ISCTE Business School
Instituto Universitário de Lisboa

Clustering of Countries According to Their Contribution to GDP Growth and its Subsequent Effect on CO2 Emissions.

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Final Dissertation for the conclusion of the Master's in Economics

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October 2019

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ABSTRACT

A study on the EKC curve and the N-shaped relationship between CO2 emissions and GDP per capita with a focus on expenditure components of GDP contributions to GDP growth. The investigation took place for a balanced panel of 46 countries with data from 1971 to 2014. Explanatory variables for trade, investment and government expenditure are included in the form of the openness ratio, investment ratio and government size. Furthermore, clustering of the 46 countries according to the contributions of the components to the GDP growth using the k-means methods was conducted. The clusters were dummied and introduced as explanatory variables in the models. For more consistency, the Within-Between or Mundlak's, a mixed model, estimator was used to estimate effects of the explanatory variables on CO2 emissions. A positive relationship between contributions of trade to GDP growth and subsequently trade and CO2 emissions was found. Furthermore, evidence for an N-shaped EKC curve was observed.

Um estudo focado na EKC e na relação polinomial de terceiro grau entre emissões de CO2 e PIB per capita com enfâse na contribuição dos componentes do PIB no crescimento do PIB. A investigação usa um painel balançado de 46 países entre os anos 1971 e 2014. Variáveis explanatórias para as trocas comerciais, investimento e despesa do governo foram introduzidas no modelo, usando o rácio de abertura, o rácio de investimento e o tamanho do governo. O método de agrupamento k-means foi usado para agrupar os 46 países de acordo com as contribuições dos componentes do PIB no crescimento do PIB. Estes agrupamentos foram introduzidos como dummies nos modelos. Para uma maior consistência o estimador de Mundlak, um estimador misto, foi utilizado. Uma relação positiva entre a contribuição das trocas comerciais e as emissões de CO2. Ainda mais, foi encontrada evidência de uma curva com a forma N.

Keywords CO2 Emissions; EKC; Mixed Model; GDP Components; Trade; Clustering

JEL Classification: Q50, Q53, Q56

AKNOWLEDGEMENTS

Foremost, I would like to thank my Supervisor Prof. Henrique Monteiro for his immense patience, knowledge and dedication to the craft. For his help with the research, analysis, writing and anything in between. Without him this thesis would not have been completed.

I would also like to thank the rest of the committee that presided my presentation: the president, Dr. and Prof. Cristina Maria Paixão de Sousa and Juri member Prof. Cátia Sofia Duarte Sousa, for their relevant questioning and experienced advice.

My thanks to my friends, Luís Casinhas, whose support was essential for the continuous development of the thesis, and Mário Lima, a brother in all that matters, for the long brainstorming sessions.

Finally, a thank you to my parents, without them I would not have gotten here. Their continuous support, patience and love was a lifeboat amidst the storm.

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1. INTRODUCTION

The last few decades have had a special focus on the sustainability of the environment. Environmental concerns have been piling up and consequently we need glimpses through studies in how to deal with them. CO2 emissions is chiefly one of the biggest concerns as the principal contributor to global warming. As such, this study aims to firstly to provide a broader and hopefully newer view into the topic of CO2 Emissions through the analysis of the contributions to GDP growth of each country in the panel; secondly to observe the shape of the relationship between CO2 and Income (Environmental Kuznet's Curve), comparing to recent studies of the EKC curve; and thirdly to compare results with the previous GDP components ratios, such as the Openness Ratio in order to ascertain their true impact. I will try to analyze this relationship from several viewpoints. The first one being through the conventional method, the ratios of the components in the total GDP growth, and the second being the clustering of countries in the panel using the k-means method.

This clustering is especially important for this thesis as I believe it could provide a unique insight for future policy design. As each country is unique in its composition, so is their policy design. By segregating the countries in the panel, according to their specific GDP growth constitution, it is my hope that policy design can have a narrower approach to mitigate CO2 emissions by targeting certain sectors of the economy.

For this purpose, I gathered a panel of 46 countries (table 10, Appendix) and tried to make it as income uniform, across different incomes, as possible, more on that in the data section.

Having the panel and subsequent data in consideration, the main hypothesis is that an N-shaped EKC curve will observed, as more and more countries move to a technological state and enter the upturn of the respective curve. As for que ratios, their impact is varied according to former studies due to contrasting effects on emissions. However, through the clustering method, my hypothesis is that the contrasting effects will be mitigated and thusly allow us to observe the impact of different GDP contributions on CO2 emissions.

2. LITERATURE REVIEW

The Environmental Kuznets's Curve (EKC) is a mainstream tool for environmental policy, relating income, measured as GDP, to environmental degradation. Derived from the original Kuznets' Curve concave shape – which drew the relation between income per capita and inequality (Kuznet, 1955) –, it depicts a decreasing marginal returns relationship (inverted U-shaped function) between environmental degradation and income. Its properties were first observed by Grossman and Krueger (1993) in a study of the potential environmental implications of the North America Free Trade Agreement (NAFTA). Using a panel data with pollution indicators from many cities all over the world from 1977-1984, they observed an inverse U-shaped curve between sulphur dioxide (SO_2), suspended particle matter (SPM) concentrations and per capita GDP. Several studies followed from this analysis, the main trend is the analysis of SO_2 and SPM (Shafik and Bandyopadhyay, 1992; Panayotou, 1993; Selden and Song, 1994), and later water pollution indicators (Grossman and Krueger, 1995), usually in the form of quadratic and/or cubic functions often in natural logs.

However, none of the approaches permitted a causal analysis of the behavior of the relationship (Arrow *et al.*, 1995), as neither the origin of the pollution nor its consequences are analyzed. The need to understand that causality caused a shift in the focus of analysis from different dependent variables, different pollutants, to potential explanatory variables that could help understand the shape of the curve and thus its causality while at the same time trying to solve the omitted variable bias, such as decomposition of the industry by their share in GDP (Panayotou, 1997), income inequality (Torras and Boyce, 1998) and economic freedom (Carlsson *et al.*, 2003).

The EKC can be potentially explained by three factors according to Stern (2017):

1. Scale Effect, as income increases so does pollution, *ceteris paribus*, as a result of increased production;
2. Composition Effect, the type of industry defines the inputs and intensity of production, thus both the quantity of pollution and the type;
3. State of Technology, both in the efficiency and process, i.e., pollution can be reduced as technology is more efficient at converting energy or it shortened the production process and thus less time is required to produce the same.

Dinda (2004) adds to this the preferences of higher-income people for a cleaner environment, that is environmental quality income elasticity behaves like a "luxury good".

Trade is a source of income growth often thought to cause directly or indirectly all three factors described by Stern. Grossman and Krueger (1993) in their study used the sum of exports and imports as a share of GDP, trying to predict the effect that open trade between Mexico, USA and Canada could have on SO_2 and SPM concentrations. They found SO_2 concentrations to be lower in cities with high levels of trade contrary to expected. Shafik and Bandyopadheyay (1992) expanded the approach to 148 countries between 1960-1990 and reached similar conclusions.

Suri and Chapman (1998) took a different approach, finding different results. Regressing with a fixed-effects estimator for total commercial energy instead of pollution, and exports and imports in the form of trade manufactured goods as a share of domestic manufactured goods production for data between 1971 and 1991, they concluded that exports increased energy consumption and thus pollution while imports decreased it. Also observing the turning point of the model, the maximum of the EKC function in per capita GDP, without trade variables to be $55,000 and for the model with trade to be $224,000, both outside of the sample range, making the relationship monotonically increasing.

In fact, using the same specification with prices as independent variable and another with CO_2 as dependent variable and applying it to a wider range of countries with an autoregressive distributed lag (ADL), all variables squared and data from 1950-1990, Agras and Chapman (1999) found that the trade variables became insignificant and with inverted signs (trade reduces pollution) in both models. With a turning point at $13,630 per capita GDP for the carbon model and above $60.000 for the energy model, leading to inconclusive results that may have resulted from overspecification. The turning point for the carbon model is well within the sample indicating an EKC, contrarily to Holtz-Eakin and Selden (1995) analysis on CO_2 emissions estimated using fixed-effects model, with a bigger panel, that an EKC existed, although the turning point was at $35,438 for the quadratic specification and $8 million above the quadratic logarithmic specification, well above sample range, thus the curve was effectively monotonically increasing.

Environmental economics theory on trade, namely the pollution haven hypothesis which states the first part, or second in N-shaped curves, of the EKC can result from the exportation of pollution from high-income countries (Dinda, 2004), coupled with the growing concern of the environmental degradation caused by CO_2 emissions, caused a pragmatic shift in EKC studies, the use of CO_2 as a dependent variable.

But one can argue that the ambiguity of the effect of trade openness on pollution is due to the inherent causality trade has on the factors that describe the EKC. Scale effects cause the trade coefficient to be positive, as trade increases income and thus pollution, while input and technological effects that may arise from increased trade have a negative effect on pollution. That is, trade can have a positive coefficient if scale effects overtake input and technological effects, and negative if they do not (Jalil and Mahmud, 2009). Several studies tried to address this issue by accounting for all three factors separately, however, even then results seem to be inconclusive. Cole (2004), with a panel data of 21 countries CO_2 and SO_2 emissions from 1980-1997, divides trade into share of dirty exports/imports to/from non-OECD countries in total exports/imports, to measure the pollution haven hypothesis, and the usual trade openness ratio, still finding a negative sign for the relationship between the openness coefficient and pollution. However, such results can be due to the endogeneity of trade or missing variable bias, as Frankel and Rose (2005) have shown by finding the openness coefficient sign can change with the introduction of Instrumental Variables (IV).

One can test for the effect of trade in a single country using time series. It has been argued that a single country time-series aiming to study the EKC should be approached more often (Dinda, 2004). Time-series permits the study of individual effects that may explain in some way the relationship. Furthermore, time-series studies allow an analysis of the long-term relationship and causality between variables. However even then results regarding the EKC seem to be conflicting, once again possibly due to omitted variable bias or differences in the samples (Peters, Briceno and Hertwich, 2004; Jalil and Mahmud, 2009; Dogan and Turkekul, 2016). What is interesting is the effect trade has on CO_2 emissions in these studies, most finding a small negative effect, sometimes insignificant, even when comparing across different countries (Halicioglu, 2009; Jalil and Mahmud, 2009; Dogan and Turkekul, 2016).

Investment is related to pollution much in the same way as trade is, through the three causing factors of the EKC described previously (Scale Effect; Composition Effects; State of Technology). Investment is usually tested to check for the pollution haven hypothesis and "race to the bottom" (Wheeler, 2001) - deregulation of business laws to encourage foreign investment often associated with environmental degradation, which in turn increases production - and thus the scale effect. This is often done by incorporating Foreign Direct Investment (FDI) as an explanatory variable, usually at a country level and thus using time series techniques. However, that does not imply the investment ratio (investment to GDP ratio) is overlooked (Ibrahim and Law, 2014).

Few studies use the investment ratio as an explanatory variable, some just use it as an instrumental variable for income (Frankel and Rose, 2005). Ibrahim and Law (2014), with data from 2000-2008 using Generalized Method of Moments (GMM) found an EKC for CO_2 for a panel of 68 countries, for both the reduced model and the extended one with the trade and investment ratios. Both ratios' coefficients were found to be negative, decreasing pollution, with the trade impact being almost insignificant, consistent with the previous studies, once again possibly due to the conflicting effects of scale and state of technology. Investment, on the other hand, while negative, was significant, thus implying the possibility of technological improvement decreasing CO_2 emissions. Both the studies that use FDI and the investment ratio use trade openness ratio as an explanatory variable, presumably to avoid omitted variable bias (Harbaugh, Levinson and Wilson, 2002; Ibrahim and Law, 2014; Lau, Choong and Eng, 2014). Trade and Investment are not the only components of GDP often discussed in EKC literature; government expenditure has its own fair share of attention. Government size is often thought to impact environmental quality, yet there are several theories on the topic with limited consensus on its empirical proof.

One of the first papers to touch upon this topic was Carlsson *et al.* (2003). They tested for the effects of political and economic freedom on the impact of government size on CO_2, for a panel of 75 countries for 30 years. They found the effect of government size on emissions to be dependent on political freedom, i.e., at high levels of freedom government size increases emissions.

Bernauer and Koubi (2006), in order to ascertain if government size influences Sulphur emissions as a result of the provision of environmental quality as a public good. With a sample of 42 countries from 1971-1996, they discover the coefficient of government ratio to be positive, thus, as government size increases so do emissions.

Halkos and Paizanos (2013) observed, for a sample of 77 countries from 1980-2000, the total effect of government ratio on SO_2 and CO_2 emissions to be negative with a 1-year lag. Similarly, in a study of the 12 richest European countries' sulphur emissions, López and Palacios (2014), found government expenditure along with the energy tax policy to have a negative impact on emissions, which is in line with his previous paper on the same topic (López *et al.*, 2011).

Total consumption is not, to the best of my knowledge, used as a regressor in EKC studies, may be due to its correlation to all other variables making multicollinearity a problem. At most, consumption of energy is used both as dependent variable (Suri and Chapman, 1998) or as an independent variable in EKC studies most usually having a positive coefficient and thus increasing pollution (Halicioglu, 2009; Dogan and Turkekul, 2016; Allard *et al.*, 2018). Consequently, consumption as a share of GDP will have to be omitted and only its contribution to GDP growth analyzed to solve for the multicollinearity issue.

