Environmental Kuznets Curve: An Application of Heterogeneous Panel Methods Robust to Cross Sectional Dependence and Structural Breaks

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CERTIFICATE

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Dedication

DEDICATED TO MY COURAGEOUS FATHER; MAZHAR QAZI WHOM I OWE MY ALL SUCCESS.

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Abstract

The combined panel data matrix set consists of a time series for each cross-sectional member in the data set, and offers a variety of estimation methods. The present study aims to compare the estimates of different panel data estimation techniques by taking the example of Environmental Kuznets Curve (EKC). EKC is a hypothesized relationship between environmental pollutants and output. Plethora of research is available to determining relationship between environmental degradation and output. However in literature it is evident that when we change the assumptions of estimation technique, coefficients also get changed (Stern 2003). Therefore; it is important to reinvestigate the EKC using several panel data techniques.

The primary objective of this study is to estimate the heterogeneous parameters and finding the cross sectional dependence of the large sample panel data. For the purpose we will not only rely on conventional panel data techniques but will also use 2nd generation test of cointegration. We hope to have clarified how to interpret the fact that the EKC hypothesis does not hold for individual countries, but emerges from the overall picture.

Since the existing literature; except few assumed slope homogeneity and cross sectional independence so we expect that our study will contribute in the field of applied econometrics by reassessing the relationship between environmental degradation and output growth in a large panel data for three different groups of countries i.e. low income countries, middle income countries and high income countries. Further presence of structural breaks is also a phenomenon which cannot be ignored in presence of long panel data. Therefore; we have also assumed it to get a clear picture.

After establishing a long run relationship we have applied Mean Group (MG), Pooled Mean Group (PMG) and Common Correlated Effect Mean Group (CCEMG) to measure the magnitude of the relationship among CO_2 and output. The results confirm the presence of inverted U shape relationship between environmental pollution and output. However; the coefficients obtained by these techniques significantly differ from each other.

Chapter: 01

Introduction

Indeed, the use of econometrics to evaluate any economic theory is not a unique idea. Recently, almost every empirical study in social science, especially in economics, uses the statistics or econometrics techniques for the testing of different hypothesis and economic theories. The main target of using these statistical tools in economics is to calculate the data based inferences about the various relationships among the variables. For example, does the use of energy have some impact on the economic growth of the nation? Does this economic development have a negative or positive influence on the quality of atmosphere? Indeed, these types of practical questions require more than the philosophy and the descriptive statistical analysis. Therefore, the use of econometrics is justified.

In this backdrop, different econometric techniques are being developed to discuss the various complexities of the empirics. Specifically; there are three main methodological strands in the context of econometrics built by considering data type. First discusses the econometrics of cross sectional data, second belongs to the econometrics of time series data and third is the econometrics of panel data. However, it is well recognized that there are many limitations accompanied by using estimation methods to estimate the cross-sectional data sets while addressing the questions to deal with causal ordering. Specifically, there are three main limitations to the cross sectional data analysis; First, Duncan (1972) and Holland (1986) posted that the unobserved variable which are biased, cannot be analyzed in the cross sectional data set. Second, the endogeniety bias is a main problem according to Hausman (1978), Berry 1984 and Finkel (1995). Third, we can conclude nothing about intra-individual changes over time while studying cross sectional data.

Therefore, the econometricians allow the panel data analysis for the measurement of the cross-sectional heterogeneity over time among the cross sectional units. Hence, there is a plethora of research which provides the number of studies on the use of various estimation methodologies of panel data for various environmental related issues in the niche of economics. However; all the techniques have some advantages over other depending on the length and width of the panels. More specifically, panel data commonly uses four procedures. These are averaging group, aggregating estimates, pooling and cross-section regression.

We can also group data in two further categories, static and dynamic panel series. If the coefficients differ randomly in the static panel data, all techniques give unbiased estimates of the mean of the coefficients. But, in the panel studies when the coefficients vary across groups, aggregating and pooling leads to inconsistent and strongly misleading results of the coefficients. Though, the cross-section study may deliver constant results while considering long run parameters. In dynamic models, aggregate and pooled estimators are not considered as steady, even if N and T are very large, the biasedness in the data can be very important. The issue erupts due to the reason that the regressors are serially correlated; wrongly ignoring coefficient heterogeneity creates serial correlation in the disturbance. This makes inconsistent and unstable measurements in models with dependent variables that are lagged, even as $T \rightarrow \infty$. Thus, this instability is quite specific from that underwent by the fixed effect estimators in smaller T panels as N $approaches\ \infty$.

Pesaran (2006) illustrated in his study that pooling or aggregating dynamic heterogeneous panels can yield deceptive inferences. Furthermore, in dynamic models the frequently used hypothesis of homogeneity is too away from the reality. More clearly, most of the estimation techniques in the panel data econometrics assume that the slope parameters are homogenous among the cross sections. Therefore, the inferences cannot vary from cross sectional unit to unit.

Moreover, when there is long panel data, where time series observations are large, then the problems of time series data also arise in the series. Hence, testing the stationarity is starting point in such series otherwise the results obtained are spurious and misleading. The tests designed for checking cross sectional dependence by the second generation techniques and the serially uncorrelated first generation methods are different. Also, some studies allow for structural breaks in presence of cross sectional dependence. But, there are number of flaws in these unit root tests.

Although, some tests can be applied under the alternative hypothesis to liberate the restriction on the homogeneous coefficient, but using it might ensure limitations. Several tests of unit root were developed by Im et al. (2003) for the random coefficients in the model. The findings revealed that homogeneous constraints imposed on the auto regressive structure were being loosened. As, the so far formed tests of unit root for panel data are based on the individual unit root tests for time series data. So, we can deduce the outcomes from the panel unit root tests that: If the entire sample of countries reject the null hypothesis of the unit root test then it is not because the coefficients are stationary.

Considering all the above arguments we considered dynamic heterogeneous panel data models and their techniques referring towards the work of Pesaran (2006). His work on multifactor error structure gave us a new approach of handling heterogeneous panels. However, before reaching to this point, we set a stage considering the conventional panel estimation techniques.

There are a number of cases in economics that can be considered to explain the heterogeneity in a panel data such as money-demand function, Labor-Demand function, Environmental Kuznets curve and measuring financial development theories. However, keeping our interest in view, we are taking the case of Environmental Kuznets Curve (EKC) for testing robustness in various econometric techniques.

Environmental Kuznets Curve (EKC) is considered as a postulated association among numerous variables of environmental degradation and economic growth. The concept of EKC was presented by Grossman and Krueger (1991) and promoted by the World Bank (Shafik and Bandyopadhyay). Researchers have explored a large variety of pollutants for validating the EKC hypothesis. Along with that, different studies have been experimented by using different econometric approaches which included: fixed and random effects, different orders of polynomials, semi-parametric and non-parametric techniques, splines and different covariate specifications (Levinson, 2008).The EKC phenomena took the importance because, very rare adequate attention was being paid to econometric diagnostic statistics. Stern (2003) explained that the statistical properties of the data used had been considered negligibly. Like dependence serial dependence of the series or random trends within a series and limited tests of model competence had been proposed. Conversely, testing which ostensible relationships or "stylized facts" are effective and which are spurious correlations is one of the main purposes of doing econometrics. The study stressed on, that most of the EKC literature is econometrically weak.

Bulk of literature is available on environmental Kuznets curve. For example; Shahbaz et al. (2014 a), Yavuz (2014), Tan et al. (2014), Shahbaz et al. (2013 a, b), Kohler

(2013), Jalil and Mahmud (2009), Ang (2007) considered the time series data of different countries and found mixed results about the presence of Kuznets curve. Similarly, number of studies considered the panel of different cross sections to check the relationship of economic degradation and economic growth (see, Shahbaz et al.; 2015, Apergis and Ozturk; 2015, Chow; 2014, Osabuohien et al.; 2014, Cho et al.; 2014, Ozean; 2013, Hamit- Hoggar; 2012, Atici; 2009).

However, the debate remains open due to the differences in the sign, size, and significance. The controversy among the researches about the direction and the turning points of the curve motivates the researchers to further investigate the relationship between the carbon emission and the GDP. We are convinced that the sign, size and significance are really sensitive to the choice of the estimation methodology. Therefore, we need to compare the findings of the different methodologies to guide the policy makers on a right track. The present study is conducted in this way.

1.1: Significance of the Study

Indeed, reassessing the phenomenon of environmental Kuznets curve is not a unique idea as plethora of research is available in this regard. However; the existing literature; except few, assumes slope homogeneity and cross sectional independence. Furthermore, structural breaks are also being ignored while checking the empirical relationship between environmental degradation and growth in output, even in the presence of long panel data. Therefore, we are convinced that the present study will contribute in the field of applied econometrics.

1.2: Objectives of the Study

The main objectives of this study are:

- To reinvestigate the connection among the deprivation of environmental condition and output growth by econometric techniques using a panel data of large sample size, considering three different groups of countries, that is, lower, middle and higher income countries.
- To consider cross sectional dependence and slope heterogeneity, along with them, will also check the presence of structural breaks in the series.
- The study will compare the results of presence of Kuznets curve from many of the techniques of panel data to find the biasedness in the coefficients.

1.3: Organization of the Study

The other chapters of this study are planned as follow; chapter 2 covers the review of existing literature. Chapter 3 is about theoretical framework and econometric specification, while; chapter 4 describes the construction of variables and data sources. Chapter 5 explains the required estimation methodology. Chapter 6 discusses about the empirical results of the study and finally, chapter 7 is conclusion of the study with policy implications.

Chapter: 02

Literature Review

The worldwide environmental alarms owing to antagonistic climatic changes on the planet earth have moved the world economies towards the usage of green energy along with substantial drop in CO2 emission. Environmental Kuznets Curve (EKC) is a hypothesized relationship among many indicators of environmental dreadful conditions and economic development with this respect. The present study will compare the results of different panel estimation techniques, and for this purpose the association among development and deprivation in environmental condition is being considered. The EKC studies can be distributed into three categories i.e. time series, cross sectional data studies and the study of panel data estimation techniques.

2.1: Studies with Time Series Data

The world understood that there was a dramatic increase in the earth average temperature which resulted in studying the hypothesis of environmental Kuznets curve in 1990's. The researchers from environmental economics theorized Environmental Kuznets curve in the same period, which got alarming attention hastily. Grossman and Krueger (1992) found at that time that greenhouse gases especially CO_2 emission had been caused by the economies due to industrialization. So, the relationship between CO_2 emission and economic development was the first to be formed. According to the hypothesis; the environmental condition gets poor with the initial increase in the income.

After the relationship being developed between emission of carbon dioxide and economic events like energy usage, growth and foreign trade, researchers revealed that there is causality between these factors and emission and found that its direction may be same or different in some means and ways. Diverse studies came forward on different individual countries and showed different results because of the dissimilarity in economic policies and features of each country. In time series data, the existence of EKC in short run for small sample could not be determined.

Focusing more, we found that Cho et al. (2010) gave an empirical study for China by using time series data annually, Japan and Korea used econometric methods of time series for creating VAR or VEC model. The study found that substantial differences were seen in the chronological configurations in the quality of environment and the EKC for these three countries. However, some limitations were there, like usage of small data sample, restricted admittance for data and as time series data was used annually only. In case of Pakistan; Ahmed (2012) made an empirical analysis for the period 1971-2008. The study used Auto Regressive Distributed Lag (ARDL) bounds test approach; it showed that the EKC phenomena existed in the case of Pakistan and more interestingly, population density along with all the other variables was also a source of deprivation in environmental condition in Pakistan. The study exposed about a short run relationship between environmental degradation and output. An inverted U shaped relationship was established between carbon dioxide emission and growth of economy in the long run studies. Furthermore, trade openness, energy usage and population density also affected environmental degradation. Therefore, the theory claimed about the EKC to be a long-run phenomenon for the case of Pakistan. Azam and Qayyum (2016) estimated empirically the study that supported the EKC hypothesis but only for the low income and the lower income countries. But, the theory failed in finding any evidence for the EKC hypothesis by using upper middle and high income countries between 1975 and 2014.

Many studies discussed the EKC hypothesis using different indicators and ecological footprints for diverse set of countries using time series data and also examined the situation of EKC in phases of energy calamities and weakening income. Simple unit root was being applied as parsimonious using small sample data and it was a weak test, as it had no means of accepting main evidence for the presence of structural break ascending within a series. When the data taken was time series at level or in the non-stationary form, the problem of spurious regression might arise. Making the stationary series by differencing was one of the solutions of the spurious regression problem. However, long-run analysis would be prevented by differencing of the series. To outwit this problem, a range of methods can be used to test if the long-run equilibrium relationship cointegration existed among the time series variables.

The ARDL test has many benefits as compared to the other techniques of cointegration, as the error correction model (ECM) may be resulting from ARDL by a simple linear conversion. Single-equation specifications are commonly being focused by empirical models. VAR models are a line to form multivariate time series by concentrating on the causal relation and dynamic structure. The idea of applying Bayesian techniques for the coefficients to be estimated in VAR is handling the coefficients as random variables, and prior probabilities are being assigned. Vector error correction model (VECM) is a way to examine whether the series share a common trend and dynamics without the risk of estimating a possibly spurious regression or not. It may also postulate that how these series are relevant with one another by the long-run trends and the short-run dynamics.

Since, Engle and Granger technique is considered as bi-variate technique so multivariate analysis could not be done using this technique of co-integration test. The theories vary with the nature of the tests being applied on the data sets. If the general features were being considered, then the EKC estimated for the study might show diverse chronological configurations for a time series model. Some countries showed curve as N-shaped while some showed U-shaped curve. All the variations found above can be seen while discussing the association between CO2 emissions and trade openness.

As plenty of literature is available on individual study of a country just like Bozkurt and Akan (2014) made a study on the economic growth and CO_2 emission of Turkey by using annual data from 1960 to 2010. The results showed that using energy had an encouraging influence on economic development whereas; carbon dioxide emission had a negative impact. Similarly, Wang and Zhou (2014) developed a study for examining the relationship between income levels and environment quality. Bayesian time series models were used with the time series data of Gansu province of China. The results suggested that the composition and scale effect had weak contribution in renewal of ecological environment. But, the methodological effect and environmental principles played important roles.

