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Examining The Impact of Macroeconomics Factors on Carbon Emissions in Selected 7-ASEAN Members: A Panel Data Analysis

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Abstract: This study investigates the relationships between urbanization, economic growth, energy consumption, transportation, and carbon emissions in seven ASEAN countries from 2011 to 2022. As released by the World Health Organization (WHO), more than 80 percent of the world's population living in urban areas were exposed to air quality levels that were above the WHO limits. The region that is most affected comes from those nations categorized as low to middle-income countries. Hence, it is best to examine why these 7 ASEAN nations categorized from the lower to upper-middle income countries are not able to control the increase in the level of their carbon emissions. The analysis would also identify the appropriate empirical model suitable for the data. Using panel data analysis applying econometric modeling which are the Pooled Ordinary Least Square, Fixed Effects Model, and Random Effects Model, the findings support the Environmental Kuznets Curve hypothesis, revealing that urbanization and economic growth significantly increase carbon emissions. The study emphasizes the need for renewable energy adoption and sustainable urban planning to reduce carbon footprints. Key recommendations include enhancing energy efficiency and promoting cleaner transportation technologies to achieve sustainable economic growth in the ASEAN region.

Keywords: *Carbon Emissions, Urbanization, Economic Growth, Energy Consumption, Transportation, 7-ASEAN, Environmental Kuznets Curve, Panel Data Analysis*

1. Introduction and Background

As countries grow economically, carbon consumption and emissions increase, leading to significant environmental consequences. The Environmental Kuznets Curve (EKC) hypothesis suggests that emissions rise until economic growth reaches a turning point, after which they decline (Salari, 2020; Munir, 2020). Large populations and industrial activities drive this trend through increased energy and transportation demands. Technological advancements and sustainable energy sources are essential for achieving economic growth while limiting emissions, benefiting the Human Development Index (HDI) through cleaner energy consumption (Yumashev et al, 2020). Urbanization in ASEAN countries fuels economic development but also raises carbon emissions due to higher energy consumption and transportation needs. By 2020, ASEAN's urban population reached 310 million, with significant growth expected (ASEAN Secretariat, 2021). Sustainable urban planning and green technologies are crucial to mitigate these impacts (Ritchie & Roser, 2020). Economic growth, measured by GDP, correlates with increased energy use and carbon emissions. ASEAN's GDP grew by 5.5% in 2022 post-pandemic (World Bank, 2023).

The region's energy demand is projected to double by 2040, with fossil fuels still dominating (International Energy Agency, 2023). Transitioning to renewable energy is vital for reducing emissions, with the ASEAN Plan of Action for Energy Cooperation aiming for 23% renewables by 2025 (ASEAN Centre for Energy, 2022). The transportation sector significantly contributes to carbon emissions due to increased vehicle usage and inadequate public transportation infrastructure. Sustainable solutions like electric vehicles and improved public transportation are necessary to mitigate this impact (ASEAN Automotive Federation, 2023). The ASEAN region's rapid economic growth has led to increased energy consumption and carbon emissions, exacerbated by population growth. This trend poses significant environmental and health challenges and impacts the transportation sector, which is crucial for socio-economic development (Li et al., 2022). Despite global efforts to reduce carbon emissions, the complex relationship between emissions, transportation efficiency, and human welfare remains underexplored, hindering effective policy formulation. The need to balance economic growth with environmental sustainability and improve transportation infrastructure is critical for achieving sustainable development goals in the region.

2. Literature Review

Understanding the interactions between economic growth, carbon emissions, energy consumption, and human development is key to sustainable development. The Environmental Kuznets Curve (EKC) hypothesis suggests that environmental degradation initially rises with economic growth but declines after reaching a certain income level. However, the income level at which this decline occurs is debated (Dinda, 2004). Around twenty factors, including energy types, trade, investment, urbanization, technology, human capital, literacy, democracy, corruption, financial development, income inequality, tourism, and natural resources, influence CO2 emissions (Adamu et al, 2020) Adopting a multidimensional approach that considers social, economic, and environmental factors is essential for sustainable development and reducing carbon emissions. Hence, urbanization, economic growth, energy consumption, and transportation should be categorized as independent variables. While carbon emission is the dependent variable.

