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Economic Growth, Energy Consumption, and Environment: Assessing Evidence from OECD Countries

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Dedicated to

Rodin Yousefi

My Son

Declaration

This dissertation was written while I was studying in the School of Economics and Finance, Curtin Business School at Curtin University of Technology. To the best of my knowledge and belief, this thesis contains no material previousely published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

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Date: _________________________

A Note of Gratitude

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ABSTRACT

The importance of energy in economic growth and industrial development is universally recognised. However, energy consumption and the resulting enhanced greenhouse gas emissions are thought to have led to a series of natural disasters. Since renewable energy technologies generate far lower emissions of greenhouse gases compared with fossil fuels, one way to reduce carbon dioxide (CO_2) emissions is to replace energy from fossil fuels with energy from renewables. Therefore, the main objective of this thesis is to identify the determinant factors of renewable and non-renewable energy consumption in 29 OECD countries. It also analyses and compares the impacts of renewable and non-renewable energy consumption on economic growth and CO_2 emissions.

Estimating the relationship between renewable and non-renewable energy consumption and economic growth shows that both energy sources stimulate economic growth in OECD countries. However, comparing their effects confirms that non-renewables are still the dominant source of energy utilised in the process of economic growth. The causality results show that there is bidirectional causality between economic growth and both renewable and non-renewable energy consumption in the short run and long run. This finding confirms the feedback hypothesis which implies that a high level of economic growth leads to high level of consumption in both renewable and non-renewable energy and vice-versa.

Finding non-renewable energy consumption being the dominant energy source motivates this research to investigate which type of non-renewable energy source (oil, natural gas or coal) is more important for economic growth. The results reveal that oil and natural gas consumption have a positive and statistically significant impact on economic growth. Against the policies that attempt to slow the growth in oil consumption, it is still the dominant fuel in the economic growth process. That there is no significant relationship between coal consumption and economic growth may be due to emerging policies that try to curb pollutant emissions by imposing an extra cost on the use of higher-carbon fuels. Natural gas that remains second position behind oil has an important feature in that it generates less carbon emissions compared with the other fossil fuels. Thus, fuel transformation at least from coal and/or oil to natural gas should be taken into account by policymakers.

The empirical estimation of the effects of urbanisation and population density on renewable and non-renewable energy consumption suggests that urbanization has a positive impact on non-renewable energy consumption while population density has a negative impact. This implies that increasing density results in a reduction in non-renewable energy consumption. The lack of existence of a significant association between renewable energy use and urbanisation and also between renewable energy use and population density illustrate that although the use of renewable energy sources has increased recently in developed countries, the main energy source available for people to use in OECD countries is still non-renewable fossil fuels.

According to an analysis of the impact of renewable and non-renewable energy consumption on CO_2 emissions, it is found that while non-renewable energy consumption increases CO_2 emissions, renewable energy consumption decreases CO_2 emissions. Thus, increases in the level of renewable energy usage can contribute to reducing pollutant emissions in OECD countries.

Investigation of the relationship between urbanisation and emissions provides support for the existence of an environmental Kuznets curve between urbanisation and CO_2 emissions, implying that at higher levels of urbanisation, environmental impact decreases. Therefore, overall evidence implies that the policy makers should focus more on urban planning as well as clean energy development to make a substantial contribution not only to non-renewable energy use reduction but also to climate change mitigation.

Key Words: Renewable energy consumption, Non-renewable energy consumption, CO_2 emissions, Urbanisation, STIRPAT model.

JEL Classification: C22, C32, Q21, Q43, Q48

ACRONYMS

ADF	Augmented Dickey-Fuller
ARDL	Autoregressive Distributed Lag
AIC	Akaike Information Criterion
AMG	Augmented Mean Group
AUT	Austria
AUS	Australia
BTU	British Thermal Units
BP	British Petroleum
BEL	Belgium
BRA	Brazil
CO_2	Carbon Dioxide
CCE	Common Correlated Effects
CHN	China
CZE	Czech Republic
CAN	Canada
DEA	Data Envelopment Analysis
DEU	Germany
DOLS	Dynamic Ordinary Least Square
DNK	Denmark
ECM	Error Correction Model
EKC	Environmental Kuznets Curve
EU	European Union
EIA	Energy Information Administration
EST	Estonia
ESP	Spain
FMOLS	Fully Modified Ordinary Least Square
FIN	Finland

FRA	France
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GNP	Gross National Product
GNI	Gross National Income
GMM	Generalised Method of Moments
GBR	Great Britain
G7	Group of Seven
HUN	Hungary
IEA	International Energy Agency
IMF	International Monetary Fund
ITA	Italy
ISL	Iceland
IRL	Ireland
IND	India
IPCC	Intergovernmental Panel on Climate Change
ISR	Israel
IPS	Im, Pesaran and Shin
JPN	Japan
KOR	Korea, South
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LUX	Luxembourg
LLC	Levin, Lin and Chu
LCO_2	Log of Carbon Dioxide
LGDP	Log of Gross Domestic Product
LIV	Log of Industrial Value Added
LF	Log of Labour Force
LK	Log of Capital
LR	Log of Renewable Energy Consumption

LN	Log of Non-Renewable Energy Consumption
LCO	Log of Coal Consumption
LOIL	Log of Oil Consumption
LNG	Log of Natural Gas Consumption
LP	Log of Total Population
LPD	Log of Population Density
LIND	Log of Industrialisation
LA	Log of GDP per capita
LS	Log of Service Sector in GDP
LU	Log of Urbanisation
LU^2	Squared Term of Urbanisation
LEI	Log of Energy Intensity
LA^2	Squared Term of GDP per capita
MEX	Mexico
NZL	New Zealand
NOR	Norway
OECD	Organisation for Economic Co-Operation and Development
OLS	Ordinary Least Square
PP	Phillips and Perron
POL	Poland
PPPs	Purchasing Power Parities
REN21	Renewable Energy Policy for the 21st Century
RUS	Russian Federation
SIC	Schwarz Information Criterion
SO_2	Sulphur Dioxide
SVK	Slovakia
SWE	Sweden
TUR	Turkey
UN	United Nations

UNDP	United Nations Development Programme
UNEP	United Nations Environment Program
UNIDO	United Nations Industrial Development Organisation
USA	United States
UK	United Kingdom
VIF	Variance Inflation Factors
WLD	World

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Chapter 1

INTRODUCTION

1.1 Background

Energy is recognised as a fuel for economic growth and industrial development. Energy along with other factors of production (such as labour and capital) is a vital input and necessary requirement for economic and social development (Ghali and El-Sakka 2004). In fact, energy industry through its vital products, which serve as inputs into nearly every good and service in the economy, acts as a contribution to sustainable economic growth (World Economic Forum 2012). Since the beginning of industrialisation, the rapid pace of economic growth in most countries has been accompanied by a large consumption of energy. Industrialisation by increasing wages and accelerating urbanisation creates an additional boost in energy demand. For instance, in China, energy consumption increased by more than 150% over the past ten years and China turned out to be the world's largest consumer of energy in 2010, surpassing the US (The World Bank 2011). However, the use of energy, especially fossil fuels as the major energy sources has many adverse environmental effects. The consumption of energy in terms of non-renewables[1] is a significant contributor to stationary energy greenhouse gas (GHG) emissions. Greenhouse gases are potentially essential to keep the earth's temperature warm. However, extra greenhouse gases, which are caused by man-made activities, absorb more and more heat and cause global warming[2]. Global warming causes climate change, which is one of the greatest challenges facing policy makers at every level, from global and international to national, regional and local. Global climate change threatens to disrupt the well-being of society, undermine economic development and alter the natural environment, making it a key policy concern of this century.

For a number of years, developed countries have caused a large accumulation of greenhouse gases due to their mode of production and way of life. The bulk of

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[1] The terms of "non-renewables" or "non-renewable energy" and "fossil fuels" are used interchangeably in this thesis.

[2] "Global warming is an average increase in the temperature of the atmosphere near the Earth's surface and in the troposphere, which can contribute to changes in global climate patterns. Global warming can occur from a variety of causes, both natural and human induced" (Intergovernmental Panel on Climate Change (IPCC) 2007).

greenhouse gas emissions in developed countries originate from their energy, industrial and transport sectors. In OECD countries[3], a total of 83.6% of GHG emissions are generated from energy consumption, of which 36.5% are from electricity and heating, 12.8% are from manufacturing and construction, and 22.7% are from transport (OECD 2011).

Carbon dioxide (CO_2) from energy represents 83% of the anthropogenic GHG emissions for Annex I countries[4] (IEA 2012). According to The Intergovernmental Panel on Climate Change (IPCC 2007), it is estimated that to stabilise global temperatures at 2ºC above pre-industrial levels, global GHG emissions in 2050 should be reduced to at least 50% below 2000 levels. This could imply reductions of up to 80% by 2050 for OECD countries. This is an enormous challenge and cannot be met without taking significant actions and proper planning. There are many types of policies either already enacted or under consideration by countries. For instance, the Kyoto Protocol commits industrialised countries, including members of the OECD, to curb domestic emissions by about 5% relative to 1990 by the 2008–2012 first commitment period. Alongside the agreement to negotiate a new climate agreement by 2015, certain countries have agreed to take commitments under a second commitment period of the Kyoto Protocol to begin in 2013 (IEA 2012). There are some climate actions that can be taken into account to achieve pollutant emissions reductions. For instance, expanding the use of renewable sources is recognised as a key solution to climate change problem. Nevertheless, replacing fossil fuels with

[3] The Organisation for Economic Co-operation and Development (OECD) is a multi-disciplinary intergovernmental organisation, tracing its roots back to the post-World War II Marshall Plan (1961). Today, it comprises 34 member countries that are committed to democratic government and the market economy and the European Commission, with the major emerging economies increasingly engaged directly in the work. The OECD provides a unique forum and the analytical capacity to assist governments to compare and exchange policy experiences, and to identify and promote good practices through policy decisions and recommendations. OECD member countries are Australia, Austria, Belgium, Canada, Chile, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States (OECD 2011).

[4] The Annex I Parties to the 1992 UN Framework Convention on Climate Change (UNFCCC) are: Australia, Austria, Belarus, Belgium, Bulgaria, Canada, Croatia, the Czech Republic, Denmark, Estonia, the European Economic Community, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Latvia, Lichtenstein, Lithuania, Luxembourg, Malta, Monaco, the Netherlands, New Zealand, Norway, Poland, Portugal, Romania, the Russian Federation, the Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, the United Kingdom and the United States.

renewable energy sources is very challenging because these energy sources have a lower energy density and are generally more expensive. Therefore this issue requires more investigation.

1.2 Research Justification and Questions of the Thesis

After numerous studies exploring the link between economic growth, energy consumption and CO_2 emissions, it is still the challenge of recent work. The reason is that energy has an essential role in economic activities and performs a key tool for sustainable development. However, concerns about continuation of dependence on non-renewable energy sources, which are the main cause of climate change, has attracted attention of governments to consider and adopt a wide range of policies to reduce emissions of CO_2. In this regard, OECD countries have been pioneers as they have achieved some progress, albeit limited, in reducing CO_2 emissions by improving efficiency of energy and curbing energy use in recent years. However, cutting emissions requires further efforts and investigations to enable the OECD to achieve such prospective goal. This research tries to identify specific policies and mechanisms that can help the OECD in their response to climate change. Focusing on the OECD in this study is also motivated by the fact that their energy policies and emissions mitigation actions have impacts on developing countries.

The issue of the relationship between energy consumption, economic growth and CO_2 emissions has been relatively well-studied for OECD countries in the literature. However, the empirical outcomes of these studies have been varied and conflicting. These diverse results might be due to using different time periods, different variables and different econometric methodologies (Ozturk 2010). This study contributes to the existing literature on the relationship between energy consumption, economic growth and CO_2 emissions in OECD countries on several fronts. First, it includes a larger dataset in the analysis than earlier studies. Second, since bivariate analysis is widely criticised for omitted variable bias, this study applies a multivariate framework in the analytical parts. Third, it utilises recent panel techniques that allow for the heterogeneous unobserved parameters and cross-sectional dependence. Fourth, unlike earlier studies, this study takes into account some important diagnostic tests such as serial correlation, heterogeneity and cross-section dependence that failing to check them can result in misleading inference and inconsistent estimated coefficients.

Finally, a panel stationarity hypothesis allowing for structural breaks is tested, something that has generally ignored previously.

The objective of the research presented in this thesis is to compare the effects of non-renewable and renewable energy sources on economic activities to find whether economic growth benefits from substituting renewable energy for non-renewable energy sources. This research also identifies the factors that stimulate or dissuade the use of renewable and non-renewable energy sources. In addition, this study analyses the impacts of renewable and non-renewable energy consumption on CO_2 emissions to realise whether renewable energy is an effective contributor to emissions mitigation compared with non-renewables.

Given this prelude, this research addresses the following research questions:

i. How does renewable energy consumption, in comparison with non-renewable energy consumption affect economic growth?

ii. Which type of non-renewable energy source has the greatest impact on economic growth and can be replaced by renewable energy sources?

iii. What are the factors that influence renewable and non-renewable energy consumption?

iv. Does renewable energy consumption contribute to CO_2 emissions mitigation?

1.3 Organisation of the Thesis

After the introduction chapter, this thesis is organised as follows: Chapter 2 provides a brief overview of the trends of renewable and non-renewable energy consumption, GHG and CO_2 emissions, economic growth, total population and urbanisation in OECD countries and compares the growth trends in OECD countries with the growth trends in other regions.

Chapter 3 analyses the impacts of renewable and non-renewable energy consumption alongside real gross fixed capital formation and labour force on output based on a neoclassical economic growth model, namely Cobb-Douglas production function. This chapter also decomposes non-renewable energy sources to coal, oil and natural gas, to show that which type of non-renewable energy sources has the greatest or the least effect on economic growth and industrial output in OECD countries. Dynamic ordinary least squares model is applied to estimate the long-run relationship between the variables. In addition, the causal relationship between the variables is tested by applying the Generalized Method of Moments (GMM) dynamic panel model.

Chapter 4 first identifies the factors that influence energy consumption based on a stochastic model, namely STIRPAT (STochastic Impacts by Regression on Population, Affluence, and Technology). Second, it investigates the effects of the factors of interest, including urbanisation, total population, population density, economic output, industrialisation and tertiarisation, on renewable energy consumption and non-renewable energy consumption in two separate models. The estimation method used in this chapter is Common Correlated Effects (CCE) introduced by Pesaran (2006). The chapter provides the Granger causality test in a panel vector error-correction model.

Chapter 5 assesses the relationship between CO_2 emissions and renewable and non-renewable energy consumption under the STIRPAT model. This chapter also looks at the relationship between urbanisation and CO_2 emissions by emphasising on the Environmental Kuznets Curve (EKC) hypothesis. The chapter employs a recently developed estimator, namely the Augmented Mean Group (AMG) by Eberhardt and Teal (2010) to estimate the long-run coefficients of the variables. In addition, the Granger causality test is performed to detect the direction of causality between the variables.

Chapter 6 presents key findings and draws main policy implications. It also discusses the limitations of the study and suggests directions of future research.

Chapter 2

ECONOMIC GROWTH, ENERGY SOURCES, EMISSIONS AND URBANISATION IN OECD COUNTRIES

2.1 Introduction

This chapter provides a brief overview of the consumption trend of different types of energy sources (non-renewables and renewables) in OECD countries and compares them with global levels and levels in other regions of the world. Moreover, the trends in factors such as economic growth, urbanisation and CO_2 emissions that are closely linked to energy consumption are also reviewed.

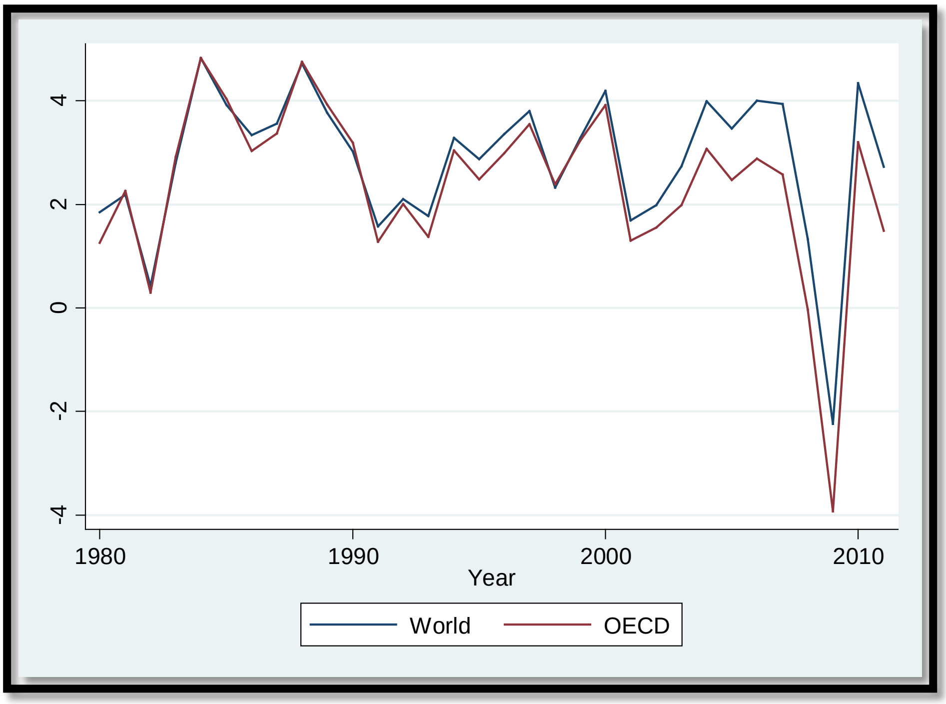
The structure of the rest of the chapter is as follows: Section 2.2 provides an overview of economic growth in OECD countries. Section 2.3 reviews the trends in total energy consumption as well as renewable and non-renewable energy consumption. The growth trend in GHG and CO_2 emissions are discussed in Section 2.4. In Section 2.5 the trends in population and urbanisation growth are studied. Section 2.6 concludes the chapter.

2.2 Economic Growth

Economic growth is an important factor in reducing poverty and generating the resources necessary for human development and environmental protection. Economic growth is driven by many factors, including product, process and organizational innovations based on technological change. Economists usually measure economic growth in terms of gross domestic product (GDP) or related indicators, such as gross national product (GNP) or gross national income (GNI) which is derived from the GDP calculation. GDP is calculated from a country's national accounts which report annual data on incomes, expenditure and investment for each sector of the economy. Figure 2.1 shows the trend in growth of GDP in the world and OECD countries. World and OECD countries show an upward growth rate over the period 1980 to 2011, except for a decline in 2008 due to the economic slowdown caused by the global financial crises. The recession of 2008 had a profound effect on economic activity in most developed countries. Although some economies have slowly recovered, the follow-on effects are likely to be felt for some time. Growth forecasts for most developed countries have been lowered. Developed economies contracted by

2.7 per cent from 2007 to 2009, with the biggest falls in Europe. Australia was one of the few developed countries to avoid recession, with GDP growing by 3.6 per cent from 2007 to 2009 (IMF 2010). The International Monetary Fund (2010) expects that for the next few years, growth in OECD countries is likely to remain relatively weak, with even the possibility of periods of negative growth. It seems many parts of the developed world still face sluggish economic growth and risks from financial crises (UN 2011).

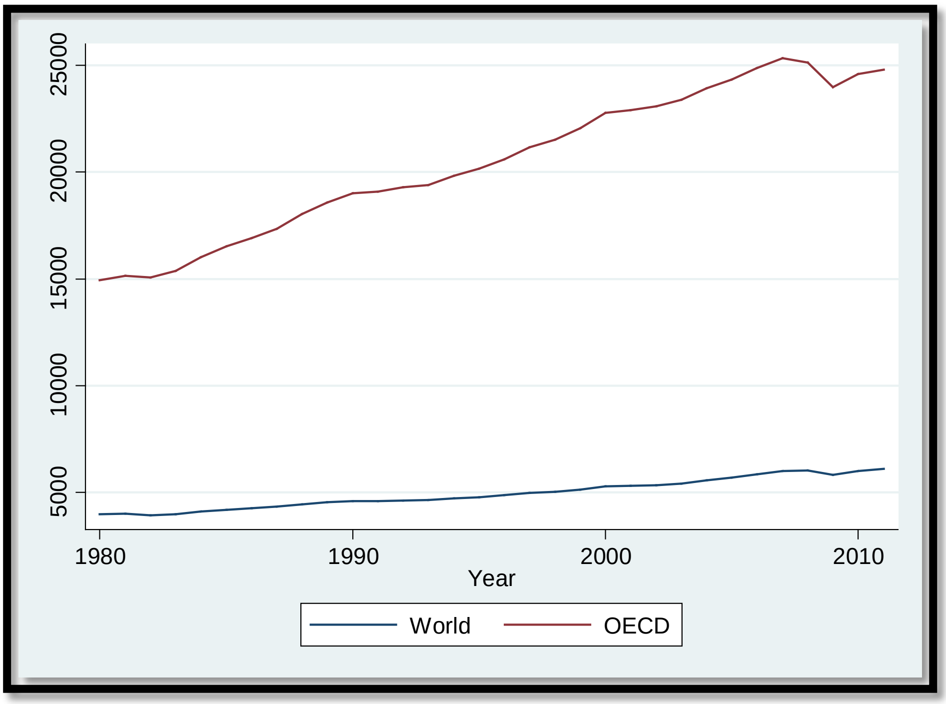
Figure 2.1: Growth of Real GDP by Region, 1980-2011
(average annual)



Data Source: World Bank (2012)

GDP per capita is a measure that results from GDP divided by the size of the nation's overall population. So in essence, it is theoretically the amount of money that each individual gets in that particular country. The GDP per capita provides a much better determination of living standards as compared to GDP alone. There is a strong correlation between GDP per capita and indicators of development such as life expectancy, infant mortality, adult literacy, political and civil rights, and some indicators of environmental quality. National income is naturally proportional to its population so it is only fitting that with the increase of the number of people, there is also an increase in GDP. However, it does not entirely mean that with high GDP, a high standard of living also results. A country with high GDP but with an overwhelmingly large population will result in a low GDP per capita; thus indicating a not so favourable standard of living since each citizen would only get a very small amount when wealth is being evenly distributed. A high GDP per capita, on the other hand, simply means that a nation has a more efficient economy. Comparing the real GDP per capita in the world and OECD countries illustrates that GDP per capita in the OECD is much higher than that of the world on average. While a positive linear trend in the annual GDP per capita is observed in OECD countries, GDP per capita follows a constant pattern in the world from the period 1980 to 2011 (Figure 2.2).

Figure 2.2: Growth of GDP per Capita by Region, 1980-2011
(average annual)



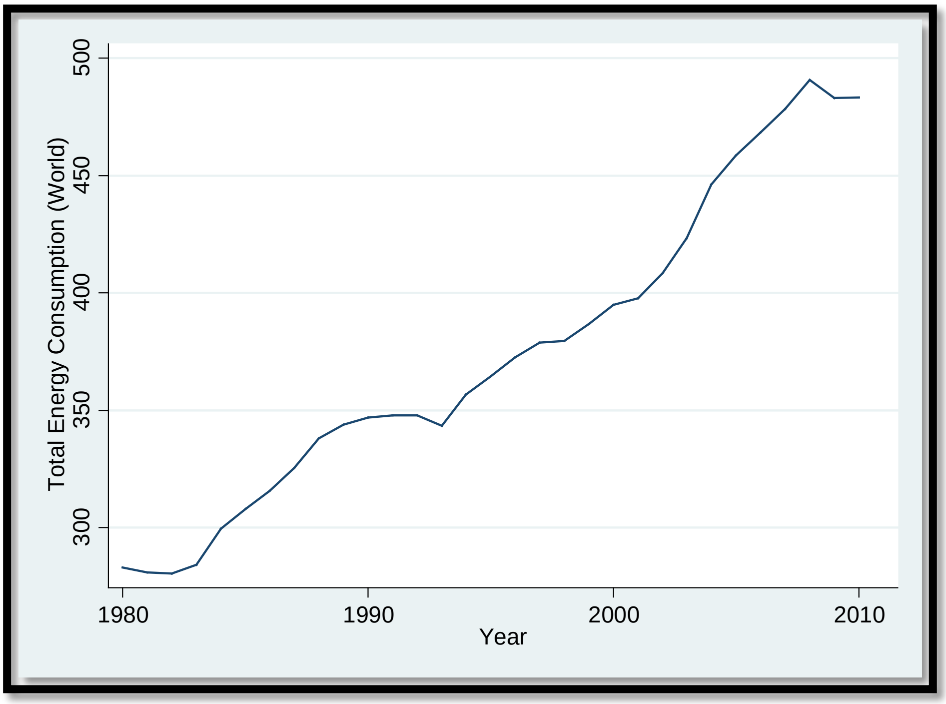
Data Source: World Bank (2012)

Worldwide economic growth and development are predominantly linked to the use of energy. The next section reviews the trend in energy consumption.

