Key impact factors on the change in carbon emission using panel data from 120 countries

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Abstract

Climate change is one of the biggest challenge humanity has ever faced. In recent years mitigation efforts all around the globe have ramped up. These efforts, however, have not been successful. This research combines the Kaya identity used to decompose carbon emissions into various factors and panel data analysis to extract the key impact factors on the changes in the growth of carbon emissions. Data from 120 different countries and territories from 1961 until 2015 have been used. The results show that changes in technology have the strongest global effects, consequently followed by changes in population growth and affluence. Finally, the impact of income inequality on the change of carbon emissions can be analysed within the framework of the IPAT methodology, with the outcome that only high income nations show a significant relationship.

1 Introduction

1.1 Research question

As the effects of climate change worsen annually and the repercussions become increasingly grim, interests in how we can combat this change in the global environment have been increasing more than ever. This is considered to be one of the biggest challenges humanity has ever faced. Decades of research on climate change have been conducted resulting in the scientific consensus that global warming is man-made [1]. In recent years, effects of this change in the environment have already been quantifiable. One of the main contributors to this man-made global warming is carbon dioxide emitted into the atmosphere by the humans [2]. Measures all around the world have been taken to mitigate carbon emissions to achieve the objectives from the Kyoto protocol [3] and moreover recently, from the Paris agreement [4]. However, even though carbon tax [5] and emission trading systems [6] have been introduced in various forms, year by year carbon emission globally increases by about 2.0% [7]. This means that currently we are still going towards the wrong direction and therefore, swift actions must be taken to combat this phenomena. This paper inspects the changes to which areas have the strongest effects on the increase in the change of human carbon emissions. Since climate change is a crucial problem on a global scale, this paper analyse carbon emissions on a global scale, taking 120 countries and territories into account.

1.2 Dependent variable

For this research, the dependent variable is the annual change in the CO_2 emissions per country in %. For this, the dataset from the World Bank has been used and modified to reflect the annual change. This dataset includes a comprehensive list of the carbon dioxide emissions from 125 different countries from the year 1960 to 2015. It takes carbon dioxide produced from the consumption of solid, liquid, and gas fuels and so-called "gas flaring" into account. Carbon dioxide emissions in this dataset are defined as those emissions stemming from the burning of fossil fuels and the manufacturing of cement. This data was collected by the Carbon Dioxide Information Analysis Center in Tennessee, United States. The relative annual change for each country included in the original dataset is calculated by figuring out the difference between the carbon emissions per capita from two consecutive years, divided by the first year.

$$\Delta F_{i,t} = \frac{F_{i,t+1} - F_{i,t}}{F_{i,t}} \tag{1}$$

Equation 1 describes the change in % from two consecutive years. If the value of carbon emission per capita increases from one year to another, this value will be positive, while if emissions decrease, the value will be negative. As can be seen from figure 1 the data is normally distributed with a positive mean close to 0. This makes an analysis more likely to produce significant correlations between the dependent and the independent variables. In addition, as described in table 1, the skewness is very low. Nevertheless, it becomes clear when looking at figure 1 that some outliers do exist. This is due to the fact that all nations and territories are included in this dataset. Some micronations have extreme changes. Changes in carbon output of over 20% from one year to another are extremely implausible. The relatively high amount of extreme changes in the output of carbon is also due to the data collection methodology by the World Bank. Estimating the green house gas emission rates of a country or a territory is difficult, especially for old data, this can become somewhat unreliable. However, due to the high number of reliable data, these outliers are somewhat insignificant. Nevertheless, some micronations have been excluded the reduce the amount of extreme outliers to produce more significant results. This is why in this paper only 120 countries have been analysed. In table 1 it can be seen that on average over the past 5 decades, CO2 emissions per capita has increased by 2.58% every year. It is important to note here that this is not the change of total carbon emissions globally. Instead, this describes the average change of the carbon output of each country in the dataset, which is not equal to the cumulative change in the global CO_2 emissions.

Number of observations	Min in %	Max in %	Mean in %	Variance in %	skewness
10192	-98.9	98.7	2.58	14.7	0.87

Table 1: Statistics of all observations of the dataset

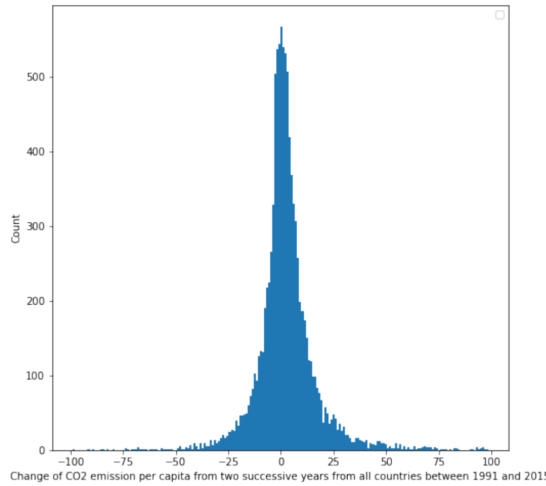

Figure 1: Histogram showing the change of CO2 emissions per capita for each country from the year 1960 to the year 2015

1.3 Overview of the paper

First of all section 2 gives quick summary on modern climate research. This is followed by a comprehensive literature review in section 3. This includes an explanation of the most used methodologies in climate economics, the IPAT methodology combined with the Kaya identity. Next, a summary of existing studies with the IPAT methodology and the Kaya identity on carbon emissions will be given. The literature review is split up into 3 different levels of analysis: sector specific, national and international or global levels. After that, the methodology that was used in this research will be explained in section 4, including a detailed explanation on what the differences, advantages but also disadvantages of this methodology compared to existing literature are. In addition, section 5 clarifies the expected relationships between the chosen independent variables with the change in carbon emissions. This is followed by the empirical analysis and finally the discussion and conclusion of these results.

