Economic Growth at the Cost of the Environment?

Analyzing The Relationship between GDP per Capita and CO2 Emissions

1. Introduction

In recent years, the drivers of global industrialisation have come to be criticised for their environmental impact as greenhouse gas levels in the Earth's atmosphere continue to be recorded at worrying rates. Given the prevailing circumstances, economic growth has long been suspected to be happening at the cost of the environment.

This study aims to primarily explore the relationship between GDP and carbon dioxide emissions in various countries across Asia. In the process, we also hope to observe indicators for the Environmental Kuznets Curve hypothesis which claims an inverted U shape exists when correlating economic growth with environmental pollution. The control variables taken into account for this study were electricity consumption, forest area, domestic credit, renewable energy consumption, mobile subscriptions and population growth. A panel dataset was created, with a time horizon of 15 years containing data for all the aforementioned variables from 12 Asian countries at various stages of development. Various regression models were tested in order to get a holistic overview of the problem at hand.

2. The Data

All of our data is sourced from the World Bank's online website. All of our variables of choice came from the literature review. As mentioned in the introduction, we wanted to examine the hypothesis of Environmental Kuznet Curves. Consequently, our dependent variable is CO_2 emissions measured in metric tons per capita. Our independent variable of interest was GDP per capita (PPP) in US dollars. These variables would be controlled with population growth, domestic credit to the private sector, energy consumption, renewable energy consumption, forest area, and mobile cellular subscriptions. Domestic credit to the private sector was a proxy for financial development and ease of doing business while forest area was a proxy for deforestation levels in the country. Mobile cellular subscriptions was an experimental variable that was not present in any literature. We wanted to see whether it was a significant variable in predicting CO_2 emissions. A summary of the variables and their units of measurement is given below.

Table 2.1: Variables of our study

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Name	**Measurement**	**Type**
CO_2 Emissions	Metric tons per capita	Dependent
GDP	$US (PPP) per Capita	Independent (Interest)
Population Growth	% Growth	Control
Domestic Credit	% of GDP	Control
Renewable Energy	Consumption as % of total energy production	Control
Forest Area	Square Kilometres	Control
Electric Power	kWh Per Capita Consumption	Control
Mobile Cellular Subscriptions	Per 100	Control

To decide on the countries that we would be selecting, we looked at the Human Development Index report of 2020 and the country rankings – the rankings can be found here. In these rankings, we decided that we would be selecting developing countries in Asia. In total we decided on 12 countries which are presented in the table below,

Table 2.2: Countries by HDI

Very High HDI	**High HDI**	**Medium HDI**
Singapore	Iran	Pakistan
Japan	China	Bangladesh
Turkey	Uzbekistan	India
Saudi Arabia	Indonesia	Tajikistan

Additionally we tried to cover all of the sub-regions within Asia. Splicing the countries along these lines, we get the following data,

Table 2.3: Countries by sub-regions in Asia

South Asia	**East Asia**	**South-East Asia**	**Middle East**	**Central Asia**
Pakistan	China	Singapore	Iran	Tajikistan
India	Japan	Indonesia	Saudi Arabia	Uzbekistan
Bangladesh			Turkey	

In terms of the time horizon, we decided on working from the start of the 21st century since it's around this time that the climate change movement started to gain wind. In 2001, the Intergovernmental Panel on Climate Change published in their third assessment report that human activities were the main cause of the rise of global temperatures in the second half of the 20th century. Going along these lines we selected data from 2000 to 2014, a fifteen year time period. In summary, we have panel data consisting of 180 rows of data with eight variables, fifteen years and twelve countries giving us 1,400+ data points.

