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DECOMPOSITION ANALYSIS OF GHG EMISSIONS IN EMERGING ECONOMIES

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We employ decomposition analysis to identify factors driving inter-region/inter-country variations in CO2 emissions. At the regional level, we have selected the ASEAN, BRICS and South Asia and at the country level we study the case of India and China. In addition to the decomposition analysis, we also validate the EKC hypothesis using different econometric forms. Based on the results of the decomposition analysis, we conclude that countries/regions do not show a similar behavior however, EKC hypothesis is validated at both regional and country levels. We fail to arrive at common determinants of emission at inter-regional/country levels. The policy implication of our study suggests that a macro level emissions reduction policy is bleak and individual countries have to be accommodated for their idiosyncrasies. From the analysis of EKC hypothesis, we infer that that CO2 emissions follow a linear trend and validate the EKC hypothesis.

Keywords: GHGs emissions, EKC, Decomposition, Emerging economies
JEL Classification: O13, Q4, Q56, B23

1. INTRODUCTION

With climate change and global warming issues taking the centre stage in all national and international corridors of power, academia is also increasingly making a query into this arena. The much sought after mitigation action is to reduce carbon emissions, collectively by all the countries across the globe. Recently, with the culmination of COP 21 meeting on 22nd April, 2016, close to 175 countries have ratified the Paris agreement. This essentially means that these nations have pledged to limit the increase in global average temperature to well below 2°C above pre-industrial levels. This ratification is quite important for international policy towards global warming and climate change. In this contest of argument, it is quite important to investigate the patterns of emissions and determinants for the emerging economies. The emerging economies are increasingly adding to the emissions given the industrial and economic development that is taking place currently.

When we look at China and India, these economies are one of the fast growing economies with higher investment in infrastructure and industries. Given the rise of these nations, the commitment on emissions reduction will have a huge impact on the future global emissions. Given the acceptance that impact of climate change is a huge problem, it is important to find out regions that are increasingly contributing to global emissions. Data shows that the growth rate in emissions is higher for the emerging economies such as India and China. Interestingly these economies are related to ASEAN and BRICS from the view point of trade, export and development. Hence, these regions makes perfect case to study the pattern of emissions. The next question is can we explain the trends in emissions in these regions? Meaning what are the factors associated with this increasing trend in emissions for these group economies or individual economies? Identification of the factors of emissions will allow policy makers and academicians to formulate better climate policy for the regions and for the international communities. This paper tries to explain the factors of emissions for the emerging economies in context using a different approach, as compared to what has been used so fat in literature. We add to the existing literature in two ways. Firstly, we arrive at the determinants of emissions and secondly, we use an index decomposition method to compare our results with the existing parametric econometric analysis explaining factors related to emissions. The reminder of the paper is as follows. Section 2 gives a detailed review of literature of decomposition studies, particularly for index decomposition analysis, Section 3 deals with data and methodology, Section 4 illustrates the empirical estimation. Section 5 gives a crisp conclusion and relevant policy suggestions.

2. LITERATURE REVIEW

Recently, there has been considerable studies are published using different methodologies to understand the impact of emissions and explaining the factors explaining emissions from micro to macro scale of analysis. Particularly, in the context of understanding economics of energy use and emissions decomposition analysis is one of the methods that is used by researchers, apart from the standard regression techniques. When we focus on the decomposition analysis this can be broadly divided into two groups, namely, structural decomposition analysis (SDA) and index decomposition analysis (IDA). There are quite a large body of research that use both SDA and IDA in analysing energy use, CO2 emissions etc. Movements energy use and emissions are decomposed into determinants such as technological, demand, and structural effects. SDA uses information from input-output tables, while IDA uses aggregate data at the sector-level. Hoekstra et al. (2003) pointed out that an advantage of IDA over SDA is a lower data requirement. But because of this, IDA is capable of less detailed decompositions of the economic structure than SDA, for example, SDA can distinguish between a range of technological effects and final demand effects that are not possible in the IDA framework.

SDA studies are often characterized by 3-10 year time periods because for many countries input–output tables are not constructed annually. Whereas, IDA studies are often highly detailed in terms of the time periods under investigation. Of these two, the methodology of this paper is based on IDA which was first used during the late 1970's to study the impact of changes in product mix on industrial energy demand (Ang and Zhang, 2000). In this seminal work, authors decomposed energy demand in three components, i.e. production effect, structural effect and the intensity effect. Production effect estimates the change in total industrial energy consumption due to change in overall level of production for the given time period whereas, structural effect and intensity effect estimates the change in industrial energy use due to changes in product mix and changes in sectoral energy intensities respectively for the given time period.

During the 1980's Laspeyres, Paasche and Marshall-Edgeworth were the decomposition methods adopted as a modification to the earlier decomposition methods. Ang et al. (1994) introduced two decomposition methods based on divisia index as (1) parametric Divisia method and adaptive weighting Divisia method. Many of the previously proposed methods were shown as a special case of the parametric Divisia method according to Ang and Lee (1994). While, Liu et al. (1992) dealt with energy consumption approach to decomposition, Ang (1994) looks into equivalent decomposition techniques for changes in aggregate energy intensity. One of the major contribution of Ang (1994) is to explain decomposition in both multiplicatively and additively. While additive decomposition involves decomposition of change in aggregate energy intensity, multiplicative method involves the decomposition of the ratio of two aggregate intensities. Decomposition results are dimensionless for multiplicative method, while for additive method results are expressed in units similar to that of the aggregate intensity.