2 Background

In the early 19th century, French scientist Joseph Fourier, besides making fundamental contributions to maths and physics, proposed that the light emitted form the Sun that reaches Earth must be equivalent to the amount of energy radiated away from Earth. However, due to the Earth's atmosphere, some of that energy is trapped inside. Similar to light entering a green house, some of the light is no longer able to escape the Earth's atmposhpere, this necessarily leads to a global warming. This is the so-called Greenhouse Effect. Centuries later it became clear that the amount of CO_2 in the atmosphere is correlated with the Greenhouse Effect. This effect is shown in figure 2. By the end of the 20th century, enough evidence was gathered to prove that carbon dioxide is in fact a greenhouse gas, and by emitting more of it, the average global temperature would increase [8]. Concerned by this development, the international community began efforts to address global warming and in 1992, the UN Conference on Environmental Development (UNCED) was held in Rio de Janeiro. 154 nations agreed to increased efforts and policies should be put in place to reduce carbon emissions. The goal was to limit the level

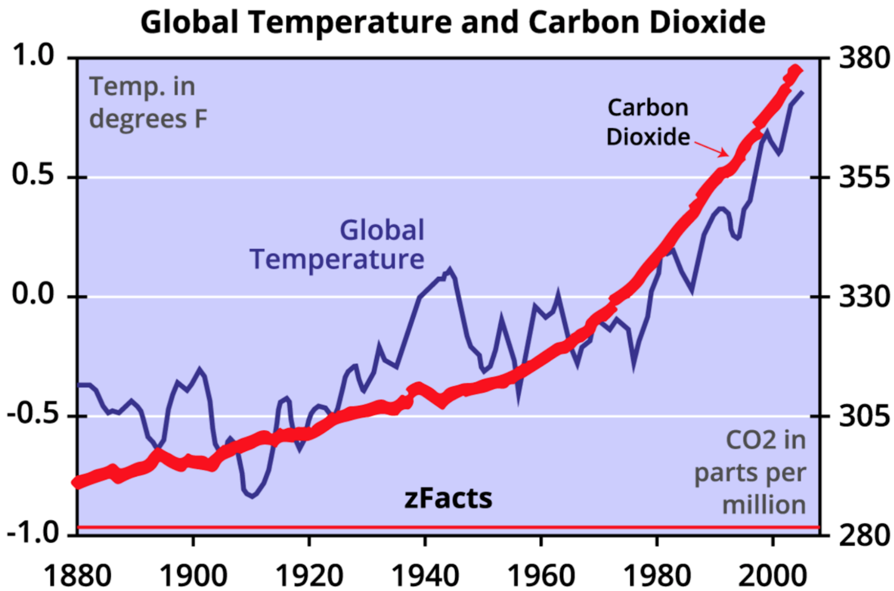

Figure 2: Correlation between CO2 level in the atmosphere and the average global temperature

of carbon emitted into the atmosphere in the year 2000 back to the level it was in 1990. However, these voluntary and non-binding measures included in the agreement did not manage to reduce carbon emissions globally. In the early days, many nations were reluctant to implement carbon mitigation policies [9]. Later, more successful agreements have been created by the Kyoto protocol [3], and more recently, the Paris agreement [4]. Here, measures all around the world have been taken to mitigate carbon emissions to achieve the goals specified in these agreements. However, looking at figure 3, it becomes even more apparent that the efficacy of current measures put in place is limited. In recent years, the growth in total carbon emissions have been slowing down - despite the much-deserved praise, it is still short of achieving the goal of decreasing carbon emissions, further highlighting the global trend that is headed in the wrong direction. Hence, it can be concluded that despite the significant efforts for emission reductions, thez are not as effective as they should be. This leads to the question of why the current efforts are not effective, and which areas should be tackled to mitigate carbon emissions in the most effective way.

3 Literature review

3.1 The Kaya identity

To analyse and understand the changes in CO_2 emissions, the most popular tool used in literature is the Kaya identity [10]. This tool has been used in most major analysis on carbon emissions. This very simple equation takes 4 factors into account and is written thus:

$$F = P \times \frac{G}{P} \times \frac{E}{G} \times \frac{F}{E}, \tag{2}$$

where

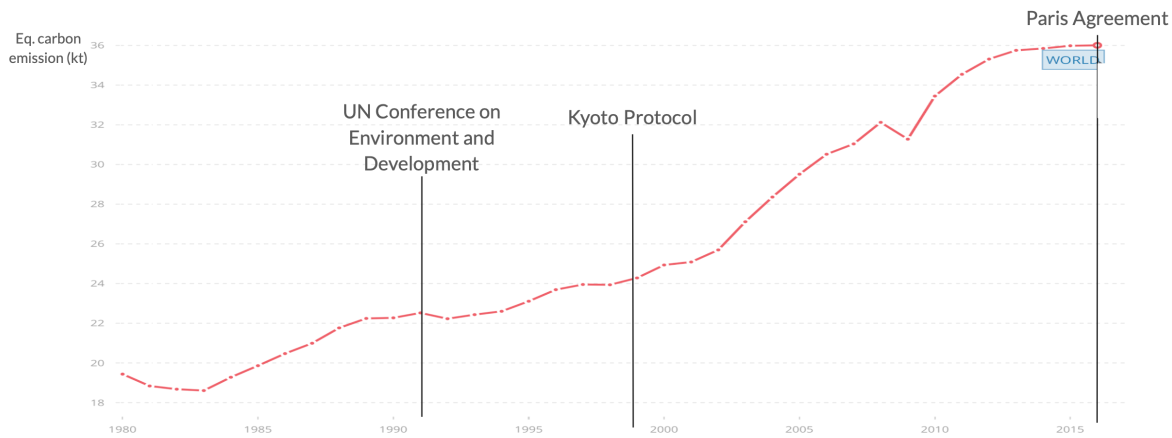

Figure 3: Carbon emissions globally, including major international agreements

- ***F*** is CO_2 emissions from human sources
- ***P*** is population
- ***G*** is GDP
- ***E*** is energy consumption.