3. Exploratory Analysis

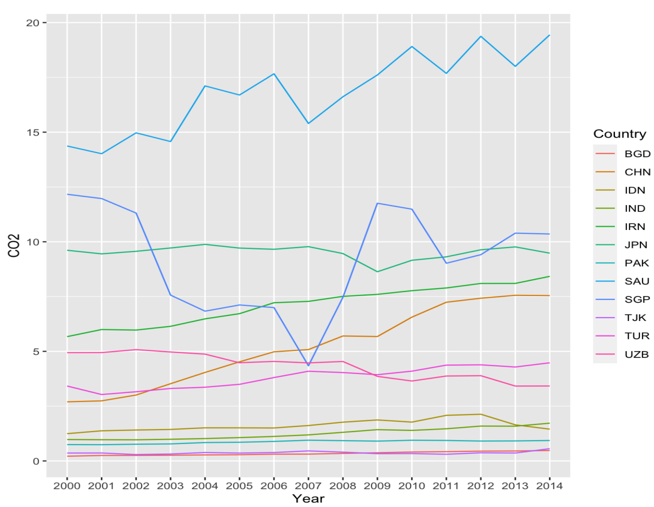
We first did some exploratory analysis on our dataset, so that we could better understand the characteristics of our data and the variables that we have chosen. This we did by first exploring the descriptive statistics of our data. Using R we were able to identify the quartiles, mean, median, the standard deviations and variances, and also the skewness and kurtosis. All of these have been attached in the table below.

	CO2 (Metric tons per capita)	GDP (US Dollars)	Forest Area (Square Kilometers)	Mobile Subscriptions (Per 100)	Domestic Credit (Percentage of GDP)	Electric Power (kWh Per Capita Consumption)	Renewable (Consumption as total % of energy production)	Population Growth (Percentage Growth)
Standard Dev	4.87	20400.8	564412.7	46.4	49.6	3003	25.6	0.86
Variance	23.7	416192817	3.18562E+11	2152.369	2457.206	9018699	656.5308	0.7539975
Kurtosis	3.71	4.50	5.45	2.97	N/A	2.34	7.76	5.00
Skewness	1.16	1.55	1.87	0.66	N/A	0.98	2.37	0.35
Minimum	0.216	1048	167.3	0.019	9.89	104.6	0	-1.48
1st Quartile	0.96	3193	16575.4	13.2	28.6	545	3.88	1.16
Median	3.87	7020	69184.6	58.9	43.3	1781	13.6	1.38
Mean	5.04	17095	357128.9	57.3	64.8	3008.9	19.8	1.52
3rd Quartile	7.57	24777	356222.5	85.5	102	4361.5	21.1	2.09
Maximum	19.4	84423	2083574.8	191	212.3	9401.4	99.8	5.32

Fig 3.1: Summary Statistics of our Data

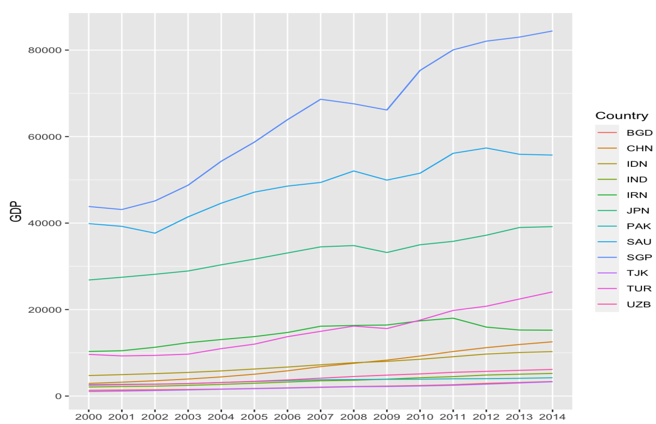
As is apparent the skewness and kurtosis of our dataset indicates that our dataset for the most part, is not symmetrical. The reason for that is most likely that the data that we have used is panel data that generally has an increasing trend, therefore both measures can not be used to check the validity of our dataset since it does not have a normal distribution. Moving towards the variances and standard deviations, these vary according to the variable since all variables have different units of measurement and hence different magnitudes. For example the variable forest area has a standard deviation of about 564,000 square kilometers whereas population growth has a standard deviation of 0.86 percentage growth. For the domestic credit, the values for Kurtosis and Skewness are not available, this is because we do not have domestic credit data for Indonesia.

After the descriptive statistics, we decided to study the variation in our variables, over time periods for the countries in our dataset. We did that by creating time-series graphs for all variables and color coding it with the countries.