Urbanization and Carbon Emissions: Numerous studies have explored the correlation between urbanization and carbon emissions. Urban areas tend to have higher emissions per capita due to increased energy use and industrial activity (Kennedy et al., 2010). Rapidly urbanizing regions often face challenges with environmental regulations (Seto et al., 2012). Sustainable urban development policies, such as promoting public transportation and energy efficiency, are crucial (Wang, 2021; Alshehhi, 2021). Therefore, this leads to the first hypothesis (H1) of this study that is:
H1: There is a relationship between urbanization and carbon emissions

Energy Consumption and Carbon Emissions: Higher energy consumption, particularly from fossil fuels, is directly associated with increased CO2 emissions (Ang, 2007) Renewable energy adoption and energy efficiency improvements are necessary to mitigate emissions (Liu et al., 2020). The relationship between human development and carbon emissions varies, with higher development often leading to increased emissions (Shahbaz et al, 2012; Sinha and Shahbaz, 2019). Hence, a hypothesis is formed as H2 below:
H2: There is a relationship between energy consumption and carbon emissions.

Economic Growth and Carbon Emissions: Economic growth often leads to higher carbon emissions, although this relationship can be complex. The Environmental Kuznets Curve (EKC) hypothesis suggests that emissions rise with economic growth up to a point, then decline (Dinda, 2004). However, this varies with economic development levels. Policies promoting sustainable growth and energy efficiency are vital (Stern, 2006). Hypothesis H3 therefore recognizes the role of the reward system towards employee productivity.
H3: There is a relationship between economic growth and carbon emissions

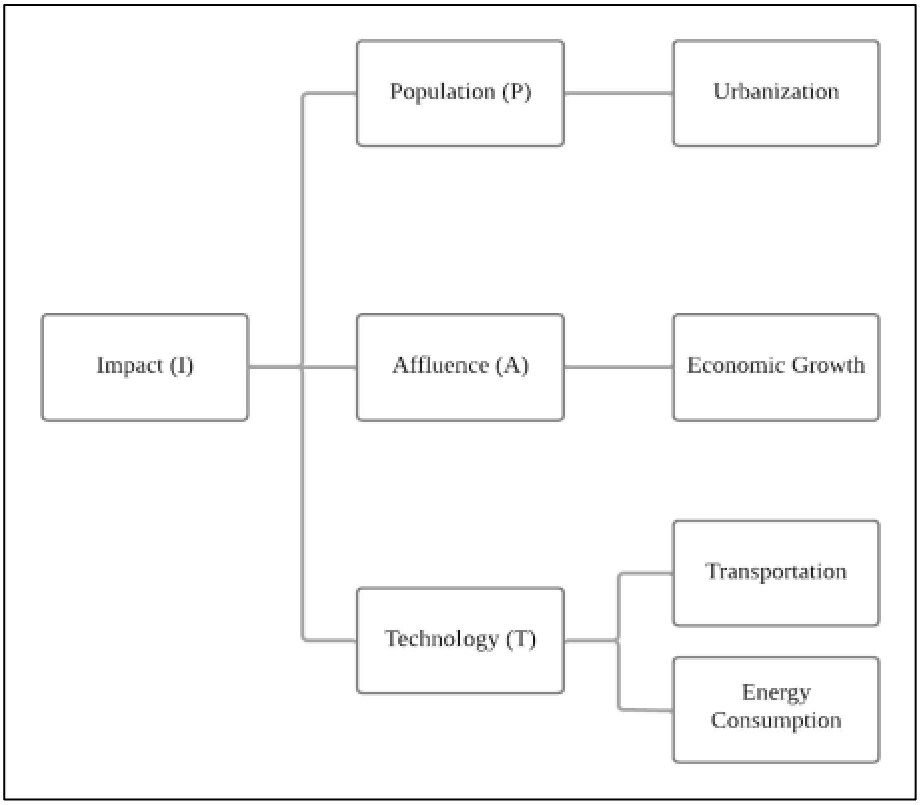
Transportation and Carbon Emissions: Transportation significantly contributes to carbon emissions. Promoting public transportation, adopting electric vehicles, and improving urban planning can reduce these emissions (Wang et al., 2023). Regulatory standards and innovative technologies are essential for achieving significant emission reductions in the transportation sector (Davis et al., 2018). Thus, the following hypothesis is formed.
H4: There is a relationship between transportation and carbon emissions

