles played by urbanization rates, education, and age structures on CO_2 emissions. Regarding the impact of urbanization rates, opinions are divided. Liddle and Lung (2010), Kang et al. (2016), Nasreen et al. (2017), and Khan et al. (2019) showed that urbanization rates and population density

amplifies pollution intensity. In contrast, other authors such as Fan et al. (2006), reported that urbanization significantly reduces carbon emissions by increasing the efficiency of resource allocation. In addition, Ponce and Marshall (2014) found that urbanization amplifies carbon emissions, but its impact depends on each country's environmental laws.

Going further, Griffith et al. (2004) showed that education plays an essential role in technological changes and might help the environment. This hypothesis was supported by the results of Guo et al. (2015), who found that education (proxied by the proportion of college-educated individuals) was associated with lower carbon emissions. Additionally, they reported statistically significant results linking carbon emissions to gender distribution, age structure, and population. Hübler (2017), however, stated that education "as a national source of knowledge raises emissions with a constant elasticity of around 0.4 over the CO_2 quantile space". Table 3 presents details of all the results.

Table 3. Socio-demographic characteristics – CO_2 emissions nexus

Authors	Method	Sample	Findings
Khan et al. (2019)	Panel auto regressive distributed lag model	China (1998–2015)	The urban population has a positive relationship with CO_2 emissions.
Hübler (2017)	Panel Quatile Regression	149 countries (1985–2012)	Education has a positive relationship with CO_2 emissions.
Nasreen et al. (2017)	Auto regressive distributed lag model	South Asian countries (1980–2012)	Population density is detrimental for environment quality in the long-run.
Kang et al. (2016)	Spatial panel data models	China (1997–2012)	The urban population has a positive relationship with CO_2 emissions.
Guo et al. (2015)	Panel random and fixed-effects	China (2003–2012)	Education have a negative relationship with CO_2 emissions.
Liddle and Lung (2010)	OLS with two-way fixed effect	17 developed countries (1960–2005)	Urban population have a positive relationship with CO_2 emissions.

2. Research design

2.1. Theoretical framework

To substantiate the choice of variables in the model, we followed the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model proposed by Dietz and Rosa (1997) and illustrated by the following equation:

$$I_{it} = \alpha P_{it}^{\beta} A_{it}^{\gamma} T_{it}^{\lambda} \varepsilon_{it} . \tag{1}$$

In Eq. (1), $i = \overline{1,N}$ and $t = \overline{1,T}$ denote the number of countries and years, respectively. I_{it} represents the environmental pressure and is proxied by CO_2 emissions, P_{it} stands for population, A_{it} represents affluence, and P_{it} accounts for technology. Moreover α represents the constant term, β, γ, and λ are the impact coefficients, and ε_{it} is the error term. The model is rewritten by the logarithm of Eq. (1) as:

$$\ln I_{it} = \ln \alpha + \beta \ln P_{it} + \gamma \ln A_{it} + \lambda T_{it} + \ln \varepsilon_{it}. \qquad (2)$$

In the model, we used the population number alongside urbanization rate as proxies for P_{it} and EKC relationship as a proxy for A_{it}. T_{it} includes three technology-related variables: energy intensity, industry share, and bioethanol production. To account for the transfer of technology, we used FDIs (Ahmad et al., 2019b). Furthermore, we used school enrolment as a proxy for technological knowhow.

2.2. Data and sources

In this paper, we use a balanced panel with annual data from 17 countries[1] covering seven years from 2010 to 2016. A detailed description of the variables we used in this study is provided in Table 4.