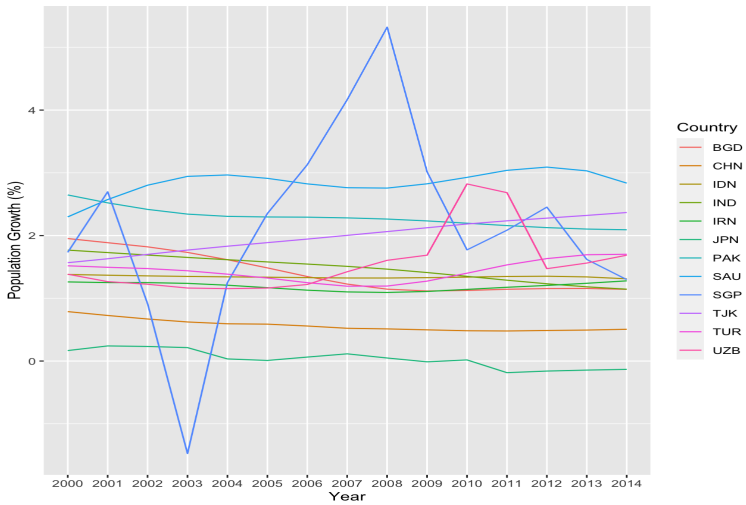


Looking at CO_2, we can see for the developing nations, like Uzbekistan and Tajikistan etc, the CO_2 emissions are low and have been somewhat constant. Pakistan has slightly higher emissions but still at the lower end of the spectrum. Saudia Arabia is seen to have the highest emissions that have an increasing rate over these 15 years. Singapore has the greatest variation in the CO_2 emissions.

Looking at the graph for GDP per capita, we can see that all countries have an increasing trend but the rates of increase vary greatly. Singapore is seen not only to have the highest value, but also has the highest rate of increase, followed closely by Saudia and Japan. Tajikistan has the lowest GDP per

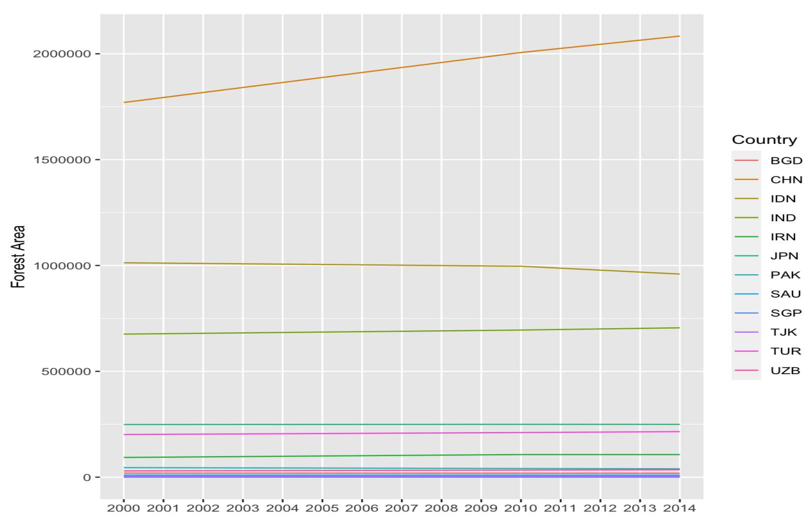


capita in this time period and the developing can be seen as having very slow rates of increase as well. Iran is the only country that seems to have a negative trend towards the end, post 2011.

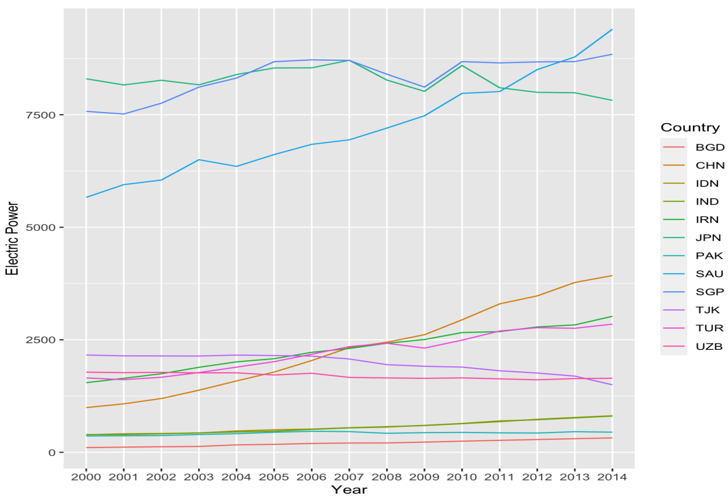


The graph for population growth does not have a specific trend to it. For the majority of the countries, the change in this time period has not been significant. Singapore although can be seen as an anomaly since it has great variations, the population growth is negative in 2003 and greater than 5% in 2008. However for the majority of the countries in our dataset, the annual population growth rate has been close to 2%.

