Essays in the Economics of Green Innovation, Energy and the Environment

Thesis by

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To my parents, **Ma** and **Baba**.

Samapti Chakraborty and **Sujan Kanta Chakraborty**.

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Ph.D. Course
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Essays in the Economics of Green Innovation, Energy and the Environment

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ॐ

नासदासीन्नो सदासीत्तदानीं नासीद्रजो नो व्योमा परो यत् |

किमावरीवः कुह कस्य शर्मन्नम्भः किमासीद्गहनं गभीरम् ॥ १॥

न मृत्युरासीदमृतं न तर्हि न रात्र्या अह्न आसीत्प्रकेतः |

आनीदवातं स्वधया तदेकं तस्माद्धान्यन्न परः किञ्चनास ॥२॥

तम आसीत्तमसा गूहळमग्रे प्रकेतं सलिलं सर्वाऽइदम् |

तुच्छ्येनाभ्वपिहितं यदासीत्तपसस्तन्महिनाजायतैकम् ॥३॥

कामस्तदग्रे समवर्तताधि मनसो रेतः प्रथमं यदासीत् |

सतो बन्धुमसति निरविन्दन्हृदि प्रतीष्या कवयो मनीषा ॥४॥

तिरश्चीनो विततो रश्मिरेषामधः स्विदासीदुपरि स्विदासीत् |

रेतोधा आसन्महिमान आसन्त्स्वधा अवस्तात्प्रयतिः परस्तात् ॥५॥

को अद्धा वेद क इह प्र वोचत्कुत आजाता कुत इयं विसृष्टिः |

अर्वाग्देवा अस्य विसर्जनेनाथा को वेद यत आबभूव ॥६॥

इयं विसृष्टिर्यत आबभूव यदि वा दधे यदि वा न |

यो अस्याध्यक्षः परमे व्योमन्त्सो अङ्ग वेद यदि वा न वेद ॥७॥

Hymn of Creation

Existence or nonexistence was not then. The bright region was not, nor the space (vyoman) that is beyond. What encompassed? Where? Under whose protection? What water was there-deep, unfathomable?

Death or immortality was not then. There was no distinction between night and day. The One breathed, windless, by itself. Other than that there was nothing beyond.

In the beginning there was darkness concealed by darkness. All this was water without distinction. The One that was covered by voidness emerged through the might of the heat-of-austerity.

In the beginning, desire, the first seed of mind, arose in That. Rishis (sages), searching in their heart with wisdom, found the bond existence in nonexistence.

Their [visions'] ray stretched across [existence and non-existence]. Perhaps there was a below; perhaps there was an above. There were givers of seed; there were powers: effort below, self-giving above.

Who knows the truth? Who here will pronounce it whence this birth, whence this creation? The Devas (Gods) appeared afterward, with the creation of this [world]. Who then knows whence it arose?

Whence this creation arose, whether it created itself or whether it did not? He who looks upon it from the highest space, the surely know. Or maybe He knows not.

– Rig-Veda X.129. 1-7

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ABSTRACT

Essays in the Economics of Green Innovations, Energy and the Environment

by

Saptorshee Kanto Chakraborty

Submitted to the Department of Economics

on 30th November, 2017, in partial fulfillment of the

requirement for the degree of

Doctor of Philosophy in Economics

My dissertation has a primary focus on macro-economic panel data models in applied green innovation and environmental economics under high dimensionality; that is, both the number of individual cross-sectional units and the number of time periods are comparatively large. The high dimensionality is widely applicable in practice, due to the increase in the availability of time-dimensional data in macro-economic literature.

The thesis comprises of four standalone chapters (Chapter II, III, IV and V) that explores various questions related to various concepts of green innovation, energy and environment.

In the first chapter, I explore the green knowledge production function and human capital spillovers in the OECD region with and without fiscal-shocks, using a latent group structure. The number of groups and the group membership are both unknown, these unknowns are determined using a variant of Classifier-Lasso technique, which estimates consistently the group structure and leads to oracle-efficient estimation of the coefficients even in the presence of cross-sectional dependence in error terms and nonstationarity. The findings suggests substantial heterogenous groups classified under three distinctive categories and their efficient estimates. I also apply a fiscal policy shock variables to measure the interactivity through trade among countries.

In the second chapter, I have tried to investigate the dynamic heterogeneous relationship between green energy innovation and energy intensity for a set of OECD countries. I find both long-term and short-term relationship in between green energy innovation and energy intensity, though the relation becomes insignificant over time,

i.e. introduction of lags in the system of equations. But I do not find any significant Granger causality in between energy intensity and green energy innovation.

In the third chapter, I investigate the long-run relationship between renewable electricity consumption and economic growth in some selected countries using a cross-sectionally augmented distributed lagged and cross-sectionally auto-regressive distributed lag model, to deal with unobserved heterogeneity both in cross-country and time varying ones. My findings suggest that, on average, there is a significant positive long-term relationship between renewable electricity consumption and economic growth

In the fourth chapter, I investigate the dynamic relationship in between economic growth and environment using a Environmental Kuznets curve hypothesis for some selected countries, which accounts for a significant amount of emission. I consider the framework of a panel structure model, to account for heterogeneity across countries. The effects of economic growth and renewable energy consumption on carbon dioxide emission are the same within groups but differ across different groups. The number of groups and the group membership are both unknown, I determine these unknowns using a variant of Classifier-Lasso technique, which estimates consistently the group structure and leads to oracle-efficient estimation of the coefficients. I find substantial number of heterogenous groups and estimates.

Thesis Supervisor
Professor **MASSIMILIANO MAZZANTI**

Thesis Co-Supervisor
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Abstract in Italian

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La mia dissertazione si è concentrata principalmente sui modelli di dati panel nell'innovazione green applicata e nell'economia ambientale sotto alta dimensionalità; cioè, sia il numero delle singole unità trasversali, che il numero dei periodi di tempo, sono relativamente elevati. L'elevata dimensionalità è ampiamente applicabile nella pratica a causa dell'aumento della disponibilità di dati nella dimensione tempo nella letteratura macroeconomica. La tesi comprende quattro capitoli indipendenti (Capitolo II, III, IV e V) che esplorano varie questioni relative a vari concetti di innovazione green, energia e ambiente.

Nel primo capitolo, esploro la funzione di produzione della conoscenza green e le ricadute del capitale umano nella regione dell'OCSE con e senza shock fiscali, usando una struttura di gruppo latente. Il numero di gruppi e l'appartenenza al gruppo sono entrambi sconosciuti, queste incognite sono determinate utilizzando una variante della tecnica Classifier-Lasso, che stima coerentemente la struttura del gruppo e porta alla stima oracolo-efficiente dei coefficienti anche in presenza di dipendenza trasversale in termini di errore e non stazionarietà. I risultati suggeriscono importanti gruppi eterogenei classificati in tre categorie distinte e le loro stime efficaci. Applico anche delle variabili dello shock della politica fiscale per misurare l'interattività tra i paesi attraverso il commercio.

Nel secondo capitolo, ho cercato di indagare la relazione eterogenea dinamica tra l'innovazione dell'energia verde e l'intensità energetica per un insieme di paesi OCSE. Ho trovato sia una relazione a lungo termine che a breve termine tra l'innovazione dell'energia verde e l'intensità energetica, sebbene la relazione diventi insignificante nel tempo, vedi l'introduzione di ritardi nel sistema di equazioni. Ma non trovo alcuna causalità Granger significativa tra l'intensità energetica e l'innovazione dell'energia verde.

Nel terzo capitolo, indago la relazione a lungo termine tra il consumo di elettricità rinnovabile e la crescita economica in alcuni paesi selezionati utilizzando un modello a intervalli distribuiti aumentato in modo trasversale e un modello a intervalli distribuiti auto-regressivo in modo trasversale, per trattare l'eterogeneità non osservata in modo trasversale (cross-country) e tempi variabili. I miei risultati suggeriscono che, in media, esiste una significativa relazione positiva di lungo termine tra il consumo di elettricità rinnovabile e la crescita economica.

Nel quarto capitolo, indago la relazione dinamica tra crescita economica e ambiente usando un'ipotesi di curva Kuznets Ambientale per alcuni paesi selezionati, che rappresenta una quantità significativa di emissioni. Considero la composizione di un modello di struttura panel, per spiegare l'eterogeneità tra i paesi. Gli effetti della crescita economica e del consumo di energia rinnovabile sulle emissioni di diossido di carbonio sono gli stessi all'interno dei gruppi, ma differiscono tra i diversi gruppi. Il numero di gruppi e l'appartenenza al gruppo sono entrambi sconosciuti, determino queste incognite utilizzando una variante della tecnica Classifier-Lasso, che stima coerentemente la struttura del gruppo e porta alla stima efficace dei coefficienti. Trovo un numero sostanziale di gruppi eterogenei e stime.

Supervisore di tesi
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Chapter 1

INTRODUCTION

1.1 Introduction

Climate change has become a global threat to human existence, at current levels of emission it is very much probable that the human civilization might have 12 years left as of today. The Paris Accord was a successful one which put forward the idea of maintaining global temperature increase below 1.5°C (IPCC, 2018). This requires active participation from public, private and civil society with a focus of a re-direction plan for the global economy. This re-direction also known as the green transition is yet to be acknowledged by traditional economists due to the complex nature of climate change and its impact on global economy. As suggested by Kattel et al. (2018) while considering the possible trajectory for sustainable growth theory one must take into account characteristics of complex systems including the impact of feedback loops, path-dependency, non-linear dynamics, endogenous risks, fundamental uncertainty and absence of optimality, traditional ideas of market failures, negative externality and public goods are no longer adequate enough for the purpose of apprehending the dynamic characteristics of a green growth transition. A very clear path to tackle this is to introduce more pathways to achieve sustainability via bottom-up investments and green innovative activities with active public and private participation at sectoral, regional, country and global levels.

This brings up tough challenges about some complex issues of definitions, measurements along with financing and introducing regulatory and consensual behavioural modifications across the economy. Achieving green growth is a huge task and on the words of Mazzucato and McPherson (2018) is much tougher than the “technological feat of getting to the moon". In a way this is very appropriate to say, since not only day-to-day behavioural modifications are required along with restructuring of current tax system, long-term financing in R&D and labor productivity are required. But also effective monetary policy and fiscal policy are very much required. For example Campiglio et al. (2018) points out the requirements of various monetary policy requirements for a brighter future including financial stress testing, Quantitative Easing, determining updated collateral frameworks. On the fiscal side adopting policies to move towards a cleaner sectoral composition will create multitude of effects in not only the countries which adopts it, but also to other countries through trade and knowledge spillovers.

1.2 Green Innovation

The concept of “Sustainable Development" was first introduced by the Brundtland report in 1987 commissioned by Environment and Development (1987) which was already coined by the International Union for Conservation of Nature and Natural Resources in their World Conservation Strategy report in 1980 (Nature and Natural Resources et al., 1980). Over the years much of the literature has evolved in addressing “Sustainable Development" and linking it to climate change and pollution based studies. The concept of sustainable development puts forward limits of usage of natural resources and consumption patters (Environment and Development, 1987). Though the limits are not in absolute terms but it is necessary to innovate to adopt a more sustainable future.

Innovation has been vital throughout human history and now it is needed most, human beings have brought an existential crisis upon themselves. With current trends in global temperature rise and pollution levels it is a matter of time when large climate catastrophes might take place. In order to avoid such catastrophic impacts, we need to adopt fundamental changes of policy, institutions and practices. These changes also needed to be implemented all over the world in all spheres of life. A paradigm shift in technology is required to be implemented, which some authors like Ekins (2010), Fussler and James (1996) have termed it as ‘Eco-innovation’. The definition has been molded a lot with inclusion and exclusion of activities and have been used in various terms like ‘Sustainable Innovation’, ‘Eco-innovation’, ‘Environmental Innovation’ and ‘Green Innovation’. We proceed with the definition of ‘Green Innovation’ as proposed by Driessen and Hillebrand (2002) and Chen, Lai, and Wen (2006).

1.3 Motivation of the thesis

Countries especially India, USA, OECD group, European Union and China have made a lot of progress in tackling climate change through investing in innovative activities. A substantial amount of literature exists in empirically addressing issues of green innovation at both in micro and macro levels (Johnstone, Haščič, and Popp, 2010, Fankhauser, 2012, Conte, European Commission, and Directorate-General for Economic and Financial Affairs, 2010, Schiederig, Tietze, and Herstatt, 2012). Most of these literature do not take into account of unobserved heterogeneity in the error terms especially cross-sectional dependence, which is a quite natural issue in spillover studies (Pesaran, 2015b). Therefore the aim of this thesis is to investigate how to measure effects of different indicators on green innovation in a multi-factor error setting to take into account such unobserved heterogeneity.

Due to complexity in measurement Green innovation is measured by Patents of certain categories mainly Y02 of IPC-CPC class (OECD, 2018b) and Research and Development indicators (OECD, 2015). We define these Y02 class of patents as *green patents* and a combination of two subclass of Y02 category, Y02C and Y02E as *green energy patents*. There has been an increase in such patent counts over the years all over the world.

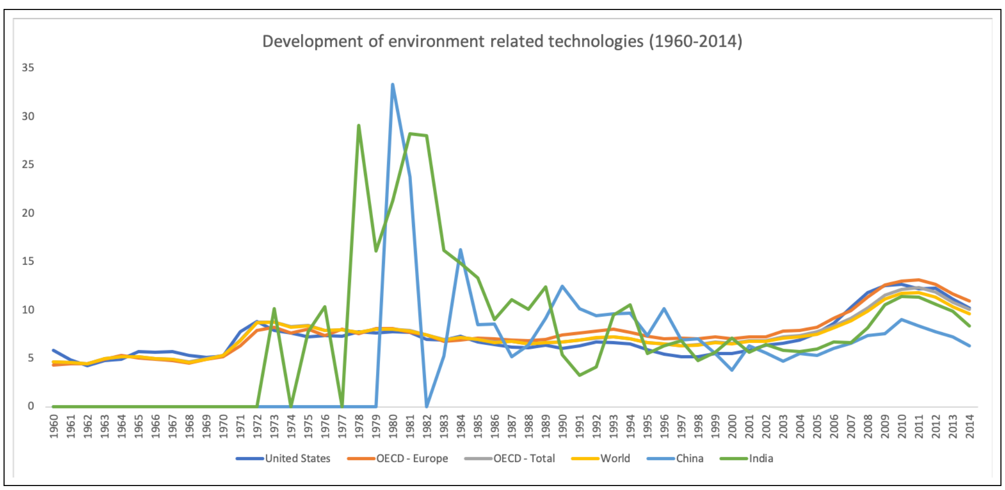


Figure 1.1: Development of Environment related technologies (in percentage ratio terms) for selected countries: 1960-2014: Source- OECD, 2018

Figure 1, depicts count of patents for Development of Environment related technologies (in percentage ratio terms to total patents) for India, USA, China, OECD Europe and OECD total for 1960-2014 time period.

1.4 Structure of the Ph.D. Thesis

Based on our research question, this Ph.D. thesis comprises four mutually-exclusive research articles on green innovation, energy consumption and environment.

Chapter 1, *Modelling the Green Knowledge Production function with Fiscal Shocks*

By A Latent Group structures For OECD Countries aims at providing a solid background for the green knowledge spillover literature in sample OECD countries. Over the years the OECD group along with countries of the European Union have focused a lot of attention on green innovation and ways to deal with climate change. But quiet a lot of heterogeneity exists in such, since innovation is not easily observable it is difficult to disentangle green knowledge formation from ordinary knowledge. We also deal with inter-country spillover in our model. Due to the fact of such complexity in the data we use some solid econometric framework to have a better understanding. We also introduce fiscal shocks generated from abroad which can affect green knowledge creation through trade linkages and government spending, borrowing from core macro-economics literature. In our empirical methodology we apply a panel variant of Lasso methodology, Classifier-Lasso, which holds oracle properties of an estimator even in the presence of cross-sectional dependence in error terms and nonstationarity and determines group membership using latent group structure. We conclude with three distinct groups, in all of our cases but the group membership changes with different explanatory variables. While using fiscal shocks, we use multi-factor error structure estimators and find baseline fiscal shock with exposure weights fixed over time has some important implications over green innovative activities, but their magnitude being miniscule. In short we can conclude, that spillover created through green knowledge production is not uniformly distributed across the OECD region and distinctive groups have emerged depending upon different types of research and development investments, human capital levels and fiscal deficit.

Chapter 2, *Energy Intensity and Green Energy Innovation: Checking heterogeneous country effects in the OECD*, in this paper my aim was to gain a better understanding of the entanglement of green energy innovative activities with energy intensity again in the OECD region. Over the years there has been some empirical evidence of energy intensity decline all over the world along with OECD countries, but most of this decline was industry specific or sector specific. Existing literature lacked in dealing with these heterogeneity both in short-run and long-run scale. For the same reason, we use some specific estimators which deals with such specifics inside their framework. We also bring in the concept of dynamics in green energy innovation and find existence of both short-term and long-term relationship in between energy intensity and green energy innovative activities. But this relationship looses its significance over time. But what we do not find is any direct causality in between our variables. This opens a very good possibility for future research.

Chapter 3, *Renewable Electricity Consumption and Economic Growth using CS-ARDL and CS-DL*, researchers have been very much intrigued to understand the relationship in between electricity consumption and economic growth. Many types of sample size and econometric methodology has been applied to quantify such relationship. Though the literature is huge, but very few articles exists which deals with unobservable heterogenity of various types in a long-run framework. For the following reason, we adopt some specific estimators to understand the long-run relationship between both renewable electricity consumption and total electricity consumption with economic growth in presence of unobservable heterogeneity. We find existence of long-term meaningful relationship but we do not find any causality in between renewable electricity consumption and economic growth.

Chapter 4, *Revisiting the literature of dynamic EKC using a Latent structure approach*, the theory of association of environmental degradation and economic growth is not new and a very important one in current global scenario. Countries needs to adjust between growth and environmental degradation, the volume of literature which deals such association is huge and mainly referred as Environmental Kuznet Curve (EKC) literature has been used extensively by applied economists with different types of empirical methodologies in various data setting. But in a panel framework, researchers assumed some selected countries when dealing with unobservable heterogenity. We do not assume such grouping and let our methodology determine our group from the data itself. We took into account some specific countries which accounts for nearly 80 % of global carbon dioxide emission and applied EKC setting. Using a Classifier Lasso framework which applies latent group methodology to deal with unobservable heterogeneity we conclude with two distinctive groups and substantial heterogeneity in types of energy consumption (renewable and total) with both positive and negative effects manifesting in data. The results provide new viewpoint about potential impacts in the EKC literature that might be relevant to policy makers.

Chapter 2

MODELLING THE GREEN KNOWLEDGE PRODUCTION FUNCTION WITH FISCAL SHOCKS BY A LATENT GROUP STRUCTURES FOR OECD COUNTRIES

2.1 Introduction

The biggest daunting challenge faced by human civilization in the post-war era is to maintain suitable ecological well-being without harming levels of economic growth patterns, this requires moving from dirtier to clean technologies without disrupting the engine of economic development (Stokey, 1998; Aghion et al., 1998, chapter 5; Acemoglu et al., 2012). But this is not easy as it is said, to do such one needs to invest in knowledge building process, adopt and implement green fiscal policies (GPF) and also be prepared for the next recession which might hamper the whole process of transition.

Following the footsteps of Griliches (1979) a lot of work has been done both at macro, mezo and micro level which relates knowledge to analyze the pathways towards creation of innovation Eberhardt, Helmers, and Strauss (2013), Charlot, Crescenzi, and Musolesi (2015), including green innovation . Side by side GFPs' are some kind of fiscal policy instruments the government must adopt to deal with climate change, waste management and water conservation, these fiscal policy instruments can be both spending or taxing of nature. As defined by Milne and Andersen (2014) (Chapter: 23), GFPs can be categorized in three stages, the first stage being taxing pollution as a part of introducing broader strategy, second introducing multiple forms of such taxation and also providing incentives to less pollutant creators and thirdly introducing environmental fiscal reform by increasing taxation on pollutant creators without hampering the overall tax system (Gramkow and Anger-Kraavi, 2018). This types of taxation has been very effective in many countries and developing countries like China, India, South Africa, Brazil are beginning to adopt such type of green fiscal reform (Martin, Preux, and Wagner, 2011 and Gramkow and Anger-Kraavi, 2018).

To achieve sustainable targets as defined by Kyoto protocol and recently Paris Accords, countries can adopt multiple measures like taxation, tax reliefs and also public spending to incentivize green innovation through research and development. But after the great financial crisis of 2007-08 and the European debt crisis in the ongoing decade the public debt in the developed countries have risen up exponentially and though most of countries have recovered from such difficult times but still economic growth, inflation and interest-rate are at near zero levels this have made policymakers focus more on fiscal policy framework rather than monetary policies. But if a new recession arrives which is a long-overdue because the current expansionary phase has been a long one historically, the question lies how much will the progress towards cleaner technology adoption be affected.

So our research focuses the mainly on three aspects, first we want to understand the evolution of green knowledge and the spillover from acquirement of knowledge production, since knowledge itself is a complex factor to be quantified we try to model green knowledge through somewhat agreed upon units of research and development along with human capital which might be considered as basic innovation inputs. To take into account fiscal policy shocks in our framework we estimate the effects of fiscal shocks on domestic debt which might affect R&D spending if recession arises and which in-turn might hamper transition towards a greener economy. The concept of fiscal stimulus and fiscal spillovers already exists in core-macroeconomic literature (Auerbach and Gorodnichenko, 2011, Auerbach and Gorodnichenko, 2012, Auerbach and Gorodnichenko, 2017, Romer and Romer, 2010) but this is first time such shocks and spillover techniques are being introduced in green innovation literature.

We intend to quantify the concept of Green Knowledge Production function for selected OECD countries, we also use some fiscal shock indicators to understand the role of fiscal policies on green innovation and knowledge production. We assume that cross-section dependence is generated by unobserved common factors which are both stationary and nonstationary in nature. Using a C-Lasso estimator as proposed by Su, Shi, and Phillips (2016) and Huang, Phillips, and Su (2018), we find distinctive groups with their coefficient being responsive and also non-responsive to green innovation. Moreover we also used five type of G-Shocks in our sample from macro-economic shock literature, to understand how countries are inter-connected through fiscal shocks via-trade linkages and we find some significant shocks though these shocks have very little magnitude of coefficients. The remainder of this paper is organized as follows, Section 2.2 outlines the contemporaneous ongoing research regarding spillover studies and empirical methodologies in spillover studies. Section 2.3 outlines the evolution of Green knowledge production function from traditional knowledge production function with implications of macroeconomic shocks, especially fiscal shocks originating from within and outside. Section 2.4 describes the model and methodology applied. Section 2.5 lays down the empirical equations and data used. Section 2.6 presents the results and section 2.7 concludes.

2.2 Literature review and outline

Our paper can be related a burgeoning literature of evaluation of spillover effects without any prior assumption of the framework of synergy among individual units (countries in our case). Lam and Souza (2014) uses a random effects approach to determine structural interaction by integrating over a class of network formation models. de Paua, Rasul and Souza (2016) identifies spillover effects and interactivity in structures by using reduced form equations for both endogenous and contextual effects. Using an adaptive elastic net approach Bonaldi, Hortaçsu, and Kastl (2015) measures systemic conditional on estimated network for banks inside the European union via liquidity auctions of European Central Bank. Rose (2018) uses a Self Tuning Instrumental Variable (STIV) approach to identify and estimate spillover effects of R&D in an oliogopolistic model for US firms. Manresa (2016a) uses a pooled Lasso estimator (a panel variant Lasso as proposed by Tibshirani (1996)) by keeping unrestricted relationship among interaction structures and observables/unobservables (time-invariant) to study R&D spillovers of US firms, her objective is a noble one since the methodology estimates the reference group and the magnitude of spillover effects without any prior information.

But all of these methodologies do not consider or considers only weak cross-sectional dependence among error terms and limited time-series dependence, through our method we try to consider strong cross-sectional dependence in error-terms as defined by Bailey, Kapetanios, and Pesaran (2016) and presence of non-staionarity in the estimation framework itself. Our focus is mainly on OECD countries which is a heterogeneous group compared to the G-7 or Eurozone, so to deal with unobservable heterogeneity especially cross-sectional dependence in error terms a prevalent phenomenon in spillover and innovation studies (Pesaran, 2015b) we apply latent group structure methodology following Huang, Phillips, and Su (2018) which employs a variant form of Lasso to handle unobserved heterogeneity in the form of non-stationarity and cross-sectional dependence. The technique also employs penalized principal component to identify individual group membership to estimate group-specific long-run relations.

Traditional fixed-effects panel data model assumes cross-sectional units are heterogeneous in terms of time-varying intercepts with a homogeneous slope coefficient, but this assumption of homogeneity in slope has been a debatable issue in econometric literature. To deal with this issue, the traditional view is to split the data into similar groups and apply standard fixed-effects model to each of them in this type of models unobserved heterogeneity enters the model additively. Time and again this method has been criticized in studies Hsiao and Tahmiscioglu (1997), Lee, Pesaran, and Smith (1997), Phillips and Sul (2007), Su and Chen (2013). Over the years different approaches have emerged to deal with unknown group structure with respect to inferencing unobserved slope heterogeneity. The first one being finite mixture models, Sun (2005) proposes a finite parametric linear mixture model; Kasahara and Shimotsu (2009), Browning and Carro (2013) uses nonparametric discrete mixture distributions to identify finite number of groups in a discrete choice panel data. Another concept is cluster analysis by using K-means algorithm. Quite a lot of progress has been made in this regard, Lin and Ng (2012), Sarafidis and Weber (2015), Bonhomme and Manresa (2015), Ando and Bai (2016) have all worked using a K-means algorithm to deal with slope based heterogenenity. Su, Shi, and Phillips (2016) have used a variant form of Lasso, C-Lasso [Classifier-Lasso] to identify latent group pattern when the slope coefficients exhibit group structure. Due to increase in availability of macro-economic data there has been a surge in theoretical econometric papers dealing with unobserved heterogeneity by imposing latent group patterns in panels of large dimensions, see Su, Shi, and Phillips (2016), Su and Ju (2018), Huang, Jin, and Su (2018) and Huang, Phillips, and Su (2018), Lu and Su (2017), Bonhomme, Jochmans, and Robin (2016), Wang, Phillips, and Su (2019). In this it is notable to mention Huang, Phillips, and Su (2018) [HPS, (2018) hereafter] have extended the technique as proposed by Su, Shi, and Phillips (2016) [SSP, (2016) hereafter] to deal with cross-sectional dependence in non-stationary time series, irrespective of I(0) or I(1) order, SSP (2016) introduces Classifier-Lasso (C-Lasso, hereafter) to study unobserved grouped patterns and HPS (2018) included penalized principal component analysis (PPC) to deal with this cross-sectional dependence and obtain three types of estimators Classifier- Lasso, post-Lasso and continuous-updated Lasso (Cup-Lasso). They asymptotically establish efficiency in estimation technique and consistency in presence cross-sectional dependence in error terms, non-stationarity and unknown group patterns by including PPC technique from Bai (2009), this also can be viewed as an extension of multi-factor error structure approach of Bai and Ng (2002), Pesaran (2006) and Moon and Weidner (2015) along with others.

Finally, our paper also relates to the rapidly flourishing literature aimed at examining fiscal policy changes on green innovation and spillovers generated through trade, we found a void in literature concerning green innovative activities, but literature is a bit more abundant concerning innovation as a whole both in micro and macro levels. Examples of some micro empirical works regarding this field are Irwin and Klenow (1996), Foreman-Peck (2013), Einiö (2014). In case of macro empirical works, Guellec and Van Pottelsberghe De La Potterie (2003) uses a dynamic panel of 17 OECD countries to investigate the direct tax subsidies and tax incentives to productivity linked through business R&D. Jaumotte and Pain (2005) investigates effects of public financial support to business R&D for 20 OECD countries for the time period of 1982-2001 and concludes with positive results, Westmore and OECD (2013) also pursues similar work by updating the dataset and concludes with similar results. A very good review of literature about macroeconomic effects of changes in R&D subsidies can be found in Minford (2015).

