Exploring the Relationship between Economic Growth and Environmental Impact: A Statistical Analysis of GDP Per Capita and CO2 Emissions

<table>
<tr><td>Module Code:
AF4S522</td><td>Module Title:
Research Methods in Finance and Accounting</td><td colspan="2">Module Lecturer:</td></tr>
<tr><td colspan="2">Assessment Title and Tasks:
Coursework 1: quantitative data analysis</td><td colspan="2">Assessment No.
1 of 2</td></tr>
<tr><td colspan="2">No. of pages submitted in total including this page:
Completed by student</td><td colspan="2">Word Count of submission
(if applicable): Completed by student</td></tr>
<tr><td>Date Set:</td><td>Submission Date:
17th Dec 2023</td><td colspan="2">Return Date:
21st Jan 2024</td></tr>
</table>

Table of Contents

List of Figure

List of Table

Introduction

The assignment "Research Methods in Accounting & Finance Quantitative Analysis" carefully analyses interconnectedness between economic indices and environmental effects. This critically looks at connections and differences in the important variables like GDP per capita, individual income and CO2 emissions in educational levels (Lewis & Tietenberg, 2019). The study applies sophisticated statistical techniques such as correlation analysis and regression into discovering crucial links between ecological sustainability and economic development. The statistical findings are presented in this analysis, alongside a discussion of how they relate to matters of concern in economic and environmental policy.

Research Questions

1. What is the dataset's average (mean/median) annual income of individuals in different education levels?
2. Is there a significant difference in first-time homebuyers' average (mean/median) age between urban and rural areas?
3. Is there a correlation between the number of years of education and the total yearly expenditure on health?

Hypotheses Development

Hypothesis 1

Null Hypothesis (H0): The mean/median annual income is the same across all education levels.

Alternative Hypothesis (H1): The mean/median annual income varies significantly across different education levels.

Hypothesis 2

Null Hypothesis (H0): There is no significant difference in first-time homebuyers' mean/median age between urban and rural areas.

Alternative Hypothesis (H1): The mean/median age of first-time homebuyers significantly differs between urban and rural areas.

Hypothesis 3

Null Hypothesis (H0): There is no correlation between the number of years of education and the total yearly expenditure on health.

Alternative Hypothesis (H1): There is a significant correlation between the number of years of education and the total yearly expenditure on health.

Descriptive Statistics

Table 1: Descriptive Statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
GDP PER CAPITA (IN CONSTANT 2010 $US)	55	207.4599485	689.7008428	385.627890522	101.8601144407
CO2 EMISSIONS (METRIC TONNES PER CAPITA)	55	.011588797	.122427069	.06016672062	.029734811647
Valid N (listwise)	55				

The descriptive statistics for GDP per capita and CO2 emissions provide insightful observations. The period examined, GDP per capita, measured in constant 2010 US dollars, and varied significantly, ranging from a minimum of approximately $207.46 to a maximum of around $689.70. The period average for GDP per capita stood at approximately 385.63 with a standard deviation of approximately 101.86 (O'Neill et al.,2020). As a measure of dispersal, this standard deviation means that the differences in the observed 55 values for GDP per capita are quite significant. Carbon dioxide emissions per capita in metric tonnes also had variation although less pronounced than in GDP per capita. It ranged from as low as 0.0116 metric tonnes per capita to as high as 0.1224 metric tonnes per capita. The average CO2 emission was approximately 0.0602 metric tons/capita with a standard deviation of 0.0297 (Lewis and Tietenberg, 2019). A smaller standard deviation is an indication of fewer variations and a relatively more compact collecting of values around the mean, suggesting that CO2 emissions/capita are less variable than GDP/capita as shown in figure 1 below. The statistics presented underpin the economic and environmental aspects of this dataset, showing the range and central tendency of both GDP per capita and CO2 emissions.