2.3 Energy Consumption

Energy is a vital factor in human life. Before the industrial revolution, humans relied on natural energy flows and animal and human power for heat, light and work and the per capita use of energy did not exceed 0.5 tonnes of oil-equivalent (toe) annually. Global total primary energy supply more than doubled between 1971 and 2010, mainly relying on fossil fuels (IEA 2012). Between 1850 and 2005, overall energy production and use grew more than 50-fold—from a global total of approximately 0.2 billion toe to 11.4 billion toe (IEA 2007). Most of this occurred in industrialised societies, which had come to rely heavily on the ready availability of energy. On a per capita basis, people in these societies now use more than 100 times the quantity of energy that was used by their ancestors before humans learned to exploit the energy potential of fire (UNDP 2000).

Figure 2.3: Total Energy Consumption in the World, 1980-2011
(quadrillion Btu)

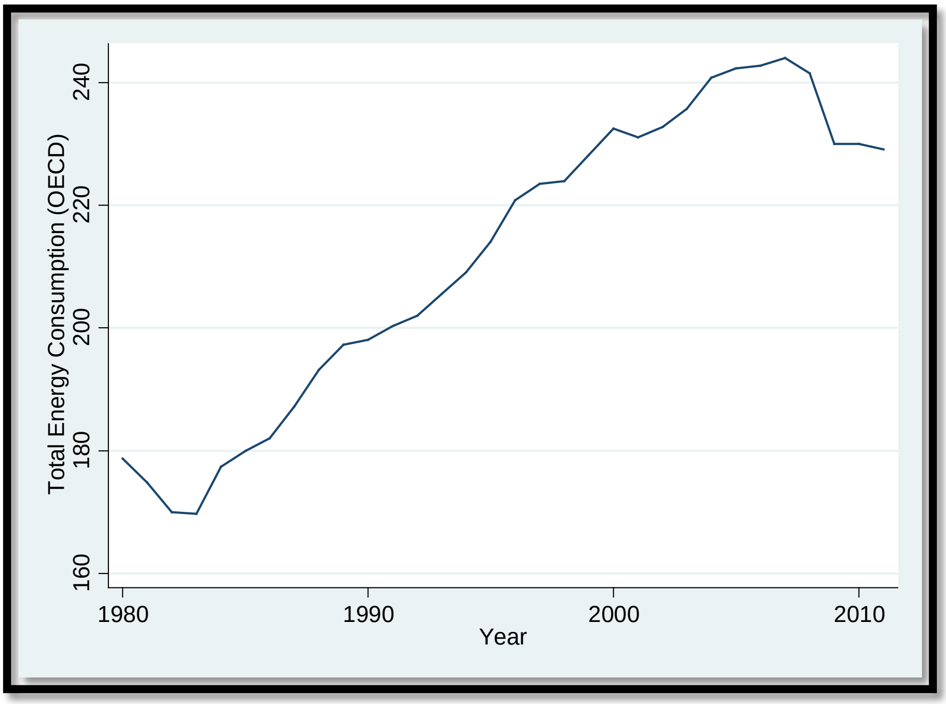


Data source: EIA (2012)

According to the Global Energy Statistical Yearbook 2011, global energy consumption rose by 2.5% in 2011, broadly in line with the historical average but well below the 5.1% seen in 2010. According to World Energy Use in 2011, after the strong growth noticed in 2010, global energy consumption increased at a much slower pace in 2011 (2.2% to 4.9%). While this slowdown was mainly due to the economic crisis that hit OECD countries, the record oil prices also played a role, limiting the growth in global oil consumption even in energy-hungry countries such as China and India. Figure 2.3 shows the rapid growth in energy consumption in the world for the period 1980 to 2011.

Consumption of energy in OECD nations was up due to a rebound of economic activities after the financial crisis of 2008 which caused a severe drop-off in demand in 2009 (IEA 2011a). Although energy consumption in OECD countries declined by 1.3% in 2011, they remained large energy consuming countries with 41% of total energy consumption. Figure 2.4 illustrates the trend in total energy consumption in OECD countries.

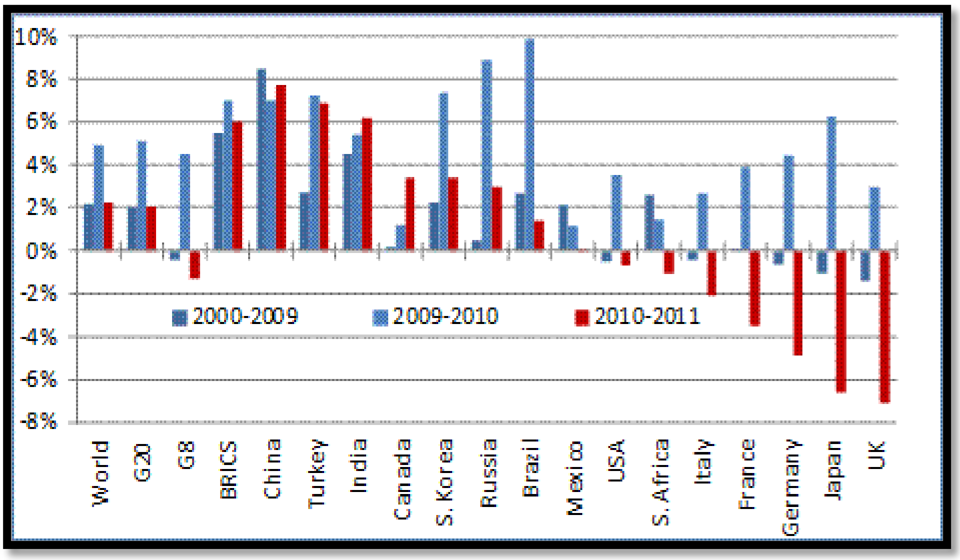
Figure 2.4: Total Energy Consumption in OECD Countries, 1980-2011 (quadrillion Btu)



Data source: EIA (2012)

The rate of decline in OECD countries was in line with the 3.2% drop in the European Union, 6.6% fall in Japan and 0.7% in the United States. In the European Union, the decline was the result of the combination of economic stagnation, soaring oil and gas prices and warm weather. Energy consumption dropped by 2.1% in Italy, 3.5% in France, 4.9% in Germany and 7.1% in the United Kingdom (Figure 2.5).

Figure 2.5: Growth in Energy Consumption in Selected Countries, 2000-2011 (%/year) (quadrillion Btu)



Source: Enerdata (2012)

In Japan, the Fukushima earthquake and tsunami of March 2011 had a dramatic impact on the energy consumption (-6.6%). Many coal-fired power plants were damaged by the earthquake leading to a 5.2% drop in coal consumption and nuclear power plants were stopped, boosting gas consumption (+12%). Electricity restrictions post-Fukushima also resulted in a 5% drop in power demand.

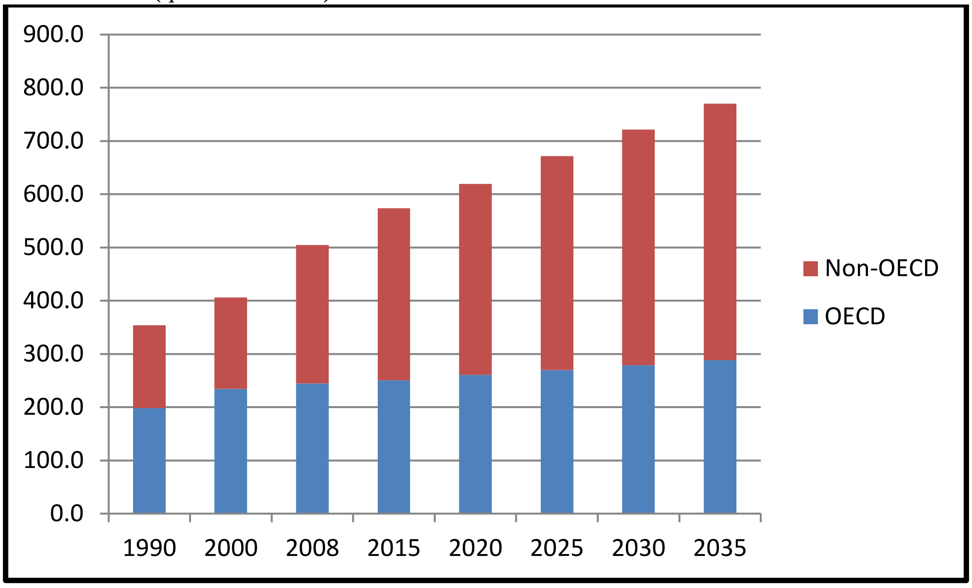
The total world energy consumption is expected to increase from about 421 quadrillion British thermal units (Btu) in 2003 to 470 quadrillion Btu in 2035 (83% increase) (Table 2.1). In 2005, the average per capita consumption of energy in the OECD countries was more than four times the per capita average in all non-OECD countries (IEA 2007). However, non-OECD energy consumption is predicted to surpass OECD energy use by the year 2015 (Table 2.1) (Figure 2.6). Furthermore, energy demand in the OECD economies will grow slowly over the projection period (2008-2035), at an average annual rate of 0.6%, whereas energy consumption in the non-OECD emerging economies will expand by an average of 2.3% per year (EIA 2011).

Table 2.1: World energy consumption by country grouping, 2008-2035 (quadrillion Btu)

Region	2003	2008	2015	2020	2025	2030	2035	% p.a.
OECD	**234.3**	**244.3**	**250.4**	**260.6**	**269.8**	**278.7**	**288.2**	**0.6**
Americas	118.3	122.9	126.1	131.0	135.9	141.6	147	0.7
Europe	78.9	82.2	83.6	86.9	89.7	91.8	93.8	0.5
Asia	37.1	39.2	40.7	42.7	44.2	45.4	46.7	0.6
Non-OECD	**186.4**	**260.5**	**323.1**	**358.9**	**401.7**	**442.8**	**481.6**	**2.3**
Europe and Eurasia	48.5	50.5	51.4	52.3	54.0	56.0	58.4	0.5
Asia	83.1	137.9	188.1	215.0	246.4	274.3	298.8	2.9
Middle East	19.6	25.6	31.0	33.9	37.3	41.3	45.3	2.1
Africa	13.3	18.8	21.5	23.6	25.9	28.5	31.4	1.9
Central and South America	21.9	27.7	31.0	34.2	38.0	42.6	47.8	2.0
World	**420.7**	**504.7**	**573.5**	**619.5**	**671.5**	**721.5**	**769.8**	**1.6**

Note: Totals may not equal sum of components due to independent rounding.
Source: EIA (2011)

Figure 2.6: Energy Consumption in OECD and Non-OECD Countries, 1990-2035 (quadrillion Btu)



Source: EIA (2011)

In general, there are two types of sources of energy in the world: renewable energy sources and non-renewable energy sources. Renewable energy sources include solar, biomass, wind, tidal, hydro, and geothermal. Non-renewable energy sources include oil, coal, natural gas, and nuclear energy. The next subsection provides a brief review of the trend in the main sources of energy in OECD countries.

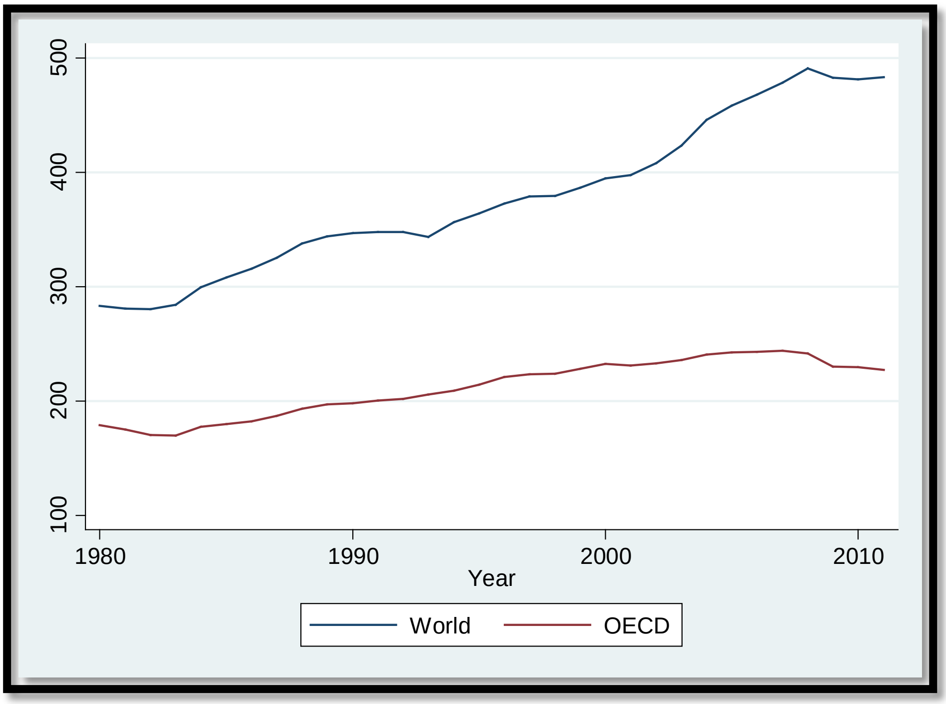
2.3.1 Non-Renewable Energy

Most energy that is used in the world today is generated from non-renewable energy sources. These sources are called non-renewable because they cannot be renewed or regenerated quickly enough to keep pace with their use. They are formed when incompletely decomposed plant and animal matter is buried in the earth's crust and converted into carbon-rich material that is useable as fuel. This process occurred over millions of years. The obvious advantage of non-renewable energy sources is that they are ready, cheap, and easy to use. It is also cheap to convert one non-renewable energy type to another. The usage of non-renewable energy sources has been increasing in step with economic growth. Most developed nations are dependent on non-renewable energy sources such as fossil fuels and nuclear power. Figure 2.7 shows the trend in non-renewable energy consumption in the world and in OECD countries. While the pace of the growth in non-renewable energy consumption remains stable in the world, it is decreasing in the OECD in recent years.

According to a World Bank report published in 2012, the fossil fuel energy consumption (percentage of total) in high income OECD countries was reported at 80.52 in 2010, implying a considerable decrease in the usage of non-renewables (Figure 2.8).

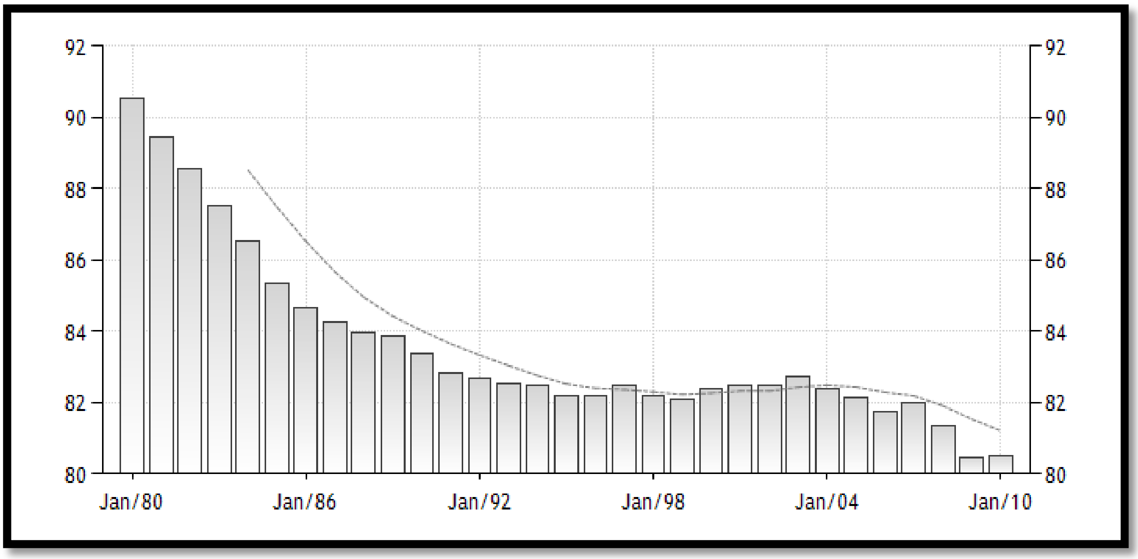
The three main types of non-renewables are coal, oil and natural gas. Comparing the trend of their consumption in OECD and non-OECD countries in 2011 indicates that coal consumption in non-OECD countries was more than two times that in the OECD. However, oil consumption in OECD countries was slightly more than non-OECD countries and about half of world consumption. Natural gas consumption in both OECD and non-OECD countries remained approximately equal (Figure 2.9).

Figure 2.7: Non-Renewable Energy Consumption by Region, 1980-2011
(quadrillion Btu)



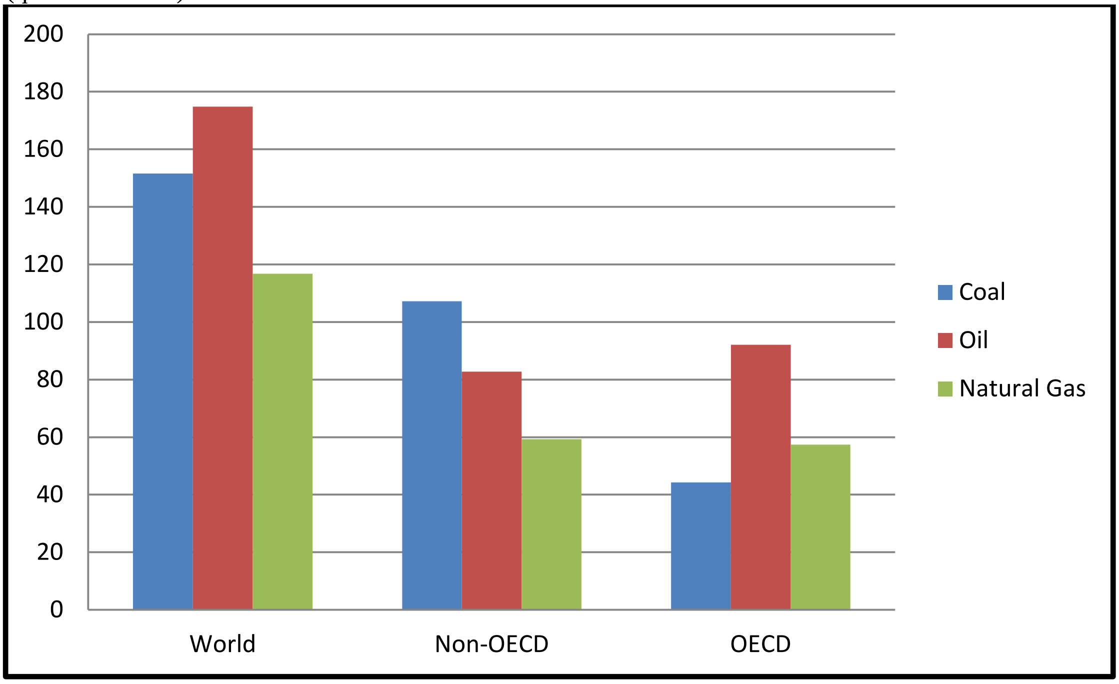
Data source: EIA (2012)

Figure 2.8: Non-Renewable Energy Consumption (% of total) in High Income OECD, 1980-2010



Data source: World Bank (2012)

Figure 2.9: Non-Renewable Energy Consumption by Energy Source, 2011
(quadrillion Btu)



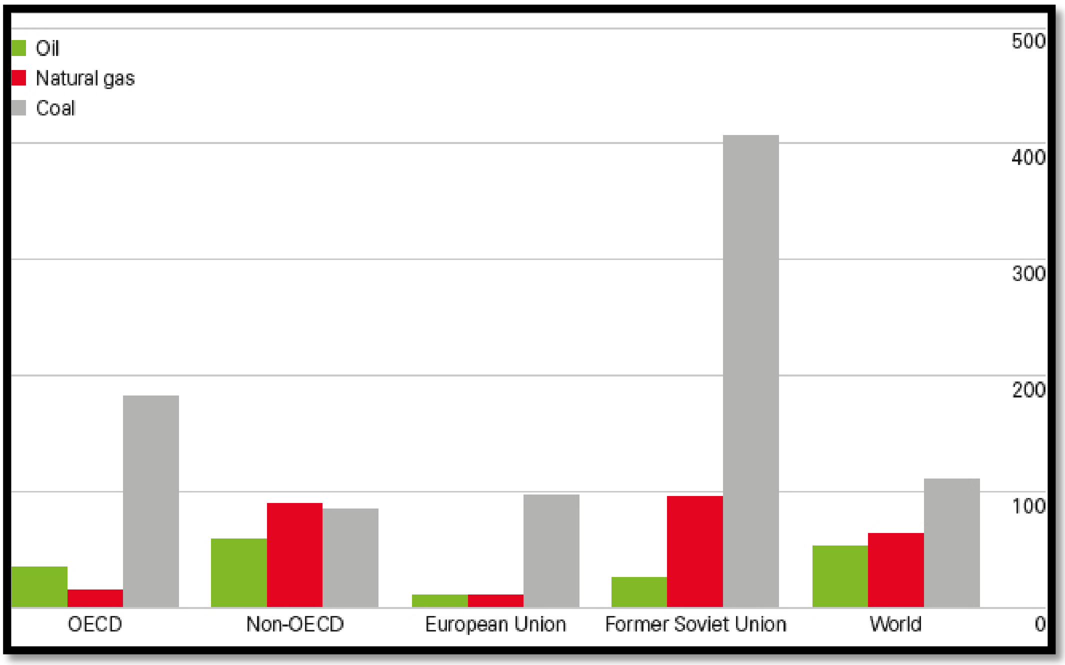
Data source: EIA (2011)

Coal formed slowly over millions of years from the buried remains of ancient swamp plants. During the formation of coal, carbonaceous matter was first compressed into a spongy material called "peat," which is about 90% water. As the peat became more deeply buried, the increased pressure and temperature turned it into coal. Coal, as the most abundant fossil fuel, is located predominantly in OECD countries (almost half the world's reserves) (Figure 2.10). However, the quality varies from one region to another. For instance, Australia, Canada and the United States all have high quality coking coal (EIA 2010). Coal demand will increase slowly in OECD North America and Pacific, but will fall in OECD Europe as gas elbows coal out of all end-use sectors and, to a slightly lesser extent, power generation.

Coal consumption increased globally by 5.4 % in 2011, which is an above average growth, and accounts for 30.3% of global energy consumption, the highest share since 1969. Currently, the world is consuming coal at a rate of about 5 billion metric tonnes per year. Consumption outside the OECD rose by an above-average 8.4%, led by Chinese consumption growth of 9.7%. Consumption in OECD countries decreased by 1.1%, with declines of 5% in the United States and Japan, and increases in the EU

(+4%), driven by Poland (+6%), Spain (+51%, after a similar decrease in 2009), Bulgaria (+24%) and Italy (+8%) (BP 2012; EIA 2011). It can be seen from Figure 2.11 that coal consumption growth in the OECD region is sluggish.