The latest one is of Alam and Murad (2016) as the theory examined the effects of energy usage, income and population growth on CO_2 emissions by using time series data annually for the period 1970 to 2012. The study was made for Indonesia, India, Brazil and China by using ARDL approach. The study checked the efficiency, stability and robustness of the model and found that the affiliation among environment and economic development was irrefutable.

2.2: Cross Sectional Studies Relating Growth and Environmental Degradation

Lei et al. (2005) combined a lengthy time perspective study for China using cross sectional data adding other five countries as well. The study also considered the essence of structural change. Two models are used in the study; first model, meant to reveal the relationship among the structural deviation, appearing economic growth and the variations enforced on using energy. The second model addressed the relationship between growth of the CO_2 emission and the structural change in energy use. He found that if the structural divergence is higher from the system of energy usage; the reduction in CO_2 emissions is more noticeable. The changes in the structure moved the state economy far from the manner impressed when the carbon dioxide emission was higher to the state in which the emission level was more tolerable to society.

Wang et al. (2012) re-examined the association among effects of environment and economic development as indicators of environmental footprints, with an assumption that production and consumption were auto correlated spatially at universal level based on Moron's I statistic. Spatial lagged and error models were being used. Entirely new vision in the spillover types was produced that took place in the space system of universal performance of environment. But this paper was just a few lines to the future dynamic research.

Sebri (2016) analyzed the relationship between water footprints and economic growth using the cross sectional data. The study examined about the variation in the per capita water footprints as a function of per capita income while staying within the framework of Environmental Kuznets curve. Moreover, the researcher also focused on the problem of the omitted variables by involving number of the controlled variables and found no evidence of an inverted u-shaped EKC. However, in many cases N-shaped relationship was evaluated which showed that; in the beginning there was a rise in the water footprints with an increase in income but then falls down with a very high increase in income.

2.3: Panel Data Studies

Moomaw (1997) interpreted about the misleading environmental Kuznets curve and examined the carbon dioxide (CO_2) emission case, as it an important atmospheric gas which has great involvement in global warming. Scatter plots of per capita CO_2 versus GDP per capita were created for the available countries data from the time span of 1950-1992.

The shape of EKC curve is very sensitive to many different factors. Considering this, Poudel et al. (2009) observed an N shaped EKC curve for 15 countries from Latin America for the time period of 1980-2000 and found that the EKC's shape was profound to the exclusion of certain group of countries, agreeing to the phenomenon that the pollution decreases as the agriculture sector is transformed into industrial and then finally to services sector. They used fixed effects and one way error component semi parametric model to estimate EKC. The sample was divided into three different groups of countries; the countries in the first group were with ominously low forestry to population ratios, second group contained transitional level of forestry to population ratios and the countries belonged to the third group were of the maximum forestry to population ratios. The study also compared the results of semi parametric versus parametric models and the parametric form was devastatingly rejected in favor of the semi parametric form for the given data. The results concluded that countries belonged to the maximum forest cover commonly exited in the rising portion of the EKC. The richer countries though exhibited N-shaped relationships between CO2 and income. Also the semi parametric panel model had several limitations which were being ignored in this research, further unit root testing and solving the problem of serial correlation needed to be addressed adequately.

“A spatial temporal econometric approach of the environmental Kuznets curve” was presented by Burnett and Bergstrom (2010) for the carbon emitting states on the level of US and explained that the major criticism on EKC literature was of ignoring spatiotemporal aspects within the data. The study focused on the major drawbacks of ignoring the spatiotemporal effects like; biased or inconsistent regression results. Misleading t and F statistics could be generated by spurious regression for EKC.

Dynamic panel model and controlled temporal dependence, spatial dependence and state-level independent effects were applied by using fixed effect estimation techniques and spatial first difference estimator to resolve the fixed effect issues. It was believed that the dynamic spatial panel approach told a stable story with magnitudes, spatial autocorrelation, expected signs and significant levels. Considering the empirical results, the theory was consistent with the customary EKC hypothesized inverted-U shaped relationship between CO2 emissions and income. But many limitation of this paper were also discussed, the major issue was that there were many problems in estimating spatial panel data. Moreover, heterogeneous parameters were being ignored in this study.

The researchers started pondering upon the controversies being found in the EKC literature and the limitations in all the existing work. Different reasons were being proposed such as the previous discussed work of Burnet and Bergstrom in which they focused on spatiotemporal effects. In this context Jobert et al. (2012) worked on environmental Kuznets curve for CO2 emission and discussed the lack of robustness to heterogeneity for this case. They applied the iterative Bayesian shrinkage procedure, using 55 countries which cover 90% of global carbon emission for the period of 1970-2008. The results with respect to development level of the countries revealed that an inverted U-shape curve was formed due to the fact that increase in gross domestic product (GDP) decreased emissions in the higher income level countries, whereas the lower-income countries caused increase in emissions. the results took each country into account by their development level and put them in five categories; developed countries, newly industrialized countries of Asia, transition economies, new emerging markets, oil exporting countries and least developed countries respectively and found that high-income countries could be eligible as environmentalist had emission paths in decreasing manner, the countries with middle-income were either environmentalists or polluters and they had trends following horizontal emissions. Finally, the lower-income countries were just only the polluters since their per capita CO_2 emission was in increasing trend.

Yin et al. (2014) made a study on China about the impact of parameters of environment and practical development on CO_2 Kuznets curve. The results indicated that CO_2 emission Kuznets curve were being observed for the case of China. The second finding was that environmental regulation had a significant moderating effect on the CO_2 Kuznets curve. The third finding was that the advancement of technology was beneficial to CO_2 emission reduction, and the lag effect was significant. The fourth finding was that energy efficiency, energy structure, and industrial structures had a significant direct impact on CO_2 emissions.

A panel data analysis was made by Farhani et al. (2014) on the environmental Kuznets curve and sustainability. They took the data of 10 Middle East countries for the period 1990-2010. In their study, two models were examined parallel. The first one was based on the traditional EKC literature, while for the second model a new concept of modified EKC literature had been shown. Three different panel unit root tests were applied to support that all the panel variables were integrated of order one. Panel cointegration test results were also applied in support of all the panel variables that were cointegrated.

Zaman et al. (2016) worked on the panel of developed and developing countries making a Trivariate analysis for Tourism development and energy consumption for the Environmental Kuznets Curve. They used the principal component analysis. The results of this study validated that the relationship between carbon dioxide emissions and income per capita in the region found to be inverted U-shaped. Further, the results substantiated six causal relationships; tourism encouraged carbon dioxide emissions, energy also contributed in carbon dioxide emissions, investment was also a source of emission, growth headed tourism in the region, investment also controlled tourism and health managed the development of tourism in the region. This study applied the two stage panel technique of regression that facilitated the endogeniety in the discussed data models.

Ahmed et al. (2015) examined about the causal correlation between economic development and CO2 emissions under the panel of twenty four European countries for the time period of 1980 to 2010 by using technological progress, biomass energy for the environmental Kuznets curve using dynamic heterogeneous panel techniques. The study implied that the environmental quality and economic development could be attained concurrently. Since, static panel tactics such as random effect, fixed effect and pooled OLS were unsuitable. Furthermore, a vigorous method like panel GMM was critiqued when long panel time series data were estimated, the work was done by applying error correction based panel auto regressive distributive lag model and estimated the model by PMG and MG estimators. The results found that there was a negative relationship between biomass energy and CO_2 emissions but it stayed statistically irrelevant, because the total energy use was small.

Mir and Storm (2016) made a production based versus consumption based on decoupling for 40 countries (35 industries) during 1995-2007. They made findings for climate policy and binding emission reduction obligations. The study focused on greenhouse gas emissions and its linkages. High average consumption level countries were known as carbon importers. The results revealed many differences in production based and consumption based emission for many countries.

Investigating the problems in estimating the environmental Kuznets curve, Wagner (2007) explained that the cloudy picture of EKC is due to the usage of bad econometric techniques. The key econometric problems were being discussed which had been ignored previously in the literature of environmental Kuznets curve (EKC). First was; in integrated regressors, usage of nonlinear transformation and in the second; the dependence of panel data cross-sectionally. He validated his claim by using different panel techniques of first generation in which the cross sectional dependence was ignored in the data and then the techniques of second generation which considered not only cross sectional dependence but also the slope heterogeneity within the data. Wagner (2007) found that such techniques were highly unsuitable for the usage of permanent cross-sectional dependence within the data.

The methods from first generation panel approached to apparently strong evidence for the pervasiveness of an EKC. Since, the series was seen to be integrated or cointegrated and the estimated results led to inverted U-shaped relationships with reasonable turning points. Nevertheless, the evidence obtained was completely spurious due to the nonstationary common factors in both the CO_2 and the GDP panels. No evidence was found of any inverted U-shaped relationship in a variety of specifications. The foremost finding of this paper was robust alongside in many directions that included sample composition, structural change and cross-sectional heterogeneity.

2.4: Conclusion

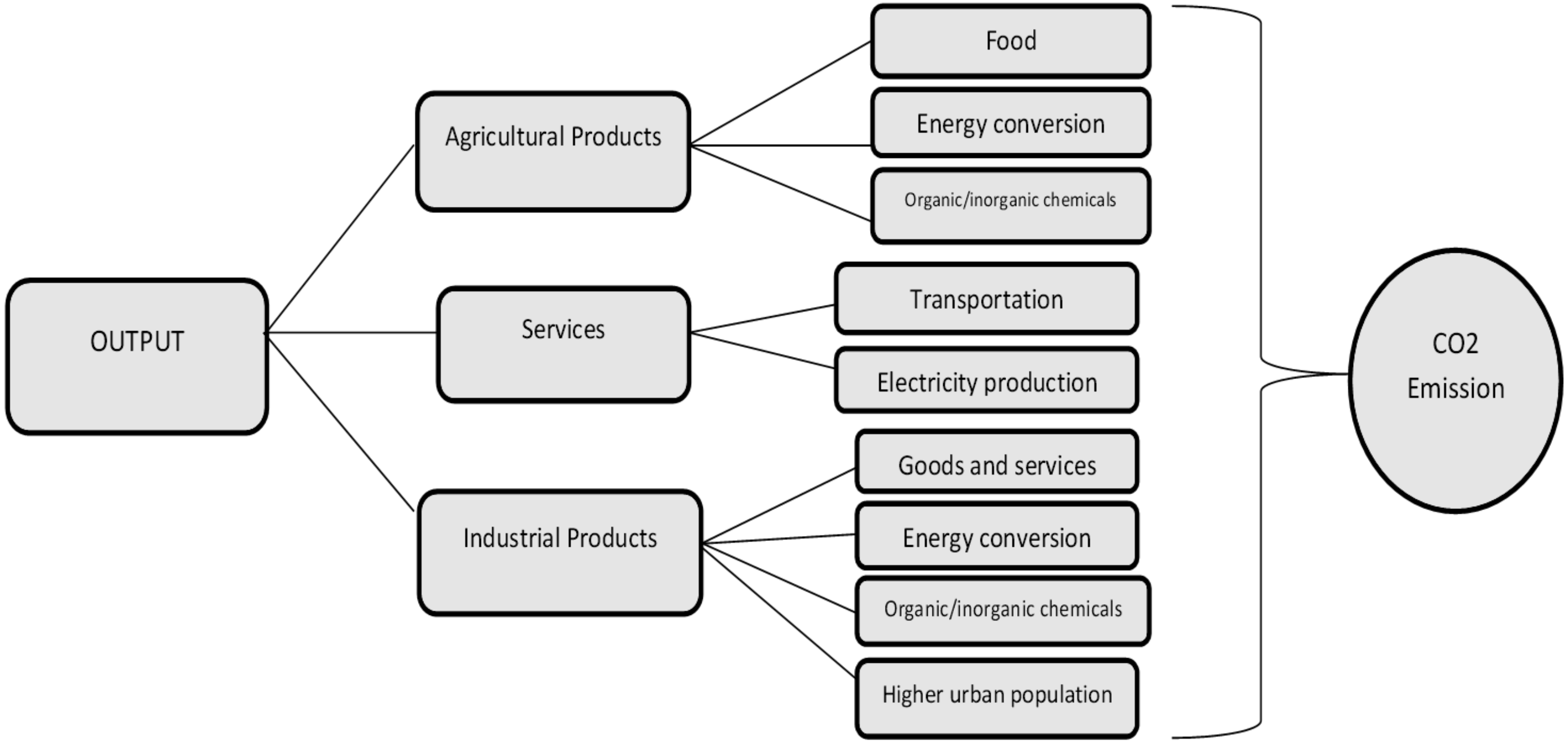
In the above section we tried to deliberate the different results found by researchers by applying several different estimation techniques on all the three types of data (time series, cross sectional and Panel) few papers have been reviewed in the above section from the excess of literature available on environmental Kuznets curve and focused on the shortcomings in the work due to which there were contradictory results. The review of literature makes it evident that huge number of studies available, measures the empirical relationship between EKC and environmental degradation considering different types of data, with different methodologies for different group of countries. However; there are three types of relationship exists between these two i.e. U shape, L shape and N shape and also the structural breaks within the data in the long run had been ignored which may cause biased results. Many researchers also ignored heterogeneity for the different level of countries. This inconsistency in the shape of the curve and the ignored factors in the literature compel us that this study will be a contribution in this regard.

Chapter: 03

Theoretical Model and Econometric Specification

Economic growth depends on production of different sectors i.e. agriculture, industry and services, pollutants (Grossman; 1991, Panayotou; 1993, Jalil and Mahmud 2009, Farhani et al. 2014). Hence, economic degradation due to pollutants and output seems to be incompatible as whenever there will be economic growth, it will ruin the environment. There is a general concept that the output of a country is produced through agriculture, Industry and Services sectors. Where agriculture not only produces food, different organic and inorganic chemicals but also leads to conversion of energy. Similarly; industry allows producing output which produces goods and services, organic and inorganic chemicals, energy conversion. Industrialization also increases urban population. Services play one of the most important roles in the progress of economy for any country including building constructions education and health sectors, transportation, production of electricity etc. Hence; increase in agriculture industry and services sector increase the environmental degradation.

The following flow chart can explain a clearer picture.