Before proceeding into the data section of this paper, according to Stern (2017), the critique of the econometrics of EKC papers must be acknowledged. The EKC regression specification must contain the cubic term, it has been argued that omitting it leads erroneously to an EKC as a result of the suppression of the emissions curve at higher values (Cole, 2004; Stern, 2017; Allard *et al.*, 2018). Furthermore, the values of the environmental impact cannot be allowed to be zero or less, unless there is deforestation, as both emissions and GDP never reach those values in the years studied. This problem can be solved by using the natural logarithms of the variables.

Omitted variable, as previously discussed, is a concerning problem in the EKC literature. It has been found by Stern and Common (2001) that the EKC turning point is incredibly sensitive to the sample chosen, a similar conclusion to Harbaugh, Levinson and Wilson (2002). Most importantly the variables must be tested for cointegration. If the variables are not cointegrated then the required steps, taking the first difference of the data or the between estimator must be taken otherwise the regression can be spurious if estimated with Fixed-Effects model.

The aim of this dissertation is to test if different ratios of the contributions of the components of GDP for GDP growth influence pollution distinctly, not just to measure the effects of the components on CO_2 emissions. For that purpose, other than trade, consumption, investment and government expenditure will also have a role to play. Could different ratios, a focus on certain components of GDP for growth cause different effects on pollution?

3. DATA AND METHODOLOGY

2.1. DATA

In order to test the effect of the contributions to GDP, data of different countries along the years is used. The panel data initially spread over 69 countries from 1960 to 2018, with all ranges of income for a better representation. The number of countries stemming from the lack of worldwide data on CO2 emissions and GDP per capita from yearly years required for an in-depth analysis. The number of missing observations was relatively large, especially for low-income and Eastern European Countries, consequently, for the sake of consistency, interpolation was not considered due to its heavy impact on predicted values. The final panel is balanced and has 46 countries (Table 10 in the Appendix) with data from 1971 to 2014 and thus is a 46x44 panel with N>T. The year range was carefully chosen. It had to be big enough to capture the variations of the contributions to growth of the countries along the years while at the same time maximize the number of countries in the balanced panel. These countries' income is not homogeneous, i.e., they belong to different income groups for better global analysis. The income groups are defined and the countries are grouped by the World Bank according to their GNI per capita (see table 9 in the Appendix), available at https://datahelpdesk.worldbank.org/knowledgebase/articles/906519. The EKC analyses environmental degradation and income per capita. CO2 emissions per capita and real GDP per capita are the instrumental variables, respectively, of environmental degradation and income per capita is usually the case in EKC related literature (Ang, 2007; Wagner, 2008; Jalil and Mahmud, 2009). For empirical consistency - previous studies show these variables may be related to the dependent variable - the openness ratio, investment ratio, government size, and the contributions of each expenditure component of GDP to the yearly GDP growth are included as well. All data is yearly and was obtained or calculated using data from the World Bank database, available at https://data.worldbank.org/.

Real gross domestic product (GDP) is measured in 2010 dollars. Per capita GDP was obtained from the division of real GDP by the population of each year due to missing data of GDP per capita for some countries in the World Bank database after which it was transformed with logarithms to better represent yearly percentage changes. CO2 emissions are measured in metric tons per capita and identically to GDP per capita, transformed with logarithms for the same reason. The expenditure components of GDP (Consumption, Government Expenditure, Investment, Exports and Imports) were calculated using the yearly weight of each component in the yearly GDP (all in 2010 dollars), and their contributions to yearly GDP growth calculated with the usual approach applied by international entities (Kranendonk and Verbruggen, 2005).

$$\left(\frac{\mathrm{C_{GDP}}}{\mathrm{GDP}}\right)_{t-1} * \Delta \mathrm{C_{GDP\,t}} \tag{1}$$

The weight of the component in the GDP of the previous year multiplied by the growth of the component in the present year gives the contribution of the component to growth in the present year.

$$\mathrm{CConsumption} + \mathrm{CGoverment\ Expenditure} + \mathrm{CCapital} + \mathrm{CTrade} = \Delta \mathrm{C_{GDP\,t}} \tag{2}$$

The contribution of trade is simply the subtraction of the negative contribution of imports to the contribution of exports (Kranendonk and Verbruggen, 2005).

Finally, the openness ratio, investment ratio and government size are the respective components of GDP, in the case of the openness ratio Exports + Imports, divided by the GDP of the same year.

Before proceeding it is important to acknowledge the advantages and shortcomings of the contribution calculation method used. There is no consensus yet on the direction of causality between consumption and exportation (Konya, 2001; Yang, 2008). An increase in the contribution of exports to GDP growth can cause an increase of consumption which in turn increases its contribution to growth, beckoning the question if one drives the other and thus is the ultimate cause of its contribution to GDP growth. Furthermore, separating the domestic impacts from the foreign ones becomes an arduous task. That is the growth of the contribution of exports to growth may result from more demand from abroad which in turn causes domestic consumption to eventually increase, or vice-versa ('Monthly Bulletin', 2005)[1].

These limitations, however, are not reason enough to exclude the analysis of the contributions. The openness ratio, often used in other studies even just to eliminate omitted variable bias, is also bound by the same limitations (Peters, Briceno and Hertwich, 2004; Jalil and Mahmud, 2009; Dogan and Turkekul, 2016). It does not distinguish in any way trade caused by internal or external factors, but its expected correlation to CO2 emissions growth makes it a variable which cannot be ignored. The contributions, although not explored extensively, may reveal important observations in the understanding of the relationship between income and environmental degradation. They also represent one of the few ways to obtain insight into the type and cause of income growth. Additionally, together they may provide information on the components of GDP without causing endogeneity in the model as would be the case if the components were introduced as absolute values and not as ratios.

2.1.1. DESCRIPTIVE STATISTICS

Table 1 gives a brief description of the basic characteristics of each variable later used in the regressions. Starting with the dependent variable, CO2 emissions, measured in metric tons per capita, we can observe a standard deviation close to the mean, indicating the variable's observations are relatively close to the mean. The minimum value is 0.2 and within the standard deviation from the mean, however, the maximum value is more distant to the mean with a value of 40.6. This last value showing the possibility of an outlier hen compared to the mean and standard deviation values. This is exacerbated by the 3rd percentile value of 9.5. GDP per capita, shows, as expected a higher discrepancy in its values. The higher Income countries pull the mean value upwards. The max stands much farther from the mean and from the 3rd percentile, once again indicating a possible outlier. Considering the standard deviations, outliers and distribution of these values, the variables will be transformed with logs, as usual in the previous

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[1] ECB's Monthly Bulletin from June 2005, p.5

literature. Consequently, the correlation table 2 represents the transformed variables.

These two variables are highly correlated to each other, as shown in Table 2, which is expected. Figure 1 shows a simple scatterplot matrix. The relationship between CO2 emissions and GDP is shown to be almost linear towards the end where a slight curvature can be distinguished. Government Size boasts the strongest correlation with both CO2 emissions and GDP of all the ratios, at 0.545 and 0.582 respectively, which problematically may end up causing multicollinearity issues with GDP in the model.

Table 1: Descriptive Statistics

Statistic	CO2 Emissions	GDP	Openness Ratio	Investment Ratio	Government Size	Government Expenditure	Consumption	Investment	Trade
N	2,024	2,024	2,024	2,024	2,024	2,024	2,024	2,024	2,024
Mean	6.4	19,538.6	0.7	0.2	0.2	0.0	0.0	0.0	0.0
St. Dev.	5.7	19,331.1	0.6	0.1	0.1	0.0	0.0	0.0	0.0
Min	0.2	237.8	0.0	0.1	0.0	-0.1	-0.2	-0.4	-0.2
Pctl(25)	1.6	3,426.2	0.4	0.2	0.1	0.0	0.0	-0.0	-0.0
Pctl(75)	9.5	31,915.5	0.7	0.3	0.2	0.0	0.0	0.0	0.0
Max	40.6	111,968.4	4.4	0.9	0.4	0.1	0.2	0.3	0.5

Table 1 - *CO2 Emissions and GDP ratio are both in logarithms while all other variables are untransformed. Openness Ratio, Investment Ratio and Government Size are calculated using the method above. Government Expenditure, Consumption, Investment and Trade are not the absolute values, but the contribution of each component as calculated above.* **All tables are from R package "stargazer": (Hlavac, 2018)**

The other two ratios have a weak correlation with CO2 emissions and GDP, drawing caution once again to multicollinearity although less concerning than Government size. It is noteworthy, as stated previously, that the openness ratio is expected to be strongly correlated to CO2 independently of the resulted coefficient in the analysis, which is often contradicting as Frankel and Rose (2005) found.

The contributions of the components of the GDP are a representation of yearly GDP growth. Introducing them in the regression as independent variables could be problematic due to their inherent connection to the GDP component ratios. As such, they will indirectly enter the regression as a dummy. This dummy will be a result of a clustering method using the GDP contributions as centroids.

Table 2: Correlation Matrix

	CO2 Emissions	GDP	Openness Ratio	Investment Ratio	Government Size
logco2	1	0.892	0.317	0.167	0.545
loggdppc	0.892	1	0.290	0.008	0.582
opennessratio	0.317	0.290	1	0.155	0.028
investmentratio	0.167	0.008	0.155	1	-0.096
governmentsize	0.545	0.582	0.028	-0.096	1

Table 2 - *Where logco2 is the logarithm of CO2 Emissions per capita, loggdppc the logarithm of GDP per capita, opennessratio the Openness Ratio, investmentratio the Investment Ratio and governmentsize the Government Size. The variables on the first column are the same as the ones across the top.*

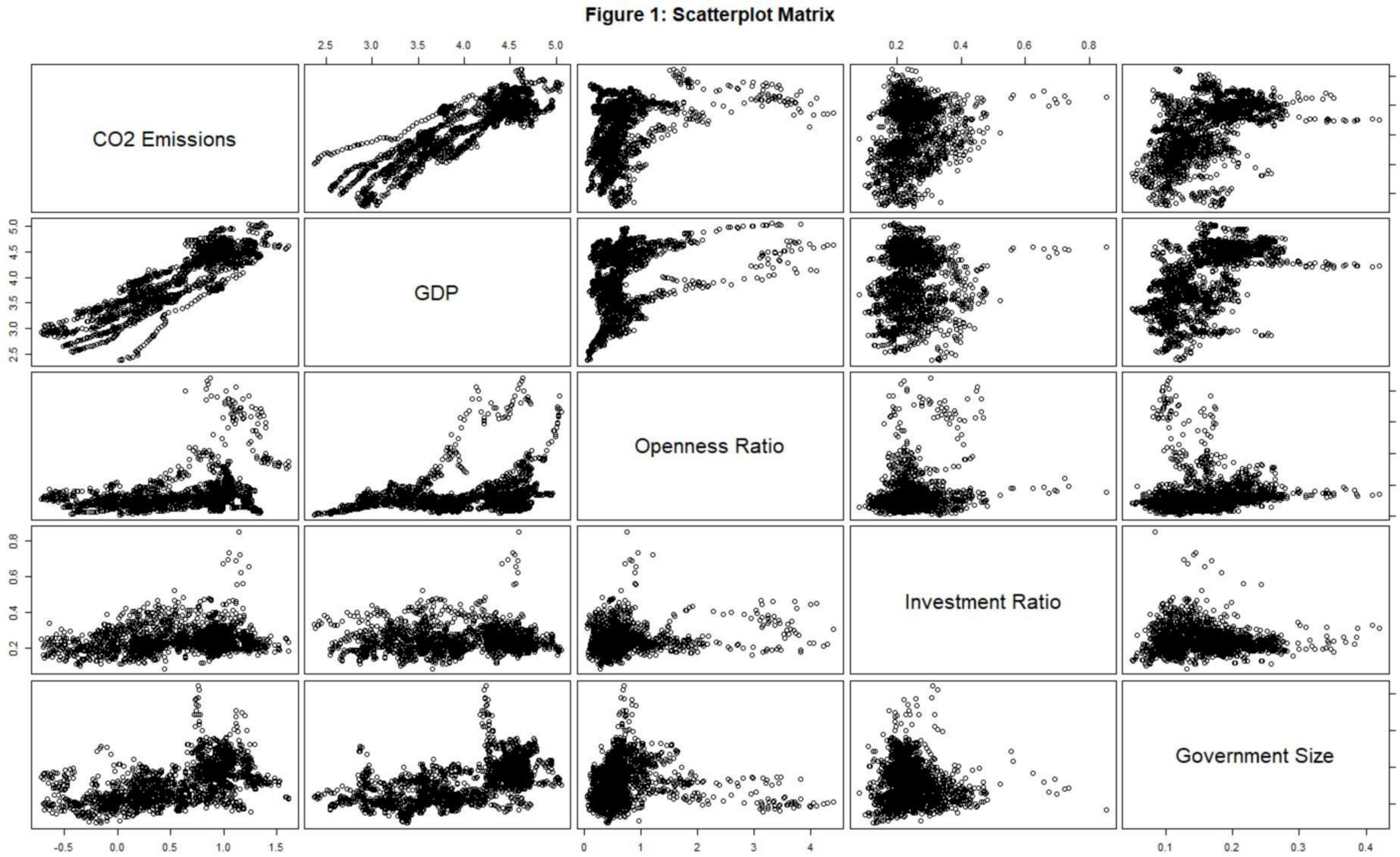


Figure 1 - *Scatterplot Matrix with all variables used in the regressions. CO2 Emissions and GDP are in logs.*

2.2. METHODOLOGY

2.2.1. MODEL

The EKC model checks the relationship between environmental degradation and income per capita. CO2 emissions and GDP (both per capita) are their replacements respectively in this study. The standard EKC model has income squared and occasionally cubed as well in an attempt to prove the variables have either an inverse quadratic function or an N-shaped polynomial relationship (Grossman and Krueger, 1995; Holtz-Eakin and Selden, 1995; De Bruyn, 1997; Panayotou, 1997; Torras and Boyce, 1998; List and Gallet, 1999; Dinda, 2004; Chandran and Tang, 2013; Stern, 2017). Explanatory variables are squared and cubed in an attempt to correct omitted variable bias, such as some measure of trade, usually the openness ratio (Suri and Chapman, 1998; Agras and Chapman, 1999; Cole, 2004; Bernauer and Koubi, 2006; Halicioglu, 2009; Jalil and Mahmud, 2009; Ibrahim and Law, 2014; Dogan and Turkekul, 2016; Allard *et al.*, 2018), or some measure of consumption, usually energy consumption (Carlsson *et al.*, 2003; Halicioglu, 2009; Chandran and Tang, 2013; Dogan and Turkekul, 2016). In the light of other studies findings, that is the absence of the GDP cubic term is EKC inducing, the cubic term shall be included in all the models along with the quadratic (Cole, 2004; Allard *et al.*, 2018). As previously stated, both CO2 emissions and GDP are in per capita values. Furthermore, considering the focus of this study, the openness ratio, investment ratio (Ibrahim and Law, 2014) and the government size (Carlsson *et al.*, 2003; Bernauer and Koubi, 2006; Halkos and Paizanos, 2013) will be included in the model. Most importantly, a dummy was created for the 5 and 3-mean clusters depicting the groups created by the K-means clusters. These dummies are introduced separately in each model for better inference, thus, for each regression method, 2 models were regressed.