As can be seen from equation 2, the Kaya identity decomposes the annual carbon emissions per capita to factors that include population, economic productivity, energy intensity and finally carbon efficiency. The background of this equation is a specific application of the $I = PAT$ identity (IPAT identity). This identity relates human impact in the environment (I) to the product of population (P), affluence (A) and technology (T). On further mathematical analysis of the Kaya identity, it can be seen that on the right hand side of the equation that all terms cancel each other out except the CO_2 emission term. This means by cancelling out all "unnecessary" terms, the equation turns into $F = F$, which would not be very useful. However, by introducing these intermediate terms with this specific decomposition, an understanding of which factors need to change in what way to achieve specific emission targets can be formulated. In addition, with historical data, it can be analysed which of these factors affect carbon emissions the most and with predictive analysis, trends in carbon emissions can be deduced as well.

Analysis with this approach has been done for many countries and sectors within. In general, this can be split up into three categories: sector specific, national, and international level. In the following, existing research on the different levels is summarised.

3.1.1 Analysis on sector specific level

Xu and Lin in 2014 [11] have analysed China's CO2 emissions from agriculture. Here, an improved Kaya identity has been utilised, which describes a full decomposition approach, which uses the Logarithmic Mean Divisia Index (LMDI) method. In fact, most published research on the sector specific level used this improved approach. This method decomposes the factors on right hand side of the Kaya identity again, into more specific factors. In addition, this approach does not analyse the change in total carbon emissions. Instead it looks at changes in the year by year evolution of carbon emissions. The mathematical expression can be seen in equation 3.

$$F = P \times \frac{G}{P} \times \frac{E}{G} \times \frac{F}{E} \quad \longrightarrow \quad \Delta F = \Delta P \times \Delta(\frac{G}{P}) \times \Delta(\frac{E}{G}) \times \Delta(\frac{F}{E}). \tag{3}$$

Studies with this approach now produce insights on the change in which factors decrease the change in carbon emissions most effectively. The result of this analysis in China suggests that the economic development effect hast the strongest impact on carbon emission. In fact, regional energy-related carbon emissions from eco-industrial parks in South Korea have been analysed [12] with the same approach. Here, the most impactful factor for carbon emissions has been identified as production effects. Furthermore, Wang et. al. 2014 [13] have decomposed energy-related carbon emissions in Xinjiang. The LMDI approach has also been used in this research. The main finding here is that the two main drivers for carbon emissions in Xinjiang are the affluence and the population effect. Additionally, improvements in carbon intensity helped to mitigate some of the carbon emissions. Finally, Ma and Cai 2018 [14] have analysed the Chinese commercial building sector with this extended Kaya identity. Similarly to the previous studies, the main result was that the growth in economic output (in this case GDP per capita) in the tertiary industry is the main driver for carbon emissions. However, in addition to this, carbon intensity in the Chinese commercial building industry (carbon emissions per produced energy) has also been found to be significant. In sum, almost without exception, the LMDI method has been used to analyse the key impact factors on carbon emission on sector-specific level. Moreover, considering the same level, most research suggest that affluence and population size have the strongest impact on carbon emissions. Nonetheless, technological advancements are also essential for carbon mitigation.

3.1.2 Analysis on national level

For country-wide analysis of carbon emissions, the Kaya identity has almost been unanimously used. Mahony (2013) [15] applied this method to decompose Ireland's carbon emissions from 1990 to 2015. This study has also utilised the approach with the extended Kaya identity (LMDI) explained in section 3.1.1. The conclusion of the empirical analysis of this paper suggests that rise in affluence and population growth increase the nation-wide carbon emissions, while energy intensity and the use of fossil fuel substitutions act to decrease emission levels. Nevertheless, changes in affluence have the strongest effect on carbon emissions. In addition, contrary to previous studies, Pui and Othman (2019) [16] have analysed carbon emissions in Malaysia with a tradition decomposition per the Kaya identity without utilising LMDI. CO_2 emissions have been decomposed into economic, technical, and social aspects. Pui and Othman suggest that the economic aspect is always connected to carbon emissions. However, a more efficient use of energy might be the most effective approach to mitigate carbon emissions nation-wide. This reduction in carbon emission could even be achieved without any economic damage. Additional research with the Kaya identity have been carried out in Cameroon [17], Switzerland [18], China [19], and many other countries with similar results. All in all, on national level, the tedious and expensive LMDI model has been used less, even though it is more more accurate and its analysis produces more meaningful results. This is mainly due to the lack of data in most countries, especially in developing nations.

3.1.3 Analysis on international and global level

On an international level, Štreimikienė and Balezentisb (2016) [20] have analysed the key impact factors of greenhouse gas emissions in the Baltic States. In this paper Index Decomposition Analysis (IDA) has been used to modify the standard Kaya identity. Similarly to the LMDI method, this method decomposes the right hand side of the Kaya identity again. However, instead of using a logarithmic approach to calculating changes in time-evolution in the data, the Shapley value is used [21]. This approach, borrowed from Game Theory, usually attempts to analyse how important each player of a coalition is to the overall cooperation. Štreimikienė and Balezentisb adapted this approach to analyse which factors in the Kaya identity are the most important. However, the dependent variable in this research is changes in carbon emissions per capita. This eliminates the possibility to study the effect of population on emissions. This study concluded that the main factors driving carbon emissions per capita is energy intensity and economic growth for all analysed countries except Lithuania. Finally to the best of my knowledge, only one paper has been published analysing carbon emissions on a global level using the Kaya identity. Shuai et al. (2017) [22] have analysed the key impact factors world wide using a modified Kaya identity, the STIRPAT model. In this model, the natural logarithm has been applied to the IPAT equation introduced in section 3.1, producing following equation:

$$Ln(I_{i,t}) = a + bLn(P_{i,t}) + cLn(A_{i,t}) + dLn(T_{i,t}) + e_{i,t}. \tag{4}$$