OUTPUT
Agricultural Products
Services
Industrial Products
Food
Energy conversion
Organic/inorganic chemicals
Transportation
Electricity production
Goods and services
Energy conversion
Organic/inorganic chemicals
Higher urban population
CO2
Emission

Researchers while analyzing the relationship between GDP and economic degradation considered emission of different pollutants e.g. Selder and Sag (1994), Dasgupta et al. (2002) and Llorca and Meunie (2009) etc. workout the relationship considering SO_2 and NOx; while, Ang (2007), Jalil and Mahmud (2009), Saboori et al. (2012), Hamit-Hagger (2012), Lau et al. (2014), Farhani et al. (2014) etc. carried out research into emission of CO_2.

In present study we are also taking the case of emission of CO_2. Similar to Begum et al. and Ahmed et al. (2016), we also assume that CO_2 is function of Y_t i.e. in production process different pollutants emit, which cause environmental degradation.

$$CO_2 = [F(Y_t)] \tag{3.1}$$

Following the seminal work of Stern (2004) the baseline equation for EKC is.

$$CO_2 = \beta_0 + \beta_1 Y_t + \beta_2 Y_t^{\,2} \tag{3.2}$$

It is mentioned in the literature that during the initial growth stages of economy; due to economic expansion, pollution rises. While, the transformation of industrial economy to services economy is due to economic structure, the increase in pollution starts decreasing. But, usage of different types of economy and different keys of pollution give significantly varying results. Therefore, several relationships are offered; an inverted U shaped relationship, a linear relationship, an inverted L shaped and even an N shape, (Dinda, 2004; Kaika and Zervas, 2013) is also being proposed. The outcomes produced, depends on the value of particular parameters and assumptions made. For example; inverted U shape relationship is found by Coondoo and Dinda (2008), Lee, Chiu and Sun (2009) and Jalil and Mahmud (2009). Lee, Chiu and Sun (2009) found N- shape relationship between production and CO_2 emission.

Following Al- Mulali et al. (2015 a) we have also considered the role of trade in explaining the nexus of economic development and environmental degradation. Ang (2009) mention that trade liberalization affect environmental degradation in two ways; firstly, with increase in trade openness, scale of the economy will rise, which will lead to more pollution in the economy. Secondly; increase in the trade liberalization will improve the production methods and consequently pollution and economic degradation will reduce. Hence; it is important to check the impact of trade openness that whether it will increase or decrease the emission of CO_2.

The preceding papers for the individual countries made use of energy consumption for representing energy sector. But, other variables are also being used by different studies as an index of energy sector. Such as, Al-Mulali et al. (2015a) worked by using fossil fuels energy usage and renewable energy usage by considering them indicators of energy consumption for analyzing the case of Vietnam during the period of 1981 to 2011. By making the use of cointegration approach of Pesaran et al. (2001), the researchers could not find the evidence of EKC. While, using the same technique for Kenya, Al-Mulali et al. (2016) found the EKC evidence. Similarly, finding the evidence of EKC hypothesis for Saudi Arabia and India, Shahbaz et al. (2013c) and Tiwari et al. (2013) validates the results by taking coal usage as substitution for energy sector. Focusing more on the study involved coal consumption, total energy consumption, electricity usage, gas usage and oil consumption as gages of energy consumption, considering the example of Malaysia. Saboori and Sulaiman (2013a) recognized the facts for EKC hypothesis and establish two way GDP and carbon dioxide emission causation connections between different energy variables and emissions.

The readings of Dina (2004), Shahbaz (2011) and formerly Panayotou (1997) designated population as one of the factors subsidizing towards the environmental degradation. Rate of economic development and population density are also important factors. The price of environment rises moderately with the growing economy and population.

Alam and Murad (2016) found that the growth in population (POPG) did not show any substantial statistical association with CO_2 emissions by using any country in quadratic model, but for linear model, India showed a positive significant relationship and Brazil showed a negatively significant association. In population, specifically people living in urban areas play more significant role in explaining the emission of CO_2 as Al-Mulai et al. (2016), Kasman and Duman (2015), Ozturk and Al-Mulai (2015), Shafiei and Salim (2014), Shahbaz et al. (2014b) all argued that urbanization is one of the factors that affect the environmental degradation.

Considering all these arguments, the econometric regression line can be written as:

$$LCO_{2it} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LGDP^2{}_{it} + \beta_3 LGDP^3{}_{it} + \beta_4 LRE_{it} + \beta_5 LTD_{it} + \beta_6 LUR_{it} + \beta_7 LFD_{it} + \mu_{it} \quad (3.3)$$

Where LCO_2 is the log of carbon dioxide emission depending upon the variables including log of gross domestic product (LGDP), the LRE; including log of geothermal, hydropower, solar, wind, tides, biomass, and biofuels, LTD is a log of trade openness which includes trade of goods log and services log as a degree of trade openness, LUR indicates log of urbanization and the cross domestic credit to the private sector log is used as sign of the financial progress dignified in millions of

2000 constant US dollars. βo is intercept, β_i denotes the slope coefficients where i varies from 1 to 6, and u_{it} represents Gaussian error term.

There are different possibilities exist depending on the value of slope coefficients; e.g. if $\beta_1 = \beta_2 = \beta_3 = 0$, it show that no relationship exist among GDP and environmental degradation. If $\beta_1 > 0 and \beta_2 = \beta_3 = 0$ it represent monotonically increasing and linear relationship, $\beta_1 < 0 and \beta_2 = \beta_3 = 0$ it show that monotonically decreasing relationship is there between GDP and CO_2 emission. While if $\beta_1 > 0, \beta_2 < 0 and \beta_3 = 0$ than relationship between GDP and CO_2 emission is of inverted U shape and if $\beta_1 < 0, \beta_2 > 0 and \beta_3 = 0$ than the relationship is of U shape. Two other possibilities are that if $\beta_1 < 0, \beta_2 > 0 and \beta_3 < 0$ output and environmental degradation show a reversed N shaped relation. If $\beta_1 > 0, \beta_2 < 0 and \beta_3 > 0$ then it will show N shape relationship.

Chapter: 04

Estimation Methodology

Estimation of Panel data is many times taken to be an efficient analytical approach in econometric data handling. If the time observations are of same number for every individual and each and every variable, then it is a well-known balanced panel. A lot of time, we have to work with unbalanced panel. The analysis of panel data erupts from the basis that each and every singular relationship will have the parameters of exactly same number. This is believed to be renowned as the pooling assumption. The addition of a dummy can catch the differences in time series and the cross section observations, which is generated due to pooling of the data. This application of dummies to catch the methodical differences between panel observations leads to something called as the fixed-effects models and the alternative to this is random-effects model.

4.1: Conventional Methods in Panel Data Econometrics

Considering the conventional panel techniques that are; the normal estimation's constant method also known as pooled OLS method gives outcomes on the bases of main pre assumption that the cross sectional dimension's data matrices have no differences. It is useful only under the hypothesis that there is homogeneity in the set of data. However, it is very limiting so we can include in estimations the random and fixed effects. Fixed effect model has two properties; it mostly catches all impacts, which do not change over a span of some time period and are particular to an individual. If the panel has more than thousands of lone individuals then a large number of dummies might be used, and here the model of fixed effect would make use of N degrees of freedom. The fixed effect model can be branched out by adding, some dummy variables of time series and its' known as "Two way fixed effect model". However model of fixed effect does not deal properly with the large number of observations, which are usually observed in estimating panel data sets. The fixed effect estimator is also famous by the name of least squares dummy variable estimation technique (LSDV) because it allows a dummy variable in each group.

The Random effects model is the parallel solution to the fixed effect method. The contrast among the two models is that, the last one handles the constant in every section as a stochastic constraint and not the other way round. A standard random variable of zero mean is included in the model. Random effect model has fewer parameters than the fixed effect model. It also permits extra explanatory variables that have same value for all findings within the group. But for the application of random effects we have to be very careful to see whether there is a reason to be using them for our model instead of the model of fixed effects. Random effect model is created under the belief that the explanatory variables are not uncorrelated with the fixed effects; this belief creates hard limitation for treatment of panel data. Mostly, the contrast between the 2 permeable ways of testing panel data models is that the model of fixed effects goes with notion that intercept term is different for each of the country, whereas the other model believes that the error term is different for individual countries.

4.2: Dynamic heterogeneous panels

Due to the limitations in the conventional techniques researchers moved towards heterogeneous dynamic panels, a model of such kind is set when the lags of dependent variable exists between the regressors. A lot of economic relationships in nature are dynamic and hence should be created like it. The panel data's time dimension (unlike cross-sectional studies) allows us to catch the dynamics of adjustment. The barrier in the dynamic panels is that, the conventional OLS estimation technique gives biased results. Therefore, diverse estimation techniques are required to be introduced. There are three types of biasedness in the dynamic panel such as; bias in the simple OLS estimator, bias in the fixed effect model, bias in the random effect model.

The solution to this biasness problem is not one but two. The first of it is to permeate variables of exogenous kind in the model. The biasness is decreased in magnitude but stays positive. The other method is to apply the instrumental variable technique given by Anderson and Hsiao (1981 and 1982) and Arellano and Bond (1991). Such instrumental variable estimators are called GMM estimators. In situations, when the individual errors in the model are said to be homoscedastic and non-auto-correlated by using both the moment i.e. first and second, the GMM estimator showed domination to the MLL estimator. Arellano (1991) estimated an equation:

$$CO_{2it} = \alpha CO_{2i(t-1)} + \eta_i + \upsilon_{it} \tag{4.1}$$

v_{it} Are assumed to have defined moments and in specific $E(v_{it}) = E(v_{it}v_{is}) = 0$ for $t \neq s$ with the notions that the values of y which have been lagged for two periods or even more are justifiable instruments for equations that have 1st differences. Hence in the truancy of any other initial conditions related to knowledge or the dispersion of the υ_{it} and the η_i. For such he forecasted the solution that TSLS or GMM should be there. The GMM estimator $\hat{\alpha}$ is created on the sample moments $N^{-1}\sum_{i=1}^{N} Z_i^{'} v$.

$$CO2_{it} = \alpha CO_{2i(t-1)} + \beta^{'} x_{it}^{*} + \eta_i + v_{it} = \partial' x_{it} + \eta_i + v_{it} \tag{4.2}$$

In this particular scenario the structure of the instruments of optimal matrix relies on if the x_{it}^{*} are preset or strictly exogenous variables. The GMM estimator of k x 1 vector is

$$\hat{\partial} = (\overline{X}' Z A_N Z' \overline{x})^{-1} \overline{X}' Z A_N Z' \overline{y} \tag{4.3}$$

The TSLS is also the same. The outcomes pointed very little finite sample biasness in the estimators of GMM and very small variances in comparison to those related to the IV estimators of the kind given by Anderson and Hsiao (1981).

4.2.1: Long Panel and Unit Root Problem:

Studies of panel data, till recent years, have dismissed the crucial stationarity (ADF and Phillips-Perron) and cointegration (Engle-Granger and Johansen) tests. But, with the increasing participation of applications of macroeconomic in the traditional panel data, in which a larger sample of countries make the cross-sectional dimension giving data over longer time series, the problem of stationarity and cointegration have erupted in panel data too. This was basically because of the reason macro panels consisted of both large N and T in relation to micro panels with larger N but smaller T.

A few of set apart outcomes that are taken out with non-stationary panels are that many t stats and interest estimators have usual limiting dispersions. If the panel data used is heterogeneous and non-stationary, problems of accumulating long tests of unit root used for applying on each data set which is time series are solved by Im et al.

(2003), Maddala and Wu (1999) and Choi (2001). The issue of spurious regression can be casted away by applying panel data; check Kao (1999) and Phillips and Moon (1999). Not like the literature of single time series spurious regression, the estimations of panel data spurious regression gives constant estimation results for the true value of the parameter where both N and T tends to ∞. These results are due to the fact that the panel estimation techniques take average among the individuals and the evidence in panel data study tends to a strong overall signal due to the independence across cross sectional data than that given by pure time series scenario. Previous findings on non-stationary panels have multi-indexed processes Phillips and Moon (2000), Banerjee (1999), Baltagi and Kao (2000) and Smith (2000) on co-integration and unit root tests for panel data.

Several tests for checking unit root in the time series literature have been branched out to the study of panel data. If the panel data models are non-stationary and heterogeneous as well, the problem of accumulating long unit root tests used on each time series model are under taken by Im et al. (2003), Maddala and Wu (1999) and Choi (2001). We can make the summary of main contrasts between panel data and time series unit-root tests as following:

- Firstly, panel accommodates to use different methods for different heterogeneous degrees between individuals.
- Secondly, in the investigation of panel data, there is no surety as to what is the validity in terms of rejection of unit root.
- Thirdly, the panel unit-root tests power grows with the growth in N. This growth in power is a lot more robust than in the size of the one analyzed in the standardized low-power DF and ADF tests used for smaller samples.

- Fourthly, in panel data models when the extra cross sectional modules are being included it give improved characteristics of panel unit-root tests, contrasting to the low-power normal ADF for time-series samples.

Non- stationary time series data follows the two removing trends first difference and regressions of time trend. First difference is with the I(1) series and time trend regression with the I(0). Unit root test is used to see if the trending series is first differenced or regressed to render a stationary data. A non-stationary time series like Y_t might actually have to be differenced more than one time before it turns into stationary. If Y_t becomes stationary after d times differencing then it is said to be of order d.

The unit-root tests for panel data are basically made on extending the ADF test by just including its part in the regression equations. But, when we are tackling the panel data, the estimation procedure can be more intricate than the technique been taken in time series. The degree of heterogeneity emerges as an important factor of panel data. The making of the panel unit root literature, related with the asymptotic behavior of a panel's T and N dimensions is considered as one of the crucial theoretical consideration.

Panel unit root tests are further categorized into first and second generation tests which considered cross sectional independence and dependence with and without structural breaks.

First Generation unit root tests (Cross sectional Independence)

Non-Stationarity tests

4.2.1.1: The Levin and Li (1992) test:

The tests can further be characterized as, the tests considering cross sectional independence; Levin and Li (LL) proposed that the first test was that made by Levin and Lin (1992). They accommodated a test which was actually an expansion of DF test. The model becomes as follow:

$$\Delta CO2_{i,t} = \alpha_i + \rho CO_{2_{i(t-1)}} + \sum_{k=1}^{n} \varphi k \Delta Y_{i(t-k)} + \partial_{it} + \theta_t + u_{it} \qquad (4.4)$$

The above model permits two way fixed effect methods, the first one coming from the αi; and the second from the θt. Like almost all of the tests of the unit root in the literature, it tails the null hypothesis as; $\rho=0$. The LL test believes that the isolated processes are independent in cross-section. This test may also be seen as an ADF or pooled DF test, possibly with varying length of lags across diverse panel sectors.