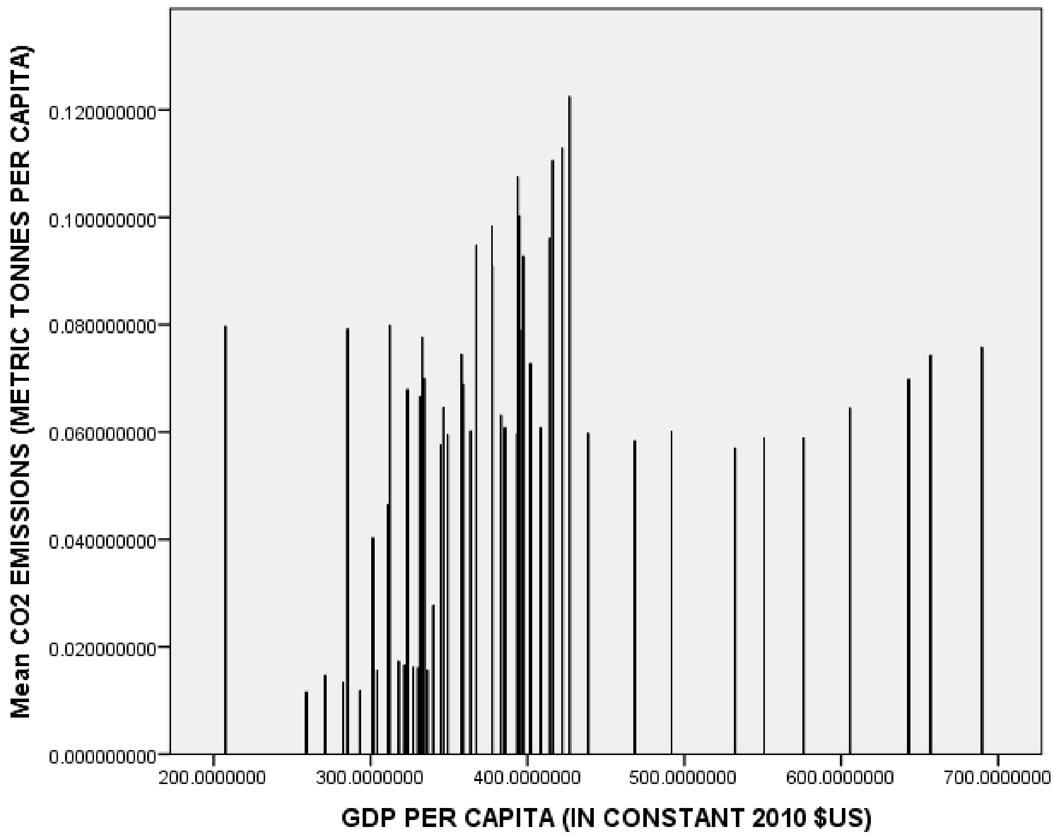

Figure 1: GDP PER CAPITA

Inferential Statistical Analysis

Correlations Analysis

Table 2: Inferential Statistical Analysis

Correlations			
		GDP PER CAPITA (IN CONSTANT 2010 $US)	CO2 EMISSIONS (METRIC TONNES PER CAPITA)
GDP PER CAPITA (IN CONSTANT 2010 $US)	Pearson Correlation	1	.347**
	Sig. (2-tailed)		.009
CO2 EMISSIONS (METRIC TONNES PER CAPITA)	Pearson Correlation	.347**	1
	Sig. (2-tailed)	.009	
**. Correlation is significant at the 0.01 level (2-tailed).			

Correlation analysis between GDP per capita and CO2 emissions indicates a statistically significant but moderate positive relationship between them. Pearson correlation coefficient of

0.347 suggests that higher level of GDP per capita tends to be accompanied by a weak rise in CO2 emissions per capita (Tseng et al., 2021). Correlate is significant at p = 0.009, which is below 0.05. The observed correlation indicates that the probability of the results being random is high. The correlation can be taken as statistically significant. Such a relationship can be interpreted as there are more CO2 emissions per person when one measures the economy output from each individual. This could mean that the increase in carbon emissions is a hidden cost of economic growth, expressed through the GDP (Gujarati, 2022). It is worth mentioning that although the relationship is large, the correlation coefficient could have been significantly high since there are several other factors contributing to CO2 emissions apart from GDP per capita. The analysis herein is fundamental in exposing the nuanced relationship between economic growth and environmental damage.