Here $X_{i,t}$ corresponds to the value X for country i at time t. Panel data analysis has been applied to extract meaningful statistics from this model and estimate the coefficients a to d. This research suggested that at a global level, affluence is the most important key impact factor, followed by technology and population. For both international studies on the key impact factors on carbon emissions, approaches which require less comprehensive datasets for each individual country has been used. This is especially apparent for the the STIRPAT model, as here no further decomposition of the factors in the Kaya identity has been performed. In the case of the Baltic States, it was possible to apply a more comprehensive model with the IDA model. This was feasible as all nations considered in this study are part of the European Union. The EU has strong regulations on data collections in regards to carbon emission within its borders, making comprehensive data widely available. On a global scale this is not the case. In general it can be said that the broader the range of the sectors and countries included is, the less specific the methodology that was used. On sector specific level, deep dives into very specialised independent variables were possible. On a global scale, broader approaches were used. To conclude, most carbon emission studies look at country and sector specific cases. However, very little studies specifically addressed the global perspective and whether or not it is possible to extend the Kaya identity in a way such that it can be used to predict global trends. In addition, by analysing the change in carbon emission and not the total carbon emission, trends might be easier to identify. A recommendation on which changes have to be made in order to decrease the growth in carbon emission can be made.

4 Methodology

As this paper focuses on a global perspective instead of a regional or national level, like most published research on this level, an approach which needs less data for each individual country is required. Data quality and quantity in many nations is often lacking. For this reason, the methodology used in this paper will follow an approach which is more in line with the STIRPAT model, instead of the LMDI model used in more specific studies.

4.1 Challenges with STIRPAT

The STIRPAT model has some challenges. First of all, the model used by Shuai et al. (2017) [22] uses total carbon emissions from a given country as the dependent variable. This is very useful if the question of interest is countries with which attributes have a high carbon footprint. In addition, it is good to inspect which the key impact factors of carbon emissions are. However, in climate research it is arguably more useful to analyse the key impact factors for carbon mitigation. In other words, for carbon mitigation efforts it is usually less important to know which factors effect the total carbon emissions the most, but rather relative changes in which factors drive the majority of changes in relative changes in emissions. There are multiple reasons for this. On the one hand, in almost all national and international agreements, carbon emission goals are set in relative terms (e.g. the European Union has a goal of cutting emissions by 55% of the 1990 levels). On the other hand, in most regions worldwide, carbon emissions are still on the rise. Currently it might be more meaningful to analyse how to change the direction of emission evolution over time. Another challenge with the STIRPAT method is that the statistical results of this model give rather subjective insights. The coefficients from equation 4 that are estimated with empirical analysis can only produce an understanding on which factor has the strongest effect on carbon emissions among population, affluence or technology. However, it is not obvious by how much one factor is more important than other. Finally, the data used by Shuai et al. is provided by the World Bank and is an older version of the dataset used in this research. As mentioned before, due to the global scope of the data, naturally some nations and territories will not have enough or only unreliable data. For this it is important to be able to identify extreme outliers within the data. Due to the nature of the logarithm however, it is hard to pinpoint these outliers. For example if a value increases by a factor of 2, the resulting increase of the logarithm is $ln(2)$:

$$ln(2 \times x) = ln(2) + ln(x). \tag{5}$$

Now if the value of x is large enough, an increase by $ln(2) = 0.69$ is barely noticable, even though the original value increased by a factor of 2 which is very unrealistic when dealing with total carbon emissions from a country.

4.2 Extended Kaya model

This paper tries to find a middle ground between the IDA method and the STIRPAT model. This means instead of decomposing the factors of Kaya identity again, the change in % of the factors are calculated directly by computing the relative change of two consecutive years (see section 1.2). In addition, with this model it is possible to described each factor of the IPAT equation (population, technology and affluence) with multiple variables. For this reason, two independent variables have been added: changes in exports and wealth inequality. First of all, the variable change in exports, which is part of the affluence factor, has been added due to extensive research suggestion that worldwide exports are positively related to per capita carbon emissions (Stretesky and Lynch 2009 [23]). In a world with steadily increasing globalisation and thus also exports, insights into how the change in exports is related to changes in the growth of carbon emissions can be helpful to create effective carbon mitigation policies. In addition, the variable of wealth inequality has been introduced, as many studies suggest a statistical significant relationship between the Gini index and national carbon emissions. Knight et al. (2017) [24] for example argued that at least for high income countries, nations with a higher Gini index have lower carbon emissions. The Gini index measures income inequality across a population, while a higher Gini index indicates greater inequality, with high income individuals receiving much larger percentages of the total income of the population. However, the problem of adding these parameters is that now a decomposition into affluence, population and technology is less obvious. All in all, panel data analysis will be applied to the following equation:

$$\Delta F = a + b \times \Delta P_{(i,t)} + c \times \Delta(\frac{G}{P})_{(i,t)} + d \times \Delta(\frac{E}{G})_{(i,t)} + f \times \Delta(\frac{F}{E})_{(i,t)} + g \times \Delta Ex_{(i,t)} + h \times Gi_{(i,t)} + e_{(i,t)}, \tag{6}$$

where the individual factors correspond to table 2.