Coming towards the forest area, it can be seen that for most countries in our data set, the rate of increase has been very minimal. In fact, the forest area has remained somewhat constant throughout this 15 year period. China has a forest area that is different in two important ways. Not only is it significantly greater than all the other countries, it also has the greatest rate of

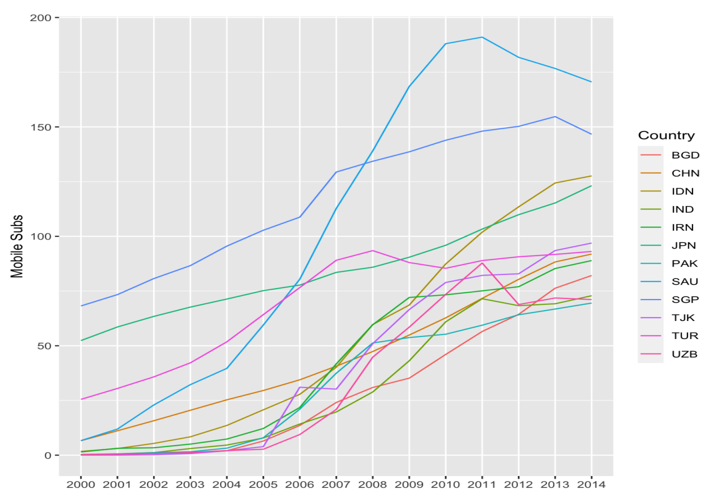


increase. Indonesia's forest area is the second highest but is also almost half that of China. It is also worth noting that Indonesia's forest area takes a dip towards the end, post 2011. Countries like Uzbekistan and Tajikistan have low forest areas as well. It is worth noting in this case that the forest areas are measured in square kilometers, and the great variance that can be seen here is probably because of the land areas that these countries cover. Since China has the largest land area in our dataset, it would make sense that China has the greatest forest area as well.

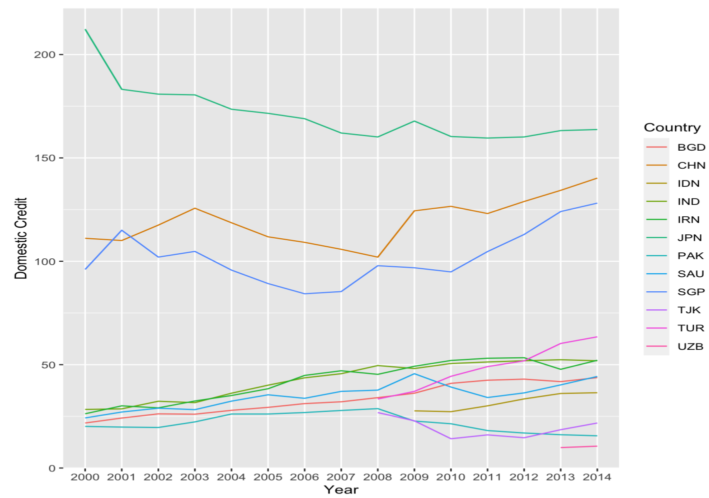


When it comes to the electricity consumption, we again see a difference between all the countries. On the lower end of the spectrum, we see Bangladesh that has an electricity consumption a little greater than 100 kWh. Japan, on the opposite end, has greater than 800 kWh. Saudia Arabia can be seen to have a great increase in the electricity consumption over these 15 years, whereas for the other countries, there were yearly variations and there seems to be no trend for the most part.