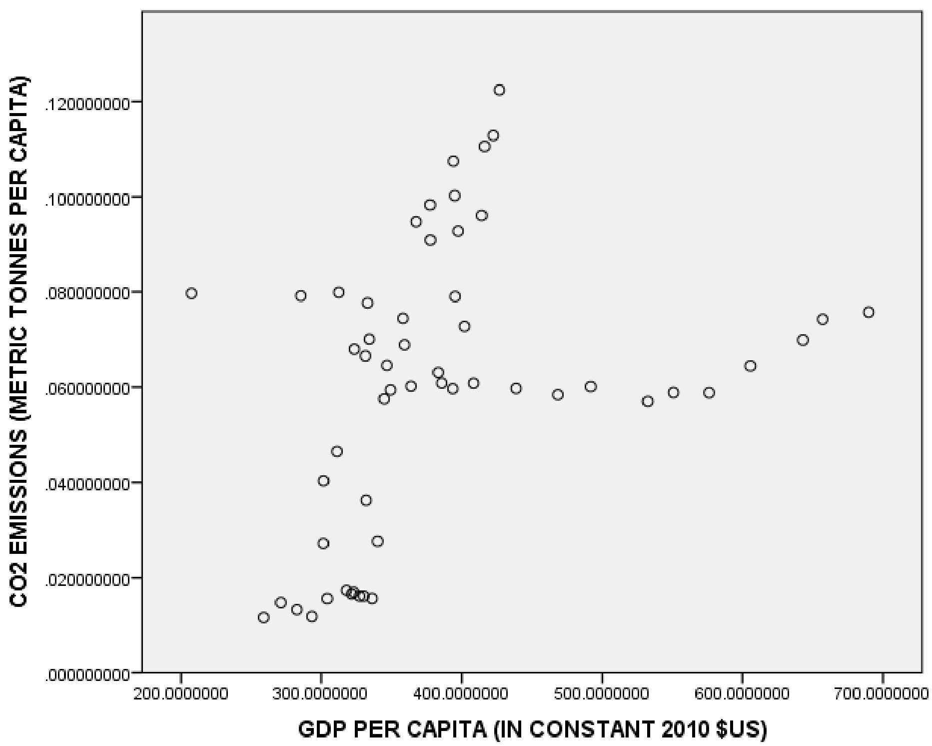

Figure 2: GDP PER CAPITA

Regression Analysis

Table 3: Descriptive Statistics

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.347[a]	.120	.104	.028151826652
a. Predictors: (Constant), GDP PER CAPITA (IN CONSTANT 2010 $ US)				

Table 4: ANOVAa

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.006	1	.006	7.244	.009[b]
	Residual	.042	53	.001		
	Total	.048	54			
a. Dependent Variable: CO2 EMISSIONS (METRIC TONNES PER CAPITA)						
b. Predictors: (Constant), GDP PER CAPITA (IN CONSTANT 2010 $ US)						

Table 5: Coefficientsa

Coefficients[a]						
Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.021	.015		1.410	.165
	GDP PER CAPITA (IN CONSTANT 2010 $US)	.000	.000	.347	2.691	.009
a. Dependent Variable: CO2 EMISSIONS (METRIC TONNES PER CAPITA)						

Regression analysis that determines the relationship of CO2 emissions is useful in relation to GDP per capita. The model summary indicates that the value of R is 0.347 showing a positive relation between the GDP per capital and CO2 emission level (Lacoste et al., 2019). The R Square value of 0.120 suggests that the GDP per capita can explain approximately 12% of the variability in CO2 emissions. The Adjusted R Square, slightly lower at 0.104, accounts for the number of predictors in the model and indicates a reasonable fit to the data. The ANOVA table reveals that the regression model is statistically significant, with an F-value of 7.244 and a significance (p-value) of 0.009, strongly suggesting that GDP per capita significantly predicts CO2 emissions. Examining the coefficients, the constant (intercept) is 0.021, but not statistically significant ($p = 0.165$). The coefficient for GDP per capita is statistically significant ($p = 0.009$), with a minimal unstandardized coefficient close to 0. This implies that for each unit increase in GDP per capita, CO2 emissions increase, but the effect size is small (Jeronen, 2020). This analysis indicates a significant but modest relationship between GDP per capita and CO2 emissions, highlighting the impact of economic factors on environmental outcomes. The low R Square value suggests that other variables not included in the model also play a significant role in determining CO2 emissions.