The initial model has the form:

$$\begin{aligned}\mathrm{CO_2Emissions} = {} & \alpha + \beta_1\mathrm{GDP}_{it} + \beta_2\mathrm{GDP^2}_{it} + \beta_3\mathrm{GDP^3}_{it} + \beta_4\mathrm{Openness\ Ratio}_{it} \\ & + \beta_5\mathrm{Investment\ Ratio}_{it} + \beta_6\mathrm{Government\ Size}_{it} + \beta_7\mathrm{xCluster} \\ & + \varepsilon_{it}\end{aligned} \tag{3}$$

OLS, Within, Between and Random Effects are used to estimate. However, the estimation of the Within model causes a fundamental problem with the focus of this study: to analyze the dummy variables of the contributions in the regressions. The Within model in the presence of hierarchical data, that is both time-invariant and time-variant data is not the most optimal model for analysis. OLS cannot be the replacement due to its inherent assumptions that every time-invariant variable can be pooled into the same population, not distinguishing them (Bell and Jones, 2014). For the effects of this study, the Within model cannot be estimated. Furthermore, the Between model, another possible choice (Stern, 2017) does not model the intended relationships for analysis. In this case, it would model the effects between countries. As such another estimation method was adopted.

2.2.2. WITHIN-BETWEEN MODEL

Random-Effects estimate model (2) using GLS and does not eliminate time-invariant variables. However, within estimation has been preferred in the EKC literature. The Random-Effects assumption of independence between the covariates and the error, that the model is completely exogenous, is a strong assumption that is very rarely correct. This is proved by the Hausman Test in Appendix (Test 1), with a value of 0.008 which rejects the null. So, the Within model is estimated, eliminating the endogeneity (Bell and Jones, 2014; Bell, Fairbrother and Jones, 2019). But there are estimation methods that model that relationship directly, one of which is an adaptation of the Random-Effects model. Mundlak (1978), suggested including the mean of the time-variant independent variables in the Random-Effects model, such that the between effects can be modelled at the same time as the within. These means are time-invariant variables. The model becomes:

$$\begin{aligned} \mathrm{CO_2Emissions}_{it} = {} & \alpha + \beta_1 \mathrm{GDP}_{it} + \beta_2 \overline{\mathrm{GDP}_i} + \beta_3 \mathrm{GDP^2}_{it} + \beta_4 \overline{\mathrm{GDP^2}_i} + \beta_5 \mathrm{GDP^3}_{it} \\ & + \beta_6 \overline{\mathrm{GDP^3}_i} + \beta_7 \text{Openness Ratio}_{it} + \beta_8 \overline{\text{Openness Ratio}_i} \\ & + \beta_9 \text{Investment Ratio}_{it} + \beta_{10} \overline{\text{Investment Ratio}_i} \\ & + \beta_{11} \text{Government Size}_{it} + \beta_{12} \overline{\text{Government Size}_i} \\ & + \beta_{13} \text{xCluster} + \beta_{14} \text{Time} + \varepsilon_{it} \end{aligned} \tag{4}$$

With the means of each time-variant variable added and the time dummies mentioned previously. Now the coefficients of the time-variant variables are the within effects while the coefficients of their means are the difference between the between and within effects (Mundlak, 1978; Bell and Jones, 2014; Dieleman and Templin, 2014). This new model has the same coefficients as the within model while at the same time being able to model between effects estimated by the more efficient random model. But it can become more complete. If the time-variant variables are demeaned, as suggested by Berlin *et al.* (1999), one can obtain a model where the within and between effects are separately modelled, allowing for clearer interpretation (Bell and Jones, 2014). Furthermore, this subtle change of the model eliminates the collinearity between the variables and their means making estimations consistent (Bell and Jones, 2014; Dieleman and Templin, 2014; Rasbash *et al.*, 2015). Equation (3) becomes:

$$\begin{aligned}\mathrm{CO_2Emissions}_{it} = {} & \alpha + \beta_1(\mathrm{GDP}_{it} - \overline{\mathrm{GDP}_i}) + \beta_2\overline{\mathrm{GDP}_i} \\ & + \beta_3(\mathrm{GDP^2}_{it} - \overline{\mathrm{GDP^2}_i}) + \beta_4\overline{\mathrm{GDP^2}_i} \\ & + \beta_5(\mathrm{GDP^3}_{it} - \overline{\mathrm{GDP^3}_i}) + \beta_6\overline{\mathrm{GDP^3}_i} \\ & + \beta_7(\mathrm{Openness\ Ratio}_{it} - \overline{\mathrm{Openness\ Ratio}_i}) \\ & + \beta_8\overline{\mathrm{Openness\ Ratio}_i} + \beta_9(\mathrm{Investment\ Ratio}_{it} \\ & - \overline{\mathrm{Investment\ Ratio}_i}) + \beta_{10}\overline{\mathrm{Investment\ Ratio}_i} \\ & + \beta_{11}(\mathrm{Government\ Size}_{it} - \overline{\mathrm{Government\ Size}_i}) \\ & + \beta_{12}\overline{\mathrm{Government\ Size}_i} + \beta_{13}\mathrm{xCluster} \\ & + \beta_{14}\mathrm{Time} + \varepsilon_{it}\end{aligned} \tag{5}$$

One last advantage of modelling the random effects as above its that the correct standard errors are automatically estimated (Bell and Jones, 2014; Rasbash *et al.*, 2015), accounting for clustering and consequently serial correlation of the errors. The last point is especially important. The Breusch-Godfrey test (Test 2 in Appendix) revealed the presence of serial correlation in the errors which would be a problem for the fixed and OLS estimators. But the RE already captures the heterogeneity of the data and explicitly models serial correlation, in fact, a study by Dieleman and Templin (2014) showed that the Within-Between was still the better choice compared to Fixed-Effects and Random-Effects for small N panels in the presence of heteroskedasticity and autocorrelation. Still, robust coefficients for heteroskedasticity can be applied for inference.

2.2.3. CLUSTER ANALYSIS

Clustering the contributions of the components of GDP growth achieves two objectives. First, it eliminates the possibility of multicollinearity between them and the ratio of the components, used in the calculation process (equation 1), and 2nd allows a division of the countries by type of contribution to GDP growth to be later introduced in the model as dummies. The last advantage is especially important given the objective of this dissertation: isolating the effects of each component and its contribution to GDO growth have on CO2 emissions. The clustering methods described below were thus applied to four contributions of the components of GDP.

Considering the nature of the data, the best clustering method and the most widely used is the k-means versus the hierarchical clustering which is computationally heavy and not appropriate for large data panels. The PAM method, like the k-means, was applied for meaningful comparison given its higher consistency in the presence of outliers (Kaushik and Mathur, 2014) but was found to have the same results. Previous economic studies have used clustering methods with country panel data (Śmiech and Papiez, 2014), and even on CO2 emissions studies although at a country level (Zhang *et al.*, 2017). The K-means clustering (Macqueen, 1967) is a simple and efficient clustering partition method, a linear algorithm. It selects k random observations and begins clustering all other observations to those, called the centroids, using the Euclidian distance until all are gathered. After which it calculates the mean of each cluster around a centroid and sets that mean as the new, centroid. Then it distributes the observations again according to the new centroids and the process repeats. Iterations are done until the last clustering is the same as the previous one. Due to its sensitivity to outliers, the components were standardized before computing the clusters. The means of each component for each country were calculated and used as observations for the cluster, otherwise the number of data points in the cluster would be upwards of 2000, making any kind of observation impossible and redundant given countries could be in different cluster at the same time on a given year.

The PAM - Partitioning Around Medoids (Kaufman and Rousseeuw, 1987; Ng and Han, 2002), or k-medoids, clustering algorithm works much in the same way as the k-means, the difference lies in the centroid. Using data observations as centroids instead of the means of the cluster as the k-means does.

Both K-means and medoids require the number of randomly selected initial observations to be given, that is, chosen before computation and not by the algorithm itself. Several tests can be done to determine the ideal number of clusters, although not always conclusive. Those tests are the Elbow Method (Kodinariya and Makwana, 2013) and the Silhouette method (Rousseeuw, 1987). The Elbow Method simulates k=1 to 10, measuring each clustering's sum of squared errors (SSE) and creating its plot (figure 2). As the SSE of the clusters tends to 0 with more clusters, because eventually, the observations become centroids, the ideal number of clusters is a low number with low SSE and thus the "Elbow" of the graph, in the case this dissertations' data, 5. As one test is often not the most indicative another was run, on figure 3 the Silhouette Test is shown. It measures how well an observation is clustered by comparing the distance to its own cluster versus others. The y-axis, silhouette width, is the average distance of the observations to the nearest centroid. Similarly, to the Elbow Method it conducts the tests for up to 10 clusters. It considers a cluster of 2 to be the most optimal number of clusters with 3 and 4 close behind. Consequently, 2, 3 and 5 – as indicated by the Elbow Test - means clustering was conducted.

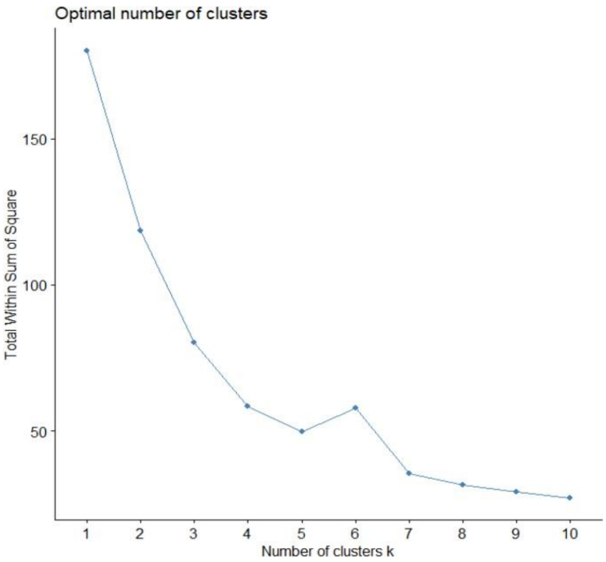


Figure 2 - Elbow Method for clustering. SSE on the y-axis and number of clusters in the x-axis. Calculates the optimal number of clusters. Most ideally the "elbow" of the figure.

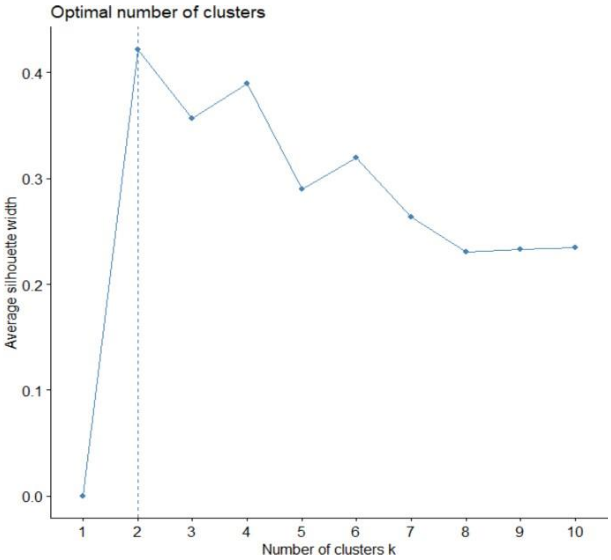


Figure 3 - Silhouette for clustering. Average Silhouette Width on the y-axis and number of clusters in the x-axis. Calculates and shows the most optimal number of clusters, in this case, 2.

The k-medoids clustering method provided almost the same result as the k-means except for the shift from one cluster to another of 1 or 2 countries, thus, only the results for the k-means will be shown. This result does not necessarily imply outliers are not affecting the clustering method, given the k-means and PAM methods both set the biggest outlier, China, on its own group. For testing purposes, regressions will be run with and without outliers to determine if they were influencing the results.