3. Research Methodology

The Environmental Kuznets Curve (EKC) hypothesis is a prominent theory that explores the relationship between economic growth and environmental degradation, including carbon emissions. According to this hypothesis, initially, as economies develop and income levels rise, environmental degradation increases. However, beyond a certain income threshold, environmental degradation starts to decline over time. In this research, a model of IPAT is being used to determine the environmental impact of the study variables. The IPAT model, also known as the I = PAT model, is a theoretical framework used to understand the environment.

Impact of human activities. It represents how human activities contribute to environmental degradation and resource depletion (Ehrlich and Holdren, 1971). The model breaks down environmental impact (I) into three components which are Population (P), Affluence (A), and Technology (T). The IPAT model provides a simple framework to understand how these three factors interact and contribute to environmental impact. It is often used in discussions about sustainability and environmental policy to identify strategies for reducing human impact on the environment. The model highlights the need for sustainable development and the importance of addressing population growth, consumption patterns, and technological choices to achieve environmental sustainability (Ehrlich and Holdren, 1971).

Figure 1: The Research Framework



Econometric Modelling

Based on the previous literature review and theory, the dependent variable and independent variables were expected to relate to each other. The regression model into a double log-linear model can standardize the gap values between the variables since the variables have differences in the unit of measurement The equation below shows the relationship between the variable chosen:

$$LCO2_{it} = \beta_0 + \beta_1 LU_{it} + \beta_2 LGDP_{it} + \beta_3 LEG_{it} + \beta_4 LSMV_{it} + \varepsilon_{it} \quad (1)$$

However, in the context of panel data, two types of variability are recognized between cross-sectional units and within time series units. Between variance refers to the observed inter-unit or cross-sectional variation, while internal variance measures the extent to which the total variance is attributable to variation within economic units. These variations can be detected using random-effects and fixed-effects models. Essentially, both econometric models take into account heterogeneity and individuality between nations and can have their intercept values while constraining the slope to be homogeneous. To accommodate such heterogeneity, the error term ε_{it} is decomposed into two independent components:

$$\varepsilon_{it} = \lambda_i + \mu_{it} \quad (2)$$

λ_i is termed as an individual-specific effect meaning each nation may have a unique characteristic such as in this case a high-income and lower-income country or even a type of urbanization definition as well as an education system. For μit is a normal error term denoting the remainder disturbance. Hence, the equation if the random effect model is chosen would be:

$$LCO2_{it} = \beta_0 + \beta_1 LU_{it} + \beta_2 LGDP_{it} + \beta_3 LEG_{it} + \beta_4 LSMV_{it} + \lambda_i + \mu_{it} \quad (3)$$

On the other hand, the fixed effect model assumes each specific effect to have intercepts that may vary across countries. Hence, the equation if the fixed effect model is chosen would be:

$$LCO2_{it} = (\beta_0 + \lambda_i) + \beta_1 LU_{it} + \beta_2 LGDP_{it} + \beta_3 LEG_{it} + \beta_4 LSMV_{it} + \mu_{it} \qquad (4)$$

To identify the coefficient of the independent variables toward the dependent variables, the hypothesis for the overall research will be as below:
H_0: The coefficient of the independent variable is equal to zero (no impact on the dependent variable).
H_1: The coefficient of the independent variable is not equal to zero (has a significant impact on the dependent variable).