4.2.1.2: The lm, Pesaran and Shin (1997) test:

One of the major drawback of the LL test is that; it restricts ρ as homogeneous across all i. lm, Pesaran and Shin (1997) expanded the above test by accommodating heterogeneity factor on the coefficients of the Yi,t- 1 variable and provides a base for procedure of testing, the one which is being created on the mean of a single unit-root statistics. This test gave distinct outcomes for each i section, letting altered particularities for the values of the parameters, the lag lengths and the residual values. Their model is represented as:

$$\Delta CO2_{it} = \alpha_i + \rho_i CO_{2_{i(t-1)}} + \sum_{k=1}^{n} \varphi k \Delta Y_{i(t-k)} + \partial_{it} + u_{it} \tag{4.5}$$

Whereas, the null hypotheses can be created as:

Ho: ρi = 0 for all i

Then, the alternative hypothesis would be:

H1: ρi < 0 , for at least one i

Im, Pesaran and Shin (1997) created the model in the limited belief about T, that it needs to be the same for all of the cross-sections, needing a panel data set in equilibrium for measuring the t statistics.

4.2.1.3: Maddala and Wu (1999) test:

Maddala and Wu (1999) tried an improvisation till some level by giving a model that could also be used with panels in unbalance state to resolve the fallbacks of all former tests. So, Maddala and Wu go along with the pre thought that the alternative of heterogeneous can be preferred. But, it does not agree with the application of the average ADF statistics by refuting that it is not the best way of measuring stationarity. Thinking that there are N unit-root tests, the MW is in the shape of

$$\Pi = -2\sum_{i=1}^{N} \ln \pi_i \tag{4.6}$$

Where Π_i is the probability limit value from regular DF (or ADF) unit-root tests for each cross-section i. Because -2$\ln(\Pi_i)$; has a x^2 distribution with 2 degrees of freedom, the Π statistic will follow a x^2 distribution with *2N* degrees of freedom as $T_i \to \infty$ for finite *N*. In order to consider the dependence between cross-sections, Maddala and Wu propose obtaining the Jr;-values by using bootstrap procedures by arguing that correlations between groups can induce significant size distortions for the tests.

So, to consider interdependence among the cross- sections within a data, Maddala and Wu proposed that attaining the values of πi by the method of bootstrapping through argument that the correlation among sets may be the cause of massive distortions in the size for the tests.

Stationarity test

4.2.1.4: Hadri (2000) test:

It is a statistical test of the hypothesis of stationarity, either around level or around a liner time trend against the alternative of the unit root in the panel data where T is assumed finite. The assumption of finite T makes our test suitable for micro panels as well as macro panels. The limiting distributions of the test are shown to be normal. Monte Carlo experiments suggest that the standard normal density accurately approximates the empirical distributions of the tests and for T greater than 10 the test have an empirical size very close to nominal 5% level.

Second Generation Panel unit root tests

4.2.1.5: Bai and Ng (2004) test:

Bai and Ng (2004) considered the possibility of unit root in the common factors. However, under their set-up the unit root properties of the common factor(s) and the idiosyncratic component of the individual series are unrelated. As a result they are able to carry out separate unit root tests in the common and the idiosyncratic components. The specification used by Bai and Ng is given by the static factor model (assuming one factor for ease of comparison):

$$y_{it} = \alpha_{io} + \alpha_{i1}t + \gamma_i f_t + \nu_{it}$$

Where f_t is the common factor, γ_i the associated factor loadings, and ν_{it} the idiosyncratic component assumed independently distributed of *ft*. The unit root properties of γ_{it} is determined by the maximum order of integration of the two series f_t and ν_{it}. Hence, γ_{it} will be *I*(1) if either ν_{it} or f_t contain a unit root. Averaging across *i* and letting *N*→∞, for each *t*, *v̄t*→0, if ν_{it} is stationary, and $\overline{\nu_t} \to \infty$, where *c* is a fixed constant if ν_{it} is *I* (1). Therefore, a unit root in f_t may be tested by testing the presence of a unit root in $\overline{\gamma_t}$ independently of whether the idiosyncratic components are *I* (0) or *I* (1)

4.2.1.6: Pesaran (2007) test:

A number of panel unit root tests that allow for cross section dependence have been proposed in the literature that use orthogonalization type procedures to asymptotically eliminate the cross sectional dependence of the series before standard panel unit root tests are applied to the transformed series. Pesaran (2007) proposed a simple panel unit root test where the standard DF (or ADF) regressions are augmented with the cross section averages of lagged levels and first-differences of the individual series. Standard panel unit root tests are then based on the simple averages of the individual cross sectionally augmented ADF statistics (denoted by CADF), or suitable transformations of the associated rejection probabilities. Asymptotic results are obtained both for the individual cross sectionally augmented ADF (CADF) statistics, and their simple averages. It is shown that the individual CADF statistics are asymptotically similar and do not depend on the factor loadings. The limit distribution of the average CADF statistic is shown to exist and its critical values are tabulated.

Small sample properties of the proposed test are investigated by Monte Carlo experiments. The common factor has been introduced to model cross section dependence of the stationary components. As a result when testing $\Phi_i = 1$, the order of integration of γ_{it} changes from being $I(1)$ if f_t is stationary, to $I(2)$ if f_t is $I(1)$.

4.3: Panel Cointegration tests:

Many researchers worked on panel unit root tests, that permitting cross sectional dependency through the data. Pesaran (2004) proposed different methods of cross-sectional error dependence (CD) which is valid for a range of panel data models comprising of static and unit root dynamic and heterogeneous models where the T is small and N is greater. The test suggested above is grounded on the means of likewise coefficients of correlation for the residuals of OLS from the specific regressions within the panel data set other than the squares of the residuals, as in the Breusch–Pagan LM test:

$$\text{CD}= \sqrt{\frac{2T}{N(N-1)}}(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij} \qquad (4.7)$$

The $\hat{\rho}_{ij=}\sum_{t=1}^{T}e_{it}e_{jt}\Big/(\sum_{t=1}^{T}e_{it}{}^{2})^{1/2}(\sum_{t=1}^{T}e_{jt}{}^{2})^{1/2}$, with e_{it} representing the residuals of OLS depends on T observations for each i = 1, . . . , N. The Monte Carlo experiment displays that the basic test of Breusch–Pagan LM has no bad effects on the panel data sets in which $N > T$, while CD test of Pesaran performed well also for minor T and huge N.

The purpose of Dynamic factor models is to find the cross sectional correlation. Moon and Perron (2004c) studied the model given below:

$$y_{it} = \alpha_i + y_{it}{}^{0} \qquad (4.8)$$

$$y_{it}{}^{0} = \rho_i y_{i,t-1}{}^{0} + \varepsilon_{it}$$

Where ε_{it} is the error term which is not observable and having a factor structure while αis are the fixed effect estimators. ε_{it} is created by M number of undetermined random factors represented by f_t and idiosyncratic shocks e_{it}.

Phillips and Sul (2003) studied the following model with common time factor that based on the disturbances that can impact individual series differently:

$$u_{it} = \delta_i \theta_t + \varepsilon_{it} \tag{4.9}$$

Where θt ~ IIN (0,1) over time span, and δi represent parameters that are the distinctive shares and they calculate the influence of the mutual time impacts on *i series*. εit ~ IIN $(0, \sigma i^2)$ across *t*, with independent εit of εjs and all θs such that $i \neq j$ and for all *s, t.* This model is a byproduct effective one-factor model which is spread independently over the time period. $E(uit\ ujs) = \delta i \delta\ j$ and cross-sectional correlation is not there if, $\delta i = 0$ for all *i,* and the cross-sectional correlation are alike when, $\delta i = \delta j = \delta 0$ for all *i,j*. Phillips and Sul (2003) suggested that the procedure of orthogonalization is based on the iterative methods of moment estimation for removing the common factor which is dissimilar from main modules. The stationarity of the idiosyncratic and factors components tested individually. For this purpose they get reliable estimated factors irrespective of that the residuals are stationary or non-stationary. To get these estimated factors we should run the regression on the data with first difference. Bai and Ng (2009) propose the same as in Choi (2001) and Maddala and Wu (1999) that resulted from the distinct tests of ADF on the defactored estimated data by merging the *p*-values as given below:

$$P_{\hat{e}}^{c} = \frac{-2\sum_{i=1}^{N} \ln p_{\hat{e}}^{c}(i) - 2N}{\sqrt{4N}} \xrightarrow{d} N(0,1) \tag{4.10}$$

Here, $p_{\hat{e}}^{c}(i)$ represent probability value of the ADF tests on the estimated particular shocks for the *ith* cross-section.

Choi (2002) used model with the factor of error specified by:

$$y_{it} = \alpha_i + f_t + y_{it}^{0} \tag{4.11}$$

$$y_{it}^{0} = \rho_i y_{i,t-1}^{0} + \varepsilon_{it}$$

The above model represents the constrained factor model in which the cross-sections reacted consistently on the particular common factor *ft* as compared to the factor models used in the above discussion. Pesaran (2003) proposed a simple method of attaining clear cross-sectional dependence and after that factor loading will be estimated. This method is deals with the idea of finding the cross sectional dependence that generated from a model with a single factor through performing the ADF regression with the lag of cross-sectional mean and by taking its first difference. So, it termed as the cross-sectional augmented Dickey Fuller (CADF) test. This regression equation is given as:

$$\Delta y_{it} = \alpha_i + \rho_i^{*} y_{i,t-1} + d_0 \bar{y}_{t-1} + d_1 \Delta \bar{y}_t + \varepsilon_{it} \tag{4.12}$$

Here, *yt* represents the mean value for *t* time period and all *N* observations. When the lagged value of the average of the cross sectional data and its first difference is present then its cross-sectional dependence is due to the factor structure. When there is serial correlation within the factor or error term then in univariate case the regression will be augmented, however for both *yit* and *yt* lagged first-differences must be added. Distribution of dickey fuller test is different from these tests distribution because in these tests the mean of cross-sectional lagged level is present. A shortened form of IPS test used by Pesaran to evades the problem of moment calculation.

Referring to the work of Jalil (2014) on energy growth using heterogeneous panel methods that shows robustness to the cross sectionally dependent data. He applied the unit root test of panel data which considered the issue of the structural breaks within the data and also checked the cross sectional dependence, recommended by Bai and Carrion-i-Silvestre (2009). He considered the generalized model of panel data as:

$$X_{i,t} = D_{i,t} + f'_t \pi_i + e_{i,t} \tag{4.13}$$

$$(1-L)F_t = C(L)u_t \tag{4.14}$$

$$(1-\rho_i L)e_{i,t} = H_i(L)\varepsilon_{i,t} \tag{4.15}$$

t = 1,...,T and i = 1,..., N, where $C(L) = \sum_{j=o}^{\infty} C_j L^j$ and $H_i(L) = \sum_{j=0}^{\infty} H_{i,j} L^j$ The factor $D_{i,t}$ represents the deterministic portion of the given model, Ft is a vector (r × 1) which used for factorizing the panel commonly and the term $e_{i,t}$ is the individual disruption term. Although, the (1 − L) factor in equation (4.15), it is not necessary for Ft to be I (1). Where, Ft can be any I (1), I (0) or a mixture of the two, as it is dependent on the rank of C (1). If, C (1) = 0 then Ft is I (0). And If C (1) is of full rank then each component of Ft is I (1). If C (1) = 0 but not of full rank, then few modules of Ft are I (1) and some are I (0). Their study depends on the similar assumptions as in Bai and Ng (2004).

Entorf (1997) showed that if the actual model comprises of random walks which are independent having drift or have no drift then he considered spurious fixed effects. He found that when N becomes predetermined and $T \rightarrow \infty$ then for spurious fixed effects models the nonsense procedure of regression exits and implications shows that t-value may be highly ambiguous. The problem of spurious regression occurs only due to non stationarity, so this problem inspired towards cointegration.

Among two variables the test of cointegration is a proper method of examining between:

1. The case in which both series X_{it} and Y_{it} having same order of integration then from estimations we get a spurious regression and the residuals that we get from this regression comprises a stochastic trend.
2. Now in other special case when both the series X_{it} and Y_{it} having same order of integration, however the residuals u_{it} stationary.

For panel data there are much kind of co integration tests, and the most known cointegration test that is also very good is grounded on the association of Engle and Granger cointegration. For different panels like heterogeneous or homogeneous Engle-Granger method is used by considering the assumption of single cointegrating vector.

Like Panel unit root tests, Panel cointegration tests are further categorized into final generation and second generation Panel cointegration techniques which considered cross section independence and dependence.

First Generation Panel Cointegration Tests:

4.3.1: The Kao (1999) test

As we know that there are different kinds of tests of unit root for panel data, similarly the tests of cointegration for panel data is also further divided in to different types. So, Kao test is the cointegration test for panel data and it focuses on the cross sectional independence.

The model can be given as:

$$CO2_{it} = \alpha_i + \beta X_{it} + u_{it} \tag{4.16}$$

The cointegration tests that are based on residuals

As Kao gave, the residual-based cointegration test if applied to equation:

$$u_{it} = eu_{i(t-1)} + v_{it}$$

The coefficients used are AR and cointegration vectors are homogeneous in Kao's test, however in the cointegration vector it does not allow when there are many exogenous variables. Second problem is that in some cases when cointegration vector occurs more than one then it's difficult to identify the vector of cointegration.

4.3.2: The McCoskey and Kao (1998) test:

McCoskey and Kao (1998) for residuals they use Lagrange multiplier test. The foremost input of this method is that its null hypothesis is of cointegration as compared to the null hypothesis of no cointegration. The model is given as:

$$CO2_{it} = \alpha_i + \beta_i X_{it} + u_{it} \tag{4.17}$$

Where

$$u_{it} = \theta \sum_{j=1}^{t} e_{ij} + e_{it}$$

So this method is just like the moving average test of unit root which is best unbiased invariant and that is also unrestricted of nuisance parameters. The null of this test is H0: θ = 0 which shows the presence of cointegration in the panel, meanwhile for θ = 0, $e_{it} = u_{it}$. The residuals can be estimated from OLS estimators and also by FMOLS (fully modified OLS) or the DOLS (dynamic OLS) estimator.