Finally, it is important to note that with this approach outliers are easily identified. This is because this model does not use logarithmization do deal with the skewdness of the data. Looking at the histograms in figure 4, a few outliers on the right hand side of the extended Kaya identity can be singled out. This is not possible with the STIRPAT model (see section 4.1). These outliers at around 100 are micronations which are neglectable for a global analysis due to their minuscule contribution to global carbon emissions. These countries have been excluded in this study to produce more meaningful empirical results.

IPAT-category	Variable	Desciption
Population	$\Delta P_{(i,t)}$	Population growth in %
Affluence	$\Delta(\frac{G}{P})_{(i,t)}$ $\Delta Ex_{(i,t)}$	Change in GDP per capita in % Change in exports in %
Technology	$\Delta(\frac{E}{G})_{(i,t)}$ $\Delta(\frac{F}{E})_{(i,t)}$	Change in energy efficiency in % Change in carbon intensity in %
Social factors	$Gi_{(i,t)}$	Gini index measuring income inequality. A scale from 0 to 1, with 0 representing perfect equality and 1 representing perfect inequality
Other	$e_{(i,t)}$ $a - h$	Error term Coefficients

Table 2: Summary of all independent variables. The variable $X_{(i,t)}$ corresponds to a variable of country i at time t.

5 Theory and arguments

Looking at the literature review, on national level the relationship between the dependent and independent variables have already been studied extensively. Most research that studied the change in the growth of carbon emissions has been done in high income countries. However, the expectation is that the key impact factors in the change in carbon emissions differ vastly in developing and developed countries. For this reason, significant differences between existing research on national level and an analysis on a global scale is expected. Furthermore, the assumption is that all variables in table 2 are statistically significant. The only exception for this is wealth inequality, where non significance might be a possibility. Literature review suggested that the Gini index only has an impact on total carbon emissions for high income countries. A relationship in less developed nations could not be observed.

5.1 Population

The global analysis with the STIRPAT model (Shuai et al., 2017 [22]) suggests that population has the weakest effect on total carbon emission per country globally. However, what was researched here is the relationship between the percentage of people living in urban environments and total carbon emissions. The result show that this is the main driver for carbon emissions in the least amount of countries. However, analysing how population growth affects changes in the growth of carbon emissions is fundamentally different. Because of this, the expectation is that the findings with the model used in this paper will have significantly different results than that of the STIRPAT model. As the yearly change in carbon emissions per capita is relatively stable [25], the assumption is that for every unit increase in population growth, change in carbon emission will increase similarly on a global scale.

5.2 Affluence

As described before, affluence is measured by two independent variables in this paper: the change in GDP per capita and the change in exports of a given country or territory. According to Shuai et al. (2017) [22], affluence is the key impact factor for carbon emissions in over half of the countries analysed.

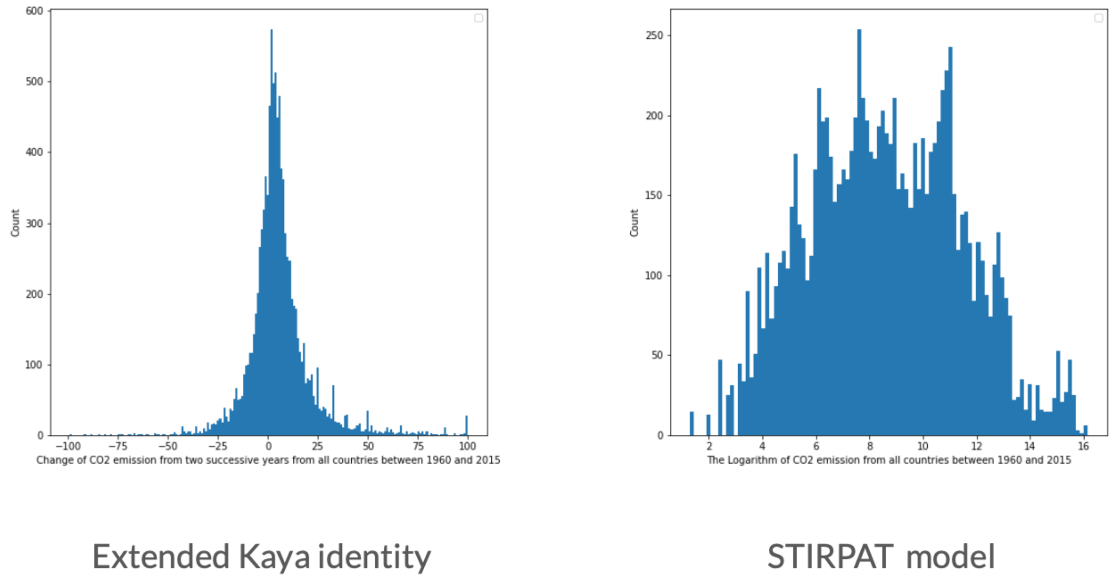

Figure 4: Comparison of the dependent variable of the extended Kaya identity (change in carbon emission in %) and the STIRPAT model (logarithm of the total carbon emissions)

The expectation is that growth in GDP per capita strongly influences change carbon emission as almost all economic output produces greenhouse gases. However, with increasing productivity, wealth of a nation naturally also increases. This might have two effects on the change of carbon emissions into the atmosphere: Firstly, with increased personal wealth of a population, environmental concerns become more important. Secondly, with higher wealth, investments into research and development increase. This leads to technological advancements which might improve carbon intensity and energy efficiency. Thus helping to decrease the growth in carbon emissions. These two factors dampen the effect increase in affluence has in the change in growth of carbon emissions. However, all in all it is still expected that affluence has a strong impact on the drivers for changes in the growth of carbon emissions. For the second independent variable under affluence, exports are expected to be less important but still significant to changes in carbon emissions [26]. This is due to fact that even in the current hyper globalised global economy, exports still make up a minority in total affluence. However, the shift of manufacturing from developed to developing nations might increase the impact exports can have on changes in carbon emissions. This is because the developing countries where manufacturing is transferred to, commercial technology is less advanced and carbon intensity from primary emissions such as in the power dispatch sector is higher. This increases the total carbon intensity of manufacturing worldwide. It has been shown that on national levels in amongst others China [27] and Iran [28], affluence is by far the most important key impact factor. However, there are also many counter examples (see section 5.2), but also in turkey it has been shown that there is no causal evidence from the real GDP per capita to carbon emission per capita [29]. In total, the expectation is that affluence is a very impact factor for the change in carbon emission, but less important than previous national and international studies suggest.