The 5-means clustering yielded interesting results that are replicated across the 3 and 2-means clustering (figure 2 and 3 Appendix.). It is important to remember the values are standardized. As there are 4 variables for the k means to cluster, 4 dimensions must be reduced to two for graphical analysis. This is achieved using principal component analysis (Pearson, 1901). The x-axis is largely depicting government expenditure contributions to growth along with, although at a smaller scale, consumption contributions. The y-axis mostly represents trade contributions. A high-income group was formed (group 1 in table 3) along with South Africa, Algeria, Mexico, Peru and Uruguay. Its centroids all have negative values, as they are in the left tail of the standardized data explained by their inherent low growth rates. However, most of these countries do have positive but low contributions to the GDP growth rate. The most similar group is 3, characterized by higher consumption contributions and most importantly a high negative value for trade contributions. In fact, this group is mainly distinguished by those negative values for trade, as almost all countries in it have negative trade. The values are somewhat logical, and a hypothesis is that these countries' domestic demand is increasing. Imports are increasing each year more than exports and since the formula for trade contributions subtracts the former to the latter's negative values. The question regarding the causality of this relationship is directly seen.

Group 2 is formed by just one country, China, a direct result of its massive government expenditure contribution to growth, coupled with investment, both in-line with the current situation in China. Although, it is important to note the high value of consumption contributions, possibly denoting a shift to domestic consumption in the country (Kharroubi and Kohlscheen, 2017). Its high values show China to lie at the right tail of the curve, and most probably an outlier in the data.

Group 5 has just 4 countries: Saudi Arabia, Luxemburg, Singapore and Ireland. This group is the direct opposite of cluster 2, which is reflected in the cluster plot in Appendix. It has the highest trade contribution out of all the clusters, they are countries whose exports are the main contributor to growth. Interestingly, the value for consumption has an opposite sign, and consequently, these countries have low consumption contributions when compared to the others, which only strengthens the previous hypothesis.

Finally, the last cluster, 4, also only has 4 countries: South Korea, Malaysia, Thailand and Israel. The most constant group, whose contributions to growth are almost identical except for trade, and all positive, denoting their position at the right tail of the distribution, showing higher overall growth rates compared to other countries.

Table 3: 5-Means Centroids

Clusters	Government	Consumption	Investment	Trade
1	-0.402	-0.807	-0.622	-0.056
2	3.574	2.342	3.977	0.326
3	-0.231	0.901	0.294	-0.788
4	1.315	1.117	1.021	0.449
5	0.913	-0.218	0.530	2.551

Table 3 - Government, Consumption, Investment and Trade are the contributions of those components to GDP. Values are the centroids calculated by k-means. Standardized values.

3 and 2-mean clustering groups are an agglomeration of the previous groups, requiring less analysis. The tables are not as representative, the fusion of the clusters changes the means of the previous centroids. A better inference is taken by analyzing the cluster plot in Appendix.

Former groups 2, 4 and 5 join, except Luxemburg which goes to former group 1, creating cluster 3 in table 5. All contributions are high and positive, resulting from the average of all countries values. Considering these countries had high values for a specific component it is not surprising the average of every contribution ends up being high as well. Furthermore, the cluster still has few countries, which means China’s values have a high impact on the mean. Group 1 and 2 remain largely unchanged, former group 1 and 3 respectively. Their previous characteristics are still evident.

Table 4: 3-Means Centroids

Clusters	Government	Consumption	Investment	Trade
1	-0.365	-0.806	-0.609	0.042
2	-0.046	0.888	0.306	-0.670
3	1.583	0.854	1.623	1.620

Table 4 - Government, Consumption, Investment and Trade are the contributions of those components to GDP. Values are the centroids calculated by k-means.

The 2-means cluster is largely uninformative, dividing the 46 countries almost by half in two groups, one of which is the initial high-income group (group 1 of the 5-mean cluster) relatively untouched.

2.2.4. PREDICTIVE HYPOTHESIS

Having finished exposing the data, treatment and modelling structure, the predictive hypothesis becomes an important and necessary step of the methodology. However, if there is one thing constant in EKC studies is that the sign of the independent variables is not constant among all studies. Openness ratio's coefficient sign is often controversial. Some studies find it negative, or even insignificant, that is as the ratio increases CO2 emissions decrease (Cole, 2004; Halicioglu, 2009; Jalil and Mahmud, 2009; Dogan and Turkekul, 2016). Jalil and Mahmud (2009) argue the sign is negative when the scale effects of trade overpower input and technological effects. Frankel and Rose (2005) stated the wrongly labelled sign could be a direct result of omitted variable bias by testing different variables along with trade. Looking at the scatter plot matrix provides an insight into the possible nature of the relationship, as the ratio increases so do CO2 emissions. Accordingly, the Openness ratio coefficient sign is expected to be positive, but it is acknowledged it may result in a negative value as explained. Also, its positive sign may just reflect the effect GDP has on CO2 emissions.

The Investment ratio is more difficult to predict. There is a lack of studies that employ it directly as a regressor. Ibrahim and Law (2014) obtained a negative coefficient for the ratio which could indicate that input and technology overpower scale effects and diminish CO2 emissions. Meaning technology makes CO2 emissions more efficient or there are fewer inputs and thus CO2 emissions decrease. The relationship shown between the data in the preliminary analysis depicts a positive relationship although constant and Pearson's correlation is weak. The expected sign of the coefficient for this variable is positive, that is CO2 emissions increase with investment. If that is the case it would proxy the pollution haven hypothesis.

Government size's correlation with both GDP and CO2 emissions, on one hand, is problematic, it may create endogeneity. But on the other hand, gives transparency to the variable. Thus, while some studies find the relationship sign to be negative (López, Galinato and Islam, 2011; Halkos and Paizanos, 2013; López and Palacios, 2014), it is expected for the sign to be positive, which goes in line with Bernauer and Koubi (2006) study.

GDP will have a positive coefficient given its plot with CO2 emissions, observed in the scatter plot showed in an earlier section. Which is highly expected and consistent with all other EKC studies. What is not so certain is the shape of the relationship, the insertion of the cubic term in the regression increases the number of possible combinations in terms of coefficients sings and thus the shape of the curve. If it is insignificant, the relationship is quadratic, but even if it is not the sign of the coefficients will determine if it is an N-shape curve or something else.

Finally, the variable aimed to verify the initial hypothesis of this study, that certain components' contribution to growth causes CO2 emissions to increase more than others, depends on the coefficients of the dummy of the clusters. The control dummy is the high-income countries group. It is expected, given economic literature, that the high trade group dummy to be significant and positively impact CO2 emissions, along with China (in case of the 5-mean cluster, as it stands alone) who is known historically to pollute more than the high-income countries.

4. RESULTS

3.1. INITIAL INFERENCE

First, Pooled OLS was estimated for initial inference. Breusch-Pagan test (Test 3 in the Appendix) with a p-value of 2.2e-16 rejects the null and thus the model has heteroskedasticity. Following, the Breusch-Godfrey/Wooldridge test for serial correlation in panel data reveals serial correlation by rejecting the null hypothesis with a p-value of 2.2e-16. Both were expected given the nature of the data (Croissant and Millo, 2008). Given both errors, the residuals are controlled for heteroskedasticity and serial correlation (Millo, 2017). Finally, a VIF test, which testes for multicollinearity show the lack of thereof. The threshold for multicollinearity is thought to be a test statistic of 4, which no variable reaches except the categorical variable. If we square GVIFDf the traditional VIF is obtained, considering every value is less than 2, multicollinearity is not verified, given the GDP is not squared or cubic, as otherwise for obvious reasons multicollinearity is present (O'brien, 2007; J. Fox and S. Weisberg, 2019).

Table 5: VIF's

	GDP	Openness Ratio	Investment Ratio	Government Size	5Cluster
GVIF	3.357	2.055	1.256	1.660	6.150
Df	1	1	1	1	4
GVIFDf))	1.832	1.434	1.121	1.288	1.255

Table 5 - VIF's of each independent variable. GVIF being the change in the standard error and confidence interval in the presence of collinearity. GVIFDf measures the coefficients of the estimator in the presence of collinearity vs no presence. If the last one is squared the traditional VIF is obtained.

Testing for the individual or time effects with the Lagrange FF Multiplier (Test 4 in the Appendix) yields the expected result, there are individual and/or time effects and consequently Pooled OLS is not efficient at estimating them, random or fixed-effects estimators should be used as is often the case in EKC studies (Dinda, 2004; Stern, 2017).

Before proceeding into random and fixed effects, a note on outliers. With Cook's distance, which measures the impact observations have on the estimation of the fitted values and consequently yields a relatively interesting approach to outlier detection, a few outliers were detected (Cook, 1977). It is important to infer that the cut-off line was not used to eliminate values but to provide relevant insight into the constitution of the data. Also, numerous iterations of this distance can be calculated each time the former outliers were detected and removed, obtaining new outliers. Thus, only 1 iteration was run, and although many observations were above the line, the most worrying ones were three observations, years 1974 and 1975 from Saudi Arabia and 2007 from Singapore. In fact, these observations were the most impactful in the entire Panel by far (Appendix). As a direct result, the most relevant models of this study were calculated with both the initial panel data and without Saudi Arabia's and Singapore's observations for relevant comparison.

Fixed effects estimator was formulated, using the Arellano method to produce robust standard errors for the within model given the presence of heteroskedasticity and serial correlation in the panel data (Arellano, 1987). As the Random-Effects model is considered inefficient by the Hausman test, the within model is the most appropriate for estimation (Shafik and Bandyopadhyay, 1992; Holtz-Eakin and Selden, 1995; Panayotou, 1997; Suri and Chapman, 1998; Torras and Boyce, 1998; List and Gallet, 1999; Carlsson *et al.*, 2003; Leitão, 2010; Stern, 2017). Time dummies were included, with 1971 as the control year. Bearing in mind the results of the Augmented Dickey-Fuller test (Test 5 in the Appendix) for unit roots rejected the null (in Appendix), which states the variables are stationary, the variables cannot be cointegrated. According to Stern (2017) if CO2 emissions and GDP are not cointegrated the within model may be estimating a spurious regression. As such, the Within-Between model seems to be the most appropriate for analysis.

A note before proceeding into the discussion, the tables below show the coefficients for the complete model estimated by OLS, Within, Between, Random and Within-Between effects, accounting for robust standard errors as mentioned previously. Further, for comparison between different models estimated by the Within-Between effects another table is added with the complete model, the model without ratios (Openness Ratio, Investment Ratio and Government Size) and finally a model without government size, all for both the 5-means clusters and 3-means clusters, for fear of causing multicollinearity or endogeneity in the model. The beforementioned tables will, furthermore, provide a comparison of these very same models estimated by the Within-Between and the panel without the observations of Singapore and Saudi Arabia, as outlined by the Cook’s distance, to discern the effect of the outliers on the regressions.