4.3.3: The Pedroni (1997, 1999, 2000) tests:

Pedroni (1997, 1999 and 2000) suggested numerous cointegration tests for panel data model that allows significant heterogeneity. This method diverges from that of McCoskey and Kao (1998) in assumption that the null hypothesis of no cointegration show trends for the cross section. Pedroni's test is good in the sense that it is used for multiple regressors, in the panel cointegration vector changes for different sections, and in cross sectional units there is heterogeneity in the errors.

Pedroni gave a regression model for the panel as:

$$CO2_{it} = \alpha_i + \partial_t + \sum_{m=1}^{M} \beta_{mi} X_{mi,t} + u_{it} \qquad (4.18)$$

To see the within and between effects in the panel seven different cointegration statistics are given. The tests given by him are divided into two types. The first one contain four kind of test which are grounded on pooling along the 'within' dimension. These tests are relatively alike to those mentioned above, and it gave the average statistics for the cointegration test in the time series structure for altered sections.

1. The panel ρ statistic
2. The panel v statistic
3. The panel t statistic (non-parametric)
4. The panel t statistic (parametric)
5. The second type contains three tests depending on pooling 'between' dimension so, these tests defines that the averaging of the data is completed in portions and thus the limiting distributions are based on piecewise numerator and denominator terms. The following tests are as follow:
6. The group ρ statistic
7. The group t statistic (non-parametric)
8. The group t statistic (parametric)

The main problem of the overhead process is that, it is a restricted priori hypothesis of a distinctive vector of cointegration.

4.3.4: The Larsson et al. (2001) test:

Larsson et al. (2001), conflicting to all the above tests, the tests that are given above grounded on Johansen's (1988) maximum likelihood estimator, they do not use the unit root test for residuals and they do not consider the assumption that cointegrating vector is distinctive. The model given by them based on the assumption that data generated for individual cross-sections is symbolized by an ECM specification. So the model is given as:

$$\Delta CO2_{i,t} = \Pi_i Y_{i,(t-1)} + \sum_{k=1}^{n} \Gamma_{ik} \Delta Y_{i,t-k} + u_{i,t} \qquad (4.19)$$

Larsson et a/. suggest that the for individual cross section in the above model use the method of maximum likelihood in which the value of trace is calculated for individual cross section unit which is represented by LR_{it}, the value of panel rank trace is calculated by taking the average of N cross-sectional trace which is represented by LR_{nt} .

Null and alternative hypotheses for this test are:

Ho: rank (Π_i) = $r_i \leq r$

Ha: rank (Π_i) =ρ

Whereas, ρ represent the number of variables used for cointegration tests among them.

Second Generation Panel Cointegration tests:

4.3.5: Westerlund (2007) test:

Westerlund (2007) gave the cointegration tests which considered cross sectional dependence using four different statistics. Out of four two statistics are used to test in which they consider the null hypothesis of no cointegration and they termed it as tests of Panel; Pt and P. the remaining two indicators used here are testing the alternative hypothesis that at least one element in the panel data must be cointegrated and known as the tests for group mean; Ga and Gt. The above discussed four tests are valid when the panel data is cross sectionally dependent and heterogeneous. However, the problem is that in bigger data series this test does not incorporate the structural breaks.

4.3.6: Westerlund and Edgerton (2008) test:

To solve the above mentioned problems, Westerlund and Edgerton (2008) panel cointegration test can be used. This test is based on the concept of considering not only the cross sectional dependence of the data but also the structural breaks within the data as well. Furthermore, Westerlund and Edgerton (2008) gave two statistics and the null hypothesis for both the statistics is "no cointegration".

4.4: Estimating Long Run and Short Run Elasticities:

Finally, we move towards estimating long term and short term Elasticities by CCEMG besides the PMG and MG estimators proposed by Pesaran (2006). Pesaran, Shin and Smith (1999) gave 2 different estimators so to resolve the biasness because of heterogeneous slopes in dynamic panels; these are the mean group (MG) estimator and the pooled mean group (PMG) estimator. The MG estimator takes out the long term parameters for the panel from an average of the long term parameters from ARDL models for separate countries. MG estimation with higher orders of lag gets highly consistent estimators of the long term parameters even when the regressors' are I (1).

The MG estimators are same over a period of time and have asymptotic normal distributions for T and N sufficiently large. However, when T is smaller, the dynamic panel data model's MG estimator is biased and could give straying conclusions, and thus should be used with care. The PMG method of estimation takes over an in between position between the MG method, in which both the intercepts and the slops are permitted to differentiate across countries, and the classical fixed effects method in which the intercept can vary but slopes are fixed. In PMG estimation, only the long term coefficients are constricted to the actual across countries, while the short term coefficients are permitted to change. Both estimations need selection of the allowable length of lag for the lone country equations. There are problems of inference. If the pooling assumption is wrong, then the estimates of PMG are no not same over a period of time and the test fails.

Pesaran (2006) gave a new outlook in measuring a general multifactor error structure using panel data model. A number of estimators were given and their asymptotic distributions were taken out. The smaller properties of the samples of mean group and pooled common coefficients effects (CCE) estimators were analyzed by Monte Carlo experiments, depicting that the CCE estimators require suitable smaller sample properties even under a considerably large degree of heterogeneity and dynamics and for comparatively smaller values of T and N. A multifactor model was shown as:

$$CO2_{it} = \alpha_i' d_t + \beta_i' x_{it} + e_{it} \tag{4.20}$$

Where d_t is a n x 1 vector of observed common effects, x_{it} is a k x 1 vector of observed individual-specific regressors on the i^{th} cross section unit at time t, and the multifactor structure are taken up by the errors

$$e_{it} = \gamma_i' f_t + \varepsilon_{it}$$

Where, f_t is the m x 1 vector of unnoticed common affects, and ε_{it} is the idiosyncratic specified errors thought to be distributed independently. The focal point of this study had been created on measurement of β_i and their means, β. He depicted that unchanging estimation of β, can be taken out for unknown but fixed m, the number of unseen factors.

Common Correlated Effects Estimators: Individual Specific Coefficients

For the single slope coefficient the CCE is prescribed as:

$$\hat{b}_i = (X_i{}'\overline{M}_w X_i)^{-1} X_i{}'\overline{M}_w X_i Y_i \qquad (4.21)$$

Where X_{it} is a k × 1 vector of observed Individual-specific regressors on the ith cross section unit, $y_i = (y_{i1} + y_{i2} + ... y_{iT})'$ and $\overline{M}w$ is an idempotent and symmetric matrix and is given by,

$$\overline{M}_w = I_t - \overline{H}_w(\overline{H}'_w \overline{H}_w)^{-1}\overline{H_w}$$

And $\overline{H}_w = (D, \bar{Z}_w)$ where D and Z are T x n and T x (k+1) matrices

Common Correlated Effects Mean Group Estimator

The estimator CCEMG is a simple average of the individual CCE estimators, $\hat{b}_i$,

$$\hat{b}_{MG} = N^{-1}\sum_{i=1}^{N}\hat{b}_i \qquad (4.22)$$

Common Correlated Effects Pooled Estimators

Pesaran created an estimator that was pooled of β and presumed that $\beta_i = \beta$ and $\sigma_i^2 = \sigma$, even though it permits the slope coefficients of the common effects to differentiate across i. estimators like these represented by CCEP is prescribed by:

$$\hat{b}_p = (\sum_{i=1}^{N}\theta_i X'_i \overline{M}_w X_i)^{-1}\sum_{i=1}^{N}\theta_i X'_i \overline{M}_w y_i \qquad (4.23)$$

Where, $\theta_i = 1/N$.

He used Monte Carlo experiments on sample properties of CCEMG and CCEP estimators of small size, estimators of CCE show robustness in the serial correlation and variance in error heterogeneity of ε_{it} across i and this mingled time series stipulation is meant to underline the robustness of the estimators of CCE in samples that are small. The biasness and CCEP and RMSE of the CCEMG estimators are quite small and very much comparable to the biasness of the related infeasible estimators. In the scenario of experiment 1a (full rank + heterogeneous slopes), the lower bound to CCEMG's RMSE is given by the RMSE of the infeasible estimator of MG.

The Monte Carlo outcomes also verified the asymptotic efficiency of the estimators of MG compared to the pooled estimator within slope heterogeneity. All in all, CCEP and CCEMG gave quite good estimators that were efficient, especially for comparatively larger N and T, CCEP performance better for small samples. This universal outcome also withstands in the case of rank deficiency. The outcomes for RMSE for the homogeneous slope experiments depict that estimators of pooled were thought to be better than MG. The loss of efficiency of the estimators of CCE compared to their unsuitable corresponding items also appear as a little more considering the case of homogeneous slope, relative to the case of heterogeneous slope experiment.

Hence under the presumption, that if m is fixed, the residuals gave stable multi factor estimates of e_{it}.The regression model permitted dynamics common effects as well as the individual specific dynamics in e_{it}

Conclusion

We tried to elaborate almost all the panel data techniques of first generation and second generation in this section and also mentioned the issues due to which the econometricians kept on proposing the new techniques. Therefore; considering the short comings of first generation panel techniques and the ignored factors, we applied second generation panel unit root and cointegration tests.

Chapter: 05

Data and Variables

This chapter has been organized to elaborate about the variables being used in our study and their significance that how the discussed variables can give the desired results for the case we focusing on. The other part explains about the type and source of data that why and from where the sample data has been collected.

5.1: The Country Sample:

The objective of this study is to make a comparison between the slope coefficients of different panel methods by using the example of environmental Kuznets curve. To accomplish the task, we have considered the sample of lower, middle and higher income countries ranging from 1980-2016. By using the diversified sample, we will be able to check that whether the relationship whether U shape, L shape or N shape exist in all samples or vary in countries with different income levels.

5.2: Variables Construction:

For our case carbon dioxide emission is the key dependent variable and we took all the independent variables based on the assumptions and by following the literature that they play a significant role in carbon emission and environmental degradation and have an effect on economic growth.

5.2.1: CO_2 Emission Per Capita

For estimating the association among output and environmental degradation diverse procedures are being used in the literature, for example; Selder and Sag (1994)

Dasgupta et al. (2002) and Llorca and Meunie (2009) used SO_2 and NOx as a proxy for environmental degradation. While Ang (2007) , Jalil and Mahmud (2009), Saboori et al. (2012), Hamit- Hagger (2012), Lau et al. (2014), Farhani et al. (2014) etc. used emission of CO_2 for detecting the environmental Kuznets curve. In present study, we are also using CO_2 emission as our dependent variable, which is explained as stopping the scorching of fossil fuels and the cement production. This includes production of carbon dioxide through the consumption of liquid, rock-hard (solid), gas fuels and the gas burning.

5.2.2: GDP Per Capita

Gross Domestic Product (GDP) defines the worth of all the belongings and facilities that are manufactured in a country in a specific period. Where GDP per capita is ratio of GDP to population of a country. As mentioned early that due to industrialization when GDP increase it also leads to rise in environmental degradation as it emit more pollution, however; when GDP increases, after attaining a specific level the environmental situation starts getting better (Masih and Masih 1996; Wolde- Ruffel 2006; jalil and Mahumd 2009).

The hypothesis leads to the idea that initial increase in the income level causes the downfall in the environmental condition and the atmospheric condition gets worse as the economic activity increases more. But when the economic activity reaches to a definite level, the environment value gets better subsequently.

Trade:

CO_2 Emission, which is used as a proxy for environmental degradation, not only affected by GDP but there are some other arguments which may negatively affect the environment. For example; trade, energy emission and urbanization. Trade openness increases the scale of economy and through increase in scale pollution will increase. On the other hand, enhancement in trade will improve the techniques of production; which is known as technique effect; will improve the environmental situation (Ang 2009; Jalil and Mahmud 2009). Trade is defined as ratio of sum of imports and exports to GDP.

Urbanization:

Similarly increase in population, especially urban population may significantly affect the environment degradation (Mulai 2016; Kasman and Duman 2015; Ozturk and Al-Mulai 2015; Shafiei and Salim 2014; Shahbaz et al. 2014b). Therefore, our study also analyses the impact of urbanization on CO2 emission. For urbanization, the number of people living in urban areas is being considered.

Energy

Like the other indicators renewable energy also has a significant effect on carbon emission. Mulali (2016) worked on the effect of renewable energy on environmental Kuznets curve and concluded that energy consumption has a substantial and adverse influence on CO2 emission for the case of Central Europe, Western Europe, Eastern Europe and East Asia, South Asia, and USA. The results of the study showed that renewable energy consumption plays no significant role in emitting CO2 for the North Africa, Middle East and Sub Saharan Africa. Furthermore, conclusions specified the EKC hypothesis presence that could be indomitable by implementing renewable energy consumption since the EKC hypothesis existed merely for the counties where the renewable energy consumption played vital role in emitting carbon dioxide. So, the EKC hypothesis was confirmed for five regions excluding Middle East, North

Africa and Sub Saharan Africa because, in these areas renewable energy had no important impact on emitting carbon dioxide . So, this indicator will be considered as a factor of carbon emission for many regions in our study.

Financial development:

Plethora of literature is available which gives evidence about the strong influence of financial expansion on energy usage. Mulali and Ozturk (2015) applied Pedroni cointegration test which showed the CO_2 emission, urbanization, GDP growth, renewable electricity production and financial development were cointegrated using a source. Furthermore, they applied FM OLS whose results revealed that financial development, GDP growth and urbanization causes upturn in CO_2emission in the long run.

The modification in financial growth can change the level of economic growth, (De Gregorio and Guidotti, 1995; Arestis and Demetriades, 1997; Levine, 1997; Calderón and Liu, 2003; Aslan and Kucukaksoy, 2006; Kandır et al., 2007; Aslan and Korap, 2011; Zhang et al., 2012).

