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Research Article

Determination of factors affecting greenhouse gases emitted to the atmosphere in eurostat countries with multiple linear regression model

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ABSTRACT

Greenhouse gases (water vapor (H_2O), carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), ozone (O_3) and numerous other harmful gases), also known as both natural and anthropogenic gaseous components of the atmosphere, increase the planet's temperature by absorbing solar radiation and trapping this energy in the atmosphere rather than reflecting it back to the Earth. Therefore, identifying the factors that influence greenhouse gases is crucial for combating climate change, protecting human health and ensuring environmental sustainability. This study aims to investigate the effect of "agriculture, forestry and fishing (AFF); manufacture of food products, beverages and tobacco products (FBT); manufacture of paper and paper products (PPP); manufacture of chemicals and chemical products (CCP); water supply, sewerage, waste management and remediation activities (WSR); transportation and storage (TS)" industrial sectors on greenhouse gases emitted into the atmosphere in 17 Eurostat countries between 2010 and 2021 using a multiple linear regression model. The results of this research show that the AFF, FBT, CCP, WSR and TS have a strong effect on greenhouse gas emissions (GHGEs), as indicated by their Pearson correlation values close to 1, while the PPP variable has a lesser effect with a value of 0.650, which is less close to 1. With the coefficient of determination R^2 value of 0.924, which very close to 1, the model effectively explains the variation in GHGEs, confirming the significant influence of these variables. Additionally, according to mean of GHGEs, France records the highest values in GHGE, AFF, FBT, PPP, CCP, WSR, and TS, while Cyprus, Slovenia, and Iceland show the lowest values. The findings are expected to provide important insights for environmental policymakers and sustainability researchers.

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INTRODUCTION

The globe is under the sway of escalating production requirements, leaving environmental imprints. On the flip side, this dynamic engenders environmental degradation linked to the generation of greenhouse gas emissions (GHGE), depletion of the protective ozone layer, the onset of global warming, climate change, and environmental sustainability. These factors have far-reaching effects on humanity, including health.

Industrial expansion throughout the 19th and 20th centuries intensified the emission of greenhouse gases and other atmospheric pollutants, which in turn accelerated the onset of global warming. In recent decades, global warming has become a critical global issue, largely driven by the continuous rise in GHGE and its associated climatic disruptions [1].

Greenhouse gases comprise several environmentally harmful constituents, such as water vapor (H_2O), carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), ozone (O_3), and many other trace gases. The Earth stays within a livable temperature range by keeping a balance between the warmth it receives from the sun and the heat it releases back into space. This balance exists because of the greenhouse effect [2], which holds part of the sun's heat and keeps the planet from becoming too cold. But when greenhouse gases rise above normal levels, more heat gets trapped than the Earth can release, disturbing this balance [3]. Over time, the planet warms faster than it can cool, bringing higher average temperatures, longer and more frequent heat waves, and serious risks to human health. Rising warmth also encourages more pollen in the air, which can worsen breathing problems and increase heat-related illnesses. Higher temperatures also promote greater pollen production, worsening respiratory conditions and increasing the risk of heat-related illnesses and deaths. In addition, prolonged drought conditions have intensified the frequency and severity of wildfires, resulting in greater risks of burns and other heat-related injuries. These changes clearly demonstrate that climate change has negative short- and long-term impacts on human health [4]. Furthermore, high greenhouse gas concentrations weaken the adaptive capacity and overall health resilience of societies, as reflected in the disease burden measured in disabilityadjusted life years (DALYs) [5].

Assessing the determinants of GHGEs holds significant value for advancing environmental sustainability. The relationship between GHGE and environmental sustainability is a critical aspect of the ongoing discourse on global environmental challenges. The planet has undergone significant alterations in its climate, prompting international organizations and governments to initiate policy measures in the battle against climate change [6]. While the scientific community universally recognizes climate change as a subject of research, regrettably, not every nation views climate change and the imperative to diminish GHGEs as political priorities [7]. Environmental factors, whether anthropogenic or natural in origin, exert a substantial influence on GHGEs levels. This influence becomes evident through the release of pollutants into the atmosphere, primarily resulting from the combustion of fossil fuels such as diesel and gasoline in densely populated urban areas, which intensifies the greenhouse effect. Beyond transportation, considerable emissions also arise from agriculture, forestry, and fisheries, as well as from the production of food and beverages, tobacco, paper products, and a wide range of chemical goods. Furthermore, emissions are associated with water supply, sewerage, waste management, remediation activities, as well as transportation and storage [8-12]. The influence of different sectors on GHGEs can be outlined as follows.