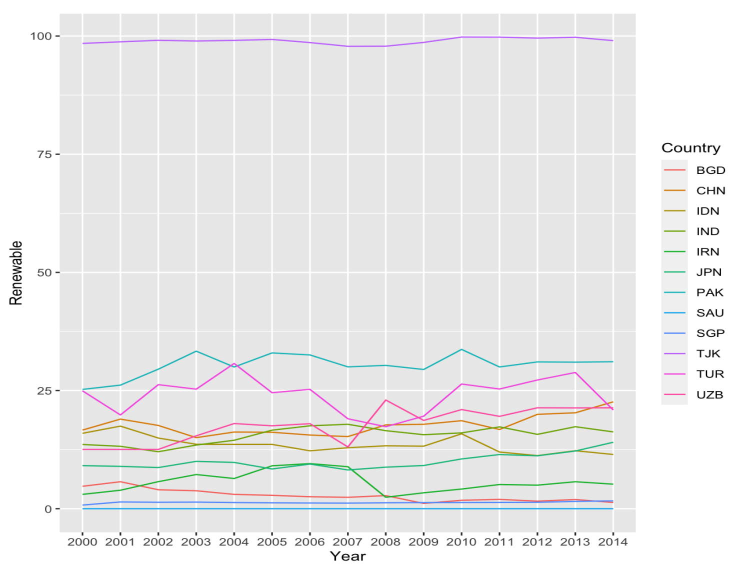
Mobile subscriptions are seen to have a general increasing trend however the increase is not linear. For countries such as Uzbekistan, Tajikistan and Pakistan etc, there is a rapid increase in subscription after 2005. After that



we can see that there is a high rate of increase, but as we approach 2014, the trend slows down. For countries such as Singapore, Japan and Turkey, we see that their subscriptions were high before 2000 as well. So accordingly, their rates of increase were not as high as the earlier mentioned countries. The most drastic increase can be seen for Saudia Arabia, as it can be seen that after 2001 there was a sharp increase in subscriptions reaching a peak in 2011, after which the subscriptions started to fall.



Moving towards domestic credit, again we see a graph that follows no particular trend. For the developing nations at the bottom of the graph, over the course of the 15 years, for some countries the domestic credit increased, whereas for some it fell. For this our dataset also has some irregularities, since Indonesia, Tajikistan, Turkey and Uzbekistan have missing values for some years. Iran leads the domestic credit however a decreasing trend can be seen. It is followed by China and Singapore.



Lastly we have renewable energy consumption. Here we can see that Tajikistan has the highest percentage of renewable energy consumed, in fact almost all of its energy consumption is renewable. Second on the list is

Pakistan, which on average consumes 75% less than Tajikistan, but more than the rest of the countries in our dataset. Saudia Arabia did not have renewable energy consumption in this time period and therefore has a constant value of 0 in our dataset. For the other countries there is neither an increasing nor a decreasing trend however yearly variations can be seen.

4. The Model

We decided to run a panel fixed effects model on our data to see the effects of GDP per capita and other control variables on our dependent variable, CO_2 emissions. Initially the summary results of our model was indicating that all of our variables were not significant. After careful deliberation with the instructor, we created various models that incorporated non-linear variables along with taking a natural log of variables that had standard deviations close to the mean of said variable. The model that we ended up with was the following,

Fig 4.1: Our Model

$$\begin{aligned}\log(CO_2) = {} & \beta_0 + \beta_1 \log(GDP) + \beta_2(\log(GDP))^2 + \beta_3 PopGrowth + \beta_4 Renewable \\ & + \beta_5 ForestArea + \beta_6 ElectricPower + \beta_7 MobileCellSubs \\ & + \beta_8 DomesticCredit\end{aligned}$$

Taking the natural logarithm would affect our interpretations that are discussed in the following section. We added a squared log of our GDP as well to look at the elasticity of the variable. The names of the variables can be revisited in table 2.1.