2.3 The Green Knowledge Production Function and Fiscal shocks

Starting from (Schumpeter, 1939, p 100) an enormous amount of literature in growth theory has pointed the role of innovation, modern growth theorists like (Romer, 1986, Rebelo, 1991, Grossman and Krueger, 1991, Aghion and Howitt, 1992) all have recognized the importance of innovation and capital (physical and human) in long-run economic growth. The important factor of innovation is that it helps in converting knowledge both assets and processes into suitable economic payoffs (McCann and Ortega-Argiles, 2013). Though knowledge creation and diffusion are distinctive phenomenons (Schumpeter, 1942) and can help in tracing the difference in between knowledge spillover and externality created by knowledge (Dominicis, Florax, and Groot, 2013). These spillovers are very much intertwined with human capital (Romer, 1986, Lucas, 1988, Dakhli and De Clercq, 2004, Aghion et al., 1998). So in short it can be easily commented that human capital and innovation are very much interactive of nature. An overwhelming amount of studies focus on the interaction in between human capital and innovation with various types of human capital (Dakhli and De Clercq, 2004, Chellaraj, Maskus, and Mattoo, 2008, Bottazzi and Peri, 2007, Ang, 2011, Ali and Alpaslan, 2017) or at different geographic levels (Griliches, 1979, Coe, 2005, Mairesse and Mohnen, 2010, Charlot, Crescenzi, and Musolesi, 2015).

However, little research has been done on the connectivity of human capital and innovation which can be used to counter global climate change (though there exists various debate on terminology of such innovative activities, for simplicity in this paper and beyond we define this type of innovative activities as **green innovation**).

The main focus of this paper is to deal with the complexity of green innovation and human capital .

We start with a variant version of Cobb-Douglas production function like Griliches (1979),

$$Y = f(L, K, R) \tag{2.1}$$

where, Y is a value-added output, inputs are labor represented by L, tangible capital represented by K and knowledge capital represented by R and f(.) is assumed to be Cobb-Douglas, Griliches (1979) assumes knowledge capital R as a complement to standard inputs. Griliches (1979) also defines knowledge capital as a function of present and past research and development expenditure,

$$R = G[W(B)RD] \tag{2.2}$$

where W(B) is the lag polynomial and B is the lag operator (refer to Crepon, Duguet, and Mairessec, 1998, and Eberhardt, Helmers, and Strauss, 2013, for more details). Griliches (1979) then re-writes (2.1) as

$$Y = AL^{\alpha}K^{\beta}R^{\gamma}exp^{\lambda t+e} \tag{2.3}$$

where A being a constant, t being the time index which captures a common linear trend λ, e is the stochastic error term and α, β, γ and λ are to estimated. Hall and Mairesse (1995) uses (2.3) to obtain output using current and past R&D levels. It is always preferred to use R&D stock instead of lagged values to take into account previous years impact. (2.3) can be re-written as in logarithmic terms (where lower-case variables denotes logarithmic counterpart of variables in (2.3)) following, (Hall and Mairesse, 1995, Hall, Mairesse, and Mohnen, 2010, Eberhardt, Helmers, and Strauss, 2013)

$$y_{it} = \alpha l_{it} + \beta k_{it} + \gamma r_{it} + \lambda_y + \psi_i + e_{it} \tag{2.4}$$

One of the main drawbacks of Griliches (1979) knowledge production function, were assumption of perfectly competitive factor markets, full capacity utilization, cross-sectional independence of the error term and absence of spillover effects. Eberhardt, Helmers, and Strauss (2013) tries to update Griliches (1979) knowledge production function by adopting newer econometric technique to deal with this shortcomings. In this regard it is interesting to mention theory of *non-excludability* *and non-rivalry* of knowledge as mentioned by Arrow (1962) and the implications of such knowledge transfer in a macroeconomic framework.

A. Green Knowledge and measuring R&D and Human capital spillovers

The economic intuition behind knowledge spillovers (both green and non-green, we only consider green case) of R&D at any level (micro, mezo or macro, we only consider macro case) is that benefits from knowledge created can be appropriated irrespective of boundary. This knowledge absorption can take many forms, like educated personnels' (like scientists, engineers) might meet and exchange ideas, or move around units (firms, universities, industries); researchers might read publications or patents of other scholars or through the novel process of reverse engineering. These flows are not very easy to be taken into account especially in numeric terms so that it can be beneficiary for econometricians. In order to estimate and measure R&D spillovers across countries or within countries, traditional research can be categorized into two ways, firstly by estimating a knowledge production function within each country which considers R&D activity and knowledge spillover and then estimate the effect of that knowledge or real outcomes. So, following (2.1), (2.2), (2.3) we use a reduced form equation to quantify our relationship

$$G_{n,t} = f(RD_{n,t}, HC_{n,t}, U_{n,t}) \tag{2.5}$$

where G can be expressed in terms of Green patents count, f is real function (which can be assumed to be a Cobb-Douglas production function for generality), t = 1,....,T represents time, n = 1,....,N represents cross-sectional units (in our case OECD countries), RD represents Research and Development spending both at Business level and Gross country levels. HC stands for Human Capital levels. In this regard it is convenient to comment that HC plays an important role because green innovative activities requires specific skills to support and enhance innovation, which also plays an important role in documenting absorptive capacity of knowledge. Unobservable characteristics as represented by $U_{n,t}$ is an important aspect in this regard. Some characteristics might affect both knowledge and primary innovation inputs, for example, highly skilled workers might non-randomly choose regions or countries for better opportunities by some prior knowledge which are cannot be captured by econometric techniques. Although green innovation is very much dependent on R&D investments and Human Capital, but since we are dealing our focus on a macro level, we also have to consider fiscal and trade related shocks which are very common in OECD countries because technological innovation never happens in isolation (David, 1990, Rosenberg, 1982)

B. Fiscal Spillover Shock and Green Innovation

Fiscal policies plays an important role in innovation promotion especially at country levels, in traditional innovation literature fiscal policies are contemplated to encourage innovation through R&D, entrepreneurship development and technology transfers. After the global financial crisis of 2008-09 the importance of innovation has been more emphasized to overcome slow growth in total factor productivity. In the green innovation scenario several distortions exists which needs to be corrected by policy intervention and the most important being undercharging for environmental costs, as of 2015 $ 5.3 trillion is used for energy subsidy purposes which accounts for 6.5 percent of the World GDP (Coady, International Monetary Fund, and Fiscal Affairs Department, 2015), the estimates are large and pervasive (about 13%-18% of GDP) in emerging and developing countries in Asia, Middle East, North Africa, and the Commonwealth of Independent states. So adjusting energy prices should provide much more welfare than subsidizing green technologies (Parry, Pizer, and Fischer, 2003). Davis (2017) estimates the global external costs of global fuel subsidies at 44 billion USD in 2014, including 8 billion USD from carbon dioxide emissions, 7 billion USD from local pollutants, 12 billion USD from congestion related to traffic and 17 billion USD from accident. If deadweight loss is taken into account, total economic cost increases substantially and the majority of these global costs are found to be from oil-producing countries. In the recent economic scenario, in which most of the western countries are in high public debt, there is an increasing pressure to understand the ramifications of climate policies specifically transition policies directed towards climate change on the fiscal side. Many countries are reluctant to consider adaptation policies due to various political agenda. This is also very much evident by reduction in public expenses to reduce governmental debt and prioritizing outcomes which are quickly achievable rather than involving in climate change activities Delpiazzo, Parrado, and Bosello (2015). A considerable amount of literature also exists dealing debt-to-gdp ratio in macroeconomic stimulus literature (Perotti, 1999, Alesina, Favero, and Giavazzi (2015)), to understand the complexity of such in green innovation we also include influence of debt in green innovative activities.

The role of any government other than being a watchdog of market activities is to generate revenue and effectively spend such revenue for the greater good. In current economic scenario, the pressure on government is much more to find an effective way to implement a proper fiscal spending. Due to rising debt and tight fiscal budgets in many developed and developing economies, governments are focusing on measures to cut down spending without hampering growth. For example after the European debt crisis, a policy treaty was adopted namely European Stability and Growth Pact (ESGP) which had two basic underlying agendas at its core, that is to maintain balanced budgets without hampering economic growth and employment levels. Krugman (2013) along with others have suggested such measures have resulted in undesirable consequences. Veugelers (2014) details the consequences of such fiscal tightening and concludes with the facts that fiscally weak countries inside the European union have taken measures to bring down R & D expenditure along with other public expenditure, harming future innovation. The phenomenon is also common across the Atlantic, especially in the USA where the consequence of reaching the debt ceiling in 2013 resulted in economic policy uncertainty and market volatility Donadelli and Grüning (2017). The world can also be said to be composed of multiple-sectors inter-connected by knowledge and trade, changes in one can affect another at ease (Hausmann, Hwang, and Rodrik, 2007, Hidalgo et al., 2007). So economic shocks generating from abroad might have important effects on innovative activities through inter-linkages mainly trade and knowledge. Though this sources of shocks might be of any kind but one particular common linkage might be fiscal policy (Auerbach and Gorodnichenko, 2012). So we introduce such fiscal shocks on green innovation literature via-trade linkages. We use Auerbach and Gorodnichenko (2011) to define a government spillover shock **GShock** originating from other countries affecting green innovative activities through trade.

2.4 Model and Methodology

Spillovers which can also be considered as a sub-class of externality is a common phenomenon especially in network economics, and addressing the issue related have always intrigued policymakers and economists. Manski (1993) defines spillover broadly into two categories: *endogenous*, in which outcomes of interest are simultaneous of nature and *contextual* the ones whose interaction takes place through covariate of others. Spillover studies are relevant nowadays in every economic studies like education, crime, consumption, technologyy adoption and productivity (De Giorgi and Pellizzari, 2014, Liu et al., 2012, De Giorgi, Frederiksen, and Pistaferri, 2016, Conley and Udry, 2010; Griliches, 1998). Most of these studies assume some pre-defined notion through which interaction among units takes place, Manresa (2016a) defines such notion as 'structure of interaction' and also comments that it is somehow misleading to use such pre-defined structures and proposes a new

Pooled-Lasso technique in which she treats such structure of interaction to be unobserved and using a sparse interaction structure. This is very much consistent with latent variable framework.

A. Latent Variables, Measurement errors and Unobservables

A very popular econometric methodology commonly used by applied economists is General Linear Model (GLM), but GLMs' have some shortcomings when there is a presence of unmodelled dependence among units, like temporal, spatial or network. Econometricians try to consider these dependence in the category of unobserved heterogeneity and have been trying long enough to deal with such (Stewart, 2014). In the literature of panel data latent factors or variables play an important role to provide consistent estimators form of time variant cross-sectional data (Bai, 2009, Pesaran, Shin, and Smith, 1999, Pesaran, 2006, Moon and Weidner, 2015).

The term "latent variables" is not new in economic/econometric literature, Koopmans (1949) used the term as distinct from "observed variables" in reference to stochastic disturbances in a standard simultaneous model of supply and demand. Kmenta (1991) solidified the definition of latent variables and defines latent variables as unobserved variables except stochastic disturbances, and classifies them under following categories:

- Variables for which exact measurements are unavailable and are represented by error contaminated substitutes. Example- National Income.
- Unobservables which can be represented only through closely related substitutes termed as "proxies". Example: Capital stock in Production function.
- Variables that are intrinsically not measurable. Example: Intelligence.

Over the years the use of latent variables in almost all three categories as mentioned above has been utilized in various economic scenarios (Griliches, 1974, Aigner and Goldberger, 1977, Doran and Kmenta, 1986, Kmenta, 1997, Greene, 1990). Innovation of any kind (Green or Non-green) is a difficult measure since it is unobservable of nature, so economists quantify innovation through Research and Development statistics, number of scientific personnel and also via patent counts, but this brings the question of measurement error in innovation studies (the existing literature lacks to deal with such). For example, R&D be it gross, government or business contains presence of measurement error since this statistics is based on finite samples and imperfect sources. This is also true for measuring human capital, since human capital is itself not measurable but taken into consideration through measures by years of schooling or level of educational attainment, one can easily comment the problems with such measures and presence of error in these measures. Where as patents which are mostly considered as an outcome of an innovative activity are an imperfect measure (Johnstone, Haščič, and Popp, 2010 page 138). So, given the fact our decided variables theoretically has presence of measurement error, we choose our model carefully to deal with such, in fact in this subsection we illustrate how to deal with them.

Tibshirani (1996) proposed a l^1 penalization term for least-square regression,

$$y_i = \sum_{j=1}^{J} \beta_j x_{i,j} + \epsilon_i$$

where the lasso estimate can be defined as:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} \left(y_i - \sum_{j=1}^{J} \beta_j x_{ij} \right)^2 + \lambda_N \sum_{j=1}^{J} |\beta_j|$$

where $\lambda_N \geq 0$ is a penalty parameter, and $\beta = (\beta_1, ..., , \beta_J)$. Because of the features of efficiency, convexity and sparsity, the Lasso technique have gained a huge amount of popularity. One must mention, the condition of sparsity is important since fact the values of many elements of $\hat{\beta}_j$ can be exactly zero (Society et al., 2010- Chapter 9). The Lasso technique is also useful in reducing measurement error for a variable selection process both in parametric and non-parametric terms (Stefanski, Wu, and White, 2014, Society et al., 2010- Chapter 8). Lasso technique has is also very much efficient in spillover studies and growth studies, because of its variable selection efficiency, (Society et al., 2010- Chapter 7, Manresa, 2016a). The lasso estimator and its various forms also posses the oracle property, i.e., it performs well enough even if its true underlying model was defined beforehand (Zou, 2006).

B. Model

Consider a following simple fixed-effects model:

$$y_{it} = \alpha_i + \beta_i x_{it} + \sum_{j \neq i} \gamma_{ij} x_{jt} + w'_{it}\theta + e_{it} \tag{2.6}$$

assuming the outcomes of i =1,....,N, y_{it} is only affected by its own x_{it} and also is influenced by other x's like $x_{1t}, ..., x_{Nt}$. Furthermore, α_i is the intercept used to capture unobserved individual-specific heterogeneity, β_i's are the slope capturing the effect of own heterogenity. γ_{ij} are used to capture the pair-specific of individual j on individual i. We assume, spillover exists, i.e., $\gamma_{ij} \neq 0$ interaction between i & j exists. w_{it} is introduced to capture all aggregate level variables to measure correlated shocks through θ, but w_{it} do not measure any kind of spillover effect and e_{it} captures the idiosynctratic shocks. This model can be used to measure various types of spillovers both overlapping and non-overlapping groups using a linear mean model, (Ballester, Calvó-Armengol, and Zenou, 2006). The linear models has a shortcoming since, it assumes homogeneity and symmetricity of spillover withing groups.

To overcome this problem, following Manresa (2016a) assumes sparsity, which can deal with heterogeneity, so that the curse of dimensionality can be dealt with easily. Another way of dealing with such heterogeneity is by heterogeneous group structures which may be called a mid-way in between heterogeneity and sparsity (Hahn and Moon, 2010, Bonhomme and Manresa, 2015, Bonhomme, Jochmans, and Robin, 2016, Su, Shi, and Phillips, 2016). We choose the later one, in group heterogeneity theory the assumption is links within each group are far more predominant than across groups. That is spillover within groups are homogenous of nature whereas across groups are heterogeneous.

i. Group Heterogeneity

Under a group heterogeneity pattern spillover effects are not pair-individual specific, but rather group specific, we explain the partitioning of the group using an Information criterion in a separate section later. Assuming K_{MAX} is the maximum number of groups attainable, N being the total number of individuals irrespective of partitioning and N_{gK} being the maximum number of individuals in each group, where g and K are not fixed, let Υ:1,....,N$\longrightarrow$1,....,N_{gK} be the mapping for individuals i and the group which to it belongs, Υ(i) = K_{MAX}. So for and i,j,

$$\gamma_{ij} = \gamma_{\Upsilon(i)\Upsilon(j)} \tag{2.7}$$

Also, for each g, being the number of groups 1,....,K_{MAX}

$$\sum_{g'=1}^{K_{MAX}} \mathbb{S}\{\gamma_{g'_g} \neq 0\} = s_g << T \tag{2.8}$$

(2.8) is derived from the sparsity condition, as in Manresa (2016a) Eq (2) and Eq (S3) of Manresa (2016b), assuming spillover exists i.e, the sum of spillover effect s_i is positive, (> 0), so now s_i becomes relatively smaller than the time-series dimension.

Intuitively, the identities of each individual collapses and remains confined within a group, and spillover within group is assumed to be similar of magnitude. If chosen K_{MAX} becomes N, or the number of individuals becomes one group each, the heterogenity can be explained by (2.6). So, choosing the number of groups is quiet important to understand the spillover effects especially dealing with heterogeneity and not-so large time dimension.

The group structure methodology also has an attractive feature to deal with omitted variable bias, due to the fact it deals with the problem of sampling. Since, spillover effects are being grouped the representative group elements have enough consistency.

ii. Green Knowledge Spillover

Now, let us bring in the concept of green knowledge in in analysis, which is somehow similar to knowledge as conceptually. Knowledge is a non-rival good and is a process which is assumed to generate externalities. Using the same concept from (2.1) and (2.2) we try to structure unobservable spillover effects in a green macro-economic sense, via a Cobb-Douglas production function.

$$OUTPUT_{it} = \alpha_i + \beta RD_{i,t-1} + \sum_{j \neq i} \gamma_{ij} RD_{j,t-1} + \theta controls_{i,t} + e_{i,t} \tag{2.9}$$

since, we are also dealing with human capital and assuming free movement of skilled labour, (2.9) can be re-written as

$$OUTPUT_{it} = \alpha_i + \beta_1 RD_{i,t-1} + \sum_{j \neq i} \gamma_{ij} RD_{j,t-1} + \beta_2 HC_{i,t} + e_{i,t} \tag{2.10}$$

introducing the concept of R&D stock instead of flow and introducing logged values, (2.10) can be re-written as

$$output_{it} = \alpha_i + \beta_1 rd_{i,t} + \sum_{j \neq i} \gamma_{ij} rd_{j,t} + \beta_2 hc_{i,t} + e_{i,t} \tag{2.11}$$

but we also use a debt indicator and a fiscal-shock which are not idiosyncratic of nature in (2.11) as explained in later sections. The spillover effects, γ_{ij} which can be simply written as

$$\gamma_{ij} = \gamma . w_{ij}$$

this can be implemented via a spatial proximity or a multi-factor error structure, we chose the later one since of its uniqueness to capture strong error-cross sectional dependence along with non-stationarity.

$$output_{it} = \beta_1 rd_{it} + \beta_2 hc_{it} + \lambda_i' f_t + u_{it} \tag{2.12}$$

iii. Green Knowledge Spillover with Fiscal shocks

We introduce the concept of fiscal spillover shock or **GShock** in green innovation literature. Time and again in core-macroeconomic literature it has been shown that adopting expansionary fiscal policies in times of recession not only stimulates output but also reduce government debt both external and internal (Auerbach and Gorodnichenko, 2012, Auerbach and Gorodnichenko, 2017) on the other hand though during uncertain periods especially in recessionary times employment drops but firms tend to invest more in research and development for innovation purposes (Bloom, 2014). Since our focus of countries is a sample of OECD countries, it is easy to assume that fiscal policy shocks of one country might be of correlated across countries. Following, Manski (1993) which states correlated shocks threaten identification of spillover effect, we use GShock from, Auerbach and Gorodnichenko (2012) but after construction we use only annual values,

$$GShock_{i,t} = \frac{\sum_{q \neq i} (M_{iq,B}/G_{q,B}) \times [e_{q,t} \times G_{q,t-1} \times E_{q,B}]}{E_{i,B}} \tag{2.13}$$

Lagged data of output, government spending, exchange rate, inflation, investment and exports were collected from OECD “Outlook and Projections Database" and then regressed upon government spending using real-time one-period-ahead percent forecast errors of each country and also for a set of countries and period fixed effects. The importance in this measure is it captures innovation in government spending which is aligned to professional forecasts and lags of macroeconomic variables. The residuals can be considered to measure the unanticipated government spending shocks, and is represented by e_{qt} in (2.13) for country q at time period t and then is aggregated using bilateral trade to understand inter-country linkages. $M_{iq,t}$ denotes country q's import from country i at time t. $E_{j,t}$ is country j's US dollar exchange rate at time t and B is the base year. So, the dollar value of country q's fiscal shock can be written as $[e_{q,t} \times G_{q,t-1} \times E_{q,B}]$ via a base-year exchange rate. By introducing $M_{iq,B}/G_{q,B}$ Auerbach and Gorodnichenko (2012) corrects the heterogeneity among countries via trade linkages between country q and recipient country i and also in the size of the government in the source country q, this term scales shock ratio of imports from country i to government purchases and then by division by base-year dollar exchange rate of country i converts the shock into units of the recipient country's currency. There are three assumptions behind this shock

1. Spillover shock occurs through imports.
2. Government purchases directly or indirectly converts to imports from other countries which sparks demand.
3. Dollar increase in government spending in country q is always less than $M_{iq,B}/G_{q,B}$ dollars of imports from country i.

A very good example of such spending shock supporting the health of an economy is the 2008-09 US fiscal stimulus.

So, we compute five **GShock** from the literature

- Baseline G shock: gs
- Baseline G shock with all fixed weights over time: gfs
- Baseline G shock with exposure weight fixed (i.e., M/G fixed) over time: ggs
- Baseline G shock with price level and exposure rate fixed over time: ges
- Baseline G shock with exposure weights fixed over time: gps

C. Methodology

One of the easiest ways to deal with unit-specific heterogeneity is time-invariant fixed-effects, but the basic assumption behind fixed-effects is that the unobserved heterogeneity is constant over time, which is strict assumption in regard to spillover studies. Presence of unobserved heterogeneity and cross-sectional dependence can cause inferential problems in nonstationary panels. We borrow from a novel estimation technique as proposed by HPS (2018) to deal with unobserved parameter heterogeneity together with cross-sectional dependence in a nonstationary panel.

The two central goals in statistical based economic modelling are ensuring high prediction accuracy and detecting relevant predictors. Moreover variable selection gains importance if the true underlying model is sparse. Identifying relevant predictors increases the prediction performance of the fitted model. Ordinary Least Square (OLS) gives nonzero estimates to all coefficients, traditional subset selection is based upon manual selection to select significant variables, but this selection procedure bears two limitations. Firstly, if the number of predictors are large, computationally it is improbable to perform subset selection and secondly subset selection bears deep-rooted distinctiveness (Breiman, 1995, Fan and Li, 2001). Subset selection also becomes difficult in presence of stochastic errors or presence of uncertainty in the variable (Fan and Li, 2001, Shen and Ye, 2002, Zou, 2006).

The Lasso model proposed by Tibshirani (1996) [as briefly explained in section 2.4 A] is a regularization technique for simultaneous estimation and variable selection. It can be defined in the following form. A l^1 penalization term for least-square regression, i.e., “absolute value of magnitude” of coefficient as penalty term to the loss function

$$y_i = \sum_{j=1}^{J} \beta_j x_{i,j} + \epsilon_i$$

where the lasso estimate can be defined as:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} \left(y_i - \sum_{j=1}^{J} \beta_j x_{ij} \right)^2 + \lambda_N \sum_{j=1}^{J} |\beta_j|$$

where $\lambda_N \geq 0$ is a penalty parameter, and $\beta = (\beta_1, ..., , \beta_J)$. If λ is zero then we will get back OLS, whereas very large value of λ will make coefficients zero hence it will under-fit. Another type of common penalization technique is l^2 norm, where “squared magnitude” of coefficient is added as penalty term to the loss function. This type of regression technique is called as Ridge Regression, which follows an euclidean norm penalization. Here, if λ is zero then one can imagine to get back OLS. However, if λ is very large then it will add too much weight and it will lead to under-fitting. So choosing λ is important . This technique works very well to avoid over-fitting issue. Lasso technique have gained a huge amount of popularity due to the features of efficiency, convexity and sparsity, sparsity is important since fact the values of many elements of $\hat{\beta}_j$ can be exactly zero (Society et al., 2010- Chapter 9). Lasso has been heavily used in various fields of applied statistics like signal processing, facial recognition, text mining, genetics, genomics, biomedical imaging, social media analysis and high-frequency finance. Recently it has gained usage in applied economics like Belloni, Chernozhukov, and Hansen (2011), Belloni, Chernozhukov, and Hansen (2013), Belloni, Chernozhukov, and Hansen (2014), and Chernozhukov, Hansen, and Spindler (2015). The Lasso is a regularization estimation procedure, in which a regression is estimated via an objective function whose purpose is to balance the in-sample goodness of fit using a penalty term, the value of the penalty term depends on the sum of the magnitude of the coefficients used in the regression (Athey, 2018). Due the penalty term, many covariates effectively becomes zero and hence gets dropped from the regression. The magnitude of this penalty term is selected by using cross-validation.

The l^1 is crucial for lasso and is used both in variable selection and regularization, the continuous shrinkage increases the predictability of Lasso as a technique due to bias-variance trade-off. The lasso technique with help of orthogonal predictors provides near-minimax optimality of soft-thresholding (Donoho et al., 1996). The lasso technique can also locate 'right' sparse representation of the model under some pre-defined conditions (Donoho and Elad, 2003), it is also consistent in variable selection provided the model satisfies some condition (Meinshausen and Bühlmann, 2006). So it is safe to assume the lasso technique satisfies oracle properties (*an oracle estimator must be consistent in parameter estimation and variable selection*).

i. Latent group structure with presence of nonstationarity and cross-sectional dependence

We adopt the estimation technique of HPS (2018) for our empirical purpose and a brief explanation of the technique is given below.

Let a dependent variable y_{it} is measured for individuals i = 1...N over time t = 1....T, and x_{it} is p× 1 vector of non-stationary regressors (irrespective of I(1) or I(0)) and e_{it} is the error term which might be composed of unobserved common factors ϵ_{it} with zero mean and finite variance. β_i's are homogenous within a group but heterogenous across groups represents long-run cointegrating relations, for p× 1 vectors of dependent variables are represented by β_i^0

$$\begin{cases} y_{it} = \beta^{0\prime}_{i} x_{it} + e_{it} \\ x_{it} = x_{it-1} + \epsilon_{it} \end{cases} \tag{2.14}$$

Now we assume, true values of β_i as β_i^0 which follows a latent group structure,

$$\beta_i^0 = \begin{cases} \alpha_1^0, \text{if } i \in G_1^0 \\ . \\ . \\ \alpha_K^0, \text{if } i \in G_K^0 \end{cases} \tag{2.15}$$

where, $\alpha_j^0 \neq \alpha_k^0$ for any j≠k, $\bigcup_{k=1}^{K} G_k^0 = 1, 2, ...N$ and $G_k^0 \bigcup G_j^0 = \emptyset$ for any j≠k, we assume the number of groups to be known and the members at this instance, and we calculate the number using an Information criterion as following HPS (2018).

To account for unobserved common patterns Bai and Ng(2004) proposes a multi-factor error structure on e_{it} which is assumed to be cross-sectionally dependent, so

$$e_{it} = \lambda^{0\prime}_{i} f_t^0 + u_{it} = \lambda^{0\prime}_{1i} f_{1t}^0 + \lambda^{0\prime}_{2i} f_{2t}^0 + u_{it} \tag{2.16}$$

where f_t^0 is a vector of r×1 of unobserved common factors, which can be broken down into f_{1t}^0 of non-stationary I(1) and f_{2t}^0 stationary I(0) processes, λ_i is a vector of factor loadings and u_{it} is the cross-sectionally independent idiosyncractic component with zero-mean and finite variance. The assumption in this regard is the cross-sectional dependence arises due to common factors.

So, (2.14) can be re-written as

$$y_{it} = \beta^{0\prime}_{i} x_{it} + \lambda^{0\prime}_{i} f_t^0 + u_{it} \tag{2.17}$$

A penalized principal component method is used to to estimate (2.17), so that the true values of α, β, Λ and f are represented by $\alpha^0, \beta^0, \Lambda^0$ and f^0 , where

$$\alpha \equiv (\alpha_1, ...\alpha_{K_0}),\ \beta \equiv (\beta_1, ...\beta_N),\ \Lambda \equiv (\Lambda_1, ...\Lambda_N)',\ and\ f \equiv (f_1, ...f_T)'$$

The main purpose is to obtain consistent estimators for group-specific long-run relations α_k and unobserved common factors f_t. For that $\alpha_k^0, \beta_i^0, \lambda_i^0$ and f_t^0 are denoted by $\alpha_k, \beta_i, \lambda_i$ and f_t

ii. Penalized Principal Component

(2.17) can be re-written as

$$y_{it} = x_{it}\beta_i^0 + f_t^0\lambda_i^0 + u_{it} = x_{it}\beta_i^0 + f_1^0{}_t\lambda_{1i}^0 + f_2^0{}_t\lambda_{2i}^0 + u_{it} \tag{2.18}$$

where $f^0 = (f_1^0, f_2^0)$, $\lambda_i^0 = (\lambda^{0\prime}{}_1, \lambda^{0\prime}{}_2)$, $y_i = (y_{i1}, ..., y_{iT})'$ the definitions of x_i, f_1^0, f_2^0 and u_{it} follows from before.