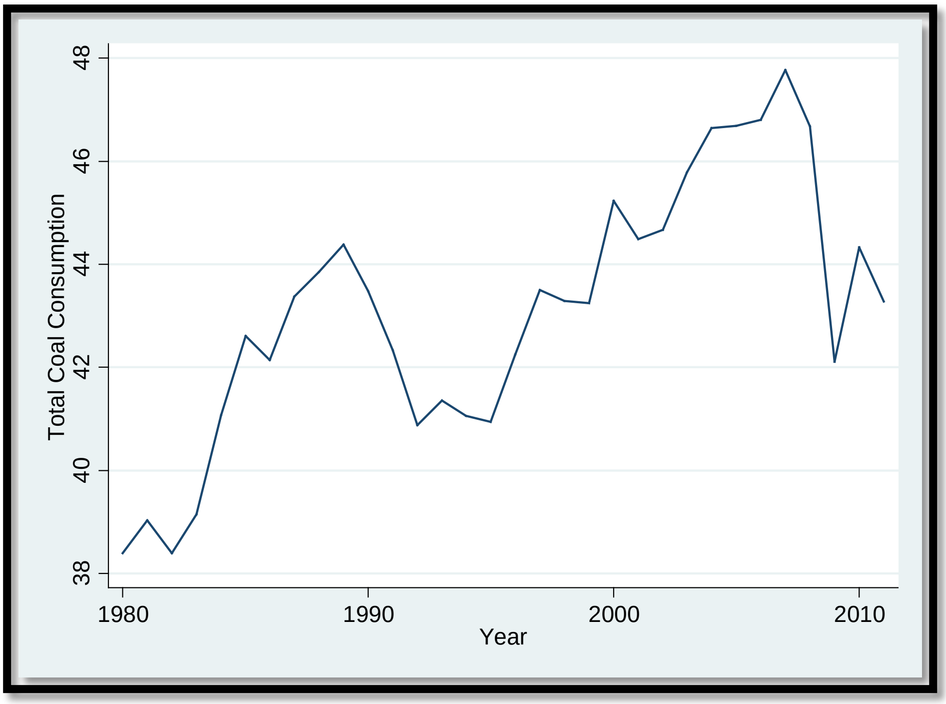
Figure 2.10: Fossil Fuel Reserves-to-Production (R/P) Ratios, 2011



Note: Coal remains the most abundant fossil fuel by global R/P ratio, although global oil and natural gas reserves have increased significantly over time. Non-OECD countries possess the majority of proved reserves for all fossil fuels, but OECD countries have a higher R/P ratio for coal.
Source: BP (2011)

The main use of coal is for power generation, because it is a relatively inexpensive way to produce power. For example, coal is used to produce over 50% of the electricity in the United States. In addition to electricity production, coal is sometimes used for heating and cooking in less developed countries and in rural areas of developed countries. If consumption continues at the same rate, the current reserves will last for more than 200 years (EIA 2012). The burning of coal produces significant atmospheric pollution as harmful nitrogen oxides, heavy metals, and carbon dioxide are also released into the air.

Figure 2.11: Coal Consumption in OECD Countries, 1980-2011
(quadrillion Btu)

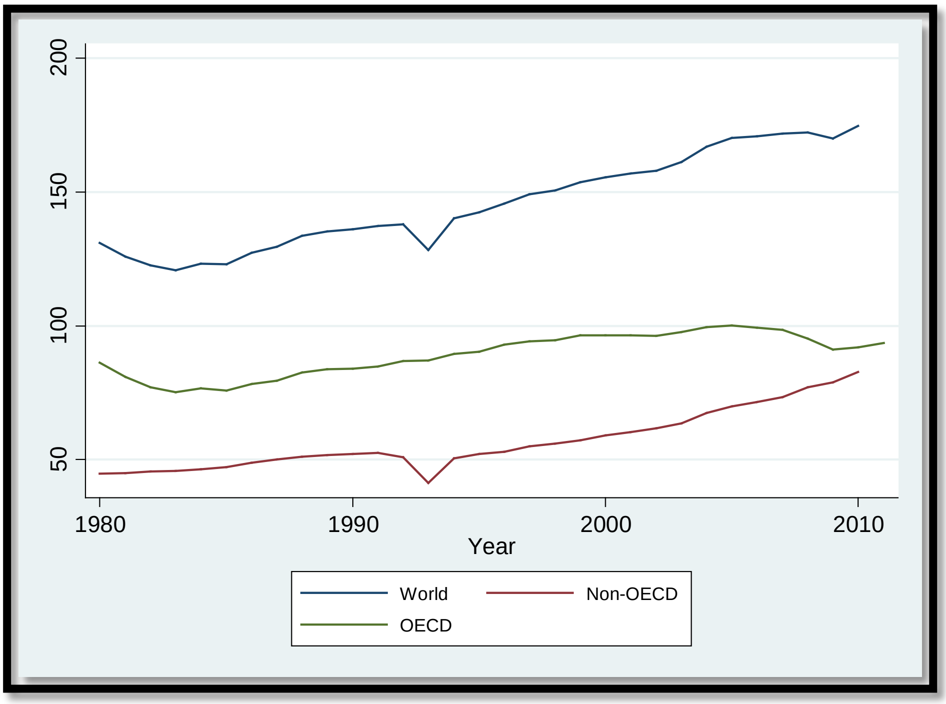


Data source: EIA (2012)

Liquid petroleum is other types of fossil fuels that are refined into many different energy products (e.g., gasoline, diesel fuel, jet fuel, heating oil). Oil forms underground in rock, which is rich in organic materials. After the oil forms, it migrates upward into porous reservoir rock such as sandstone or limestone, where it can become trapped by an overlying impermeable cap rock. Wells are drilled into these oil reservoirs to remove the gas and oil. Over 50 % of the world's oil is found in the Middle East; sizeable additional reserves occur in North America. Most known oil reserves are already being exploited, and oil is being used at a rate that exceeds the rate of discovery of new sources. If the consumption rate continues to increase and no significant new sources are found, oil supplies may be exhausted in another 30 years or so. Despite its limited supply, oil is a relatively inexpensive fuel source. It is a preferred fuel source over coal. An equivalent amount of oil produces more kilowatts of energy than coal. It also burns cleaner, producing about 50% less sulphur dioxide (EPA 2011).

Global oil consumption grew, between 2006 to 2011, by a below-average 0.6 million barrels per day (b/d), or 0.7%, to reach 88 million b/d. OECD consumption declined by 1.2% (600,000b/d), the fifth decrease in six years, falling to the lowest level since 1995 (BP 2011). Figure 2.12 demonstrates the trend in oil consumption. It is observed that world oil consumption declined in 2009, but recovered in 2010 and it is expected to continue increasing in 2011 and beyond. Comparing oil consumption in the OECD and the developing non-OECD nations shows that oil consumption in OECD countries has been much higher than that of in non-OECD countries for the period 1980 to 2010. However, although oil is expected to remain the largest source of energy, its share of total energy consumption will decline in the OECD in the near future. Economic theory proposes that when oil prices increase, the economy is expected to move away from consuming oil to other energy sources. However, Wong et al. (2012) find that despite soaring oil prices, OECD countries remain heavily dependent on oil consumption.

Figure 2.12: Total Oil Consumption by Region, 1980-2011
(quadrillion Btu)



Data source: EIA (2012)

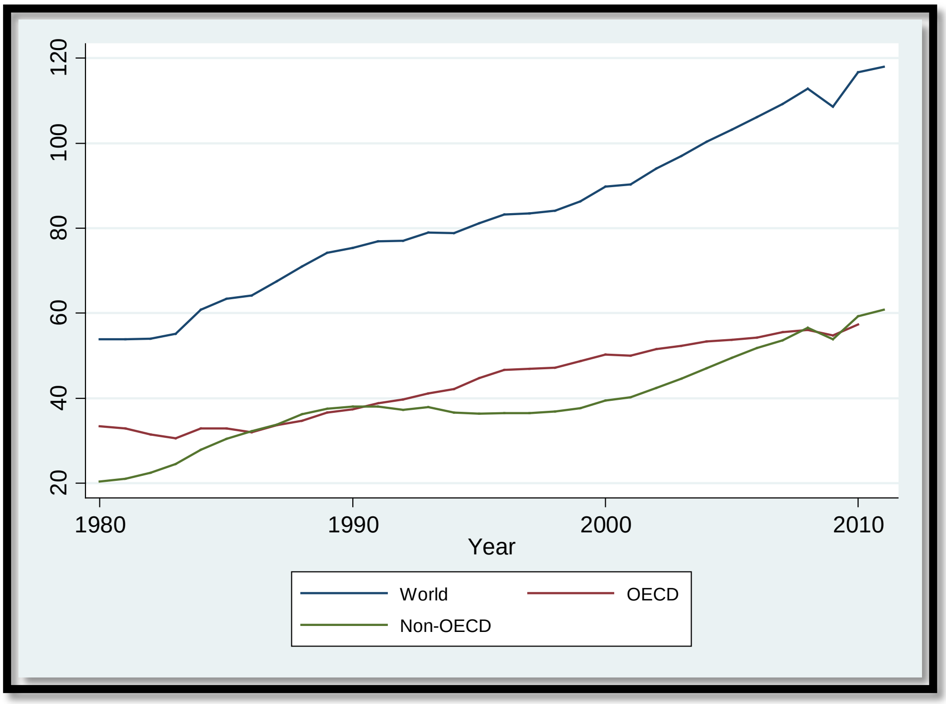
Oil, however, does cause environmental problems. The burning of oil releases atmospheric pollutants such as sulphur dioxide, nitrogen oxides, carbon dioxide and carbon monoxide.

The use of natural gas is growing rapidly. Besides being a clean burning fuel source, natural gas is easy and inexpensive to transport once pipelines are in place. In developed countries, natural gas is used primarily for heating, cooking, and powering vehicles. The current estimate of natural gas reserves is about 100 million metric tonnes. At current usage levels, this supply will last an estimated 100 years. Most of the world's natural gas reserves are found in Eastern Europe and the Middle East (EIA 2010). According to the US Energy Information Administration, natural gas is the world's fastest-growing fossil fuel, with consumption increasing at an average rate of 1.6% per year. The global recession of 2008 to 2009 resulted in a decline of nearly 4% in natural gas demand in 2009. As the recession receded and economic growth resumed, natural gas demand reached an estimated 113.1 trillion cubic feet in 2010, exceeding annual consumption levels before the economic downturn (Cedigaz 2010). Most growth in consumption occurs in non-OECD countries, where demand increases nearly three times as fast as in OECD countries. Global natural gas consumption increased by 2.3% in 2011, a much slower pace compared to 2010 (+8.2%) (BP 2012).

While consumption of natural gas remains flat in OECD countries, non-OECD countries account for slightly more than half of gas consumption in the world (Figure 2.13). Consumption growth was below average in all regions except North America, where low prices drove robust growth. The largest volumetric gains in consumption were in China (+21.5%), Saudi Arabia (+13.2%) and Japan (+11.6%). These increases were partly offset by the largest decline on record in the European Union gas consumption (-9.9%), as a result of high gas prices, economic stagnation and warm weather (EIA 2011).[5]

[5]Gas consumption fell dramatically for the largest consumers (-6% in Italy, -13% in the Netherlands and Germany and -17% in the United Kingdom).

Figure 2.13: Natural Gas Consumption by Region, 1980-2011
(quadrillion Btu)

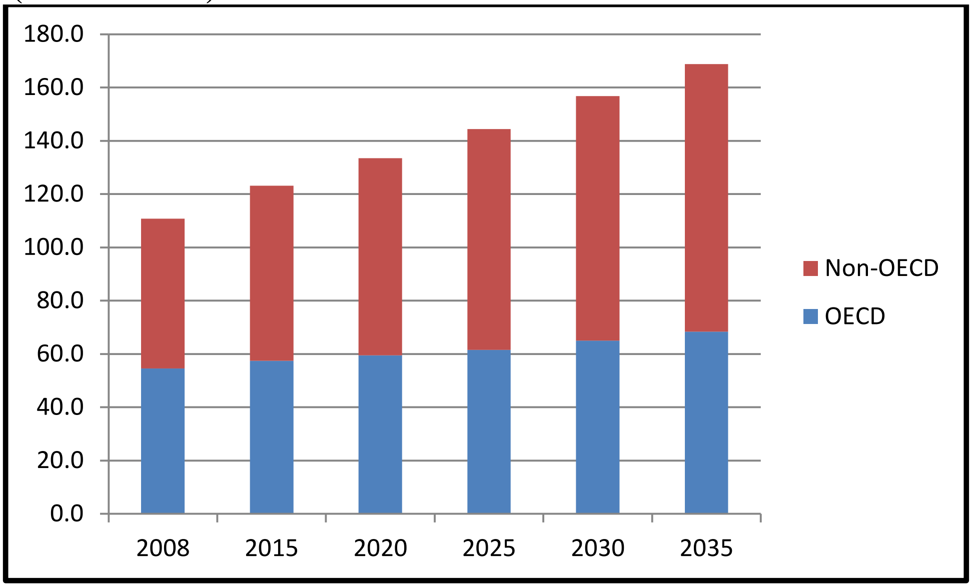


Data source: EIA (2012)

Growth in natural gas consumption is particularly strong in non-OECD countries, where economic growth leads to increased demand over the projection period. Consumption in non-OECD countries will grow by an average of 2.2% per year through 2035, nearly three times as fast as the 0.8% annual growth rate projected for natural gas demand in the OECD countries. As a result, non-OECD countries will account for 76% of the total world increment in natural gas consumption, as the non-OECD share of world natural gas use increases from 51% in 2008 to 59% in 2035 (EIA 2011) (Figure 2.14).

Natural gas continues to be the fuel of choice in many regions of the world in the electric power and industrial sectors, in part because of its lower carbon intensity compared with coal and oil, which makes it an attractive fuel source in countries where governments are implementing policies to reduce greenhouse gas emissions, and also because of its significant price discount relative to oil in many world regions. In addition, it is an attractive alternative fuel for new power generation plants because of low capital costs and favourable thermal efficiencies (EIA 2011).

Figure 2.14: World Natural Gas Consumption, 2008-2035
(trillion cubic feet)



Source: EIA (2011)

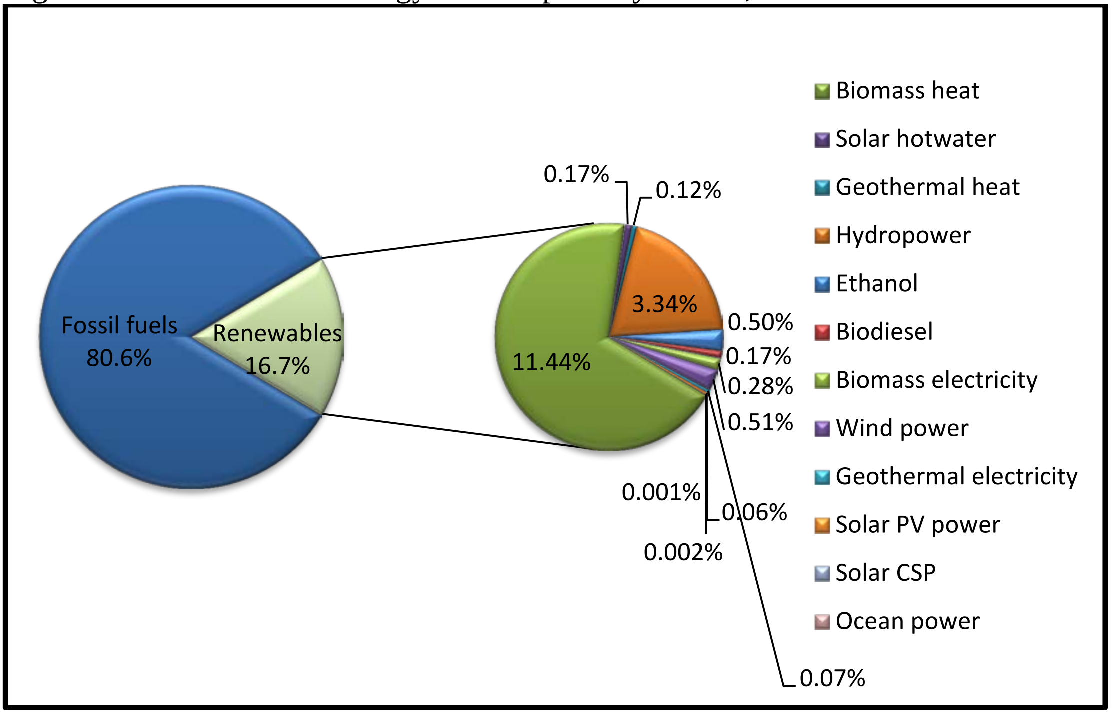
2.3.2 *Renewable Energy*

In recent years, renewable energy has increasingly attracted public and policy attention particularly for its potential to contribute to reductions in pollutant emissions. Renewable energy sources are derived directly from nature, like the sun, rain, wind, tides, and they are not depleted by their use. For instance, solar energy is widely used to generate electricity in many countries. In addition, geothermal, wind, tides, and biomass energy from plants are also used. Renewable energy sources are abundant and have very low or zero carbon emissions, so they are environmentally friendly.

Renewable energy in 2010 supplied an estimated 16.7% of global final energy consumption. Of this total, an estimated 8.2% came from modern renewable energy such as hydropower, wind, solar, geothermal, biofuels, and modern biomass. Traditional biomass, which is used primarily for cooking and heating in rural areas of developing countries, and could be considered renewable, accounted for approximately 8.5% of total final energy. Hydropower supplied about 3.3% of global final energy consumption, and hydro capacity is growing steadily from a large base. All other modern renewables provided approximately 4.9% of final energy consumption in 2010, and have been experiencing rapid growth in many developed and developing countries alike (REN21 2012) (Figure 2.15).

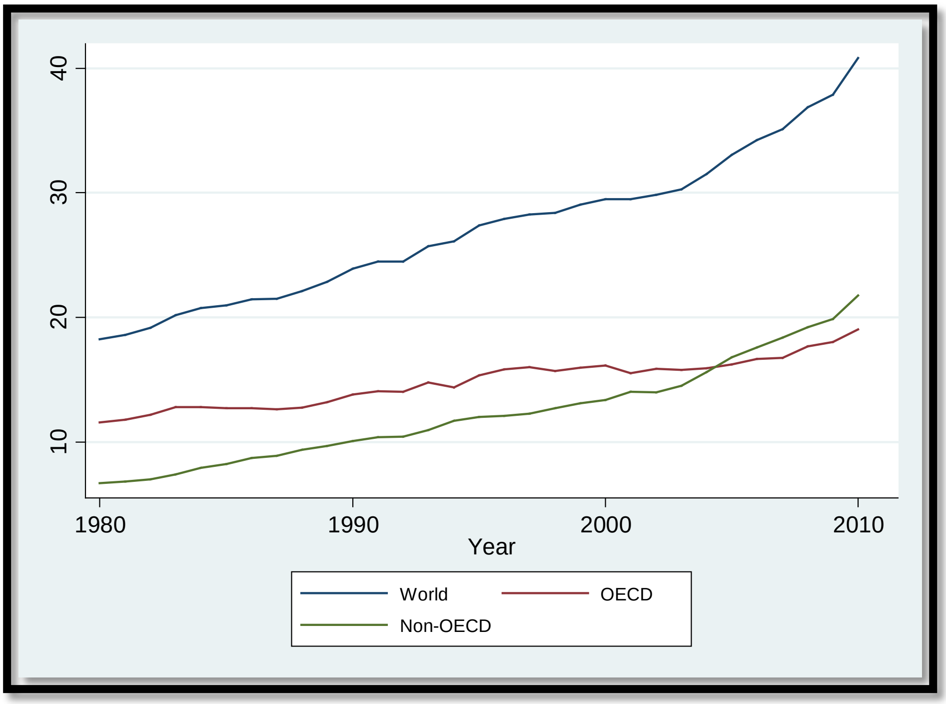
In OECD countries, renewables account for 2.2% of energy consumption in 2010, compared to 0.6% in the non-OECD. In OECD countries, growth in the share of renewables is related to the diffusion of wind energy, solar energy and biomass. In Europe, renewables account for 11% of primary consumption in 2010, with rapid growth in southern Europe. This share was 6% in the United States and 3% in Japan in 2010. The share of renewable power in global energy consumption reached 1.3% in 2010, up from 0.6% in 2000. While the aggregate shares remain low, for some individual countries renewable power now contributes a significant share of primary energy consumption. Eight countries have a renewables share of more than 5%, led by Denmark with 13.1%.

Figure 2.15: Total World Energy Consumption by Source, 2010



Source: REN21 (2012)

Figure 2.16: Total Renewable Energy Consumption by Region, 1980-2011
(quadrillion Btu)



Data source: EIA (2012)

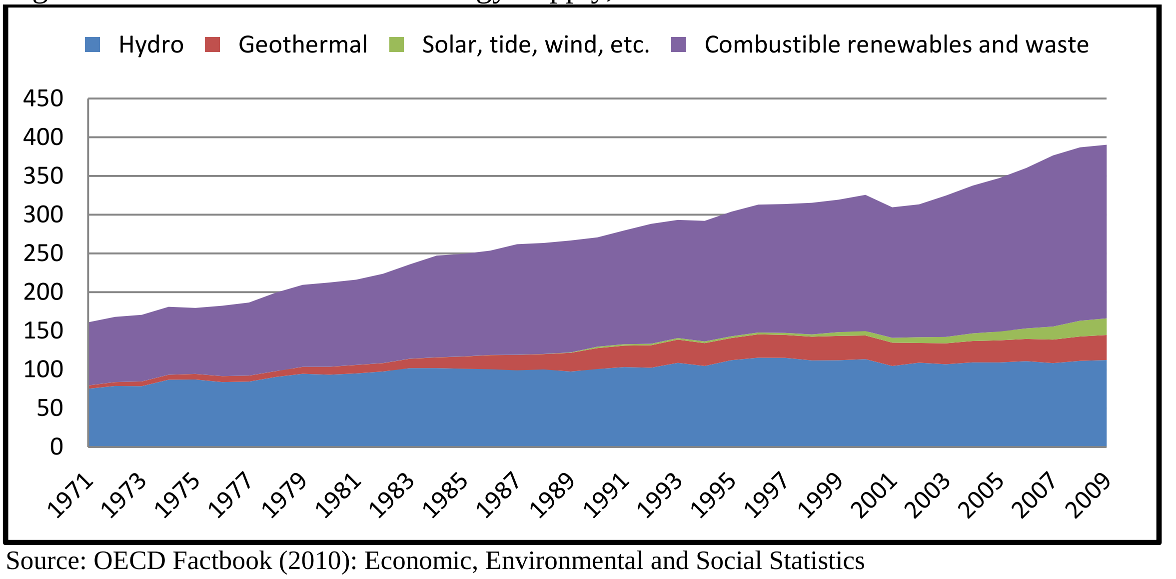
The OECD remains the main source of renewable power generation (77.5% of world total in 2010), but non-OECD growth has accelerated sharply since 2007 and has exceeded OECD growth in percentage terms in each of the past three years (Figure 2.16).

At least 118 countries, more than half of which are developing countries, had renewable energy targets in place by early 2012, up from 96 one year before, although some slackening of policy support was seen in developed countries. In the United States, renewables provided 12.7% of total domestic electricity in 2011, up from 10.2% in 2010, and accounted for about 11.8% of domestic primary energy production. In Germany, renewable sources met 12.2% of total final energy consumption and accounted for 20% of electricity consumption (up from 17.2% in 2010) (UNEP 2012).

In OECD countries, total renewables supply grew by 2.4% per annum between 1971 and 2010 as compared to 1.2% per annum for total primary energy supply. Annual growth for hydro (1.1%) was lower than for other renewables such as geothermal

(5.3%) and biofuels and waste (2.9%). Due to a very low base in 1971, solar and wind experienced the most rapid growth in OECD member countries, especially where government policies have stimulated expansion of these energy sources (OECD Factbook 2010) (Figure 2.17).

Figure 2.17: OECD Renewable Energy Supply, 1971-2009



Source: OECD Factbook (2010): Economic, Environmental and Social Statistics

2.4 GHG and CO_2 Emissions

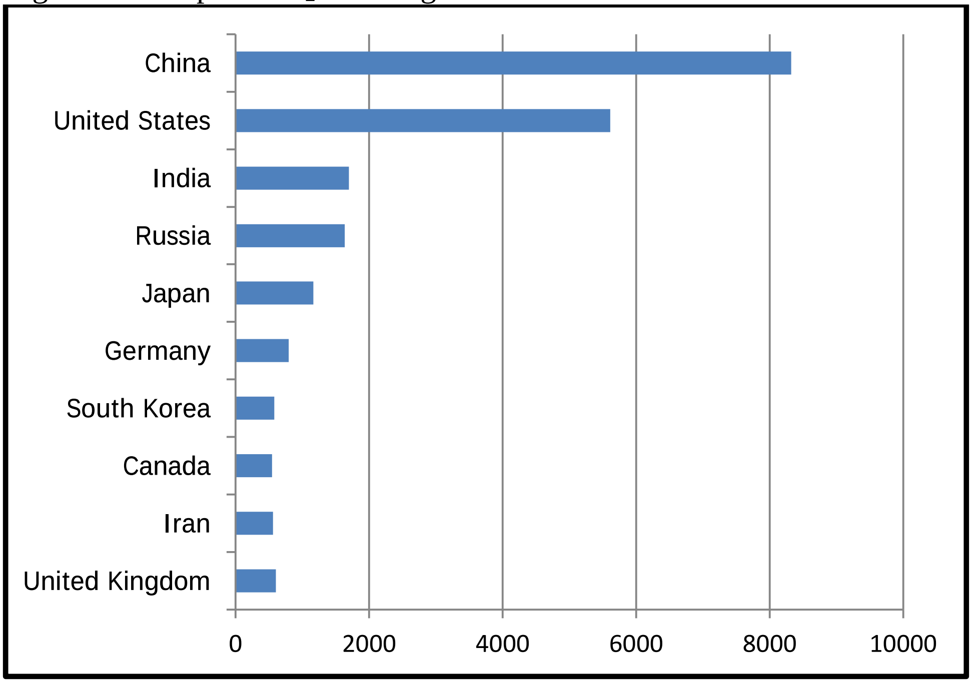
Climate change has become one of the important issues in the recent years. Observations of increases in global average temperatures, widespread melting of snow and ice, and a rising global average sea level indicate that the climate is already warming. Since pre-industrial times, increasing emissions of GHGs due to human activities have led to a marked increase in atmospheric GHG concentrations. Global emissions of GHGs rise 1.4% per year (IPCC 2007). World GHG emissions have roughly doubled since the early 1970s, and on current policies could rise by over 70% during 2008 to 2050. Historically, energy related GHG emissions were predominantly from the richer developed countries of the OECD, so that the rise in GHG concentration from the industrial revolution to today is largely accounted for by economic activity in these countries (OECD 2008).