Ang and Lee (1994) reviewed some important methodological and application issues related to the technique of the decomposition of industrial energy consumption. Apart from theoretical studies some of the empirical studies include Shrestha and Timilsina (1996), and Ang and Pandiyan (1997). Shrestha and Timilsina (1996) analyses the evolution of CO2 intensity of the electricity sector in 12 selected Asian countries during 1980-1990. They used Divisia index decomposition to investigate the role of generation mix and fuel intensity in COx intensity changes. The changes in electricity sector CO2 intensity were decomposed into three components; (1) effect due to changes in fuel intensity, (2) the generation mix and (3) the fuel quality. A key finding of this study is that power sector CO2 intensities of most Asian countries were mainly influenced by changes in fuel intensities, rather than shifts in generation structure.

The study by Sun (1998) has been a very important contribution to the literature of index decomposition analysis, that presents a complete decomposition model. This paper tries to overcome the problem of the residual term that arise in the general decomposition model. This paper has the contribution in improving the reliability and accuracy of the decomposition model. The underlying concept which is argued in this paper is to decompose residuals according to the principle of "jointly created and equally distributed" hypothesis. Here, the residual is essentially the interaction of the effects, for example, interaction of structural and intensity effect in an energy intensity model. This residual is then divided equally to the contributions of each effects.

Albrecht et al. (2002) presented a complete decomposition technique based on the Shapley value and used it to study CO2 emissions in four OECD countries. However, Ang et al. (2003) showed that the perfect decomposition technique of Albrecht et al. (2002) and the method proposed by Sun (1998) are similar. Ang et al. (2003) argues that both techniques share similar properties. Apart from Shapely decomposition there are three other methods of perfect decomposition, where decomposition can be carried out both additively and multiplicatively. These methods are log mean Divisia index method-I (LMDI-I), log mean Divisia index method-2 (LMDI-II) and mean rate of change index method (MRCI). Among these, LMDI-I and LMDI-II has relatively easier formulas and the effects to be estimated have the same mathematical form irrespective of the number of factors considered.

Similarly, a comprehensive review of literature on decomposition analysis is presented in Ang and Zhang (2000). While industrial energy demand was the main focus in the earlier years, there have been an increasing number of studies dealing with energy-induced greenhouse gases and other harmful gas emissions. Coming to the results, for the industrialized countries, declining sectoral energy intensity has generally been found to be the main contributor to decreases in the aggregate energy intensity and aggregate CO2 intensity (the ratio of energy-induced CO2 emissions to economic output). The impact of structural change is smaller in comparison. As compared to industrialized countries, the findings for the developing countries are more varied but the impact of changes on sectoral energy intensity has also been greater than that of structural change in most countries. It also highlights the drawback of the Sun (1998) complete decomposition technique. Basically, it is presently applicable only to additive decomposition and the decomposition formulae become very complicated when the number of factors exceeds three. Also, this review points that the most preferred techniques for decomposition has been the logarithmic mean Divisia index method and the refined Laspeyres index (Sun, 1998) method because of their numerous desirable properties. First, both methods yield perfect decomposition results although the mechanisms involved are quite different. Second, when zero values exist in the data set, the refined Laspeyres method is more convenient to apply because the logarithmic mean Divisia method contains logarithmic terms. Third, the logarithmic mean Divisia method has uniform and concise formulae for all the factors and they can be easily derived irrespective of the number of factors. Fourth, the refined Laspeyres index method is presently only applicable to additive decomposition, whereas the Divisia index method is applicable to both additive and multiplicative decomposition.

Apart from country specific studies there have been plenty of cross country/region decomposition studies, which equips analysts and decision-makers with better understanding of the underlying causes of variation in an aggregate between countries. But, cross-country decomposition is often characterized by large variations in explanatory factors, such as GDP and fuel shares in energy consumption, which arise from inherent differences between the countries compared (Zhang and Ang, 2001). In such a situation, application of the conventional decomposition methods could lead to a large residual, this complicates the interpretation pf the results. Zhang and Ang (2001) illustrated that such a problem can be resolved by using perfect decomposition techniques like refined laspeyres method (RLM) or Logarithmic mean weight Divisia method (LDM). Another issue is the choice of GDP measure- exchange rate converted GDP or purchasing power adjusted GDP impacts the results given by cross-country decomposition.

Structural comparability is yet another issue in cross country analysis due to variations among countries in data collection and presentation. Despite of the plethora of literature on index decomposition analysis there is no consensus among the researchers on the preferred index decomposition technique, which are broadly divided into the Laspeyres index and the Divisia index. The Laspeyres index measures the percentage change in some aspect of a group of items over time, using weights based on values in some base year while the Divisia index is a weighted sum of logarithmic growth rates, where the weights are the components' shares in total value, given in the form of a line integral. Ang (2004) tries to address these problems. Similarly, Ang (2005) provide a practical guide to carry out a decomposition analysis using LMDI-I approach.