5.3 Technology

Under the label technology two independent factors have been included. Firstly, changes in energy efficiency and secondly changes in carbon intensity. This is because improvements to energy intensity has largely been attributed to improvements in technology driven by research and development [30]. Shuai et al. (2017) [22] have argued that technology has smaller effects on total carbon emission globally. However, it is the main driver for the decrease of carbon emission in developed countries. Compared to lower income countries, high income nations have relatively low changes in affluence and population compared to the rest of the world. Thus the expectation is that changes in energy efficiency or carbon intensity will have strong impacts on the change of carbon emissions. All in all, the prediction is that advancement in technology has a strong impact on the change in carbon emissions. However, technological improvements will have stronger effects in high income countries compared to low income countries.

5.4 Social factors

Social factors is a category which has not been yet been extensively studied within the context of the IPAT methodology. For this reason it is difficult to estimate how much income inequality will affect changes in carbon emissions. Knight et al. (2017) [24] have argued that that countries with a higher Gini index have lower carbon emissions. The reasoning behind this is that if only a small proportion of the population has a high income, only this small population consumes a lot of resources. This leads to the fact that only a fraction of the people have a high carbon footprint. This means the larger the income inequality in a given nation is, the smaller is the proportion of high polluting people. In such countries, carbon emissions per capita are relatively low. However, this does not give direct insights on how carbon emissions change with the Gini index. In the same paper it was argued that only individuals with high income are willing to participate in pro-environmental action. In fact, only high income individuals have the means to lower their carbon footprint. If there might be a fraction of the population which struggles to meet basic needs such as security, reduction in carbon emissions are not a priority. For these reasons if there is high income inequality, no or low efforts for carbon mitigation might be in place. This leads to the fact that with lower income inequality positive changes in carbon emissions might occur leading to a positive relationship between the Gini index and changes in carbon emissions. In other words the expectation is the lower the Gini index of a country is, the steeper are the decreases in carbon emissions of the same nation.

6 Empirical analysis

The empirical analysis is split up into 2 sections. For the first part, it is checked if the full potential of the information that is stored in panel data can be taken advantage of. Here the Hausman test was completed to see whether fixed or random effect should be used. Next, the Breusch-Pagan Lagrange multiplier has been used to analyse if there are variances between the nations and if there exists a measurable panel effect. For the second part, the panel data analysis itself was carried out. Random effects has been utilised to estimate the empirical results for the coefficients of equation 6.

6.1 Hausman Test and Breusch-Pagan Lagrange multiplier (LM)

To preform panel data analysis, it first of all has to be established whether fixed or random effects should be used to run the analysis. When running fixed effects, it is assumed that an independent variable for a given country might influence (in terms of a bias) another independent or the dependent variable and this has to be taken into account. In essence this describes the assumption that there exists a correlation between the error term of a specific country and the predicted variables. Fixed effects removes biases originating from time invariant characteristics. This is essential to extract the net effects of the independent variable to changes in carbon emissions in the case of this research. Furthermore, it is important to note that with a fixed effect model, each nation is treated differently. This means that an individual error term of a country should not be correlated with any other country.

If these error terms are in fact correlated between countries, fixed effects can not be used since these interferences might not be correlated. This need to be taking into consideration, which can be done by using random effects.
The main differences between random and fixed effects is that in random effects, variations between countries are assumed to be random and uncorrelated with the independent variables. In other words, if differences between the countries influence the dependent variable directly, random effects should be used. The Hausman test was developed to quantify which model should be used, fixed or random effects. It measures whether or not the error terms are correlated. In general, the Hausman test looks at if the fixed effects and random effects estimates of the coefficients are significantly different. The null hypothesis is that individual effects are uncorrelated with other independent variables. The statistical results of the Hausman test can be found in table 3. The result clearly shows that differences in the coefficients are not systematic. This means the null hypothesis, that individual effects are uncorrelated with the other independent variables could not be rejected. Random effects should be used. This means variations across countries are random and uncorrelated with the independent variables.

Now that is has been established that random effects should be used, it is important to test for random effects themselves. The Breusch-Pagan Lagrange multiplier tests if there exists a panel effect in the data. This is done by checking if there exist variances across countries. The null hypothesis that variances across countries are zero could be rejected. This means there are significant differences between the nations, therefore a panel data analysis with random effects is appropriate.

Coefficients	Fixed (f)	Random (r)	Difference	Standard Error
Population growth	1.181828	1.110234	0.071594	0.185087
Change in carbon intensity	1.0318	1.029699	0.002101	0.0048887
Change in energy efficiency	0.8097621	0.8092129	0.0005492	0.0045266
Change in GDP per capita	0.2180981	0.2208038	-0.0027056	0.001912
Change in exports	0.0730509	0.0799065	-0.0068556	0.0027155
Gini index	-0.0359779	-0.0190462	-0.0169317	0.0303336

Table 3: Statistical result of the Hausman test with $X = (f - r)'[(V_f - V_r)^{-1}](f - r) = 8.84$ and $P > X = 0.1830$.