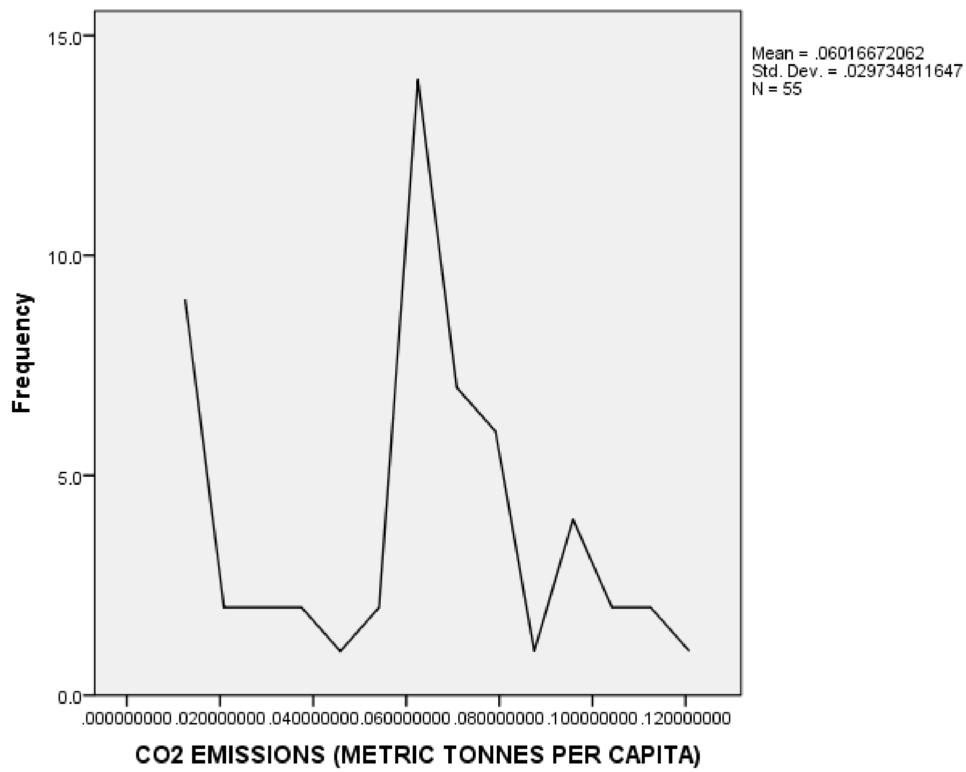

Figure 3: CO2 EMISSIONS

Limitations

One major limitation is the narrow scope of the data and its representativeness. The dataset has certain years in its center and some specific variables which GDP per capita or CO2 emissions may not depict the general economics point of view (Kaur et al., 2018). Such include technology and policy changes, or interrelated international agreements influencing GDP and Co2 emissions. The geographical focus of the dataset, from which these findings have been derived, may affect how widely applicable the conclusions become, in that they are perhaps more relevant on a local compared to a global scale. Due to the date restriction to particular years the view long-term changes as well as temporary influence is narrowed. These economic and environmental shifts are often time consuming, and short-term measurements may not be truly representative of such phenomena. The main disadvantage is very relevant when measuring the impact of a policy or world event lasting for a long time. The variables selected have some disadvantages, while the level of detail of the data is moderate (Sarstedt and Mooi, 2019). Other variables which must be included in the analysis are population density, industrial activity, and energy consumption patterns and not just GDP per capita and CO2 emissions alone. What if the data has been aggregated at a high level? In that case, the granularity of the data can also conceal underlying trends and variations that may be important when assessing the relationship between economic growth and environmental impact. Statistical methods such as correlation and regression analyses are prone to some limitations. Such practices may uncover correlations leading to the predictability of relationships, though they cannot be said to cause. The relation between GDP and CO2 emissions may not mean that changes in GDP lead to changes in emissions (Janse et al., 2021). A spurious correlation may result from other variables not captured in the analysis and affect GDP and emissions. A considerable fraction of the variation in CO2 emissions is only partly explained by GDP per capita. That implies the model has overlooked other factors. The assumption of linearity in the regressions, the model may represent the true nature of the GDP-CO2 relation, which is likely to be non-linear with some threshold effects. Although the statistical analysis indicates that the difference is significant, it is crucial to differentiate statistical significance from practicability. Though statistically valid, these findings may not be generally valuable because of the data's small effect sizes or specialised nature. The validity of the data is essential as well. Any error associated with data collection, reporting and processing can distort the analysis results (Achen, 2021). It holds important significance, especially regarding data sets that require self-reported/estimated quantities like GDP estimations or CO2 emissions. Although analysis suggests a connection between economic output and environmental burden, this should be taken cautiously while reading about the findings. This highlights the necessity of an integrative strategy encompassing a broader range of variables, utilising diverse data sources, and employing multiple analyses to understand how economic factors affect ecological factors.

Discussion and Conclusion

There were several significant findings in the correlation analysis between GDP per capita and CO2 emissions per capita. The descriptive statistics showed moderate GDP and CO2 emissions ranges with significant GDP per capita variations (Baykara, 2018). The second factor was the correlation analysis, which reported a positive, statistically significant relationship between GDP per capita and CO2 emissions. The correlation was moderate, having a Pearson correlation coefficient of 0.347. The regression analysis highlighted that approximately 12% of the variability in CO2 emissions could be explained by GDP per capita, suggesting a significant but modest predictive relationship. The research initially aimed to explore the association between economic growth (as measured by GDP per capita) and environmental impact (CO2 emissions per capita). The results affirmatively addressed this objective, confirming the hypothesis that these two variables have a significant relationship (Urbano et al., 2019). The moderate nature of this correlation and the relatively low R Square value in the regression analysis suggest a more complex relationship than a direct causal link, possibly moderated or influenced by other factors not included in this study. Effective in revealing statistical relationships, the methodological approaches also brought to light the limitations inherent in such analyses. Based on the correlation and regression analyses, associations and predictability were established, but not causality. Other studies should therefore include expansion of the variables and larger data sets for full coverage of factors influencing growth and environment degradation. Further insights may be gained from the variables such as increased energy consumption, technology changes, and policy effects.