Following Bai (2009), the least square objective function is defined by

$$SSR(\beta_i, f_1, \Lambda_1) = \sum_{i=1}^{N}(y_i - x_i\beta_i - f_i\lambda_{1i})'(y_i - x_i\beta_i - f_i\lambda_{1i}) \tag{2.19}$$

the constraint of this equation follows, $\frac{f_1' f_1}{T^2} = I_{r_1}$ also $\Lambda_1'\Lambda_1$ is diagonal. The projection matrix can be defined as $Mf_1 = I_T - Pf_1 = I_T - \frac{f_1' f_1}{T^2}$.

So, now the least square estimates of β_i for each given f_i becomes

$$\hat{\beta}_i = (x_i' M_{f_1} x_i)^{-1} x_i' M_{f_1} y_i$$

Therefore, for given β_i, $e_i = y_i - x_i\beta_i = f\lambda_i + u_i$ tends to posses a pure factor structure. If we defines, $e = (e_1, e_2, ..., e_N)$ as T×N matrix and $\Lambda_1 = (\lambda_{11}, ..., \lambda_{1N})'$ a N × r_1 matrix, then f_1 can be obtained through least square using

$$tr[(e - f_1\Lambda_1')(e - f_1\Lambda_1')']$$

Using principal component analysis of pure factor models following Conor and Korajzcyk (1986) and Stock and Watson (2002), Bai (2009) and HPS (2018) defines Λ_1 can be concentrated out by its least square estimator $\Lambda_1 = e' f_1(f_1' f_1)^{-1} = e' f_1/T^2$, so now (10) can be re-written as

$$tr(e' M_{f_1} e) = tr(e'e) - tr(f_1' ee' f_1/T^2) \tag{2.20}$$

So given f we can estimate β and given β we can estimate f, the final least squares estimator $(\hat{\beta}, \hat{f}_1)$, which is the solution for a system of non-linear equations,

$$\hat{\beta}_i = \left(x_i' M_{\hat{f}_1} x_i\right)^{-1} (x_i' M_1 x_i) \tag{2.21}$$

$$\hat{f}_1 V_{1,NT} = \left[\frac{1}{NT^2}\sum_{i=1}^{N}(y_i - x_i\hat{\beta}_i)(y_i - x_i\hat{\beta}_i)'\right]\hat{f}_1 \tag{2.22}$$

where $V_{1,N\,T}$ is a diagonal matrix consisting of the r_1 largest eigen value of the matrix inside the brackets, arranges in a decreasing order and $M_{\hat{f}_1} = I_T - \frac{1}{T^2}\hat{f}_1\hat{f}_1{}'$, $\frac{1}{T^2}\hat{f}_1{}'\hat{f}_1 = I_{r_1}$.

(2.21) and (2.22) can be shown that $\hat{\Lambda}_1'\hat{\Lambda}_1$ is a diagonal matrix which becomes,

$$\frac{1}{N}\hat{\Lambda}_1'\hat{\Lambda}_1 = T^{-2}\hat{f}_1'\left(\frac{1}{NT^2}\sum_{i=1}^{N}(y_i - x_i\hat{\beta}_i)(y_i - x_i\hat{\beta}_i)'\hat{f}_1\right) = \left(\frac{1}{T^2}\hat{f}_1'\hat{f}_1\right)V_{1,N\,T} = V_{1,N\,T}$$

Since, β_i and f_1 can be estimated from (2.21) and (2.22), we follow a penalized principal component method to estimate $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}$, where $\boldsymbol{\beta}$ tends to exhibit latent group properties. So,

$$Q_{NT}^{\lambda,K}(\boldsymbol{\beta},\boldsymbol{\alpha},f_1) = Q_{NT}(\boldsymbol{\beta},f_1) + \frac{\lambda}{N}\sum_{i=1}^{N}\prod_{k=1}^{K}||\beta_i - \alpha_k|| \tag{2.23}$$

in this scenario, $Q_{NT}(\boldsymbol{\beta},f_1) = \frac{1}{NT^2}\sum_{i=1}^{N}(y_i - x_i\beta_i)'M_{f_1}(y_i - x_i\beta_i)$, $\lambda = \lambda(N,T)$ is the tuning parameter. Using PPC criterion to minimize (2.23) we get the Classifier-Lasso estimators of β_i and α_k

So now we update the estimates of non-stationary common factors by minimizing f_1 as in (2.24) and for stationary common factors by minimizing f_2 as in (2.25); for (2.24) the restriction for identification is $\frac{1}{T^2}\hat{f}_1'\hat{f}_1 = I_{r_1}$ and similarly from above $\hat{\Lambda}_1'\hat{\Lambda}_1$ is a diagonal matrix

$$\hat{f}_1V_{1,N\,T} = \left[\frac{1}{NT^2}\sum_{k=1}^{K}\sum_{i\in\hat{G}_k}(y_i - x_i\hat{\alpha}_k)(y_i - x_i\hat{\alpha}_k)'\right]\hat{f}_1 \tag{2.24}$$

and for (16) the identification restrictions are, $\frac{1}{T^2}\hat{f}_2'\hat{f}_2 = I_{r_2}$ and a diagonal matrix $V_{2,N\,T}$

$$\hat{f}_2V_{2,N\,T} = \left[\frac{1}{NT}\sum_{k=1}^{K}\sum_{i\in\hat{G}_k}(y_i - x_i\hat{\alpha}_k - \hat{f}_1\hat{\lambda}_{1i})(y_i - x_i\hat{\alpha}_k - \hat{f}_1\hat{\lambda}_{1i})'\right]\hat{f}_2 \tag{2.25}$$

So, now we apply bias-correction in post-lasso estimators of β and α. This tend to take into consideration of unobserved stationary common factors, endogeneity and serial correlation arising from weakly dependent error terms.

SSP (2016) and HPS (2018) have also established the oracle properties of the C-Lasso and its variant estimators, so that the sparsity of this type of estimators are well enough for applied purposes.

D. Estimating number of unobserved factors and groups

The theory is to assume the r_1^0 and r^0 as true values of generic number of nonstationary factors r_1 and r as the generic value of total number of nonstationary and stationary factors. This two values are estimated by an Information criterion

$$IC_1(r) = logV_1(r, \hat{G}^r) + rg_1(N,T) \tag{2.26}$$

and

$$IC_2(r) = logV_2(r_1, \hat{f}_1^{r_1}) + r_1 g_2(N,T) \tag{2.27}$$

where g_1(N,T) and g_2(N,T) are two penalty functions, and following Bai (2009), Bai and Ng (2002), HPS (2017) and SSP (2016) one can determine the values of g_1(N,T) and g_2(N,T) as $g_1(N,T) = (\frac{N+T}{(NT})log(min(N,T)$ and $g_2(N,T) = g_1(N,T) \times \frac{T}{4log(log(T)}$.

Whereas to determine the number of groups K a BIC type criterion is followed, it is assumed being the true number of groups K_0 is bounded by a finite-integer from above K_{MAX} , so for this a new Information criterion is proposed,

$$IC_3(K,\lambda) = logV_3(K) + pKg_3(N,T) \tag{2.28}$$

where g_3(N,T) is a penalty function. The minimizer IC_3 (K, λ) with respect to K is assumed to be K_0 for values of λ. HPS(2018) proves $\lambda = c_\lambda \times T^{-3/4}$.

2.5 Taking the model to the Data

A. Data

Dealing with the empiric of Green Knowledge spillover on a macro-level is of extreme challenge, due to problems of identification of measurement error in output, endogeneity among inputs and perplexity of spillover with fiscal shocks (being generated inside and outside countries, we do not take into account any monetary shock). We use green patent data of IPC-CPC (**Y02**) category (Development of environment-related technologies) in ratio terms with respect to total patents from OECD Patents in environment-related technologies database (OECD, 2018b). A simple time-series figure of patents counts for our sample of countries is depicted in Figure 2.1. (for better understanding please refer to section A in appendix at the end of the chapter). We also include Human capital from PWT 9.0 (Feenstra, Inklaar, and Timmer, 2016) (for better understanding please refer to section B in appendix at the end of the chapter). One can say this solves the biasness in measurement error of outputs, due to the fact we are specifying specific types of patents (Griliches (1998) page-319). Following Manresa (2016a) we proceed with given Knowledge i.e., past R&D investments, so it can be said to be uncorrelated from any type of future or ongoing shocks so the estimator is unbiassed. But we also deal with fiscal shocks to deal with other types of endogeneity and government spending shocks. R&D data is collected from OECD-stats database following the methodology proposed by (Coe, Helpman, and Hoffmaister, 2009) as explained in Section C of appendix. We compute both Business Enterprise Reseach and Development (BERD) and Gross domestic Expenditure on Research and Development (GERD). Human capital data is from Penn World Table and Debt to GDP ratio is fro IMF statistics.

We choose a sample of 25 OECD countries as mentioned below in the table (2.1) for a time-period of 1971-2014.

Table 2.1: Country sample- For equations- 2.29, 2.30, 2.31, 2.32

Australia	Finland	Ireland	Mexico	Spain
Austria	France	Israel	Netherlands	Sweden
Belgium	Germany	Italy	New Zealand	Switzerland
Canada	Greece	Japan	Norway	UK
Denmark	Iceland	Korea	Portugal	USA

Then we introduce the government spillover shock **GShock** following Auerbach and Gorodnichenko (2012) to our analysis (the construction of the variable is explained if the following section), but to make our data balanced we only consider a shorter sample of countries for the following years 1985- 2009, the sample of countries are mentioned in table (2.2)

Table 2.2: Country sample: for equations- 2.33, 2.34

Australia	Ireland	Norway
Austria	Italy	Portugal
Canada	Japan	Spain
Denmark	Korea	Sweden
Finland	Mexico	Switzerland
France	Netherlands	UK
Germany	New Zealand	USA

B. Estimation Strategy

We divide our estimation into three categories, first we check the heterogeneous effects of research and development (business enterprise research and development, BERD and gross expenditure on research and development, GERD) and human capital on green innovative activities, then we introduce a debt to gdp ratio alongside to understand the dynamics of fiscal deficit effect on green innovation at a macro-level. Finally we introduce a G-Shock in our data, and introduce five types of governmental shocks to check the heterogeneous effects of such on our sample.

So from (2.17) in short our analysis can be written as following:

$$gp_{it} = \beta_i^g gerd_{it} + \beta_i^h hc_{it} + \lambda_i' f_t + u_{it} \tag{2.29}$$

$$gp_{it} = \beta_i^b berd_{it} + \beta_i^h hc_{it} + \lambda_i' f_t + u_{it} \tag{2.30}$$

$$gp_{it} = \beta_i^g gerd_{it} + \beta_i^h hc_{it} + \beta_i^d dgdp_{it} + \lambda_i' f_t + u_{it} \tag{2.31}$$

$$gp_{it} = \beta_i^b berd_{it} + \beta_i^h hc_{it} + \beta_i^d dgdp_{it} + \lambda_i' f_t + u_{it} \tag{2.32}$$

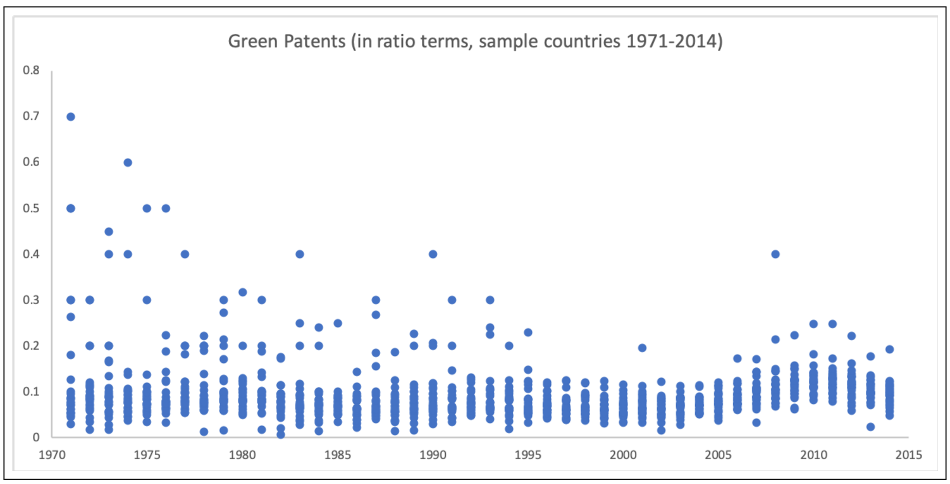
where, i is the country index, t is the time index, gp is the ratio of green patents to total patents, gerd and berd are reseach and development stock for gross and business enterprise respectively, hc represents human capital for innovation outside the R&D sector and other aspects of human capital not captured by formal R&D. dgdp represents debto-to-gdp ratio. In the following section we explain the construction of the variables. The fixed effects are captured by the factor structure and the unobserved common patterns are modelled by the multi-factor error structure

$\lambda_i' f_t + u_{it}$, assuming errors are cross-sectionally dependent with unobserved common patterns. We also consider $(\beta_i^g, \beta_i^b, \beta_i^h, \beta_i^d)$ as long-run cointegrating relations with latent group structures.

$$gp_{it} = \beta_i gerd_{it} + \beta_i hc_{it} + \beta_i gs_{it} + \beta_i gfs_{it} + \beta_i ggs_{it} + \beta_i ges_{it} + \beta_i gps_{it} + \lambda_i' f_t + u_{it} \tag{2.33}$$

$$gp_{it} = \beta_i berd_{it} + \beta_i hc_{it} + \beta_i gs_{it} + \beta_i gfs_{it} + \beta_i ggs_{it} + \beta_i ges_{it} + \beta_i gps_{it} + \lambda_i' f_t + u_{it} \tag{2.34}$$

Figure 2.1: Green Patents (in ratio terms, sample countries 1971-2014) [Source: OECD 2018]



We do this because of the unavailability of long-term data from all the fiscal forecast indicators for every country in our sample.

2.6 Results

A. Cross-sectional dependence test

We use Pesaran (2015a), Bailey, Kapetanios, and Pesaran (2016) and Ertur and Musolesi (2017) to calculate the degree of the Cross-sectional Dependence statistic along with estimated confidence bands of α, the exponent of cross-sectional dependence defined over the range [0,1] for our required variables as depicted in Table 2.3, the null of the CD test depending upon the increase of T and N. When T is fixed and N$\longrightarrow \infty$, the null for CD test is given by $0 \leqslant \alpha \leqslant 0.5$ and when T and N$\longrightarrow \infty$ at the same rate, the null for CD test is given by $0 \leqslant \alpha \leqslant 0.25$ (which is our case). So, the value of α in the range of [0.5,1] depicts different degree of strong cross-sectional dependence and in between [0, 0.5] depicts different degree of weak cross-sectional dependence.

Table 2.3: CD Results

Variables	CD statistic	$\widehat{\alpha}_{0.5}$	$\widehat{\alpha}$	$\widehat{\alpha}_{0.95}$
gp	34.42	0.8202	0.8917	0.9633
gerd	85.01	0.9229	0.9801	1.0373
hc	107.98	0.9507	1.0033	1.0559
berd	84.34	0.9201	0.9759	1.0318
dgdp	39.78	0.84846	0.9111	0.9736

In our case for all the variables, the CD statistic strongly rejects the null hypothesis suggesting the fact that the exponent of cross-sectional dependence lies in the range [0.25, 1]. To figure out the degree of cross-sectional dependence, one has to look at the bias-corrected estimates of α and the 90% confidence bands around it. In our case the exponent of cross-sectional dependence is estimated at approximately one for all variables at levels and more than 0.90 for all variables in first differences. In addition, the 90% confidence bands are highly above 0.5 and include unity. This confirms our preliminary finding and suggests presence of strong cross-sectional dependence in both dependent and explanatory variables for our analysis.

B. Second-generation panel unit root tests

The literature related to Panel Unit root tests have evolved over time, Quah (1994) and Breitung and Meyer (1994) introduced unit root testing in panel framework which was based on similar analysis from time-series literature. The so-called first generation of panel unit root tests do not consider correlation in between cross-sectional error components which were developed by Levin, Lin, and James Chu (2002)and Im, Pesaran, and Shin (2003). The second-generation panel unit-root tests do consider of errors being cross-sectionally correlated. Three main approaches in this regard are, Maddala and Wu (1999) and developed by various other authors thereafter, which applies bootstrapping to panel unit root test but this approach is mainly feasible for large T and relatively small N. Bai and Ng (2004), Bai and Ng (2010)proposed to decompose the observed series into two unobserved components, common factors and idiosyncratic errors and test for unit roots in both of these components, the test is also known as PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common Components) it provides indirect test for unit roots in observed series. The third approach was put forward by Pesaran, 2006, Pesaran

(2007) and extended by Pesaran, Vanessa Smith, and Yamagata (2013), in Pesaran, 2006, Pesaran (2007) a new test is proposed underlying the idea of cross-section average (CA) augmentation approach which augments individual Dickey-Fuller (DF) regressions with cross-section averages to take into account of error of cross-section dependence, then these cross-sectionally augmented DF regressions can be further augmented with lagged changes, to deal with possible serial correlation in the residuals. These doubly augmented DF regressions are referred to as CADF regressions. The panel unit root test statistic is then computed as the average of the CADF statistics. The average statistic is free of nuisance parameters but, due to non-zero cross correlation of the individual, CADF; statistics, the average statistic has a non-normal limit distribution as N and T tends towards infinity. Pesaran, Vanessa Smith, and Yamagata (2013) extends this approach to the case of multi-factor error structure using Sargan-Bhargava type statistics. But the problem with CA approach is it is complicated to implement, since this test is implemented when testing for unit roots in test statistics with nonstandard asymptotic distributions. Recently, Reese and Westerlund (2016) has put forward a new approach combining PANIC and CA, since PANIC approach uses Principal Component (PC) analysis, so it might present distorted results when N is small. PANICCA on the other hand leads to much improved small sample performance, when N is small or medium.

Weak cross-sectional dependence can be addressed with simple-correction of the tests but strong cross-sectional dependence causes the test statistic to be more divergent (Westerlund and Breitung, 2013). Pesaran, Vanessa Smith, and Yamagata (2013) states, that the effect of cross-sectional dependence can be reduced by demeaning the data in first-generation unit root tests if the pair-wise errors' covariances do not strongly digress across individuals.

Table 2.4 reports the outcomes of three first-generation unit root tests with cross-sectionally demeaned data Im, Pesaran, and Shin (2003)test and Choi (2001) the alternative P, Z, L* and Pm tests. The result shows the dependent variable gp is of stationary in nature and the independent variables gerd, berd, hc and dgdp are of non-stationary in nature i.e., being generated by unit root stochastic processes.

Due to the presence of strong cross-sectional dependence in our data we also employ second-generation unit root tests, these tests use multi-factor error structure using heterogeneous factor loadings to model various forms of cross-sectional dependence. We employ Pesaran (2007) (CADF, CIPS)[Table: 2.5]; Bai and Ng (2004) (PANIC) and Reese and Westerlund (2016)(PANICCA) [Table: 2.6] to investigate more in-

Table 2.4: First-generation unit root test**

Variables	IPS	P	Z	L*	P_M
gp	0.0000	0.0000	0.0000	0.0000	0.0000
gerd	0.0234	0.0007	0.0020	0.0010	0.0001
berd	0.0111	0.0002	0.0050	0.0008	0.0000
hc	0.9958	0.6462	0.9958	0.9954	0.6662
dgdp	0.4334	0.7327	0.9164	0.9070	0.7445

(**) p-values. Variables gp is in ratio terms and gerd and hc are in logarithmic terms

depth sources of unit roots among the variables. PANIC decomposes each variable into deterministic, common and idiosyncratic components, so that the origin of the cause of non-stationarity can be traced i.e., whether it arises from common component or the idiosyncratic component or both.

Table 2.5: Second-generation unit root test- CADF, CIPS**

Variables	$CADF^{+}$	$CIPS^{+}$
gp	-2.108	-2.819
gerd	-1.907	-1.799
berd	-1.700	-1.981
hc	-1.614	-2.419
dgdp	-1.985	-1.786

[(+: statistics). Variables gp, in ratio terms and gerd and hc are in logarithmic terms. Critical values, CADF: -2.080 (cv10), -2.160 (cv5) -2.300 (cv1) and CIPS: -2.04 (10%),-2.11(5%) -2.23 (1%)]

Bai and Ng (2004) requires the number of common factors needed to represent the cross-sectional dependence, we assume only one common factor following Westerlund and Urbain (2015) which indicates small number of unobserved common factors are sufficient enough to deal in macroeconomic examples. The test PANICCA is mix of both Bai and Ng (2004) and Pesaran (2007), in which they use Cross-sectional Averages instead of Principal component estimates as used by Bai and Ng (2004) to proxy for factors by pooling individual ADF t statistics on defactored residuals to test for nonstationarity of the idiosyncratic components

Table 2.6: Second-generation unit root test- PANIC, PANICCA**

Variables			PANIC**	
	ADF	P_a	P_b	PMSB
gp	0.0001	0.1214	0.1415	0.3799
gerd	0.0001	0.997	1	1
berd	1	0.9728	1	1
hc	0.0001	0	0	0.0207
dgdp	0.0001	0.4945	0.4943	0.6574
			PANICCA**	
	ADF	P_a	P_b	PMSB
gp	0.0849	0	0.003	0.517
gerd	1	0.1805	0.1747	0.5852
berd	0.001	0.8257	0.8844	0.9569
hc	0.001	0	0	0.0231
dgdp	0.001	0.2752	0.2828	0.4458

(**) p-values. Variables gp is in ratio terms and gerd and hc are in logarithmic terms

C. Estimation results

i. Information criteria

To estimate the number of unobserved factors we employ the BIC type penalty function following (Bai and Ng (2004) , SSP 2016, HPS 2018) and set $g_1(N,T) = (\frac{N+T}{(NT})log(min(N,T)$ to determine the total number of unobserved common factors and $g_2(N,T) = g_1(N,T) \times \frac{T}{4log(log(T)}$ to determine the number of unobserved non-stationary factors, where N = 25 and T = 44, we find the level and differenced indicates one unobserved common factor, which also verifies Westerlund and Urbain (2015) which indicates small number of unobserved common factors are sufficient enough to deal in macroeconomic example.

ii. Determining the number of groups

Group selection is one of the most important criteria in this kind of estimation technique, we select the number of groups following previous literature, SSP 2016, HPS 2018. The exact number of groups are typically unknown but a finite integer K_{max} is assumed which is considered to be an upper bound to the true number of groups K_0. The tuning parameter is chosen as $\lambda = c\lambda \times T^{-3/4}$ where c takes five candidates 0.01, 0.02, 0.05, 0.10 and 0.20. We fix K_{max} arbitrarily at 6. For each combination of the number of groups and the tuning parameter c, we compute the information criterion value accordingly. The results are reported in table 2.7, 2.8, 2.9, 2.10.

Table 2.7: Information Criterion values: eq 2.29

	0.01	0.02	0.05	0.1	0.2
1	-5.9114	-5.9114	-5.9114	-5.8571	-5.9114
2	-5.9638	-5.9638	-5.8314	-5.7426	-5.7421
3	-5.8153	**-5.9981**	-5.6651	-5.5738	-5.5774
4	-5.7004	-5.6902	-5.5016	-5.4107	-5.4033
5	-5.5287	-5.5185	-5.4092	-5.2746	-5.2571
6	-5.3559	-5.3468	-5.2789	-5.1771	-5.1315

We choose 3 groups and set $c_\lambda = 0.02$, and apply it to C-Lasso technique for equation 2.29, since of the minimum value of I.C., **-5.9981** being accredited.

Table 2.8: Information Criterion values: eq 2.30

	0.01	0.02	0.05	0.1	0.2
1	-5.9725	-5.9726	-5.9726	-5.9726	-5.9726
2	-5.9572	-5.9748	-5.9745	-5.8346	-5.8147
3	-5.7877	**-5.9819**	-5.8055	-5.716	-5.7989
4	-5.6672	-5.6307	-5.5376	-5.6302	-5.626
5	-5.4709	-5.5265	-5.3779	-5.4815	-5.5305
6	-5.2175	-5.3425	-5.2062	-5.2822	-5.3926

We choose 3 groups and set $c_\lambda = 0.02$, and apply it to C-Lasso technique for equation 2.30, since of the minimum value of I.C., **-5.9819** being accredited. We choose 3 groups and set $c_\lambda = 0.05$, and apply it to C-Lasso technique for equation 2.31, since of the minimum value of I.C., **-5.6936**.

Table 2.9: Information Criterion values eq 2.31

	0.01	0.02	0.05	0.1	0.2
1	-5.4423	-5.4424	-5.4425	-5.4424	-5.4425
2	-5.6402	-5.6068	-5.5869	-5.5935	-5.5833
3	-5.6926	-5.6711	**-5.6936**	-5.4433	-5.3511
4	-5.1703	-5.1817	-5.1449	-5.1809	-5.2907
5	-4.9359	-5.1438	-5.1441	-4.8042	-4.9629
6	-4.6977	-4.7995	-4.8464	-4.5467	-4.6406

We choose 3 groups and set $c_\lambda = 0.05$, and apply it to C-Lasso technique for equation 2.32, since of the minimum value of I.C., **-5.8818**.

Table 2.10: Information Criterion values eq 2.32

	0.01	0.02	0.05	0.1	0.2
1	-5.8007	-5.8007	-5.8008	-5.8008	-5.8005
2	-5.7747	-5.7749	-5.7778	-5.7218	-5.8466
3	-5.7405	-5.7335	**-5.8818**	-5.5135	-5.62
4	-5.1636	-5.1512	-5.2083	-5.3021	-5.325
5	-4.9347	-4.9935	-4.9531	-5.0539	-5.1125
6	-4.6685	-4.7024	-4.7174	-4.8427	-4.8334

iii. Post Classifier Lasso results

Table 2.11, 2.13, 2.15, 2.17 report the Cup-Lasso estimates with one unobserved non-stationary common factors for equations 2.29, 2.30, 2.31, 2.32, we also report the group classification for each of the equations in Table 2.12, 2.14, 2.16, 2.18. We will explain the results in a concise form in the next subsection.

Table 2.11: POST- Classifier-LASSO results : eq 2.29

	Group 1	Group 2	Group 3
gerd	0.005323312***	-0.041036067	-0.016168494
	(0.007874287)	(0.012613428)	(0.004013536)
hc	-0.345069953	-0.449300837	0.032991704***
	(0.057083789)	(0.105114664)	(0.034164233)

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

For equation 2.29, when we apply C-Lasso to understand the effect of human capital (hc) and gross- expenditure of r&d (gerd) on green innovation measure through green patents, we find gerd significant for Group 1 with 10% level and positive value and hc being significant for Group 3 with 10% level and positive value, for other two groups in their category results are not significant with negative sign.

As mentioned earlier we found three groups with membership in each group being 12, 10 and 3 respectively. The members countries are given in table 2.12.

For equation 2.30, when we apply C-Lasso to understand the effect of human capital (hc) and business- expenditure of r&d (berd) on green innovation measure through green patents, we find berd significant for Group 1 with 10% level and positive value

Table 2.12: GROUP MEMBERSHIP : eq 2.29

Group 1 membership = **12**	Australia, Austria, Denmark, Germany, Ireland, Israel, Korea, Mexico, Norway, Portugal, Switzerland, United States
Group 2 membership = **10**	Belgium, Canada, Finland, France, Italy, Japan, Netherlands, Spain, Sweden, United Kingdom,
Group 3 membership = **3**	Greece, Iceland, New Zealand

Table 2.13: POST- Classifier-LASSO results : eq 2.30

	Group 1	Group 2	Group 3
berd	0.146690311*** (0.006696195)	-0.004902611 (0.004394472)	-0.003437177 (0.007063436)
hc	-3.724429116 (0.136115107)	0.052223711*** (0.037190415)	-0.296077921 (0.059088037)

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

and hc being significant for Group 2 with 10% level and positive value, for other two groups in their category results are not significant with negative sign.

Table 2.14: GROUP MEMBERSHIP : eq 2.30

Group 1 membership = **1**	Iceland
Group 2 membership = **17**	Australia, Austria, Belgium, Canada Denmark, Finland, France, Germany Italy, Japan, Netherlands, Norway Spain, Sweden, Switzerland United Kingdom, United States
Group 3 membership = **7**	Greece, Ireland, Israel Korea, Mexico New Zealand, Portugal

As mentioned earlier we found three groups with membership in each group being 1, 17 and 7 respectively. The members countries are given in table 2.14.