3.2. ALL ESTIMATORS

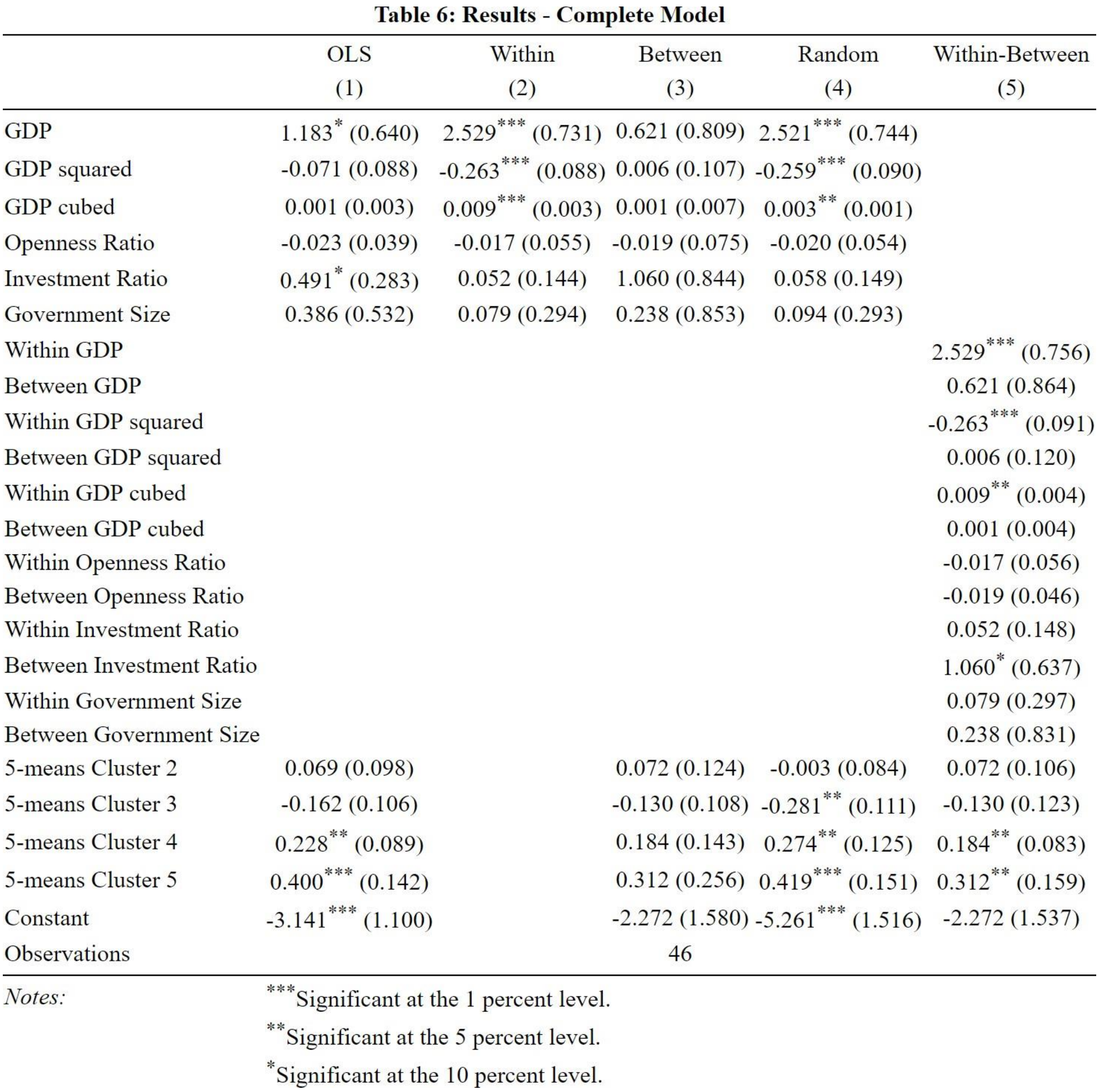


Table 6: Results - Complete Model

	OLS (1)	Within (2)	Between (3)	Random (4)	Within-Between (5)
GDP	1.183* (0.640)	2.529*** (0.731)	0.621 (0.809)	2.521*** (0.744)	
GDP squared	-0.071 (0.088)	-0.263*** (0.088)	0.006 (0.107)	-0.259*** (0.090)	
GDP cubed	0.001 (0.003)	0.009*** (0.003)	0.001 (0.007)	0.003** (0.001)	
Openness Ratio	-0.023 (0.039)	-0.017 (0.055)	-0.019 (0.075)	-0.020 (0.054)	
Investment Ratio	0.491* (0.283)	0.052 (0.144)	1.060 (0.844)	0.058 (0.149)	
Government Size	0.386 (0.532)	0.079 (0.294)	0.238 (0.853)	0.094 (0.293)	
Within GDP					2.529*** (0.756)
Between GDP					0.621 (0.864)
Within GDP squared					-0.263*** (0.091)
Between GDP squared					0.006 (0.120)
Within GDP cubed					0.009** (0.004)
Between GDP cubed					0.001 (0.004)
Within Openness Ratio					-0.017 (0.056)
Between Openness Ratio					-0.019 (0.046)
Within Investment Ratio					0.052 (0.148)
Between Investment Ratio					1.060* (0.637)
Within Government Size					0.079 (0.297)
Between Government Size					0.238 (0.831)
5-means Cluster 2	0.069 (0.098)		0.072 (0.124)	-0.003 (0.084)	0.072 (0.106)
5-means Cluster 3	-0.162 (0.106)		-0.130 (0.108)	-0.281** (0.111)	-0.130 (0.123)
5-means Cluster 4	0.228** (0.089)		0.184 (0.143)	0.274** (0.125)	0.184** (0.083)
5-means Cluster 5	0.400*** (0.142)		0.312 (0.256)	0.419*** (0.151)	0.312** (0.159)
Constant	-3.141*** (1.100)		-2.272 (1.580)	-5.261*** (1.516)	-2.272 (1.537)
Observations			46		

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 6 – Models estimated by OLS, Within, Between, Random and Within-Between with all regressors. Where GDP is per capita and in natural logarithm form, the within variables are the demeaned variables and the between the mean of each variable. The clusters were changed, the High-Income cluster was set as the control dummy. Cluster 2 is cluster 4 from table 3, cluster 4 is 5 and 5 (China) is 2. Cluster 1 and 3 remain unchanged.

With pooled OLS, in Table 6, only GDP is significant, at 10%, with a positive coefficient. GDP squared and cubed are both insignificant, with the first negative and the second positive. Effectively creating an N-shaped curve. However, the non-significance of the squared and cubic term may imply there is no Kuznets curve of any kind, only logarithmic relationship. It is the only estimator that considers GDP squared to not be significant in explaining the relationship between income per capita and CO2 emissions per capita. GDP cubed is more controversial.

With the Within estimator, all terms of GDP are significant at 1% significance level. We have an N-shaped curve with the first term of GDP positive, the second negative and the third positive. The significance of GDP squared in the Within versus the OLS estimators lies not in the specific method of the within, demeaning the variables to isolate the time-variant characteristics of the variables, as the Random and Within-Between - the last by definition has the same coefficients as the Within model for the demeaned variables - have the same coefficients.

The Between estimator calculates the average of every variable by group, Country in this case, and regresses those variables instead of the original time-invariant, effectively transforming the data into cross-sectional. The between effects does not yield relevant results, which is to be expected given the nature of the study is analyzing the relationship of a country's GDP, and subsequently its yearly growth, and its yearly CO2 emissions, the within effects. It is, however, an important step to take given the last model is an amalgamation of the Within and Between effects estimated by the Random-effects model.

The Random-effects estimator GDP coefficients are approximate to the Within's, and therefore the Within-Between estimator. Once again there is an N-shape relationship, with all terms of the GDP significant, the first two at 1% and the cubed term at 5% significance level. The relationship appears to be cubic in nature.

With the Within-Between estimator, the within effects coefficients of the GDP's are the same as the Within estimator coefficients. GDP and GDP squared are significant at 1%, while GDP cubed is significant at 5%. The underlying relationship is cubic just as with the previous estimators. The strength of this model lies not in its ability to estimate better the relationship between GDP and CO2 emissions but in its ability to model time-invariant variables along with time-variant, as opposed to the elimination of the previous in the Within estimator. Overall, GDP appears to have a cubic N-shaped relationship with CO2 emissions. The signs of the coefficients are consistent with previous studies (Carlsson *et al.*, 2003; Dinda, 2004; Allard *et al.*, 2018), although the lack of consensus and contradicting results in previous studies impede a concrete conclusion. The non-significance of the cubic term of GDP is not uncommon (Cole, 2004; Allard *et al.*, 2018), implying the relationship between CO2 emissions and income may not be so simple, may in-fact be unique to each country or omitted variable bias is at play.

The openness ratio sign is negative across all estimators, as openness ratio increases CO2 emissions decrease, with similar values very close to 0 and insignificant in all models. Therefore, results may be inconclusive on its impact on CO2 emissions. These results are not surprising and in line with several studies, the significance of trade has been controversial. (Cole, 2004; Halicioglu, 2009; Jalil and Mahmud, 2009; Ibrahim and Law, 2014; Dogan and Turkekul, 2016). Even if that is the case, the fact that the coefficient remains negative across all models is an important observation. The predictive hypothesis for Openness ratio was for its sign to be positive and the significance to be low and shifting between estimators. The last one is checked but not the first. This could be due to, as mentioned before, its inability to isolate domestic and foreign demand and/or the oppression technological and input effects have on scale effects, the so-called technique and composition effects (Stern, 2017). It is interesting to note, before the application of Arellano’s robust standard errors (Arellano, 1987) for autocorrelation and heteroskedasticity, the openness ratio was significant. The Within-Between method obtains the same significance values as a direct effect of accounting for autocorrelation in the standard error, as it is expected.

Investment, like the openness ratio, has a consistent sign across all estimators, remaining always positive, just as predicted. As Investment increases so do CO2 emissions, which is in line with the Pollution Haven Hypothesis. Only the model estimated by OLS and Within-Between find the Investment ratio to be significant, however, given the inconsistency of pooled OLS in the presence of unobserved heterogeneity, which is surely the case, the other estimator's results are more trustworthy. Thus, the investment ratio’s between effects is the one that appears to be relevant for the fitted values. The positive coefficients are contradicting with (Ibrahim and Law, 2014) investment coefficient, which they found to be negative using the GMM (Generalized Method of Moments). Thus, one cannot rule out the possibility that just as the Openness ratio, the Investment ratio’s directional impact on CO2 emissions can change along with different independent variables. This variability will be tested in the next section by reducing the model’s variables and estimating it with the Within-Between model. One last note in the Investment ratio, it presents the largest relative value of between effects to its within effects. There is a cross-sectional effect in Investment that causes an increase in CO2 emissions although given its standard deviation it could be an impact caused by outliers.

Government size beckons more care, its strong linear correlation to GDP can cause multicollinearity. Its non-significance across all models is strange considering the strong correlation it shared with CO2 emissions. It could be a direct result of multicollinearity with GDP. GDP is capturing the effect Government Size has on CO2 emissions. The positive coefficient, as government size increases CO2 emissions increase, supports this hypothesis. It is worth checking in the reduced models and the 3-means cluster if its sign and/or significance will vary.

Regarding clusters, analysis is more robust if done by the Within-Between model as stated previously. However, some consistencies across models can be perceived. The first is the significance of cluster 5, composed by 1 country: China, at 1% significance value in the OLS and Random-Effects models and at 5% in the Within-Between. That is, compared to group 1, the High-Income group, China produces more CO2 emissions, which is to be expected. It is only one country, but the high values of its contribution to growth make it an exceptional case that cannot be joined to any other cluster, and conclusions harder to take. The second consistency is the significance at 5% of cluster 4 - Saudi Arabia, Luxemburg, Singapore and Ireland – with the OLS, Random and Within-Between estimator. Compared to group 1, these countries contribute more to CO2 Emissions. An important conclusion especially considering the group is characterized by their very high trade contributions to GDP growth. This could be a direct result of the scale effects of trade and subsequently its effects on CO2 emissions. One could argue the positive coefficient to be the result of Government consumption contribution to GDP growth, considering cluster 4 has a relatively high government contribution and lie at the right tail of the distribution. However, cluster 3 and 1 both have negative government contributions to growth, and cluster 3 while it has a negative coefficient, it contributes less to CO2 emissions than group 1 which has also negative, and higher than group 3, government contribution. Moreover, Group 3 has an important characteristic, negative trade contributions, which could be the reason for its negative coefficient. Thus, at first glance, the value of trade contributions seems to be the most relevant factor in determining the direction and significance of the cluster dummies compared to the control group.