Table 4. Socio-demographic characteristics – CO_2 emissions nexus

Variable	Description	Source
CO_2 emissions (Dependent)	The emissions are measured in metric tons per capita generated by firms and households residing within-country *i* in year *t*.	WB, BPSR
GINI Index (Threshold)	It is equal to zero in case of perfect equality (the same income for all households) and is one when we have perfect inequality (all income is designated to a single household).	WB
Ethanol fuel (covariate)	Ethyl alcohol issued as motor fuel and is perceived as an additive for gasoline. It is expressed in thousand barrels per day.	Knoema
GDP per capita (covariate)	Represents the gross domestic product divided by midyear population and is expressed in us dollars.	WB
Population (covariate)	Total population relies on the de facto definition of population, which counts all residents regardless of legal status or citizenship.	WB
Urbanization rate (covariate)	Percentage of people living in urban areas as defined by national statistical offices.	WB
Energy intensity (covariate)	An indication of how much energy is used to produce one unit of economic output. It is expressed in Joules per US dollar.	WB
Industry share (covariate)	It comprises value added in mining, manufacturing construction, electricity, water, and gas as percent of grass domestic product.	WB
Foreign direct inv. (covariate)	It is the sum of equity capital, reinvestment of earnings, and other capital. It is expressed in billions US dollars.	WB
School enrollment (covariate)	The ratio of children of official school age who are enrolled in school to the population of the corresponding official school age.	WB

Note: *WB = World Development Indicators of the World Bank; BPSR = BP Statistical Review of World Energy.

To make the modeling more rigorous, we tested the multicollinearity by employing the variance inflation factor (VIF) approach for all the explanatory variables.

Table 5. Descriptive statistic

Variables	Mean	Maximum	Minimum	St. Dev	VIF
CO_2 emissions	315.63	1571.00	40.80	355.96	NA
GINI Index	0.31	0.42	0.24	0.04	NA
Fuel ethanol	4.94	17.00	0.50	4.64	4.14
GDP per capita	33 812.22	51 655.50	7664.40	11 455.94	2.26
Industry (%) GDP	0.24	0.38	0.17	0.48	1.53
Urban population	0.75	0.98	0.53	0.11	2.82
School enrollment	0.65	0.94	0.46	0.19	1.19
Energy intensity	5.03	15.41	2.80	2.45	3.41
Population	41 933 923	5 363 352	144 342 396	36 165 367	2.69
Foreign direct Inv.	37.56	0.13	331.94	65.24	1.06

Given the results presented in Table 5, we can observe that the covariates were moderately correlated, i.e. the VIF does not exceed the threshold of 5 (Kline, 1998). For this reason, we were able to overlook any multicollinearity problems in the analysis.[2] In addition, to test for slope homogeneity, we employed the test proposed by Blomquist and Westerlund (2013), which accounts for potential serially correlated errors. The results are presented below:

Table 6. Blomquist and Westerlund Slope Homogeneity Tests

Null Hypothesis	Δ_{test}	p-value
Slope coefficients are homogenous	−1.187	0.235

The hypothesis of slope homogeneity reported in Table 6 cannot be rejected in favor of the alternative (p > 10%). Therefore, we proceeded with the analysis approach without accounting for additional heterogeneity techniques in the panel data.

2.3. Econometric approach

Shifting from a high-polluting manufacturing-sector-based system to a low technology-intensive or low-polluting service economy requires a period of transition. For this reason, classical estimation methods, such as panel OLS or panel GMM models (among others), which have been widely utilized by recent papers on this topic (Hübler, 2017) might not be tractable. To overcome this problem, we used the newly developed panel smooth transition regression (PSTR) model to estimate the impact of biofuel consumption on CO_2 emissions.

The implementation of a PSTR implies the existence of a threshold level dividing the sample into two or more regimes, with a smooth transition between them where the impact

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[2] The collinearity issue appeared when squared GDP per capita was included in the model to test the validity of EKC.

of biofuel consumption on CO_2 emissions differs as signs or as magnitude. Identifying the threshold variable is not an easy task. According to Boyce (1994), a more pronounced income concentration is leading to more political leverage by rich people on environmental policies, which is causing higher levels of CO_2 emission. Furthermore, other studies investigating the CO_2 emissions–income inequality nexus, such as Hübler (2017) and Mader (2018), have led to the idea that income inequality behaves more like a threshold variable rather than a significant driver for carbon emissions. For the abovementioned reasons, in this paper, we used income inequality proxied by the GINI index as the threshold variable.