For equation 2.31, when we apply C-Lasso to understand the effect of human capital (hc) and gross- expenditure of r&d (gerd) and debt-gdp ratio (dgdp) on green innovation measure through green patents, we find gerd significant for Group 2 with

Table 2.15: POST- CUP-LASSO results : eq 2.31

	Group 1	Group 2	Group 3
gerd	-0.018574315 (0.026929496)	0.007917289*** (0.008299823)	-0.01114053 (0.003216006)
hc	-0.438794061 (0.252089748)	-0.254873843 (-0.254873843)	-0.012894626 (-0.012894626)
dgdp	0.017674734*** (0.012685904)	-0.003638012 (0.011581591)	0.009035279*** (0.003569003)

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

10% level and positive value and dgdp being significant for Group 1 and Group 3 with 10% level and positive value, for other groups in their category results are not significant with negative sign. For hc, in all three groups the coefficients are negative without any level of significance.

Table 2.16: GROUP MEMBERSHIP : eq 2.31

Group 1 membership = **10**	Austria, Denmark, Finland, Germany Greece, Iceland, Ireland Korea, New Zealand, Portugal
Group 2 membership = **10**	Australia, Belgium, Canada, Italy Japan, Netherlands, Norway Spain, United Kingdom, United States
Group 3 membership = **5**	France, Israel Mexico, Sweden, Switzerland

We found three groups with membership in each group being 10, 10 and 5 respectively. The members countries are given in table 2.16.

For equation 2.32, when we apply C-Lasso to understand the effect of human capital (hc) and business- expenditure of r&d (berd) and debt-gdp ratio (dgdp) on green innovation measure through green patents, we find berd significant for Group 1 and Group 2 with 10% level and positive values and dgdp being significant for Group 1 and Group 2 with 10% level and positive value, hc has positive coefficient with 10% level significance for Group 2 and Group 3. For other groups in their category results are not significant with negative signed coefficients.

Table 2.17: POST- CUP-LASSO results : eq 2.32

	Group 1	Group 2	Group 3
berd	0.003003989*** (0.009507318)	0.001030705*** (0.004433412)	-0.027267814 (0.014607955)
hc	-0.186506212 (0.112361387)	0.01748895*** (0.0409458)	0.412704465*** (0.150333382)
dgdp	0.035235995*** (0.015161108)	0.005649531*** (0.004917282)	-0.064634375 (0.028137968)

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

Table 2.18: GROUP MEMBERSHIP : eq 31

Group 1 membership = **14**	Belgium, Canada, Denmark, Finland Greece, Ireland, Israel, Italy Japan, Netherlands, Norway Portugal, Sweden, Switzerland
Group 2 membership = **6**	Austria, Germany, Korea Mexico, United Kingdom United States
Group 3 membership = **5**	Australia, France Iceland, New Zealand, Spain

We found three groups with membership in each group being 14, 6 and 5 respectively. The members countries are given in table 2.18.

iv. Classification Results

Considering the fact **BERD** (Business Expenditure on Research and Development) is the biggest share on **GERD** (Gross Expenditure on Research and Development) OECD (2015), results in Table 2.11 and 2.13 and their respective Group classifications in Table 2.10 and 2.12 are similar. When using the PPC based estimation methods, we find similar heterogeneous behaviour for model (2.29) and (2.30). Considering Iceland becomes the sole member of Group 1 in table 14 with significant berd is not surprising to the fact, due to the of its economic composition which is more based on private research and development. Infact, Iceland is one of the few countries which meets EU Barcelona target of 3% and the private sector accounts for more than 40% of R&D expenditure. In other cases in Table 2.12 and 2.14, results are nearly correlatable. In Table 2.12 and 2.14 Group 3 consists of countries which accounts for less than 1% of global R&D stock, but for Group 2 in Table 2.14 and Group 1 and 2 in Table 2.12, the membership is mostly of countries which are leaders in Innovation both Green and Non-green and also account for more than 60% of global R&D stock. When we introduce debt-gdp ratio in our analysis, the group membership does not vary a lot according to results in Table 2.15 and 2.17 and their respective Group classifications in Table 2.16 and 2.18 are similar. In this regard, it is very necessary to mention a strange clustering can be found in G7 countries in most of the cases, which is very accordance to Keller (2004) which states major technical change leading to productivity growth in OECD countries are mostly originating from from abroad through channel of international technology diffusion.

In summary, while we treat green innovation without any fiscal spillover using PPC- base method with one unobserved global non-stationary factor, we find heterogeneous behaviour in green technologies using a Cup-Lasso estimate. Human capital and expenditure in Research and Development plays an important part in our findings.

v. Green Innovation with fiscal shocks results using CCEMG, AMG type estimators

Since G-Shocks are not always positive it is not possible to adopt Convex optimization techniques (also for the same reason of negative values we did not use logarthim for shock responces), so we focus only on Pesaran (2006) CCEMG type techniques. Results for three of these type of techniques, MG (mean group), CCEMG (Common Correlated Effects Mean Group) and AMG (Augmented Mean Group) are reported in table 2.19 and 2.20.

When checking with gross expenditure (gerd), human capital (hc) and different fiscal shocks response on green innovation we find varying shock responses on green innovation, we find only, Baseline G shock with exposure weights fixed over time (gps) being significant for MG and AMG type estimators with very minute negative coefficient value, other shocks were not significant and were mostly minute in coefficient values. For indicators only hc was significant with positive coefficient. The RMSE for all the three strategies we less being around 0.01 in value. CD and CIPS tests p-values small so the null hypothesis were rejected.

For business expenditure (berd), human capital (hc) and different fiscal shocks re-

Table 2.19: Static Heterogeneous Estimation Results for equation 2.33

gp			
	MG	**CCEMG**	**AMG**
gerd	-0.003 (-0.16)	-0.014 (-0.84)	-0.018 (-1.7)
hc	0.207 (1.6)	0.202 (0.36)	0.263***(2.91)
gs	0.00 (1.57)	0.00 (1.57)	-0.00 (-0.28)
gfs	0.00 (0.70)	0.00 (0.88)	-0.00 (-0.26)
ggs	0.00 (1.6)	-0.00 (-1.12)	0.000 (0.52)
ges	-0.000 (-0.85)	-0.000 (-1.53)	0.000 (0.10)
gps	-0.000**(-2.50)	-0.000 (-1.08)	-0.00** (-2.15)
constant	-0.041 (-0.34)	-0.205 (-0.64)	-0.022 (-0.28)
RMSE	0.0178	0.0102	0.0137
CD test	0.000	0.000	0.000
CIPS test	0.000	0.000	0.000
Observations	525	525	525

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.CD is the cross-section dependence, CIPS is the non-stationarity test. RMSE stands for Root Mean Squared Error.]

sponse on green innovation we found similar results like for gerd, only in this case berd was significant for AMG type estimator with negative coefficients, hc was significant for MG and AMG type estimators with positive coefficients. For the shocks, all of them had minute coefficients but some were significant this time. Baseline G shock (gs) was significant with 10% level for MG type estimator with positive minute coefficient. Baseline G shock with exposure weight fixed (i.e., M/G fixed) over time (ggs) was significant at 5% level for MG type estimator with positive minute coefficient. Baseline G shock with price level and exposure rate fixed over time (ges) was also significant at 5% level for MG type estimator with positive minute coefficient. Baseline G shock with exposure weights fixed over time (gps) was significant with 10% level for both MG and AMG type estimators but with negative minute coefficients. The RMSE for all the three strategies we less being around 0.01 in value. CD and CIPS tests p-values small so the null hypothesis were rejected.

2.7 Conclusion

The main contribution of this paper was to quantify the concept of Green Knowledge Production function for selected OECD countries, we also used some fiscal shock

Table 2.20: Static Heterogeneous Estimation Results for equation 2.34

gp			
	MG	**CCEMG**	**AMG**
berd	-0.006 (-0.43)	-0.002 (0.23)	-0.022*** (-3.27)
hc	0.253*** (2.66)	0.525 (0.94)	0.218***(2.97)
gs	0.000*** (2.14)	0.00 (1.00)	-0.00 (-0.99)
gfs	0.00 (0.68)	0.00 (1.16)	-0.00 (-0.28)
ggs	0.000** (1.98)	-0.00 (-0.16)	0.000 (0.51)
ges	-0.000** (-2.12)	-0.000 (-0.44)	0.000 (0.30)
gps	-0.000**(-2.55)	-0.000 (-0.22)	-0.000** (-2.14)
constant	-0.062 (-0.66)	-0.142 (-0.84)	-0.020 (-0.27)
RMSE	0.0179	0.0091	0.0142
CD test	0.000	0.000	0.000
CIPS test	0.001	0.000	0.000
Observations	525	525	525

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.CD is the cross-section dependence, CIPS is the non-stationarity test. RMSE stands for Root Mean Squared Error.]

indicators to understand the role of fiscal policies on green innovation and knowledge production. We assumed that cross-section dependence is generated by unobserved common factors which are both stationary and nonstationary in nature. Using a C-Lasso estimator as proposed by SSP (2016) and HPS (2018), we find distinctive groups with their coefficient being responsive and also non-responsive to green innovation. Moreover we also used five type of G-Shocks in our sample from macro-economic shock literature, to understand how countries are inter-connected through fiscal shocks via-trade linkages and we find some significant shocks though these shocks have very little magnitude of coefficients.

2.8 Section in Appendix

A. We use OECD (OECD, 2018b), we only use Development of environment-related technologies (**Y02** IPC-CPC class) as a ratio to All technologies. Which can be describes as to inventions or more jurisdictions (with family size 1 or greater) or in two or more jurisdictions (family size 2 or greater). The data is collected based on the definition of Paris Convention applicable to as the set of all patent applications protecting the same 'priority'.

B. We use Penn World Table version 9.0 (Feenstra, Inklaar, and Timmer, 2016 to consider Human Capital data in our analysis, in short the data can be defined as educational attainment data across countries. For a better understanding refer to Feenstra, Inklaar, and Timmer (2016)

C. The BERD and GERD data were collected from the OECD-STAT database, which is based on the OECD (2015), we tried to extend Coe and Helpman (1995) and Coe, Helpman, and Hoffmaister (2009). The time-series for the countries were from 1970-2015 in terms of National Currency, some countries had some missing values. The missing time series values for each country are given below in Table 2.21.

   In the sample of countries, Canada, France, Italy, Japan, Netherlands and USA had no missing observations, Germany and Spain had one missing observations in both BERD and GERD those were linearly interpolated. For other countries we followed the methodology from Coe, Helpman, and Hoffmaister (2009).

   OECD also supplies BERD data under ANBERD (Analytical Business Enterprise Research and Development) database which is under the STAN family database. The ANBERD data is of three versions ISIC Rev. 4 (1987 onwards), ISIC Rev.3 (1987-2010/11) and ISIC Rev. 2 (1973-1997/98) with the country-list expanding over time. For fifteen countries the business research development data is more than the BERD data. For these countries the correlation between ANBERD and BERD lies between 0.99 and 1. We interpolated the missing values of BERD with those available from ANBERD. This reduced the missing values for these countries indicated by the values inside the brackets in Table A.1. For Austria, the GERD data is more than

Table 2.21: GERD and BERD: 1970-2014

Country	BERD	corr. BERD and ANBERD	GERD
Australia	12	0.99 (3)	24
Austria	24	1 (20) [8]	9
Belgium	6	0.99 (6)	9
Canada	0	-	0
Denmark	4	0.99 (4)	4
Finland	7	1(2)	7
France	0	-	0
Germany	1	-	1
Greece	20	1 (16)	22
Iceland	13	0.99 (10)	12
Ireland	6	0.99 (2)	6
Israel	21	1 (21)	21
Italy	0	-	0
Japan	0	-	0
Korea	25	1 (25)	21
Mexico	20	1 (20)	23
Netherlands	0	-	0
New Zealand	22	1 (13)	22
Norway	11	0.99 (2)	11
Portugal	7	1 (7)	7
Spain	1	-	1
Sweden	17	0.99 (8)	17
Switzerland	25	0.99 (11)	25
UK	10	0.99 (2)	10
USA	0	-	0

BERD data, and after the substitution from ANBERD for some of the BERD, the ratio of BERD/GERD was seem to be constant at 0.55 from 1970-1993 and increased from 0.63 to 0.71 in between 1998-2015, by using the ratio we linearly interpolated the missing values for Austria and 12 more values of BERD were filled bring down the missing years to 8.

We then converted the BERD and GERD values from national currency using the following formula,

$$BERD_{cppp} = [(BERD_{nc})/GDPP]/PPP_{2010}$$

$$GERD_{cppp} = [(GERD_{nc})/GDPP]/PPP_{2010}$$

where (BERD_{cppp} and GERD_{cppp}) are data transformed to PPP exchange rates, PPP_{2010} is the purchasing power parity exchange rate in local currency per US dollar in 2010 and GDPP is the GDP price deflator, 2010=100.

Remaining missing observations were estimated using OLS prediction, of berd on gdpbv and ibv. Where berd is natural logarithm value of BERD_{cppp} and gdpbv is natural logarithm value of real value added in business sector, ibv is logarithm value of real non-residential private investment, these data of gdpbv and ibv were collected from World Bank data archive. The predicted values were collected from these regressions, which had R^2 were in between 0.95-0.99. This way the missing values of BERD_{cppp} were filled.

For GERD_{cppp}, we again used predicted values from OLS to fill up missing values, using gerd on rb, gdpv and itv. Where gerd is natural logarithm value of GERD_{cppp}, berd is natural logarithm value of BERD_{cppp}, gdpv is real value-added and itv is real private investment. The R^2 in these case were mostly above 0.98, and so the predicted values were used to fill missing GERD_{cppp}.

To calculate the stock of R&D for both GERD_{cppp} and BERD_{cppp} we used perpetual inventory rate as proposed by coe-1995 with a depriciation rate of δ to be 0.05 or 5% level.

Chapter 3

ENERGY INTENSITY AND GREEN ENERGY INNOVATION: CHECKING HETEROGENEOUS COUNTRY EFFECTS IN THE OECD

3.1 Introduction

The 2015 United Nations Climate Change Conference (COP-21) strengthened the need for clean and energy efficient technologies to tackle Climate change and Global Warming. As of 2016, 13.7% or 1,182 Mtoe (1,819 Mtoe in 2015) of global energy supply are of clean nature (IEA, 2018b) but evidently it is not enough to achieve the target of limiting global warming to 2°C. IEA (2011) report points out the shortcomings of adoption of future sustainable energy systems, declaring the path towards achieving sustainable energy as "too slow". The International Energy Agency (OECD and IEA, 2006) has classified renewable energy in three different generations: First generation are those which have already reached sophistication, like hydro-power, biomass combustion and geothermal energy. Second generation are those which are experiencing rapid development in technologies, like solar energy, wind power and some improved forms of bio energy. Third generation technologies are the ones which are still early in their stages of advancement, like concentrating solar power, ocean energy, integrated bio-systems and improved geothermal.

Solid bio-fuels accounts for 62.4% of the global renewable supply, whereas hydro power accounts for 18.6%, the rest is comprised of liquid bio-fuels, solar, tide, renewable municipal waste, geo-thermal and bio-gas (IEA, 2018b). Since 1990 the annual rate of average growth of renewable has recorded at 2% which is slightly higher than the growth rate of total primary energy supply, 1.7%. The share of renewable energies in total energy supply varies from region to region, Figure 3.1, depicts a detailed account. OECD countries accounted for only 9.9% of share of renewable energies in total energy supply for the year 2016. Consumption of renewable energies also varies across regions, while in OECD half of renewable primary energy supply is used to generate electricity and heat but in non-OECD countries renewable energy usage mostly occurs in residential, commercial and public services sector (IEA, 2018b). Renewable resources are the second biggest provider for global electricity production. In 2016 electricity produced from renewable resources accounted for 23.8% of total electricity produced in the world, the highest being coal (39.2%) third being gas (23.6%) followed by nuclear (10.6%) and oil (3.2%). Inside renewable energies, hydroelectric is the main contributing technology to produce electricity, it is responsible 16.3 % of total world electric production and 68.4% total renewable electricity. Also, 2016, electricity generated from Geo-thermal, solar, wind and tide energy technologies accounted for 5.5% of total world electricity supply and 23.2% of world renewable electricity. In comparison with 1990, there has been a surge in production of electricity through renewable energies, the growth rate recorded in this scenario was 3.7% per-annum, a slightly higher than 2.9 of% total electricity average growth rate. In 1990, electricity produced from renewable resources accounted for 19.4% of the total electricity produced, this share increased to 23.8% in 2016.

The varying penetration of renewable energy in different regions of the world is very much in accordance with Acemoglu et al. (2012) which properly points out the existence of a persistent lack of diffusion of green technology innovation. Very few studies have dealt with the effects of energy intensity on green innovation especially on the innovative technologies which brings forth new renewable ways to consume or supply energy. Recently Chen, Han, and Liu (2016), focus on energy intensity and green innovation within Chinese regions. Our focus is primarily on the heterogeneity among the OECD countries. Variations among OECD countries is an interesting phenomenon if one looks within a larger time-scale.

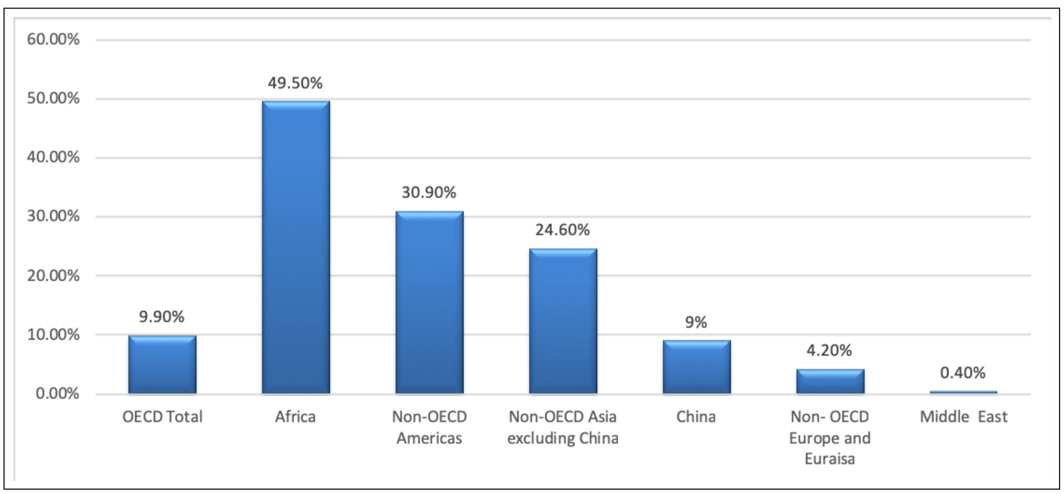


Figure 3.1: 2016 shares of renewables of regional TPES [Source: IEA,2018]

A note on renewable energy in the OECD

The OECD was build in as co-operative agency among wealthy nations to build a road-map for economic prosperity, it started its journey in 1961 with 20 nations and is now comprised of 35 nations. The OECD sets up standards and policies in all fields of economics including energy. The OECD countries together account for 10.2% of total renewable energy supply in 2017 (OECD, 2018a). For OECD Europe this share increased from 14.0% in 2016 to 14.3% in 2017, the change in OECD Americas was from 8.4% to 8.6% and for OECD Asia it was an increase from 4.9%

to 5.0% (IEA, 2018a). Figure 3.2 presents a detailed picture of renewable energy consumption in OECD countries from 1998-2017.

In the OECD area the increase of energy usage from renewable sources had an annual average growth rate of 2.6% over the time period 1990-2017, while the growth rate of non-renewable energies was 0.4% (non-renewable energies includes: oil, gas, coal & nuclear). During this time period the contribution of renewable energies to total primary energy supply grew from 6.0% to 10.2%. Inside renewable energies, supply from bio-fuels accounts for 53.5% while hydro-electric power accounts for 22.3% followed by 11.1% wind, 6.3% solar & tidal and 6.9% from geo-thermal sources in the OECD for the year 2017. In decadal comparison, average annual growth rate of renewable energies were higher in the period of 2000-2017, accounting to 3.1% compared to 1.7% in between 1990-2000. Above-average growths were recorded in solar PV (38.4%), solar thermal (22.5%), wind (20.7%), liquid bio-fuels (17.6%) and biogas (8.4%), while solid bio-fuels & charcoal (1.4%), geothermal (1.4%) and hydro (1.1%) grew at a lower rate than the average (IEA, 2018a). The sources of renewable energy like solar photo-voltaic, wind power, biogas, solar thermal and liquid bio-fuels recorded a two-digit growth during this period. On the other-hand, traditional renewable energy source like hydro-electricity grew at a much slower pace and the growth was also more in the developing world compared to the developed, the non-OECD countries grew at a rate of 4.0% and the OECD countries grew at a rate of 0.7% during 1990-2016.

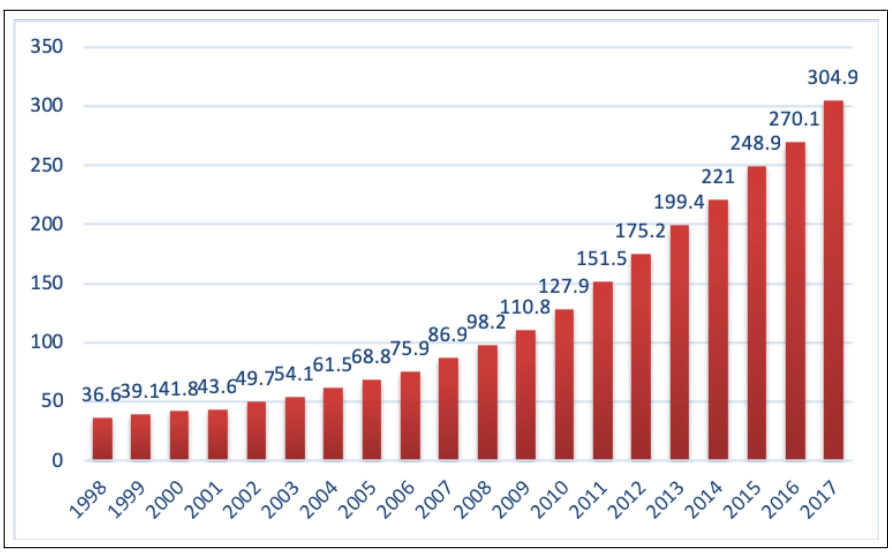


Figure 3.2: Consumption of renewable energy in OECD countries from 1998 to 2017 (in million metric tons of oil equivalent) [Source: IEA (2018a)]

Inside the OECD, OECD Europe accounts for 14.3% of renewable energy in its total primary energy supply, with an increase by 7.3% in the share since 2000. Renewable share in OECD Americas increased to 9.1% in 2017 from 6.3% in 2000 and for OECD Asia-Oceania the increase was to 5.2% in 2017 from 3.4% in 2000. The European Union which is a dominant policy making structure inside the OECD Europe, has implemented various policies to increase the share of renewable energy to 20% by 2020 and has also implemented various fixed feed-in tariff, time-dependent feed-in tariff, target price feed-in tariff and fixed feed-in premium (Kitzing, Mitchell, and Morthorst, 2012) with an aim to cut down emission from electricity generation since it is one of the main contributors to global GHGs. Electricity production, from renewable resources (excluding generation from pumped storage plants) increased by 5.1% during 2016 to 2017 in the OECD region (2731.8 TWh in 2017 & 2598.3 TWh in 2016) which also represents 24.9% of total electricity production.

Electricity produced from hydroelectric power accounts for 51.4 % of renewable electric sources as of 2017 but if one looks at the overall growth rate from 1990 it is 0.6% the lowest in the OECD region. Wind energy electricity accounts for 25.5% of renewable electricity production with an annual average growth rate of 21.2%. A more detailed growth rate of renewable electricity production average growth rate over the time period of 1990-2017 has been depicted in Figure 3.3.

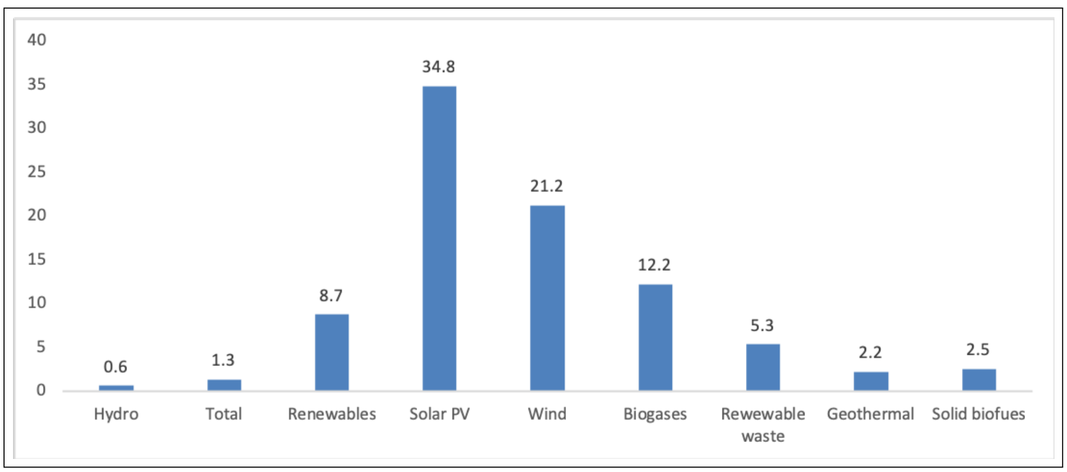


Figure 3.3: Annual growth rate of electricity production in OECD countries between 1990-2017 in % [Source: IEA (2018a)]

Inside the OECD area, OECD European countries recorded an increase of 3.6% average annual increase in renewable electricity production, OECD Americas recorded 2.1 % and OECD Asia- Oceania 2.2%. Disparity is also very prevalent among countries itself, in Table 3.1 we provide the decadal change of electricity produced from renewable sources from 1971-2015 for major OECD countries along with OECD and Non-OECD total (IEA, 2018a). One can easily observe the sharp differences among countries.

Table 3.1: Electricity Output (GWh) composition Renewable sources decadal change

Country	**1971-1980**	**1981-1990**	**1991-2000**	**2001-2010**	**2011-2015**
Austria	76.58	4.10	33.03	6.50	15.59
Belgium	331.34	-17.41	94.77	504.09	72.68
Canada	55.38	12.23	17.53	8.32	6.54
Denmark	70.83	1775	427.15	112.60	33.71
France	41.70	-23.53	16.24	0.58	38.75
Germany	35.12	-16.40	108.93	176.57	51.37
Ireland	79.82	-19.14	58.84	262.99	44.90
Italy	13.66	-24.94	11.72	41.61	31.27
Japan	5.92	10.97	-7.14	24.98	34.37
Netherlands	n/a	-25.71	217.86	239.09	11.14
New Zealand	42.10	22.99	9.18	30.66	4.65
Non-OECD	87.63	43.10	30.58	67.04	28.99
Norway	32.20	30.72	28.78	-2.29	15.32
OECD	25.25	16.62	14.52	35.71	20.45
Portugal	32.02	84.59	30.67	80.12	1.06
Spain	-6.13	16.39	24.03	98.32	10.92
Sweden	14.21	22.70	27.69	-1.46	21.86
Switzerland	22.70	-15.81	15.91	-11.22	20.85
UK	15.87	33.67	87.30	170.02	141.96
USA	7.66	36.90	-5.64	69.21	7.46

[Source: IEA (2018a)]

To push for a more sustainable future and to decrease the amount of non-renewable consumption, governments inside the OECD countries have introduced various policies at country level and also at local level. Table 3.2 lists a yearly count of these policies by country from 2005-2014. Renewable Energy Policy data which concerns about the renewable energy policy adopted, was constructed from the IEA-IRENA database IEA (2018a). This database lists renewable energy national policies adopted each year.

In this paper we attempt to determine the relationship between green energy innovation and energy intensity for major OECD countries for a time span of 1975-2014.