6.2 Panel data analysis with random effect

As mentioned before, this paper uses data fully provided from the world bank for 120 different countries and territories and altered with equation 1. Estimating the coefficients has been done with equation 6 and the statistical results on a global level have been summarised in table 4. Here the statistical result of a panel data analysis on the change of CO_2 emission with random effects are shown. Model 1 summarises the results of all 120 included countries. Model 2 presents the statistical outcomes for countries the World Bank labels as high income, while model 3 only includes low income countries. It is important to note that for all three models, the Hausman test and the Breusch-Pagan Lagrange multiplier has been preformed, yielding the same results: random effects should be used, while there exists a significant panel effect.

Change in CO_2 emissions	Coeff.	Std. Err.	$P > z$	95% Conf.	
Model 1: Global					
Population growth	1.110234	.1735458	0.000	0.77009	1.450377
Change in carbon intensity	0.2208038	0.007978	0.000	0.2051672	0.2364403
Change in GDP per capita	0.8092129	0.0179951	0.000	0.7739432	0.8444827
Change in energy efficiency	1.029699	0.0147666	0.000	1.000757	1.058641
Change in exports	0.0799065	0.0095744	0.000	0.0611409	0.0986721
Gini index	-0.0190462	0.0239371	0.426	-0.065962	0.0278696
Model 2: High income					
Population growth	1.191194	0.1796112	0.000	0.8391623	1.543225
Change in carbon intensity	0.2307363	0.0136643	0.000	0.2039549	0.2575178
Change in GDP per capita	0.7862531	0.0275488	0.000	0.7322584	0.8402477
Change in energy efficiency	1.078289	0.0291313	0.000	1.021193	1.135386
Change in exports	0.0839758	0.019832	0.000	0.0451059	0.1228458
Gini index	0.0478406	0.0207539	0.021	0.0071636	0.0885176
Model 3: Low income					
Population growth	1.652051	0.5160049	0.001	0.6407004	2.663402
Change in carbon intensity	0.2077054	0.0191217	0.000	0.1702275	0.2451832
Change in GDP per capita	0.8396456	0.0391898	0.000	0.762835	0.9164561
Change in energy efficiency	1.008425	0.0303558	0.000	0.9489288	1.067921
Change in exports	0.067955	0.0210658	0.001	0.0266669	0.1092432
Gini index	-0.0753937	0.0557275	0.176	-0.1846176	0.0338301

Table 4: Statistical result of a panel data analysis on the change of CO_2 emission. Model 1 summarises the results of all 120 included countries. Model 2 presents the outcome of the statistical analysis for high income countries, while model 3 only includes low income countries.

7 Discussion

To start of with, from model 1 in table 4 it can be seen that changes in the combination of both independent variables under technology have the strongest effect on the change in carbon emissions globally. The interesting result is that the coefficient for energy efficiency is almost 5 times as big as the on for carbon intensity. This means that it is a great deal more important to focus on the decrease of the energy that is consumed for every unit of economic output, rather than to decrease the emissions stemming from energy production. Furthermore, it is interesting that this result is different to most previous studies on national level. In addition, population growth is the independent variable with the highest overall coefficient on a global level. This support the fact that population growth is one of the key impact factors on changes in carbon emissions. Every unit increase in population growth increases the change in carbon emission the most, out of all variables. This finding differs from the results found in previous studies on a global level [22]. Here it was suggested that population is the least important factor out of the IPAT equation for driving carbon emissions. Moreover, contrary to previous research, changes in affluence are the least important impact factor on the change of carbon emissions with the exception of the Gini index. However, as predicted, change in GDP per capita is more impactful than exports. In fact, the effect is about 10 times as strong, while change in exports is still significant but there are just small effects. Finally, on a global scale, social aspects (the Gini index) did not show any significance. Looking at model 2 and 3, significant differences between high and low income countries can be identified. First of all, both population growth and change in affluence (GDP per capita and exports) has a stronger effect in low income countries. This is not very surprising. In the majority of high income countries, affluence and population is relatively constant compared to the developing world. The change in carbon emissions thus have to be driven by the other factors. Especially population growth with a coefficient of 1.65 in low income countries is strikingly more impactful than for high income countries. The effect of growth in GDP per capita is in fact very similar between model 2 and 3. Nonetheless, an increase in the growth of GDP per capita increases the change in carbon change more in low income countries. This supports the initial assumption that because manufacturing in developing countries is more carbon intensive, changes in affluence has a stronger impact. However, the coefficient for changes in the amount a nation exports is slightly higher in high income nations, which is very surprising. This does not support the assumption that globalisation increases the rate of the growth of carbon emissions. Nonetheless, this difference between the two coefficients is extremely small and almost insignificant. All in all, in low and high income nations, changes in GDP per capita dominates affluence in regards to changes in carbon emissions. Changes in exports are insignificant in comparison, especially differences between low and high income nations can be disregarded.

As anticipated, technology has a much more significant effect in high income countries. This can be traced back to the same reasoning mentioned before that affluence and population are relatively constant in high income nations. Finally, it is interesting to see that for social factors, effects are only significant for high income countries for total carbon emissions [24], but also for changes in the growth of carbon emissions. However, contrary to total carbon emissions, the relationship between the the Gini index and changes in carbon emissions is positive. This means income inequality increases the change in carbon emissions only for wealthy nations, just as expected. This effect has been visualised in figure 5. Here it can clearly be seen that the higher a nation's GDP per capita is, the more does income inequality affect changes in carbon emission. This effect becomes significant for nations with a GDP per capita above 40000 USD per capita (PPP). A possible explanation for this was given in section 5.4. In short, only individuals with a high enough income are willing or able to participate in pro-environmental action. This means that only wealthy people are actively affecting changes in carbon emissions. However, in developing nations there exists no urge to lower environmental impact regardless of the distribution of income, as more essential needs have to be met first. Thus from this it can be derived that in wealthy nations with high income inequality, the part of the population with low income drives the increase in emissions.