1. **Agriculture, forestry and fishing:** This industry is a big source of CH_4 emissions, mostly because of how livestock is cared for and how manure is thrown away. Using fertilizers and different ways to care for the soil can also make N_2O. Also, cutting down trees to make room for farming makes the warming effect worse by raising CO_2 levels in the air.
2. **Manufacture of food, beverages and tobacco products:** This sector contributes to GHGEs primarily through intensive energy use in processing, packaging, and refrigeration. Additional emissions arise from the combustion of fossil fuels for heat and electricity generation, as well as from waste management and transportation activities associated with production and distribution.
3. **Manufacture of paper and paper products:** Since wood raw materials are used in this sector, it may contribute to C_{O2} emissions. There may also be energy-related GHGEs due to energy-intensive production processes.
4. **Manufacture of chemicals and chemical products:** Chemical production processes may cause GHGEs. Chemical plants, in particular, can release greenhouse gases such as N_2O and other chemical emissions into the atmosphere.
5. **Water supply, sewerage, waste management and remediation activities:** This sector can cause CH_4 emissions during sewage and waste management. It can also produce energy-related greenhouse gases during energy use and operation of facilities.
6. **Transport and storage activities:** Transportation is a sector where CO_2 emissions are especially high due to the use of fossil fuels. The transportation sector is a major source of greenhouse gases into the atmosphere.

There are studies in the literature that use multiple linear regression models to determine the factors affecting greenhouse gases [13-20]. Based on this, the aim of this study is to examine the effect of "agriculture, forestry and fishing (AFF); manufacture of food products, beverages and tobacco products (FBT); manufacture of paper and paper products (PPP); manufacture of chemicals and chemical products (CCP); water supply, sewerage, waste management and remediation activities (WSR); transportation and storage (TS)" industrial sectors on greenhouse gases emitted into the atmosphere in 17 Eurostat countries between 2010 and 2021 using a multiple linear regression model. Up to this point, the connections between these explanatory factors and GHGEs have not been looked at in the 17 Eurostat countries. This study employs a country-specific comparative methodology, introducing an innovative model to analyze these correlations.

This research provides a significant contribution through its detailed assessment of several industrial sectors in the European context. Based on previous studies, it provides a more detailed and holistic view of how different sectors contributed to GHGEs across the 17 Eurostat countries between 2010 and 2021. Whereas much of the existing literature has tended to analyze either single sectors or broad aggregates, this study extends the discussion by examining cross-sectoral linkages and the cumulative effects of industrial activities on total emissions. Adopting this multi-sectoral perspective provides a more holistic understanding of the emissions structure and deepens our understanding of the complex dynamics underlying cross-sector interactions.

To determine the strength of each explanatory variable's influence on the GHGEs, it is benefited from a multiple linear regression model. For this goal, in Section 2, greenhouse gas dataset and the multiple linear regression model that will be investigated in the analysis of this data are handled. The findings and the interpretation of the results are discussed in Section 3 and finally, concluding remarks are given in Section 4.

GREENHOUSE GAS DATASET AND MODELLING

Greenhouse gas dataset consists of "greenhouse gases (CH_4 in CO_2 equivalent, HFC in CO_2 equivalent, PFC in CO_2 equivalent, SF_6 in CO_2 equivalent, NF_3 in CO_2 equivalent (in tonne)); AFF; FBT; PPP; CCP; WSR; TS" variables belonging to Belgium, Bulgaria Hungary, Netherlands, Austria, Poland, Portugal Slovenia, Finland, Norway, Switzerland, France, Spain, Iceland, Greece, Cyprus, Latvia countries between 2010-2021 years [21].

Regression analysis involves utilizing features extracted from a dataset as independent variables in a regression model to estimate the dependent variable, which assumes a continuous value. This predictive outcome is achieved by understanding the association between the independent (input, explanatory) variable x and the dependent (output) variable y.

A basic form of regression analysis is the simple regression analysis, where a sole feature is employed to anticipate the value of the dependent variable. The equation for the linear regression model is articulated as follows:

$$y = \beta_0 + \beta_1 x + \varepsilon$$

where y represents the dependent variable, x is the independent variable, β_i signifies the parameters to be estimated for $i = 0, 1$ and ε denotes the error term.