Table 3.2: Renewable Policy Counts 2005-2014

Country	05	06	07	08	09	10	11	12	13	14
Australia	2	4	4	9	9	6	5	6	2	2
Austria	1	0	3	1	2	4	1	2	2	0
Belgium	2	3	3	1	1	1	2	0	1	2
Canada	1	3	9	2	4	2	4	0	2	0
Denmark	1	0	1	1	3	1	1	2	0	0
Finland	2	0	2	2	0	2	0	0	0	0
France	1	3	4	3	4	2	2	0	1	0
Germany	3	2	1	1	4	3	4	2	0	1
Greece	1	1	0	0	1	4	0	0	0	0
Ireland	4	3	6	4	1	2	0	1	0	1
Italy	1	1	3	8	1	3	5	2	1	3
Japan	0	0	2	2	2	1	0	2	0	1
Netherlands	1	2	1	1	1	2	4	0	1	0
NewZealand	0	0	4	4	2	2	1	0	0	2
Norway	1	0	1	2	0	1	0	4	3	0
Portugal	2	1	1	1	3	4	1	0	1	2
Spain	1	0	4	4	3	4	7	5	8	5
Sweden	3	5	2	2	5	2	5	1	1	0
Switzerland	0	0	1	2	1	1	0	0	3	0
UK	2	4	2	4	3	3	2	0	2	1
USA	6	9	9	9	8	1	0	1	1	0

[Source: IEA-IRENA database, IEA (2018a)]

We apply various estimators to deal with issues present in our data, like error-cross-sectional dependence, non-stationarity and cointegration. Since the data is of long-time series, we checked for both short-run and long-run estimates using dynamic common correlated effects estimators (Chudik and Pesaran, 2015) along with CS-ARDL (Chudik and Pesaran, 2015). We also included results of static homogeneous and heterogeneous estimators. We find both long-term and short-term relationship in between energy intensity and green energy innovation in our sample, though the relation becomes insignificant over time, i.e. introduction of lags in the system of equations but we do not find any Granger causality in between energy intensity and green energy innovation, this might be very interesting of nature. The nexus of long-term relationship without any causality might be arising due to heterogeneous slopes or non-linearity, which needs to be investigated using specific estimators.

The rest of this paper is as follows: section 3.2 introduces related literature along with the research question, section 3.3 explains the econometric methodology adopted, section 3.4 explains the data. Section 3.5 analyses and discusses the empirical results. Section 3.6 concludes.

3.2 Overall issues regarding Energy intensity

There is a growing consensus that traditional economic models need to be updated to address climate change, biodiversity losses and check related resource depletion while addressing key social and economic challenges like development, poverty and inequality reduction. The global financial crisis of 2008-09 and the recession which followed thereafter has accentuated this debate. To overcome this the concept of "green economy" has been put forward (Barbier, 2010, United Nations Climate Change Secretariat, 2015). One of the key aspects in this policy scenario is to unlock the full potential of renewable energies so as to shift the economy towards a sustainable future and also adopt technologies which are more efficient than the previous ones, especially in energy sector (United Nations Climate Change Secretariat, 2015).

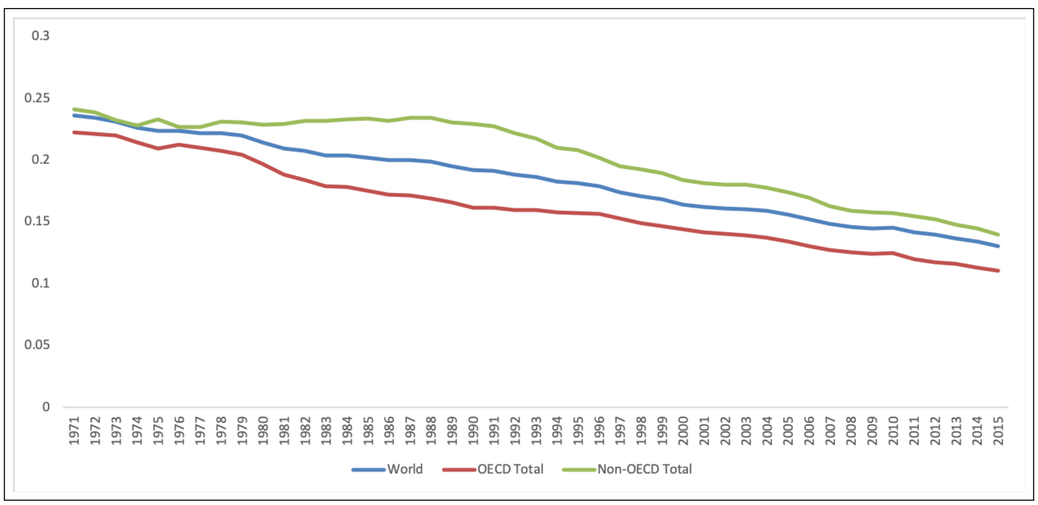


Figure 3.4: Energy Intensity in OECD, Non-OECD and World (1971-2015) [Source: IEA (2018a)]

Empirical research has verified the linkages in between environmental innovation with various environmental policies and energy prices. There exist two different branches in this regard, one of the branches has its core focus on Pollution Abatement Control Expenditure (PACE) which proxies for environment regulations most of the research in this regard have found positive relationship in between PACE and environmental innovation. Brunnermeier and Cohen (2003) for USA and Lanjouw and Mody (1996) for 17 different countries found positive correlation between PACE and environmental innovation. But these studies lack to take into account heterogeneity across the samples. Johnstone et al. (2012) used survey data on environmental policy stringency to overcome this heterogeneity but concluded with similar results. The other branch deals with energy prices as proxy for environmental innovation, Aghion et al. (2016), Aghion et al. (2012), Newell, Jaffe, and Stavins (1999) had their focus on a single industry to measure the effects of environmental innovation through energy prices. Popp, Hascic, and Medhi (2011) focused his research on 11 different technologies in USA and concluded the positive relationship in between energy prices and innovation. Recently Johnstone, Haščič, and Popp (2010), Verdolini and Galeotti (2011), Ley, Stucki, and Woerter (2016) have concentrated on multiple countries and multiple industries in the same time to assess the effect of environmental innovation due to energy prices and have found positive correlation in between them.

Climate policies are focused in addressing two issues simultaneously, adopting green innovation & diffusion to address climate change including energy crisis Acemoglu et al. (2012), and reducing energy intensity of production processes to drive down carbon emission. Energy intensity which can be defined as quantity of energy used over the value of production has declined over the period of time in the developed world. A considerable amount of literature exists to determine the roots and causes of this decline and its impact on the developed countries. Figure 3.4 depicts the decline of energy intensity in the countries of OECD, NON-OECD and World from 1971-2015. Mulder and Groot (2012) and Voigt et al. (2014) attribute the decline in the level of energy intensity to specific efficient energy usage within sectors rather than the economic shift to cleaner energy usage.

In this paper, we try to focus on the importance of innovation in renewable energy technologies for facilitating the transition of OECD economies into a more energy efficient one using patent statistics (especially the Green patent type). Of all the appropriate measures of Technology innovation, Research and Development investment and Patent statistics are most widely used. Patents are strongly correlated with R & D expenditure and are considered a good proxy for knowledge capital (Aghion et al., 2014). We also try to deal with the omitted variable bias problem in our study which is a common phenomenon in a cross-sectional energy intensity related study. Energy Intensity and Green Innovation techniques share a very complicated relation, green technological adoption itself increases efficiency. Ma and Stern (2008) uses the EKC (Environmental Kuznets Curve) to decompose the effects of economic activity into scale, composition and technique effects. We use industrial structure following Chen, Han, and Liu (2016) to capture the composition effect on this regard. Technique effect can be captured by introduction of new technology on energy usage. Studies on green technology and energy intensity in the OECD are very rare. Wurlod and Noailly (2018) uses manufacturing industrial sector data of 17 OECD countries to asses the impact of green innovation on energy intensity and found green innovative activities have really been responsible for the decline in the energy intensity. The study arrives at the result that an 1% increase in green patenting activities will lead to a decline of 0.03% of energy intensity in that sector, they also conclude the relationship is more sector-specific and magnitude of effect increases over time. But the question of heterogeneity remains, further our focus is more on specific class of green innovative patents which has more focus on energy efficiency and renewable energy.

In retrospect to reduce emission of greenhouse gasses (GHG) technological transfer plays an important role through diffusion and spillover. Verdolini and Galeotti (2011) uses a sample of 38 countries to understand green innovation flow movements across technologies and countries and concluded that spillover between countries has significantly positive impact on further innovation. Furthermore the nature of spillover can be both vertical and horizontal of nature, it will be interesting to take into account both observed and unobserved heterogeneity. Unobserved heterogeneity will be an important aspect to deal with since any global event (like political developments, oil price rise, war, financial crisis, new tariffs e.t.c) might trigger reactionary phenomenon in energy usage both of renewable energies and non-renewable energies which in-turn will hamper energy intensity and green innovation relation.

3.3 Model and methodology

Model

Using a panel data model, we try to examine the impact of energy intensity on green energy innovation on OECD countries. Energy intensity is an interesting research issue, since it is a very good measure of technological progress. Green technology is an important factor which leads to a considerable impact on energy intensity, since it accentuates emission-reduction techniques and also improves energy-saving within an economy. Following the EKC literature we can comment (as explained in the earlier section), Green technologies effect energy efficiency and to capture the effect of unobservables we use a variable Industrial structure, Energy Research & Development will also exert some effect on green energy innovation through technological progress.

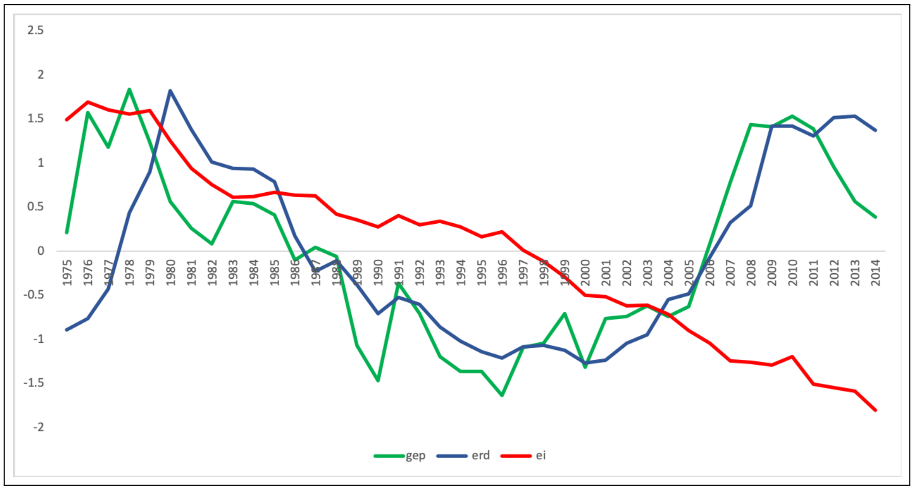


Figure 3.5: Comparison of ERDD, EI, GEP for sample countries, 1975-2014

With the availability of longer time-series data across countries the usage of panel data in macroeconomic studies has gained extreme popularity. Panel data techniques are very well adjusted to model various sources of heterogeneity. A standard feature of panel data is the usage of severe restrictions on the cross-sectional dependence across units, for fixed effects model it assumes the form of independence across units and the time-effects term critically restricts this nature in case for random effects model. Previous literature was mostly focused on interactive fixed effect structure, however this came with a cost from the fact of endogeneity between regressors and error terms.

Two main approaches were put forward to model estimation and inference in an unobservable multi-factor error setting. One of them uses principal component (PC) estimation to model the factor structure and estimates it along with the rest of the model this technique was put forward by Bai (2009)) and has been extended thereafter. The second approach which is referred as common correlated effects (CCE) estimation technique introduced by Pesaran (2006), treats factors as nuisance terms and is used for introducing a parsimonious means to model cross-sectional dependence. The aim is mainly to remove the effects of such nuisance terms by proxying them using their observable counterparts which is done by the form of cross-sectional averages and explanatory variables. The CCE appraoch has been also extended over time and it performs well-enough in a dynamic setting. Both the PC and CCE approach has been compared and a satisfactory summary can be found out in Westerlund and Urbain (2015), they comment that theoretically PC performs better than CCE if the panel regression coefficient of interest is equal to zero, in other cases CCE performs better.

Using long-term panel data, the model aims to examine the effect of energy intensity on green energy innovation related activities to provide additional insights regarding OECD countries energy transition towards sustainable future. We employ both dynamic panel (DCCE) and a ARDL type (CS-ARDL) to obtain short- and long-run coefficients on this regard[1].

Dynamic common correlated effects (DCCE)

The DCCE (Chudik and Pesaran, 2015) is a dynamic case developed upon common correlated effects (CCE) by Pesaran (2006) which accounts for cross-sectional dependence and heterogeneous slopes. The basic assumption of DCCE & CCE is that the coefficients are randomly distributed around a common mean

$$\beta_i = \beta + \nu_i, \nu_i \sim IID(0, \sigma_\nu)$$

The data generating process includes an unobserved common factor, f_t, along with a heterogeneous unit-specific factor loading component λ_i, let

$$y_{it} = \alpha_i + \lambda_i y_{it-1} + \beta_i x_{it} + u_{it} \tag{3.1}$$

$$u_{it} = \gamma_i^{'} f_t + e_{it}$$

the term $\gamma_i^{'} f_t$, represents for a presence of strong cross-sectional dependence. Pesaran (2006) adds cross-sectional averages of both dependent and independent variables to account for cross-sectional dependence (with $\gamma_i = 0$) consistency exits, $(N, T) \xrightarrow{j} \infty$

And stacking together the coefficients in a vector,

$$[\pi_i = (\alpha_i, \lambda_i, \beta_i)]$$

the mean group estimator can be defined as

$$\hat{\pi}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\pi}_i$$

Chudik and Pesaran (2015) extends the Pesaran (2006) to its dynamic form by adding ρ_T lags of the cross-sectional averages to account for strong cross-sectional dependence, the dynamic model is consistent if (N, T, ρ_T)$\xrightarrow{j}\infty$

$$\frac{(\rho_T^3)}{T} \longrightarrow \varrho_1, 0 < \varrho_1 < \infty$$

and

$$N/T \longrightarrow \varrho_2, \varrho_2 > 0$$

The required conditions are, the number of lags is restricted to allow for sufficiency in degrees of freedom, so $\sqrt[3]{T}$ lags are added, so $\rho_T = \sqrt[3]{T}$, also the number of cross-sectional units and time periods should grow at same rate.

$$y_{i,t} = \beta_{0,i} + \alpha_i y_{i,t-1} + \beta_i x_{i,t} + \sum_{l=0}^{\rho_T}(\vartheta_{i,l,y}\bar{y}_{i,t-l} + \vartheta_{i,l,x}\bar{x}_{i,t-l}) + \epsilon_{i,t} \tag{3.2}$$

where, bar denotes the cross-sectional averages and ρ_T denotes the number of lags. The strong unobserved cross-sectional dependence is approximated by averaging the cross-sectional units. Individual coefficients are estimated for each cross-sectional unit and then averaged to obtain the mean group estimator, while $\vartheta_{i,l,y}$ and $\vartheta_{i,l,x}$ are used as control variables.

One of the benefits of the method is that the model treats slope heterogeneity, cross-sectional dependence and variable non-stationarity within.

Cross-sectional Auto-Regressive Distributed Lag model (CSARDL)

An important econometric methodology to deal long-run relationship is Cointegration, which was proposed by Engle and Granger (1987). Pesaran and Smith (1995), extended the methodology for panel data naming it autoregressive distributed lag (ARDL) model. In panel data framework two extreme alternative approaches exist to deal with parameteric heterogeneity, one being mean group (MG) which estimates equations differently for each country and average of each coefficients are then examined. Pesaran and Smith (1995) points out the results of MG type estimators are consistent when the time-series dimension is of large enough. Fixed effects (FE), Random effects (RE) and generalized method of moments (GMM) type estimators which might be considered of being on the other extreme, simply pools the dynamic nature of the data and treat things homogeneously. In between these two extreme approaches lies pooled mean group (PMG) type estimator proposed by Pesaran, Shin, and Smith (1999), this approach involves aspects of both averaging and pooling of estimators, allowing for heterogeneity in intercepts, short-run coefficients and error variances but the long-run coefficients being homogeneous across cross-sectional units. The PMG estimator takes average of each cross-sectional units and generates consistent short-run estimates for these cross-sectional units.

Chudik and Pesaran (2015) and Chudik et al. (2016) introduced CS-ARDL a new ARDL type estimator to deal cross-sectional dependence, in presence of I(0) or I(1) order of integration irrespective of the order and report pooled long-run type estimates, the estimator also takes into account omitted variable bias. The only requirement in this type of estimator, apart from the existence of long-term relationship in between the concerned variables, is that the dynamic specification of the model; so that the weak exogeneity among the regressors comes into account and the residuals are not correlated anymore.

Let us discuss the CS-ARDL model in detail, but first let's start from a basic ARDL model of order 1 with a multifactor error structure:

$$y_{it} = c_{it} + \phi y_{it-1} + \beta'_{0i} x_{it} + \beta'_{1i} x_{it-1} + u_{it} \tag{3.3}$$

$$u_{it} = \gamma'_i f_t + \epsilon_{it} \tag{3.4}$$

$$\omega_{it} = \begin{pmatrix} x_{it} \\ g_{it} \end{pmatrix} = c_{\omega i} + \alpha_i y_{it-1} + \Gamma'_i f_t + v_{it} \tag{3.5}$$

where $i = 1, ...N; t = 1, ...T$, x_{it} is a $k_x \times 1$ vector of regressors of i cross-sectional units at time t, c_{yi} and $c_{\omega i}$, g_{it} is $k_g \times 1$ is a vector of covariates specific to ith cross-sectional unit, k$_g$ $\geq$ 0, $k_x + k_g = k$, ϵ_{it} represents the idiosyncratic errors, f$_t$ is a m×1 vector of unobserved common factors, it can be both stationary on nonstationary of nature. Γ_i is a m×k matrix for factor loadings (k≥m), α_i is a k×1 vectors of unknown coefficients and the assumption behind v $_{it}$ is that it follows a general linear covariance stationary process distributed independently of the idiosyncratic error terms, ϵ_{it}. , see (Kapetanios, Pesaran, and Yamagata, 2011). The main intrinsic feature of this technique is the unobserved common factors or heterogeneous time effects can be proxied by adding cross-sectional averages of the observables (See Pesaran, 2006 and Chudik and Pesaran, 2015). Chudik and Pesaran (2015) derive that the unobserved common factors f $_t$, can be proxied by de-trended common averages of z$_t$ = (y$_i t$, x'$_i t$, g'$_i t$)' and their respective lags, but the necessary condition being N is sufficiently large.

$$f_t = G(L)\tilde{z}_{wt} + O_P(N^{-1/2}) \tag{3.6}$$

where G(L) is a distributed lag function, $\tilde{z}_{wt} = \bar{z}_{wt} - \bar{c}_{zw}$ is a k+1 dimensional vector of detrended cross-sectional averages, $\bar{c}_{zw} = \Sigma_{i=1}^{N} w_i(I_{k+1} - A_i)^{-1}c_{zi}$ with $A_i = A_{0i}^{-1}A_{1i}$,

$$A_{0i} = \begin{bmatrix} 1 & -\beta'_{0i} & 0 \\ 0_{k_x\times 1} & I_{k_x} & 0_{k_x\times k_g} \\ 0_{k_g\times 1} & 0_{k_g\times k_x} & I_{k_g} \end{bmatrix}$$

and

$$A_{1i} = \begin{bmatrix} \phi_i & -\beta'_{1i} & 0_{1\times k_g} \\ \alpha_{x_i} & 0_{k_x\times k_x} & 0_{k_x\times k_g} \\ \alpha_{g_i} & 0_{k_g\times k_x} & 0_{k_g\times k_g} \end{bmatrix}$$

The weights are specified by the normalization condition: $\Sigma_{i=1}^{N} w_i = 1$, finally substituting (5) in (2), the final form can be written as

$$y_{it} = c^*_{yi} + \phi_i y_{it-1} + \beta'_{0it}x_{it} + \beta'_{1i}x_{it-1} + \delta'_i(L)\bar{z}_{wt} + O_P(N^{-1/2}) + \epsilon_{it} \tag{3.7}$$

$$\delta_i(L) = \sum_{l=0}^{\infty} \delta_{il}L^l = G'(L)\gamma_i \tag{3.8}$$

and

$$c^*_{yi} = c_{yi} - \delta'_i(1)\bar{c}_{zw}$$

To estimate (2) using MG and PMG estimators, some conditions needs to fulfilled.

- The number of cross-sectional averages must be at least as large as the number of unobserved common factors

- A sufficient number of lags of cross-sectional averages needs to be included in the individual equations of the panel.
- The model needs the time-series dimension to be large enough so that it can be estimated for each cross-sectional unit

For MG type estimator, θ can be written as $\theta = E(\theta_i)$, so the long run-coefficients are

$$\theta_i = \frac{\beta_{0i} + \beta_{1i}}{1 - \phi_i} \tag{3.9}$$

For the PMG type estimates, the individual long-run coefficients must be same across all cross-sectional units, and the PMG estimator uses a maximum likelihood approach to calculate estimates using a variant form of Newton- Raphson algorithm

$$\theta_i = \theta,\ i = 1, \ldots, N \tag{3.10}$$

3.4 Data and Measurement Issues

The main idea of this paper is to empirically test the heterogeneous interaction energy intensity on green energy innovation related activities inside the OECD countries. Our sample consists mostly of advanced industrialized countries *Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom* and *USA*. These countries have invested in Green Energy Research and Development activities over the years (from 1970's) and also have introduced various policies to foster investment in Green Energy related activities. The time period of our sample is from 1975 to 2014.

We set up the following regression equation:

$$gep_{it} = \alpha_{it} + \beta_{1,it} ei_{it} + \beta_{2,it} erd_{it} + \beta_{3,it} is_{it} + \epsilon_{it} \tag{3.11}$$

The set of variables used in our empirical analysis concerns a potentially many hosts of factors, including innovation measurement, environmental policy indicators and traditional macroeconomic characteristics.

Green energy innovation indicator (**gep**): Keeping up with the tradition, we use patent counts as a proxy for innovation performance, which is very much aligned to previous literature on Renewable Energy and related policies (Popp, Hascic, and Medhi, 2011 Johnstone, Haščič, and Popp, 2010, Nesta, Vona, and Nicolli, 2014, Fu et al., 2018). We use data from OECD (OECD 2018) for *Capture, storage, sequestration or disposal of greenhouse gases* (**Y02C**) and *Climate change mitigation technologies related to energy generation, transmission or distribution* (**Y02E**) category as expressed in ratio terms Environment-related technologies (**ENVTECH: Y02**) category OECD (2018b). Energy Intensity (**ei**) represents the energy usage per unit of GDP, data for energy intensity was collected from IEA IEA (2018b). Energy Research, Development and Demonstration (**erd**) flow data has been collected from IEA database, [for the years 1975-1984, France possess data for only Nuclear Energy in the ERD&D section IEA (2018b); a few missing data were linearly interpolated]. We calculate the ERD&D stock using perpetual inventory method as in Coe and Helpman (1995) and Coe, Helpman, and Hoffmaister (2009) assuming depreciation rate to be 0.05. For Industrial structure (**is**), we use services value added to GDP from World Bank database, since traditional literature suggests secondary industry has a larger influence on energy consumption, so improving services value added to GDP will take into account omitted variable bias to determine the nature of interaction between green energy innovation and energy intensity.

Variables gep, ei are in ratio terms and erd and is are in logarithmic terms. Since we are considering a dynamic case, (3.12) includes an extra term of lagged dependent variable and can be rewritten as

$$gep_{it} = \alpha_{it} + \beta_{0,it} gep_{it-1} + \beta_{1,it} ei_{it} + \beta_{2,it} erd_{it} + \beta_{3,it} is_{it} + \epsilon_{it} \tag{3.12}$$

For the CS-ARDL type, we do not take into account industrial structure, since the sole purpose of our empiric is to test the interaction of green energy innovation and energy intensity and we were using industrial structure to account for omitted variable bias. CS-ARDL type model takes into account omitted variable bias inside the framework so no extra variable is required to account for such (Chudik and Pesaran, 2015).

So, our new equation becomes,

$$y_{it} = c^*_{yi} + \sum_{l=1}^{p} \phi_{il} y_{i,t-l} + \sum_{l=0}^{p} \beta'_{il} x_{i,t-l} + \sum_{l=0}^{q} a_{il} \overline{y}_{t-l} + \sum_{l=0}^{q} b'_{il} \overline{x}_{t-l} + \epsilon_{it} \tag{3.13}$$

where y_{it} is the gep i at time t, x_{it} represents erd and ei for the same country i during that same time-period t.[2] $\overline{y}_t$ and $\overline{x}_t$ denotes the cross-sectional averages of y_{it} and

x_{it} at time period t. The important decision for ARDL models is to choose the lag length long enough to ensure the residuals become serially uncorrelated of the error-correction, but choosing too many lags imposes excessive parameter requirements on the data. We keep the lag length at 3, i.e., we set p$\leq$ 3, similar approaches have been employed by Chudik and Pesaran (2015), Chudik et al. (2016), Chudik et al. (2013), Mohaddes and Raissi (2017) following Pesaran (2007).

3.5 Empirical Results

Cross-sectional Dependence

Overlooking sample cross-sectional dependence might provide ambiguous inferences, Chudik and Pesaran (2015) defines the nature of cross-sectional dependence weak or strong depending upon the degree of it.

Using Pesaran (2004), Pesaran (2007), Pesaran (2015a), Bailey, Kapetanios, and Pesaran (2016) and Ertur and Musolesi (2017) we calculate the degree of the Cross-sectional Dependence statistic along with estimated confidence bands of α, the exponent of cross-sectional dependence defined over the range [0,1] for our required variables depicted in Table:3.3. Pesaran (2015b) defines the null of the CD test depending upon the increase of T and N. When T is fixed and N$\longrightarrow\infty$, the null for CD test is given by $0 \leqslant \alpha \leqslant 0.5$ and when T and N$\longrightarrow\infty$ at the same rate, the null for CD test is given by $0 \leqslant \alpha \leqslant 0.25$ (which is our case). So, the value of α in the range of [0.5,1] depicts different degree of strong cross-sectional dependence and in between [0, 0.5] depicts different degree of weak cross-sectional dependence.

Table 3.3: CD test and exponent of cross-sectional dependence of the variables

Variables	CD statistic	$\widehat{\alpha_{0.5}}$	$\widehat{\alpha}$	$\widehat{\alpha_{0.95}}$
gep	34.13	0.899	0.963	1.028
ei	49.49	0.92	1.0007	1.081
erdd	22.24	0.862	0.9199	0.977
is	74.16	0.927	0.984	1.041

In our case for all the variables, the CD statistic strongly rejects the null hypothesis suggesting the fact that the exponent of cross-sectional dependence lies in the range [0.25, 1]. To figure out the degree of cross-sectional dependence, one has to look at the bias-corrected estimates of α and the 90% confidence bands around it. In our case the exponent of cross-sectional dependence is estimated at approximately one for all variables at levels and close to 0.90 for all variables in first differences. In addition, the 90% confidence bands are highly above 0.5 and include unity. This confirms our preliminary finding and suggests presence of strong cross-sectional dependence in both dependent and explanatory variables for our analysis.

Second generation panel unit root tests

Empirical assessment in innovation, particularly green innovation studies, using panel data do not consider the fact of cross-sectional dependence in error terms. In that regard, we have to trace the evolution of literature concerning panel unit root tests. Over the years, the literature related to Panel Unit root tests have evolved, panel unit root literature was put forward by Quah (1994) and Breitung and Meyer (1994). The so-called first generation of panel unit root tests do not consider correlation in between cross-sectional error components which were developed by Levin, Lin, and James Chu (2002) and Im, Pesaran, and Shin (2003). The second-generation panel unit-root tests do consider of errors being cross-sectionally correlated. Three main approaches in this regard are, Maddala and Wu (1999) and was developed by various other authors thereafter, which applies bootstrapping to panel unit root test, but this approach is mainly feasible for large T and relatively small N. Bai and Ng (2004)and Bai and Ng (2010) proposed to decompose the observed series into two unobserved components, common factors and idiosyncratic errors and test for unit roots in both of these components, the test is also known as PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common Components) it provides indirect test for unit roots in observed series. The third approach was put forward by Pesaran (2006) and Pesaran (2007) and later extended by Pesaran, Vanessa Smith, and Yamagata (2013). In Pesaran (2006) and Pesaran (2007) a new test is proposed underlying the idea of cross-section average (CA) augmentation approach which augments individual Dickey-Fuller (DF) regressions with cross-section averages to take into account of error for cross-sectional dependence, then these cross-sectionally augmented DF regressions can be further augmented with lagged changes, to deal with possible serial correlation in the residuals. These doubly augmented DF regressions are referred to as CADF regressions. The panel unit root test statistic is then computed as the average of the CADF statistics. The average statistic is free of nuisance parameters but, due to non-zero cross correlation of the individual, CADF; statistics, the average statistic has a non-normal limit distribution as N and T tend towards infinity. Pesaran, Vanessa Smith, and Yamagata (2013) extends this approach to the case of multi-factor error structure using Sargan-Bhargava type statistics. The problem with CA approach is that it is complicated to implement, because it involves nonstandard asymptotic distributions. Recently, Reese and Westerlund (2016) has put forward a new approach combining PANIC and CA, since PANIC approach uses Principal Component (PC) analysis, so it might present distorted results when N is small. PANICCA on the other hand leads to much improved small sample performance, when N is small or medium.