CO_2 is considered to be the major contributor to global warming. CO_2 concentration in the air is responsible for more than 60% of the greenhouse gas content. The largest growth in CO_2 emissions has come from the power generation and road transport sectors, followed by industry, households and the service sector (EEA 2006). Global emissions of carbon dioxide have risen by 106%, or on average 1.9% per year, since 1971. In 1971, the current OECD countries were responsible for 67% of the world CO_2 emissions. As a consequence of rapidly rising emissions in the developing world, the OECD contribution to the total fell to 42% in 2010 (IEA 2011). However, the evidence indicates that 6 countries out of the top 10 CO_2 emitting countries are still OECD members (the United States, Japan, Germany, Korea, Canada and the United Kingdom) (Figure 2.18).

In 2010, the United States alone generated almost 18% of world CO_2 emissions, despite having a population of less than 5% of the global total. Conversely, China contributed a comparable share of world emissions (24%) while accounting for 20% of the world population. India, with 17% of population, contributed more than 5% of CO_2 emissions (IEA 2012). By far, the largest increases in non-OECD countries occurred in Asia, where China's emissions of CO_2 from fuel combustion have risen by 5.8% per annum between 1971 and 2010. Two significant downturns in OECD CO_2 emissions occurred following the oil shocks of the mid-1970s and early 1980s (Figure 2.19).

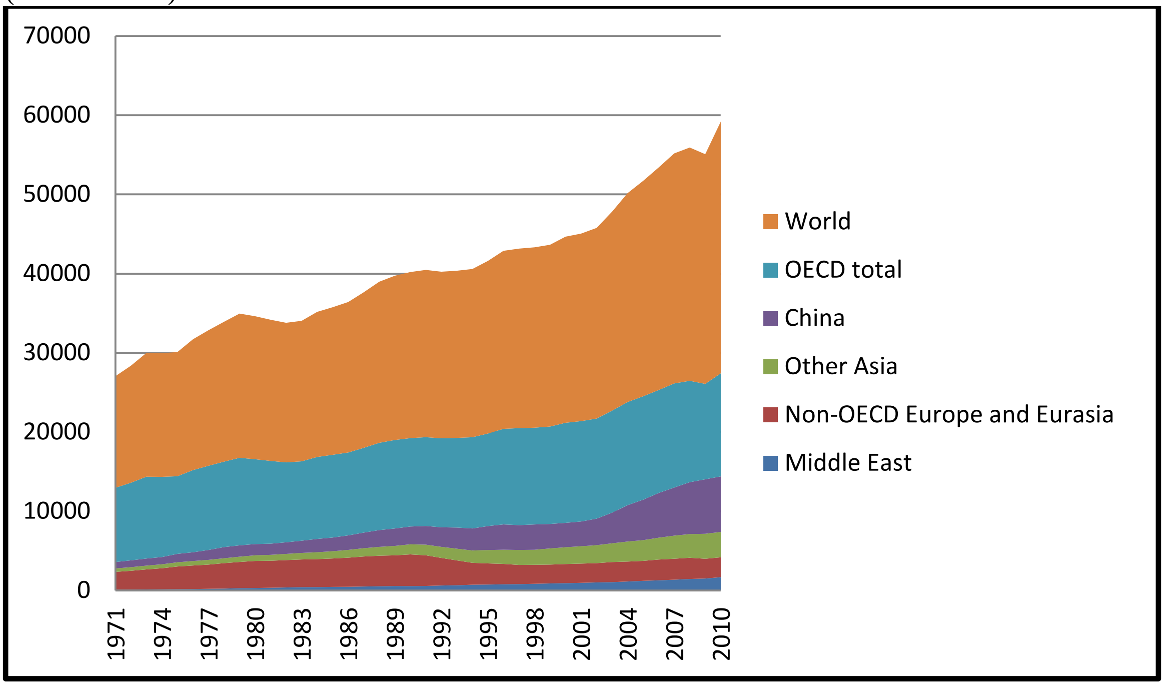
Emissions from the economies in transition declined over the last decade, helping to offset the OECD increases between 1990 and the present. However, this decline did not stabilise global emissions as emissions in developing countries continued to grow. With the economic crisis in 2008—2009, world CO_2 emissions declined by 1.5% in 2009, but increased by 3% in 2011, reaching an all-time high of 34 billion tonnes in 2011.

Figure2.18. Top 10 CO_2 Emitting Countries in 2010



Data source: EIA (2012)

Figure 2.19: CO_2 Emissions from Fuel Combustion by Region, 1971-2010 (million tonnes)



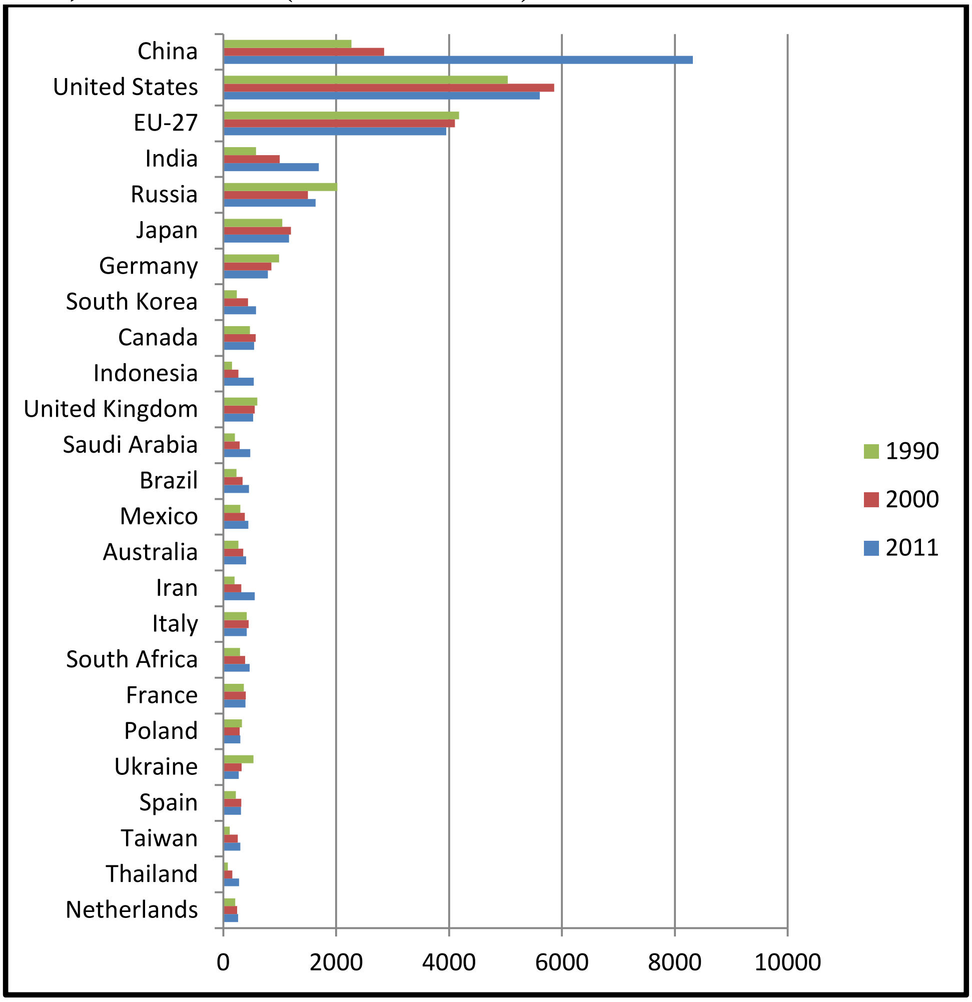
Source: OECD Factbook (2011): Economic, Environmental and Social Statistics

With a decrease in 2008 and a 5% surge in 2010, the past decade saw an average annual increase of 2.7%. The top 6 emitting countries and regions, including the European Union (EU27), produce 70% of total global emissions, whereas the top 25 emitting countries are responsible for more than 80% of total emissions (Figure 2.20/ Table 2.2). The fact that global emissions continued this historical growth trend in 2011 seems remarkable at first sight, considering that in many OECD countries CO_2 emissions in fact decreased—in the European Union by 3%, in the United States by 2% and in Japan by 2%—mainly due to weak economic conditions in many countries, mild winter weather in several countries and high oil prices.

The strong economic recovery in 2010 in most OECD countries did not continue in 2011. In Europe, CO_2 emissions from industries regulated by the EU Emissions Trading System (EU ETS) decreased in 2011 by 2%, after an increase of 3% in 2010 and an exceptional decline in CO_2 emissions of 12% in 2009 (EC 2012).

In the United States, industrial emissions from fuel combustion increased by 0.4% in 2011, after a 5% jump in 2010 and steep declines of 3% and 7% in 2008 and 2009, which were mainly caused by the recession in 2008–2009, high oil prices compared to low fuel taxes, and an increased share of natural gas (EIA 2012). Total emissions in the European Union (EU27) decreased in 2011 by 3% to 3.8 billion tonnes, and in the United States by 2% to 5.4 billion tonnes. In 2011, CO_2 emissions also decreased in Japan by 2% to 1.2 billion tonnes, whereas CO_2 emissions increased in, for example, Australia (by 8%) and Canada (by 2%) as well as in Spain (by 1%). In Russia, emissions increased by 3% to 1.8 billion tonnes. Total CO_2 emissions for all industrialised countries that have quantitative greenhouse gas mitigation targets under the Kyoto Protocol decreased in 2011 by 0.7% (including the United States, which did not ratify the Kyoto Protocol) (Table 2.3).

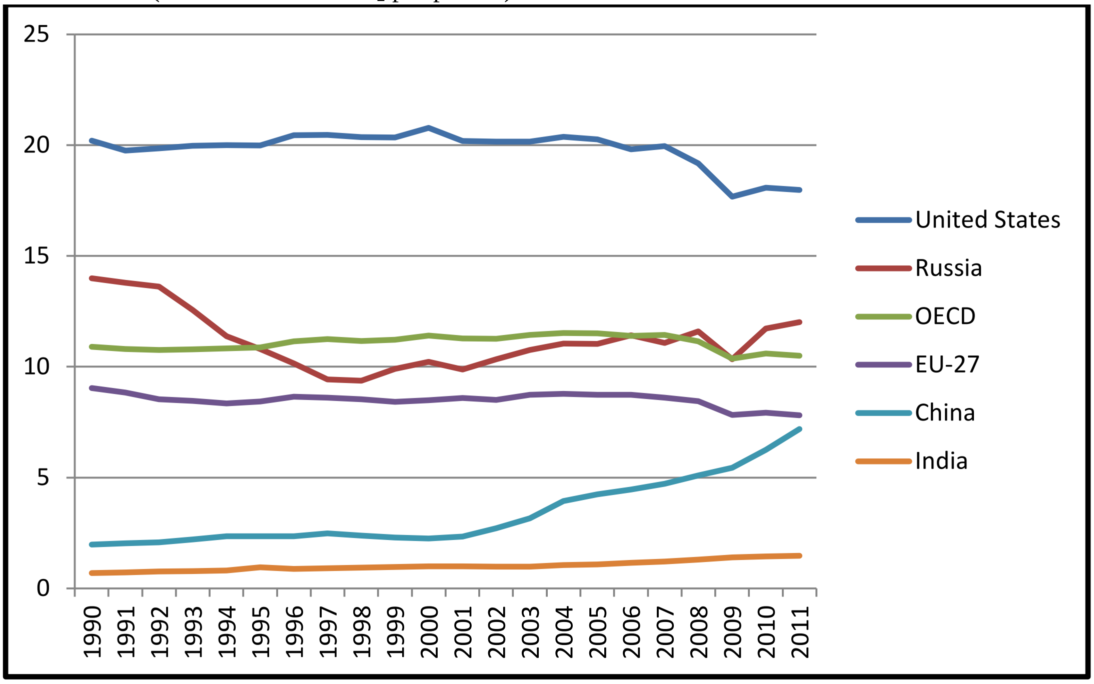
Figure 2.20: Total CO_2 Emissions per Country from the Consumption of Energy, 1990, 2000 and 2011 (million metric tonnes)



Data Source: EIA (2012)

The trends in CO_2 emissions per inhabitant of the top 5 emitting countries are shown in Figure 2.21. Although per capita emissions in India have doubled since 1990, it is clear that with 1.6 tonnes in 2011 the country's per capita emissions are still much lower than those in industrialised countries.

Figure 2.21: CO_2 Emissions per capita from the Consumption of Energy by Countries, 1990-2011 (metric tonnes of CO_2 per person)



Data Source: EIA (2012)

Table 2.2: CO_2 emissions in 2011 (million tonnes) and CO_2/capita emissions, 1990–2011 (tonne CO_2/person)

Country	Emission 2011	Per capita emissions				Change 1990-2011	Change 1990-2011 in %	Change in CO_2 1990-2011in %	Change in population 1990-2011, in %
		1990	2000	2010	2011				
United States	5420	19.7	20.8	17.8	17.3	-2.4	-12%	9%	19%
EU27	3790	9.2	8.4	7.8	7.5	-1.7	-18%	-12%	6%
Germany	810	12.9	10.5	10.2	9.9	-3	-23%	-21%	4%
United Kingdom	470	10.3	9.3	8.1	7.5	-2.8	-27%	-20%	8%
Italy	410	7.5	8.1	6.9	6.7	-0.8	-11%	-4%	7%
France	360	6.9	6.9	6.1	5.7	-1.2	-17%	-9%	10%
Poland	350	8.2	7.5	8.8	9.1	0.9	11%	11%	1%
Spain	300	5.9	7.6	6.3	6.4	0.5	8%	29%	16%
Netherlands	160	10.8	10.9	10.5	9.8	-1	-9%	2%	11%
Russian Federation	1830	16.5	11.3	12.4	12.8	-3.7	-22%	-25%	-4%
Japan	1240	9.5	10.1	10	9.8	0.3	3%	7%	3%
Canada	560	16.2	17.9	16	16.2	0	0%	24%	19%
Australia	430	16.0	18.6	17.9	19.0	3	19%	57%	24%

Source: UNPD, 2010 (WPP Rev. 2010)

Table 2.3: Trends in CO_2 Emissions per Region/Country, 1990-2011 **(billion tonnes)**

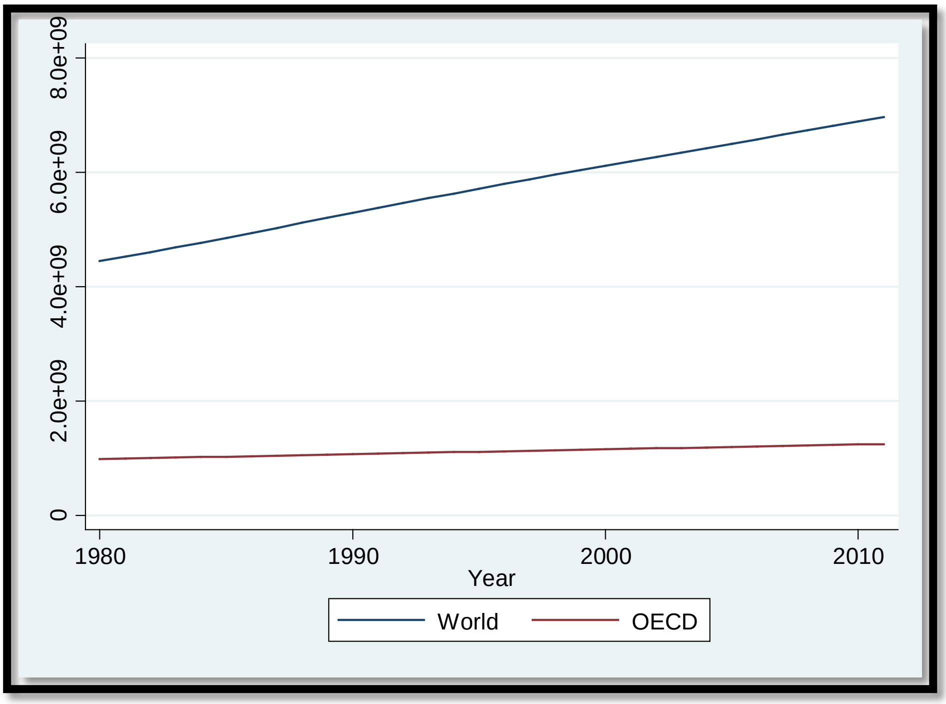
	1990	1992	1994	1996	1998	2000	2002	2004	2005	2006	2007	2008	2009	2010	2011
USA	4.99	5.04	5.26	5.44	5.65	5.87	5.83	5.94	5.94	5.84	5.91	5.74	5.33	5.53	5.42
EU27	4.32	4.12	4.02	4.15	4.07	4.06	4.11	4.23	4,19	4.21	4.15	4.09	3.79	3.91	3.79
EU15	3.33	3.29	3.23	3.34	3.32	3.33	3.39	3.47	3.43	3.43	3.37	3.32	3.07	3.16	3.02
France	0.39	0.41	0.38	0.40	0.42	0.41	0.41	0.41	0.41	0.40	0.39	0.40	0.38	0.38	0.36
Germany	1.02	0.94	0.92	0.94	0.90	0.87	0.87	0.88	0.85	0.86	0.84	0.86	0.80	0.84	0.81
Italy	0.43	0.42	0.41	0.42	0.43	0.46	0.47	0.48	0.48	0.49	0.47	0.46	0.41	0.42	0.41
Spain	0.23	0.25	0.24	0.24	0.27	0.31	0.33	0.35	0.36	0.35	0.37	0.33	0.30	0.29	0.30
UK	0.59	0.58	0.56	0.57	0.55	0.55	0.55	0.55	0.55	0.56	0.54	0.53	0.49	0.50	0.47
Netherlands	0.16	0.17	0.17	0.18	0.18	0.17	0.18	0.18	0.18	0.17	0.17	0.17	0.16	0.17	0.16
EU12 (new members)	1.00	0.83	0.79	0.80	0.75	0.73	0.72	0.76	0.76	0.78	0.78	0.77	0.72	0.75	0.76
Poland	0.31	0.30	0.31	0.30	0.29	0.29	0.28	0.31	0.31	0.32	0.32	0.32	0.31	0.34	0.35
Japan	1.16	1.18	1.23	1.26	1.22	1.28	1.30	1.31	1.32	1.30	1.33	1.25	1.18	1.26	1.24
Australia	0.27	0.28	0.29	0.31	0.35	0.36	0.37	0.40	0.41	0.42	0.42	0.44	0.44	0.40	0.43
Canada	0.45	0.45	0.47	0.49	0.52	0.55	0.55	0.57	0.57	0.55	0.59	0.57	0.53	0.54	0.56

Source: Trends in global CO_2 emissions; 2012 Report

2.5 Population Growth and Urbanisation

Population dynamics are one of the key factors to consider when thinking about development. In the past 50 years the world has experienced an unprecedented increase in population. After growing very slowly for most of human history, the world's population more than doubled in the last half century to reach 6 billion in late 1999. And, in late 2011, it surpassed 7 billion (UN 2011) (Figure 2.22). In 2010, OECD countries accounted for 18% of the world's population of 6.9 billion. China accounted for 19% and India for 18%. Within the OECD, in 2009, the United States accounted for 25% of the OECD total, followed by Japan (10%), Mexico (9%), Germany (7%) and Turkey (6%). In the three years to 2010, growth rates above the OECD population average (0.6% per year) were recorded in Mexico and Turkey (high birth rate countries) and in Australia, Canada, Chile, Korea, Luxembourg, Norway, Spain, Sweden, Switzerland, and the United States.

Figure 2.22: Total Population, 1980-2011

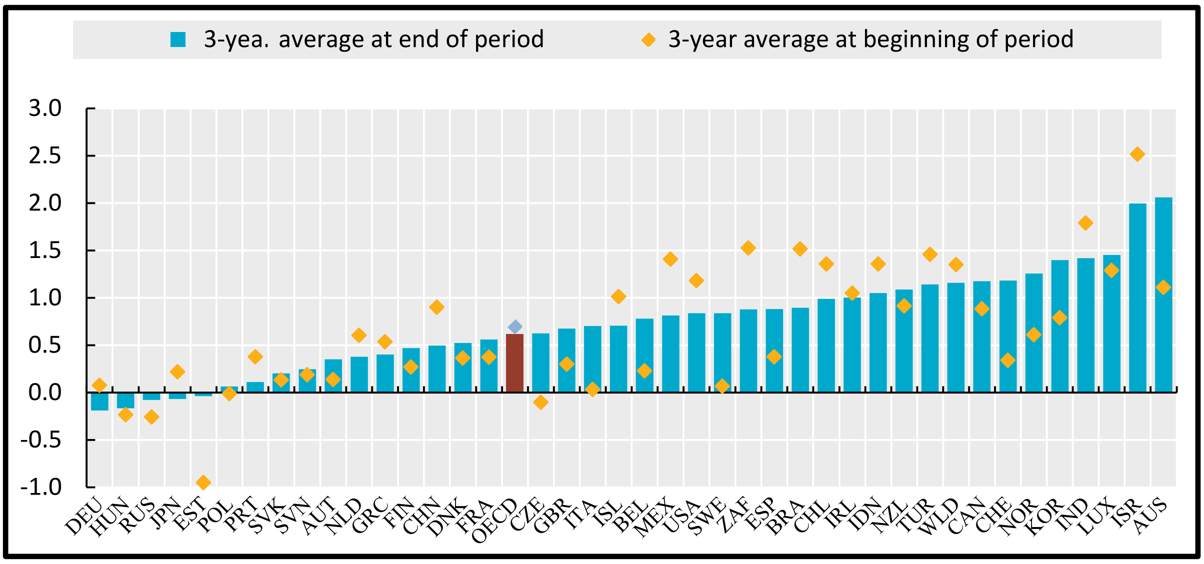


Data Source: World Bank (2012)

New Zealand and Ireland also recorded population growth rates above the OECD total which can be attributed to both a birth rate equal to the replacement rate and a positive net migration rate. Growth rates were very low, although still positive, in Estonia, Poland and Portugal (Figure 2.23) (National Intelligence Council, 2012). According to the 2010 Revision, the world population is expected to reach 10.1 billion by 2100, reaching 9.3 billion by the middle of this century. The population of OECD countries is expected to grow by less than 0.2% per year until 2050.

For the first time in our history, 52% of the world's population lives in urban areas. By 2030, six of out every ten people will live in cities; by 2050, this number will increase to roughly 70% of the global population (or 6 billion). The percentage of a country's population that lives in urban areas is used to measure urbanisation. Demographically, the term urbanisation denotes the redistribution of population from rural to urban settlements over time. The most important feature of urbanisation is that it provides one of the most significant growth drivers for the global economy (Opportunities in an Urbanising World).