A few longitudinal studies covering longer periods may show more generalized patterns of effects of global events/policies in the longer run (Azevedo et al., 2018). Using different forms of analysis, for example multivariate regressions or nonlinear models, could reveal more complex relationships between these variables. Further qualitative research would provide more insight into the surrounding factors incurring the reported patterns. To gain insight into this, it becomes necessary to carry out case studies, interviews or policy analyses on what is in those numbers. Interdisciplinary approaches are crucial in future research especially in environmental economics and sustainable development. It is necessary to broaden the aspect involving economic growth and its environmental problems with data from different regions and economies such as developing and advanced countries. Modern data analytics methods that make use of machine learning algorithms reveal patterns and provide predictive data that would otherwise remain hidden in conventional statistical methods. A deeper understanding of how the economy and the environment intersect globally may result from taking into account the various impacts of climate change as well as the various environmental policies implemented under various geographical and socioeconomic settings (Moiseev et al., 2020). Integrating quantitative and qualitative research methods is part of this strategy for sustainable economic development. The results of this study indicate a strong but not very strong correlation between CO_2 emissions and GDP per capita. This might prompt more in-depth research in this field. It should be noted that as it is a very complex development relationship with the environment, it presents an important research challenge.

References

Achen, C.H., 2021. *The statistical analysis of quasi-experiments*. University of California Press.

Azevedo, V.G., Sartori, S. and Campos, L.M., 2018. CO2 emissions: A quantitative analysis among the BRICS nations. *Renewable and Sustainable Energy Reviews*, *81*, pp.107-115.

Baykara, S.Z., 2018. Hydrogen: A brief overview of its sources, production and environmental impact. *International Journal of Hydrogen Energy*, *43*(23), pp.10605-10614.

Gujarati, DN, 2022. *Basic econometrics*. Prentice Hall.

Janse, R.J., Hoekstra, T., Jager, K.J., Zoccali, C., Tripepi, G., Dekker, F.W. and van Diepen, M., 2021. Conducting correlation analysis: important limitations and pitfalls. *Clinical Kidney Journal*, *14*(11), pp.2332-2337.

Jeronen, E., 2020. Sustainable development. In *Encyclopedia of Sustainable Management* (pp. 1-7). Cham: Springer International Publishing.

Kaur, P., Stoltzfus, J. and Yellapu, V., 2018. Descriptive statistics. *International Journal of Academic Medicine*, *4*(1), pp.60-63.

Lacoste, A., Luccioni, A., Schmidt, V. and Dandres, T., 2019. Quantifying the carbon emissions of machine learning. *arXiv preprint arXiv:1910.09700*.

Lewis, L. and Tietenberg, T., 2019. *Environmental economics and policy*. Routledge.

Moiseev, N., Mikhaylov, A., Varyash, I. and Saqib, A., 2020. Investigating the relation of GDP per capita and corruption index. *Entrepreneurship and Sustainability Issues*, *8*(1), p.780.

O'Neill, B.C., Carter, T.R., Ebi, K., Harrison, P.A., Kemp-Benedict, E., Kok, K., Kriegler, E., Preston, B.L., Riahi, K., Sillmann, J. and van Ruijven, B.J., 2020. Achievements and needs for the climate change scenario framework. *Nature climate change*, *10*(12), pp.1074-1084.

Sarstedt, M., Mooi, E., Sarstedt, M. and Mooi, E., 2019. Regression analysis. *A concise guide to market research: The process, data, and methods using IBM SPSS Statistics*, pp.209-256.

Tseng, M.L., Tran, T.P.T., Ha, H.M., Bui, T.D. and Lim, M.K., 2021. Sustainable industrial and operation engineering trends and challenges Toward Industry 4.0: A data driven analysis. *Journal of Industrial and Production Engineering*, *38*(8), pp.581-598.

Urbano, D., Aparicio, S. and Audretsch, D., 2019. Twenty-five years of research on institutions, entrepreneurship, and economic growth: what has been learned?. *Small business economics*, *53*, pp.21-49.