Weak cross-sectional dependence can be addressed with simple-correction of the tests but strong cross-sectional dependence causes the test statistic to be more divergent (Westerlund and Breitung, 2013). Pesaran (2007) states, that the effect of cross-sectional dependence can be reduced by demeaning the data in first-generation unit root tests if the pair-wise errors' covariances do not strongly digress across individuals.

Table 3.4 reports the outcomes of three first-generation unit root tests with cross-sectionally demeaned data, Im, Pesaran, and Shin (2003) (IPS) test and Choi (2001) the alternative P, Z, L* and Pm tests. The result shows the dependent variable gep is of stationary in nature and one of the independent variables erdd is of stationary in nature the other independent variables are being generated by unit root stochastic processes.

Table 3.4: First-generation unit root test**

Variables	IPS	P	Z	L*	P_M
gep	0.000	0.000	0.000	0.000	0.000
ei	0.1399	0.173	0.192	0.2015	0.177
erd	0.0001	0.0001	0.0000	0.0000	0.0000
is	0.0981	0.1963	0.1522	0.1132	0.2037

(**) p-values. Variables gep, ei are in ratio terms and erd and is are in logarithmic terms

Due to the presence of strong cross-sectional dependence in our data we also employ second-generation unit root tests, these tests use multi-factor error structure using heterogeneous factor loadings to model various forms of cross-sectional dependence. We employ Pesaran (2007) (CADF, CIPS), Bai and Ng (2004) (PANIC) and Reese and Westerlund (2016) (PANICCA) to investigate more in-depth sources of unit roots among the variables. PANIC decomposes each variable into deterministic, common and idiosyncratic components, so that the origin of the cause of non-stationarity can be traced i.e., whether it arises from common component or the idiosyncratic component or both. Bai and Ng (2004) requires the number of common factors needed to represent the cross-sectional dependence, we assume only one common factor following Westerlund and Urbain (2015) which indicates small number of unobserved common factors are sufficient enough to deal in macroeconomic examples. The test PANICCA is a mix of both Bai and Ng (2004) and Pesaran (2007), in which they use Cross-sectional Averages instead of Principal component estimates, as used by Bai and Ng (2004) to proxy for factors by pooling individual ADF t statistics on defactored residuals to test for nonstationarity of the idiosyncratic components.

Table 3.5: Second-generation unit root test- CADF, CIPS**

Variables	CADF	CIPS
gep	-1.813	-3.043
ei	-1.744	-2.266
erd	-1.957	-2.589
is	-2.185	-2.233

(**) p-values. Variables gep, ei are in ratio terms and erd and is are in logarithmic terms

Table 3.6: Second-generation unit root test- PANIC, PANICCA**

PANIC**				
	ADF	P_a	P_b	PMSB
gep	0.0001	0.0000	0.0017	0.0628
ei	0.6253	0.9653	0.998	1
erd	0.0223	0.0206	0.0497	0.1427
is	0.1971	0.9889	1	1
PANICCA**				
	ADF	P_a	P_b	PMSB
gep	0.1082	0.000	0.0082	0.1058
ei	0.0001	0.9237	0.9799	0.9999
erd	0.8919	0.0121	0.0352	0.1489
is	0.001	0.9157	0.9861	1

(**) p-values. Variables gep, ei are in ratio terms and erd and is are in logarithmic terms

Testing for Cointegration

We only used second-generation cointegration tests which takes into consideration cross-sectional dependence as a feature of the test. Banerjee, Dolado, and Mestre

(1998) showed that residual based test (such as Pedroni, 2004 can lead to severe power loss, since it does not take into consideration cross-sectional dependence and structural breaks. For this reason, we use Westerlund (2007) error correction based panel cointegration test, this test was developed to calculate two group mean statistics and two panel statistics in order to test for null of no cointegration against two distinct alternatives. One of the alternatives is at least one cross-section is cointegrated to account for heterogeneity and the other alternative is the whole panel is cointegrated to assume homogeneous long-run relation among the cross-sections. A conditional error mean is considered for the purpose of construction of the test statistic (Persyn and Westerlund, 2008). This test can also be used in both the presence or absence of cross-sectional dependence. The results are reported in table 3.7 using 1000 bootstrap replications.

Table 3.7: Westerlund (2007) Cointegration test

Statistics	Value	Z-value	P-value	Robust P-value
G_t	-1.605	0.468	0.680	0.083
G_a	-1.531	4.607	1.000	0.719
P_t	-5.740	0.225	0.589	0.082
P_a	-1.882	1.733	0.958	0.183

(**) p-values. Variables gep, ei are in ratio terms and erd and is are in logarithmic terms

Banerjee and Silvestre (2017) which uses a standard CIPS panel on residuals stemming from Pesaran (2006) CCEP model estimation. The test also controls the dependence among the cross-sectional units that conform the panel using an unobserved common factor structure which is proxied by cross-sectional averages. This test (CADFCp) can also be interpreted as a complementary examination of scale effects of weak type. The results are displayed in table 3.8,

Engle and Granger (1987) residual-based cointegration test has been extended in the panel framework by Di Iorio and Fachin (2013)) using a bootstrap strategy, we use this test since it performs relatively well in small samples and is also a second-generation cointegrating test, i.e., it deals with cross-sectional dependence (we use 5000 replications). The performed results are given in Table 3.9

Table 3.8: Cointegration test based on Banerjee and Silvestre (2017)

Model 1: Constant (CADFC$_p$)	lag = 3	lag = 2	lag = 1	lag = 0
Panel cointegration CCE statistics	-3.622	-3.622	-3.822	-4.640
CCE stats. Cross-section 1	-2.099	-2.099	-3.024	-3.397
CCE stats. Cross-section 2	-1.793	-1.793	-2.864	-4.802
CCE stats. Cross-section 3	-1.075	-1.075	-1.866	-4.131
CCE stats. Cross-section 4	-3.782	-3.782	-4.774	-4.191
CCE stats. Cross-section 5	-4.974	-4.974	-6.196	-7.195
CCE stats. Cross-section 6	-2.979	-2.979	-4.867	-5.719
CCE stats. Cross-section 7	-5.498	-5.498	-4.785	-6.796
CCE stats. Cross-section 8	-2.265	-2.265	-3.662	-2.827
CCE stats. Cross-section 9	-5.620	-5.620	-3.526	-5.645
CCE stats. Cross-section 10	-6.148	-6.148	-4.217	-3.676
CCE stats. Cross-section 11	-3.500	-3.500	-2.425	-3.605
CCE stats. Cross-section 12	-3.700	-3.700	-3.804	-3.998
CCE stats. Cross-section 13	-6.043	-6.043	-1.745	-2.685
CCE stats. Cross-section 14	-2.036	-2.036	-3.577	-4.442
CCE stats. Cross-section 15	-3.035	-3.035	-5.666	-6.831
CCE stats. Cross-section 16	-3.388	-3.388	-3.198	-4.552
CCE stats. Cross-section 17	-2.916	-2.916	-3.445	-5.765
CCE stats. Cross-section 18	-3.391	-3.391	-3.878	-5.693
CCE stats. Cross-section 19	-3.423	-3.423	-4.481	-3.926
CCE stats. Cross-section 20	-4.255	-4.255	-4.583	-4.614
CCE stats. Cross-section 21	-4.146	-4.146	-3.680	-2.954
5% significance level	-2.27	-2.27	-2.31	-2.30
10% significance level	-2.17	-2.17	-2.21	-2.21

Estimation results

We employ a variety of estimators to deal with the empirics concerning green energy innovation and energy intensity with the OECD area. The first set of estimators restrict homogeneity within slopes and assume error cross-sectional independence, like pooled OLS (POLS), fixed effects (FE) and fixed effects instrumental variable (FE-IV), the results are detailed out in Table 3.10. Table 3.11 reports estimated models for the cases of heterogeneous slopes which were obtained using mean group (MG), common correlated effects mean group (CCEMG) and augmented mean group (AMG) in static sense. Table 3.12 details three dynamic tests, namely dynamic common correlated effects ordinary least square (DCCE-OLS), dynamic common correlated effects two stage least square (DCCE-2SLS) and dynamic com-

Table 3.9: Di Iorio and Fachin (2013)cointegration test

Block size = 6	ADF	p-value
Median	-0.3536	0.4842
Mean	-0.7121	0.1208
Max	0.5303	0.1646
Individual HEG statistics rank	unit ID	HEG
Cross-section 1	9	-3.3276
Cross-section 2	14	-2.8239
Cross-section 3	12	-2.4702
Cross-section 4	4	-1.4211
Cross-section 5	6	-1.3575
Cross-section 6	5	-1.0885
Cross-section 7	18	-1.0423
Cross-section 8	13	-0.9829
Cross-section 9	11	-0.4935
Cross-section 10	2	-0.3851
Cross-section 11	7	-0.3536
Cross-section 12	1	-0.3371
Cross-section 13	15	-0.1458
Cross-section 14	3	-0.0859
Cross-section 15	16	-0.0641
Cross-section 16	10	-0.0036
Cross-section 17	19	0.0078
Cross-section 18	17	0.2376
Cross-section 19	8	0.2643
Cross-section 20	20	0.3877
Cross-section 21	21	0.5303

mon correlated effects ordinary GMM (DCCE-GMM).

We find presence of strong cross-sectional dependence in our variables of interest and also order integrated, for which we adopt dynamic heterogeneous framework, where the idiosyncratic shocks have a multi-factor error structure.

Static type results: homogeneous and heterogeneous

In the homogeneous cases we conclude **ei** is negative for all our estimators, Pooled OLS (POLS), Fixed effect (FE) and Fixed Effect Instrumental Variable (FE-IV) but only significant for POLS and FE-IV [the instrument list for ei includes, year dummy variables, erd, is and one-period lagged ei]. Whereas, **is** is also negative but significant for all the type of estimators and **erd** is significant only for POLS with a negative value but insignificant for other estimators though with positive sign. In terms of goodness of fit for each of the estimates, the root mean square errors (RMSE) of the traditional models POLS, FE FE-IV are generally large. There exists significant error cross-sectional dependence which can lead to substantial bias of slopes and over-rejection of null hypothesis in which the estimator becomes zero (Pesaran, 2006). More, non-stationary residuals are also detected in estimated results of table 3.10, this spuriousness occurs because of presence of non-stationarity in variables. So our findings suggest, we need to take care of error cross-sectional dependence and non-stationarity and traditional models are not appropriate in this regard.

Table 3.10: Static Homogeneous Estimation Results

gep			
	POLS	**FE**	**FE-IV**
ei	-0.965 (-7.57)***	-0.961 (-1.16)	0.906 (-2.87)***
erd	-0.013 (-6.08)***	0.007 (0.36)	0.008 (0.90)
is	-0.354 (-3.74)***	-0.701 (-3.63)***	-0.793 (-6.61) ***
constant	1.842(4.61)***	3.288 (3.93)***	
Adj. R_{square}	0.274	0.262	0.263
RMSE	0.128	0.103	0.099
CD test	0.010	0.165	0.000
CIPS test	0.005	0.547	0.236
Observations	840	840	840
Time effects	No	Yes	Yes
Individual effects	No	Yes	Yes

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.CD is the cross-section dependence, CIPS is the non-stationarity test. RMSE stands for Root Mean Squared Error.]

For static heterogeneous type cases, we find **ei** is negative with statistically significant levels for all of our estimators, Mean group (MG), Common Correlated Effects Mean group (CCEMG) and Augmented Mean group (AMG), whereas **erd** is significant for MG type but not for the others, with a positive sign for all three estimators. The **is** is positive and significant for AMG type and significant with negative sign for MG type, but for the CCEMG estimator it is not significant but with a positive sign. The goodness of fit for each of the estimates, i.e., the root mean square errors

(RMSE) are smaller than the homogeneous ones. We can correctly observe all the estimation techniques applied take care of non-stationarity and error cross-sectional dependence. This can be explained due to the fact that heterogeneous estimators filter out unobservables by adding additional variables. Residual attributes like cross-sectional dependence and stationarity are also very important feature of residuals in this regard. There exists a significant error cross-sectional dependence in the homogeneous cases, which might lead to rejection of null hypothesis and substantial bias of slopes in which the estimator equals zero (or size distortion) (Pesaran, 2006). Non-stationary residuals are also present in the homogeneous cases, so we can infer using panel dataset in OECD countries to explore the extent of linkages of green energy innovation and energy intensity may yield misleading results is residual cross-sectional dependence and non-stationarity are not treated properly.

Table 3.11: Static Heterogeneous Estimation Results

gep			
	MG	**CCEMG**	**AMG**
ei	-2.006(-2.15)**	-1.148(-1.98)**	-2.264(-4.21)***
erd	0.059(3.96)***	0.000(0.04)	0.008(0.66)
is	-0.260(-1.85)*	0.183(0.54)	0.234(2.00)**
constant	1.229(1.78)*	-1.102(-1.60)	-0.54(-1.11)
RMSE	0.0959	0.0721	0.0822
CD test	0.000	0.001	0.000
CIPS test	0.000	0.000	0.000
Observations	840	840	840

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.CD is the cross-section dependence, CIPS is the non-stationarity test. RMSE stands for Root Mean Squared Error.]

Dynamic type heterogenous estimation results

We present the results dynamic heterogeneous type cases in table 3.12, we used three estimators in this case, DCCE-OLS, DCCE-2SLS and DCCE-GMM using Chudik and Pesaran (2015), Ditzen (2018) and Neal (2015)

Our findings are someway consistent with the Static cases, **ei** is not significant in any of the estimators but bears a negative sign with DCCE-OLS and DCCE-GMM but is positive for DCCE-2SLS. **erd** is also somehow similar and bears no significance

Table 3.12: Dynamic Heterogeneous Estimation Results

gep			
	DCCE-OLS	**DCCE-2SLS**	**DCCE-GMM**
gep_{lag}	-0.006*(-0.09)	0.359(2.37)**	0.338(2.32)**
ei	-0.745 (-0.72)	0.032(0.03)	-0.281 (-0.28)
erd	-0.006(-0.35)	-0.023(-1.23)	-0.027 (-1.24)
is	0.168(0.56)	0.094(0.30)	0.158 (0.45)
CD test	0.000	0.000	0.000
CIPS test	0.000	0.000	0.000
Observations	777	756	756

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.CD is the cross-section dependence, CIPS is the non-stationarity test.]

in all of the three cases with negative coefficients. **is** is positive but not significant and lagged **gep** is significant at 5% levels in DCCE-2SLS and DCCE-GMM but negatively related at 10% in DCCE-OLS.

CS-ARDL

We present the results of CS-ARDL in table 3.13 and table 3.14 (in table 3.14 we use Carbon-dioxide intensity instead of Energy intensity; see notes 2), using MG estimator energy intensity (ei) is significant with a negative sign for lag 1 with 1%, but for lag 2 and lag 3, though the signs of the coefficient are positive, the relationship with green energy innovation becomes insignificant of nature. In case of carbon-dioxide intensity (co), for lag 1 and lag 2 the relationship is significant with 1% and 5% levels respectively and with negative coefficients, but the coefficient becomes positive with introduction of more lags, i.e., lag 3 and becomes statistically insignificant of nature. Energy research and development demonstration (erd) is not significant in any of the cases, the signs of the coefficient are positive except for lag 3 in table 3.13.

Testing for panel non-causality

We use the methodology developed by Dumitrescu and Hurlin (2012) and Lopez and Weber (2017) to examine the causality between the variables. The methodology assumes that the coefficients are different across cross-sectional units and is more reliable and robust to cross-sectional dependence, as compared to traditional

Table 3.13: CS-ARDL: Green Energy Innovation- Energy Intensity

d.gep	**lag1**	**lag2**	**lag3**
d.erd	0.147(0.454)	0.194(0.652)	-0.084(1.1)
d.ei	-1.404(0.495)***	0.848(0.788)	1.4104(1.512)
λ	-1.298(0.0399)***	-1.624(0.0905)***	-1.7829(0.1248)***

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

Table 3.14: CS-ARDL: Green Energy Innovation- CO2 Intensity

d.gep	**lag1**	**lag2**	**lag3**
d.erd	0.295(0.4179)	0.0728(0.376)	0.0804(0.705)
d.co	-1.125(0.3165)***	-1.16(0.584)**	0.5669(1.014)
λ	-1.3204(0.0387)***	-1.619(0.0752)***	-1.75(0.1205)***

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

Granger causality tests. To consider cross-sectional dependence the test uses a block bootstrap procedure to correct critical values. We use SIC criterion to select the lag length and apply first difference of the variables, since the test requires stationarity among the variables.

Table 3.15: Heterogeneous Panel Causality results

Null hypothesis	w-bar	Z-bar Stat.	Prob
gep does not Granger-cause ei	3.8514	1.5928	0.1112
ei does not Granger-cause gep	3.3544	0.6631	0.5073
gep does not Granger-cause erd	6.2741	6.1253	0.0000
erd does not Granger-cause gep	4.0513	1.9668	0.0492
gep does not Granger-cause is	5.2251	4.1628	0.0000
is does not Granger-cause gep	2.7626	-0.4442	0.6569

The empirical results of short-run heterogeneous panel non-causality tests are presented in table 3.15, the finding shows evidence of causality in between green energy innovation (gep) and energy research and development demonstration (erd), and also in between green energy innovation (gep) and industrial structure (is).

3.6 Conclusion

This paper attempts to determine the relationship between green energy innovation and energy intensity for major OECD countries for a time span of 1975-2014.

We applied various estimators to deal with issues present in our data, like error-cross-sectional dependence, non-stationarity and cointegration. Since the data is of long-time series we checked for both short-run and long-run estimates using dynamic common correlated effects estimators (Chudik and Pesaran, 2015) along with CS-ARDL (Chudik and Pesaran, 2015), we also included results of static homogeneous and heterogeneous estimators.

We find both long-term and short-term relationship in between energy intensity and green energy innovation in our sample, though the relation becomes insignificant over time, i.e. introduction of lags in the system of equations. But we do not find any Granger causality in between energy intensity and green energy innovation, this might be very interesting of nature. The nexus of long-term relationship without any causality might be arising due to heterogeneous slopes or non-linearity, which needs to be investigated using specific estimators.

Notes

1. Apart from dynamic panel, a causality test can also help to establish short-run relationship whereas a panel cointegration can be used to determine long-run estimators. one of the drawbacks of granger causality is, it does not investigate the causal relationship of individual members of the panel, so if one tests each panel member individually it creates over parameterization and loss of degrees of freedom (Smyth and Narayan, 2015). Also, the presence of no-cointegration in a panel might be arising from omitted variable bias and/or unobserved common factors and it is certainly not necessary that every member in the panel are not cointegrated if the whole panel has no presence of cointegration (Pesaran, 2012, Westerlund, Thuraisamy, and Sharma, 2015).

2. We also produce results of Carbon dioxide intensity (co), measured similar way as Energy Intensity in our CS-ARDL model, data is from IEA (IEA, 2017.

Chapter 4

RENEWABLE ELECTRICITY CONSUMPTION AND ECONOMIC GROWTH USING CS-ARDL AND CS-DL

4.1 Introduction

The electricity consumption - economic growth nexus has been studied extensively over the years, however with conflicting results, researchers have concluded uni-directional, bi-directional and neutral relationship in between electricity consumption and economic growth (Payne, 2010, Apergis and Payne, 2011). In general, most of these approaches assume cross-sectional independence and short run dynamics. This paper re-visits the nexus of renewable electricity consumption and economic growth in selected countries and focuses particularly on the ways to deal with cross-sectional heterogeneity in the long-run estimates.

We adopt two specific types of estimators to deal with cross-country heterogeneity as proposed by Chudik and Pesaran (2015) cross-sectionally augmented distributed lag (CS-ARDL) and Chudik et al. (2013) cross-sectionally augmented distributed lag (CS-DL). We investigate the long-run effects of renewable electricity consumption on economic growth of thirty-three countries over the period 1971-2015. In contrast with the previous literature in electricity consumption-economic growth nexus, the econometric approaches as explained in Section 4.3, the CS-ARDL and CS-DL approach take into account three important features of panel data (i.e. dynamics, heterogeneity and cross-sectional dependence). The panel techniques adopted in this paper also allow for countries to be affected by common factors (like oil price shocks, monetary policy and fiscal shocks) due to slope coefficients being different across countries and cross-country averages (and their lags) being proxy for unobserved common factors.

Our findings suggest that, significant positive long-term relationship exists between per-capita economic growth and renewable electricity consumption but we do not find any kind of Granger causality, though when we try similar analysis in between per-capita economic growth and per-capita total electricity consumption we do not find any significant relationship but while checking for causality, we do find per-capita economic growth being a causal factor for total electricity consumption

The remainder of the paper is organized as follows, Section 4.2, reviews literature, Section 4.3 discusses the type of estimation techniques adopted, Section 4.4 describes the data and the model applied, Section 4.5 presents the results and Section 4.6 concludes.

4.2 Electricity Growth Nexus

Energy is undeniably the most important contributor to economic progress, with current trends energy demand is expected to double itself by 2050 (World Energy Council, 2007). Which makes the questions on climate change and non-renewable energy consumption and economic growth really important.

The nexus between economic growth and energy consumption has been studied extensively by applied researchers, it all started with Kraft and Kraft (1978). Various forms of energy consumption measures has been used to understand the nexus of which electricity consumption using different data-samples (cross-sectional and time-series units) and econometric methodologies to investigate this relationship and have concluded with different results. After over-viewing previous research from an empirical perspective one can state four possible hypothesis :

i **Growth hypothesis**: Unidirectional causality from energy (electricity) to growth. In this scenario, consumption of energy (electricity) tends to posses a great influence on the economic growth process. If the relationship is of positive nature, then implementation of pollution reduction measures will bring down domestic output. But if the relationship is of negative nature, then lowering energy (electricity) consumption positively boosts economic output. The positive relationship exists mostly in countries which tend to have high energy intensity or low energy efficiency sectors.

ii **Conservation hypothesis**: Unidirectional causality from growth to energy (electricity), scope for energy (electricity) conservation policies to be effective without harming growth. In this case, real GDP growth influences the consumption of energy (electricity). One can state that the decisions to bring down energy (electricity) consumption pertains to have only limited or marginal impact on the economy.

iii **Feedback hypothesis**: Bi-directional causality. In this scenario, increasing energy (electricity) consumption pushes to economic growth which further increases energy (electricity) consumption, that is energy (electricity) consumption and economic growth are very much interdependent. So if new emission reduction environmental policies are introduced growth and consumption will decrease, but if economic stimulus is adopted then there will be a surge in GDP and energy (electricity) consumption.

iv **Neutrality hypothesis**: Energy (electricity) and growth are neutral to nature, indicating energy (electricity) conservation policies have no effect on growth. This is possible for countries in which the real GDP growth relies to much of a greater extent on service sector vis-à-vis low energy (electricity) consumption. So policies aimed to reduce energy consumption with a focus on bringing down emission do not effect or reduce domestic output. The economy can be considered to be decoupled from the dynamics of energy (electricity) consumption.

For space limitation we do not want to go deeper in the recent review of literature, the following papers extensively provides surveys in this context (Ozturk, 2010, Payne, 2010, Omri, 2014, Halkos and Tzeremes, 2014, Tiba and Omri, 2017, Marinaș et al., 2018)

The idea to include sustainability and social inclusion while measuring economic development can be attributed to Stiglitz-Sen-Fitoussi Report (Stiglitz, Sen, and Fitoussi, 2009) and Sustainable Development Goals. Scarcity of energy affects development especially quality of life. Recently, increase of energy prices along with strategic goals to tackle emission rates have contributed to more detailed study of the linkages in between renewable energy consumption and economic growth. The literature regarding the relationship between renewable electricity consumption and economic growth has relatively been overlooked by researchers. Much of the economic growth in market based economies can be attributed to industrial output which is energy intensive of nature. Due to the future energy policies and the inclination of countries to a more green future, countries have been investing towards a renewable electricity and energy infrastructure. In that scenario it is very important to understand such implications on economic growth.

4.3 Empirical Approaches

In this section, we propose the approach applied to deal with the renewable electricity consumption and economic growth in the long-run.

We begin with a simple panel data model that can summarize much of the existing work on the empirics of economic growth:

$$\Delta y_{it} = (\phi - 1)y_{it} + \beta' x_{it} + c_{yi} + \eta_t + \epsilon_{it} \tag{4.1}$$

$$i = 1, ...N; t = 1, ...T$$

where Δy_{it} is the growth rate of real GDP per-capita of country i; y_{it-1} is the lagged value, x_{it} is a vector of explanatory variables, η_t is the time-specific effect, c_{yi} is the country-specific effect and ϵ_{it} is the error term.

Much of empirical growth literature is based on the estimates of Eq. (4.1) using various techniques of fixed/random or cross-sectional technique. Most of these techniques clearly suffer from endogeneity problem due to the fact that y_{it-1} and ϵ_{it} are correlated, this correlation is of much larger magnitude if there is a presence of unobserved country specific factors (like global financial or monetary shocks, oil-price shocks). Traditional static fixed or random estimators do not work in such cases due to presence of such serial correlation and also due to heteroscedasticity. Since the inter-linkage between economic growth and electricity consumption (renewable in our case) is of very complex nature, we include lagged value of GDP per-capita on the right hand side in order to to eliminate fixed effects from Eq. (4.1), which in any standard OLS- based technique implies violation of orthogonality between error and independent variables. Though a GMM type estimator might be appropriate in this regard, we do not apply such technique because it restricts slope coefficients to be identical across i. GMM techniques also assume homogeneity in time-effects and cross-sectional independence in error terms, for details please refer (Pesaran and Smith, 1995, Mohaddes and Raissi, 2017). We choose two different type of estimators which deals with such problems, namely CS-ARDL and CS-DL as explained below.

CS-ARDL

The most important econometric methodology to deal long-run relationships is Cointegration, which was proposed by Engle and Granger (1987). Pesaran and Smith (1995) introduced a methodology for panel data and named it as autoregressive distributed lag (ARDL) model. In panel data framework two extreme alternative approaches exist to deal with parameteric heterogeneity, one being mean group (MG) which estimates equations differently for each country and average of each coefficients are then examined, Pesaran and Smith (1995) points out the results of MG type estimators are consistent when the time-series dimension is of large enough. Fixed effects (FE), Random effects (RE) and generalized method of moments (GMM) type estimators which might be considered of being on the other extreme, they simply pools the dynamic nature of the data and treats things homogeneously. In between these two extreme approaches lies pooled mean group (PMG) type estimator proposed by Pesaran, Shin, and Smith (1999), this approach involves aspects of both averaging and pooling of estimators, allowing for heterogeneity in intercepts, short-run coefficients and error variances, with the long-run coefficients being homogeneous across cross-sectional units. The PMG estimator takes average of each cross-sectional units and generates consistent short-run estimates for these cross-sectional units.

Chudik and Pesaran (2015) and Chudik et al. (2016) introduced CS-ARDL, a new ARDL type estimator to deal with cross-sectional dependence, in presence of I(0) or I(1) order of integration irrespective of the order and report pooled long-run type estimates, the estimator also takes into account omitted variable bias. The only requirement in this type of estimator, apart from the existence of long-term relationship in between the concerned variables, is that of dynamic specification of the model, so that the weak exogeneity among the regressors comes into account and the residuals are not correlated anymore.