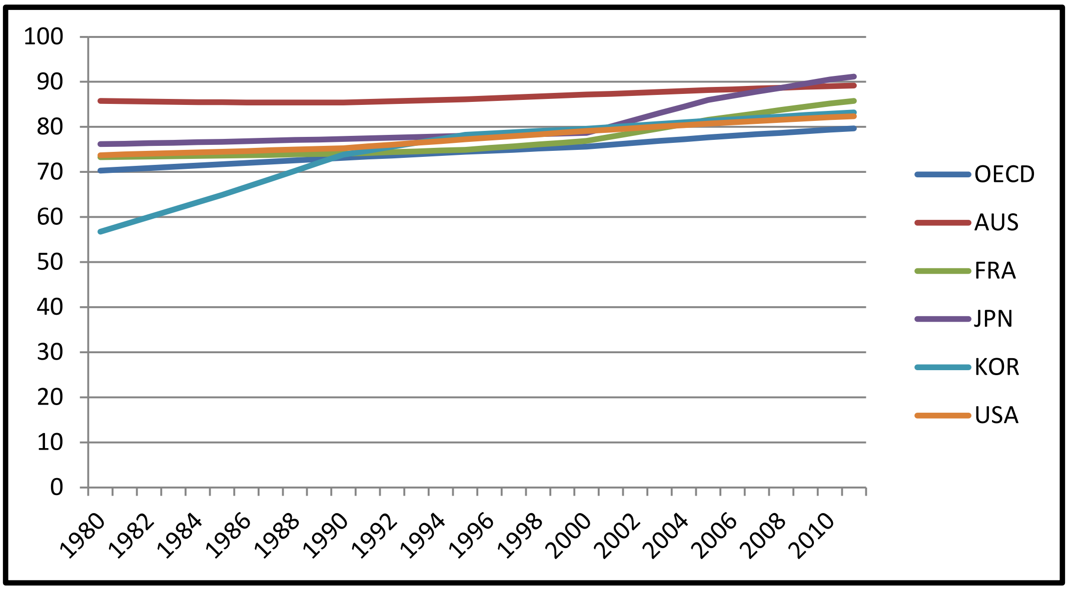
Figure 2.23: Population Growth Rates, 2008-2010
(average annual growth in percentage)



Source: OECD Factbook (2011): Economic, Environmental and Social Statistics

The most recent phenomenon shaping urbanization around the world is the development of post-industrial cities whose economic base depends on service and information rather than manufacturing. In the 19th and early 20th centuries, urban growth was occurring mainly in the developed nations. Great Britain and some European countries were the first countries, which become urbanized. The reason for this was the spread of industrialization and the associated rapid increase in the use of fossil fuels. According to the United Nations, the levels of urbanization in 1995 were high across the Americas, most of Europe, parts of western Asia and Australia. Currently, Australia, Korea, France and Japan are the most urbanized OECD countries (Figure 2.24). Although, urbanisation is higher in OECD countries, it seems emerging economies are urbanising at a faster pace. According to Urbanisation and Governance, efforts to manage urban growth have been an important feature of urban planning in OECD countries.

Figure 2.24: Urban Population, 1980-2011
(% of Total)



Data Source: World Bank (2012)

Interaction between urbanisation and environmental change is controversial. While some argue that urbanisation has a negative effect on environmental change, others believe that urbanisation can actually have a positive overall effect on environmental change. They point out climate change can decrease with urban scale for several reasons. First, urban authorities and local governments have the potential to effectively implement mitigation programmes, because of the type of responsibilities they hold in relation to land use planning, local public transportation and the enforcement of industrial regulations. Second, the concentration of people and industries in large cities provides the opportunity for technological innovations, such as combined heat and power and waste-to-energy generation plants that can generate electricity more efficiently; and it also makes mass transit systems cost and time effective. Third, this concentration also provides the opportunity for the rapid spread and adoption of new ideas and innovations, both in technical and behavioural solutions (Dodman 2009).

2.6 Conclusion

The objective of this chapter is to provide a brief overview of the trends in economic growth, population growth, urbanisation, energy consumption and pollutant emissions in OECD countries. The evidence indicates that against a considerable decrease in energy consumption in recent years, OECD countries still consume a large amount of energy. Investigating the trend in consumption of the non-renewable energy sources shows that OECD countries are still dependent on using this type of energy. For instance, oil consumption in OECD countries is more than non-OECD countries and about half of world consumption.

It is clear that using non-renewable energy sources results in significant atmospheric pollution. Currently, trends in CO_2 emissions from fuel combustion illustrate the need for further investigation for all countries to shape a more sustainable energy future. Special emphasis should first be on the industrialised nations that have the highest per-capita incomes and are responsible for the bulk of cumulative emissions. The next chapter explores the relationship between energy consumption and economic growth in detail for OECD countries.

CHAPTER 3

THE NEXUS BETWEEN ENERGY CONSUMPTION AND ECONOMIC GROWTH: A DECOMPOSITION ANALYSIS

3.1 Introduction

Energy is a fundamental resource in the economy and there is a very strong link between energy use and both the level of economic activity and economic growth. Hence, economic growth is directly related to energy consumption and is affected by energy availability. For instance, the industrial sector has the greatest proportion of economic activity and consumes about one third of total energy use worldwide (UNIDO 2010). According to EIA (2011), energy is consumed in the industrial sector for a wide range of activities, such as processing and assembly, space heating and conditioning, and lighting; but it should be considered that the use of energy (especially in the case of fossil fuels) generates negative impacts such as pollutant emissions. Therefore, countries may choose the policies that mitigate pollutant emissions such as increasing energy efficiency via substituting in cleaner sources (i.e. renewable energy) for fossil fuels like coal, gas, and oil. Although renewable energy has received a good deal of attention particularly for power generation and for residential applications, its use in important economic sectors is still limited.

Many studies have been conducted to examine the relationship between economic growth and energy consumption. Researchers agree that the reason for the interest in such investigations arises because of increased worldwide concern about the impact of energy use and environmental policies on countries' economies. Results from these investigations are different due to country specific factors, structure of the economy, energy type chosen, period of analysis and methodologies used. Therefore, scholars are not of a uniform opinion on the impact of energy consumption on a country's economic growth. In addition, the direction of causation between energy consumption and economic growth has important policy implications. A unidirectional causality running from output to energy consumption may imply that energy conservation policies have little adverse or no effects on economic growth. For example, in the case of causality running from output to energy consumption, implementing energy conservation policies could lead to a rise in total output. However, a unidirectional causality running from energy consumption to income may imply that energy consumption affects economic growth. For example, reducing energy consumption could lead to a fall in income or employment. The finding of bidirectional causality or feedback between energy consumption and output implies that a high level of economic growth leads to a high level of energy demand and vice-versa.

Although numerous studies have dealt with the relationship between energy consumption and economic growth, most of them focus on just aggregated energy consumption. Recently, the literature has started paying more attention to the effect of energy consumption on economic growth in terms of renewable and non-renewable energy sources. However, the magnitude and the direction of the effects of renewable and non-renewable energy consumption on economic growth in OECD countries have not been established and they are still unclear. Therefore, this chapter aims to investigate both renewable and non-renewable energy consumption in OECD countries in order to differentiate the relative impact of the two types of energy sources on economic growth. In addition, as it seems that non-renewables are still the dominant energy sources utilised in economic sectors, the impacts of coal, natural gas, and oil (petroleum) consumption on economic growth are also examined in order to make comparisons. Furthermore, the effects of disaggregated energy consumption on the industrial sector, which has an important role in the economic growth of countries, are also investigated. The empirical findings are based on data for selected OECD countries over the period 1980 to 2011.

The remainder of the chapter is organised as follows: Section 3.2 presents a review of the existing literature. Methodology is described in Section 3.3, followed by the empirical results in Section 3.4. Finally, Section 3.5 concludes the chapter.

3.2 Review of the Existing Literature

There are a large number of studies on the causal relationship between energy consumption and economic growth in the literature. The seminal paper on this topic is Kraft and Kraft (1978), who finds a unidirectional causality from income to energy consumption in the US by applying a bivariate model. Following Kraft and Kraft (1978), many studies have assessed the causality relationship between energy consumption and income and achieved different results. For instance, the lack of a causal relationship between economic growth and energy is consistent with the neutrality found by Erol and Yu (1987) and Yu and Jin (1992) for the US, Soytas and

Sari (2003) for Indonesia, Poland, Canada, the US and the UK, and Joyeux and Ripple (2007) for seven East Indian Ocean countries. The evidence of unidirectional causality from income to energy is consistent with Yu and Choi (1985) for South Korea, Al-Iriani (2006) for Gulf Cooperation Countries, Joyeux and Ripple (2010) for the 30 OECD countries and 26 non-OECD countries, Zhang et al. (2012) for OECD countries; and unidirectional causality from energy to income is found by Yu and Choi (1985) for the Philippines, Fatai et al. (2004) for Indonesia and India, Wolde-Rufael (2004) for Shanghai, Zhang et al. (2012) for newly industrialized countries. The bidirectional causality between income and energy is also found by Glasure and Lee (1997) for South Korea and Singapore, Yang (2000) for Taiwan, Soytas and Sari (2003) for Argentina, Fatai et al. (2004) for Thailand and the Philippines, Erdal et al. (2008) for Turkey, and Fuinhas and Marques (2012) for southern European countries.

There are some studies that use a multivariate setting to investigate the energy–income nexus. For example, a neutral relationship between income and energy is found by Masih and Masih (1996) for Malaysia, Singapore and the Philippines, Bowden and Payne (2009) for the US, and Salim et al. (2008) for Bangladesh. The evidence of unidirectional causality from income to energy is consistent with Masih and Masih (1996) for Indonesia, Oh and Lee (2004) for South Korea, Salim et al. (2008) for China and Thailand, Bartleet and Gounder (2010) for New Zealand, Aziz (2011) for Malaysia and Wolde-Rufael (2012) for Taiwan. A unidirectional causality from energy to income is found by Stern (1993) for the US, Masih and Masih (1996) for India, Masih and Masih (1998) for Sri Lanka and Thailand, Asafu-Adjaye (2000) for India and Indonesia, Soytas and Sari (2003) for Turkey, Lee (2005) for 18 developing countries, Salim et al. (2008) for India and Pakistan, Apergis and Payne (2009a) for eleven countries of the Commonwealth of Independent States and Apergis and Payne (2011a) for lower-middle income and lower income countries. A bidirectional causality between income and energy is also found by Asafu-Adjaye (2000) for Thailand and the Philippines, Hondroyiannis et al. (2002) for Greece, Salim et al. (2008) for Malaysia, Lee et al. (2008) for a set of 22 OECD countries, Belke et al. (2010) for 25 OECD countries, Apergis and Payne (2011a) for high income and upper-middle income countries, Kaplan et al. (2011) for Turkey, Shahiduzzaman and Alam (2012) for Australia.

As seen above, a considerable number of studies have assessed the energy consumption and economic growth nexus. However, the empirical results appear to be controversial as the bivariate model, which is mostly applied in earlier studies, is severely criticized, particularly with the econometric issue of omitted variables. However, despite employing a multivariate model, there is still no consensus on the literature.

Another approach taken in the literature decomposes total energy consumption by energy source, namely coal, natural gas, and oil (petroleum). For instance, in China from 1985 to 2002, Zou and Chau (2006) show that oil consumption is a useful variable that predicts change in the economy in the short run and long run and thereby has a significant impact on the Chinese economy. Yoo (2006) demonstrates that bidirectional causality exists between oil consumption and economic growth in Korea from 1968 to 2002. Evidence of two-way causality between oil consumption and economic growth is found by Zhao et al. (2008) in China. The same result is found by Aktas and Yilmaz (2008) in the case of Turkey. Yuan et al. (2008) find bidirectional causality between oil consumption and GDP and one-way causality from GDP to coal consumption in China from 1963 to 2005.

Comparing major OECD and non-OECD countries over the period 1980–2005, Jinke et al. (2008) provide evidence of unidirectional causality running from GDP to coal consumption in Japan and China, and no causality relationship between coal consumption and GDP in India, South Korea and South Africa. However, it is worth noting that Jinke et al. use bivariate model that may yield biased results.

In contrast, employing a multivariate panel framework, Apergis and Payne (2010a) find that coal consumption negatively affects economic growth in the long run for 25 OECD countries over the period 1980 to 2005. The results of the panel vector error correction model show bidirectional causality between coal consumption and economic growth in both the short run and long run.

Using a Toda-Yamamoto causality test for six major coal consuming countries for the period 1965 to 2005, Wolde-Rufael (2009) reveals that there is unidirectional causality running from coal consumption to economic growth in India and Japan; unidirectional causality running from economic growth to coal consumption in China and South Korea and bidirectional causality between economic growth and coal consumption in South Africa and the US.

Applying annual data of emerging market economies during the period from 1980 to 2006, Apergis and Payne (2010b) show both short-run and long-run bidirectional causality between coal consumption and economic growth.

Bloch et al. (2012) examine the relationship between coal consumption and income based on supply-side and demand-side frameworks in China over the period 1965 to 2008. They find that there is a unidirectional causality from coal consumption to output in both the short and long run under the supply-side analysis, while there is a unidirectional causality running from income to coal consumption in the short and long run under the demand-side analysis. In addition, the impulse response functions and variance decompositions confirm the causality test results under both supply-side and demand-side models.

Pradhan (2010) finds mixed results for different countries: unidirectional causality from oil consumption to economic growth in Bangladesh and Nepal; unidirectional causality from economic growth to oil consumption in India and Sri Lanka; and bidirectional causality between oil consumption and economic growth in Pakistan.

Employing the Toda-Yamamoto causality test in the US over the period 1949 to 2006, Payne (2011) provides evidence on unidirectional causality from petroleum consumption to economic growth. In contrast, Chu and Chang (2012) find unidirectional causality from economic growth to oil consumption in the US, and unidirectional causality from oil consumption to growth in Germany and Japan over the period 1971 to 2010.

Bashiri Behmiri and Pires Manso (2012) investigate crude oil consumption and economic growth, controlling for crude oil price and the dollar exchange rate for twenty-seven OECD countries over the period 1976 to 2009. A bidirectional causality relationship between crude oil consumption and GDP is found both in the short run and long run, confirming the feedback hypothesis. The authors point out that crude oil conservation policies affect OECD economic growth in the short run and long run, and therefore, policymakers should be aware that increasing crude oil prices or reducing crude oil consumption adversely affects the economic growth rate of the OECD countries.

For the US, after finding two breaks at 1983:4 and 1998:4, Yildirim et al. (2012) find a negative relationship between coal consumption and industrial production for the period of 1973:1–1983:4 and a positive relationship for the period of 1983:5–1998:4. For the last period that covers 1983:5–2011:10, the cointegration relationship turned to negative. Moreover, the causality results show that in the first period there is no causal relationship between coal consumption and industrial output. In the second period there is a causal relationship from industrial output to coal consumption. In the last period, there is a bidirectional causal relationship between coal consumption and industrial output.

Apergis and Payne (2010c) study the relationship between natural gas consumption and economic growth for a panel of 67 countries within a multivariate framework over the period 1992–2005. The results confirm the existence of a long-run equilibrium relationship between real GDP, natural gas consumption, real gross fixed capital formation, and the labor force. Furthermore, the results of the panel vector error correction model reveal bidirectional causality between natural gas consumption and economic growth in both the short and long run.

Using the leveraged bootstrapped simulation techniques for G7 countries over the period 1970 to 2008, Kum et al. (2012) reveal that there is unidirectional causality from natural gas consumption to growth in Italy, unidirectional causality from growth to natural gas consumption in the UK, bidirectional causality in France, Germany, and US, and finally, no causality in the cases of Canada and Japan.

Recently, another line of standard research focuses on the link between renewable energy consumption and economic growth. Chien and Hu (2007) analyse the effects of renewable energy on technical efficiency in developed (OECD) and developing countries (non-OECD) during the period 2001–2002 by data envelopment analysis (DEA). The findings indicate that technical efficiency is higher in developed economies than in developing economies. Furthermore, the results show that while the share of renewable energy in total energy supply is higher in developing economies due to widespread biomass use in the residential sector, the share of geothermal, solar, tidal and wind fuels in renewable energy is higher in developed economies.

Similarly, employing the Structural Equation Modelling (SEM) approach, Chien and Hu (2008) evaluate the impact of renewable energy on GDP based on the expenditure approach for 116 economies in 2003. The authors find a positive relationship between renewable energy and GDP via the path of increasing capital formation. However, the authors reveal that renewable energy use does not improve the trade balance having no import substitution effect.

Apergis and Payne (2010d) study the causal relationship between renewable energy consumption and economic growth with the inclusion of gross fixed capital formation and labour force for twenty OECD countries from 1985 to 2005. Short-run and long-run bidirectional causality are found between renewable energy consumption and GDP by estimating a panel vector error correction model. Using panel data from 1992 to 2007 for 13 countries within Eurasia, Apergis and Payne (2010e) reveal both short-run and long-run bidirectional causality between renewable energy consumption and economic growth. Using the heterogeneous panel cointegration test and panel error correction model for a panel of six Central American countries over the period 1980 to 2006, Apergis and Payne (2011b) find a bidirectional causality relationship between renewable energy consumption and economic growth in both the short run and long run.

In the case of China for the period 1978 to 2008, Fang (2011) examines the effect of renewable energy on economic growth and welfare within the framework of Cobb-Douglas production functions. The author reveals that a 1% increase in renewable energy consumption increases real GDP by 0.12%, whereas the impact of renewable energy consumption on economic welfare is insignificant. The latter result might be due to using ordinary least squares (OLS) method without checking the assumptions that are necessary to produce unbiased estimators using OLS.

For 16 emerging market economies over the period 1990 to 2007, Apergis and Payne (2011c) find a positive but not significant relationship between renewable energy and economic growth under a fully modified OLS model in the long run. They explain that economic growth of emerging countries is heavily relied on non-renewable energy sources. Causality results from the panel error correction model support unidirectional causality from economic growth to renewable electricity consumption in the short run and bidirectional causality in the long run. Apergis and Payne state that in higher levels of economic growth, more renewable energy sources will become available. Therefore, the interdependent relationship between economic growth and renewable energy in the long-run is as expected. In addition, the results indicate that there is bidirectional causality between non-renewable electricity consumption and economic growth in both the short run and long run.

Tiwari (2011) examines the effects of hydroelectricity consumption as a proxy for renewable energy sources and coal consumption as a proxy for non-renewable energy sources on economic growth in European and Eurasian countries for the period 1965 to 2009. The results estimated from a Panel Vector Autoregressive (PVAR) approach demonstrate that while the growth rate of non-renewable energy consumption has a negative impact, the growth rate of renewable energy consumption has a positive impact on the growth rate of GDP.

Applying a Larsson et al. (2001) panel cointegration test, Apergis and Payne (2012a) investigate the Granger causal relationship between renewable and non-renewable electricity consumption and economic growth in six Central American countries from 1990 to 2007. The results from the panel error correction model indicate unidirectional causality from renewable electricity consumption to economic growth in the short run, but bidirectional causality in the long run. The results also indicate bidirectional causality between non-renewable electricity consumption and economic growth in both the short run and long run.

A new trend in the literature is to compare the effects of renewable and non-renewable energy consumption simultaneously on economic growth. Apergis and Payne (2012b) investigate the impact of renewable and non-renewable energy consumption on economic growth, including real gross fixed capital formation and the labor force, for 80 developed and developing countries over the period 1990 to 2007. The results, obtained from a Pedroni (1999, 2004) heterogeneous panel cointegration test, reveal the existence of a long-run equilibrium relationship between real GDP, renewable energy consumption, non-renewable energy consumption, real gross fixed capital formation and the labor force with the long-run elasticity estimates positive and statistically significant. In addition, the findings from the panel error correction model indicate bidirectional causality between renewable and non-renewable energy consumption measures and economic growth in both short run and long run.

Tugcu et al. (2012) assess the long-run and causal relationships between renewable and non-renewable energy consumption and economic growth by using classical and augmented production functions in G7 countries for the period 1980 to 2009. The causality results based on the augmented production function, in which human capital and R&D are included, show that there is unidirectional causality from non-renewable energy consumption to economic growth in Japan; unidirectional causality from renewable energy to economic growth in Germany, and bidirectional causality between renewable energy and economic growth in UK and Japan. The results, estimated under a classical production function, demonstrate that there is bidirectional causality between non-renewable energy and growth in all G7 countries. In the end, the authors conclude that the augmented production function explains the relationship between energy and growth more effectively.

There is also another strand in the literature including the studies that investigate the relationship between disaggregated renewable energy and/or disaggregated non-renewable energy consumption and economic growth. Yang (2000) assesses the effects of coal, oil, and natural gas consumption on economic growth in Taiwan for the period 1954 to 1997. The author reveals a bidirectional causality between coal consumption and growth, unidirectional causality from growth to oil consumption, and unidirectional causality from natural gas consumption to growth.

Sari et al. (2008) study the relationship between disaggregated energy consumption; including coal, natural gas, hydro, solar and wind power, wood and waste; industrial output and employment in the US using the autoregressive distributed lag (ARDL) approach. The results show that with the exception of coal, there is no cointegration between industrial output and each energy source, when industrial output is the dependent variable. The authors find that, in the long-run, industrial production and employment are the key determinants of all measures of disaggregated energy consumption, except for natural gas and wood energy consumption.

Analysing the impact of disaggregated energy and employment on industrial production using the monthly data from 2001:1–2005:6 and applying the generalised forecast error variance decomposition approach in the US, Ewing et al. (2007) conclude that the traditional energy sources (coal, fossil fuels, and natural gas) explain a greater amount of the variation of industrial output than do the renewable energy (waste, hydroelectric, solar, wood, and wind). However, no energy source is found to explain the forecast error variance of industrial output more than employment.

Zamani (2007) examines Granger causality between GDP and different kinds of energy consumption, including total energy, gas, electricity, and petroleum, covering the period from 1967 to 2003 for the case of Iran. The author also investigates the relationship in the industrial sector. The findings indicate a long-run unidirectional causality from GDP to total energy and bidirectional causality between GDP and gas as well as between GDP and petroleum consumption for the whole economy. In the industrial sector, the author finds a causality running from industrial value added to total energy, electricity, gas, and petroleum consumption and from gas consumption to industrial value added. Moreover, a short-run causality running from GDP to total energy and petroleum consumption, and also from industrial value added to total energy and petroleum products consumption is obtained in this sector.

Pirlogea and Cicea (2012) investigate the relationship of energy consumption by fuel, including renewable energy, coal, natural gas, and oil, with economic growth in separate equations for Romania and Spain as well as for 27 European Union (EU-27) countries from 1990 to 2010. The results indicate that there is a unidirectional nexus from renewable energy consumption to growth in Romania and from natural gas consumption to growth in Spain in the short run. No causal relationship is found between any type of energy and growth in the EU-27.

Considering the relationship between disaggregate energy consumption and industrial output in South Africa from 1980 to 2005, Ziramba (2009) provides evidence of bidirectional causality between oil consumption and industrial production; and no causality between coal consumption and industrial production.

Payne (2011b) uses the Toda-Yamamoto long-run causality tests for the US from 1949 to 2006 and finds no causality between coal consumption and real GDP; unidirectional causality from real GDP to natural gas consumption; and unidirectional causality from petroleum consumption to real GDP.

Yildirim et al. (2012) applies a Toda-Yamamoto procedure and a bootstrap-corrected causality test in order to investigate the effects of different kinds of renewable energy on economic growth, controlling for employment and investment, in the US for the period 1949 to 2010. The results provide only one significant causal nexus from biomass-waste-derived energy consumption to growth, implying energy production from waste as an alternative energy resource should be considered by policy makers.[6]

As can be observed, despite an impressive body of empirical literature that exists on the relationship between energy consumption and gross domestic product, the research on the effects of fossil fuels and other energy sources on countries' economies is limited. Moreover, a general conclusion from the studies reviewed in this section is that there is no consensus neither on the existence nor on the direction of causality between energy consumption and economic growth in the literature. Therefore, the present study aims to contribute to the literature by identifying the impacts of different sources of energy on the real gross domestic product and also on the industrial sector in OECD countries. Unlike previous work, this study takes into account some important diagnostic tests including cross-sectional dependency, heterogeneity, and serial correlation, to prevent misleading inference and inconsistent estimates in the models.

3.3 Methodology

3.3.1 Theoretical Framework

This section explores the theoretical and conceptual aspects of relevance to the relationship between disaggregated energy consumption and economic growth under the framework of Cobb-Douglas production function.

The current understanding of economic growth is largely based on the neoclassical growth model developed by Solow (1956). The neo-classical economic models do not include energy as a factor of production and they consider the economy as a closed system within which goods are produced by inputs of capital and labour. However, the role of energy as an important factor of production has received increasing attention in recent decades. A commonly used production function, which is known as an appropriate instrument for finding relationships between output and economic factors, is the Cobb-Douglas form, written as:

$$Y_t = A\, K_t^{\alpha}\, L_t^{\beta} \tag{3.1}$$

[6] A summary of literature is reported in Appendix Table 3.1.

where Y_t represents aggregate output at time t, K_t is capital, L_t is labour, and A is the technology parameter. α and β measure the elasticities of output with respect to capital and labour. Recent literature concerning economic growth indicates that capital, labour, technological progress, and energy are the basic elements of economy growth in the developed countries. Therefore, economic growth models are built on five variables such as output, capital, labour, energy, and technological progress (Yuan et al. 2008). Based on the previous studies (Nourzad 2000, Wei 2007, Yuan et al. 2008, and Liao et al. 2010), this study presents a Cobb-Douglas production function taking energy as an input along with the other traditional inputs (labour and capital) in the following mathematical form:

$$Y_t = A\, K_t^{\alpha}\, L_t^{\beta}\, E_t^{\gamma} \tag{3.2}$$

where E_t is energy and γ is the elasticity of output with respect to energy.