Data and Variables

Table 1: Data and Variables

Variable	Key Title	Definition	Measurement	Source
CO2 emissions (CO2)	Dependent Variable	Annual total emissions of carbon dioxide (CO_2), excluding land-use change.	CO2 in tonnes	Our World Data
Urbanization (U)	Independent Variable	Urban population refers to people living in urban areas as defined by national statistical offices.	Total urban population in person	World Bank
Economics Growth (*GDP*)	Independent Variable	GDP per capita is gross domestic product divided by midyear population.	GDP per capita (current US$)	World Bank
Energy Consumption (*EG*)	Independent Variable	Annual average electricity generation per person.	Electricity generation per capita in kilowatt-hours	Our World Data
Transportation (*SMV)*	Independent Variable	Total sales of motor vehicles that include passenger vehicles and commercial vehicles	Total sales of motor vehicles in unit	ASEAN Automotive Federation

4. Results

The study has 84 observations throughout the year from 2011 to 2022 for 7 selected ASEAN member nations i.e. Malaysia, Indonesia, Brunei, Thailand, Philippines, Singapore, and Vietnam. The results are acceptable as per discussion since the data are collected from reliable sources. An array of appropriate econometric and statistical analyses is utilized to ensure a consistent empirical analysis is conducted.

Descriptive Statistics
Table 2 shows the descriptive statistics analyzed for both independent and dependent variables. The data spanning from 2011 to 2022, provides a comprehensive view of several key development indicators across multiple nations, focusing on CO_2 emissions (CO_{2it}), total urban population (U_{it}), GDP per capita (GDP_{it}), energy generated per capita (EC_{it}), and the total of transportation (SMV_{it}).

Table 2: Descriptive Analysis

	$CO2_{it}$	U_{it}	GDP_{it}	EG_{it}	SMV_{it}
Mean	2.16E+08	41281426	17906.63	4437.09	452540.2
Median	2.14E+08	31298700	6238.962	2505.737	337459
Maximum	7.29E+08	1.60E+08	88428.7	12994.19	1436335
Minimum	6933290	302374	1953.557	717.786	10949
Std. Dev.	1.79E+08	44823393	21990.09	3783.214	400576.6
Skewness	0.897275	1.551394	1.450337	0.749014	0.601559
Kurtosis	3.177309	4.275652	3.887038	2.094519	2.154353
Jarque-Bera	11.38146	39.39106	32.20262	10.72394	7.569135
Probability	0.003377	0	0	0.004692	0.022719
Sum	1.82E+10	3.47E+09	1.50E+06	3.73E+05	38013374
Sum Sq. Dev.	2.67E+18	1.67E+17	4.01E+10	1.19E+09	1.33E+13
Observations	84	84	84	84	84

As seen in Table 2, the dataset provides key statistical insights into CO_2 emissions, urbanization, GDP, and transportation. The mean values, such as 2.16E+08 for CO_2 emissions (CO_{2it}), 41,281,426 for urbanization (Uit), and 17,906.63 for GDP (GDP_{it}), offer a broad understanding of average levels over the period. Median values, including 2.14E+08 for $CO2_{it}$ and 6,238.962 for GDP_{it}, highlight central data points less affected by extremes. The range of data indicates significant variability, with GDP_{it} ranging from 1,953.557 to 88,428.70 and transportation (SMV_{it}) from 10,949.00 to 1,436,335. Standard deviations further reflect this variability, showing considerable dispersion around the mean. Positive skewness in GDP_{it} (1.45) and Uit (1.55) suggests distributions with longer right tails, while kurtosis values, such as 4.28 for urbanization, imply more frequent extreme values. The Jarque-Bera test results indicate a non-normal distribution for most variables, necessitating non-parametric methods for further analysis. With 84 observations for each variable, this descriptive statistical analysis establishes a foundation for deeper inferential studies, highlighting key trends and disparities within the dataset.

Correlation Analysis

Table 3 summarizes the results of the correlation analysis. It provides the correlation for each variable. The dataset reveals significant correlations between key variables and CO2 emissions.

Table 3: Correlation Matrix Analysis

Variable	$CO2_{it}$	U_{it}	GDP_{it}	EG_{it}	SMV_{it}
$CO2_{it}$	1				
Uit	0.887747 (0.0000)*	1			
$GDPit$	-0.585018 (0.0000)*	-0.5183 (0.0000)*	1		
$EGit$	-0.655323 (0.0000)*	-0.660176 (0.0000)*	0.827549 (0.0000)*	1	
$SMVit$	0.81097 (0.0000)*	0.670821 (0.0000)*	-0.556818 (0.0000)*	-0.590147 (0.0000)*	1