When we look at the IDA literature in general the work by Ang (2015) is one of the most comprehensive review of recent IDA literature and focuses on the implementation issues of the logarithmic mean Divisia index (LMDI) decomposition methods. Whereas, Liu et al. (2007) is an example of empirical study evaluate the change in industrial carbon emissions from 36 industrial sectors in China from 1998-2005. Using LMDI technique to decompose the changes of industrial CO2 emissions into carbon emissions coefficients of heat and electricity, energy intensity, industrial structural shift, industrial activity and final fuel shift. The analysis shows that the major contributors to the change of China's industrial sectors' carbon emissions in the period 1998-2005 were the industrial activity and energy intensity. The impact of other factors like emissions coefficients of heat and electricity, fuel shift and structural shift was comparatively less significant.

Focusing on the emissions in general and for the CO2 emissions in particular we can refer to Ang and Xu (2013) for a detailed review. It is noted that only after 1990's IDA technique was extended to study GHGs emissions particularly in case of the CO2 emissions. This is the time when climate change and it's impacts were considered to be one of the major challenges for the international policy context. It was found that energy intensity change was generally the key driver of changes in the aggregate carbon intensity in most sectors and countries. In comparison, the contribution of activity structure change and that of carbon factor change have been less significant. Wang

(2013) decomposes energy intensity changes for countries between the years 1980 and 2010 in to five components. It is found that technological progress, capital accumulation and output structure change contributed positively to the declines of energy intensity while decrease in labor-energy ratio increased it. Spatial and temporal heterogeneity existed regarding the relative importance of the five components.

Mundaca et al. (2014) attempts regional decomposition analysis of CO2 emissions from fuel combustion. The study covered eight regions of the world- Africa, Asia, Latin America and the Caribbean, Middle East, Non-OECD Europe and FSU, Oceania, OECD Europe, and OECD North America. Determinants were estimated in relative and absolute terms for the period 1971-2010. The results show that most regions have recently performed worse than their historical trends and lack of meaningful progress is identified. Whereas, specific drivers for certain regions suggest some level of continuous improvement (e.g, reduced energy intensity in Asia, decarbonisation of energy supply in OECD Europe), they are not adequate to offset the effects of economic growth and increased energy use.

Similarly, Xu and Ang (2014) step ahead to introduce two multi-level decomposition procedures that are referred as (1) the multilevel-parallel (M-P) model, and (2) the multilevel-hierarchical (M-H) model. It is an analytical study that looks into the conceptual and methodological aspects of multilevel IDA. M-P model is very similar to the conventional single-level model in calculation procedure, the properties and features of all the existing IDA methods in the literature are applicable to the M-P model. In the M-H model the effects are estimated step by step. Whether or not an IDA method is still equally applicable depends on its feasibility for further decomposition to give sub-effects. This investigation shows that it is directly feasible for multiplicative IDA methods linked to the Divisia index and for additive IDA methods linked to the Laspeyres index. One of the computational issues highlighted was adopting different decomposition procedures in the multi-level analysis, different decomposition results will be obtained for the M-P model and the M-H model, even though the same IDA method is applied. Ang et al. (2015) attempts a multi-country comparisons of energy performance. The study reviews two spatial decomposition analysis models- B-R model and the R-R model, which have been used by researchers in comparisons involving more than two regions.

Thus, overall we see that while to 1990, the main focus of researchers was on studying the relative impacts of changes in the aggregate level of a group of industrial activities, activity structure of the group, and activity energy intensities on energy consumption. Studies on other energy consuming sectors, namely transportation, residential, and service, started to emerge after the early 1990s. At the same time, after 1990, rising concerns about global warming have led to increased use of IDA in energy-related CO2 emissions studies. The growth in CO2 emissions studies has been very strong. In the past ten years, application of IDA has also gone beyond the traditional areas of energy and emissions.

For the Indian context, there have been comparatively fewer such studies. For example, Reddy and Ray (2011), attempts to develop and examine physical energy intensity indicator in five Indian industrial sub sector- iron and steel, aluminium, textiles, paper and cement. It employs decomposition analysis to separate structural effect from a pure intensity effect for each industry. Here, decomposition analysis was carried out at two stages. One is the decomposition of the total energy consumption/CO2 emissions into output effect, intensity effect and structural effect. Second is the decomposition of the energy intensity or CO2 intensity into intensity effect and output effect. Time series decomposition analysis is employed and the method used is similar to Sun (1998) for the study period 1991-2005. The results show that the combined effect (considering both structural and intensity effects together) on both iron and steel and paper and pulp industries is negative while it is positive for aluminium and textiles. The intensity effect for all the industries, except textiles, is negative showing improvement in energy efficiency, especially iron and steel. However, energy intensity in textiles has risen due to increased mechanization. Structural effect is positive in aluminium and iron and steel industries indicating a movement towards higher energy-intensive products. In the case of aluminium, positive structural effect dominates over negative intensive effect whereas negative intensive effect dominates iron and steel industry.