According to Liao et al. (2010) and Arbex and Perobelli (2010), energy is classified into two categories; clean energy (renewable) and non-clean energy (non-renewable) and the production procedure uses both resources as sources of energy. Consequently, the above function is adjusted as:

$$Y_t = A\, K_t^{\alpha}\, L_t^{\beta}\, R_t^{\gamma_1}\, N_t^{\gamma_2} \tag{3.3}$$

where R_t is renewable energy and N_t is non-renewable energy. Here γ_1 and γ_2 are the elasticity of output with respect to renewable and non-renewable energy, respectively. The logarithmic form of the production function provides a log-linear form and yields:

$$ln\, Y_t = ln\, A + \alpha\; ln\, K_t + \beta\; ln\, L_t + \gamma_1\, ln\, R_t + \gamma_2\; ln\, N_t + u_t \tag{3.4}$$

In the above model, Y, as the dependent variable, represents real gross domestic production, K, L, R, and N, as independent variables, stand for capital, labour, renewable, and non-renewable energy consumption, respectively. The economic explanations of α, β, γ_1, and γ_2 are the elasticities of output with respect to capital, labour, renewable energy and non-renewable energy, respectively.

To investigate the effects of different kinds of non-renewable energy (fossil fuels) on economic growth, *E* in Equation 3.2 is replaced by *CO*, *OIL*, and *NG* which stand for coal consumption, oil consumption and natural gas consumption, respectively.

$$Y_t = A\, K_t^{\alpha}\, L_t^{\beta}\, CO_t^{\rho_1}\, OIL_t^{\rho_2}\, NG_t^{\rho_3} \tag{3.5}$$

The logarithmic form of the production function including the latter variables takes the following form:

$$ln\, Y_t = ln\, A + \alpha\ ln\, K_t + \beta\ ln\, L_t + \rho_1\, ln\, CO_t + \rho_2\ ln\, OIL_t + \rho_3\, ln\, NG_t + u_t \tag{3.6}$$

where ρ_1, ρ_2, and ρ_3 are the elasticities of the output with respect to coal, oil and natural gas consumption, respectively.

In order to find out how different types of energy affect industrial productions, Equations 3.4 and 3.6 are also estimated for industrial output as the dependent variable.

3.3.2 Econometric Approach

This section presents the general econometric methods for the panel data employed in this study. In the empirical analysis, the properties of the variables need to be examined to avoid the possibility of spurious regression. In the first step, the integrational properties of the series are ascertained. To achieve this and in order to provide an analysis of sensitivity and robustness, this study performs five different unit root tests, including an augmented Dickey and Fuller (1979) (ADF), the Phillips and Perron (1988) (PP), Breitung (2000), Levin et al. (2002) (LLC), and Im et al. (2003) (IPS). All of these tests treat the presence of a unit root, implying non-stationarity as the null hypothesis, and the absence of the unit root, or stationarity as the alternative hypothesis.

According to Perron (1989), although different tests are widely used to check for stationarity, failure to allow for structural breaks can lead to deceptive results. In order to overcome this problem, a panel stationarity test allowing for multiple structural breaks by following Carrion-i-Silvestre et al. (2005) is also applied in this study. The procedure of this test is based on the panel data version of the Kwiatkowski (1992) univariate test developed in Hadri (2000). Some of the features of this test are that first, it allows for the structural changes to shift the mean and/or the trend of the individual time series. Second, each individual in the panel can have a different number of breaks located at different dates.

In the second step, panel cointegration relationships between the variables are tested. The concept of cointegration was first introduced by Granger (1981) and developed further by Engle and Granger (1987), Phillips and Ouliaris (1990) and Johansen (1988, 1991). The basic idea is that if two or more time series variables are individually integrated of order n, then there is a possibility of at least one linear combination of them to be integrated of a lower order such that $\tilde{n} < n$. Such a relationship between the variables infers cointegration. Cointegrated variables exhibit strong steady-state relationship over the long run, having common trends and co-movements. The theory of cointegration establishes that there exist linear combinations of integrated variables that cancel out common stochastic trends. This phenomenon gives rise to equilibrium relationships among integrated variables, which means that in the long run these variables show co-movement with each other.

In this study, four panel cointegration tests of Kao (1999), Pedroni (1999, 2004), Johansen Fisher proposed by Maddala and Wu (1999), and the recently introduced test by Westerlund (2007) are applied. Pedroni (1999, 2004) develops a number of statistics based on the residuals of the Engle and Granger (1987) cointegration regression. The tests proposed in Pedroni allow for heterogeneity among individual members of the panel, including heterogeneity in both the long-run cointegrating vectors and in the dynamics. Consequently, Pedroni allows for varying intercepts and varying slopes. Kao (1999) test follows the same approach as the Pedroni tests, but it specifies cross section specific intercepts and homogeneous coefficients on the first stage regressors. Monte Carlo comparison by Gutierrez (2003) shows that, in homogeneous panels, Kao's (1999) test have higher (lower) power than Pedroni's (1999) test when a small-T (high-T) are included in the panel.

The Johansen Fisher panel cointegration test is based on the aggregates of the p-values of the individual Johansen maximum eigenvalues and trace statistic.

In this study, four error-correction-based panel cointegration tests proposed by Westerlund (2007) are employed. The tests take no cointegration as the null hypothesis and are based on structural dynamics so that they do not impose any common factor restriction. The null is tested by inferring whether the error correction term in a conditional error correction model is equal to zero. If the null of no error correction is rejected, then the null hypothesis of no cointegration is also rejected.

The panel cointegration test is conducted under four different models:

Model I: Output = *f* (gross fixed capital formation, total labour force, renewable energy consumption, non-renewable energy consumption)

Model II: Industrial output = *f* (gross fixed capital formation, total labour force, renewable energy consumption, non-renewable energy consumption)

Model III: Output = *f* (gross fixed capital formation, total labour force, coal consumption, oil consumption, natural gas consumption)

Model IV: Industrial output = *f* (gross fixed capital formation, total labour force, coal consumption, oil consumption, natural gas consumption)

The next step is to implement the Granger causality test. The two-step procedure from the Engle and Granger (1987) model is employed. The first step is to estimate the long-run model in order to obtain the estimated residuals, (error correction term; ECT henceforth). The second step is to estimate the Granger causality model with a dynamic error correction model.

With panel data, the most commonly estimated models are fixed effects and random effects models. Fixed effects models control for the effects of time-invariant variables with time-invariant effects. In the fixed effects model, the individual-specific effect is a random variable that is allowed to be correlated with the explanatory variables. In the random effects model, the individual-specific effect is a random variable that is uncorrelated with the explanatory variables.[7] It should be noted that using these methods without controlling for some diagnostic tests such as cross-sectional dependence, heteroskedasticity, and serial correlation can cause bias in the standard errors and less efficiency in the results. Therefore, it can be said that choosing an appropriate estimation method also depends on identifying the diagnostic tests in a panel data model.

[7] For more information about fixed effects and random effects models, see Madalla (2001) and Baltagi (2006).

The impact of cross-sectional dependence in dynamic panel estimators is of considerable importance. Cross-section dependence can arise due to spatial or spillover effects, or could be due to unobserved (or unobservable) common factors.[8] Assuming that cross-sectional dependence stems from common factors that are unobserved but uncorrelated with the explanatory variables, the estimators that assume *iid* (independent and identically distributed) of disturbances turn out to be consistent but insufficient and produce biased standard errors. Conversely, if the unobserved components that create interdependencies across the cross-section are correlated with the explanatory variables, the estimators will be biased and inconsistent. In the present study, three tests including Friedman (1937), Frees (1995), and Pesaran (2004) are applied to check for cross-section dependence. The latter, called the CD test, is closely related to Friedman's test statistic. Pesaran indicates that the CD test allows for a wide variety of models, including heterogeneous dynamic models with multiple breaks and non-stationary dynamic models with small or large N and T.

The problem of heteroskedasticity in cross-section data occurs when the variance of the unobservable error (disturbance) is not constant. Although heteroskedasticity does not affect the parameter estimates, it does bias the variance of the estimated parameters. The often used tests for heteroskedasticity are the Breusch-Pagan test, or the Lagrange Multiplier test, the likelihood ratio test, and the standard Wald test. The weakness of these tests is being sensitive to the normality assumption. Therefore, in this study, a modified Wald test is used to check the presence of panel heteroskedasticity, as it works even when the normality assumption is violated.

Autocorrelation is also sometimes called "lagged correlation" or "serial correlation", which refers to the correlation between members of a series of numbers arranged in time. Positive autocorrelation might be considered a specific form of "persistence", a tendency for a system to remain in the same state from one observation to the next. Wooldridge (2002) derives a flexible test for detecting serial correlation in panel data models.

The results of the diagnostic tests are provided at this stage to be able to select an appropriate method for estimating the long-run relationship between the variables in

[8] Different forms of cross-section dependence are discussed and formally defined in Pesaran and Tosetti (2011).

all the four models. The results of the diagnostic tests for the four models are provided in Table 3.1.

Table 3.1: Diagnostic tests for Models I, II, III and IV

	FE Estimation	RE Estimation
Model I		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.102	0.119
Frees (*Q*)	6.236*	5.253*
Friedman (*P*-value)	0.286	0.374
Heteroskedasticity		
Modified Wald (*P*-value)	0.000***	
Serial Correlation		
Wooldridge (*P*-value)	0.000***	
Model II		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.129	0.144
Frees (*Q*)	5.335*	5.338*
Friedman (*P*-value)	0.293	0.301
Heteroskedasticity		
Modified Wald (*P*-value)	0.000***	
Serial Correlation		
Wooldridge (*P*-value)	0.000***	
Model III		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.381	0.549
Frees (*Q*)	4.858*	4.093*
Friedman (*P*-value)	0.404	0.605
Heteroskedasticity		
Modified Wald (*P*-value)	0.001***	
Serial Correlation		
Wooldridge (*P*-value)	0.000***	
Model IV		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.420	0.441
Frees (*Q*)	4.688*	3.793
Friedman (*P*-value)	0.453	0.459
Heteroskedasticity		
Modified Wald (*P*-value)	0.000***	
Serial Correlation		
Wooldridge (*P*-value)	0.008***	

Note: FE and RE denote fixed effects and random effects estimations. *** and * indicate that the *P*-value or test statistic is significant at the 1% and 10% levels, respectively.

The Pesaran's test does not reject the null hypothesis of no cross-sectional dependence under a fixed effects specification in each model and while Friedman's test confirms cross-sectional independence, Feers's test indicates the existence of cross-sectional dependence. The conclusion with respect to the existence or not of cross-sectional dependence in the errors under random effects estimation is in line with fixed effects estimation. Pesaran's test might be the preferred selection since the properties of the two other tests are not completely known in dynamic panels. Therefore, the results of the Pesaran's test under fixed and random estimations (i.e. the existence of cross-section independence) are accepted in the four models. The results of heteroskedasticity and serial correlation tests confirm the existence of the problem of heteroskedasticity and serial correlation at a 1% level of significance in the models (Table 3.1).

3.3.3 Estimation Technique

Panel cointegration tests are only able to indicate whether or not the variables are cointegrated and if a long-run relationship exists between them. To obtain efficient estimates of the long-run relationship in the case of heteroskedasticity and serial correlation, this study applies dynamic ordinary least squares (DOLS). In this section the algebraic analysis of the DOLS estimator is discussed. The DOLS model developed by Stock and Watson (1993) involves regressing the dependent variable on constant and explanatory variable on levels, leads and lags of the first difference of all *I*(1) explanatory variables. This method is superior to a number of other estimators as it can be applied to systems of variables with different orders of lags. The inclusion of leads and lags of the differenced explanatory variable corrects for simultaneity, endogeneity, serial correlation and small sample bias among the regressors (Stock and Watson 1993).

Consider the following fixed effect panel regression:

$$y_{it} = \alpha_i + x_{it}^{'}\beta + u_{it},\ i = 1, \cdots, N,\ t = 1, \cdots, T, \tag{3.7}$$

where y_{it} is a matrix (1,1), β is a vector of slopes (k,1) dimension, α_i is individual fixed effect, u_{it} is the stationary disturbance terms. It is assumed that x_{it} (k,1) vectors are integrated processes of order one for all i , where:

$$x_{it} = x_{it-1} + \varepsilon_{it}$$

The DOLS estimator uses parametric adjustment to the errors by including the past and the future values of the differenced $I(1)$ regressors. The dynamic OLS estimator is obtained from the following equation:

$$y_{it} = \alpha_i + x_{it}^{'}\beta + \sum_{j=-q_1}^{j=q_2} c_{ij}\Delta x_{i,t+j} + v_{it} \tag{3.8}$$

where c_{ij} is the coefficient of a lead or lag of first differenced explanatory variables. The estimated coefficient of DOLS is given by:

$$\widehat{\beta}_{DOLS} = \sum_{i=1}^{N}(\sum_{t=1}^{T} z_{it}z'_{it})^{-1}\,(\sum_{t=1}^{T} z_{it}\hat{y}_{it}^{+})$$

where $z_{it} = \left[x_{it} - \bar{x}_{i,}\Delta x_{i,t-q}, \dots, \Delta x_{i,t+q}\right]$ is a $2(q+1) \times 1$ vector of regressors.

In order to describe the procedure of the estimation of the dynamic error correction model, consider a bivariate dynamic panel model following Holtz-Eakin et al. (1988):

$$y_{it} = \alpha_0 + \sum_{j=1}^{m} \alpha_j y_{it-j} + \sum_{j=1}^{m} \beta_j x_{it-j} + f_i + \varepsilon_{it}, \quad i = 1, 2, \cdots, N \tag{3.9}$$

where y_{it} and x_{it} are the dependent variable and the causal variable at time t for country i respectively. f_i is the fixed effect and the lag length m is sufficiently large to ensure that ε_{it} is a white noise error term and the α's and β's are the coefficients of the linear projection of y_{it} on a constant, past values of y_{it} and x_{it} and the individual effect f_i. Taking differences in Equation 3.9 to eliminate the fixed effects leads to the model:

$$\Delta y_{it} = \sum_{j=1}^{m} \alpha_j\, \Delta y_{it-j} + \sum_{j=1}^{m} \beta_j x_{it-j} + u_{it}, \qquad i = 1, 2, \cdots, N \tag{3.10}$$

where $\Delta y_{it-j} = y_{it-j} - y_{it-j-1}$ for $j = 0, 1, .., m$,

$\Delta x_{it-j} = x_{it-j} - x_{it-j-1}$ for $j = 1, 2, ..., m$ and $u_{it} = \varepsilon_{it} - \varepsilon_{it-1}$.

The final dynamic error correction models, based on Equation 3.10 and considering Model I, Model II, Model III, and Model IV studied in this study, can be specified as follows:

$$\Delta LGDP_{it} = a_0 + \sum_{j=1}^{m} \theta_{11ij}\Delta LK_{it-j} + \sum_{j=1}^{m} \theta_{12ij}\Delta LF_{it-j} + \sum_{j=1}^{m} \theta_{13ij}\Delta LR_{it-j}$$

$$+\sum_{j=1}^{m}\theta_{14ij}\Delta LN+\gamma_{1i}e_{it-1}+u_{1it} \quad (3.11)$$

$$\Delta LIV_{it}=b_0+\sum_{j=1}^{m}\theta_{11ij}\Delta LK_{it-j}+\sum_{j=1}^{m}\theta_{12ij}\Delta LTLF_{it-j}+\sum_{j=1}^{m}\theta_{13ij}\Delta LR_{it-j}$$
$$+\sum_{j=1}^{m}\theta_{14ij}\Delta LN+\gamma_{1i}e_{it-1}+u_{1it} \quad (3.12)$$

$$\Delta LGDP_{it}=c_0+\sum_{j=1}^{m}\theta_{11ij}\Delta LK_{it-j}+\sum_{j=1}^{m}\theta_{12ij}\Delta LF_{it-j}+\sum_{j=1}^{m}\theta_{13ij}\Delta LCO_{it-j}$$
$$+\sum_{j=1}^{m}\theta_{14ij}\Delta LOIL+\sum_{j=1}^{m}\theta_{14ij}\Delta LNG+\gamma_{1i}e_{it-1}+u_{1it} \quad (3.13)$$

$$\Delta LIV_{it}=d_0+\sum_{j=1}^{m}\theta_{11ij}\Delta LK_{it-j}+\sum_{j=1}^{m}\theta_{12ij}\Delta LF_{it-j}+\sum_{j=1}^{m}\theta_{13ij}\Delta LCO_{it-j}$$
$$+\sum_{j=1}^{m}\theta_{14ij}\Delta LOIL+\sum_{j=1}^{m}\theta_{14ij}\Delta LNG+\gamma_{1i}e_{it-1}+u_{1it} \quad (3.14)$$

The residuals obtained from estimating the long-run relationship between the variables in Model I, Model II, Model III, and Model IV are used as dynamic error correction terms in the above equations. The causal relationship between the variables is tested considering each variable in turn as a dependent variable in each equation.

Because Δy_{it-1} is correlated with the first difference error term, $u_{it}(=\varepsilon_{it}-\varepsilon_{it-1})$ (Equation 3.10), it is necessary to use instrumental variable procedures to cope with this problem (endogeneity). A possible solution is represented by the Generalised Method of Moments (GMM) technique. Therefore, this study employs a generalised method of moments (GMM) dynamic panel model to estimate the Equations. 3.11–3.14.

There are two widely used variants of GMM estimators in dynamic panel models: the GMM estimator in first difference, proposed by Arrelano and Bond (1991), and the system GMM estimator proposed by Blundell and Bond (1998). The first-differenced GMM approach consists of taking the equation to be estimated in first-differences in order to eliminate the specific-effect component. Then, lagged levels of the right hand side variables are used as instruments. Blundell and Bond (1998) point out that the first-differenced GMM estimator has poor finite sample properties, and it is downwards biased, especially when *T* is small. This occurs when the lagged levels of the series are only weakly correlated with subsequent first-differences, so that the instruments available for the first-differenced equations are weak. In the system GMM estimator, lagged differences of the series are used as instruments for the equations. They are derived from the estimation of a system of two simultaneous equations, one in levels (with lagged first differences as instruments) and the other in first differences (with lagged levels as instruments). Consider the first-order autoregressive panel data model:

$$y_{it} = \alpha y_{i,t-1} + u_{it} \quad i = 1, \cdots, N; \;\; t = 2, \cdots, T; \;\; u_{it} = \eta_i + v_{it} \tag{3.15}$$

where it is assumed that η_i and v_{it} have an error components structure with

$$E(\eta_i) = 0, \qquad E(v_{it}) = 0, \qquad E(v_{it}\eta_i) = 0, \qquad i = 1, \cdots, N; \; t = 2, \cdots, T$$

$$E(v_{it}v_{is}) = 0, \;\; i = 1, \cdots, N \; and \; t \neq s$$

and the initial condition satisfies

$$E(y_{i1}v_{is}) = 0, \;\; i = 1, \cdots, N; \; t = 2, \cdots, T$$

Blundell and Bond (1998) consider the additional assumption that:

$$E(\eta_i \Delta y_{i2}) = 0,$$

which holds when the process is mean stationary:

$$y_{i1} = \frac{\eta_i}{1-\alpha} + \epsilon_i$$

with $E(\varepsilon_i) = E(\varepsilon_i \eta_i) = 0$.

If all the moment conditions hold, then the following $(T-1)(T-2)/2$ moment conditions will be valid

$$E(u_{it}\Delta y_i^{t-1}) = 0, \qquad t = 3, \dots, T,$$

where $\Delta_{yi}^{t-1} = (\Delta y_{i2}, \Delta y_{i3}, \dots, \Delta y_{it-1})'$.

Defining

$$Z_{li} = \begin{bmatrix} \Delta y_{i2} & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & \Delta y_{i2} & \Delta y_{i3} & \cdots & 0 & \cdots & 0 \\ . & . & . & \cdots & . & \cdots & . \\ 0 & 0 & 0 & \cdots & \Delta y_{i2} & \cdots & \Delta y_{iT-1} \end{bmatrix}; u_i = \begin{bmatrix} u_{i3} \\ u_{i4} \\ \vdots \\ u_{iT} \end{bmatrix}$$

The last moment conditions can be written as:

$$E(Z_{li}'u_i) = 0,$$

with the GMM estimator based on these moment conditions given by

$$\widehat{\alpha_l} = \frac{y_{-1}'Z_lW_N^{-1}Z_l'y}{y_{-1}'Z_lW_N^{-1}Z_l'y_{-1}}$$

The full set of linear moment conditions is given by

$$E(y_i^{t-2}\Delta u_{it}) = 0 \qquad t = 3, \cdots, T,$$

$$E\left(u_{it}\Delta y_{i,t-1}\right) = 0 \qquad t = 3, \cdots, T,$$

or

$$E(Z_{si}'p_i) = 0,$$

where

$$Z_{si} = \begin{bmatrix} Z_{di} & 0 & \cdots & 0 \\ 0 & \Delta y_{i2} & \cdots & 0 \\ . & . & \ddots & . \\ 0 & 0 & \cdots & \Delta y_{iT} \end{bmatrix}; P_i = \begin{bmatrix} \Delta u_i \\ u_i \end{bmatrix}$$

The GMM estimator based on these moment conditions is

$$\widehat{\alpha_s} = \frac{q_{-1}'Z_sW_N^{-1}Z_s'q}{q_{-1}'Z_sW_N^{-1}Z_s'q_{-1}}$$

with $q_i = (\Delta y_i', y_i')'$. This estimator is called the system GMM estimator.[9]

This study uses the system GMM estimator which seems to have superior finite sample properties.

3.3.4 Data Description

Annual data for a set of 29 OECD countries covering the period from 1980 to 2011 are collected on gross domestic product, industrial output, capital, labour force,

[9] The calculation of the first-difference GMM and the system GMM estimators are discussed in more detail in Arrelano and Bond (1991) and Blundell and Bond (1998), respectively.

renewable energy consumption, non-renewable energy consumption, coal consumption, oil consumption, and natural gas consumption for a balanced panel with 928 observations for the selected OECD countries. The 29 sample countries are Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, South Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States. Due to unavailability of data, only 29 of the 34 countries that comprise the OECD are included in the analysis. The rationale behind selecting the time period from 1980 to 2011 is the availability of data.

In this study, real GDP in billions of constant 2000 U.S. dollars using purchasing power parities (PPPs) are used as a proxy for economic output. Capital, which is used as an input in the production function in fact refers to already-produced durable goods. Since capital stock data are not easy to collect and measure, gross fixed capital formation is usually used as a proxy for growth of capital stock. Particularly, in accordance with the perpetual inventory method assuming a constant depreciation rate indicates that changes in investment closely follow changes in the capital stock[10]. Thus, data of real gross fixed capital formation in billions of constant 2000 U.S. dollars are used in this study. Data on total labour force in millions, as well as industrial value added (as a proxy for industrial output) in billions of constant 2000 U.S. dollars are also applied. All the data mentioned above are obtained from the World Development Indicator Database (2012).

According to the Energy Information Administration (EIA), non-renewable energy sources include coal and coal products, oil, and natural gas. Therefore, in this study, non-renewable energy consumption is measured as the aggregate of the consumption of all these sources in quadrillion Btu units. Data on total coal consumption, total petroleum consumption, and dry natural gas consumption are also collected in quadrillion Btu units.

Renewable energy consumption in quadrillion Btu units is measured as wood, waste, geothermal, wind, photovoltaic, and solar thermal energy consumption. All the data

[10] See Soytas and Sari (2006), 742.

related to energy consumption are sourced from the U.S. Energy Information Administration.

All the variables are converted into natural logarithms prior to conducting the analysis, so that the parameter estimates of the model can be interpreted as elasticity estimates. The summary statistics of the variables are presented in Appendix Table 3.2 describing the number of observations, mean, variation (standard deviation) and bounds (minimum and maximum). To test for multicollinearity between the independent variables in each model, the variance inflation factors (VIF) for each predictor is calculated. VIF analysis is probably the most widely used approach, since it makes it possible to detect multicollinearity and to measure its effects on estimate precision. VIFs of 10 or higher indicate that there is a problem with multicollinearity. The results, presented in Appendix Table 3.3, indicate no existence of multicollinearity between the independent variables in each of the models.