Linear regression analysis involves establishing the relationship between independent variables and the dependent variable by fitting a linear or non-linear curve to the data. For an accurate curve fitting, a measure of goodness-of-fit must be defined to discern the curve that provides a superior fit compared to others. In the context of simple linear regression, the objective is to determine the slope and intercept values of the line that minimize the goodness-of-fit measure.

In the multiple linear regression model

$$y = \beta_0 + \beta_i x_i + \varepsilon$$

where x_i denotes the independent variables for $i = 0, 1, ..., n$.

The most basic assumption of the multiple linear regression model is that the dependent variable has a normal distribution. This situation is checked with Kolmogorov-Smirnov and Shapiro-Wilk tests. If $p > 0.05$, this means that the distribution has a normal distribution. For regression coefficients estimates, the least squares method (LSM) are used. The regression analysis is done using IBM SPSS Statistics 21.

In the context of the multiple linear regression model,

1. The null hypothesis H_0 asserts that all regression coefficients are equal to zero, denoted as $H_0 = \beta_0 = \beta_1 = \beta_2 = \ldots = \beta_n$. Conversely, the alternative hypothesis H_1 suggests that at least one β_i coefficient is different from zero. The overall significance of the multiple linear regression model is assessed using an F-test and the empirical significance level (the so-called p-value). If p-value<0.05 is satisfied, H_0 is rejected and so, H_1 is accepted.
2. For the individual significance testing of regression parameters, t-tests are employed. The information given in number 1 regarding the p value is also valid here.

The coefficient of determination R^2 represents the percentage of the dependent variable explained by the independent variables included in the model. The coefficient of determination, ranging from 0 to 1, elucidates the proportion of variability in the GHGEs variable explicated by the estimated model. A heightened determination coefficient signifies a greater extent of the model's ability to clarify the variability observed in the dependent variable.

RESULTS AND DISCUSSION

During the period from 2010 to 2021, the analysis of industrial sector variables such as "AFF (x_1); FBT (x_2); PPP (x_3); CCP (x_4); WSR (x_5); TS (x_6)" allows for the investigation of their impacts on GHGEs (y). This analysis enables the application of a country-specific comparative approach to identify the determinants influencing the distribution of greenhouse gases across the 17 Eurostat nations. This approach allows us to explore the presence of correlations between the considered categories, a prerequisite for establishing a cause-and-effect relationship among them. Utilizing this method, we could construct model resulting in an empirical model represented by a regression equation, which is articulated as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \varepsilon.$$

The results of the normality tests for GHGEs based on country data are presented in Table 1. Upon close examination of Table 1, it is observed that the p values for the normality tests across all countries exceed the threshold of 0.05. This indicates that the assumption of normality is satisfied for the dataset. As a result, it is appropriate to proceed with the application of the multiple linear regression model to analyze the relationships between the variables in the study.

In Table 2, the Pearson correlation coefficients are reported for the independent variables, which include AFF, FBT, CCP, WSR and TS, and the dependent variable, which is GHGEs. When Table 2 is investigated, it is seen that Pearson correlation coefficients close to 1 and then, it is said that independent variables have a strong relationship with the dependent variable.

Among AFF, FBT, CCP, WSR, and TS demonstrate a notably strong influence on GHGEs, underscoring their predictive importance. But, conversely, the PPP variable shows a relatively weaker impact on GHGEs. While PPP still contributes to variations in emission levels, its influence appears modest relative to the other explanatory factors included in the analysis. This situation can also be seen through Figure 1.

In Figure 1, country-based scatter plot matrix of GHGEs, AFF, FBT, PPP, CCP, WSR and TS variables is given. Upon examining the scatter matrix graph presented in Figure 1, it is evident that a strong positive linear relationship exists between all independent variables and the GHGEs dependent variable, with the exception of the PPP variable. In contrast, the relationship between the PPP independent variable and the GHGEs dependent variable appears to be weakly positive and not particularly linear.