Other studies include Paul and Bhattacharyya (2004), which employed total decomposition approach on total energy consumption and energy intensities at sectoral level (agriculture, industry, transport, and others). They have shown that technical effect contributes significantly to energy conservation at sectoral level. A yet another attempt was Bhaduri and Chaturvedi (2002), which employed both multiplicative and additive decomposition techniques for changes in industrial energy use in two groups of industries (i) Ferro alloys, cement, lime, plaster, dyeing wool, starch, zinc, forging and slaughtering and (ii) aluminium, glass, fertilizer, structural clay, and synthetic resin. The results obtained from both multiplicative as well as additive decomposition techniques are similar and hence the choice of techniques does not alter the conclusions reached. The results show that there is a significant shift in production structure from high to low energy intensive industries. Since both these effects act in opposite directions, there will be no substantial reduction in aggregate energy intensity. In this exercise we have tried to explore the linkages between the structural change, aggregate energy intensity changes and the sectoral energy intensity changes. Another comprehensive study in Indian context is Sahu and Narayanan (2010), which explored the linkages between the structural change, aggregate energy intensity changes and the sectoral energy intensity changes by decomposing the energy intensity in Indian manufacturing.

This review of literature in the areas of IDA has clearly established the importance of the methodology of IDA in the context of environmental studies in general for the emissions trends in particular. Based on the extensive and rich arguments from the IDA literature, we focus on the index decomposition method to understand the trends and factors related to the GHGs emissions. The choice of region in this case has been the emerging economies that include China and India and the regional groups such as the ASEAN and BRICS countries. Given the increasing contributions from these economies, it is vital to study the trends of these economies for better international, regional and country level policies.

3. DATA AND METHODS

The aim is to explore the drivers of greenhouse gas emissions, particularly CO2 emissions using index decomposition analysis and validate the results using the standard Environmental Kuznets Curve (EKC) hypothesis. We collect information and data from the secondary sources mostly from the World Development Indicators (WDI) of the World Bank Database. We use aggregate data of the following economies: India, China, Russia, Brazil, South Africa, Indonesia, Malaysia, Philippines, Singapore, Thailand, Brunie Darussalam, Vietnam and the aggregate world data. As noted earlier decomposition can be carried out either at group or sub-group levels. We use these standard groups as defined by the World Bank database, namely BRICS[1], ASEAN[2] and South Asia. Given the importance of the emerging economies in emissions patterns we also analyse for China and India separately. In this study, we analyse five ASEAN economies such as Indonesia, Malaysia, Philippines, Singapore and Thailand. This choice of economies from the ASEAN has been governed purely by data availability. The time period covered for this study is from 1990-2011. The study period is chosen based on continuous data availability for all countries for all variables used in analysis. Table-1 illustrates the variables used in the analysis, both for the decomposition analysis and validating the EKC hypothesis.

As explained earlier, the decomposition analysis is a mathematical tool, unlike regression analysis, which is not governed by the CLRM assumptions. In this study, we decompose the inter region/country variations in CO2 emissions. The choice of technique is multivariate decomposition for non-linear response models. It is developed to understand within group inequality using non-linear framework, where identification of equation doesn't have the properties of linear equation related to normal distribution. The reason for the use of this technique in particular and index decomposition analysis in general can be attributed to the fact that historical emissions data cannot be explained adequately by linear regression models and therefore one of the most popular alternative technique is index decomposition analysis. Further, we establish the EKC hypothesis for the sample. In the most general form, EKC has an inverted U-shape. In this study, we try to examine the shape of EKC with different models. We basically want to establish if there is coherence in results obtained from the two techniques.

[1] BRICS is a grouping acronym that refers to the countries of Brazil, Russia, India, China and South Africa, which are all deemed to be at a similar stage of newly advanced economic development.

[2] ASEAN (Association of Southeast Asian Nation) is a political and economic organisation of ten Southeast Asian countries. Its aims include accelerating economic growth, social progress, and socio-cultural evolution among its members, alongside protection of regional stability as well as providing a mechanism for member countries to resolve differences peacefully

Table 1. Definition of variables

Code	Variable	Definition	Unit of Measurement
CO2EMI	CO2 emissions	Carbon dioxide emissions stemming from the burning of fossil fuels and the manufacture of cement.	Kilo tonnes (Kt)
CO2MANC	CO2 emissions from manufacturing industries and construction	CO2 emissions from manufacturing industries and construction contains the emissions from combustion of fuels in industry.	% of total fuel combustion
CO2OTH	CO2 emissions from other sectors, excluding residential buildings and commercial and public services	CO2 emissions from other sectors, less residential buildings and commercial and public services, contains the emissions from commercial/ institutional activities, residential, agriculture/ forestry, fishing and other emissions.	% of total fuel combustion
CO2TRAN	CO2 emissions from transport	CO2 emissions from transport contains emissions from the combustion of fuel for all transport activity, regardless of the sector.	% of total fuel combustion
TOTINDEMI	Total Emissions from Industry	It is the sum of emissions from manufacturing industries and construction, transport and other sectors excluding residential buildings and commercial and public services	% of total fuel combustion
CO2INT	CO2 intensity	Carbon dioxide emissions from solid fuel consumption refer mainly to emissions from use of coal as an energy source.	kg per kg of oil equivalent energy use
GHGEMI	Other greenhouse gas emissions, HFC, PFC and SF6	Other greenhouse gas emissions are by-product emissions of hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride.	thousand metric tons of CO2 equivalent
TOTPOP	Population, total	Total population is based on the de factor definition of population, which counts all residents regardless of legal status or citizenship except for refugees not permanently settled in the country of asylum.	
GDPPERCAP	GDP per capita, PPP (constant 2011 international $)	GDP per capita based on purchasing power parity (PPP), PPP GDP is gross domestic product converted to international dollars using purchasing power parity rates.	
ENERUSEPERCAP	Energy use	Energy use refers to use of primary energy before transformation to other end-use fuels.	kg of oil equivalent per capita
RURPOP	Rural population	Rural population refers to people living in rural areas as defined by national statistical offices.	
URBPOP	Urban population	Urban population refers to people living in urban areas as defined by national statistical offices.	
AGRIVALADD	Agriculture, value added	Agriculture includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs.	% of GDP
INDVALADD	Industry, value added	Industry includes manufacturing. It comprises value added in mining, construction, electricity, water, and gas. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs.	% of GDP