3.4 Empirical Results

3.4.1 Panel Unit Root Test

The results of the unit root tests, including augmented Dickey and Fuller (1979) (ADF), the Phillips and Perron (1988) (PP), Breitung (2000), Levin et al. (2002) (LLC), and Im et al. (2003) (IPS) are presented in Table 3.1. All of these tests treat the presence of a unit root, implying non stationarity as the null hypothesis, and the absence of the unit root or stationarity as the alternative hypothesis. Individual trends and constants are included in the tests. The statistics significantly confirm that the level values of all series, except for natural gas consumption in ADF and LLC tests, non-renewable energy consumption and oil consumption in PP test, are non-stationary and all variables in all tests are stationary at the 1% significance level of the first difference.

Table 3.2 provides the results of the panel stationarity test with structural breaks following Carrion-i-Silvestre et al. (2005). These results indicate that the null hypothesis of stationarity is rejected by either the homogeneous and heterogeneous long-run variance for all the variables at the 5% level and for most of the variables at the 2.5% and 1% levels. Thus, it can be concluded that all the variables are non-stationary at their levels even when allowing structural breaks. The country by country tests with multiple breaks allowing for a maximum of five breaks are also calculated by means of Monte Carlo simulations based on 20,000 replications. Results are provided in Appendix Table 3.4.

Overall, the results of the panel unit root tests for all the variables used in this chapter confirm that the level values of all series are non-stationary and all variables are stationary at the first difference, that is, all variables are integrated of order one. Consequently, panel cointegration tests can be employed to study the long-run equilibrium process.

Table 3.2: Panel unit root test without structural breaks for the variables used in Models I, II, III and IV

Method	LGDP	LIV	LK	LF	LR	LN	LCO	LOIL	LNG
ADF									
Level	23.273	40.250	27.629	25.886	66.246	59.896	59.820	67.069	65.796
	(1.000)	(0.300)	(0.999)	(0.999)	(0.213)	(0.406)	(0.409)	(0.779)	(0.091)*
First	167.840	193.833	150.183	128.652	576.129	476.156	261.092	210.483	320.925
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
PP									
Level	39.232	47.084	46.350	7.128	18.682	72.556	60.176	76.627	35.385
	(0.972)	(0.846)	(0.864)	(1.000)	(1.000)	(0.094)*	(0.396)	(0.056)*	(0.157)
First	183.760	266.439	214.003	269.668	953.254	502.794	665.580	482.487	406.252
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Breitung									
Level	4.336	1.848	0.183	1.071	6.170	-1.093	-0.637	-0.157	0.504
	(1.000)	(0.967)	(0.572)	(0.858)	(1.000)	(0.137)	(0.261)	(0.437)	(0.693)
First	-2.929	-4.525	-4.563	-6.262	-10.406	-8.048	-8.221	-1.913	-4.990
difference	(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.007)***	(0.000)***
LLC									
Level	13.007	-0.523	7.691	1.162	2.525	-0.971	-1.174	0.768	-2.786
	(1.000)	(0.300)	(1.000)	(0.877)	(0.994)	(0.165)	(0.120)	(0.779)	(0.002)***
First	-5.711	-8.444	-3.274	-3.791	-22.953	-18.642	-9.272	-5.521	-15.254
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
IPS									
Level	5.128	2.756	3.573	3.525	3.187	1.288	-0.381	0.103	0.103
	(1.000)	(0.997)	(0.999)	(0.999)	(0.999)	(0.901)	(0.351)	(0.541)	(0.541)
First	-7.832	-11.469	-7.119	-5.780	-26.069	-21.815	-12.892	-13.485	-13.485
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***

Note: Probabilities of the test statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% level respectively. The Schwarz Information Criterion (SIC) has been used to determine the optimal lag length. The nulls for all tests are unit roots and all the regressions include an intercept and trend.

Table 3.3: Panel unit root test with structural breaks for the variables used in Models I, II, III and IV

Variables	Bartlett Kernel	Quadratic Kernel	Bootstrap critical values 5%	2.5%	1%
LGDP					
Homogeneous	11.127*	11.265*	11.012	11.893	12.075
Heterogeneous	11.090**	11.304**	10.208	10.919	11.871
LIV					
Homogeneous	18.384**	19.561***	17.091	17.628	18.631
Heterogeneous	20.004**	21.431***	18.562	19.853	20.673
LTLF					
Homogeneous	9.139***	9.140***	5.509	5.854	6.006
Heterogeneous	11.973***	12.002***	6.704	7.310	7.656
LK					
Homogeneous	7.841***	7.843***	7.092	7.806	8.666
Heterogeneous	8.722**	8.734**	6.695	7.723	8.991
LR					
Homogeneous	7.734**	7.611**	6.821	7.010	7.812
Heterogeneous	6.913***	6.742***	5.431	5.912	6.729
LN					
Homogeneous	8.893**	8.897**	8.711	8.991	9.123
Heterogeneous	9.710**	9.783**	9.512	9.703	10.111
LCO					
Homogeneous	16.287**	17.298***	13.276	15.387	16.289
Heterogeneous	18.287*	18.8925**	17.905	18.762	19.284
LOIL					
Homogeneous	13.276*	13.775**	12.892	13.287	14.287
Heterogeneous	12.738**	13.274**	11.782	12.371	13.825
LNG					
Homogeneous	14.287*	14.871*	14.382	15.104	16.385
Heterogeneous	14.625*	15.472**	14.373	15.412	16.511

Note: The number of structural breaks is up to 5. The long-run variance is estimated using both the Bartlett and the Quadratic spectral kernel with automatic spectral window bandwidth selection as in Sul et al. (2005). Furthermore, all bootstrap critical values allow for cross-sectional dependence. ***, ** and * indicate that the test statistic is significant at 1%, 2.5%, and 5% levels, respectively.

The existence of non-stationarity at the same integration order is the priority in order to implement cointegration analysis. Since not only non-stationarity but also same integration of order one in all the variables of interest are attained, the next step is to determine whether a long-run relationship between the variables in each model exists.

Table 3.4: Kao cointegration test for Models I, II, III and IV

	ADF	
	t-statistic	Prob.
Model I	-5.567	0.000***
Model II	-2.058	0.019**
Model III	-2.014	0.022**
Model IV	-5.939	0.000***

Note: *** and ** indicate rejection of the null hypothesis of no cointegration at the 1% and 5% significance levels, respectively.

3.4.2 *Panel Cointegration Test*

The results of Kao (1999), Pedroni (2004), Westerlund (2007) and Johansen Fisher proposed by Maddala and Wu (1999) for the Models I–IV are reported in Table 3.3, Table 3.4, Table 3.5, and Table 3.6, respectively. The results of the Kao (1999) test, reported in Table 3.3, suggest evidence of cointegration between variables at the 1% level of significance in Model I and Model IV and at the 5% level of significance in Model II and Model III. The results of Pedroni's (2004) heterogeneous panel tests (Table 3.4) are as follows: for Model I, the null of no cointegration is rejected at the 1% significance level in panel v-statistic and group rho-statistic, and at the 5% significance level in panel ADF-statistic and group PP-statistic; for Model II, the null is rejected at the 1% significance level in panel v-statistic, panel ADF-statistic, and group ADF-statistic and at the 10% significance level in group PP-statistic; for Model III, the null is rejected at the 1% significance level in panel v-statistic, panel ADF-statistic, group PP-statistic, and group ADF-statistic; for Model IV, the null is rejected at the 1% significance level in panel v-statistic, panel ADF-statistic, and group ADF-statistic and at the 5% significance level in group PP-statistic.

The results of the Johansen panel cointegration test, provided in Table 3.5, from both a trace test and a maximum eigen-value test indicate the existence of cointegration in all the four models. The results of the Westerlund (2007) test (Table 3.6) confirm the presence of cointegration at a 1% significance level in Model I under group-t, group-a, and panel-a statistics, in Model II under group-t and panel-t statistics, in Model III and Model IV under group-t, group-a, panel-t, and panel-a statistics.

To summarize, it is clearly seen that the results of the Kao, Pedroni, Johansen Fisher, and Westerlund tests for cointegration are consistent, implying that a long-run equilibrium relationship exists between GDP, capital, labour force, renewable and non-renewable energy consumption in selected OECD countries.

Table 3.5: Pederoni cointegration test for Models I, II, III and IV

	Statistic	Prob.	Weighte	
			Statistic	Prob.
Model I				
Alternative hypothesis: common AR coefs. (within-dimension)				
Panel v-Statistic	20.54	0.000***	10.994	0.000***
Panel rho-Statistic	3.123	0.999	3.753	0.999
Panel PP-Statistic	-0.697	0.242	-0.036	0.485
Panel ADF-Statistic	-1.802	0.035**	-2.656	0.004***
Alternative hypothesis: individual AR coefs. (between-dimension)				
Group rho-Statistic	4.893	0.000***		
Group PP-Statistic	1.999	0.048**		
Group ADF-Statistic	0.187	0.385		
Model II				
Alternative hypothesis: common AR coefs. (within-dimension)				
Panel v-Statistic	2.453	0.007***	-2.140	0.005***
Panel rho-tatistic	0.722	0.765	2.247	0.987
Panel PP-Statistic	-1.124	0.130	-0.708	0.703
Panel ADF-Statistic	-2.357	0.007***	-2.515	0.005***
Alternative hypothesis: individual AR coefs. (between-dimension)				
Group rho-Statistic	3.625	0.999		
Group PP-Statistic	-1.644	0.059*		
Group ADF-Statistic	-2.427	0.007***		
Model III				
Alternative hypothesis: common AR coefs. (within-dimension)				
Panel v-Statistic	17.216	0.000***	10.451	0.000***
Panel rho-tatistic	4.270	1.000	4.413	1.000
Panel PP-Statistic	-1.007	0.165	-0.307	0.379
Panel ADF-Statistic	-2.896	0.001***	-2.456	0.007***
Alternative hypothesis: individual AR coefs. (between-dimension)				
Group rho-Statistic	6.769	1.000		
Group PP-Statistic	-2.365	0.009***		
Group ADF-Statistic	-3.566	0.000***		

	Statistic	Prob.	Weighte	
			Statistic	Prob.
Model IV				
Alternative hypothesis: common AR coefs. (within-dimension)				
Panel v-Statistic	-1.967	0.975	-0.986	0.88
Panel rho-tatistic	-4.384	0.000***	4.906	1.000
Panel ADF-Statistic	-2.792	0.001***	-2.852	0.002***
Alternative hypothesis: individual AR coefs. (between-dimension)				
Group rho-Statistic	6.483	1.000		
Group PP-Statistic	-1.646	0.049**		
Group ADF-Statistic	-4.631	0.000***		

Note: Intercept and deterministic trend are included. The optimal lag length is selected by Akaike Information Criterion. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels respectively.

Table 3.6: Johansen Fisher cointegration test for Models I, II, III and IV

Model	Fisher	Prob.	Fisher	Prob.
Model I				
None	579.7	0.000**	342.2	0.000**
At most 1	272.7	0.000**	197.6	0.000**
At most 2	182.7	0.000**	167.6	0.000**
At most 3	163.2	0.000**	102.39	0.000**
At most 4	79.45	0.047**	77.74	0.055*
Model II				
None	399.5	0.000**	263.2	0.000**
At most 1	192.7	0.000**	107.3	0.000**
At most 2	120.9	0.000**	82.19	0.020**
At most 3	80.92	0.025**	68.87	0.155
At most 4	85.75	0.010**	85.75	0.010**
Model III				
None	789.2	0.000**	447.0	0.000**
At most 1	411.5	0.000**	233.9	0.000**
At most 2	226.4	0.000**	136.3	0.000**
At most 3	136.3	0.000**	85.45	0.011**
At most 4	95.00	0.001**	78.66	0.036**
At most 5	88.78	0.005**	88.78	0.005**
Model IV				
None	787.6	0.000**	467.5	0.000**
At most 1	403.2	0.000**	203.4	0.000**
At most 2	238.1	0.000**	128.5	0.000**
At most 3	146.0	0.000**	96.30	0.001**

Model	Fisher	Prob.	Fisher	Prob.
At most 4	96.20	0.001**	81.80	0.021**
At most 5	86.98	0.008**	86.98	0.008**

Note: The Schwarz Information Criterion (SIC) has been used to determine the optimal lag length. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels, respectively.

Table 3.7: Westerlund cointegration test for Models I, II, III and IV

Statistic	Value	*P*-value
Model I		
Group-t	-12.235	0.000***
Group-a	-10.817	0.000***
Panel-t	-1.635	1.000
Panel-a	-8.687	0.000***
Model II		
Group-t	-3.965	0.000***
Group-a	-0.322	1.000
Panel-t	-7.645	0.000***
Panel-a	-0.324	1.000
Model III		
Group-t	-7.675	0.000***
Group-a	-7.555	0.000***
Panel-t	-6.264	0.000***
Panel-a	-5.010	0.000***
Model IV		
Group-t	-4.919	0.000***
Group-a	-7.271	0.000***
Panel-t	-2.654	0.000***
Panel-a	-4.908	0.000***

Note: *** indicates that the test statistic is significant at 1% level. Following Westerlund (2007) maximum lag length is selected according to $4(T/100)^{2/9}$. The null hypothesis of the test is “no cointegration”.

3.4.3 Long-Run Estimation

Table 3.7 presents the results of estimating the long-run relationship between the variables in the four Models I, II, III, and IV based on the DOLS method. For real gross domestic product (Model I), the coefficients of real gross fixed capital formation (capital), total labour force, renewable, and non-renewable energy consumption are positive and significant at the 1% level. These results show that in the long run a 1% increase in capital, total labour force, renewable, and non-renewable energy consumption will enhance real GDP by 0.556%, 0.180%, 0.024%, and 0.245%, respectively. Comparing the coefficients of the independent variables indicates that capital has the largest effect on real GDP in the long run. In addition, the elasticities of real GDP with respect to renewable and non-renewable energy consumption demonstrate that both types of energy stimulate economic growth in OECD countries. However, comparing the magnitudes of their coefficients confirms that non-renewables are still the dominant type of energy utilised in the process of economic growth. When it comes to energy policy, it seems governments normally focus on security of supply and prices of energy. However, it is important that governments promote technological innovation and investment in renewable energy sector. This, in turn, can create employment opportunities and increase GDP.

Comparison with other studies in which the effects of renewable and non-renewable energy consumption are simultaneously investigated on economic growth show that the results obtained here are consistent with those reported by Apergis and Payne (2012b) for 80 developed and developing countries. However, the results are different from those by Apergis and Payne (2011c) and Apergis and Payne (2012a) who find positive and significant impact only for non-renewable energy consumption in 16 emerging countries and in six Central American countries, respectively. Finding positive and significant relationship between renewable energy consumption and economic growth in the long term is also found by Chien and Hu (2008) for 116 different countries, Apergis and Payne (2010d) for 20 OECD countries, Apergis and Payne (2010e) for 13 Eurasian countries, Apergis and Payne (2011b) for six Central American countries, Menegaki (2011) for European countries, and Fang (2011) for China.

In Model II in which industrial value added is the dependent variable (Table 3.7), the coefficients of capital, labour force, and renewable and non-renewable energy consumption are positive and statistically significant at the 1% level except for renewable energy consumption which is statistically insignificant. The findings show that a 1% increase in any of capital, labour force, or non-renewable energy consumption enhances industrial output by 0.460%, 0.205%, and 0.171%, respectively in the long run. Similar to the previous model, capital has the highest elasticity compared with the other independent variables. The evidence indicates that although the share of the use of non-renewable energy is declining compared with the share of renewable sources, non-renewables still play a considerable role in industrial production today. Therefore, since renewable energy is negligible compared to that derived from fossil fuels, it still requires more time and a huge investment to switch over to renewable energy sources in the industrial sector.

Table 3.8: Coefficients of DOLS estimates for Models I, II, III and IV

	Model I	Model II	Model III	Model IV
LK	0.556 (42.73)***	0.460 (13.90)***	0.584 (45.15)***	0.469 (14.88)***
LTLF	0.180 (7.16)***	0.205 (3.09)***	0.270 (10.18)***	0.217 (3.35)***
LR	0.024 (4.57)***	0.015 (1.14)		
LN	0.245 (12.25)***	0.171 (3.37)***		
LCO			0.003 (0.46)	0.031 (1.82)*
LOIL			0.144 (6.77)***	0.113 (2.19)**
LNG			0.020 (5.60)***	0.030 (3.43)***

Note: The related statistics are presented in parentheses. ***, **, and * indicate that the test statistic is significant at 1%, 5%, and 10% levels. Lags and leads of two are included into the regressions.

Considering Model III (Table 3.7), the results indicate that all the three types of the non-renewable energy consumption, including coal, oil and natural gas consumption are positively related to real GDP in the long run. The coefficients of oil and natural gas consumption are statistically significant at the 1% level, whereas the coefficient of coal consumption is statistically insignificant. The results for capital and labour force remain the same as Model I. Significant elasticities of real GDP with respect to oil and natural gas consumption suggest that a 1% increase in oil consumption increases economic growth by 0.144%, while a 1% increase in natural gas consumption increases economic growth by 0.020% in the long term. Finding no significant relationship between coal consumption and GDP growth may be due to emerging policies that try to curb pollutant emissions by imposing a cost on higher-carbon fuels. Demand for coal as the most carbon intensive fossil fuel is gradually declining in developed countries. In this respect, Apergis and Payne (2010a) find a negative and significant relation between coal consumption and real GDP in OECD countries in the long run. They explain that the negative effect is the result of inefficient and excessive use of coal and the possibility that the immediate economic benefit associated with the use of coal is outweighed by the economic costs imposed on the environment by carbon dioxide emissions.

A positive and significant association between oil consumption and real GDP obtained in this study is consistent with that of Bashiri Behmiri and Pires Manso (2012) for 27 OECD countries. Even though policies seek to slow consumption growth of oil, it is still the dominant fuel, particularly in the transport sector. According to EIA, since developed countries tend to have higher vehicle ownership per capita, oil consumption within the OECD transportation sector usually accounts for a larger share of total oil consumption than in non-OECD countries. On the other hand, oil is used in many ways, from the manufacture of goods, to transport of goods and people, to food production, to operating construction equipment, to mining. Therefore, it should not be surprising to find that there is a close tie between GDP growth and oil consumption.

A positive and significant impact of natural gas consumption on real GDP indicates that natural gas, as a non-renewable energy source, has a substantial role in economic growth in OECD countries. Natural gas which seems to have the number-two position behind oil has an important feature in that it generates less carbon emissions compared with the other fossil fuels. Thus, fuel transformation, at least from coal and/or oil to natural gas, should be taken into account by policymakers. The results of the long-run effect of natural gas consumption on the real GDP is consistent with those reported by Apergis and Payne (2010c) who also find a positive and significant relationship between natural gas use and real GDP for a panel of 67 countries.

In Model IV (Table 3.7), capital, labour force, coal consumption, oil consumption, and natural gas consumption are positively related to industrial output. While the long-run coefficients of capital, labour force, and natural gas consumption are significant at the 1% level, the coefficient of coal consumption and oil consumption are statistically significant at the 10% and the 5% levels, respectively. The results indicate that a 1% increase in capital or labour force enhances industrial output by 0.469% and 0.217%, respectively. These coefficients are quite close to the magnitudes of the coefficients obtained for capital and labour force in Model II. In addition, the coefficients of the non-renewable energy variables show that a 1%

increase in coal consumption, oil consumption, or natural gas consumption increases industrial output by 0.031%, 0.113%, and 0.030%, respectively. Finding a positive relationship between coal consumption and industrial output is in contrast with the negative relationship between coal consumption and industrial output found by Yildirim (2012) in the US. He claims that the use of coal in the industrial sector is affected by changes in coal prices. It appears that the industrial sector in developed countries still benefits from the use of coal. The reason is that coal is an abundant and affordable source of energy and also it is easy to transport and store.

Comparing the coefficients of the three sources of non-renewable energy demonstrates that oil is the most utilised fuel in the industrial sector in OECD countries. Although, oil is a relatively cheap fuel and readily available, it is non-renewable and will eventually run out. Thus, it is essential that decision makers replace oil with alternative sources of energy that are renewable and efficient.

3.4.4 Panel Granger Causality

The results of the short-run and long-run Granger causality tests for Model I, Model II, Model III, and Model IV are presented in this section. Beginning with Model I, the results reported in Table 3.8 show that real gross fixed capital formation, total labour force, renewable and non-renewable energy consumption each has a positive and significant effect on real GDP. The coefficients of all the variables are significant at the 1% level except for total labour force which is significant at the 5% level. This suggests that real gross fixed capital formation, total labour force, renewable and non-renewable energy consumption do Granger cause economic growth in the short run. In estimating the second equation in which real gross fixed capital formation is the dependent variable, the impacts of real GDP, total labour force on the real gross fixed capital formation are positive and statistically significant at the 1% and 5% level, respectively. In addition, the effects of renewable and non-renewable energy consumption on the real gross fixed capital formation are also positive and significant at the 1% level. This shows that economic growth, total labour force, renewable and non-renewable energy consumption cause the real gross fixed capital formation in the short run. In regards to the third equation, only real gross fixed capital formation has a positive and significant impact at the 5% level on the total labour force. This result indicates that real gross fixed capital formation is the only factor that Granger cause total labour force in the short run.

Table 3.9: Panel causality test for real GDP (Model I)

Dependent Variables	Source of causation (independent variable)					
	Short run					Long run
	ΔLGDP	ΔLK	ΔLF	ΔLR	ΔLN	ECT
ΔLGDP	_	0.508 (58.41)***	0.146 (2.49)**	0.014 (8.54)***	0.109 (13.55)***	-0.334 (-21.12)***
ΔLK	1.478 (67.96)***	_	0.112 (2.58)**	0.021 (9.23)***	0.104 (9.38)***	-0.767 (-40.38)***
ΔLF	0.016 (0.49)	0.053 (2.51)**	_	0.001 (0.87)	0.005 (0.57)	-0.017 (-0.77)
ΔLR	2.739 (4.51)***	1.725 (4.92)***	0.138 (0.22)	_	0.899 (0.33)	2.048 (4.90)***
ΔLN	0.626 (5.73)***	0.191 (2.90)***	0.203 (1.76)*	0.035 (0.55)	_	0.309 (3.92)***

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% level respectively. The optimal lag length for the variables is two and determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

With respect to the fourth equation for renewable energy consumption, real GDP and real gross fixed capital formation each has a positive and statistically significant effect at the 1% level on renewable energy consumption. This demonstrates that real GDP and real gross fixed capital formation Granger cause renewable energy consumption in the short run. Finally, for the last equation, real GDP, real gross fixed capital formation, and total labour force positively and significantly influence non-renewable energy consumption, implying these variables Granger cause non-renewable energy consumption in the short run.

In sum, the empirical results indicate that there is bidirectional causality between real GDP and real gross fixed capital formation, between real GDP and renewable energy consumption, between real GDP and non-renewable energy consumption; and unidirectional causality from labour force to real GDP. Bidirectional causality is also found between real gross capital formation and labour force, between real gross capital formation and renewable energy consumption and between real gross capital formation and non-renewable energy consumption. Furthermore, unidirectional Granger causality running from labour force to non-renewable energy consumption, and no causality between labour force and renewable energy and also between renewable energy use and non-renewable energy use are obtained in Model I in the short run.

The results of bidirectional causality between real GDP and renewable energy consumption as well as between real GDP and non-renewable energy consumption are consistent with Apergis and Payne (2012b) who also investigate the two types of energy simultaneously for 80 developed and developing countries. The results on the relationship between real GDP and non-renewable energy consumption is also similar to the finding of Apergis and Payne (2011c) for 16 emerging economies and Apergis and Payne (2012a) for six Central American countries. However, the results with respect to the relationship between economic growth and renewable energy use are different with those (Apergis and Payne 2011c; Apergis and Payne 2012a) who find unidirectional causality from GDP to renewable energy use and unidirectional causality from renewable energy use to GDP, respectively.

Focusing on the causality between economic growth and renewable energy consumption, the result obtained in this study is consistent with Apergis and Payne (2010d) for 20 OECD countries, Apergis and Payne (2010e) for Eurasia countries and Apergis and Payne (2011b) for Central American countries.

The finding of bidirectional causality between economic growth and the two types of energy confirms the feedback hypothesis implying that a high level of economic growth leads to high level of consumption in both renewable and non-renewable energy and vice-versa. However, the governments should substitute renewable energy sources for non-renewable energy sources and encourage more usage of renewables in order to mitigate CO_2 emissions.

The long-run dynamics displayed by the error correction terms in Model I confirm evidence of the presence of bidirectional causality between renewable energy consumption and real GDP as well as between non-renewable energy consumption and real GDP. In addition, the coefficient of the error correction term in the first equation suggests that the deviation of real GDP from short run to the long run is corrected by 33% each year; and convergence to equilibrium after a shock to real GDP takes about 3 years[11] (Table 3.8).