The results for the model summary, ANOVA, and the coefficients of the multiple linear regression analysis are presented in Tables 3, 4, and 5, respectively. When we examine Table 3, we observe that the independent variables included in the regression model explain the variation in the dependent variable, GHGEs, to a considerable extent. This is evident from R^2, which is very close to 1. This high score signifies that about 92.4% of the variation in GHGEs is accounted for by the independent variables in the model. This indicates that the model effectively predicts GHGEs, with the chosen variables providing significant explanatory power for the observed emission patterns. Furthermore, the magnitude of the R^2 value highlights the reliability of the model in explaining the relationships between GHGEs and their predictor variables, confirming that the model used in this study has a clearly defined and statistically robust framework.

An analysis of Table 4 reveals that the explanatory variables, taken together, have a statistically significant impact on GHGEs. The p-value obtained from the F-test is much smaller than the conventional significance threshold of 0.05, indicating that the overall regression model is

Table 1. Tests of normality for country-based GHGEs

Country	Kolmogorov-Smirnov	Shapiro-Wilk	Country	Kolmogorov-Smirnov	Shapiro-Wilk
	Sig.	Sig.		Sig.	Sig.
Austria	0.200	0.640	Latvia	0.200	0.997
Belgium	0.141	0.177	Netherland	0.061	0.028
Bulgaria	0.200	0.870	Norway	0.082	0.494
Cyprus	0.200	0.448	Poland	0.200	0.555
Finland	0.200	0.615	Portugal	0.065	0.093
France	0.200	0.868	Slovenia	0.200	0.604
Greece	0.200	0.733	Spain	0.176	0.182
Hungary	0.200	0.313	Switzerland	0.066	0.090
Iceland	0.162	0.082			

Table 2. Pearson correlation coefficient values

		AFF	FBT	PPP	CCP	WSR	TS
GHGEs	Pearson correlation	0.954	0.934	0.650	0.871	0.920	0.801

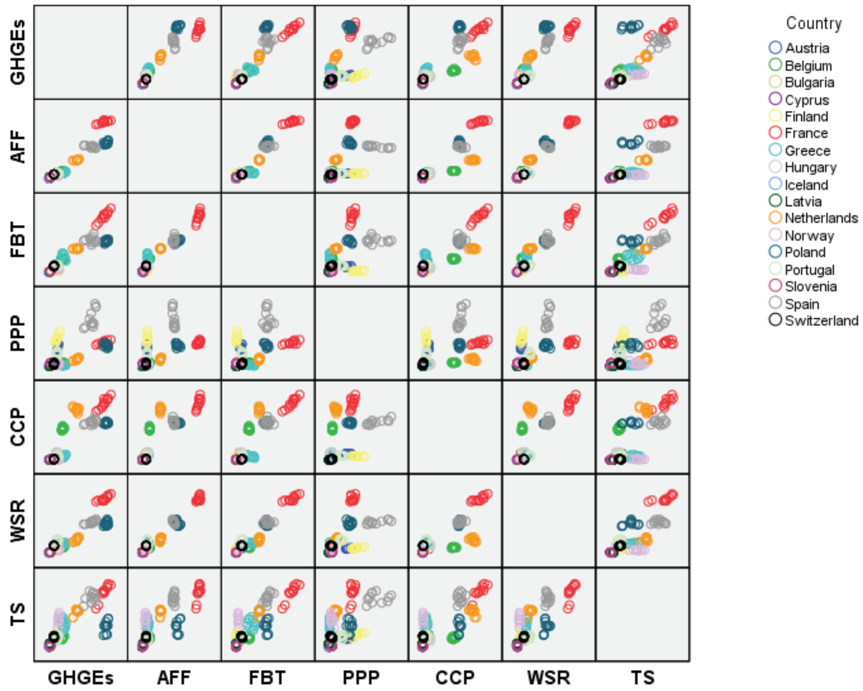

Figure 1. Country-based scatter plot matrix of GHGEs, AFF, FBT, PPP, CCP, WSR and TS variables.

statistically sound and meaningful. This finding implies that the independent variables, when assessed collectively, play a substantial role in explaining the observed variation in the dependent variable, rather than this variation being due to random factors. In other words, the model effectively captures consistent and meaningful relationships between the explanatory variables and GHGEs. Since the p-value lies well below the 0.05 significance level, we can confidently reject the null hypothesis that "the independent variables do not influence the dependent variable," reinforcing the evidence that the explanatory variables jointly contribute to the model's explanatory power.

The statistical data obtained support that the multiple linear regression model has a strong predictive power and show that the relationships between the independent variables and GHGEs are not random but statistically significant.

To assess the individual contribution of each independent variable to the overall model, Table 5 must be carefully examined.