The PSTR approach relies on the panel transition regression (PTR) methodology of Hansen (1999), given by Eq. (3):

$$Y_{it} = \begin{cases} \mu_i + \alpha_1' X_{it} + \varepsilon_{it}, & S_{it} \leq \tau \\ \mu_i + \alpha_2' X_{it} + \varepsilon_{it}, & S_{it} > \tau \end{cases}, \tag{3}$$

where $i = 1,\dots, N$ and $t = 1,\dots, T$ denote the time and country dimensions of the panel, respectively. In Eq. (3), the Y_{it} is given by CO_2 emissions; S_{it} is the threshold variable, i.e. the level of inequality, which is measured with the help of the GINI index and compared to the threshold value τ to estimate the model; X_{it} is a vector of the explanatory variables mentioned in the theoretical framework; μ_i are country fixed effects; and ε_{it} is the error term.

In PTR representation, the two groups of data above and below a threshold value are distinct and clearly identified with an abrupt transition between regimes. To overcome this issue and to allow for gradual and smooth shifts via $j = 1, \dots, r$ transition functions between $r + 1$ distinct regimes at the same time, González et al. (2005) introduced the PSTR representation, which is given by:

$$Y_{it} = \mu_i + \beta_0' X_{it} + \sum_{j=1}^{r} \beta_j' X_{it} F\left(S_{it}^{(j)}; \gamma_i; \tau_j \right) + \varepsilon_{i,t}. \tag{4}$$

In Eq. (4), we allow for r transition functions $F\left(S_{it}^{(j)}; \gamma_i; \tau_j \right)$, which are normalized to lie between 0 and 1 and have three main components: the GINI index, which is the threshold variable; γ_j, which measures the slopes of each transition function estimated by the PSTR model; and τ_j, which is the location parameter. Based on Teräsvirta's (1994) recommendations, we used a logistic representation for the transition function in the PSTR model:

$$F\left(S_{it}^{(j)}; \gamma_i; \tau_j \right) = \left[1 + \exp\left(-\gamma \prod_{l=1}^{m} \left(S_{it} - \tau_l \right) \right) \right]^{-1}, \tag{5}$$

where $\gamma > 0$ and $\tau_{1j} \leq \tau_{2j} \leq \dots \leq \tau_{mj}$ represent the number of thresholds between two extreme regimes within a given transition function. As Omay and Öznur Kan (2010) argued, to make the model tractable, a value of 1 or 2 for m is recommended. When $m = 1$, the model was described by a transition function having a first-order logistic structure. In this case, if $\gamma \to 0$, the PSTR model became a fixed effects standard linear model; if $\gamma \to \infty$, we had a PTR model developed by Hansen (1999); and if $\gamma \nrightarrow 0$ and $\gamma \nrightarrow \infty$, low and high values of S_{it} correspond to the two extreme regimes with one transition function between them. For $m = 2$ with $\gamma \nrightarrow 0$ and $\gamma \nrightarrow \infty$, the transition function was 1 for both low and high values of S_{it}, minimizing at

$(\tau_1 + \tau_2)/2$, and when $\gamma \to \infty$, we had a PSTR model with three regimes, which became a standard linear model with fixed effects when $\gamma \to 0$.

To compute the parameters from Eq. (4), we first had to eliminate the fixed effects by removing the individual means. Once the first step was complete, we could estimate the model using a nonlinear least squares (NLS) method. The cornerstone of the NLS approach is to estimate γ and τ by performing a two-dimensional grid search and retain those values that minimize the concentrated sum of squared errors. Once the optimization is performed, given an initial couple (γ, τ), we could estimate β_0 and β_1 via OLS and then apply NLS to obtain the vector of estimates $(\hat{\gamma}, \hat{\tau})$.