5. Interpretations and Visualizations

Using our collected data, we estimate the equation given above to obtain the following regression results,

Table 5.1: R-Studio regression summary

Variable	Estimate	Std. Error	t-value	p-value
log(GDP)	1.8680e+00	3.8979e-01	4.7924	4.694e-06 ***
I(log(GDP)^2)	-9.3910e-02	2.2280e-02	-4.2150	4.818e-05 ***
PopGrowth	-3.6272e-02	1.8896e-02	-1.9195	0.057251
Renewable	-7.2729e-03	5.3867e-03	-1.3502	0.179467
Forest_Area	2.3175e-06	5.4721e-07	4.2352	4.455e-05 ***
Electric_Power	-6.0189e-05	3.7571e-05	-1.6020	0.111743
Mobile_Cell_Subs	1.8528e-03	6.2156e-04	2.9808	0.003471 **
Domestic_Credit	5.2054e-03	1.1734e-03	4.4361	2.020e-05 ***

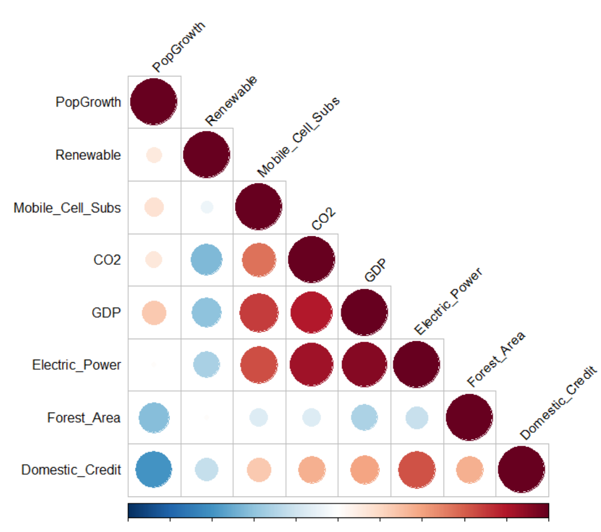
Total Sum of Squares	5.4827
Residual Sum of Squares	1.3961
R-Squared	0.74535
Adj. R-Squared	0.7057
F-statistic	44.637 on 8 and 122 DF, p-value: < 2.22e-16

A number of key observations can be gathered on the basis of the resulting regression estimates. First and foremost, given the log-log form of our model in terms of the independent variable, tons of CO_2 emissions per capita, and our independent variable of interest, GDP, we observe a positive elasticity of y with respect to x. With a t-value of 4.79 and a p-value of approximately 0.0005%, this effect comes out to be statistically significant. Put precisely, the estimates imply that a 1% increase in a country's GDP causes a 1.86% increase in CO_2 emissions per capita. Taking the example of Pakistan, this estimate implies that applying the historical 2015 GDP per capita growth rate of 2.567% to our equation, we would have expected an increase of 4.78% or 44 kgs of CO_2 emissions per capita on basis of 2014's CO_2 emissions. When taken in perspective of Pakistan's population of roughly 199 million in 2015, this relationship implies a total increase of 8.76 million tons of CO_2 emissions in the country from 2014 to 2015.

On the other hand, we further attempted to modify our assumptions regarding this relationship and tried incorporating a nonlinearity effect by taking the square of GDP. Including this interaction term on GDP, we arrive at a negative beta estimate with a statistically significant t-value of 4.2. The beta estimate of -0.0939 for this squared elasticity model suggests a nonlinear relationship with a diminishing marginal impact of GDP on CO_2 emissions, which may also be seen as a possible indicator for the environmental Kuznet's curve.

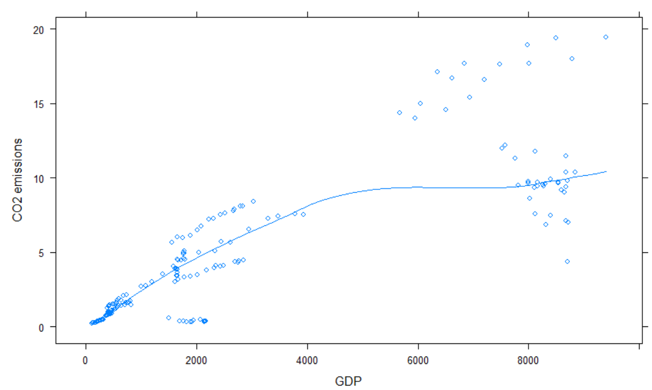
Apart from these observations regarding our primary independent variable of interest, we also find other statistically significant relationships as part of our model. At the forefront, we observe a statistically significant impact of domestic credit on CO_2 emissions at a t-value of around 4.44. Since we use domestic credit extended to the private sector as a proxy for the ease of doing business in our observed countries, our beta estimate appears to suggest a positive relationship between the existence of a business friendly environment and an increase in CO_2 emissions. Furthermore, we observe a statistically significant impact of mobile cellular subscriptions and CO_2 emissions at a t-value of 2.98. We assume this variable to also act as a proxy of openness in the business environment of a country along with development of an informal or formal economy and although the beta estimate is small in value, however, it adds weight when taken at scale and suggests a positive relationship with our dependent variable as a unit increase causes an increase of 0.002 tons of CO_2 emissions per capita. Additionally, however, we also observe a statistically significant positive beta estimate for forest area. Here, the result may seem to contradict the theoretical relationship that CO_2 emissions should decrease with an increase in forest area. A possible reason could be the existence of an omitted variable bias where forest area is confounding the impact caused by a correlated missing variable, while on the other hand, the relationship may also hold which could signify the naturally occurring growth in CO2 emitted by an increasing number of plants and vegetation, although with a very minimal impact as captured by the beta estimate.