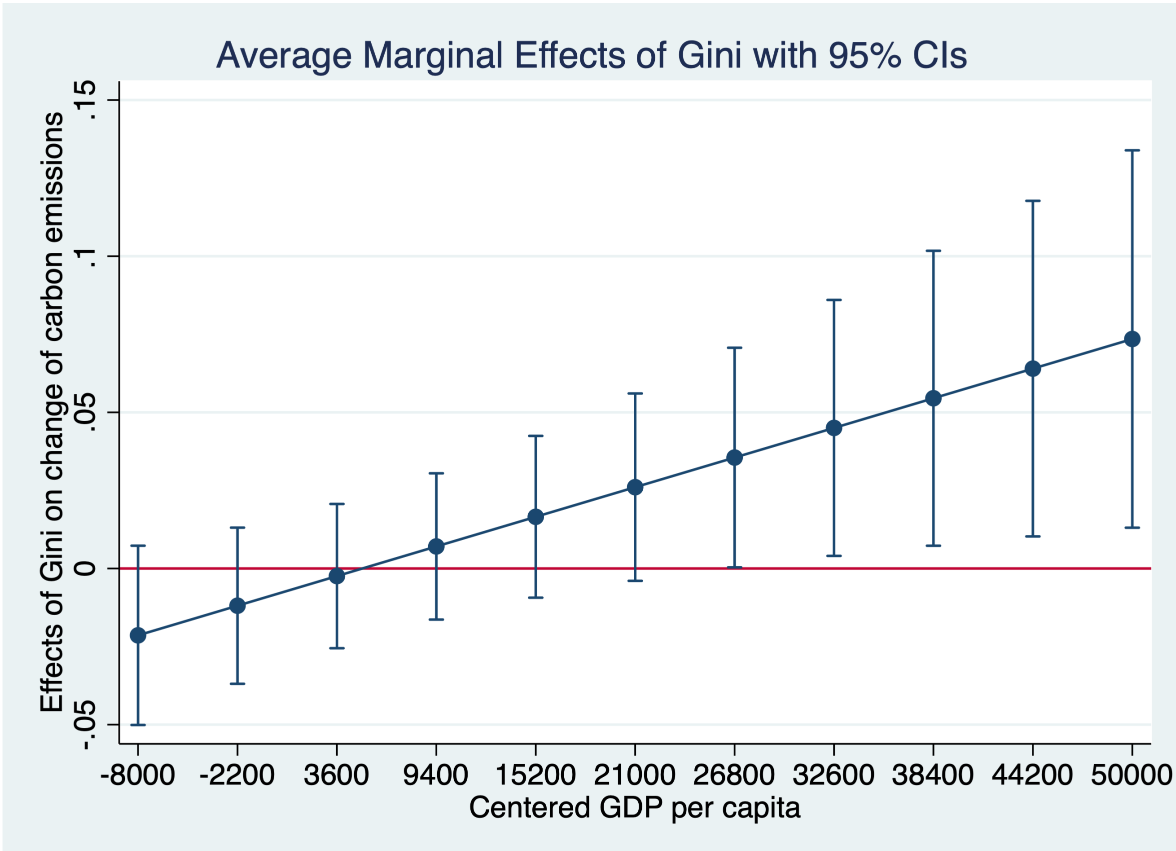

Figure 5: Interaction between Gini and GDP per capita on carbon emission. GDP per capita is varied from 0 to 60000 USD per capita (PPP).

8 Conclusion and policy implications

To conclude, the adjusted extended Kaya identity used in this paper was successful in extracting the key impact factors in the change of carbon emissions. An analysis on a global scale has produced similar results as the research done on national level. Especially it was confirmed that in high income nations, technological is the main driver for change in the growth of carbon emission. In addition, it was able the reproduce the fact that income inequality is only significant for high income nation. However, results and interpretations with this model differ from previous studies on national and global level. Most importantly, by looking at the change in the growth of carbon emissions on a global level, affluence has a much weaker effect than most national studies suggest.

The results summarised in table 4 have some important policy implications, which can be split up into low and high income nations. Obviously very few nations are willing to decrease their economic output to reduce carbon emission. Countries are only willing to participate in carbon mitigation efforts, if the total welfare of a nation increases. Currently the welfare of a nation is highly dependent on economic growth. Because of this, decreases in the growth of carbon emissions must be driven from different areas. To reduce the growth of carbon emissions, without affecting economic productivity, first and foremost the problem of population growth has to be tackled especially in developing countries. Technological advancements and economic growth are less important, but certainly still important. The Kyoto protocol and the Paris agreement both already have provisions of developed nations (Annex 1 countries) pledging to help developing nations (Annex 2 countries) to improve technological advancements. The focus here should be on improving energy efficiency. This mean that more funds should be put in to decreasing the amount of carbon that is produced for every unit of economic output. This can be done by decreasing the amount of energy machinery in manufacturing need (increase efficiency). Investments into renewable energy are less important in changing the direction of growth in carbon emissions due to the coefficient of carbon intensity being significantly smaller. Finally, for low income countries, counter intuitively it is more important to increase the average income of the population. Before all the basic needs are met, no focus on pro environmental actions can be taken. Once poverty is eradicated, income inequality can be tackled to decrease the growth of carbon emissions. However, at least in the context of climate change, improving income inequality will not help in the mitigation of carbon emissions. In high income countries, population growth is already almost constant and due to the fact that countries are not willing to decrease their economic output, technological advancements and social factors would have to be worked on. Conveniently, the key impact factor on change in carbon emission in high income countries is technology. As mentioned before, the focus should be put in decreasing the amount of carbon that is emitted from every unit of economic output. This can be combined with knowledge and technological advancements with developing nations, for them to also improve. Finally, tackling income inequality in very rich nations might also help to reduce the growth carbon emission.

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