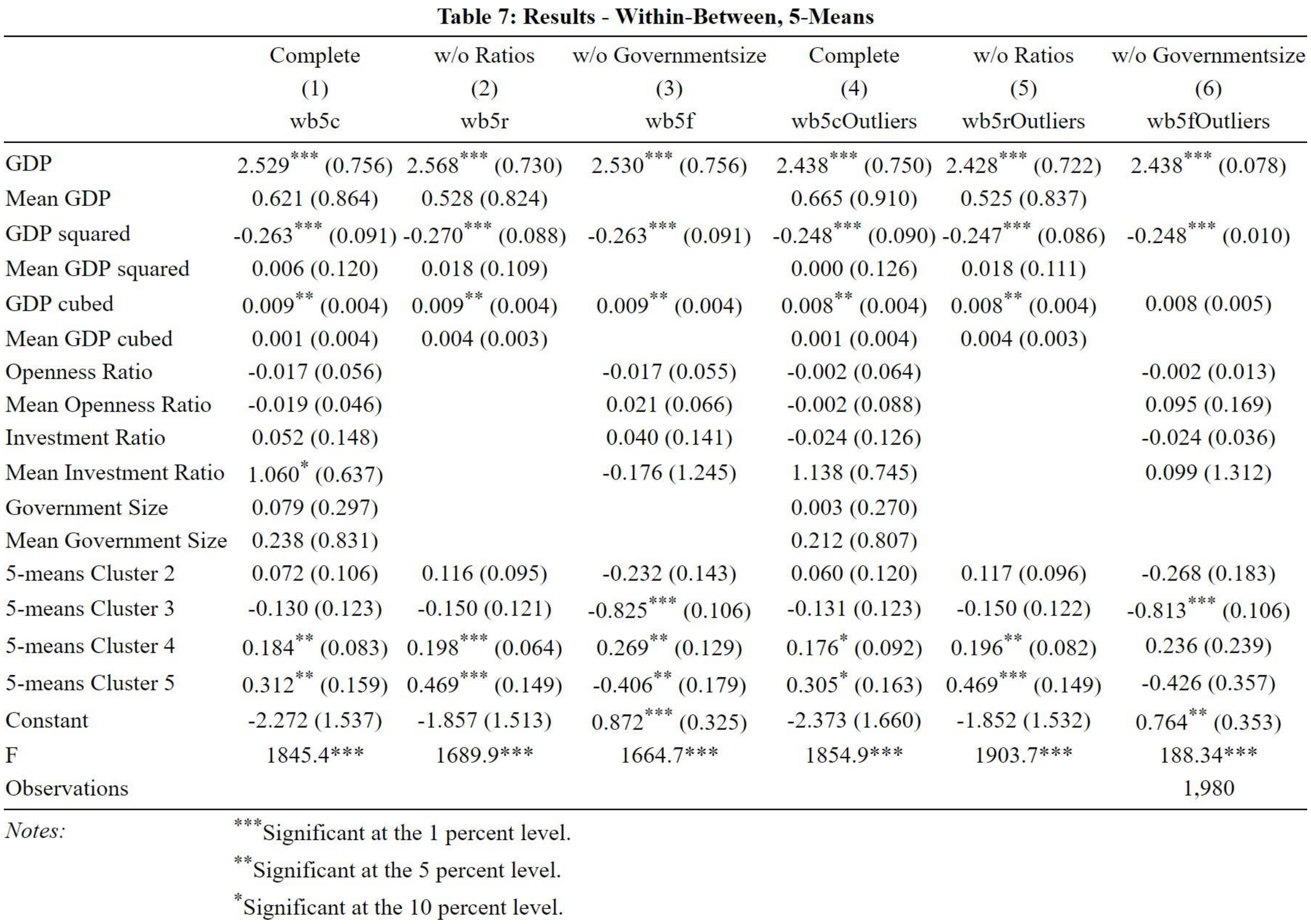


Table 7: Results - Within-Between, 5-Means

	Complete	w/o Ratios	w/o Governmentsize	Complete	w/o Ratios	w/o Governmentsize
	(1)	(2)	(3)	(4)	(5)	(6)
	wb5c	wb5r	wb5f	wb5cOutliers	wb5rOutliers	wb5fOutliers
GDP	2.529*** (0.756)	2.568*** (0.730)	2.530*** (0.756)	2.438*** (0.750)	2.428*** (0.722)	2.438*** (0.078)
Mean GDP	0.621 (0.864)	0.528 (0.824)		0.665 (0.910)	0.525 (0.837)	
GDP squared	-0.263*** (0.091)	-0.270*** (0.088)	-0.263*** (0.091)	-0.248*** (0.090)	-0.247*** (0.086)	-0.248*** (0.010)
Mean GDP squared	0.006 (0.120)	0.018 (0.109)		0.000 (0.126)	0.018 (0.111)	
GDP cubed	0.009** (0.004)	0.009** (0.004)	0.009** (0.004)	0.008** (0.004)	0.008** (0.004)	0.008 (0.005)
Mean GDP cubed	0.001 (0.004)	0.004 (0.003)		0.001 (0.004)	0.004 (0.003)	
Openness Ratio	-0.017 (0.056)		-0.017 (0.055)	-0.002 (0.064)		-0.002 (0.013)
Mean Openness Ratio	-0.019 (0.046)		0.021 (0.066)	-0.002 (0.088)		0.095 (0.169)
Investment Ratio	0.052 (0.148)		0.040 (0.141)	-0.024 (0.126)		-0.024 (0.036)
Mean Investment Ratio	1.060* (0.637)		-0.176 (1.245)	1.138 (0.745)		0.099 (1.312)
Government Size	0.079 (0.297)			0.003 (0.270)		
Mean Government Size	0.238 (0.831)			0.212 (0.807)		
5-means Cluster 2	0.072 (0.106)	0.116 (0.095)	-0.232 (0.143)	0.060 (0.120)	0.117 (0.096)	-0.268 (0.183)
5-means Cluster 3	-0.130 (0.123)	-0.150 (0.121)	-0.825*** (0.106)	-0.131 (0.123)	-0.150 (0.122)	-0.813*** (0.106)
5-means Cluster 4	0.184** (0.083)	0.198*** (0.064)	0.269** (0.129)	0.176* (0.092)	0.196** (0.082)	0.236 (0.239)
5-means Cluster 5	0.312** (0.159)	0.469*** (0.149)	-0.406** (0.179)	0.305* (0.163)	0.469*** (0.149)	-0.426 (0.357)
Constant	-2.272 (1.537)	-1.857 (1.513)	0.872*** (0.325)	-2.373 (1.660)	-1.852 (1.532)	0.764** (0.353)
F	1845.4***	1689.9***	1664.7***	1854.9***	1903.7***	188.34***
Observations						1,980

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 7 – Regressions for the 5-means clustering with the Within-Between model with the entire panel and without Singapore's and Saudi Arabia's data. Where GDP is per capita and in natural logarithm form, the within variables are the demeaned variables and the between the mean of each variable. The Given F-test is calculated considering robust standard errors. The clusters were changed, the High-Income cluster was set as the control dummy. Cluster 2 is cluster 4 from table 3, cluster 4 is 5 and 5 (China) is 2. Cluster 1 and 3 remain unchanged.

3.3. WITHIN-BETWEEN

3.3.1. 5-MEANS CLUSTER

Table 7 reveals the coefficients and their standard deviations of the different models estimated by the Within-Between estimator. Model 1 is the same as in equation 4, while Model 2 and 3 are adaptations of 1. 2 excludes the components of GDP ratio, Openness Ratio, Investment Ratio and Government Size and 3 excludes just Government Size along with the means of the GDP terms, a precaution against the concerns about it causing multicollinearity with GDP, or variable bias. Models 4, 5 and 6 are mirroring the other three but with a new panel data without Singapore and Saudi Arabia, the biggest influencers of the fitted results, allowing for the analysis of the impact of Singapore and Saudi Arabia in the coefficients and significances of the model. Model 1, the complete, is the same as model 5 in table 6 and serves as a baseline.

Model 2 is not too different from the first, however, all GDP variables remain relevant in explaining the relationship. The difference between model 1 and 2, as explained above, is the omission of the ratios in model 2. The only change from one model to the other was the increase in the significance of cluster 4 and 5, which could be due to the gain in degrees of freedom or from a subtle correlation between the ratios and the clusters. The N-shaped curve is retained with the significance of the cubed variable. Model 3, without Government Size, maintains similar GDP coefficients to the previous two models. The relationship between CO2 emissions and GDP remains cubic, giving further evidence for an N-shaped curve. As seen in the VIF (table 5) the expected multicollinearity between GDP and Government Size was not present, the lack of change in the coefficients of GDP and their significance goes against the hypothesis of a correlation between the two variables.

The ratios, other than the investment ratio remain non-significant. An unsurprising result as stated in the analysis of all regressors above. However, investment is only significant in the complete model and only the between effect at that. There is some time-invariant characteristic of Investment that the model considers relevant in explaining CO2 emissions. Model 3 fails to consider the variable significant, in fact, the coefficient of the between effects of investment turns negative when excluding Government Size.

The cluster, however, does not remain unchanged. Some interesting results come across. From model 1 to 2 change is subtle, to reiterate, cluster 4 and 5 are now significant at 1%, maintaining the possible causal reverse relationship between contributions to trade and CO2 emissions. The second change is the coefficient of the dummy for China, it becomes higher, related to the first explanation. The omission of Government Size in model 3, however, has more implicative effects. Cluster 3's coefficient increases massively and is now significant at a 1% significance value. The explanation is that both variables can be correlated in some way. Cluster 3's countries contribute much less to CO2 emissions than the High-Income group, in fact, they contribute the less out of all the clusters. Cluster 2 and 5 give another clue to the relationship between the clusters and Government Size. Both coefficients change direction. In fact, the model now considers China to contribute less to CO2 emissions compared to High- Income countries. It could be possible that Government Size was isolating some correlation between the clusters and the error, especially considering China's Government contributions are massive compared to other countries. The clusters are now attempting to explain government expenditure variations. These results make the earlier hypothesis – trade contributions are correlated to higher CO2 emissions – stronger. Cluster 2 has, the second- highest government contributions after China, while Cluster 3 has the lowest trade contributions and is the most negative cluster.

Excluding Singapore and Saudi Arabia from the data has several interesting results. In the first model, we have that the significance of both cluster 4 and 5 decreases, which is interesting since Singapore belongs to cluster 4, thus it would make sense for that cluster to be affected, not cluster 5. The decrease of cluster 5 could be from fewer degrees of freedom. In model 5, the situation is clear, only the significance of group 4 is affected, as it loses its biggest contribution to trade. The lack of outlier in the data does give an utmost important conclusion. Contributions to trade are most probably a big factor for determining the fitted values of CO2 emissions. The fact that cluster 4, the group with the highest contribution to trade, still maintains its significance, makes that conclusion more robust. In model 6, the reversion of the direction of cluster 2 and 5 occurs again. For China, it makes sense, given its massive Government Expenditure, but cluster's 2 change is more dubious, although at some level is reasonable. The most interesting is the difference between the F-test of model 3 and 6. While in the first three the F-test does not reveal much, for the last three it does. The value of the statistics drops massively in model 6. Interestingly the only relevant cluster in model 6 is the 3rd, which contributes less to CO2 emissions than High-Income countries, and is the cluster with lowest trade contributions to growth. One last note, model 6 is the first and only model of the 5-means Within-Between to have the cubed GDP term non-significant, and interestingly a quadratic inverted U-shaped curve, the classical EKC.

Not only do the clusters and the GDP coefficients, change but also does the Investment ratio coefficient. Its coefficient turns negative in the absence of Singapore and Saudi Arabia in the data, obtaining a result similar to Ibrahim and Law (2014), which is interesting since Singapore's investment ratio does not vary much compared to the average (0.34 to 0.2). On the other hand, Singapore's Openness ratio is clearly outside of the mean. With an average value of 3.4 versus the overall mean of 0.7. Obtaining a negative Investment ratio is not unreasonable, it adheres to the scale effects theory, an increase in investment as a ratio of GDP leads to higher emission of CO2, much the same as the Openness ratio whose coefficient maintains its negative value through all models with the exception of the OLS.

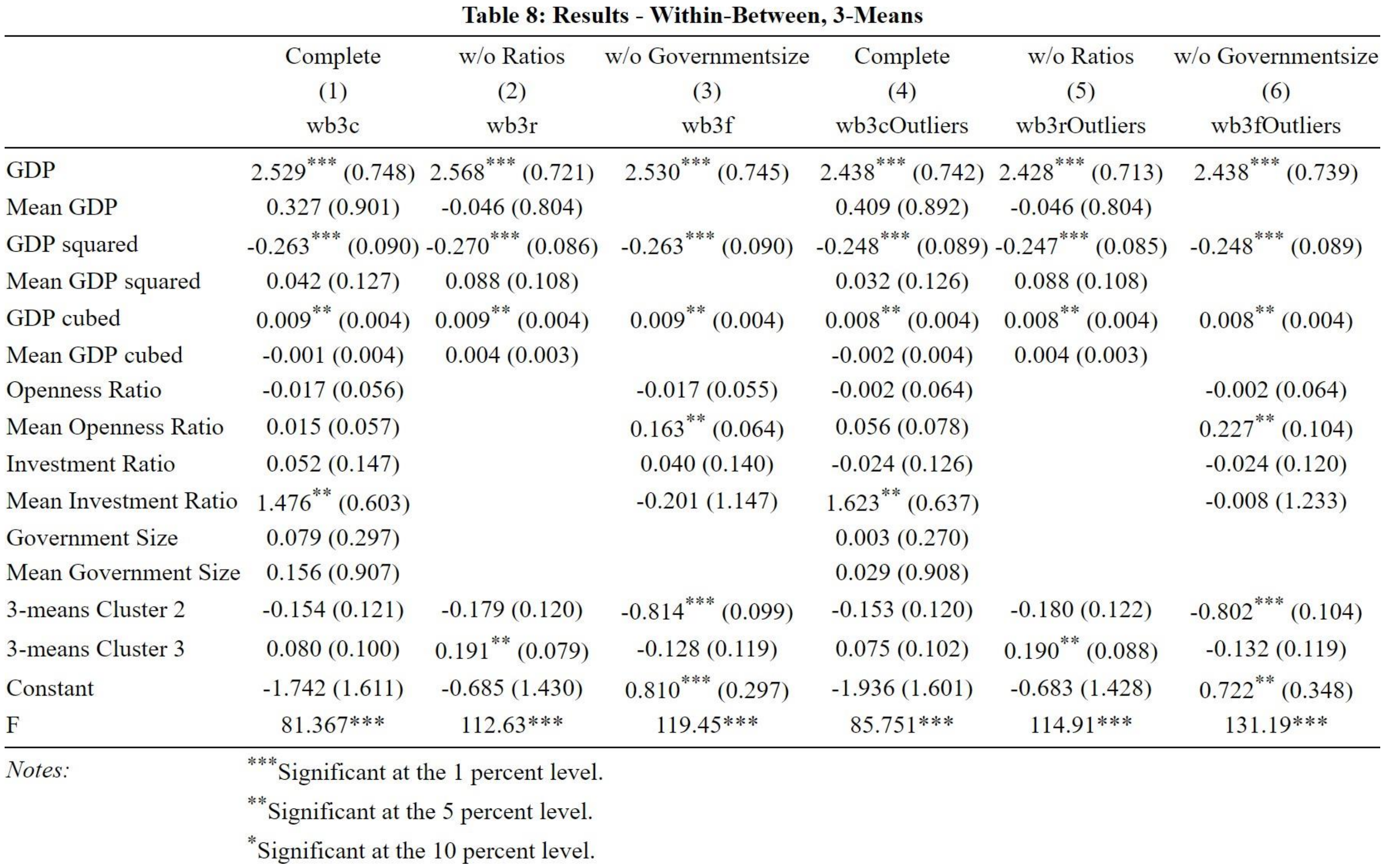


Table 8: Results - Within-Between, 3-Means

	Complete (1) wb3c	w/o Ratios (2) wb3r	w/o Governmentsize (3) wb3f	Complete (4) wb3cOutliers	w/o Ratios (5) wb3rOutliers	w/o Governmentsize (6) wb3fOutliers
GDP	2.529*** (0.748)	2.568*** (0.721)	2.530*** (0.745)	2.438*** (0.742)	2.428*** (0.713)	2.438*** (0.739)
Mean GDP	0.327 (0.901)	-0.046 (0.804)		0.409 (0.892)	-0.046 (0.804)	
GDP squared	-0.263*** (0.090)	-0.270*** (0.086)	-0.263*** (0.090)	-0.248*** (0.089)	-0.247*** (0.085)	-0.248*** (0.089)
Mean GDP squared	0.042 (0.127)	0.088 (0.108)		0.032 (0.126)	0.088 (0.108)	
GDP cubed	0.009** (0.004)	0.009** (0.004)	0.009** (0.004)	0.008** (0.004)	0.008** (0.004)	0.008** (0.004)
Mean GDP cubed	-0.001 (0.004)	0.004 (0.003)		-0.002 (0.004)	0.004 (0.003)	
Openness Ratio	-0.017 (0.056)		-0.017 (0.055)	-0.002 (0.064)		-0.002 (0.064)
Mean Openness Ratio	0.015 (0.057)		0.163** (0.064)	0.056 (0.078)		0.227** (0.104)
Investment Ratio	0.052 (0.147)		0.040 (0.140)	-0.024 (0.126)		-0.024 (0.120)
Mean Investment Ratio	1.476** (0.603)		-0.201 (1.147)	1.623** (0.637)		-0.008 (1.233)
Government Size	0.079 (0.297)			0.003 (0.270)		
Mean Government Size	0.156 (0.907)			0.029 (0.908)		
3-means Cluster 2	-0.154 (0.121)	-0.179 (0.120)	-0.814*** (0.099)	-0.153 (0.120)	-0.180 (0.122)	-0.802*** (0.104)
3-means Cluster 3	0.080 (0.100)	0.191** (0.079)	-0.128 (0.119)	0.075 (0.102)	0.190** (0.088)	-0.132 (0.119)
Constant	-1.742 (1.611)	-0.685 (1.430)	0.810*** (0.297)	-1.936 (1.601)	-0.683 (1.428)	0.722** (0.348)
F	81.367***	112.63***	119.45***	85.751***	114.91***	131.19***

Notes: ***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 8 - Regressions for the 5-means clustering with the Within-Between model with the entire panel and without Singapore's and Saudi Arabia's data. Where GDP is per capita and in natural logarithm form, the within variables are the demeaned variables and the between the mean of each variable. The Given F-test is calculated considering robust standard errors. Clusters are the same as in table

3.3.2. 3-MEANS CLUSTER

Analyzing the 3-means clusters provides a different perspective, an insight into the significance of the cluster. Beginning with the models estimated with the initial data. All terms of GDP are significant at least at 5% significance value, indicating a polynomial 3rd degreed relationship. Since the first term is positive, the second negative and the third positive, an N-shaped curve can be identified just like in the previous analysis. The values of the GDP coefficients did not change much, as such correlation between the GDP and the clusters is unlikely.