Let us discuss the CS-ARDL model in detail, but first let's start from a basic ARDL model of order 1 with a multifactor error structure:

$$y_{it} = c_{it} + \phi y_{it-1} + \beta'_{0i} x_{it} + \beta'_{1i} x_{it-1} + u_{it} \tag{4.2}$$

$$u_{it} = \gamma'_i f_t + \epsilon_{it} \tag{4.3}$$

$$\omega_{it} = \begin{pmatrix} x_{it} \\ g_{it} \end{pmatrix} = c_{\omega i} + \alpha_i y_{it-1} + \Gamma'_i f_t + v_{it} \tag{4.4}$$

where $i = 1, ...N; t = 1, ...T$, x_{it} is a $k_x \times 1$ vector of regressors of i cross-sectional units at time t, c_{yi} and $c_{\omega i}$, g_{it} is $k_g \times 1$ is a vector of covariates specific to i^{th} cross-sectional unit, $k_g \geq 0$,$\mathrm{k}_x + k_g = k$, ϵ_{it} represents the idiosyncratic errors, f_t is a $m \times 1$ vector of unobserved common factors, it can be both stationary on nonstationary of nature. Γ_i is a $m \times k$ matrix for factor loadings ($k \geq m$), α_i is a $k \times 1$ vectors of unknown coefficients and the assumption behind v_{it} is that it follows a general linear covariance stationary process distributed independently of the idiosyncratic error terms, ϵ_{it}. , see Kapetanios, Mitchell, and Shin (2014). The main intrinsic feature of this technique is that the unobserved common factors or heterogeneous time effects can be proxied by adding cross-sectional averages of the observables (See Pesaran, 2006 and Chudik and Pesaran, 2015). Chudik and Pesaran (2015) derive that the unobserved common factors f_t , can be proxied by de-trended common averages of

$z_t = (y_{it}, x'_{it}, g'_{it})'$ and their respective lags, but the necessary condition being N is sufficiently large.

$$f_t = G(L)\tilde{z}_{wt} + O_P(N^{-1/2}) \tag{4.5}$$

where G(L) is a distributed lag function, $\tilde{z}_{wt} = \bar{z}_{wt} - \bar{c}_{zw}$ is a $k+1$ dimensional vector of detrended cross-sectional averages, $\bar{c}_{zw} = \Sigma_{i=1}^{N} w_i (I_{k+1} - A_i)^{-1} c_{zi}$ with $A_i = A_{0i}^{-1} A_{1i}$,

$$A_{0i} = \begin{bmatrix} 1 & -\beta'_{0i} & 0 \\ 0_{k_x \times 1} & I_{k_x} & 0_{k_x \times k_g} \\ 0_{k_g \times 1} & 0_{k_g \times k_x} & I_{k_g} \end{bmatrix}$$

and

$$A_{1i} = \begin{bmatrix} \phi_i & -\beta'_{1i} & 0_{1 \times k_g} \\ \alpha_{x_i} & 0_{k_x \times k_x} & 0_{k_x \times k_g} \\ \alpha_{g_i} & 0_{k_g \times k_x} & 0_{k_g \times k_g} \end{bmatrix}$$

The weights are specified by the normalization condition: $\Sigma_{i=1}^{N} w_i = 1$, finally substituting (4.5) in (4.2), the final form can be written as

$$y_{it} = c^*_{yi} + \phi_i y_{it-1} + \beta'_{0it} x_{it} + \beta'_{1i} x_{it-1} + \delta'_i(L)\bar{z}_{wt} + O_P(N^{-1/2}) + \epsilon_{it} \tag{4.6}$$

$$\delta_i(L) = \sum_{l=0}^{\infty} \delta_{il} L^l = G'(L)\gamma_i \tag{4.7}$$

and

$$c^*_{yi} = c_{yi} - \delta'_i(1)\bar{c}_{zw}$$

To estimate (4.2) using MG and PMG estimators, some conditions need to fulfilled

- The number of cross-sectional averages must be at least as large as the number of unobserved common factors
- A sufficient number of lags of cross-sectional averages needs to be included in the individual equations of the panel.
- The model needs the time-series dimension to large enough, for the reason to estimate values of each cross-sectional units.

For MG type estimator, θ can be written as $\theta = E(\theta_i)$, so the long run-coefficients are

$$\theta_i = \frac{\beta_{0i} + \beta_{1i}}{1 - \phi_i} \tag{4.8}$$

For the PMG type estimates, the individual long-run coefficients must be same across all cross-sectional units, and the PMG estimator uses a maximum likelihood approach to calculate estimates using a variant form of Newton- Raphson algorithm

$$\theta_i = \theta, i = 1, ..., N \tag{4.9}$$

CS-DL

The CS-ARDL approach has some conceptual shortcomings, due to the fact it first estimates the short-run coefficients and then computes the long-run coefficients based on (4.8) with the short-run estimates being replaced by their long-run counterparts (Pesaran, 2015b). However the problem arises if the rate of convergence towards the long-run estimate is slow and also if the time dimension is not sufficiently long enough. Another problem might arise if the sampling uncertainty is of large dimension and the short-run coefficient are subject to small T bias (see Pesaran, 2015b, page: 782). Therefore, one of the most important requirement is the correct specification of the lag order. Chudik and Pesaran (2015) proposed a different estimation approach in which long-run coefficients are estimated directly without estimating the short-run ones. This approach also comes from the ARDL approach and can be written as:

$$y_{it} = \theta_i x_{it} + \alpha_i'(L)\Delta x_{it} + \tilde{u}_{it} \tag{4.10}$$

where $\tilde{u}_{it} = \lambda_i(L)^{-1}u_{it}$, $\lambda_i(L) = 1 - \lambda_i L^l$ and $\alpha_i(L) = \Sigma_{l=0}^{\infty}\Sigma_{s=l+1}^{\infty}\lambda_i^s\beta_i L^l$. θ_i is directly estimated from (4.10) with some assumptions, $|\lambda_i| < 1$, exponents of $\alpha_i(L)$ are decaying exponentially in absence of feedback effects of lagged values of dependent variable on the explanatory variables. Consistent estimate of θ_i can be obtained by least square regressing of y_{it} on x_{it}, $\{\Delta x_{it-l}\}_{l=0}^{\rho T}$ and cross-sectional averages to deal with unobserved common factors present inside u_{it}.

The final CS-DL estimator looke like:

$$y_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1}\delta_{il}x_{i,t-l} + \sum_{l=0}^{p\bar{y}}\omega_{yil}\bar{y}_{t-l} + \sum_{l=0}^{p\bar{x}}\omega_{xil}'\bar{x}_{t-l} + \epsilon_{it} \tag{4.11}$$

where $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$ and $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$ and $p_{\bar{x}}$ is set equal to integer of $T^{1/3}$, $p = p_{\bar{x}}$ and $p_{\bar{y}}$ is set to 0.

So, the cross-sectional augmented distributed lag (CS-DL) mean group estimator can be written by

$$\widehat{\theta}_{MG} = \frac{1}{N}\sum_{i=1}^{N}\widehat{\theta}_i \tag{4.12}$$

and

$$\widehat{\theta}_i = (\tilde{X}_i' M_{qi} \tilde{X}_i')^{-1} \tilde{X}_i' M_{qi} \tilde{y}_i \tag{4.13}$$

The CS-DL pooled estimator of the long-run coefficients can be written as

$$\widehat{\theta}_P = \left(\sum_{i=1}^{N} w_i \tilde{X}_i' M_{qi} \tilde{X}_i'\right)^{-1} \sum_{i=1}^{N} w_i \tilde{X}_i' M_{qi} \tilde{y}_i \tag{4.14}$$

The CCE estimator Pesaran (2006), only includes a fixed number of regressors but in CS-DL type θ_{MG} and θ_P includes ρ_T lags ofΔx_{it} and its cross-sectional averages. The length of ρ_T increases with T, following Pesaran (2006), Chudik and Pesaran (2015) and Chudik et al. (2016) the optimal lag length can be determined.

4.4 Data

This section presents the data we used to examine the long-term effects of renewable electricity consumption on economic growth in the OECD, using both CS-ARDL and CS-DL.

We obtain per-capita renewable electricity consumption (REN) in GWh and per-capita gross-domestic product (GDP) in billion 2005 US dollars which represents economic growth in our case, from IEA (International Energy Agency) (IEA, 2018b), in the end we convert every variable to its natural logarithmic terms to reduce heteroscedasticity. Since our analysis allows for slope heterogeneity across our sample of countries, we needed a sufficient number of time periods to estimate country-specific coefficients, one of the requirements of CS-DL is $30 \leqslant T < 100$ (Chudik et al., 2013, Pesaran, 2015b) where T is the number of time-periods. For the above reason, we only select countries who had the maximum number of time data points available and we end up with 33 countries as listed in Table 4.1 for 45 years (1971-2015). We also compare our results with total electricity consumption (ele), the data is also from IEA (IEA, 2018b).

Table 4.1: List of countries in our sample

Australia	Greece	New Zealand
Austria	Hungary	Norway
Belgium	Iceland	Poland
Canada	India	Portugal
Chile	Ireland	Slovak Republic
China	Italy	Spain
Czech Republic	Japan	Sweden
Denmark	Korea (South)	Switzerland
Finland	Luxembourg	Turkey
France	Mexico	United Kingdom
Germany	Netherlands	United States of America

In table 4.2 we display the descriptive statistics of each variables in our sample. We present total as well as decadal simple correaltion coefficient between REN and

Table 4.2: Descriptive Statistics

Variables	GDP	REN	ELE
Mean	26.14622105	3109.468307	7047.162228
St. Dev	13.93018802	6672.208809	6670.866862
Min.	0.481767437	0	117.1609852
Max.	91.30977131	56782.47734	56794.56193
Skewness	0.82933714	4.143397245	2.963922057
Kurtosis	2.152172355	21.95513886	14.25913855

GDP for each country is our sample at Table 4.3.

Figure 4.1 illustrates a simple bivariate relation GDP and REN for our sample of countries in our considered time-period. This gives a clear indication between a positive relationship between the two variables. For a comparative purpose we also display the bivariate relation GDP and ELE in Figure 4.2.

4.5 Model

In accordance with previous empirical literature, we use a standard log-linear functional specification of long-run relationship between renewable electricity consumption and real gross-domestic product in our sample of countries. The function can be expressed in the following way:

$$GDP_{it} = \alpha + \beta REN_{it} + \epsilon_{it}$$

we also provide the results for total electricity consumption, using the same specification-

Table 4.3: Time-correlation between GDP and Renewable Electricity consumption

	total sample	71-80	81-90	91-00	01-10	11-15
Australia	0.48	0.34	-0.02	-0.50	0.20	0.82
Austria	0.90	0.94	0.57	0.83	0.50	0.14
Belgium	0.67	0.86	0.34	0.89	0.79	0.50
Canada	0.71	0.98	0.48	0.45	0.43	0.67
Chile	0.89	0.09	-0.04	-0.13	0.31	0.66
China	0.98	0.83	0.95	0.95	0.99	0.99
Czech Republic	0.83	0.85	-0.19	0.86	0.68	0.42
Denmark	0.85	0.64	0.75	0.95	0.55	0.97
Finland	0.90	-0.16	0.24	0.71	0.70	-0.52
France	0.09	0.74	-0.67	-0.05	-0.12	0.04
Germany	0.77	0.77	-0.58	0.89	0.91	0.95
Greece	0.50	0.35	-0.60	0.75	0.37	-0.85
Hungary	0.84	0.46	0.48	0.51	0.76	0.98
Iceland	0.90	0.95	0.79	0.97	0.55	0.95
India	0.96	0.88	0.55	-0.24	0.93	0.74
Ireland	0.73	0.51	-0.45	0.76	0.26	0.98
Italy	0.31	0.52	-0.83	0.60	-0.81	-0.94
Japan	0.50	-0.41	0.57	0.08	0.14	0.76
Korea	0.73	0.61	0.83	0.12	0.46	0.89
Luxembourg	0.76	0.67	-0.43	0.80	0.86	0.59
Mexico	0.66	-0.33	0.67	0.19	0.69	0.25
Netherlands	0.86	0.86	0.51	0.99	0.83	0.65
New Zealand	0.52	0.21	0.50	-0.02	0.24	0.14
Norway	0.75	0.80	0.61	0.24	0.37	0.64
Poland	0.87	0.60	-0.28	0.95	0.93	0.97
Portugal	0.62	0.55	0.16	0.33	0.31	-0.21
Slovak Republic	0.79	0.73	-0.05	0.60	0.27	0.63
Spain	0.58	0.03	-0.17	0.43	0.15	-0.51
Sweden	0.65	0.55	0.78	0.40	0.20	0.44
Switzerland	-0.05	0.08	-0.71	0.30	-0.29	0.42
Turkey	0.89	0.87	0.69	0.60	0.48	0.44
United Kingdom	0.68	0.82	0.58	0.88	0.59	0.99
United States	0.29	-0.33	-0.24	-0.33	0.53	0.77

$$GDP_{it} = \alpha_{it} + \beta ELE_{it} + \epsilon_{it}$$

To examine the long run effects of renewable electricity consumption on economic growth, we estimate the following panel CS-ARDL model:

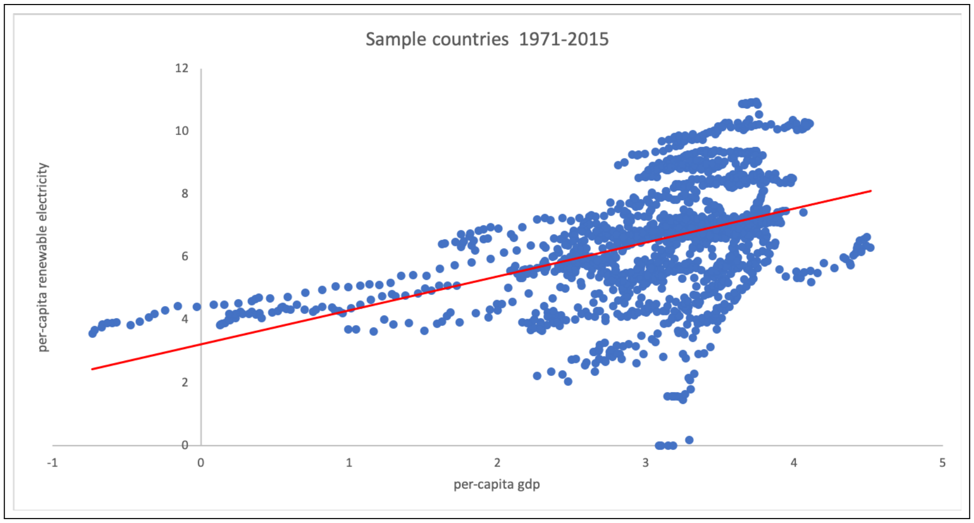


Figure 4.1: Renewable Electricity - GDP: 1971-2015 in logarithmic scale

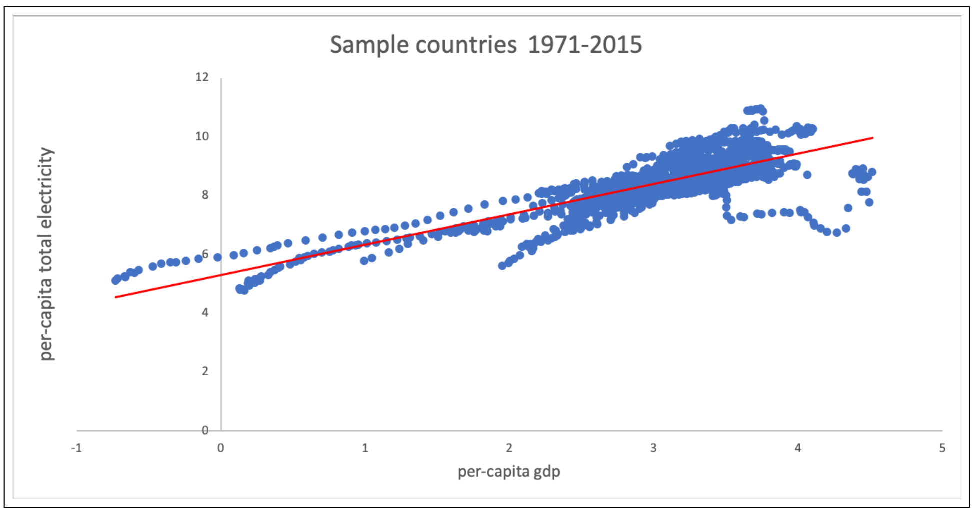


Figure 4.2: Total Electricity - GDP: 1971-2015 in logarithmic scale

$$y_{it} = c_{yi}^{*} + \sum_{l=1}^{p} \phi_{il} y_{i,t-l} + \sum_{l=0}^{p} \beta_{il}' x_{i,t-l} + \sum_{l=0}^{q} a_{il} \overline{y}_{t-l} + \sum_{l=0}^{q} b_{il}' \overline{x}_{t-l} + \epsilon_{it} \tag{4.15}$$

where y_{it} is the gdp per-capita for country i at time t, x_{it} represents renewable electricity consumption per-capita for the same country i during that same time-period t. $\overline{y}_t$ and $\overline{x}_t$ denotes the cross-sectional averages of y_{it} and x_{it} at time period t. The important decision for ARDL models is to choose the lag length long enough to ensure the residuals becomes serially uncorrelated of the error-correction although choosing too many lags imposes excessive parameter requirements on the data. We keep the lag length at 3, i.e., we set p≤ 3, according to similar approaches that have been employed by Chudik and Pesaran (2015), Mohaddes and Raissi (2017), Chudik et al. (2016) following Pesaran (2007).

We also employ CS-DL to estimate the long-run effects of renewable electricity consumption on the economic growth of our sample of countries for different truncation lag orders, $p = 1, 2, 3$,

$$y_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1} \delta_{il} x_{i,t-l} + \sum_{l=0}^{p\overline{y}} \omega_{yil} \overline{y}_{t-l} + \sum_{l=0}^{p\overline{x}} \omega_{xil}' \overline{x}_{t-l} + \epsilon_{it} \tag{4.16}$$

where y_{it} is the gdp per-capita for country i at time t, x_{it} represents renewable electricity consumption per-capita for the same country i during that same time-period t. $\bar{x}_t = N^{-1} \sum_{i=1}^{N} x_{it}$ and $\bar{y}_t = N^{-1} \sum_{i=1}^{N} y_{it}$ and $p_{\bar{x}}$ is set equal to integer of $T^{1/3}$. Since in our case T = 45, $p_{\bar{x}} = 3$

4.6 Results

Cross-section dependence test

We first check the nature of cross-section in between our variables, we use Pesaran (2004) to test the degree of magnitude of cross-sectional dependence, the results are depicted in Table 4.4, the null hypothesis being strict cross-sectional independence, which is rejected for all the concerned variables.

Table 4.4: CD Results- I

Var.	CD-test	p-value	mean ρ	mean abs (ρ)
gdp	144.727	0.000	0.94	0.94
ren	92.551	0.000	0.60	0.60
ele	130.784	0.000	0.85	0.85

Then we follow along the lines of (Pesaran, 2015b, Bailey, Kapetanios, and Pesaran, 2016 and Ertur and Musolesi, 2017) to calculate the degree of the Cross-sectional Dependence statistic along with estimated confidence bands of α, the exponent of cross-sectional dependence defined over the range [0,1] for our required variables as depicted in Table 4.5, the null of the CD test depending upon the increase of T and N. When T is fixed and N $\rightarrow \infty$, the null for CD test is given by $0 \leqslant \alpha \leqslant 0.5$ and when T and N $\rightarrow \infty$ at the same rate, the null for CD test is given by $0 \leqslant \alpha \leqslant 0.25$ (which is our case). To this extent, the value of α in the range of [0.5,1] depicts different degree of strong cross-sectional dependence and in between [0,

Table 4.5: CD Results- II

Variables	CD statistic	$\widehat{\alpha_{0.5}}$	$\widehat{\alpha}$	$\widehat{\alpha_{0.95}}$
gdp	140.122	0.958	1.002	1.047
ren	94.03	0.92	0.99	1.065
ele	122.12	0.95	1.002	1.049

0.5] depicts different degree of weak cross-sectional dependence. In our case for all the variables, the CD statistic strongly rejects the null hypothesis suggesting the fact that the exponent of cross-sectional dependence lies in the range [0.25, 1]. To figure out the degree of cross-sectional dependence, one has to look at the bias-corrected estimates of α and the 90% confidence bands around it. In our case the exponent of cross-sectional dependence is estimated at approximately one for all variables at levels and more than 0.90 for all variables in first differences. In addition, the 90% confidence bands are highly above 0.5 and include unity. This confirms our preliminary finding and suggests presence of strong cross-sectional dependence in both dependent and explanatory variables for our analysis.

Second generation Panel Unit root tests

Table 4.6 reports the outcomes of three first-generation unit root tests with cross-sectionally demeaned data Im, Pesaran, and Shin (2003), along with first-difference of each variable, we use BIC lags for each case

Table 4.6: Second generation Panel Unit root tests- I

Variable	Statistic	p-value
gdp	7.45	1.00
ren	3.44	0.997
ele	5.54	1.00
dgdp	-19.8	0
dren	-40.62	0
dele	-30.54	0

We then apply Pesaran (2007) and Pesaran, Vanessa Smith, and Yamagata (2013) to understand the non-stationarity in a multi-factor error structure framework and like our previous case, the variables become stationary at first difference, the reports are presented in Table 4.7, we choose 3 lags, following the literature which sets lag equal to integer of $T^{1/3}$, as in our case T = 45, we choose the lag length to be 3.

Table 4.7: Second generation Panel Unit root tests- II

Variable	t-bar	Z[t-bar]	p-value
gdp	-1.72	0.271	0.607
ren	-2.065	-1.8	0.036
ele	-1.472	1.823	0.966
dgdp	-2.611	-5.141	0
dren	-3.529	-10.747	0
dele	3.008	-7.565	0

Test for Panel Cointegration

We finally apply Westerlund (2007), and Persyn and Westerlund (2008) to understand the order of integration among our variables, table 4.8 represents the relationship in between per-capita gdp and per-capita renewable electricity consumption only. We conclude with presence of cointegration among our variables. The mean-group

Table 4.8: Cointegration Results

Statistic	Value	Z-value	P-value	Robust P-value
G_τ	-1.887	3.390	1.000	0.890
Ga	-7.485	3.824	1.000	0.890
P_τ	-10.074	2.356	0.991	0.680
Pa	-5.376	3.332	1.000	0.760

test (G_τ) averages heterogeneous OLS estimates of the speed of adjustment of their standard errors, while the panel test (P_τ) provides estimates of the aggregate speed of adjustment and its standard error. Because both G_τ and P_τ distributions assumes error-correction models and are independently distributes, one can say the tests take into consideration of cross-sectional dependence by bootstrapped standard errors. We choose 3 lags and 100 bootstrap replications.

Long run estimates

We first investigate the long-run effects of renewable electricity consumption on economic growth represented by per-capita gdp using traditional panel ARDL approach, in this approach the long-run effects are calculated using OLS estimates of the short run coefficients of (4.2). We use a lag range from 1 to 3, since we are using economic growth variable with a per-capita gdp as measure for well-advanced and developing countries, a lag order of 3 is sufficient enough to take account fully short-run dynamics and chalk out feedback effects. Equation (4.2) also allows for significant degree of cross-sectional dependence (particularly in the short-run).

Pesaran and Smith (1995), Pesaran (1997) and Pesaran, Shin, and Smith (1999) points out that traditional ARDL models can be used for long-run estimation taking into account both endogeneity of regressors and I(0) or I(1) nature of variables. Additionally, following the argument of Pesaran and Smith (2014), in which they comment in favour of parsimonious models when object of interest is not the *ceteris paribus* impact of a regressor, we do not employ any control variables in our relationship.

In table 4.9, we report the results of the plain ARDL model for both Fixed Effects (FE) and Mean Group (MG) estimates with no cross-sectional correction. The first three columns for the first two rows of the table report the fixed effects estimates and the last three columns report the mean group estimates. In the last two rows we report the results when we use total electric consumption instead of renewable electric consumption.

Table 4.9: Fixed Effects (FE) and Mean Group (MG) estimates of the Long-run effects based on traditional ARDL approach

	FE (1,1)	**FE (2,2)**	**FE (3,3)**	**MG (1,1)**	**MG (2,2)**	**MG (3,3)**
ren	0.006***	0.008***	0.004***	0.001***	0.009***	-0.014***
	(0.007)	(0.01)	(0.011)	(0.018)	(0.02)	(0.029)
λ	-0.64	-0.68	-0.65	-0.66	-0.75	-0.713
	(0.037)	(0.034)	(0.041)	(0.03)	(0.035)	(0.044)

	FE (1,1)	**FE (2,2)**	**FE (3,3)**	**MG (1,1)**	**MG (2,2)**	**MG (3,3)**
ele	0.116*	0.078**	0.079***	0.325	0.262	0.24
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)
λ	-0.65	-0.69	-0.66	-0.705	-0.76	-0.74
	(0.039)	(0.037)	(0.041)	(0.032)	(0.039)	(0.04)

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

The results show that renewable electricity consumption is significant and positively related to economic growth except for the mean group type estimator with three lags, where it is significant at 1% level but the coefficient is negative. For total electricity consumption, the fixed effects model shows significance and the level of significance increases with introduction of lags, but for the mean group estimator there exists no significant relationship though the coefficients are positive.

CS-ARDL

We present the results of CS-ARDL in table 4.10, using MG estimator for both renewable and total electricity consumption. Like the ARDL model, the results are very similar in the CS-ARDL model, renewable electricity consumption has significance level at 1% for all the three lag levels but the coefficient becomes negative at the third lag though is positive for the first two lags. This strengthens the idea that in the short-run the effect of renewable electricity on economic growth is positive but over the time the effect becomes less of importance. However, for total electricity in the case of CS-ARDL, no significance exists but the coefficients are of positive nature.

Table 4.10: Mean Group (MG) estimates of the Long-run effects based on CS-ARDL Approach

	CS-ARDL(1)	**CS-ARDL(2)**	**CS-ARDL(3)**
$\widehat{ren}$	0.022***	0.014***	-0.018***
	(0.015)	(0.02)	(0.03)
λ	-0.683	-0.736	-0.689
	(0.042)	(0.05)	(0.058)
	CS-ARDL(1)	**CS-ARDL(2)**	**CS-ARDL(3)**
$\widehat{ele}$	0.259	0.238	0.249
	(0.08)	(0.06)	(0.07)
λ	-0.761	-0.803	-0.763
	(0.044)	(0.047)	(0.055)

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

CS-DL

The MG estimates based on CS-DL regressions are summarized in Table 4.11 for both renewable electricity and total electricity. For renewable electricity consumption, the mean group estimates are statistically significant and positive over time, lag 1 is significant at 5% level, whereas for lag 2 and lag 3 the significance is at 1% level. Yet for the total electricity consumption case, the coefficients are positive without being significant for any of the chosen lag length.

Causality analysis

The ARDL (including CS-ARDL and CS-DL) type estimators are efficient to determine the existence of long-run relationships among concerned variables, in our

Table 4.11: Mean Group (MG) estimates of the Long-run effects based on CS-DL Approach

	CS-DL(1)	**CS-DL(2)**	**CS-DL(3)**
$\widehat{ren}$	0.019**	0.0211***	0.0149***
	(0.0103)	(0.0157)	(0.01911)
RMSE(σ)	0.0223	0.0219	0.0217
	CS-DL(1)	**CS-DL(2)**	**CS-DL(3)**
$\widehat{ele}$	0.217	0.204	0.247
	(0.057)	(0.058)	(0.061)
RMSE(σ)	0.0201	0.0199	0.0196

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

case renewable electricity consumption and economic growth. But this type of estimators do not indicate the direction of causality which is a very important aspect in energy/electricity - economic growth nexus literature. Accordingly, to determine the nexus of causality, we implement a new type of Granger causality, using the methodology proposed by Dumitrescu and Hurlin (2012) and Lopez and Weber (2017)

The null hypothesis of the test is of homogeneous non-causality against the alternative of heterogeneous causality. The test uses fixed coefficients in a vector autoregressive (VAR) framework. The framework assumes that the coefficients are different across cross-sectional units and is more reliable and robust to cross-sectional dependence as compared to Granger causality tests. To consider cross-sectional dependence the test uses a block bootstrap procedure to correct critical values. We use BIC criterion to select the lag length, opting for 2 lags and apply first difference of the variables since the test requires stationarity among the variables. The test also uses dissimilar log-structures and heterogeneous unrestricted coefficients. Another advantage of this test is the Wald statistics to test for Granger non-causality,which are calculated for each cross-sections separately and then is averaged out to compute for the whole panel. Dumitrescu and Hurlin (2012) also verify the asymptotic behind the test and state that the panel test value converges to a normal distribution of homogeneous non-causality when T and N goes to infinity with the rate of T being faster than N.

The empirical results of short-run heterogeneous panel non-causality tests are presented in table 4.12, the findings show no evidence of causality between renewable electricity consumption and gross-domestic product, though unidirectional causality exists between GDP and total electricity consumption.

Table 4.12: Heterogeneous Panel Causality results

Null hypothesis	w-bar	Z-bar Stat.	Prob
GDP does not Granger-cause REN	1.3819	1.5512	0.1209
REN does not Granger-cause GDP	1.0140	0.0570	0.9545

Null hypothesis	w-bar	Z-bar Stat.	Prob
GDP does not Granger-cause ELE	1.7753	3.1493	0.0016
ELE does not Granger-cause GDP	0.9744	-0.1039	0.9173

4.7 Conclusions

The nexus between economic growth and energy consumption, especially electricity consumption, has gained quiet a momentum among researchers recently, the bulk of this literature has used methodologies which do not take cross-sectional dependence into consideration. Our goal was to examine if any long-term relationship and causality exists in between renewable electricity consumption and growth for some highly advanced countries along with some emerging superpowers which became big economic superpowers from 1971-2015.