The basic results of the above readings supported the financial growth results into economic growth and later on the economic growth outcomes into financial growth. By the results of financial growth and economic growth the energy consumption increased. Shahbaz et al. (2013b) gave empirical evidence and also indicated that financial development reduces CO_2 emissions. Therefore, considering the strong evidences about the effects on environment of financial development, we add broad money in percentage of GDP as a significant indicator in our analysis. The data of all these variables is collected from World Development Indicators (2016)

Chapter: 06

Estimation Results

The empirical results of the all the above discussion are present in this section. Firstly, the study checked the stationarity of the data by applying panel unit root tests of both first and second generation and moved further by checking heterogeneity within the data and used panel cointegration techniques of again both first and second generation and in the end checked long run Elasticities with and without structural breaks for all the three types of countries being used (high income, middle income and low income). The results of all these tests are mentioned below.

Unit Root Test without Structural Breaks:

The unit root test is performed on the investigated series of interest so as to conclude the respective order of integration. It is important to note that no variable should surpass the integration of order I (1) in order to avoid the spurious results and order of integration will be helpful to select the suitable econometric model. The panel unit-root tests results are shown in Table 6.1

$$H_o = \text{The series is non- stationary}$$

$$H_1 = \text{The series is stationary}$$

Table 6.1Panel unit root tests without structural breaks: p-values are given with null hypothesis that series is I (1).			
	Lag 0	Lag1	Lag2
Maddala and Wu (1999)			
CO2 emission	0.2816	0.7501	0.9272
output	0.3064	0.0547	0.3574
output square	0.2961	0.2865	0.6108
Energy	0.7026	0.9563	0.9623
Trade	0.0441	0.7068	0.7545
financial development	0.3574	0.7665	0.8130
urbanization	0.7540	0.3405	0.5115
Pesaran (2007)			
CO2 emission	0.0795	0.5728	0.2082
output	0.0150	0.8547	0.9648
output square	0.2718	0.1117	0.4259
Energy	0.6587	0.5426	0.6298
Trade	0.5495	0.3527	0.8826
financial development	0.9004	0.8329	0.4662
urbanization	0.9538	0.7601	0.7273

As the table shows that the p-values of most of the coefficients in both the tests (Maddala and Wu and Pesaran) are larger than the critical value therefore, the null hypothesis is not rejected that means the unit root problem exists. The study checked the stationarity of the series at first difference and second difference level and found the series are non-stationary. The null hypothesis is explained as: if a panel unit root occurs in the variables, the variables are not stationary, while the alternative hypothesis indicates that if a panel unit root does not occur in the variables, the variables are stationary. Pesaran statistics has value 5.9971; so it rejects the null hypothesis of no cross section dependence. Therefore, this result may nullify the outcomes of Maddala and Wu (1999). To eliminate this problem, the study used

Pesaran (2007) panel unit root test which assume the cross section dependence. The estimation results are shown in the lower panel of Table 6.1

However, ARDL framework is an applicable approach because as shown that at different lag orders the different order of integration is shown. Panel unit root tests have extraordinary power as in comparison to the other time series unit root tests therefore, the researchers use panel unit root tests in the estimations. Hypothetically, the panel unit root tests are amended for panel data structure as these tests considered various time series unit root tests.

Panel unit root tests with structural breaks:

The con of the Pesaran (2007) test is that it doesn't consider the structural breaks in the estimations. For this reason, the study is using Bai and Carrion-i-Silvestre (2009) panel unit root test as it considers the case of structural breaks and cross section dependence. The results obtained are presented in Table 6.2, which shows that including the structural breaks do not modify the result of panel series. If the p-values of all the lag coefficients at constant and trend, mean shift and trend shift are more than the critical value; therefore, we do not reject the null hypothesis: series is I(1) that is the series is non- stationary. At the first difference, if the variables are stationary, the resulting step will be the evaluation of the long run relationship between the variables by using the panel cointegration test.

Table 6.2 Panel unit root tests with structural breaks: p-values are given with null hypothesis that			
	Lag 0	Lag1	Lag2
Constant and trend			
CO2 emission	0.3565	0.8654	0.8117
output	0.8504	0.5617	0.7706
output square	0.3455	0.8751	0.2580
Energy	0.1271	0.2793	0.6501
Trade	0.8200	0.1725	0.6293
financial development	0.5043	0.3187	0.1576
urbanization	0.7646	0.0341	0.2336
Mean shift			
CO2 emission	0.9586	0.7602	0.3299
output	0.4049	0.7266	0.9533
output square	0.8885	0.4676	0.8314
Energy	0.5482	0.5322	0.7595
Trade	0.5232	0.3817	0.2126
financial development	0.8311	0.0455	0.1016
urbanization	0.2798	0.4546	0.0563
Trend shift			
CO2 emission	0.5701	0.2240	0.6995
output	0.9740	0.8577	0.9531
output square	0.0135	0.4570	0.9287
Energy	0.4549	0.8218	0.4265
Trade	0.6270	0.2444	0.0672
financial development	0.1858	0.6321	0.9319
urbanization	0.3269	0.3797	0.4996

Slope heterogeneity test:

As compared to the normal time series and cross section data, the heterogeneity and the serial correlation problem is more controlled in panel data (Baltagi, 2005). Next, the study will check the condition of slope homogeneity and two tests are used for this purpose, the standard version of Swamy's test and adjusted version of the Swamy's test adjusted for the small sample properties. The results are shown in Table 6.3. The table shows the rejection of the null hypothesis of homogenous slope parameters, which indicates the use of long run estimates. These estimates are comprised of panel vector autoregressive model or error correction model by using the generalized method of moments and the results of pooled least square estimators will be ambiguous in exploring the relations between energy and economic growth. Therefore, the study will be with heterogeneous estimations.

Table 6.3 Slope heterogeneity test.	
Swamy's stats	8.113
Adjusted Swamy's stats	7.9133

Panel Cointegration Test:

Now the long run relationship between the variables will be estimated by using Westerlund (2007) and Westerlund and Edgerton (2008) panel cointegration tests. Westerlund (2007) test is valid when the heterogeneous panel data and cross section dependence is present, but the structural breaks are not considered. Therefore, to encounter structural breaks, the study will use Westerlund and Edgerton (2008) panel cointegration tests. Westerlund proposed four normally distributed tests, Gt, Ga, Pt, and Pa. The first two tests are mean-group tests as; they are made under the assumption of unit-specific error correction parameters. The last two tests are designed considering the common error-correction parameter through cross-sectional unit assumptions. The suggested investigations provide slope parameters and cross-sectional unit-specific short run dynamics along with cross-sectional unit-specific trend. Furthermore, to consider the cross-sectional dependence Westerlund (2007) generalized the test techniques by using a bootstrap methodology. The results found from the Westerlund's tests are slightly varied. The Gα and Pα tests outcomes show the acceptance of the null that is no cointegration, while Gt and Pt tests, at 10% significance level, show panel cointegration. The estimated results of Westerlund (2007) panel cointegration test are shown in Table 6.4 and Westerlund and Edgerton (2008) are shown in Table 6.5. The results presented show the rejection of null hypothesis that is no cointegration.

Table 6.4 Westerlund error correction panel cointegration tests.			
Null hypothesis:			
No cointegration			
Statistic Value p-Value Robust			
	Stats	p-value	Robust p-value
Gt	-3.911761	0.071039	0.00811
Ga	-5.557583	0.016742	0.006527
Pt	-6.369853	0.029981	0.002954
Pa	-19.36467	0.035232	0.009894
Note: Gt and Ga are the groups mean statistics. Pt and Pa are panel mean statistics.			

Table 6.5 Panel cointegration test results with structural breaks and cross sectional dependence.				
Model	Gt	Ga	Pt	Pa
No Break	5.845105	0.003756	3.11682E+14	0.055431
Mean Shift	2.467817	0.001847	2.777421332	0.024376
Regime Shift	4.427497	0.009593	2.054666029	0.0741
Note: The test is implemented using the Campbell and Perron (1991) automatic procedure to select the lag length.				

As shown in table, group-t and panel-t shows that cointegration doesn't exist in the model, so the null hypothesis is rejected. Thus, the general indication from Westerlund (2007) test and Westerlund and Edgerton (2008) tests illustrates that there is a long-run relationship among the dependent and independent variables in both the cases. This issue is described in the next subsection.

Since, the results of panel cointegration recommend the occurrence of a long-run relationship amongst emissions, income per capita and income per capita squared and the other variables, the study will continue with the calculation of the long-run coefficients by using the given model. The next step is to estimates the long run and short run elasticities in the study. Numerous estimators are applied for estimating the cointegration vector based on the dynamics of data in the literature. To apply these estimators, the study uses MG, PMG and CCEMG estimators. The long run estimates of MG, PMG and CCEMG estimators are shown in Table 6.6, 6.7 and 6.8. The study estimates a number of regressions considering different samples. First, several regressions through PMG, MG and CCEMG estimators are estimated for the energy trading countries, keeping the coefficient robustness.

The next task is to estimate the long run and short run Elasticities. Several estimators are used for estimating the cointegration vector in the literature based on the dynamics of data. For this purpose, we use MG, PMG and CCEMG estimators. The long run estimates of MG, PMG and CCEMG estimators are presented in Table 6.

Table 6.6: The long run effect of energy consumption on economic growth- high Income Countries

Dependent variable is CO2 emission

Regressors	PMG	MG	CCMG		PMG	MG	CCMG		PMG	MG	CCMG
GDP	0.5997*	0.5465*	0.2356**		0.4568***	0.7748***	0.0998***		0.6773***	0.4503**	0.6652***
	(0.3253)	(0.3221)	(0.1033)		(0.1597)	(0.1570)	(0.0365)		(0.1878)	(0.1937)	(0.1565)
GDP square	-0.4848***	-0.8813*	-0.5850***		-0.8329***	-0.6292***	-0.1618*		-0.1305*	-0.2455***	-0.1734***
	(0.1060)	(0.4663)	(0.1927)		(0.2163)	(0.1221)	(0.0905)		(0.0685)	(0.0345)	(0.0670)
Energy	0.3803**	0.3208	0.6939***		0.2182**	0.4062***	0.2198**		0.6604***	0.2976***	0.6602***
	(0.1843)	(0.9775)	(0.0655)		(0.1037)	(0.1733)	(0.1045)		(0.1436)	(0.1083)	(0.1431)
Trade	NA	NA	NA		0.5472***	0.6056***	0.8321***		0.4678***	0.6580***	0.2241
	NA	NA	NA		(0.2341)	(0.1772)	(0.1466)		(0.0571)	(0.1233)	(0.1930)
Financial Development	NA	NA	NA		NA	NA	NA		0.7256***	0.6659***	0.6583***
	NA	NA	NA		NA	NA	NA		(0.1765)	(0.2823)	(0.1753)
Urbanization	NA	NA	NA		NA	NA	NA		0.0221	0.9339*	0.4172
	NA	NA	NA		NA	NA	NA		(0.8432)	(0.5502)	(0.3856)
Constant									0.2733**	0.4773***	0.0572**
									(0.1223)	(0.1495)	(0.0270)

Note: *, **, and *** indicate significance at 10%, 5% and 1%.

The basic model for high income countries has been estimated using GDP per capita, squared GDP per capita and renewable energy, we can see the clear evidence of U-shaped relationship between income and environmental degradation, later by adding the variable of trade we see change in magnitude but the relation remains the same as we apply all the three estimators PMG, MG and CCEMG. And the shape of the curve remained the same as we added financial development and then urbanization. This means that initially with the increase in income the environmental condition decreases but latterly the environmental quality improves with the increase in income per capita. It is essential to elaborate here about taking structural breaks into account through CCEMG does not change the sign and significance of the key factors. In a more clear way, the entire variables pass in significant way for emitting carbon dioxide, in all three estimators which infers that the use of GDP per capita, squared GDP per capita, trade openness, renewable energy, financial development and urbanization has a substantial effect on the economic development of countries. We can see that all the estimators are consistent for high income, middle income and low income countries. Since, the MG estimator derives the long-run parameters for the panel from an average of the long-run parameters and PMG estimator estimate by taking average of the pooled data parameters in the long run. These both estimators have consistent estimates but they do not capture the structural breaks and does not explain the slope heterogeneity. But, the PMG estimators also allow checking heterogeneity for short run estimates. As we have a long run relationship in the data so, structural breaks should be taken into account to check the robustness. For this purpose CCMG estimator is being applied which identifies the structural breaks also. From the values in the table 6.6 we see that it validates the EKC hypothesis as there is a positive and significant relationship between carbon emission and income per capita and negative and significant relationship of carbon emission with squared-income per capita and the relationship remains the same even by adding the other variables like energy, trade, financial development and urbanization. Such as, 1% GDP increase causes 57% emission of carbon dioxide. But, as the GDP increases by square there is a decrease in carbon dioxide emission by 48%. Similarly through MG and CMG, we confirm the hypothesis that with the increase in GDP square the carbon dioxide emission decreases by 88.1% and 58.5%. Moving further, we can also see that with the increase in energy, carbon dioxide emission also increases like by 38.03% in PMG. By further adding trade to our analysis, we see that carbon dioxide emission increases by 54.72% by increase in trade. Moreover by adding financial development to the analysis, we see that by increase in financial development, carbon dioxide emission increase by 66.59%. By increase in urbanization, we see that carbon dioxide emission increases by 41.72%. The CCMG estimator also gives the same relationship as of PMG and MG estimators but with the higher magnitude.

Almost same picture can be seen for middle income countries as of high income countries. Again we obtained an inverted U-shaped relationship between carbon emission and income per capita and it remained the same as we add the other variables with income but we cannot see a significant change with increasing economy which may be due to that some middle income countries like China are not making prominent attempts to save the environment and are just focusing on increasing the economy which show robust picture.

For the low income countries we see that the PMG estimator gives a positive relation even with the increase in income. Which means that some low income countries does not have any resources of increasing the economy and the environmental degradation level does not increases which causes robustness.