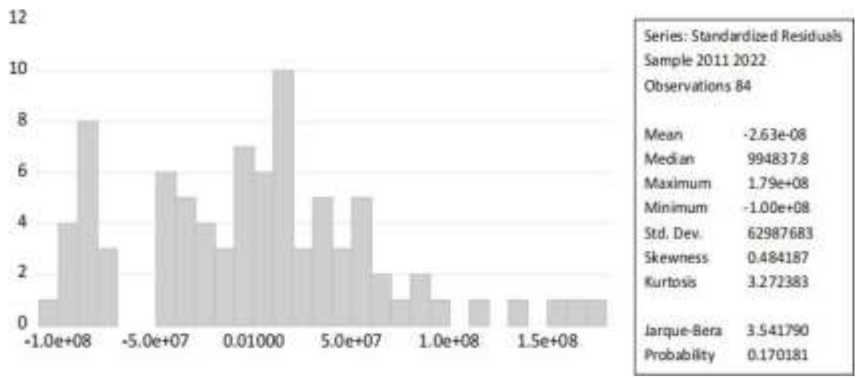
*p-value is significant at the 0.05 level (2-tailed).

There is a strong positive correlation between CO_2 emissions and urbanization (0.887747), indicating that as the urban population grows, emissions increase significantly, supported by a t-statistic of 17.46322 and a p-value of 0.0000. This aligns with studies like Sun et al. (2022), which link urbanization to higher emissions due to increased energy use and transportation demands. Conversely, GDP per capita has a negative correlation with CO2 emissions (-0.585018), with a t-statistic of -6.531981 and p-value of 0.0000, supporting the Environmental Kuznets Curve hypothesis that economic growth initially increases emissions but later decreases them due to better energy efficiency and technology (Wang & Su, 2019).

Energy consumption per capita also shows a strong negative correlation with CO2 emissions (-0.655323), with a t-statistic of -7.856248 and p-value of 0.0000, suggesting that higher energy efficiency and cleaner energy sources reduce emissions (Sun & Huang, 2020). Additionally, motor vehicle sales have a significant positive correlation with CO2 emissions (0.810970), with a t-statistic of 12.55136 and p-value of 0.0000, linking increased vehicle usage to higher emissions (Sun et al., 2022). Overall, the analysis highlights the impact of urbanization and transportation on emissions, while GDP per capita and energy consumption per capita have more complex influences moderated by economic and technological factors.

Normality Analysis

Table 4: Summary of Normality Analysis



The standardized residuals have a mean of -2.63e-08, close to zero, indicating they are centered around the mean. The standard deviation of 62987683 indicates its variability whereas the skewness of 0.484187 suggests a slight positive skewed. The value of kurtosis which is 3.272383 is close to normal and more importantly the insignificant of the Jarque-Bera test indicates that the residuals are normally distributed. Consequently, this supports the validity and reliability of the regression model.

Panel Data Analysis

Table 5 presents the Panel Data Analysis between the Pooled OLS model, Fixed Effect Model, and Random Effect Model.

Table 5: Results of Panel Data Analysis: Pooled, Fixed and Random Effects Models

Model	Pooled	Fixed	Random
C	39923392	-164E+08	-126E+08
	(0.0691)**	(0.0000)*	(0.0104)*
$LUit$	2.514561	6.949834	5.830096
	(0. 0000)*	(0.0000)*	(0.0000)*
$LGDPit$	-909.1336	272.3406	275.5442
	(-0.126)	(-0.6525)	(-0.6321)
$LEGit$	3280.68	12602.4	15425.27
	(-0.3916)	(0.0218)*	(0.0013)*
$LSMVit$	164.5868	71.99216	62.29263
	(0.0000)*	(0.0040)*	(0.0085)*
R-squared	0.876486	0.981293	0.647258

*p-value is significant at 0.05 level

The Pooled OLS regression results show a significant positive relationship between urban population (LU_{it}) and CO_2 emissions (LCO_{2it}), with a coefficient of 2.514561, t-statistic of 10.45439, and p-value of 0.0000. GDP per capita ($LGDP_{it}$) has an insignificant negative effect on emissions (coefficient: -909.1336, p-value: 0.1260). Energy generation per capita (LEG_{it}) also shows an insignificant positive relationship with emissions (coefficient: 3280.680, p-value: 0.3916). Motor vehicle sales ($LSMV_{it}$) significantly increase emissions (coefficient: 164.5868, p-value: 0.0000). The model's R-squared is 0.876486, explaining 87.65% of emissions variability. These results emphasize the impact of urban growth and transportation on emissions, suggesting the need for targeted policies.