3. Results

3.1. Linearity investigation

Before estimating the regression outlined in Eq. (4), we need to investigate whether a nonlinear relationship between CO_2 emissions and fuel ethanol production exists. To assess the robustness of the results, we employed three linearity tests to investigate the existence of possible regime-switching effects (i.e. *H0: r = 0* vs. *H1: r = 1*) among the data sample. Here, *r* denotes the number of transition functions between the extreme regimes. The estimates and the corresponding p-values are given in the second column of Table 7.
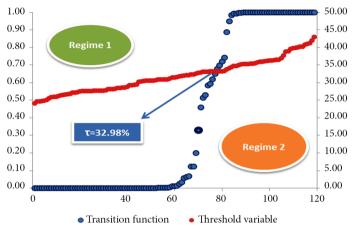
Table 7. Descriptive statistic of econometric variables

Test	*H0: r = 0* vs. *H1: r = 1*	*H0: r = 1* vs. *H1: r = 2*
Lagrange Multiplier – Wald (LMW)	0.0000	0.3620
Lagrange Multiplier – Fischer (LMF)	0.0000	0.6600
Likelihood Ratio	0.0000	0.3270

The results outlined in Table 7 reject the null hypothesis (i.e. that there is a linear relationship between fuel ethanol production and CO_2 emissions) in favor of the alternative. To make the PSTR model tractable, however, some non-remaining linearity tests need to be carried out to identify the appropriate number of transition functions. According to the results presented in the third column of Table 2, we were able to reject the alternative hypothesis and accept the null. This result shows that one transition function between two extreme regimes can capture the nonlinear effect in terms of CO_2 emissions generated by the GINI index.

3.2. Baseline model

First, in line with the recommendations presented in Section 3.1, we identified one transition function with a threshold value for the GINI index equal to 32.98% that divided the sample into two extreme regimes. In the first one (where the transition function was 0), there were 48.3% of cases, while 29.4% were in the second extreme regime (where the transition function was 1). The rest represented transition observations. Figure 1 illustrates the logistic transition function versus income inequality values.

From a mathematical perspective, the intersection point between the two lines had the following coordinates: the threshold value of the GINI index and the inflection value, which changes the shape of the logistic transition function from convex (Regime 1) to concave (Regime 2). A small value for the estimated slope parameter $(\gamma = 2.866)$ was noticed, indicating a smooth and gradual movement from one regime to another. This fact illustrated that a threshold methodology was appropriate for the data structure.

Figure 1. PSTR regimes

In Table 8, we report the estimates for Eq. (4) considering a logistic transition function (i.e., $m = 1$). In Regime 1, we found a negative relationship between fuel ethanol production and CO_2 emissions. This suggests that using ethanol as fuel might contribute to reductions in CO_2 emissions, especially in countries where income inequality is not very high (Austria, Belgium, Czech Republic, Finland, Germany, Hungary, Netherlands, and Sweden). Once the scale of the GINI index exceeded the threshold and we moved forward into Regime 2, the impact of biofuel consumption on CO_2 emissions became positive (Italy, Romania, Russia, Spain, and Turkey). We found inconclusive results for France, the United Kingdom, and Poland.

This is an exciting and novel conclusion. Indeed, biofuel production allows the mitigation of greenhouse gases, especially in technologically advanced economies, such as those of German-speaking or Scandinavian countries. In developing countries, however, such as Romania, Russia, and Turkey, or industrialized countries with many migrants working in agriculture or polluting industries (Spain and Italy), building refineries to produce ethanol might come with a high environmental cost, at least in the first stage.

Moreover, we revealed an inverted U-shaped EKC between carbon emissions and economic development in both regimes, confirming the current consensus in the literature (Cole, 2005; Galeotti et al., 2006; Kasman & Duman, 2015). The EKC relationship was amplified in Regime 2, however, indicating that economic expansion is detrimental to the environment, especially in countries with high levels of inequality (mainly developing economies). The same behavior across regimes was also specific to energy intensity, confirming the results of Shahbaz et al. (2015) regarding its positive and statistically significant impact on CO_2 emissions.