Apart from these results, our other variables of population growth, electric power, and renewable energy consumption appeared to be statistically insignificant in the presence of other explanatory variables. Considering the relationship of electric power, we believe the estimate observed is insignificant since other variables like domestic credit may capture the underlying impact. On the other hand, renewable energy consumption as a variable possibly appears insignificant since it was largely a recent trend in our chosen countries over the observed time period and the impact on CO_2 emissions is not captured accurately.



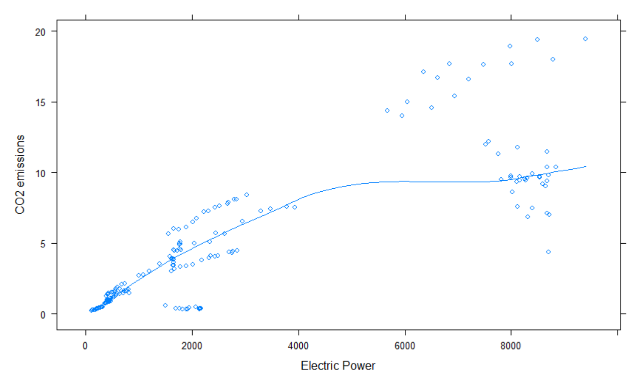
Looking at the correlation matrix, we see some of the significant relationships that we initially hypothesized that would exist but there were a few surprise relationships as well.

GDP was theorized to have a negative correlation with CO_2 emissions according to the literature review. According to it, GDP should form a U-shaped curve with the amount of CO_2 emissions over the years. But in our correlation matrix, we see that the correlation coefficient of CO_2 emissions and GDP comes out to be very high (around 70-80%).

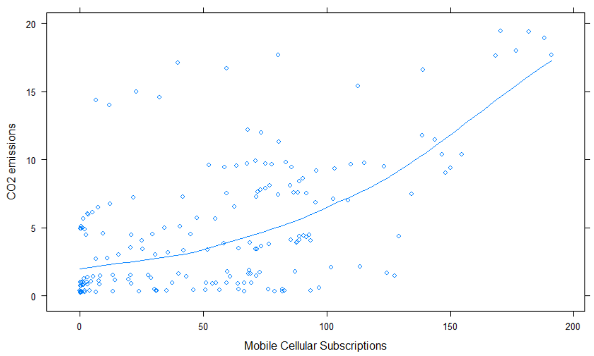


Moreover, the scatter plot curve between these two variables was not U-shaped as theorized in the literature review; in fact it was similar to a kuznet curve – and precisely the first half of the curve for developing countries – reinforcing our initial hypothesis that the relationship between these two variables can be explained on the basis of the kuznet curve.