In the Random Effect Model, the analysis reveals that urban population (LU_{it}) significantly increases CO2 emissions ($LCO2_{it}$) with a coefficient of 5.830096, a t-statistic of 11.96177, and a p-value of 0.0000. Energy generation per capita (LEG_{it}) also shows a significant positive relationship with emissions, with a coefficient of 15425.27, and a p-value of 0.0013. Transportation ($LSMV_{it}$) contributes to higher emissions, indicated by a coefficient of 62.29263, and p-value of 0.0085. GDP per capita ($LGDP_{it}$) has a positive but statistically insignificant effect on emissions (coefficient: 275.5442, p-value: 0.6321), reflecting mixed results in the literature. The model's overall fit is robust, with an R-squared value of 0.647258 and an adjusted R-squared of 0.629398, explaining 64.73% of emissions variability. These results highlight the significant impact of urban growth and transportation on emissions, with more complex roles for GDP per capita and energy consumption.

The Fixed Effect results indicate that the urban population (LU_{it}) significantly increases carbon emissions ($LCO2_{it}$), with a coefficient of 6.949834, t-statistic of 10.95493, and p-value of 0.0000, suggesting higher emissions with urban growth (Wang et al., 2021). Energy generation per capita (LEG_{it}) also significantly impacts emissions, with a coefficient of 12602.40, t-statistic of 2.343718, and p-value of 0.0218,

highlighting the role of energy consumption (Sun et al., 2022). Transportation ($LSMV_{it}$) has a positive impact on emissions, with a coefficient of 71.99216, a t-statistic of 2.975761, and a p-value of 0.0040, indicating higher vehicle usage increases emissions (Tang et al., 2021). GDP per capita ($LGDP_{it}$) shows a positive but statistically insignificant effect on emissions, with a coefficient of 272.3406, t-statistic of 0.452104, and p-value of 0.6525, reflecting mixed findings in the literature (Wang & Su, 2019). The model is robust, with an R-squared value of 0.981293, explaining 98.13% of emissions variability, confirming the significance of urban population, energy consumption, and vehicle sales as primary drivers of carbon emissions.

In analyzing the three-panel data models-Pooled OLS, Fixed Effects, and Random Effects-the Fixed Effects model is the most suitable for representing the relationship between the variables and annual CO2 emissions. It has the highest R-squared value (0.9813), explaining 98.13% of the variance in CO2 emissions, compared to the Pooled OLS (0.8765) and Random Effects (0.6473) models. The Fixed Effects model's significant F-statistic indicates a good fit, with significant coefficients for urban population, energy per capita, and vehicle sales, showing these variables strongly influence CO_2 emissions. The Fixed Effects model accounts for unobserved heterogeneity with individual-specific intercepts, reducing omitted variable bias.

The Hausman test conducted further supports this model over the Random Effects model due to a lower probability value, indicating a correlation between regressors and the error term. Supporting literature that has similar results Ouyang et al. (2020) also demonstrated the effectiveness of the Fixed Effects model in environmental analyses. Therefore, the Fixed Effects model would be the best choice for analyzing the determinants of CO_2 emissions using the data.

Hausman Test

Table 6: Hausman Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	12.156931	4	0.0162*

*p-value is significant at 0.05 level

The Hausman test for cross-section random effects in the panel data analysis produced a Chi-square statistic of

12.156931 with a p-value of 0.0162. Since the p-value is less than 0.05, the null hypothesis that the preferred model is the random effects model is rejected. This result indicates that there are significant differences between the fixed and random effects estimates, suggesting that the fixed effects model is more appropriate for your data. Hence the equation can be shown as:

$$LCO2_{it} = -1.64E+08 + 6.949834LU_{it} + 272.3406LGDP_{it} + 12602.4LEG_{it} + 71.99216LSMV_{it} + \mu_{it}$$

Discussion

The analysis of the descriptive statistics, correlation matrix, panel data models, and the Hausman test offers valuable insights into the determinants of CO2 emissions across the selected ASEAN countries from 2011 to 2022. The descriptive statistics reveal substantial variability in the dataset, with skewed distributions and non-normality, necessitating careful selection of modeling approaches. The correlation matrix indicates strong relationships between CO2 emissions and key variables such as urbanization, GDP per capita, energy generation, and transportation, with urbanization and transportation showing the most significant positive correlations.