As expected, the industry added value (%) GDP had positive and identical coefficients in both regimes. Therefore, as long as this indicator deepens, the CO_2 emission levels across European countries are likely to worsen. This fact confirms the previous findings reported by Hübler (2017), which were based on a quantile regression framework. However, the impact elasticities reported in Table 8 were much lower. One possible explanation for the differing results may be the fact that across Europe, in comparison with the rest of the world, the industry has passed the transition phases of growth.

Table 8. Estimation results

Variables	Regime 1: β_0	Non-linear part: β_1	Regime 2: $\beta_0 + \beta_1$	Impact in Regime 2 vs. Regime 1 (absolute values)
Fuel ethanol	−0.0882***	0.1876***	0.0994***	↑
GDPc	1.5798***	0.04428***	1.62408***	↑
GDPc^2	−0.7517***	−0.2382***	−0.9899***	↑
Industry (%) GDP	0.0219**	−0.0084	0.0219**	=
Urban population	0.0094	0.0381***	0.0381***	↑
School enrollment	0.0066***	−0.0041**	0.0025**	↓
Energy intensity	0.1190***	0.0754**	0.1944**	↑
Population	0.9981*	−1.3050**	−0.3069*	↓
Foreign direct inv.	0.0034	−0.0142**	−0.0142**	↑
R-squared	99.80%			
The slope – γ	2.8660			
Threshold	32.98%			
Observations	119			

Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Regarding the urbanization rate, the PSTR results revealed that its impact is only visible for GINI values higher than 32.98%. This result confirms the findings of Kang et al. (2016) and Khan et al. (2019) for China but contradicts the conclusions stated by Liddle and Lung (2010), who investigated 17 developed countries. Surprisingly, education seems to encourage emission expansion rather than environmental awareness, especially in the first extreme regime. As Griffith et al. (2004) argued, education usually plays an essential role in the context of technological changes and is expected to help the environment. This fact was confirmed by Câmpeanu et al. (2017), Crețan and Iacob (2009), and Gherghina and Duca (2013) when investigating the impact of education on socio-economic environment. The results confirm the previous findings reported in Hübler (2017), however, that "education, as a national source of knowledge, raises emissions with a constant elasticity of around 0.4 over the CO_2 quantile space".

Regarding financial development, we failed to identify any significant relationship indicating that FDI inflow aggravates environmental pollution, as previously reported by Xie et al. (2020), Nasir et al. (2019), Rahman et al. (2019b), Liu et al. (2017), and Lan (2012). More to the point, FDIs are diminishing environmental degradation, especially in countries with high income inequality, where the governments, via the European Commission, have set mandatory emissions targets for high-polluting companies.

Finally, population size exhibited a positive impact on the level of CO_2 emissions in Regime 1, which confirms the previous conclusions from the literature (Nasreen et al., 2017). The impact was negative across countries from Regime 2, however, which is counterintuitive. We leave this question to be answered in future research.

3.3. Robustness of results

In this section, we check the robustness of the results. In Model A, we included the GINI index among the covariates, and in Model B, we estimated Eq. (4) based on a logistic quadratic transition function. In Model C, we used a standard fixed-effect specification.

Table 9. Robustness checks

Variables	Model A		Model B		Model C	Robustness
	β_0	$\beta_0 + \beta_1$	β_0	$\beta_0 + \beta_1$	β	
Fuel ethanol	−0.0805***	0.0832***	−0.0896***	0.0805***	−0.0049**	✔
GDPc	1.7296***	1.7296***	1.72455***	1.7246***	1.5477***	✔
GDPc^2	−0.8207***	−0.8207***	−0.8139***	−0.8802**	−0.7476***	✔
Industry (%) GDP	0.0197**	0.0197***	0.0000	0.0000	0.0154***	✘
Urban population	0.0000	0.0000	0.0000	0.0000	−0.0233*	✘
School enrollment	0.0078***	0.0032**	0.0069***	0.0036*	0.0049***	✔
Energy intensity	0.1245***	0.1245***	0.1101***	0.1101***	0.1137***	✔
Population	0.9013*	0.9013*	0.0000	0.0000	1.4054**	✘
Foreign direct inv.	0.0000	−0.0123**	0.0000	−0.0102*	0.0017	✘
GINI Index	0.0361**	0.0361				
The slope – γ	1.3533		0.3189			
Threshold	32.23%		32.74%			
R-squared	98.32%		98.77%		99.30%	

Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

The linearity tests strongly rejected the null hypothesis for Models A and B, which was in line with the baseline specification. Furthermore, the PSTR results in Table 9 revealed thresholds that were close to the values derived from the initial model. Overall, the findings confirmed the first hypothesis, according to which there is a nonlinear functional link between CO_2 emissions and biofuel production. Moreover, their usage can reduce environmental degradation, especially in countries where income inequality is low. Also, we provide strong empirical evidence revealing the existence of an inverted U-shaped correlation between economic development and carbon leakages, while failing to identify significant results showing that financial development and demography amplify CO_2 emissions.

4. Discussion and political implications

A natural question arising from the findings refers to the real capacity of a particular country to produce enough cereals that can be processed into fuel ethanol on a large scale. We chose to investigate the case of Romania (mainly due to data availability) and decide if the construction of bio-refineries would be able to provide a sustainable foundation. Featuring a complex pedo-climatic diversity that is favorable for the agriculture sector, Romania was noticed worldwide in 2018 for its production of corn. This cereal, also known as maize, is one of the most ubiquitous grains in the world and takes up more area in Romania than any other crop. Cereal grain production in Romania of the seven raised species (wheat, rye, barley, almond, rice, maize, and sorghum) ranged from 5 to 6.3 million hectares between 1990 and 2017 (Figure 2).
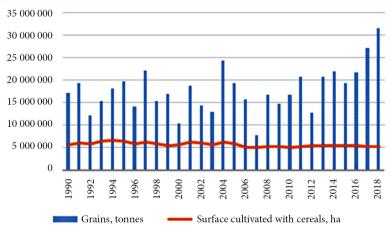

Figure 2. Grain statistics

This dynamic, especially in the last few years, can be attributed to the importance of cereals in household diets, their nutritional value, and the Romanian culture. Grains are present in the human diet in quantities of about 450 kg/capita on a yearly average (Table 10).

In this context, if we decrease the annual production of the necessities of the population, an average surplus of 572.10 kg of cereals per capita from 1990–2017 still remains. As Figure 2 highlights, cereal production is not stable from one year to another, mainly due to

Table 10. The amount of grain required for human nutrition (source: Romanian National Insitute of Statistics, Own Calculations)

Cereals	Kg/capita
Wheat	133.00
Maize	208.49
Barley	109.50
Total	450.99

natural environmental conditions (Romania does not have a sufficiently developed irrigation system). The smallest production requirement for population consumption failed to be reached in just one year (2007), however. According to these observations, the possible surplus could be allocated to other economic destinations, e.g. fuel ethanol production. According to Patni et al. (2013), one ton of grains can produce 288 liters of first-generation ethanol fuel. A detailed description of the case of Romania can be found in Table 11.

Consequently, the grain surplus from Romania could lead to the production of 164.76 liters of fuel ethanol per capita. With a population of 19.5 million, Romania could produce about 2.5 million tons of fuel ethanol per annum. Fuel ethanol can also be extracted from secondary cereal processing (290–333 liters from one ton of straw) as Glithero et al. (2013) argued. In this case, due to the grains – straw ratio, second – generation fuel ethanol production is closer to the main one.

In an attempt to produce ethanol from wheat grain and straw, Ghayur et al. (2011) found that straw is produced with 20% less ethanol than grains. Considering that the grain–straw ratio is 1:1 and that 40% is residue, 3.7 million tons of bioethanol could have been produced in Romania in 2017. These simple math starts with the premise that vegetable residue is 20% lower than the bioethanol yielded from grains (288 liters/ton from the previous calculation). If we sum the first generation of fuel ethanol (2.5 million tons) with the second generation (3.7 million tons), an average quantity of 6.2 million tons could have been obtained in Romania over one year, although the technological flows are different. This quantity would be more than enough for the implementation of an environmental protection program that uses the consumption of fuel ethanol as a gasoline additive.