Source: WDI, The World Bank.

4. EMPIRICAL ANALYSIS

This section explains the pattern of CO2 and GHG emissions across countries, across time period and across regions. From the database, we select four variables of interest such as CO2 emissions (CO2EMI), total industrial emissions (TOTINDEMI), CO2 intensity (CO2INT) and GHG emissions (GHGEMI). Table 2, presents the descriptive statistic of variables.

Table 2. Summary statistics (full sample overtime**)**

Variable	Observation	Mean	Std. Dev.	Min	Max
CO2EMI	306	1769515	3850351	4231.718	22300000
TOTINDEMI	306	46.935	15.165	17.126	79.581
CO2INT	284	2.398	0.619	0.531	4.072
GHGEMI	306	599470.3	1550946	54.4	8343799

Source: WDI Indicators.

We can see from Table 2, that mean carbon emissions and carbon intensity across the countries/regions is 1.76 million kilotonnes and 2.39kg, per kg of oil equivalent (kgoe) of energy use, respectively. Given the distance of the minimum and maximum carbon emissions and carbon intensity it needs further investigation to understand the country level differences. We present the descriptive statistics annually in the appendix Table 1A. The trend in emissions and output are clearly showing an increasing trend given the minimization of trade barrier and opening of major economies.

From Table 1A, we observe that CO2 emissions have increased, upward from 1990 to 2011, with an average CO2 emissions of 1,216 thousand kilotons in 1990 to 2,842 thousand kilotons in 2011, an approximate increase in average emissions by 1,626 thousand kilotons in a time span of two decades. The increase in the average emissions of other GHG's has not been gradual, rather it has been riddled with ups and downs. For a decadal comparison of emissions and other variables of interest, results are summarized in Table 3. While the average CO2 emissions during the decade 1990-1999 was 1,363 thousand kilotons, it was around 2,103 thousand kilotons during 2000-2011. For other GHG emissions, the decadal average has actually fallen from 639 to 566 thousand kilotons.

Table 2A, in appendix, gives summary statistics at country levels. Within countries, China, Russia and India are leading the emissions charts with average CO2 emissions at 4,635, 1,660 and 1,256 thousand kilotons respectively leading to an overall higher average for South Asian region. In comparison, countries like Philippines, Singapore and Vietnam has low average CO2 emissions. However, when it comes to other GHG emissions, while Russia retains its position in the emissions race India and china losses out to Brazil and Indonesia. Moving away from the normative definition and adopting alternative definition of region, we further try to understand the inter-regional variation of the indicators- CO2 emissions, CO2 intensity and other GHG emissions for BRICS vs Rest of the sample (ROS, henceforth). Similar attempts have been made for ASEAN vs ROS, South Asia vs ROS and world vs ROS. The results are summarized in Table 4. We can observe that, as compared to rest of the sample and rest of the regions, ASEAN has minimum average CO2 emissions lurking at approximately 151 thousand kilotons. South Asia and BRICS average CO2 emissions are closer to those of ROS. Similar is the case with their CO2 intensity but not with other GHG emissions, where there is huge disparity between region average and ROS average.

Table 3. Summary statistic (decadal time frame)

	CO2EMI (in 000)	TOTINDEMI	CO2INT	GHGEMI (in 000)
1990-1999	1363.490	47.817	2.228	639.079
	(2900.125)	(16.594)	(0.889)	(1605.675)
2000-2011	2103.036	46.210	2.223	566.935
	(4464.081)	(13.892)	(0.839)	1508.560)

Source: WDI Indicators.

Now having a broad idea on emissions and its pattern, we further investigate the inter-country growth rates for the select indicators. Growth rates are computed using Semi-logarithmic linear function from 1990-2011. The results are summarized in Table 5. For CO2 emissions, of all countries under consideration, only Russia and Singapore has shown a declining trend. As can been observed from the table, reason might lie into declining CO2 intensity for both the countries. For India, the growth of CO2 emissions has been positive for the two decades, however, growth in total industrial emissions shows a negative sign, possibly, because of falling emissions from manufacturing industries and construction, other sectors excluding residential and commercial buildings and public services. But, there has been no overall decline recoded in CO2 intensity. The scenario, as depicted in the table, is similar for China, Indonesia and South Asia.