Table 6.7: The long run effect of energy consumption on economic growth: Middle Income Countries											
Regress	PMG	MG	CCMG		PMG	MG	CCMG		PMG	MG	CCMG
GDP	0.3266	0.7877	0.4030		0.9001	0.4137	0.5998		0.7933	0.5075	0.1042
	(0.1679)	(0.3408)	(0.1886)		(0.0418)	(0.1747)	(0.3507)		(0.0272)	(0.1370)	(0.0445)
GDP Square	-0.4755	-0.3713	-0.3675		-0.1171	-0.6669	-0.2619		-0.3234	-0.9586	-0.1296
	(0.1074)	(0.0337)	(0.1755)		(0.0173)	(0.2356)	(0.0448)		(0.1380)	(0.3661)	(0.0639)
energy	0.9050	0.6188	0.5648		0.6620	0.9927	0.3643		0.8567	0.9741	0.6495
	(0.2851)	(0.3411)	(0.2763)		(0.3895)	(0.7610)	(0.1528)		(0.4217)	(0.4723)	(0.7338)
trade	*NA*	*NA*	*NA*		0.6735	0.8305	0.9147		0.2921	0.3556	0.9368
	NA	*NA*	*NA*		(0.3377)	(0.3176)	(0.3216)		(0.0526)	(0.1463)	(0.3801)
Financial Development	*NA*	*NA*	*NA*		*NA*	*NA*	*NA*		0.5018	0.5399	0.4407
	NA	*NA*	*NA*		*NA*	*NA*	*NA*		(0.1891)	(0.1550)	(0.1888)
urbanization	*NA*	*NA*	*NA*		*NA*	*NA*	*NA*		0.7369	0.9422	0.1285
	NA	*NA*	*NA*		*NA*	*NA*	*NA*		(0.2806)	(0.5899)	(0.0523)
Constant	0.8101	0.3721	0.5321		0.7165	0.5469	0.3441		0.9871	0.6615	0.6307
	(0.1026)	(0.2335)	(0.2141)		(0.1952)	(0.1791)	(0.1801)		(0.5695)	(0.1483)	(0.4238)
Note: *, **, and *** indicate significance at 10%, 5% and 1%.											

Table 6.8: The long run effect of energy consumption on economic growth. Low Income Countries											
Regress	PMG	MG	CCMG		PMG	MG	CCMG		PMG	MG	CCMG
GDP	0.4689	0.6191	0.4389		0.1284	0.9857	0.2914		0.9558	0.6164	0.6572
	(0.1670)	(0.1987)	(0.0341)		(0.9231)	(0.2734)	(0.1150)		(0.5142)	(0.1767)	(0.0603)
GDP Square	0.3252	0.5738	-0.8407		0.4320	-0.3672	-0.2824		0.4504	-0.4459	-0.7544
	(0.1462)	(0.1987)	(0.1721)		(0.8873)	(0.1318)	(0.0970)		(0.1587)	(0.0961)	(0.1929)
Energy	0.6265	0.4303	0.1608		0.9032	0.4654	0.4079		0.7258	0.3112	0.5923
	(0.1778)	(0.0967)	(0.0741)		(0.9838)	(0.5382)	(0.9439)		(0.1238)	(0.1758)	(0.1904)
Trade	*NA*	*NA*	*NA*		0.4898	0.9999	0.0092		0.6241	0.5632	0.5468
	NA	*NA*	*NA*		(0.3258)	(0.2185)	(0.4072)		(0.0735)	(0.3032)	(0.2767)
Financial Development	*NA*	*NA*	*NA*		*NA*	*NA*	*NA*		0.0904	0.3882	0.3235
	NA	*NA*	*NA*		*NA*	*NA*	*NA*		(0.0336)	(0.1115)	(0.2351)
Urbanization	*NA*	*NA*	*NA*		*NA*	*NA*	*NA*		0.3406	0.5590	0.1918
	NA	*NA*	*NA*		*NA*	*NA*	*NA*		(0.1398)	(0.1746)	(0.2994)
Constant	0.9879	0.1891	0.8031		0.0221	0.6797	0.6893		0.8382	0.9520	0.3351
	(0.1672)	(0.6401)	(0.5433)		(0.4381)	(0.0275)	(0.5835)		(0.2379)	(0.3509)	(0.1498)
Note: *, **, and *** indicate significance at 10%, 5% and 1%.											

Chapter: 07

Conclusion

Estimating Panel data is mostly considered as an effectual diagnostic technique for working with econometric data. The panel data collective matrix set comprises of time series for every cross-sectional participant in the data set, and it deals with a range of estimation techniques. The elementary notion behind panel data analysis comes from the idea that the individual relationships will all have the same constraints. Since the existing literature; except few assumed slope homogeneity and cross sectional independence so we expect that our study will contribute in the field of applied econometrics by reassessing the association among deprivation in environment and output development in enormous panel data set for the three different groups of countries i.e. lower, middle and higher income countries.

In our study, the stationarity of the data with the conventional panel data approach is checked using unit root tests and also used the cointegration tests of 2nd generation panel data focusing on the backdrops. Not just the cross sectional dependence and slope heterogeneity is being considered but the presence of structural breaks is also being analyzed in the series. We found the long run Elasticities with the data by using MG, PMG and CCMG estimators by considering the techniques of dynamic heterogeneous panel data models, referred to work of Pesaran (2006).

The EKC hypothesis was applied to check the dependence of environmental deprivation close to economic growth. This study has the principal objective of estimating heterogeneous parameters and finding the cross sectional dependence of the large sample panel data. It has been illuminated in the study that the facts of EKC hypothesis have no evidence of existence for individual countries; however it occurs from the general representation. The EKC concept finds a statistical connection of pollution emissions and GDP between many countries either at a single point at a time or between numerous countries at different level of times. Then, it concludes from this dynamic correlation; time advancement for general pollution routes that are depending on the GDP. Focusing on the results shown in chapter 6, if the countries typology has been looked once regarding per capita GDP, it is seen that the countries with higher income can be qualified as environmentalists, since they have decreasing emission tracks, the countries with middle income can be considered either as environmentalists or polluters and show horizontal emission trends and lastly, the countries with lower income are just considered as polluters, as their per capita CO_2 emissions is continuously increasing. Making the point more concrete, ponder as a last image which provides CO_2 emission drifts regarding to GDP in few countries with different levels of progress. The literature shows that the income levels changes with the correlation of the carbon emission and income per capita changes. More divergent development paths have been suggested since, the states with lower income showed the greater changeability in emission per capita than the high income states. The inference that it may be problematic to forecast the emission levels for low-income countries forthcoming, the turning point. Coherently, the larger part of the EKC work is about; correlation between these air pollutant and per capita income do not display a "U - inverted" shape. Carbon dioxide increases when per capita income increases. Nitrogen dioxide, instead, shows an "N - shape" pattern (Falco, 2001). So, by considering the traditional panel techniques and applying the 2^{nd} generation methods we can examine the shape of the EKC curve for large panel and different income level of countries.

We also tried to capture the structural breaks in the data of the income categories and checked the robustness in the parameters which was yet the most ignored part of the 2^{nd} generation panel data models.

Policy Recommendations:

Environmental pollution is one of the top category problems in the present era. Many countries have serious focus in this regard but as per the results of our study reveal that yet, more work should be done to improve avoid the carbon emission which is a factor of environmental pollution. As shown above that some middle income countries like China are just working to increase the economic growth but have not policy to improve the environmental quality. So, serious concerns should be shown by the middle income and lower income countries who are working with cheap sources of development which harm the environment.

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Literature Review Table

Author	Period	Country/Region	Methodology	Variables	Does EKC hypothesis prevails?
Shahbaz (2013a)	1980–2010	Romania	ARDL bounds testing	CO_2 emission, GDP, GDP square, and energy consumption.	Yes
Apergis and Ozturk (2015)	1990-2011	14 Asian countries	GMM	CO_2 emission, GDP per capita, land, population density and industry	Yes
Ahmed and Long (2012)	1971–2008	Pakistan	ARDL bounds testing	CO_2 emission, GDP, GDP square, energy consumption, trade openness and population	Yes
Ozturk and Al-Mulali (2015)	1996–2012	Cambodia	Generalized Method of Moments (GMM) and the Two-stage Least Squares (TSLS).	GDP, urbanization, trade openness, control of corruption and governance	No

Jalil and Mahmud (2009)	1975–2005	China	ARDL bounds testing, and Pair wise Granger causality.	CO2 emission, GDP, GDP square, Energy consumption, and trade openness.	Yes
Farhani et al. (2014)	1971–2008	Tunisia	ARDL bounds testing and VECM Granger causality	CO2 emission, GDP, GDP square, energy consumption, trade openness	Yes
Ozturk and Acaravci (2013)	1960–2007	Turkey	ARDL bounds testing and VECM Granger causality.	CO2 emission, GDP, GDP square, energy consumption, trade openness, and financial development.	Yes
Wang et al. (2011)	1995–2007	China	Pedroni cointegration and VECM Granger causality.	CO2 emission, GDP, GDP square, and Energy consumption.	Yes
Al-Mulali et al. (2015a)	1981–2011	Vietnam	ARDL bounds testing.	CO2 emission, GDP, fossil fuels energy consumption, renewable energy consumption, capital, labor,	No

				export and imports	
Al-Mulali et al. (2016)	1980–2012	Kenya	ARDL bounds testing	GDP, fossil fuel energy consumption, renewable energy consumption urbanization, and trade openness	No
Cho et al. (2014)	1971–2000	OECD countries	Pedroni cointegration and fully modified OLS,	CO2 emission, GDP, GDP square, energy consumption	Yes
Ozcan (2013)	1990–2008	Middle East	Westerlund panel cointegration test, Pedroni cointegration test, fully modified OLS, VECM Granger causality.	CO2 emission, GDP, GDP square, and Energy consumption	No
Shahbaz et al.	1980–2012	African countries	Pedroni	CO2 emission,	Yes

(2015)			cointegration, fully modified OLS and VECM Granger causality	GDP, GDP square, energy intensity	
Al-mulali et al. (2015b)	1980–2010	Latin America and the Caribbean countries	Kao cointegration, fully modified OLS and VECM Granger causality	CO_2 emission, GDP, GDP square, renewable energy and financial development	Yes
Chandran and Tang (2013)	1971–2008	ASEAN	Johansen–Jusellius cointegration test and VECM Granger causality.	CO_2 emission from transportation, energy consumption, GDP, and GDP square.	Yes in Indonesia Malaysia and Thailand; No for Singapore
Saboori and Sulaiman (2013b)	1971–2009	ASEAN	ARDL bounds testing and VECM Granger causality.	CO_2 emission, GDP, GDP square, and energy consumption.	Yes for Singapore and Thailand
Pao et al. (2011)	1990–2007	Russia	Johansen–Jusellius cointegration, VECM Granger causality.	CO_2 emission, GDP, GDP square, and energy consumption.	No
Tan et al. (2014)	1975–2011	Singapore	Johansen–	CO_2 emission,	No

			Jusellius cointegration test and VAR Granger causality.	energy consumption, GDP, and GDP square.	
Hamit-Haggar (2012)	1990–2002	China	Random and fixed effect Model	Industrial waste water, SO_2 emission, GDP, GDP square, trade openness, and foreign direct investment (FDI).	Yes
Cho et al. (2010)	1971-2006	China, Korea and Japan	VAR/VEC	CO_2, GDP, and Openness	Yes
Azam and Qayyum (2016)	1975- 2014.	Tanzania, Guatemala, China and USA	VAR/VEC	CO_2 emission, GDP, GDP square, energy consumption, urbanization growth rate, and trade openness	Yes
Bozkurt and Akan (2014)	1960-2010	Turkey	Cointegration tests	Carbon Dioxide Emissions, GDP and Energy consumption	Yes
Wang et al. (2014)	1980-2012	Gansu province	Bayesian approach	Climate, water, soil, vegetation and pollution load	Yes

Alam and Murad (2016)	1970–2012	India, Indonesia, China and Brazil	ARDL bound testing	CO2 emission, GDP, population growth and energy consumption	Yes
Wang et al. (2012)	2005	150 countries	Moran’s I statistic	GDP, Population and bio capacity	No
Poudel et al. (2009)	1980-2000	15 Latin American countries	fixed effects, one way error component semi-parametric panel data model	CO2 emission, GDP per capita, population density, illiteracy and forestry	Yes
Burnett and Bergstrom (2010)	1963-2008	USA	Spatial fixed effect estimation techniques and spatial first difference estimator	CO2 emission, GDP, CDD and HDD, energy production and population	Yes
Jobert et al. (2012)	1970 - 2008	55 countries	Bayesian shrinkage estimators	CO2 emissions, GDP per capita and energy consumption	Yes
Yin et al. (2014)	1999-2011	China	random effect with GLS method	CO2 emissions, GDP, environmental regulation, technical progress, Population,	Yes

				Energy efficiency, Energy structure, Industrial structure, International Trade, Foreign direct investment	
Farhani et al. (2014)	1990-2010	10 MENA countries	Pedroni cointegration test, FMOLS and DOLS	CO2 emission, GDP per capita, HDI, energy consumption and trade openness	Yes
Zaman et al.(2016)	2005-2013	East Asia & Pacific, European Union and High income OECD and Non-OECD countries.	principal component analysis	tourism development comprises tourism expenditures, number of tourist arrivals, energy use, carbon dioxide emissions, GDP per capita, gross fixed capital formation and total health expenditures	Yes

Ahmed et al. (2015)	1980 - 2010	24 European countries	MG and PMG estimators	CO2 emissions, biomass energy consumption, GDP per capita and technological innovation	Yes
Mir and Storm (2016)	1995-2007	40 countries (35 industries)	Fixed effect model	CO2 emission, GDP per capita,	Yes
Wagner (2015)	1950–2000	100 countries	1st generation and second generation panel techniques of cointegration	CO2 emission, SO2 emission, GDP per capita, USSR and CSSR	No

Appendix

Pesaran (2006) Multifactor Residual Model:

Let y_{it} be the observation on the ith cross section unit at time t for i = 1, 2… N; t = 1,2, ..., T, and suppose that it is generated according to the following linear heterogeneous panel data model

$$y_{it} = \alpha_i' d_t + \beta_i x_{it} + e_{it} \qquad (1)$$

where d_t is a n × 1 vector of observed common effects (including deterministic such as intercepts or seasonal dummies), x_{it} is a k × 1 vector of observed individual-specific regressors on the ith cross section unit at time t, and the errors have the multifactor structure

$$e_{it} = \gamma_i' f_t + \varepsilon_{it} \qquad (2)$$

In which f_t is the m × 1 vector of unobserved common effects and εit are the individual-specific (idiosyncratic) errors assumed to be independently distributed of (d_t, x_{it}). In general, however, the unobserved factors, f_t, could be correlated with (d_t, x_{it}), and to allow for such a possibility we adopt the following fairly general model for the individual specific regressors

$$x_{it} + A_i' d_t + \Gamma_i' f_t + v_{it} \qquad (3)$$

where A_i and Γ_i are n × k and m × k, factor loading matrices with fixed components, v_{it} are the specific components of x_{it} distributed independently of the common effects and across i, but assumed to follow general covariance stationary processes. Unit roots and deterministic trends can be considered in x_{it} and y_{it} by allowing one or more of the common effects in d_t or f_t to have unit roots and/or deterministic trends. In what follows, however, we focus on the case where d_t and f_t are covariance stationary.