The panel data analysis demonstrates that among the three models-Pooled OLS, Fixed Effects, and Random Effects-the Fixed Effects model is the most robust and appropriate for this dataset. The Fixed Effects model captures 98.13% of the variance in CO2 emissions, making it the best fit, particularly due to its ability to account for unobserved heterogeneity across countries. The significant coefficients for urbanization, energy generation per capita, and transportation suggest that these factors are primary drivers of CO2 emissions, highlighting the need for policy interventions in these areas.

The Hausman test further confirms the superiority of the Fixed Effects model, rejecting the Random Effects model and validating the fixed effects approach in dealing with individual-specific characteristics. This finding aligns with existing literature, which often favors the Fixed Effects model in environmental studies due to its precision in capturing country-specific effects. Therefore, the results underscore the critical impact of urbanization, energy consumption, and transportation on CO2 emissions in the ASEAN region, emphasizing the importance of targeted policies to mitigate environmental impacts.

5. Conclusion and Recommendations

Based on the analyses conducted, the findings revealed that urbanization significantly increases carbon emissions due to higher energy demand and transportation needs. Economic growth initially raises emissions, but advanced economies can reduce emissions through cleaner technologies and improved energy efficiency. Energy consumption, especially from fossil fuels, is a major driver of emissions, highlighting the need for a shift to renewable energy (Thu Huong & Xuan, 2022). The transportation sector also contributes significantly to emissions, necessitating improvements in public transport and the promotion of electric vehicles (Poulova et al., 2021). The policy implications are clear of which government should promote renewable energy (RE) by incentivizing solar, wind, and hydroelectric power to reduce reliance on fossil fuels (International Energy Agency, 2023). Thus, ASEAN has taken initiatives under its Energy Policy focusing on deploying these RE potentials to promote a higher share of RE in the power generation mix.

Effective urban planning and the development of sustainable infrastructure, such as public transportation, energy-efficient buildings, and green spaces, are essential to mitigate the environmental impacts of urban growth (Chien et al., 2022). Economic incentives, including tax benefits for green technologies, subsidies for clean energy, and penalties for excessive emissions, can drive businesses and individuals toward sustainability (Destek & Aslan, 2020). ASEAN leaders in 2018 have established a collaborative platform known as ASEAN Smart Cities Network (ASCN) of which cities from the ten members work towards the common goal of smart and sustainable urban development. Considering the opportunities and challenges posed by rapid urbanization and digitalization, the primary goal of the ASCN is to improve the lives of its citizens, using technology as an enabler. It adopts an inclusive approach to smart city development that is respectful of human rights and fundamental freedoms as inscribed in the ASEAN Charter.

Future research should focus on several key areas to advance understanding of the relationship between macroeconomic factors and carbon emissions in ASEAN countries. Longitudinal studies can capture long-term trends and dynamic relationships, providing deeper insights into how macroeconomic factors impact emissions over time (Uzar, 2020). Sectoral analysis can offer detailed insights into specific emission drivers within different sectors, enabling more effective targeted policies (Danish & Wang, 2019). Additionally, exploring the impact of technological advancements such as digitalization, automation, and innovation on reducing emissions is crucial (Nathaniel et al., 2021). Understanding the behavioral aspects of energy consumption can inform more effective policies by shedding light on the social dimensions of sustainability (Al-Mulali et al., 2020). Comparative studies between ASEAN countries and other regions can highlight successful strategies and areas for improvement (Adebayo et al., 2022). Finally, addressing potential endogeneity issues and exploring alternative methodologies will enhance the robustness of future studies. By focusing on these areas, future research can provide comprehensive insights to support effective and sustainable policy development in the ASEAN region.

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