Multivariate decomposition for non-linear response models has been employed to identify the reasons for variations in CO2 emissions for three regions and two countries- BRICS, ASEAN, South Asia, India, China and World as a whole. The reason India and China are taken independently is because both economies are competing each other in terms of output growth, which will lead to aggrandized levels of emissions in both the economies. On one hand, China is the hub of international manufacturing of goods and services. On the other hand, India play a dominant role in the IT, ITES and service sector. Therefore, these two economies will greatly influence the global emissions in the future and are thus tackles separately in this study.

Table 4. Summary Statistic (Region Wise)

Group	CO2EMI (in 000)	TOTINDEMI	CO2INT	GHGEMI (in 000)
BRICS	1650.085	44.874	2.634	314.579
	(1846.899)	(17.607)	(0.624)	(409.312)
ROS	1834.659	48.059	2.003	754.866
	(4592.161)	(13.568)	(0.891)	(1887.959)
South Asia	1418.470	40.420	2.448	69.766
	(466.633)	(2.856)	(0.193)	(38.894)
ROS	1796.709	47.439	2.208	640.504
	(3993.897)	(15.611)	(0.889)	(1602.752)
ASEAN	151.100	49.377	2.238	158.199
	(111.112)	(12.308)	(0.616)	(443.157)
ROS	2677.809	45.564	2.219	847.123
	(4568.859)	(16.426)	(0.973)	(1865.766)
World	25500.000	43.579	2.400	6950.652
	(6861.559)	(0.847)	(0.525)	(1100.108)
ROS	1570.033	48.071	2.160	587.245
	(3668.456)	(15.315)	(0.882)	(1509.775)

Source: WDI Indicators.

Table 5. Growth Rate of Variable across Economics

Country	CO2EMI	CO2MANC	CO2OTH	CO2TRAN	TOTINDEMI	CO2INT	GHGEMI
India	0.051	-4.275	-2.838	0.056	-7.058	0.011	0.058
Brazil	0.034	1.629	-1.432	2.308	2.504	0.004	0.032
Russian Federation*	-0.007	2.007	-3.250	1.381	0.138	-0.003	0.001
China	0.061	-10.387	-3.996	3.588	-10.795	0.007	0.066
South Africa	0.018	-10.236	1.369	1.830	-7.037	-0.002	0.110
Indonesia	0.062	-7.104	-0.492	6.850	-0.746	0.027	-0.225
Malaysia	0.065	-14.257	1.399	-5.451	-18.309	0.005	-0.140
Philippines	0.031	-12.015	-1.273	-5.471	-18.759	0.015	-0.008
Singapore	-0.033	22.071	-0.205	0.506	22.372	-0.068	0.077
Thailand	0.054	9.179	-2.214	-9.564	-2.599	0.005	0.055
Brunei Darussalam	0.021	17.282	NA	-1.566	15.715	-0.016	-0.136
Vietnam	0.100	2.513	-2.782	-0.048	-0.317	0.040	0.000
NON-OECD	0.033	4.298	0.378	-2.414	2.262	NA	0.012
South Asia	0.051	-4.441	-2.602	0.087	-6.956	0.012	0.047
World	0.020	-1.236	-1.818	0.286	-2.768	0.003	0.015

*: Data available only for 20 years, NA: CAGR not computed.
Source: WDI Indicators.

To have a comprehensive understanding of emissions decomposition, we have further classified emissions into GHG emissions and CO2 emissions. The response models are verified and re-estimated using different variables to arrive at identifiable indicators, which can explain inter-regional differences in emissions. The identifiable indicators are total population, GDP per capita, energy use per capita and CO2 emissions. The results of the decomposition analysis are reported from Table 6-10. These tables report the Z scores and the Delta. The estimation gives three components: first one relates to difference in characteristic (E), difference in coefficient (C) and total difference (R).

We will first interpret the variations in emissions due to differences in country/region characteristics (E). In Table 6, Z scores of China, BRICS and world are significant and negative sign which implies that there CO2 emissions are decreasing over the period of time because of the similar characteristic within the group. However, CO2 emissions are rising for India, South Asia and ASEAN due to country characteristics. As can be observed from the Table 6, GDP per capita is not a significant determinant of CO2 emissions for most regions/countries. One of the reasons can be that most of the countries/ regions considered in the study are more of less on a similar growth trajectory. We can, thus, safely drop GDP per capita from the response model and re-estimate the model. The results are summarized in Table 7.

We observe, from Table 7, that Z score of China, ASEAN and world are significant and negative i.e. CO2 emissions have decreased over the time. Rest are significant and positive. An Interesting point to note, in Table 7, is that on dropping GDP per capita from the model, Z score of BRICS goes from being negative to positive and of China goes from statistically insignificant to significant and negative. This reflects that GDP plays a crucial role in Chinese CO2 emissions determination than its influence in Indian case, as the direction of the emissions was retained when GDP was dropped from the model. This can also be the reason behind BRICS changing its emissions direction after GDP is dropped from the model. This essentially means that any policy for BRICS won't be effective if China is not given special attention. Examining the difference in delta for the two models, one can predict the potential impact of dropping GDP per capita on emissions. In case of India, South Asia, ASEAN and BRICS emissions reduces by 0.025%, 0.038%, 0.004% and 0.157% respectively, while it increases up to 0.135% for China

The "C" represents the series characteristics, which essentially reflects the statistical behaviour of each series in a sample. In Table 6, all the countries/region are statistically significant in terms of the statistical properties of the sample or sub-sample whereas, in Table 7, all except world are statistically significant. 'R' represents the total effect from both E and C, which is significant and negative for India, South Asia and world in both Table 6 and 7, which reflects a possibility of CO2 emissions reduction for these countries. However, there is no common variable which explains this reduction across region/countries and across the two response models in Table 6 and 7.