The ratios are once again mostly non-significant, with the same exception as before, the between Investment ratio and a new addition the between Openness ratio effect. The time-invariant characteristics of the ratios are correlating at some level with the time-invariant variables, the clusters. This time at 5% significance value, the increase in significance could also result from the increase in degrees of freedom or from bigger clustering of countries that eliminate the previously captured effect. The mean investment, investment ratio change direction across the models, bringing into attention the same problem, the coefficients could be changing signs due to the absence of Government Size.

Regarding the clusters, in the first model, they are considered, for the first time all non-significant. Considering the earlier preoccupation with the clusters correlating in some way with the ratios, model 2 provides an interesting contrast. Without the ratios in the regression, cluster 3 – former clusters 5 (China), 2 (high growth Eastern countries) and 4 (high trade countries) – becomes significant at 5%. These countries, as predicted, contribute more to CO2 pollutions than High-Income countries. In model 3, the cluster is non-significant in exchange for cluster 2, which contributes by far less to CO2 emissions than the control group. This group is composed of the lowest trade contribution countries.

Removing Singapore’s and Saudi Arabia’s observations does not change much from the corresponding models. Model 1 and 4 are mostly the same, just with slight variations in the coefficients while retaining the same significance. The F-statistics increases, proving that modelling without Singapore and Saudi Arabia provides more significant, less biased, results. Model 2 retains cluster 3’s significance while model 4 retains clusters 2’s and the cross-sectional Openness ratio’s significance. Thus, removing Singapore and Saudi Arabia did make the data more robust, however, it did not affect the coefficients and the regression by much.

The investment ratio, much like in the 5-means regressions, relationship with CO2 emissions changes direction, which can once again, imply the variability of Investment, not only when new variables are included, but when certain countries are excluded from the Panel. One thing is certain, comparing the 5-means regressions to the 3-means regressions does yield some revelations. The first being the possible competition for explanatory power between the clusters and the ratios, which is why some between effects in the 3-means regressions become significant when reducing the number of clusters and thus the division of countries in specific characteristics. Furthermore, GDP and CO2 emissions retain a cubic relationship throughout almost all the models.

5. CONCLUSION

Not surprisingly, the OLS estimator efficiency remains at best uncertain. The Lagrange FF Multiplier rejects the null and consequently there are individual and/or time effects. This possibly arises from the complexity of effects not accounted for in the models and left unexplained in the residuals. The Random-Effects estimator follows along the same lines, the Hausman test indicates the model cannot be estimated efficiently as the possibility of a correlation between the residuals and the explanatory variables cannot be rejected. The obvious replacement would be Fixed-Effects. However, bearing in mind the results of the Augmented Dickey-Fuller test for the CO2 emissions and GDP per capita, which reject the null, indicating variable is stationary and thus cannot be cointegrated.

The relationship between GDP and CO2 emissions remains similar throughout the models. The Within, Random-Effects and Within-Between estimators and the corresponding models (5 and 3-means) showed all the GDP terms to significant and depicting an N-shaped curve, with GDP positive, GDP squared negative and GDP cubed positive. The only exceptions being the OLS estimator which only considered GDP to be significant, essentially making the relationship between CO2 emissions and GDP to be purely logarithmical, and model 6 of Table 7, estimated by Within-Between, which is the 5-means model without government size and with the 5-means cluster. This last model is the only one to depict a classical U-shaped EKC. Given most of the estimators and models depict an N-shaped curve, this study puts into question the validly of the classical EKC curve and is more in line with the recent polynomial curve studies' findings.

The openness ratio remains insignificant across all models and estimators. As a proxy of exports, it was expected to have a positive coefficient, yet possibly due to the correlation with the clustering's fails to explain effects on CO2 emissions. The investment ratio and Government Size go much along the same lines, showing insignificance across all models, for the same reason as the openness ratio.

The clusters more consistent across models and can infer some interesting analysis. In the 5-means model, clusters 4 and 5 are consistently significant. The countries in the cluster contribute more to CO2 emissions than the control group, the High-Income countries. Cluster 4 composed by high trade countries could be a better proxy for trade than the trade ratio. Furthermore, the signs show the relationship to be positive, which is in line with the predicted hypothesis that increasing trade leads to increased CO2 emissions. The scale effects of trade are overpowering the input and technological effects. Furthermore, cluster 5 is a dummy for China, a heavy CO2 emissions country. Their significance, as opposed to the insignificance of the other clusters, implies the value of trade contributions is better at determining the direction and significance of the cluster dummies compared to the control group. The 3-means models are harder to analyze due to the inherent aggregation of countries caused by the lesser number of clusters. Cluster 3 is considered relevant in the model without ratios which is not surprising given it's constituted partially by cluster 4 and 5 of the 5-means.

The models without Singapore and Saudi Arabia do not reveal much in terms of the significance of clusters when compared to the other models. Clusters 4 and 5 of the 5-means remain relevant. Cluster 4 maintains its significance even when 2 of its countries were removed, strengthening the relationship between trade contribution to the growth and CO2 emissions.

Overall, the best model to explain CO2 emissions are the complete models, that is models 1 Table 7 and 8. Of which the first one, with the 5-means clusters, is more effective at explaining causal relationships considering the broader number of clusters.

Finally, several issues are still to be solved. Better proxies for the ratios should be found. They could be in some way competing for explanatory power with GDP. Furthermore, the insignificance of the openness ratio and investment ratio are still a puzzling result.

All in all, the relationship found between trade and CO2 emissions provides the intended glimpse into possible CO2 mitigation, and insight into future policy design with a narrower focus. By focusing on the impacts scale effects of trade have, governments can opt to apply focused policies to mitigate C02 emissions in the sector. Moreover, the observed N-shaped EKC curve is essential for policy design, providing insight into the behavior of CO2 in respect to income. As it seems that the initial assessment provided by the standard EKC, that CO2 emissions decrease when income increases, is outdated. Policy makers should start focusing on diminishing the negative impact that arises from the second upturn of the N-shaped EKC.

6. APPENDIX

Algeria Argentina Armenia Australia Austria Bangladesh Belgium Brazil Bulgaria Canada Chile China Colombia Croatia Czech Republic Denmark Ecuador Egypt, Arab Rep, Estonia Finland France Georgia	Greece Guatemala Hungary Iceland India Indonesia Ireland Israel Italy Japan Kazakhstan Kenya Korea, Rep, Lithuania Luxembourg Malaysia Mexico Mongolia Netherlands New Zealand Norway Pakistan Peru	Philippines Poland Portugal Romania Russian Federation Saudi Arabia Singapore Slovak Republic Slovenia South Africa Spain Sri Lanka Sweden Switzerland Thailand Tunisia Turkey Ukraine United Kingdom United States Uruguay Uzbekistan Vietnam

Table 9 – Countries in unbalanced Panel

Lower-Middle-Income	**Upper-Middle-Income**	**High-Income**
Egypt, Arab Rep.	Algeria	Australia
India	Brazil	Austria
Indonesia	China	Belgium
Kenya	Colombia	Canada
Pakistan	Ecuador	Chile
Philippines	Guatemala	Denmark
Tunisia	Malaysia	Finland
	Mexico	France
	Peru	Greece
	South Africa	Ireland
	Sri Lanka	Israel
	Thailand	Italy
	Turkey	Japan
		Korea, Rep.
		Luxembourg
		Netherlands
		New Zealand
		Norway
		Portugal
		Saudi Arabia
		Singapore
		Spain
		Sweden
		United Kingdom
		United States
		Uruguay

Table 10 – The 46 Countries in the Balanced Panel sorted by Income type according to the World Bank.

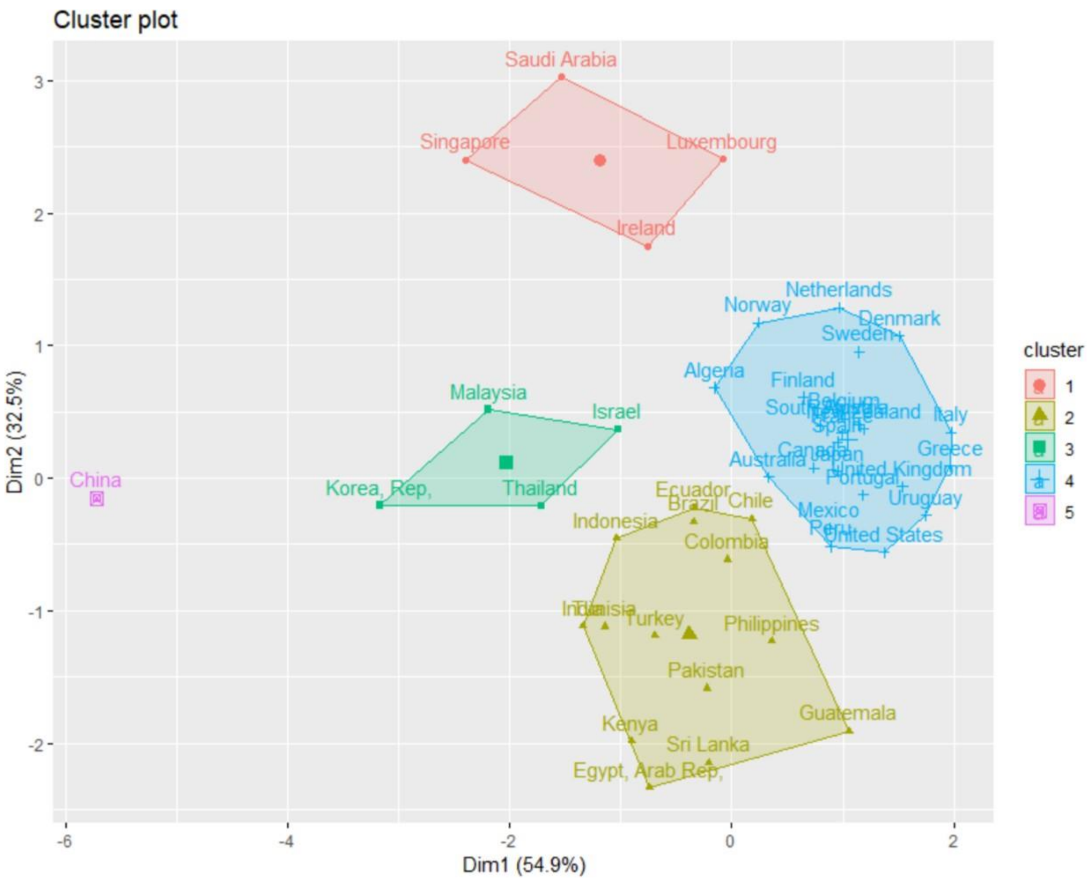


Figure 4 - Clustering groups of the 5-means clusters.