Table 3. Model summary[b]

Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.961[a]	0.924	0.921	30954154.25937

a. Predictors: (Constant), TS, PPP, CCP, WSR, FBT, AFF

b. Dependent Variable: GHGEs

Table 4. ANOVA[a]

Model		Sum of squares	Df	Mean Square	F	Sig.
1	Regression	2.287E+18	6	3.812E+17	397.891	0.000[b]
	Residual	1.888E+17	197	9.582E+14		
	Total	2.476E+18	203			

a. Dependent Variable: GHGEs

b. Predictors: (Constant), TS, PPP, CCP, WSR, FBT, AFF

Table 5. Coefficients[a]

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% Confidence ınterval for B	
		B	Std. error	Beta			Lower bound	Upper bound
1	(Constant)	19989595.20	3385050.94		5.905	0.000	13314007.204	26665183.210
	AFF	4.018	0.594	0.846	6.763	0.000	2.847	5.190
	FBT	10.086	4.892	0.253	2.062	0.041	0.438	19.734
	PPP	10.036	2.306	0.127	4.352	0.000	5.489	14.584
	CCP	1.282	0.843	0.085	1.521	0.130	-0.380	2.943
	WSR	-4.647	2.023	-0.268	-2.297	0.023	-8.636	-0.658
	TS	-0.321	0.376	-0.036	-0.855	0.394	-1.063	0.420

a. Dependent Variable: GHGEs

Table 5 presents the statistical significance of each independent variable in predicting GHGEs. Their p-values of CCP and TS, 0.130 and 0.394 respectively, exceed the standard significance threshold of 0.05. Given these values, it can be inferred that CCP and TS contribute little to the model's explanatory power and have a limited effect on predicting GHGEs.

Table 5 also presents the parameter estimates for the model using LSM. The estimates for the intercept and the coefficients of the independent variables are given as follows: β_0 =19989595.207, β_1 = 4.018, β_2 = 10.086, β_3 = 10.036, β_4 = 1.282, β_5 = -4.647, β_6 = -0.321. These coefficients indicate the extent to which each independent variable is believed to influence GHGEs, assuming the other factors remain constant. In addition, the 95% confidence intervals calculated for each estimate show that the true population parameters are likely to fall within these ranges with 95% confidence. This information helps assess the direction and magnitude of each effect, as well as the precision of the resulting estimates.

Given that the CCP and TS variables were found to be statistically insignificant, it seemed logical to assess whether removing them from the model would improve the model. For this purpose, the regression analysis was re-estimated after removing these two variables from the model. The results showed that removing CCP and TS did not significantly affect the R^2 value.

This analysis shows that the model could still explain changes in GHGEs even after these variables were taken out. Therefore, excluding the CCP and TS variables did not lead to any changes in the model. Although these variables were statistically insignificant, they did not improve the overall performance of the model. This result demonstrates that the existing definition is both robust and appropriate for elucidating the relationship between the independent variables and GHGEs. And then, the original model was retained in its entirety without further adjustments.

Figure 2 presents the country-based mean values for GHGEs, along with the independent variables AFF, FBT, PPP, CCP, WSR, and TS.

An analysis of the mean values for GHGEs reveals that France and Finland have the highest averages, suggesting that these countries are the leading contributors to total emissions. In contrast, Cyprus, Slovenia, and Iceland exhibit the lowest average values. A similar trend is observed for the AFF variable, with France consistently ranking highest, while Cyprus, Slovenia, and Iceland are at the lower end of the spectrum.

In the context of FBT, France maintains the highest average, while the smaller economies of Cyprus, Slovenia, and Iceland routinely report the lowest figures. In terms of PPP, Spain has the highest average, whereas Switzerland and Iceland demonstrate the lowest values. In terms of CCP, France once again records the highest average, while Cyprus, Slovenia, and Iceland show the lowest results.

In the context of WSR, France consistently shows the highest average, while Cyprus, Slovenia, and Iceland show the lowest. In terms of TS, the findings show that France and Finland exhibit the highest averages, while Cyprus, Slovenia, and Iceland consistently appear at the lower end of the spectrum.

The findings collectively demonstrate that France is a prominent emitter across several sectors, while Cyprus, Slovenia, and Iceland contribute relatively little amounts to overall GHGEs, highlighting structural and economic disparities across these nations.