Decomposition analysis is a mathematical tool and probably does not depend on an economic theory. As a result, it becomes extremely important to validate the results obtained from decomposition analysis using an appropriate theory. In this study we will investigate if EKC hypothesis holds true for the CO2 emissions.

$$Emission = f\,(GDPPERCAP, TOTPOP, timetrend, RURPOP, URBPOP, ENERUSEPERCAP, INDVALADD, AGRIVALADD) \quad (1)$$

The variants of the above mentioned equation, as a determinant of emissions, has been estimated using different compositions and different functional forms. For instance, to validate EKC we start with a non-linear relationship of GDP per capita (GDPPERCAP) with emissions.

This results are presented in Table 8. From Table 8, we can observe that in this case, model-1 (M1) validates EKC hypothesis, as it gives an inverted U-shape relationship between GDP and CO2 emissions. Similarly, M2 explains the long run validity of EKC by including a cubic function of GDPPERCAP. It illustrates an N-shaped relationship between GDP and CO2 emissions. In M3, time trend is statistically insignificant i.e. CO2 emissions do not vary with time. In M4, total population is statistically significant and positive, which insinuates that with an increase in population the emissions would go up as well. M5 illustrates the positive dependency of CO2 emissions on rural population. Similarly, in M6 it does with urban population. M7 illustrates the non-linear relationship of CO2 emissions with energy use. It illustrates that initially emissions increase with energy use. However, after a threshold is reached the emissions decline with energy use. One of the reasons underlying this change could introduction of new and cleaner technologies over time which leads to emissions reduction in longer run. M8 illustrates the positive and significant relationship between the emissions and agricultural value added.

5. CONCLUSION

In this study, we carried out a decomposition analysis to study the factors driving the inter region/country variations in GHG emissions, particularly for the CO2 emissions. The regions/countries under investigation are ASEAN, BRICS, South Asia, India, China and aggregate data for the world. Additionally, we also examined the EKC hypothesis using different functional forms of econometric models. From the decomposition analysis, we conclude that countries/region do not show a similar behaviour, in explaining CO2 emissions. We fail to arrive at common determinants of emissions, at inter region/country levels. The policy implication of such a result is that the possibility of a macro level emissions reduction policy is bleak and individual country has to be accommodated for its idiosyncrasies. From the EKC validation exercise, we infer that that CO2 emissions follows a normal linear equation and validated for the sample of economies. We in this study suggest that each pollutants within GHG emissions should be scrutinized individually. Scientific reason for this is evident as each pollutant differ from each other in terms of origin of pollution, nature etc. A common international programme on emissions reduction may not be productivity, if independent economies are not focusing on domestic emissions reduction policies.

Table 6. Decomposition of CO2 Emissions (Model 1)

	Z-scores						Delta				
CO2EMI	India	China	South Asia	ASEAN	BRICS	World	India	China	South Asia	ASEAN	BRICS
E	13.94*	-1.53	12.13*	10.19*	-6.93*	-19.03*	-0.453	-0.815	-0.220	-0.904	-0.771
C	12.63*	3.65*	11.6*	-9.22*	6.18*	-20.6*	-1.432	-1.382	-1.646	-0.900	-1.184
R	-8.21*	46.58*	-6.24*	25.43*	-1.51	-300.26*	-0.978	-1.119	-0.985	-0.902	-0.992
TOTPOP	6.97*	1.69***	5.69*	10.1*	16.14*	-18.8*	-1.042	-1.108	-1.050	-0.905	-0.918
GDPPERCAP	1.6	1.25	0.88	-3.22*	-4.79*	-6.91*	-6.908	-7.145	-5.319	-0.945	5.996
ENERUSEPERCAP	-7.29*	-10.18*	-6.29*	-3.3*	-4.02*	8.09*	-43.170	-25.89	-55.517	-1.104	-1.170
TOTPOP	-9.06*	-0.63	15.03*	13.36*	5.65*	-0.89	-0.797	-0.907	-0.746	-0.649	-1.224
GDPPERCAP	-1.05	-0.95	-0.48	4.68*	4.45*	-1.05	-0.801	-0.724	-0.879	-1.121	-1.561
ENERUSEPERCAP	6.59*	9.28*	5.85*	-6.39*	1.85***	-5.2*	-1.290	-1.307	-1.377	-0.960	-1.019

*Significant at 1% level, ** Significant at 5% level, ***Significant at 10% level.