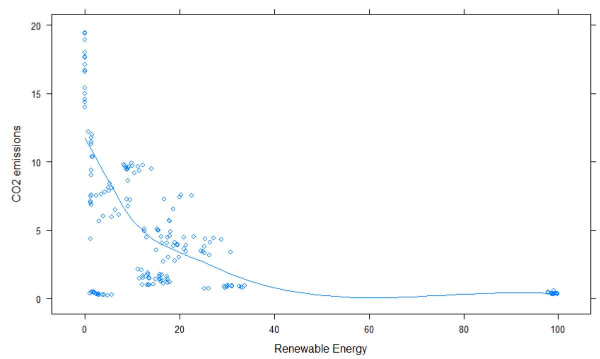
The highest correlation that existed with the CO_2 emissions in our model was the one with the electric power consumption. The correlation coefficient came out to be around 84%. Most of this relationship can be explained in terms of the production of electrical power. Most of our electric power comes from the power plants using thermal fuels, which are a direct contributor of emitting CO_2 into the atmosphere. The scatterplot of CO_2 emissions with power consumption is similar to the one of CO_2 emissions with GDP.



This can be explained in terms of the high correlation coefficient of GDP and Power Consumption.



One surprise correlation that we found was that of CO_2 emissions with the number of mobile cellular subscriptions. CO_2 has a moderate positive relationship with Mobile Cellular Subscriptions with the correlation coefficient coming around 60%. This can be explained in terms of the production of the phones and mobile cellular server maintenance. A lot of CO_2 is emitted in the production of the mobile phones, which is directly proportional to Mobile cellular subscriptions. Moreover, due to the two year life span of phones, the production of mobile phones increases, causing carbon emissions.



The only significant negative correlation that we found with the CO_2 emissions was the one of renewable energy. This relationship had a negative correlation value of around 50%. Looking at the scatter plot between CO_2 emission and Renewable energy, we see that there exists a negative exponential correlation between the two variables. Why? Increasing the utilization of renewable energy resources instead of fossil fuels leads to a decrease in CO_2 emissions.

6. Next Steps

Our model does consist of some shortcomings. A variable like Population Growth should have come out to have a significant, positive correlation with CO_2 emissions according to our literature review. Additionally, renewable energy consumption should have had a significant and negative correlation. For future research, a variable like urban population could have been used instead of population growth. Additionally, we would require a wider time horizon – upto 30 years or more – since variables like renewable energy production and forest area will remain constant in short time horizons – you can't switch to renewables and grow forests within fifteen years. It takes time to shift electric power consumption from fossil fuels to renewables. For example, Saudi Arabia's renewable energy production was 0 for twelve years in our data.

Moreover, we only experimented with Mobile Cellular Subscriptions as a determinant of CO_2 emissions. More such variables could be added to see interesting correlations. One such variable was Literacy Rate. A hypothesis for this could be that pollution would decrease as the population got more literate and understood their carbon footprint.

Lastly, our data only consisted of developing nations in Asia. To fully test the existence of an Environmental Kuznet Curve, we would require the addition of developed nations such France, Germany, UK, USA and more to see the complete picture. On top of this, if future researchers test this hypothesis with multiple different models of panel data analysis along with our suggestions, then a deeply comprehensive conclusion could be reached for the existence of an Environmental Kuznet Curve.

7. Conclusion

Our research and model indicated that there are signs for the presence of the Environmental Kuznet Curve in our time horizon and selection of Asian countries. While our model fell short on some variables, which we have outlined in the previous section, it is still useful in understanding the relationship between GDP per capita and CO_2 emissions. We can see there is a significant and positive correlation between GDP per capita and CO_2 emissions. This has major policy implications for developing nations. If the environment is not considered during the process of economic growth, then this will have drastic consequences in the future in the form of storms in some places and droughts in others. Additionally, our control variables of domestic credit and mobile cellular subscriptions have implications too. As ease of business increases, the environmental load of that nation increases. Subsequently, important environmental measures need to be consolidated. We also found through the cellular subscriptions variable that the telecommunications and mobile industries have a significant impact on the environment too and as such require legal controls to stem their impact.

We would like to incorporate the suggestions in our Next Steps section to further enrich present research around economies and the environment.

Citations

BBC News. "A Brief History of Climate Change." BBC News, 20 Sept. 2013, www.bbc.com/news/science-environment-15874560.

Dong, Kangyin, et al. "Does Natural Gas Consumption Mitigate CO2 Emissions: Testing the Environmental Kuznets Curve Hypothesis for 14 Asia-Pacific Countries." *Renewable and Sustainable Energy Reviews*, vol. 94, 2018, pp. 419–29. *Crossref*, doi:10.1016/j.rser.2018.06.026.