Figure 3 illustrates the mean values of GHGEs at the country-level throughout the study period, providing a visual representation of the variations in emission levels among nations. An analysis of these trends indicates that France consistently exhibits the greatest values for both GHGEs and the corresponding independent variables — AFF, FBT, PPP, CCP, WSR, and TS. This pattern suggests that France has consistently been a leading contributor to both GHGEs and the associated economic sectors during the observed years.

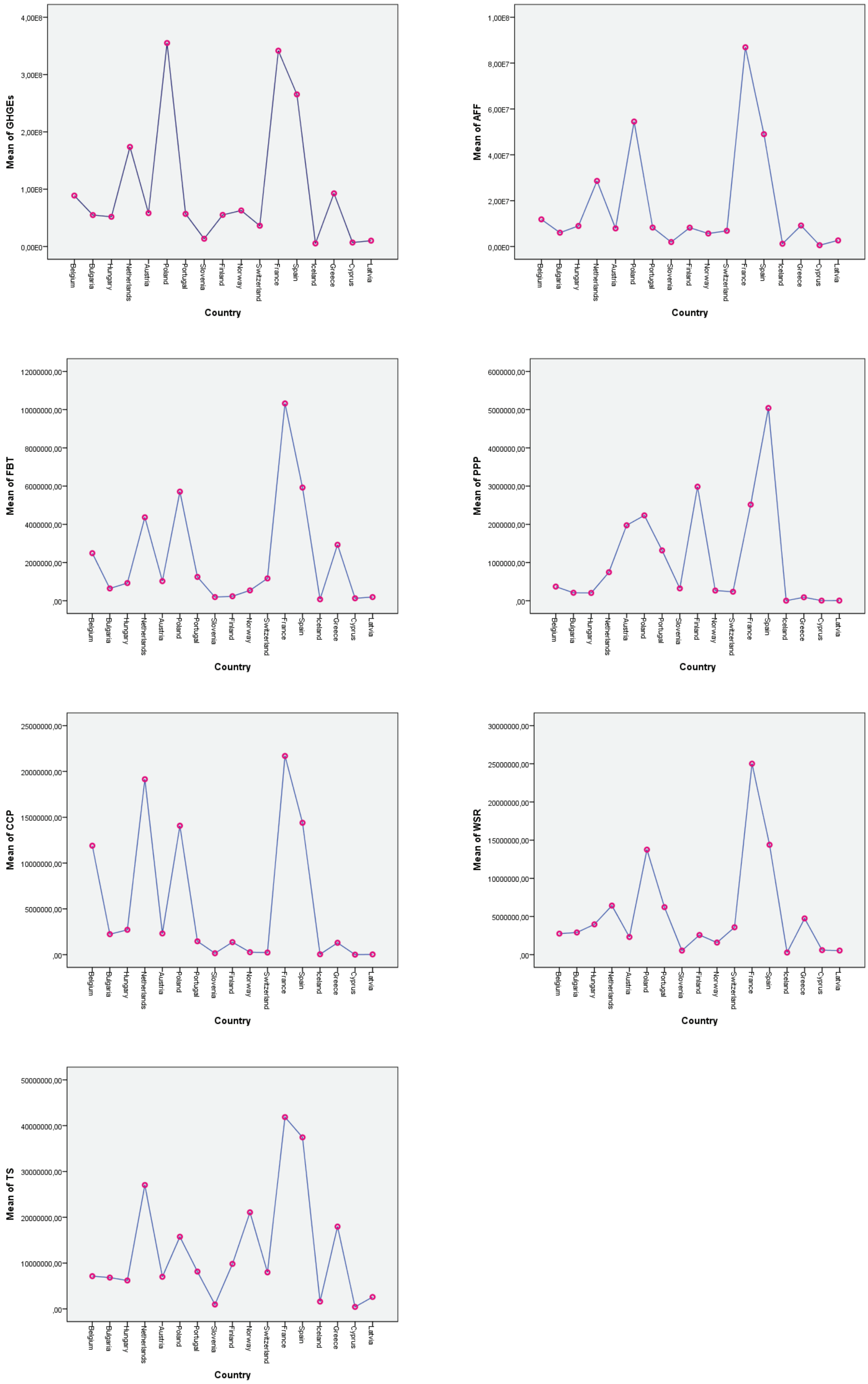

Figure 2. Country-based mean of GHGEs, AFF, FBT, PPP, CCP, WSR and TS graphics.