We use two recent methodologies which take into account cross-sectional dependence in long-term framework, namely CS-ARDL and CS-DL. We can conclude, that significant positive long-term relationship exists between per-capita economic growth and per-capita renewable electricity consumption but we do not find any kind of Granger causality. Although, when we try similar analysis in between per-capita economic growth and per-capita total electricity consumption we do not find any significant relationship but while checking for causality, we do find per-capita economic growth being a causality factor for total electricity consumption.

Chapter 5

REVISITING THE LITERATURE OF DYNAMIC EKC USING A LATENT STRUCTURE APPROACH

5.1 Introduction

The Rio convention of 1992 followed by the Kyoto summit of 1997 and recently the COP21 summit of Paris are some of the milestones for policymakers to reduce the extent of Greenhouse gas (GHG) emissions to maintain a sustainable future. But still, the effect of GHG on planet earth might lead to increase in temperature by 3 °C by 2050 (United Nations Climate Change Secretariat, 2015) leading to some catastrophic climatic changes all-over the world. This also might lead to an economic reduction in output in developed and developing countries, the annual GDP growth might reduce to 2 to 4% by 2040 and 10% by 2100. So common global agenda is to reduce emission levels in both developed and developing countries without hampering economic progress. Some of the policies in such regard is to fund and technology transfer to developing world and increase in usage of renewable energies (IEA, 2018a).

The relationship between climate change and economic development has been studied well enough (Grossman and Krueger, 1991, Grossman and Krueger, 1995, Holtz-Eakin and Selden, 1995, Carson 2010), some extensive reviews can be found in Borghesi (2000), Brock and Taylor (2010), Uchiyama (2016) . Also the relationship between growth and emission including innovation has been extensively used in policy making literature especially for developed countries Stern Review (Dietz, 2011). From an econometric point-of view a lot of methodologies have bee applied starting from simple time-series methodologies to very complex ones, like trying to deal with various forms of heterogeneity using GAMS, Bayesian and Heterogenous estimators to tackle cross-sectional dependence (Musolesi, Mazzanti, and Zoboli, 2010, Mazzanti and Musolesi, 2013, Mazzanti and Musolesi, 2017). All these papers have shown presence of strong forms of heterogeneity in developed countries.

This paper adopts a panel structure model to account for such form of heterogeneity. In our panel data model cross-sectional units form a number of groups, within these groups the slope coefficients are similar but they vary across groups, both the number of groups and individual group membership is unknown. This methodology of determining number of groups and group membership provides a new look on the EKC literature. We apply a recent classification method C-Lasso by Su, Shi, and Phillips (2016) [SSP (2016) hereafter] and Huang, Jin, and Su (2018)[HJS (2018) hereafter]. The methodology is novel of its kind as it provides a consistent estimator to unknown group-structure and also delivers oracle-efficient estimates for the coefficients for each group. We use data from thirty-four countries in our sample for a period of 1971-2015 and we conclude with two groups, revealing marked heterogeneity in the economic growth- emission literature. The primary finding reveals that

1. the effect of renewable energy consumption is positive in one group and negative in other.
2. some developmental patterns are evident in the data, with some distinctions.

The rest of the paper is organized as follows, section 5.2 provides a brief literature review, section 5.3 explains the panel structure model and C-lasso technique provided by SSP (2016) to account for latent group structure across different countries within the time period 1971-2015, section 5.4 describes the data and the model. Section 5.5 provides the results and section 5.6 concludes.

5.2 Background and Literature Review

From the beginning of the 20^{th} century there has been an increase extreme weather based damages, and this weather based damages are hypothesized to be led by global warming. These environmental issues can be broadly classified into two main categories, local which relates to environmental pollution and other being influenced by global warming and ozone depletion. Scientists and economists have agreed upon the fact that unrestricted economic activities are one of the main causes of environmental destruction, one such being mass consumption of fossil fuels. The *Limits to Growth* by Club of Rome laid the foundation interaction of economic activities and environmental issues.

The Environmental Kuznet Curve hypothesis (EKC, hereafter) depicts the relationship between economic growth and the environment, briefly it can be said that when someone explores per-capita income and per-capita measure for any of the environmental variables, one might find an inverted-U shaped curve which can be explained as that during early stages of development environmental degradation increases but in-turn falls back after per-capita income exceeds a certain level (i.e, turning point), the literature was proposed by Simon Kuznets (Kuznets, 1955) to understand the relationship in between per-capita national income and income inequality. With the introduction of the concept of sustainable development the EKC literature has gained a lot of momentum among researchers.

Grossman and Krueger (1991), Shafik and Bandyopadhyay (1992) were one of the first to deal with the EKC literature. A lot of survey papers exists in the EKC field some being, Stern (1998), Stern (2004), Dasgupta et al. (2002), Dinda (2005). The EKC literature has been a hot debatable issue among scholars for a long time, this is due to the fact availability of new data sets on various dimensions have increased over time. Besides, previous research has left some unresolved issues which are being studied with new econometric techniques. We do not dig deeper in such issues due to conciseness, a very good review of all the issues (both Theoretical and Empirical) regarding EKC can be found out in (Uchiyama, 2016)[Chapter2]. Recently there has also been a surge relating to the Integrated Assessment Models (IAMs), which narrates the study of human feedback and influences on climate change and reduction of greenhouse gasses. The idea being coupling different models like climate change models, land-use models, energy models along with models describing economic growth to have a better understanding on the issue of climate change. The conclusions from IAMs are very helpful in providing insights to policy makers and general public. Some very well known examples of IAMs contribution to policy reports are Special Report on Renewable Energy (IPCC, 2011), World Energy Outlook 2011 (IEA, 2011) and EU Energy Roadmap 2050 (Commission, 2012).

Our study is novel in nature, we not only deal with time-varying coefficients that may capture the instability of the EKC but we also use an unknown latent group structure methodology to partition our sample of countries into groups in order to focus on slope heterogeneity, a nearby research can be of Mazzanti and Musolesi (2013) where they classify groups before-hand and then deal with heterogeneity and structural breaks, also Li, Qian, and Su (2016) where they consider structural breaks and interactive fixed effects to deal with heterogeneity but those both these papers lack unknown group structure.

5.3 Econometric Methodology

Traditional fixed-effects panel data model assumes cross-sectional units are heterogeneous in terms of time-varying intercepts with a homogeneous slope coefficient, but this assumption of homogeneity in slope has been a debatable issue in econometric literature. To deal with this issue, the traditional view is to split the data into similar groups and apply standard fixed-effects model so that unobserved heterogeneity enters the model additively. Time and again this method has been criticized in studies (Hsiao and Tahmiscioglu, 1997, Lee, Pesaran, and Smith, 1997, Phillips and Sul, 2007, Su and Chen, 2013). Over the years different approaches have emerged to deal with unknown group structure with respect to inferencing unobserved slope heterogeneity. The first one being finite mixture models, Sun (2005) proposes a finite parametric linear mixture model; Kasahara and Shimotsu (2009), Browning and Carro (2013) uses nonparametric discrete mixture distributions to identify finite number of groups in a discrete choice panel data. Another concept in use is of cluster analysis by using K-means algorithm, quite a lot of progress has been made in this regard, (Lin and Ng, 2012, Sarafidis and Weber, 2015, Bonhomme and Manresa, 2015, Ando and Bai, 2016) have all worked using a K-means algorithm to deal with slope based heterogenenity. SSP(2016) have used a variant form of Lasso, C-Lasso to identify latent group pattern when the slope coefficients exhibit group structure, HJS (2018) extend it to cointegrated panels and Huang, Phillips, and Su (2018) has extended it to non-stationary panel data while dealing with cross-sectional dependence which is very useful to tackle problems relatable to spillover based studies. In our analysis we do not assume any group structure in our data, but we deal with the heterogeneity in slope by applying a new group structure concepts.

A. Model

We adopt the estimation technique of SSP (2016) for our empirical purpose and a brief explanation of the technique is given below, which takes the following form:

$$y_{it} = {\beta^{0}}'_{i} x_{it} + \phi_i + \tau_i + \varepsilon_{it},\ i = 1, ..., N, t = 1, ..., T \tag{5.1}$$

where i and t denotes country and time period, β_i's are homogenous within a group, but heterogenous across groups represents long-run cointegrating relations and x_{it} is $p \times 1$ vector of slope coefficients for country i is represented by β_i^0 , ϕ_i and τ_i are individual fixed and time effects. Now a latent country specific group structure is imposed on the β_i^0

$$\beta_i^0 = \begin{cases} \alpha_1^0, \text{if } i \in G_1^0 \\ . \\ . \\ \alpha_K^0, \text{if } i \in G_K^0 \end{cases} \tag{5.2}$$

where, $\alpha_j^0 \neq \alpha_k^0$ for any j≠k, $\bigcup_{k=1}^{K} G_k^0 = 1, 2, ...N$ and $G_k^0 \bigcup G_j^0 = \emptyset$ for any j≠k, we assume the number of groups to be known and the members at this instance, and we calculate the number using an Information criterion as following SSP (2016) as described later.

B. Methodology

After eliminating individual fixed effects and time effects from (5.3) by following Hsiao (2003),[Chapter 3.6] (Lu and Su, 2017, Wang, Phillips, and Su, 2018) we obtain

$$\tilde{y}_{it} = \beta_i' \tilde{x}_{it}' + \tilde{\tau}_t + \tilde{\varepsilon}_{it} \tag{5.3}$$

where $\tilde{\varepsilon}_{it} = \varepsilon_{it} - \bar{\varepsilon}$, $\tilde{\tau}_t = \tau_t - \bar{\tau}$ and $\bar{\tau} = T^{-1} \sum_{t=1}^{T} \tau_t$. So we eliminate $\tilde{\tau}_t$ from (5.3)

$$\ddot{y}_{it} = \beta_i' \tilde{x}_{it} - \frac{1}{N} \sum_{j=1}^{N} \beta_j' \tilde{x}_{jt} + \ddot{\varepsilon}_{it} \tag{5.4}$$

where $\ddot{y}_{it} = y_{it} - \bar{y}_{i}. - \bar{y}_{\cdot t} + \bar{y}$, $\bar{y}_{\cdot t} = \frac{1}{N} \sum_{i=1}^{N} y_{it}$, $\bar{y} = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} y_{it}$ also $\ddot{u}_{it}$, $\bar{u}_{\cdot t}$and $\bar{u}_t$ are similarly defined.

We assume the number of groups, as K_0 and proceed, later we calculate the number as described in the following section, so now we can estimate $\beta \equiv (\beta_1^0, ..., \beta_N^0)$ and $\alpha_{K_0} \equiv (\alpha_1^0, ..., \alpha_{K_0}^0)$ by minimizing from SSP(2016)

$$Q_{2NT,\lambda}^{K_0}(\boldsymbol{\beta}, \boldsymbol{\alpha}_{k0}) = Q_{2,NT}(\boldsymbol{\beta}) + \frac{\lambda}{N} \sum_{i=1}^{N} \prod_{k=1}^{K_0} ||\beta_i - \alpha_k|| \tag{5.5}$$

where,

$$Q_{2NT}(\boldsymbol{\beta}) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\ddot{y}_{it} - \beta_i'\tilde{x}_{it} + \frac{1}{N}\sum_{J=1}^{N}\beta_j'\tilde{x}_{jt}\right) \tag{5.6}$$

Then post-Lasso estimates can be obtained easily, by pooling all the observations within each estimated group and then estimating the group-specific parameters for each group separately after individuals are demeaned over-time and across individuals. So that the standard error for each group-specific estimates can be worked out.

C. The Information criteria

The tuning parameter, λ, is chosen following SSP (2016), $\lambda = c\ s_Y^2\ T^{-1/3}$, where s_Y is the sample standard deviation of Y_{it} and c is some constant. We use three different values of c (0.05, 0.10, 0.20, 0.25) to examine the sensitivity of the results to c (thus λ). By assuming K is upper-bounded by K_{MAX}, we choose K by minimizing the following information criterion (IC)

$$IC(K,\lambda) = ln[(\hat{\sigma}^2_{(K,\lambda)}] + K_p + \frac{1}{\sqrt{NT}} \tag{5.7}$$

5.4 Empirics and data

In accordance with the previous literature we follow a simple dynamic model, to explain the relationship for the EKC model.

$$y_{it} = \alpha_i + \beta_{1i} y_{it-1} + \beta_{2i} x_{i,t} + \epsilon_{it} \tag{5.8}$$

Where y_{it} can be denoted by environmental quality indicator of i-th individual at t-th time period and x_{it} can be denoted by a vector of p×1 explanatory variables, α_i is the fixed effect and ϵ_{it} is an idiosyncratic error term.

We choose to use carbon dioxide emission per-capita as our environmental quality indicator and per-capita gross domestic product and per-capita renewable energy consumption as our explanatory variables.

$$co_{i,t} = \alpha_i + \beta_{1i} lco_{i,t-1} + \beta_{2i} gdp_{i,t} + \beta_{3i} ren_{i,t} + \varepsilon_{i,t} \tag{5.9}$$

Where co stands for log of per-capita Carbon dioxide emission in tonnes, gdp stands for log of per-capita Gross domestic product at ppp terms in constant 2005 United

States billion dollars, ren refers to per-capita renewable energy consumption in thousand tonnes of oil equivalent Refer to Table 5.2 reports the descriptive statistics. We use annual data for a list of countries (see Table 5.1 for details) for a period of 1971-2015.

Table 5.1: List of countries in our sample

Argentina	Greece	Norway
Australia	India	Portugal
Austria	Indonesia	Singapore
Belgium	Ireland	South Africa
Brazil	Israel	Spain
Canada	Italy	Sweden
Chile	Japan	Switzerland
China	Korea	Turkey
Denmark	Malaysia	United Kingdom
Finland	Mexico	United States
France	Netherlands	
Germany	New Zealand	

We also use per-capita total primary energy consumption in million tonnes of oil equivalent represented by tpes instead of per-capita renewable energy consumption to find out the difference in between the two and (5.9) takes of the following form

$$co_{i,t} = \alpha_i + \beta_{1i} lco_{i,t-1} + \beta_{2i} gdp_{i,t} + \beta_{3i} tp_{i,t} + \varepsilon_{i,t} \tag{5.10}$$

Data for Carbon dioxide emission, GDP in 2005 PPP USD billions and TPEC in million tonnes of oil equivalent along with population in millions to convert data in per-capita terms were acquired from IEA (IEA, 2017) and Renewable Energy consumption in million tonnes of oil equivalent were collected from OECD (OECD, 2018a). Figure 5.1 and figure 5.2 gives a better picture of the nexus in between our variables.

5.5 Results

A. Cross-sectional dependence

To understand the nature of cross-section in between our variables, we use Pesaran (2004), Pesaran (2015a) the results are depicted in Table 5.3, the null hypothesis being strict cross-sectional independence, which is rejected for all the concerned variables.

Table 5.2: Descriptive Statistics

Stats	co	gdp	ren	tp
Mean	1.703292521	2.944506161	12.09826655	0.921676156
Median	1.906508231	3.168719138	12.14258311	1.084635511
S.D.	0.822766457	0.830660445	1.496333641	0.758474987
Skewness	-1.164539894	-1.604199548	-1.003505798	-0.806301671
Kurtosis	1.382695094	3.155450364	1.828957014	0.101800116
Minimum	3.096898003	4.363983164	14.91524298	2.139484098
Maximum	-1.543182117	-0.730293777	5.547263944	-1.317134987

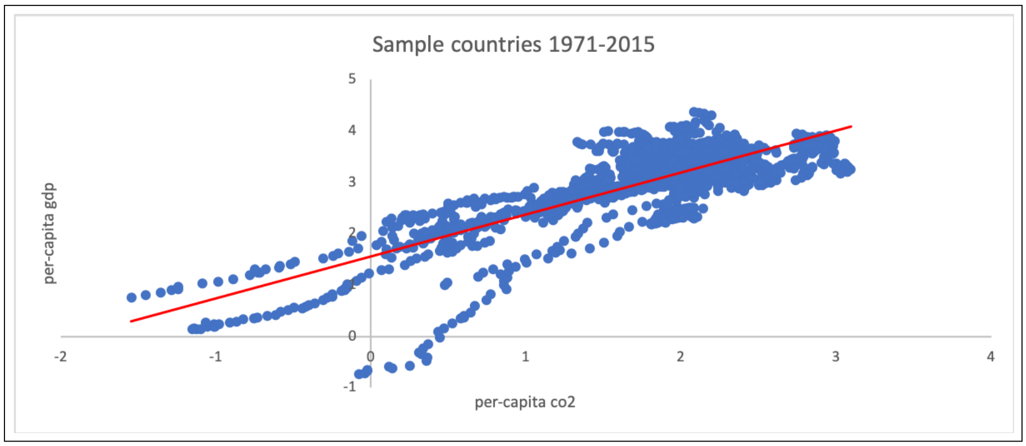


Figure 5.1: CO2-GDP nexus: 1971-2015 in logarithmic scale

Table 5.3: CD Results- I

Var.	CD-test	p-value	mean ρ	mean abs (ρ)
co	32.519	0.000	0.20	0.62
gdp	144.463	0.000	0.91	0.91
ren	62.172	0.000	0.39	0.68
tp	91.101	0.000	0.57	0.70

B. Unit root tests

Table 5.4 reports the outcomes of three first-generation unit root tests with cross-sectionally demeaned data Im, Pesaran, and Shin (2003) along with first-difference of each variable, we use BIC lags for each case.

To understand the non-stationarity in a multi-factor error structure framework we then apply Pesaran (2007) and Pesaran, Vanessa Smith, and Yamagata (2013) and like the previous case, the variables become stationary at first difference, the reports are presented in Table 5.5, we choose 3 lags, following the literature which sets lag

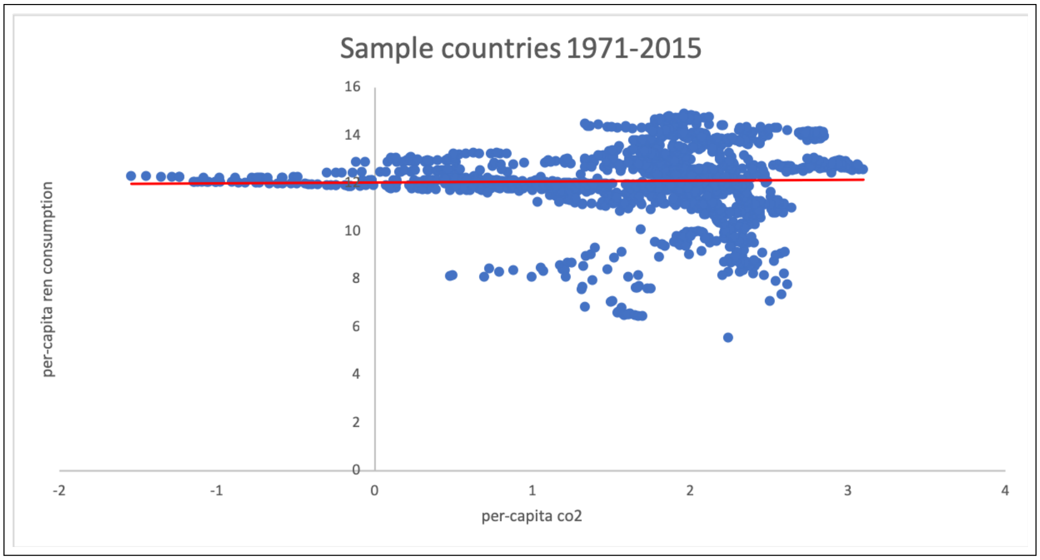


Figure 5.2: CO2-REN nexus: 1971-2015 in logarithmic scale

Table 5.4: Second generation Panel Unit root tests- I

Variable	Statistic	p-value
co	1.4724	0.9295
gdp	6.3442	1.00
ren	3.5853	0.998
tp	3.0232	0.9987
dco	-33.6143	0.000
dgdp	-20.7582	0.000
dren	-37.490862	0.000
dtp	-37.2535	0.000

equal to integer of $T^{1/3}$, in our case T = 45, and so the lag length becomes 3.

Table 5.5: Second generation Panel Unit root tests- II

Variable	t-bar	Z[t-bar]	p-value
co	-1.354	2.582	0.995
gdp	-1.903	-0.827	0.204
ren	-1.822	-0.322	0.374
tp	-1.713	0.352	0.638
dco	-3.266	-9.281	0.000
dgdp	-2.778	-6.252	0.000
dren	-3.319	-9.611	0.000
dtp	-3.058	-7.988	0.000

C. Cointegration

After checking for stationarity we focus on cointegration relationship among our variables, and we apply Westerlund (2007), Persyn and Westerlund (2008) to understand the order of integration among our variables. Table 5.6 represents the cointegration relationship among co, gdp and ren and Table 5.7 represents cointegration relationship between co, gdp and tp. We choose 3 lags, 3 leads and 1000 bootstrap replications.

Table 5.6: Cointegration Results- co, gdp, ren

Statistic	Value	Z-value	P-value	Robust P-value
G_τ	-1.947	4.032	1.000	0.841
Ga	-5.236	6.678	1.000	1.000
P_τ	-9.563	4.186	1.000	0.655
Pa	-4.273	5.361	1.000	0.963

We conclude with presence of cointegration among our variables for both the cases. The mean-group test (G_τ) averages heterogeneous OLS estimates of the speed of adjustment of their standard errors, while the panel test (P_τ) provides estimates of the aggregate speed of adjustment and its standard error.

Table 5.7: Cointegration Results- co, gdp, tp

Statistic	Value	Z-value	P-value	Robust P-value
G_τ	-1.999	3.673	1.000	0.737
Ga	-6.480	5.689	1.000	0.993
P_τ	-10.095	3.596	1.000	0.516
Pa	-4.474	5.187	1.000	0.807

As because both G_τ and P_τ distributions assume error-correction models and are independently distributed, so one can say that the tests take into consideration of cross-sectional dependence by bootstrapped standard errors.

D. Group Selection

Group selection is one of the most important criteria in this kind of estimation technique, we select the number of groups following, Lin and Ng (2012), SSP 2016. The exact number of groups are typically unknown but a finite integer K_{max} is assumed which is considered to be an upper bound to the true number of groups K_0. The tuning parameter is chosen as $\lambda = c\lambda \times T^{-3/4}$ where c takes five candidates 0.05, 0.10, 0.15, 0.20 and 0.25. We fix K_{max} arbitrarily at 7.

Table 5.8: Number of Groups: Equation 5.9

	c = 0.05	c = 0.10	c = 0.15	c = 0.20	c = 0.25
K = 1	-1.5658	-1.5658	-1.5658	-1.5658	-1.5658
K = 2	-1.6431	-1.6431	**-1.6971**	-1.6800	-1.6800
K = 3	-1.6360	-1.6047	-1.6166	-1.6249	-1.6249
K = 4	-1.5754	-1.5686	-1.5770	-1.4620	-1.6001
K = 5	-1.4860	-1.4839	-1.5178	-1.5218	-1.4909
K = 6	-1.4717	-1.4621	-1.4365	-1.4483	-1.4546
K = 7	-1.3833	-1.3944	-1.2729	-1.2870	-1.4824

For each combination of the number of groups and the tuning parameter c, we compute the information criterion value accordingly. The results are reported in table 5.8 & 5.9.

Table 5.9: Number of Groups: Equation 5.10

	c = 0.05	c = 0.10	c = 0.15	c = 0.20	c = 0.25
K = 1	-1.7137	-1.7137	-1.7137	-1.7137	-1.7137
K = 2	-1.6905	-1.6905	-1.6905	-1.7144	**-1.7984**
K = 3	-1.6365	-1.6492	-1.6573	-1.6746	-1.6760
K = 4	-1.5805	-1.5805	-1.5946	-1.6008	-1.6189
K = 5	-1.4971	-1.5290	-1.5654	-1.5654	-1.5677
K = 6	-1.5187	-1.5089	-1.5143	-1.5143	-1.5232
K = 7	-1.4467	-1.4577	-1.4631	-1.4631	-1.4721

In both the case we conclude with 2 latent groups, i.e. the minimum value for the I.C (Information Criteria).

E. PLS estimation results

We now present the results of post-Lasso regression for each group along with fixed effects for both equation (5.9) and equation (5.10) as presented in Table 5.10 and Table 5.12. The results in Table 5.10 suggest, the estimate for the coefficient of gdp is always positive and significant for both the groups and the pooled regression. For lagged carbon dioxide values the coefficients also follow similar pattern. However, for renewable energy consumption the pooled regression and Group 2 coefficients are of negative magnitude and without any level of significance, for Group 1 the coefficient is positive with 1% level of significance.

The report for the classification results for based on equation (5.9) are depicted in Table 5.11, two groups are computed from the technique and the first group

Table 5.10: PLS estimation results: Equation 5.9

Variables	Pooled FE	Group 1	Group2
gdp	0.0404*** (0.0301)	0.54421*** (0.056204)	0.051668** (0.055458)
ren	-0.0166 (0.0193)	0.0077604* (0.016652)	-0.033307 (0.046728)
lagged co	0.9886*** (0.0192)	0.44074*** (0.046442)	0.94265 *** (0.033615)

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

Table 5.11: GROUP: Equation 5.9

Group 1 membership = **21**	**Argentina**, **Australia**, **Austria**, **Brazil**, **Chile**, **China**, **Greece**, **India**, **Indonesia**, **Israel**, **Japan**, **Korea**, **Malaysia**, **Mexico**, **New Zealand**, **Norway**, **Portugal**, **Singapore**, **South Africa**, **Spain**, **Turkey**
Group 2 membership = **13**	**Belgium**, **Canada**, **Denmark**, **Finland**, **France**, **Germany**, **Ireland**, **Italy**, **Netherlands**, **Sweden**, **Switzerland**, **United Kingdom**, **United States**

comprised of 21 members and the second group of 13 members. Strangely except for some countries most of the EU countries along with United States and Canada belong to Group 2. Additionally, the fact that the coefficient of renewable energy consumption in long-run has a negative value and is not significant is a very important contribution from our research.

Table 5.12: PLS estimation results: Equation 5.10

Variables	Pooled FE	Group 1	Group 2
gdp	-0.1575 (0.0249)	-0.16731*** (0.032995)	-0.1583 (0.055516)
tp	0.2522*** (0.0390)	0.07158*** (0.04822)	-0.010036 (0.041428)
lagged co	0.8726*** (0.0290)	0.42737*** (0.043904)	0.94521 *** (0.050246)

[Values inside parenthesis indicates values for standard errors. Symbols ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.]

The results in Table 5.12 suggest, the estimates for the coefficient of gdp is always negative and only significant for Group 1. For total primary energy consumption the estimates of coefficients are positive with 10% significance level for both Pooled FE and Group 1 but for Group 2 the coefficient value is negative and not significant. The lagged co values are similar with the results of equation (5.9) are always positive and significant at 10% level.

Table 5.13: GROUP: Equation 5.10

Group 1 membership = **26**	**Argentina**, **Australia**, **Austria**, **Brazil**, **Chile**, **China**, **Denmark**, **Finland**,**Greece**,**India**, **Indonesia**, **Ireland**, **Israel**, **Italy**, **Japan**, **Korea**, **Malaysia**, **Mexico**, **Netherlands**, **New Zealand**,**Norway**, **Portugal**, **Singapore**, **Spain**, **Turkey**, **United States**
Group 2 membership = **8**	**Belgium**, **Canada**, **France**, **Germany**, **South Africa**, **Sweden**, **Switzerland**, **United Kingdom**

The report for the classification results for based on equation (5.10) are depicted in Table 5.13, two groups are computed from the technique and the first group same as before 26 members and the second group of 8 members. There is also a significant amount of change in membership from Table 5.11, in this case South Africa moves to Group 2 from Group 1, but Denmark, Finland, Italy, Netherlands, USA move to Group 1 from Group 2 when compared between the two equations (5.9) and (5.10).

5.6 Conclusion

This paper revisits the EKC literature by applying a new novel econometric C-Lasso methodology to provide data determined approach to the classification of countries into common groups. A panel structure model is used to capture the inherent heterogeneity across countries and the C-Lasso mechanism determines the group membership and the estimates for each group.

We find some definitive group patterns and substantial heterogeneity in types of energy consumption (renewable and total) with both positive and negative effects manifesting in data. The results provide new viewpoint about potential impacts in the EKC literature that might be relevant to policy makers.

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