Table 7. Decomposition of CO2 Emissions (Model 2)

	Z score						Delta				
CO2EMI	India*	China	South Asia*	ASEAN#	BRICS	World	India*	China	South Asia*	ASEAN#	BRICS
E	13.6*	-6.4*	13.85*	-9.52*	14.92*	-17.81**	-0.478	-0.680	-0.258	-0.908	-0.928
C	12.27*	11.44*	13.2*	-9.01*	4.81*	-18.91**	-1.419	-1.506	-1.626	-0.896	-1.049
R	-7.89*	45.12*	-5.96*	23.97*	-1.43	-286.96**	-0.978	-1.119	-0.985	-0.902	-0.992
TOTPOP	7.19*	1.12	5.82*	-9.54*	15.08*	-17.76**	-1.035	-1.045	-1.046	-0.908	-0.933
ENERUSEPERCAP	-16.61*	-38.01*	-17.19*	-0.86	-8.53*	3.89**	-141.927	-93.366	-200.178	-1.004	-2.272
TOTPOP	11.55*	-2.42**	16.35*	12.58*	3.21*	-7.18**	-0.890	-0.885	-0.872	-0.829	-1.056
ENERUSEPERCAP	15.88*	35.65*	16.73*	-4.76*	6.84	-19.22**	-1.204	-1.238	-1.287	-0.988	-1.031

*Significant at 1% level, ** Significant at 5% level, ***Significant at 10% level.

Table 8. Test of EKC Hypothesis

	M1	M2	M3	M4	M5	M6	M7	M8
VARIABLES	CO2EMI	CO2EMI	CO2EMI	CO2EMI	CO2EMI	CO2EMI	CO2EMI	CO2EMI
GDPPERCAP	201.5***	378.4***	355.3***	326.9***	304.5***	86.95***	249.6***	317.6***
	(21.80)	(30.61)	(40.64)	(38.70)	(40.91)	(27.63)	(60.80)	(39.62)
GDPPERCAPSQ	-0.00187***	-0.00947***	-0.00916***	-0.00757***	-0.00857***	-0.00136*	-0.00734***	-0.00723***
	(0.000223)	(0.00102)	(0.00108)	(0.00106)	(0.00105)	(0.000750)	(0.00133)	(0.00110)
GDPPERCAPCU		6.96e-08***	6.82e-08***	5.37e-08***	6.61e-08***	7.23e-09	5.77e-08***	5.10e-08***
		(9.18e-09)	(9.32e-09)	(9.16e-09)	(9.03e-09)	(6.33e-09)	(1.05e-08)	(9.56e-09)
Time Trend			-6,212	12,069	-19,704***	18,626***	-10,393	19,645**
			(7,194)	(7,493)	(7,587)	(4,515)	(7,368)	(8,583)
TOTPOP				0.00340***				
				(0.000588)				
RURPOP					-0.00396***			
					(0.000890)			
URBPOP						0.0127***		
						(0.000588)		
ENERUSEPERCAP							708.5**	
							(306.0)	
ENERUSEPERCAPS							-0.0532**	
							(0.0229)	
AGRIVALADD								-67,589***
								(13,388)

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10.

APPENDIX

Table 1A: Summary Statistics (Annual)

Year	CO2EMI (in 000)	TOTINDEMI	CO2INT	GHGEMI (in 000)
1990	1216.198	50.402	2.214	563.121
1991	1253.232	49.641	2.171	643.341
1992	1307.302	48.486	2.193	702.101
1993	1311.209	47.995	2.198	566.397
1994	1337.021	47.705	2.237	601.567
1995	1389.430	48.018	2.231	531.746
1996	1431.952	47.522	2.284	513.192
1997	1457.811	46.990	2.323	895.689
1998	1455.587	45.872	2.247	854.411
1999	1456.760	45.858	2.178	514.106
2000	1496.784	45.463	2.242	437.618
2001	1557.530	45.353	2.249	404.669
2002	1589.276	45.689	2.199	622.666
2003	1759.750	45.734	2.157	633.732
2004	1921.841	45.787	2.161	529.313
2005	2042.836	45.536	2.177	629.070
2006	2186.524	46.844	2.127	649.123
2007	2270.128	46.996	2.210	638.861
2008	2399.646	46.687	2.275	490.000
2009	2512.053	46.850	2.323	418.683
2010	2657.184	46.672	2.232	639.140
2011	2842.879	46.904	2.328	710.340

Data Source: WDI Indicators.

Table 2A: Summary Statistic (Country Levels)

Country	CO2EMI (in 000)	TOTINDEMI	CO2INT	GHGEMI (in 000)
Brazil	314.876	77.262	1.614	904.765
Brunei Darussalam	6.105	26.311	2.450	4.165
China	4635.193	45.681	3.148	140.166
India	1256.019	38.235	2.546	62.241
Indonesia	301.345	54.455	1.909	699.543
Malaysia	141.106	51.442	2.741	51.543
Non-OECD	14300.000	56.590	0.000	5917.732
Philippines	66.322	56.233	1.809	11.147
Russian Federation	1660.534	28.679	2.515	452.996
Singapore	41.452	27.564	2.163	1.825
South Africa	384.753	33.040	3.337	25.310
South Asia	1418.470	40.420	2.448	69.766
Thailand	205.276	57.190	2.567	26.937
Vietnam	71.907	62.323	1.936	11.132
	46.893	4.311	0.564	10.152

Data Source: WDI Indicators.

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