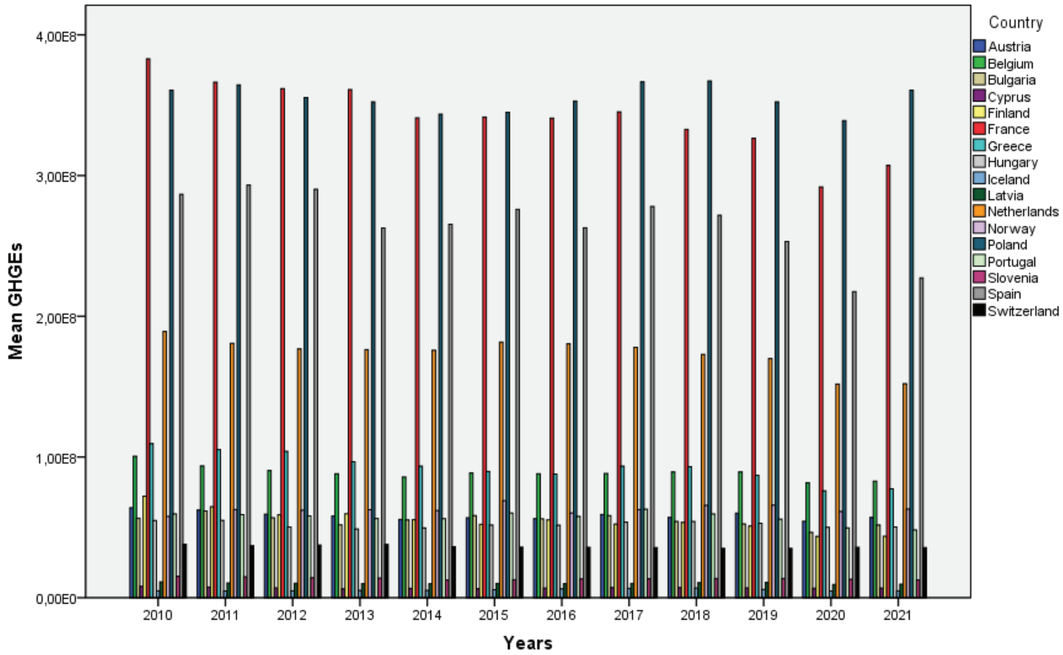

Figure 3. Average GHGEs by country and year graphic.

Conversely, Cyprus, Slovenia, and Iceland consistently demonstrate the lowest values across the same set of criteria. Their total contribution to GHGEs and associated economic sectors seems rather minor, positioning them at the bottom end of the distribution throughout the investigated timeframe. This pattern persists consistently over time, with minimal fluctuation in their respective contributions to emissions and sectoral activity. The analysis of Figure 3 leads to the conclusion that the general distribution of GHGE values, along with the independent variables, remains fairly consistent year after year. France stays at the top because it has the greatest average values for most variables. Cyprus, Slovenia, and Iceland, on the other hand, always have the lowest average values. Importantly, these relative positions have not changed much or at all over time. This suggests that the differences in GHGEs and related economic activity in these countries have stayed mostly the same during the study period.

CONCLUSION

This study explores the effects of several industrial sectors—AFF, FBT, PPP, CCP, WSR, and TS—on overall atmospheric greenhouse gases emissions. The analysis relies on data from 17 Eurostat countries spanning 2010–2021 and applies multiple linear regression to assess the connection between sectoral activities and total emission levels.

The results show that some core sectors, particularly AFF, FBT, CCP, WSR, and TS, exert a significant influence on total greenhouse gases emissions. High Pearson correlation coefficients approaching one confirm a strong and positive link between activity within these sectors and overall emission levels. In practical terms, increased production or economic intensity in these industries is closely associated with higher greenhouse gas outputs. This highlights their decisive role in shaping national emission structures. By contrast, the PPP sector displays a relatively weaker association with total greenhouse gases emissions, with a correlation coefficient of 0.650. Although PPP contributes to emissions, its effect appears less pronounced compared with the other independent variables, implying a more modest role in driving greenhouse gases emissions among the analyzed countries.

The strength of the regression model is reflected in its coefficient of determination (R^2) of 0.924, suggesting that approximately 92.4% of the variation in total emissions is explained by the selected independent variables. This high explanatory power demonstrates how strongly sectors such as AFF, FBT, CCP, WSR, and TS influence emission outcomes across the dataset.