$$y_{it} = \alpha_i' d_t + \beta_i' x_{it} + \gamma_i' f_t + \varepsilon_{it} \qquad (4)$$

Combining (4) and (3)

$$y_{it} + x_{it} = (\alpha_i' + A_i')d_t + \beta_i' x_{it} + (\gamma_i' + \Gamma_i') f_t + \varepsilon_{it} + v_{it} \qquad (5)$$

$$y_{it} + x_{it} = (\alpha_i' + A_i')d_t + \beta_i'(A_i' d_t + \Gamma_i' f_t + v_{it}) + (\gamma_i' + \Gamma_i') f_t + \varepsilon_{it} + v_{it}$$
$$Y_{it} + x_{it} = (\alpha_i' + A_i' + \beta_i' A_i')d_t + (\gamma_i' + \Gamma_i' + \beta_i' \Gamma_i') f_t + \beta_i' v_{it} + v_{it} + \varepsilon_{it}$$

$$Z_{it} = \begin{pmatrix} y_{it} \\ x_{it} \end{pmatrix} = \begin{pmatrix} \alpha_i' & 0 \\ \beta_i A_i & A_i' \end{pmatrix} d_t + \begin{pmatrix} \gamma_i & 0 \\ \beta_i \Gamma_i' & \Gamma_i' \end{pmatrix} f_t + \begin{pmatrix} \varepsilon_{it} + \beta_i' v_{it} \\ v_{it} \end{pmatrix}$$

$$Z_{it} = B_i' d_t + C_i' f_t + u_{it}$$

$$B_i = (\alpha_i \, A_i) \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix}, C_i = (\gamma_i \, \Gamma_i) \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix}$$

Assumption 1 (common effects): The (n+m)×1 vector of common effects, gt = (d0 t, ft0)0, is covariance stationary with absolute summable autocovariances, distributed independently of the individual-specific errors, εit0 and vit0 for all i,
t and t0.

Assumption 2 (individual specific errors): The individual specific errors εit and vjt0 are distributed independently for all i,j, t and t0.

(a) For each i, εit and vit follow linear stationary processes with absolute summable auto-covariance:

εit =∞ X c

=0

aicζi,t-c,

Assumption 3 (factor loadings): The unobserved factor loadings, γi and Γi, are independently and identically distributed across i, and of the individual specific errors, εjt and vjt, the common factors, gt = (d0 t, ft0), for all i, j and t with fixed means γ and Γ, respectively, and finite variances

Assumption 4 (random slope coefficients): The slope coefficients, βi, follow the random coefficient model

General Approach to Estimation of Panels with Common Effects:

$$\bar{Z}_{\omega t} = \bar{B}'_{\omega} d_t + C'_{\omega} f_t + \bar{v}_{wt}$$

$$\bar{Z}_{\omega t} = \sum_{j=1}^{N} \omega_j z_{jt}$$

$$\bar{B}_{\omega} = \sum_{i=1}^{N} \omega_i B_i \qquad , \ \bar{C}_{\omega} = \sum_{i=1}^{N} \omega_i c_i \qquad , \ \bar{v}_{\omega t} = \sum_{i=1}^{N} \omega_i v_{it}$$

Suppose, Rank $(\bar{C}_{\omega}) = m \le k+1 \qquad \forall$ N

$$\Rightarrow \quad f_t = (\bar{C}_w \ \ \bar{C}'_w)^{-1} \, \bar{C}_w \ (\bar{Z}_{wt} - \bar{B}'_w d_t - \bar{v}_{wt})$$

$$\bar{\Gamma} = (E(\gamma_i), E(\Gamma_i)) = (\gamma, \Gamma)$$

CCE: Individual Specific Coefficients

$$\hat{b}_i = (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w y_i \qquad (6)$$

$$\overline{M}_w = I_t - \overline{H}_w(\overline{H}_w' \quad H_w)^{-1}\overline{H}_w' \qquad (7)$$

$$\overline{H}_w = (D, \overline{Z}_w) \qquad (8)$$

$$y_i = D\alpha_i + X_i\beta_i + F\gamma_i + \varepsilon_i$$

$$y_i = \frac{\hat{b}_i}{(X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w}$$

Combining (6) and (8)

$$\frac{\hat{b}_i}{(X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w} = D\alpha_i + X_i\beta_i + F\gamma_i + \varepsilon_i$$

$$\hat{b}_i = (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w[D\alpha_i + X_i\beta_i + F\gamma_i + \varepsilon_i]$$

$$\hat{b}_i = (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w \; D\alpha_i + (X_i'\overline{M}_w X_i)^{-1}(X_i X_i'M_w)\beta_i + (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w F\gamma_i + (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w\varepsilon_i$$

$$\hat{b}_i - \beta_i = (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w D\alpha_i + (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w F\gamma_i + (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w\varepsilon_i$$

Where

$(X_i'\overline{M}_w X_i)^{-1}(X_i X_i'M_w)\beta$ is equal to identity according to assumption

$D_t = (d_1, d_2 ..., d_t)$ where $d_t = \dfrac{t}{T}$

$$\hat{b}_i - \beta_i = (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w \frac{t}{T}\alpha_i + (X_i'\overline{M}_w X_i)^{-1}(X_i X_i'M_w)\beta_i + (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w F\gamma_i + (X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w\varepsilon_i$$

$$\hat{b}_i - \beta_i = \frac{(X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w t\alpha_i + T(X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w F\gamma_i + T(X_i'\overline{M}_w X_i)^{-1} X_i'\overline{M}_w\varepsilon_i}{T}$$

As according to assumption α_i is a nuisance parameter

$$\hat{b}_i - \beta_i = (\frac{X_i'\overline{M}_w X_i}{T})^{-1} (\frac{X_i'\overline{M}_w F}{T})\gamma_i + (\frac{X_i'\overline{M}_w X_i}{T})^{-1} (\frac{X_i'\overline{M}_w \varepsilon_i}{T})$$

$$X_i = G\Pi_i + V_i$$

And $$\overline{H}_w = G\overline{P}_w + \overline{U}_w *$$

G= (D, F) , $\Pi_i = (A_i', \Gamma_i')$, $V_i = (V_{i1}, V_{i2}, ..., V_{iT})'$

$$\overline{P}_w = \begin{pmatrix} I_n & \overline{B}_w \\ 0 & \overline{C}_w \end{pmatrix} , \ \overline{U}_w * = (0, \overline{U}_w)$$

Where $\overline{P}_w$ is (n+m)x(n+k+1) matrix

$$\overline{U}_w = (\overline{U}_{w1}, \overline{U}_{w2}, ..., \overline{U}_{wT})$$

$$\|\overline{B}_w\| = \sum_{i=1}^{N} |w_i| \|B_i\| \langle k \qquad \text{and} \qquad \|\overline{C}_w\| = \sum_{i=1}^{N} |w_i| \|C_i\| \langle k$$

$\|B_i\|$ and $\|C_i\|$ are bounded

$$\frac{X_i'G}{T} = \Pi_i'(\frac{G'G}{T}) + \frac{V_i'G}{T} = O_p(1)$$

$$(\frac{G'G}{T}) = O_p(1) \quad , \quad (\frac{G'F}{T}) = O_p(1)$$

$$\frac{X_i'\overline{H}_w}{T} = (\frac{X_i'G}{T})\overline{P}_w + O_p(\frac{1}{N}) + O_p(\frac{1}{\sqrt{NT}})$$

$$\frac{\bar{H}_w'\bar{H}_w}{T} = \bar{P}_w'(\frac{G'G}{T})\bar{P}_w + O_p(\frac{1}{N}) + O_p(\frac{1}{\sqrt{NT}})$$

$$\frac{\bar{H}_w'F}{T} = \bar{P}_w'(\frac{G'F}{T}) + O_p(\frac{1}{\sqrt{NT}})$$

$$\Rightarrow \quad \frac{X_i'\bar{M}_w F}{T} = \frac{X_i'M_q F}{T} + O_p(\frac{1}{N}) + O_p(\frac{1}{\sqrt{NT}})$$

Where, $\bar{M}_q = I_t - \bar{Q}_w(\bar{Q}_w'\bar{Q}_w)'\bar{Q}_w'$ with $\bar{Q}_w = G\bar{P}_w$

Since, $F \subset G$ then $\bar{M}_q F = \bar{M}_g F = 0$

$$\Rightarrow \quad \frac{X_i'\bar{M}_w F}{T}\bar{C}_w = O_p(\frac{1}{N}) + O_p(\frac{1}{\sqrt{NT}})$$

$$\bar{C}_w = (\bar{\gamma}_w + \bar{\Gamma}_w\beta + \sum_{i=1}^{N} w_i\Gamma_i v_i, \bar{\Gamma}_w)$$

$$\bar{\Gamma}_w = \sum_{i=1}^{N} w_i\Gamma_i$$

$$\Rightarrow \quad (\frac{X_i'\bar{M}_w F}{T})(\bar{\gamma}_w + \bar{\Gamma}_w\beta + \sum_{i=1}^{N} w_i\Gamma_i v_i) = O_p(\frac{1}{N}) + O_p(\frac{1}{\sqrt{NT}})$$

Integrated variables:

While estimating long run relationships from dynamic heterogeneous panels Pesaran (1995) estimated the integrated variables

Consider aggregating the micro relations

$$y_{it} = \beta_i x_{it} + \varepsilon_{it} \qquad (1)$$

$$\beta_i = \beta + \eta_i \quad , \qquad \eta_i \sim iid(0, w^2)$$

$$\bar{y} = \beta \overline{x_t} + \overline{v_t}$$

$$\bar{v} = \overline{\varepsilon_t} + N^{-1} \sum_{i=1}^{N} \eta_i x_{it}$$

Suppose

$$x_{it} = x_{i,t-1} + v_{it} \quad , \qquad u_{it} \sim (0, \tau_i^2)$$

$$\operatorname{cov}(\overline{v_t}, \overline{v_{t-s}}) = \operatorname{cov}(\overline{\varepsilon_t}, \overline{\varepsilon_{t-s}}) + \frac{w^2 \tau^2}{N}(t-s) \qquad t \rangle s$$

$$v(\overline{v_t}) = v(\overline{\varepsilon_t}) + (\tau^2 w^2 / N)t$$

$$\tau^2 = N^{-1} \sum_{i=1}^{N} \tau_i^2$$

$$y_{it} = (\beta + \eta_i) x_{it} + \varepsilon_{it}$$

$$y_{it} = \beta x_i + \eta_i x_{it} + \varepsilon_{it}$$

Multiplying by $\sum_{i}^{N} x_i$ and $\sum_{i=1}^{N} x_i^2$ on both sides

$$\sum_{i=1}^{N} \frac{\tilde{y}_i \tilde{x}_i}{\tilde{x}_i^2} = \frac{\beta \sum_{i=1}^{N} \tilde{x}_i^2}{\sum_{i=1}^{N} \tilde{x}_i^2} + \frac{\sum_{i=1}^{N} \eta_i \tilde{x}_i^2}{\sum_{i=1}^{N} x_i^2} + \sum_{i=1}^{N} \frac{\tilde{\varepsilon}_i \tilde{x}_i^2}{x_i^2}$$

$$\Rightarrow \hat{\beta}_c = \frac{\sum_{i=1}^{N} \tilde{y}_i \tilde{x}_i}{\sum_{i=1}^{N} \tilde{x}_i^2} = \beta + \frac{\sum_{i=1}^{N} \eta_i \tilde{x}_i^2}{\sum_{i=1}^{N} \tilde{x}_i^2} + \frac{\sum_{i=1}^{N} \tilde{\varepsilon}_i \tilde{x}_i^2}{\sum_{i=1}^{N} x_i^2}$$

Suppose x_{it} is a random walk with drift

$$x_{it} = x_{i,t-1} + \mu_i + u_{it}\,,\quad u_{it} \to (0, \tau_i^2)$$

Then, $x_{it} = x_{i0} + \mu_{it} + \sum_{j=1}^{t} u_{ij}$

$$\tilde{x}_i = \mu_i + (\frac{T+1}{2}) + \sum_{j=1}^{T} (T+1-j) u_{ij} \Big/ T$$

Hence,

$$E(N^{-1} \sum_{i=1}^{N} \tilde{x}_i^2) = (\frac{T+1}{T})^2 (\sum_{i=1}^{N} \mu_i^2 \Big/ N) + \sum_{i=1}^{N} \sum_{i=1}^{T} \sum_{k=1}^{T} (T+1-j)(T+1-k) E(u_{ij} u_{ik}) \Big/ NT^2$$

It yields

$$E(N^{-1} \sum_{i=1}^{N} \tilde{x}_i^2) = (\sum_{i=1}^{N} \mu_i^2 \Big/ N)(\frac{T+1}{2})^2 + \frac{\tau^2}{T^2} \sum_{j-1}^{T} (T+1-j)^2$$

Applying limit as N $\to \infty$ for a fixed T

$$Lim \underset{N\to\infty}{Lim} E(\sum_{i=1}^{N} \tilde{x}_i^2 \Big/ N) = (\frac{T+1}{2})^2 \underset{N\to\infty}{Lim} (\sum_{i=1}^{N} \mu_i^2 \Big/ N) + \frac{T(T+1)(2T+1)}{6T^2} \underset{N\to\infty}{Lim} (\sum_{i=1}^{N} \tau_i^2 \Big/ N)$$

$$\Rightarrow \qquad E\left(\sum_{i=1}^{N} \tilde{x}_i^2 \, \eta_i \big/ N\right) = 0$$

$$\text{Similarly,} \quad E\left(\sum_{i=1}^{N} \tilde{x}_i^2 \, \varepsilon_i \big/ N\right) = 0$$

Hence, as N $\rightarrow \infty$, $\hat{\beta}^c \xrightarrow{p} \beta$ for a finite T