Table 11. The amount of bioethanol obtained from agricultural products (source: Romanian National Insitute of Statistics, Own Calculations)

Agricultural product	Fuel ethanol from agricultural products, litres / tonne
Wheat	342
Barley	250
Rice	430
Maize	360
Sweet sorghum	65
Bagasse and other cellulose biomass	280
Average	288

If we take the model of the Inbicon Biomass Refinery projects in Denmark, through which 450,000 tons of agricultural waste are processed each year, the amount obtained as waste from Romania's agriculture in one year would cover the processing needs for 28 second-generation biorefineries. Lignin is a byproduct of the production of bioethanol that can be used to produce green electricity and spent grain for animal feed or can be converted into higher-value organic chemicals. At the same time, the surplus of cereal grains after covering human food requirements (e.g. 22,797,000 tons of cereals in 2018) can be processed in the existing biorefineries to obtain first-generation bioethanol (from this calculation, 9,631,000 liters or 7,512,000 tons for the year 2018). As bioethanol is an additive in gasoline, at a concentration of 5–10%, it does not affect engines.

Overall, the sustainability analysis shows us that a country like Romania can produce ethanol as an alternative to gasoline. We strongly recommend that similar countries build biorefineries, especially if their agricultural architecture allows it. Even if the effects of these investments do not appear immediately (in fact, the impact on the environment will be adverse in the first stage of production), CO_2 emissions will diminish in the long run as long as economic inequality is reduced. Moreover, promoting the low-carbon economy and encouraging entrepreneurs to engage in the economic activity of processing renewable resources adheres to the requirements for air pollution mitigation. As a result, rural economic diversification might occur alongside an increase in economic growth. In addition, we suggest that economic growth, energy intensity, and education can be utilized as critical instruments to protect against environmental degradation through economic and energy reforms.

Given the limited timeframe of the bioethanol production data, future research will focus on extending this period and will include macroeconomic variables such as inflation, interest rates, and bank performance. We will also employ an average treatment effect approach for the European countries (Străchinaru & Dumitrescu, 2019) to investigate the impact of CO_2 emissions generated by investment in biorefineries.

Conclusions

This paper provides an extensive assessment of fuel ethanol consumption and the CO_2 emissions–income nexus with the help of a newly developed PSTR model. We highlight several contributions that this work makes to the literature. First, the linearity tests show a regime-switching when studying the critical drivers of CO_2 emissions. Also, we present strong evidences showing that the GINI index acts as a powerful threshold variable for CO_2 emissions in the baseline PSTR approach, as well as for all the robustness trials.

We also report a negative relationship between fuel ethanol consumption and CO_2 emissions based on a sample of 17 European countries, although this is seen only in countries with low income inequality. In countries with high levels of inequality, it is much more difficult to avoid environmental degradation in the short-term by promoting policies and regulations to intensify the use of biofuels. We suggest investment in biorefineries in such countries, especially when agricultural architecture allows it. Furthermore, we show the validity of the EKC hypothesis, regardless of the level of inequality.

Overall, the findings are useful to policymakers from the EU as these emissions (alongside those of other gases) have led to climate change, as observed through their widespread effects on ecosystems, economies, human health, and general well-being in Europe. At the same time, extreme climates (e.g. extreme heat, heavy rainfall, and droughts) have increased in frequency and intensity in many regions. As a result, through the Paris Agreement (December 12, 2015), the EU has committed itself to reducing its greenhouse gas emissions by at least 40% by 2030. With the same conviction, on November 28, 2018, the European Commission presented its long-term strategy for creating modern, competitive, and climate-neutral economic prosperity by 2050. We believe this study could provide a scientific basis for governments to promote policies in specific countries with different levels of CO_2 emissions.

Author contributions

Mariana Bran conceived the study and was responsible for the design of the methodology. Mihai Dinu was responsible for data collection and interpretation, whereas Cosmin Octavian Cepoi conducted the statistical analysis and discutions section.

Disclosure statement

The authors declare no conflict of interest.

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