Significant differences across countries are also evident in both average emission levels and sectoral contributions. France exhibits the highest mean values for total greenhouse gases emissions as well as for sectoral components—AFF, FBT, PPP, CCP, WSR, and TS—making it the leading emitter within the group. In contrast, Cyprus, Slovenia, and Iceland record the lowest averages for these same variables and contribute less to overall emissions.

Over time, these cross-country patterns remain fairly stable. Only minor fluctuations occur in the relative ranking of nations or the influence of particular sectors on emissions. This consistency suggests that the structural forces shaping greenhouse gases emissions have changed little between 2010 and 2021. Such persistence points to the continued importance of these industries in defining the emission profiles of the studied countries.

The findings provide valuable guidance for policymakers, sustainability experts, and environmental stakeholders aiming to reduce greenhouse gas emissions. They emphasize the importance of targeted, sector-based approaches focused on industries with the greatest impact. Since AFF, FBT, CCP, WSR, and TS have substantial effects on emissions, prioritizing mitigation within these sectors should form the basis of effective environmental strategy. The model's strong explanatory value ($R^2 = 0.924$) reinforces the urgency of focused action directed at high-emission sources. Without timely, sector-specific intervention, achieving global mitigation targets will be extremely difficult.

A stronger grasp of how industrial activities contribute to greenhouse gas emissions makes it possible to build policies that support growth without sacrificing environmental goals. Many European economies still depend on energy-intensive industries for jobs and income, yet this reliance also exposes them to higher emission levels. Cutting emissions therefore requires more than new technologies; it calls for structural shifts in the way economies are organized. Decision-makers should focus on strategies that promote cleaner production methods, diversify energy sources, and strengthen circular-economy practices that separate economic expansion from environmental harm.

For these actions to be successful, cooperation among all levels of government is necessary. Local, regional, and national authorities each have their own duties in planning, supervision, and enforcement. Institutions should be equipped with stronger administrative capacity, greater transparency, and closer collaboration between public and private sectors. Working together across different fields can spark new ideas and practical solutions. In addition, financial measures such as carbon pricing, specific subsidies, or environmentally focused tax adjustments can encourage industries to adopt more sustainable methods and reduce their environmental footprint.

Attention must also turn to the human side of the transition. Shifting to low-carbon production should be fair and inclusive, supported by retraining programs that help workers adapt to new roles. By linking environmental, economic, and social goals in this way, governments can make progress on climate targets while protecting economic stability and maintaining public confidence.

Concentrating on the most influential sources of emissions allows governments to develop more effective and efficient reduction policies. Recognizing the key factors behind greenhouse gases emissions is essential for sound policy design. Determining which sectors and activities—such as energy generation, industrial processes, or agriculture—contribute most enables decision-makers to implement well-targeted strategies for emission reduction, improving the overall success of climate initiatives.

Recognizing the primary drivers of emissions also aids in setting clear priorities for resource allocation. Focusing financial and human capacity on sectors with the highest reduction potential ensures a more meaningful environmental impact.

In addition, identifying emission determinants supports technological innovation and progress. When policymakers and researchers understand the principal challenges more clearly, they can better develop and promote cleaner technologies and sustainable solutions. For instance, measures that boost energy efficiency or accelerate the shift toward renewable sources can advance the transition to greener production systems.

This understanding forms a reliable basis for putting environmental policies into practice and checking how well they work. Policymakers can benefit from regularly examining emission records and seeing whether current actions are producing the desired results. Ongoing observation makes it easier to notice problems early and make the necessary changes before existing programs lose their effectiveness. Keeping this process active allows policies to adapt to new environmental and economic conditions, helping climate strategies stay strong and effective over time.

Looking beyond national borders, understanding what drives emissions also builds stronger cooperation between countries. When governments compare their results and share what has worked for them, it creates opportunities for open discussion and learning from one another. This kind of collaboration leads to coordinated global efforts rather than fragmented actions, making progress toward emission reduction far more realistic.

Identifying the main factors behind greenhouse gas emissions lays the groundwork for designing and improving environmental policies. This understanding also drives practical innovation and strengthens collaboration among countries. When policy choices rely on real data and shared experience rather than assumptions, actions to reduce emissions become clearer, more efficient, and better aligned with long-term sustainability and global confidence.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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