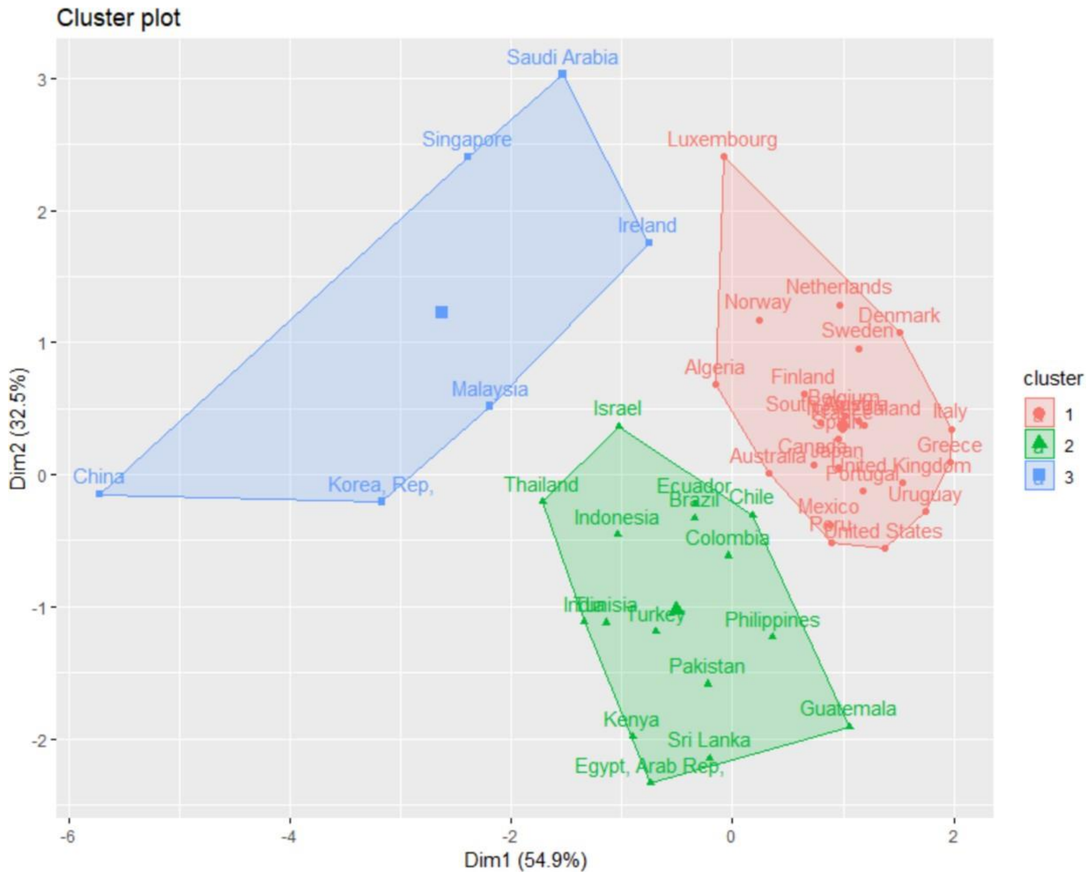


Figure 5 - Clustering groups of the 3-means clusters.

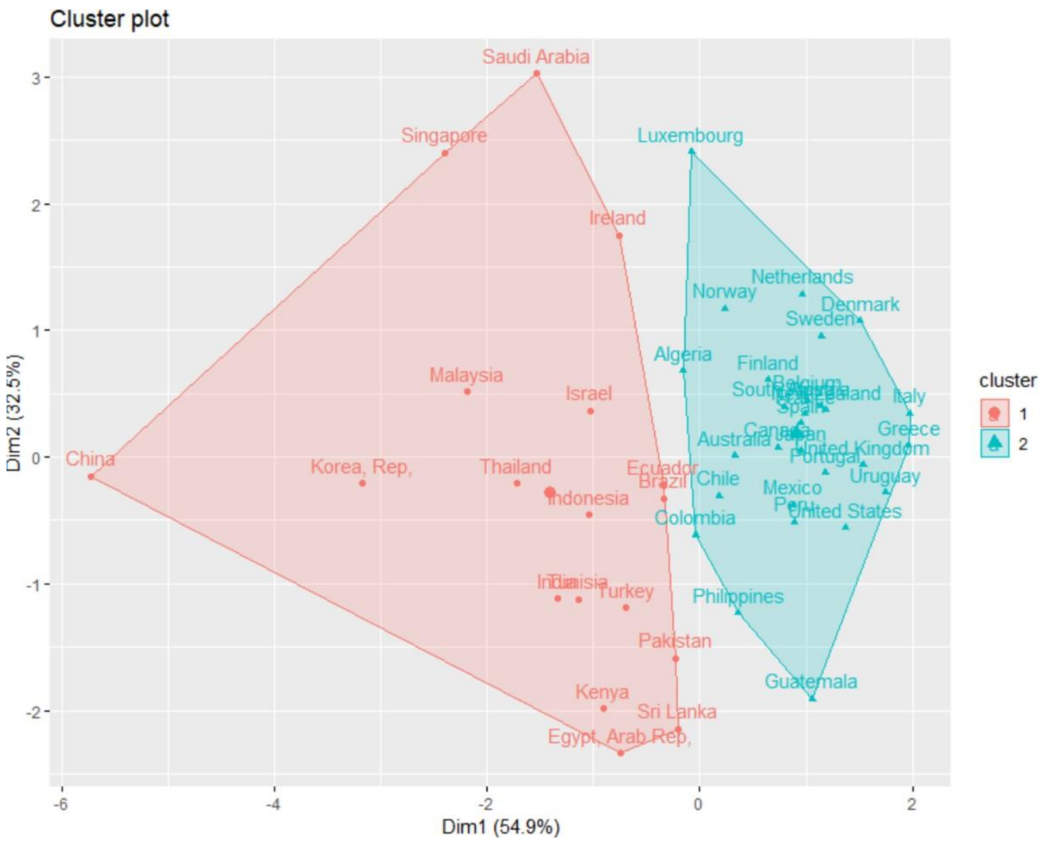
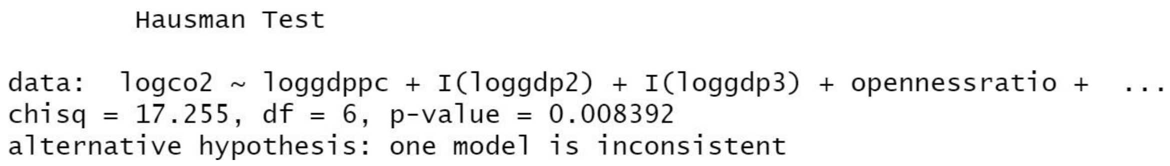


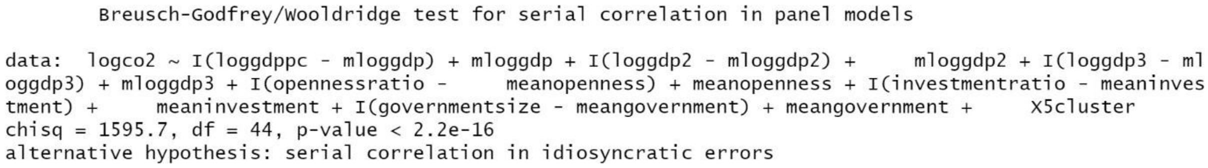
Figure 6 – Clustering groups of the 2means clusters



```
Hausman Test

data:  logco2 ~ loggdppc + I(loggdp2) + I(loggdp3) + opennessratio +  ...
chisq = 17.255, df = 6, p-value = 0.008392
alternative hypothesis: one model is inconsistent
```

Test 1 – Hausman test for the residuals of the Random-Effects estimator



```
Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  logco2 ~ I(loggdppc - mloggdp) + mloggdp + I(loggdp2 - mloggdp2) +     mloggdp2 + I(loggdp3 - ml
oggdp3) + mloggdp3 + I(opennessratio -     meanopenness) + meanopenness + I(investmentratio - meaninves
tment) +     meaninvestment + I(governmentsize - meangovernment) + meangovernment +     X5cluster
chisq = 1595.7, df = 44, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Test 2 – Breusch-Godfrey/Wooldridge test for the serial correlation in the residuals of the model.

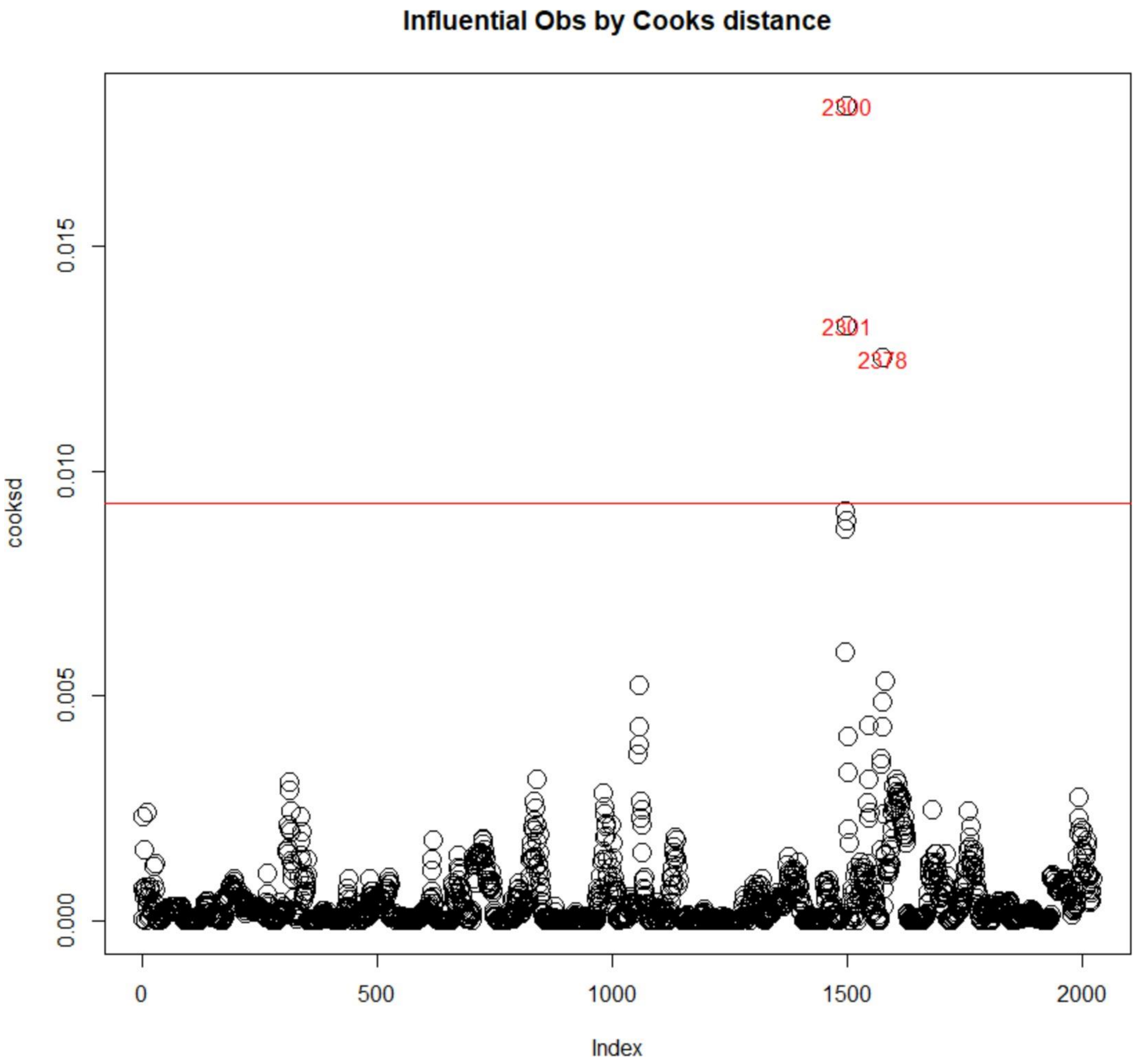
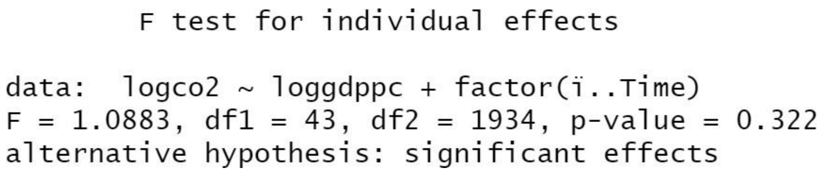


Figure 7 – Graph of Cook's distance method, with the cut-off line and eliminated observations in red.

```
        Breusch-Pagan test

data:  logco2 ~ loggdppc + I(loggdp2) + I(loggdp3) + opennessratio +     investmentratio + governmentsi
ze + X5cluster
BP = 204.72, df = 10, p-value < 2.2e-16
```

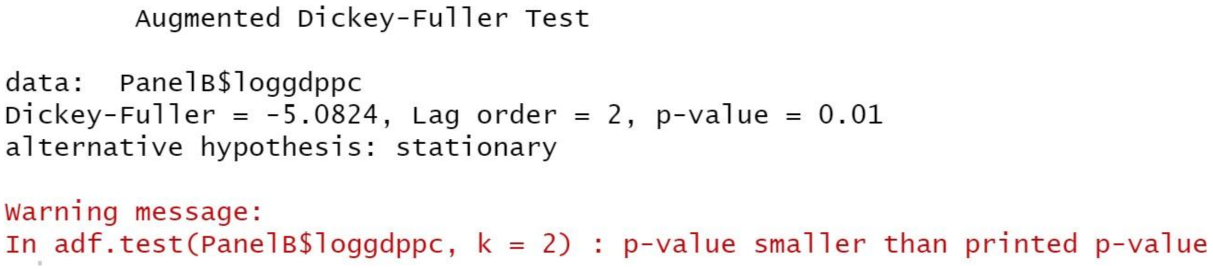
Test 3 – Breusch-Pagan test forheteroscedasticity.



```
        F test for individual effects

data:  logco2 ~ loggdppc + factor(ï..Time)
F = 1.0883, df1 = 43, df2 = 1934, p-value = 0.322
alternative hypothesis: significant effects
```

Test 4 – Lagrange FF Multiplier to test for fixed effects in the model.



```
        Augmented Dickey-Fuller Test

data:  PanelB$loggdppc
Dickey-Fuller = -5.0824, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(PanelB$loggdppc, k = 2) : p-value smaller than printed p-value
```

Test 5 – Augmented Dickey-Fuller test to check for stationarity of GDP in relation to CO2 emissions.

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