[11] The number of years is calculated as the inverse of the absolute value of the ECT.

Table 3.10: Panel causality test for industrial output (Model II)

Dependent Variables	Source of causation (independent variable)					
	Short run					Long run
	ΔLIV	ΔLK	ΔLF	ΔLR	ΔLN	ECT
ΔLIV	_	0.746	0.155	0.019	0.375	-0.816
		(47.49)***	(2.29)**	(6.83)***	(2.50)**	(-52.59)***
ΔLK	0.921	_	0.167	0.018	0.104	0.927
	(56.92)***		(2.30)**	(6.26)***	(7.11)***	(64.59)***
ΔLF	0.027	0.032	_	0.001	0.007	0.019
	(2.36)**	(1.78)*		(0.54)	(0.82)	(0.99)
ΔLR	1.319	1.121	0.212	_	0.569	1.154
	(3.46)***	(3.19)***	(0.32)		(0.36)	(3.09)***
ΔLN	0.269	0.394	0.317	0.025	_	-0.312
	(3.51)***	(5.63)***	(2.43)**	(0.44)		(-4.18)***

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% level respectively. The optimal lag length for the variables is two and determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

Turning to Model II (Table 3.9), the results of Granger causality between the variables in the first equation indicate that real gross capital formation and renewable energy consumption have a positive and statistically significant effect at the 1% level and labour force and non-renewable energy consumption have a positive and significant effect at the 5% level on industrial output. The findings suggest that capital, labour force, and both renewable and non-renewable energy consumption do Granger cause industrial output in the short run. Considering the causality relationship between industrial output and the other variables in rest of the equations, the results show that industrial output positively and significantly influences gross capital formation, labour force, and both renewable and non-renewable energy consumption. This suggests that industrial output Granger cause capital, labour force, and both renewable and non-renewable energy use in the short run.

Overall, the results of Model II (Table 3.9) indicate that there is bidirectional causality between industrial output and each of capital, labour force, renewable and non-renewable energy consumption. The two-way relationship between industrial output and both kinds of energy which supports a feedback hypothesis implies that renewable and non-renewable energy consumption mutually influences each other in OECD countries in the short run. Therefore, energy conservation in terms of either renewable or non-renewable may lead to a reduction in industrial production. On the other hand, any negative shock in the process of industrial output can have a negative impact on energy.

With respect to the long-run causality relationship between the variables, the error correction terms suggest that there is bidirectional causality between industrial output and either of renewable and non-renewable energy consumption in the long run. The negative and significant coefficient of the error correction term in the first equation in Model II denotes that industrial output readjusts towards a common international equilibrium relationship after 1.2 years after a shock (Table 3.9).

The causality results of Model III, provided in Table 3.10, indicate that all the three types of non-renewable energy (i.e. coal, oil, and natural gas) have a positive relationship with real GDP. However, only the coefficients of oil and natural gas consumption are statistically significant, implying that oil consumption and natural gas consumption Granger cause real GDP in the short run. The effects of coal consumption, oil consumption, and natural gas consumption on capital are positive and significant, whereas only natural gas consumption has a positive and significant impact on labour force. This suggests that all the three types of non-renewable energy Granger cause capital, and only natural gas consumption causes labour force in the short run. For coal consumption, only capital has a positive and significant impact on it. Real GDP and capital have a positive and significant effect on oil consumption. Real GDP, capital, and oil consumption positively and significantly affect natural gas consumption in the short run. These findings demonstrate that capital causes coal consumption, real GDP and capital cause oil consumption, and finally, real GDP, capital and oil consumption Granger cause natural gas consumption in the short run.

Overall, the results confirm evidence of two-way causality between oil consumption and real GDP as well as between natural gas consumption and real GDP and no causality between real GDP and coal consumption in the short term. The result of the relationship between economic growth and coal consumption is consistent with Jinke et al. (2008) for India, South Africa, and South Korea and also with Payne (2011) for the US. However, it is different from Apergis and Payne (2010a) and Apergis and

Payne (2010b) who find a bidirectional causality between real GDP and coal consumption in OECD countries and in emerging market economies, respectively.

Finding two-way causality between real GDP and oil consumption is similar to the results obtained by Yoo (2006) for Korea, Zhao et al. (2008) and Yuan et al. (2008) for China, Yilmaz (2008) for Turkey, Pradhan (2010) for Pakistan, and Bashiri Behmiri and Pires Manso (2012) for OECD countries. However, this result is in contrast with earlier results which show a one-way causality from oil consumption to economic growth found by Payne (2011a) for the US and Chu and Chang (2012) for Germany and Japan. The result also contrasts with unidirectional causality from economic growth to oil consumption found by Yang (2000) for Taiwan, Zamani (2009) for Iran, and Chu and Chang (2012) for the US. Bidirectional causality between real GDP and natural gas consumption found in this study is in line with Apergis and Payne (2010c) for a panel of 67 countries, and also with Kum et al. (2012) for France, Germany, and the US. However, this result contrasts with the unidirectional causality running from economic growth to natural gas consumption found by Pirlogea and Cicea (2012) for Spain.

The long-run causality results based on the error correction terms in Model III (Table 3.10) indicate that there is two-way causality between real GDP and oil consumption and also between real GDP and natural gas consumption. Moreover, the coefficient of the error correction term in Model III suggests that the deviation of real GDP from short run to the long run is corrected by 32% each year; and coupling toward equilibrium after a shock, takes 3 years.

In the last model (Model IV), the results represented in Table 3.11 demonstrate that all the three fossil fuel variables, coal, oil, and natural gas consumption have positive and statistically significant on industrial output in the short run. In the equations in which coal, oil, and natural gas are the dependent variables, the findings show that industrial output has a positive and significant impact on each of them. Thus, it can be concluded that there is bidirectional causality between industrial output and each of coal, oil, and natural gas consumption in the short term. This conclusion supports the feedback hypothesis which suggests that in this case industrial value added and each type of non-renewable energy consumption influence each other simultaneously. Therefore, restraint in the use of coal, oil, or natural gas may reduce industrial output. On the other hand, any restriction in the process of industrial output leads to a reduction in energy consumption that can, in turn, intensify the declining trend in industrial production. Finding a two-way relationship between industrial output and oil consumption is in line with that of Ziramba (2009) for South Africa; and finding bidirectional causality between industrial output and coal consumption is in line with that of Yildirim (2012) for the US. However, these results are in contrast with Zamani (2007) who finds one-way causality from industrial output to oil consumption for Iran; and also with Ziramba (2009) who reveals no causality between industrial output and coal consumption in South Africa. The long run causality results in Model IV (Table 3.11) showing that industrial output, gross fixed capital formation, the labor force, coal consumption, oil consumption, and natural gas consumption each respond to deviations from long-run equilibrium as displayed by the significant coefficients of their respective error correction terms. The results also reveal that there is two-way causality between industrial output and each of the non-renewable types of energy in the long run.

Table 3.11: Panel causality test for industrial output (Model III)

Dependent Variables	Source of causation (independent variable)						
	Short run						Long run
	ΔLGDP	ΔLK	ΔLF	ΔLCO	ΔLOIL	ΔLNG	ECT
ΔLGDP	_	0.507	0.147	0.001	0.102	0.008	-0.326
		(60.72)***	(2.50)**	(0.52)	(13.40)***	(9.37)***	(-32.58)***
ΔLK	1.495	_	0.607	0.006	0.153	0.016	0.736
	(71.25)***		(1.82)**	(1.92)**	(13.63)***	(13.04)***	(41.45)***
ΔLF	0.036	0.012	_	0.001	0.004	0.002	0.008
	(1.10)	(1.69)*		(0.38)	(0.48)	(1.79)*	(0.36)
ΔLCO	-0.174	0.498	0.594	_	0.050	-0.006	-0.510
	(-0.41)	(2.03)**	(1.37)		(0.42)	(-0.56)	(-1.73)*
ΔLOIL	0.625	0.196	0.104	0.008	_	0.001	0.333
	(5.55)***	(2.97)***	(2.85)	(0.92)		(0.52)	(4.22)***
ΔLNG	6.428	4.807	1.544	0.096	1.335	_	-6.519
	(6.45)***	(8.47)***	(1.48)	(1.13)	(4.84)***		(-9.57)***

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels respectively. The optimal lag length for the variables is two and determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

Table 3.12: Panel causality test for industrial output (Model IV)

Dependent variables	Source of causation (independent variable)						
	Short run						Long run
	ΔLIV	ΔLK	ΔLF	ΔLCO	ΔLOIL	ΔLNG	ECT
ΔLIV	_	0.810	0.770	0.020	0.205	0.049	-0.785
		(48.67)***	(1.77)**	(4.09)***	(13.37)***	(29.64)***	(-52.28)***
ΔLK	0.851	_	0.366	0.029	0.276	0.052	0.845
	(58.04)***		(2.60)***	(6.22)***	(19.98)***	(34.19)***	(68.80)***
ΔLF	0.037	0.032	_	0.001	0.002	0.001	0.030
	(2.20)**	(1.91)*		(0.37)	(0.24)	(0.83)	(1.88)*
ΔLCO	0.945	1.245	0.499	_	0.300	0.063	-1.005
	(4.35)	(5.70)***	(1.16)		(2.55)**	(3.83)***	(-4.78)***
ΔLOIL	0.771	0.902	0.085	0.024	_	0.055	-0.798
	(13.91)***	(16.88)***	(0.68)	(2.50)**		(12.77)***	(-15.37)***
ΔLNG	8.323	8.571	2.157	0.164	1.880	_	8.581
	(28.84)***	(30.07)***	(1.37)	(2.72)***	(9.66)***		(32.67)***

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% level respectively. The optimal lag length for the variables is two and determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

3.5 Conclusion

The objective of this chapter is to investigate the effects of renewable and non-renewable energy consumption alongside real gross fixed capital formation and labour force on economic growth based on a neoclassical economic growth model. In addition, as it seems that non-renewables are still the dominant energy sources utilized in economic sectors, the individual impacts of coal, natural gas, and oil (petroleum) consumption on economic growth are also examined in order to make a comparison among them. Furthermore, the effects of disaggregated energy consumption on the industrial sector which has an important role in the economic growth of countries are also investigated. The empirical findings are based on a dataset for selected OECD countries over the period 1980 to 2011.

This study uses recently developed panel unit root and panel cointegration tests and also applies a more recently used method, Dynamic OLS (DOLS) in order to estimate the long-run relationship between the variables. The results of cointegration tests indicate the existence of a long-run equilibrium relationship between all the variables in all of the four models. With respect to the long-run estimation, for real gross domestic product (Model I), the coefficients of real gross fixed capital formation (capital), total labour force, renewable, and non-renewable energy consumption are positive and significant at 1% level. The elasticities of real GDP with respect to renewable and non-renewable energy consumption demonstrate that both types of energy stimulate economic growth in OECD countries. However, comparing the magnitudes of their coefficients confirms that non-renewables are still the dominant type of energy utilized in the process of economic growth. Similar results are obtained for industrial output, indicating that although the share of the use of non-renewable energy is declining compared with the share of renewable sources, non-renewables still play a considerable role in industrial production in developed countries today.

The results related to the three types of the non-renewable energy consumption show that oil and natural gas have a positive and statistically significant impact on real GDP, whereas the coefficient of coal consumption is statistically insignificant. Finding no significant relationship between coal consumption and GDP growth may be due to emerging policies that try to curb pollutant emissions by imposing a cost on higher-carbon fuels. Demand for coal as the most carbon intensive fossil fuel is gradually declining in developed countries. On the other hand, even though policies seek to slow consumption growth of oil, it is still the dominant fuel particularly in the transport sector. According to the EIA, since developed countries tend to have higher vehicle ownership per capita, oil consumption within the OECD transportation sector usually accounts for a larger share of total oil consumption than in non-OECD countries. In addition, oil is used in many ways, from the manufacture of goods, to transport of goods and people, to food production, to operating construction equipment, to mining. Therefore, it should not be surprising to find that there is a close relationship between GDP growth and oil consumption. A positive and significant impact of natural gas on real GDP denotes that natural gas as a non-renewable energy source has a substantial role in economic growth in OECD countries. Natural gas, which seems to be of secondary importance behind oil, has an important feature in that it generates less carbon emissions compared with the other fossil fuels. Thus, fuel transformation at least from coal and/or oil to natural gas should be taken into account by policymakers. Finally, the long-run results suggest that there is a positive and statistically significant relationship between coal, oil, and natural gas consumption and industrial output. It appears that industrial sectors in developed countries still benefit from the use of coal. The reason may be that coal is an abundant and affordable source of energy and also it is easy to transport and store.

The major causality results show that there is bidirectional causality between real GDP and renewable energy consumption as well as between real GDP and non-renewable energy consumption in both the short run and long run. This finding confirms the feedback hypothesis which implies that a high level of economic growth leads to high level of consumption in both renewable and non-renewable energy and vice-versa. However, governments should encourage the substitution of renewable energy sources for non-renewable energy sources in order to mitigate emissions. The same results are achieved for industrial output, suggesting that energy conservation in terms of either renewable or non-renewable may lead to a reduction in industrial production. Moreover, the results confirm evidence of two-way causality between oil consumption and real GDP, between natural gas consumption and real GDP and also no causality between real GDP and coal consumption in the short term and long term. For industrial output, the causality results reveal that there is bidirectional causality between industrial output and each of coal, oil, and natural gas consumption in the short term and long term. Therefore, it can be concluded that restraint in the use of coal, oil, or natural gas may decrease industrial output. On the other hand, any restriction in the process of industrial output leads to a reduction in energy consumption that can in turn intensify the diminishing trend of industrial production.

As discussed in this chapter, both renewable and non-renewable energy consumption affect economic activities. Therefore, identifying and investigating the factors that influence energy consumption is important not only to the process of economic growth, but to the purposes of reducing pollutant emissions. The following chapter addresses this issue.

Appendix to Chapter 3

Appendix Table 3.1: Summary of Literature on Decomposed Energy Consumption-Output Nexus

Study	Country (Period)	Methodology	Main Variable	Finding
Jinke et al. (2008)	OECD and non-OECD countries (1980-2005)	Cointegration and Granger causality	GDP and coal consumption	Unidirectional causality running from GDP to coal consumption in Japan and China, and no causality relationship between coal consumption and GDP in India, South Korea and South Africa.
Apergis and Payne (2010a)	25 OECD countries (1980-2005)	Cointegration, fully modified OLS (FMOLS) and Granger causality	GDP and coal consumption	Negative relationship between GDP and coal consumption in the long run and bidirectional causality between coal consumption and economic growth in both the short run and long run.
Wolde-Rufael (2009)	6 major coal consuming countries (1965-2005)	Toda-Yamamo causality	GDP and coal consumption	Unidirectional causality running from coal consumption to economic growth in India and Japan; unidirectional causality running from economic growth to coal consumption in China and South Korea and bidirectional causality between economic growth and coal consumption in South Africa and the US.
Bloch et al. (2012)	China (1965-2008)	Cointegration, Granger causality and generalized forecast error variance decomposition	GDP and coal consumption	Unidirectional causality from coal consumption to GDP in the short and long run under the supply-side analysis and a unidirectional causality from GDP to coal consumption in the short and long run under the demand-side analysis.
Bashiri Behmiri and Pires Manso (2012)	27 OECD countries (1976-2009)	Cointegration, FMOLS and Granger causality	GDP and oil consumption	Bidirectional causality between crude oil consumption and GDP in the short run and long run.

Apergis and Payne (2010c)	67 countries (1992-2005)	Cointegration, FMOLS and Granger causality	GDP and gas consumption	Bidirectional causality between natural gas consumption and GDP in the short and long run.
Apergis and Payne (2010d)	20 OECD countries (1985-2005	Cointegration, FMOLS and Granger causality	GDP and renewable energy consumption	Bidirectional causality between renewable energy consumption and GDP in the short and long run.
Apergis and Payne (2012a)	6 Central American countries (1990-2007)	Cointegration, FMOLS and Granger causality	GDP, renewable and non-renewable electricity consumption	Unidirectional causality from renewable electricity consumption to GDP in the short run, but bidirectional causality in the long run and bidirectional causality between non-renewable electricity consumption and economic growth in the short run and long run.
Apergis and Payne (2012b)	80 developed and developing countries (1990-2007)	Cointegration, FMOLS and Granger causality	GDP, renewable and non-renewable energy consumption	Bidirectional causality between renewable and non-renewable energy consumption measures and GDP in both short run and long run.
Pirlogea and Cicea (2012)	Romania, Spain and 27 European Union (1990- 2010)	Cointegration and Granger causality	GDP per capita, renewable energy, coal, natural gas, and oil consumption	Unidirectional causality from renewable energy consumption to GDP per capita in Romania and from natural gas consumption to GDP per capita in Spain in the short run. No causal relationship between any type of energy and GDP per capita in the EU-27.
Ziramba (2009)	South Africa (1980-2005)	Toda-Yamamoto causality	Industrial output, oil and coal consumption	Bidirectional causality between oil consumption and industrial production and no causality between coal consumption and industrial production.
Payne (2011b)	US (1949-2006)	Toda-Yamamoto causality	GDP, coal, natural gas and petroleum consumption	No causality between coal consumption and GDP, unidirectional causality from GDP to natural gas consumption and unidirectional causality from petroleum consumption to GDP.

Appendix Table 3.2: Summary statistics of the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
LGDP	928	26.19066	1.530577	22.3644	30.09438
LN	928	0.6131858	1.562073	-3.79691	4.45892
LR	928	-2.034407	1.991509	-8.4684	1.5453
LF	928	15.78872	1.509211	11.7592	18.9189
LK	928	24.56575	1.544678	20.7338	28.43705
LIV	928	24.84426	1.569915	21.1034	28.4856
LCO	928	-1.254828	1.959478	-7.16912	3.12987
LOIL	928	0.0202459	1.468055	-3.85801	3.69854
LNG	928	-1.09754	1.842353	-6.8782	3.20365

Appendix Table 3.3: Multicollinearity

Independent Variables	VIF	1/VIF
Model I, II		
LN	8.25	0.121212
LK	5.21	0.191938
LTLF	1.77	0.564971
LR	1.89	0.529100
Mean VIF	4.28	
Model III, IV		
LOIL	9.17	0.109051
LK	6.44	0.155279
LTLF	4.37	0.223136
LCO	4.16	0.240384
LNG	2.13	0.469483
Mean VIF	5.25	

Note: The VIF values are all below than 10, implying that there is no multicollinearity.

Appendix Table 3.4: Estimated breaks for individual countries

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
Australia	LF	2	1983	1997			
	LGDP	4	1986	1989	1994	2001	
	LIND	3	1983	1996	2002		
	LK	2	1984	1994			
	LR	2	1986	1994			
	LN	1	1981				
	LCO	1	1982				
	LOIL	2	1985	1992			
	LNG	1	1986				
Austria	LF	3	1982	1989	1993		
	LGDP	4	1982	1992	1998	2002	
	LIND	2	1982	1992			
	LK	1	1988				
	LR	3	1981	1989	1999		
	LN	2	1983	1998			
	LCO	1	1988				
	LOIL	2	1982	1997			
	LNG	1	1984				
Belgium	LF	2	1983	1989			
	LGDP	3	1988	1996	2002		
	LIND	2	1983	2003			
	LK	2	1983	1994			
	LR	1	1991				
	LN	2	1988	1999			
	LCO	2	1980	1992			
	LOIL	1	1981				
	LNG	1	1985				
Canada	LF	2	1985	1997			
	LGDP	2	1983	1998			
	LIND	3	1983	1995	2002		
	LK	2	1984	1998			
	LR	3	1986	1997	2001		
	LN	1	1983				
	LCO	2	1982	1998			
	LOIL	3	1980	1996	2003		
	LNG	1	1988				
Chile	LF	2	1987	1996			
	LGDP	2	1988	1999			
	LIND	3	1983	1996	2001		
	LK	2	1980	1990			
	LR	2	1988	1999			
	LN	2	1987	1999			
	LCO	1	1982				
	LOIL	1	1982				

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LNG	1	1989				
Denmark	LF	2	1987	1995			
	LGDP	3	1982	1993	2000		
	LIND	2	1984	1992			
	LK	1	1988				
	LR	2	1986	1998			
	LN	1	1984				
	LCO	1	1982				
	LOIL	3	1987	1996	2004		
	LNG	1	1989				
Finland	LF	1	1987				
	LGDP	3	1985	1997	2002		
	LIND	2	1983	1994			
	LK	2	1981	1989			
	LR	2	1991	2003			
	LN	1	1990				
	LCO	1	1982				
	LOIL	1	1986				
	LNG	2	1983	1991			
France	LF	2	1982	1998			
	LGDP	2	1983	1999			
	LIND	2	1989	2001			
	LK	2	1988	2002			
	LR	3	1988	1989	2001		
	LN	2	1983	1998			
	LCO	1	1984				
	LOIL	2	1985	1996			
	LNG	1	1983				
Germany	LF	1	1985				
	LGDP	4	1984	1994	1998	2002	
	LIND	2	1985	1997			
	LK	1	1983				
	LR	2	1983	1999			
	LN	2	1984	1991			
	LCO	2	1983	1998			
	LOIL	2	1986	2000			
	LNG	1	1988				
Greece	LF	1	1986				
	LGDP	3	1987	1997	2002		
	LIND	1	1985				
	LK	1	1988				
	LR	2	1983	1998			
	LN	2	1982	1996			
	LCO	1	1981				

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LOIL	1	1984				
	LNG	1	1981				
Hungary	LF	1	1986				
	LGDP	1	1984				
	LIND	2	1983	1994			
	LK	1	1989				
	LR	3	1982	1997	2001		
	LN	2	1983	1997			
	LCO	2	1982	1999			
	LOIL	1	1983				
	LNG	1	1988				
Iceland	LF	1	1994				
	LGDP	3	1985	1992	1999		
	LIND	2	1987	1997			
	LK	1	1987				
	LR	2	1983	1992			
	LN	1	1991				
	LCO	1	1983				
	LOIL	2	1980	1998			
	LNG	1	1993				
Ireland	LF	2	1985	1999			
	LGDP	4	1982	1989	1994	2001	
	LIND	2	1985	1997			
	LK	1	1984				
	LR	2	1981	1987			
	LN	2	1988	1995			
	LCO	1	1981				
	LOIL	2	1986	1999			
	LNG	1	1989				
Italy	LF	1	1991				
	LGDP	4	1983	1990	1998	2002	
	LIND	2	1983	1989			
	LK	1	1984				
	LR	1	1986				
	LN	2	1980	1997			
	LCO	1	1984				
	LOIL	3	1982	1989	1994		
	LNG	2	1982	1987			
Japan	LF	1	1981				
	LGDP	2	1984	1998			
	LIND	3	1986	1995	2002		
	LK	2	1988	2001			
	LR	2	1983	1999			
	LN	2	1986	2000			
	LCO	1	1982				

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LOIL	2	1989	1996			
	LNG	1	1989				
South Korea	LF	2	1985	1991			
	LGDP	2	1988	2000			
	LIND	3	1987	1997	2001		
	LK	2	1987	1994			
	LR	1	1997				
	LN	2	1980	1995			
	LCO	1	1984				
	LOIL	3	1982	1997	2004		
	LNG	2	1989	1995			
Luxembourg	LF	2	1986	1998			
	LGDP	3	1981	1989	1998		
	LIND	2	1987	2001			
	LK	1	1984				
	LR	2	1987	1994			
	LN	1	1982				
	LCO	1	1989				
	LOIL	1	1982				
	LNG	1	1992				
Mexico	LF	2	1981	1997			
	LGDP	2	1991	2002			
	LIND	2	1995	2001			
	LK	1	1984				
	LR	2	1989	1994			
	LN	2	1989	1997			
	LCO	2	1980	1998			
	LOIL	1	1998				
	LNG	1	1982				
Netherlands	LF	3	1984	1988	1992		
	LGDP	2	1983	1997			
	LIND	2	1983	1999			
	LK	2	1993	2000			
	LR	1	1997				
	LN	1	1980				
	LCO	1	1983				
	LOIL	3	1985	1998	2003		
	LNG	2	1987	1997			
New Zealand	LF	2	1989	1994			
	LGDP	3	1983	1997	2000		
	LIND	2	1986	1994	2002		
	LK	2	1983	1991			
	LR	2	1981	1986			
	LN	1	1982				
	LCO	1	1983				

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LOIL	2	1989	2001			
	LNG	1	1984				
Norway	LF	2	1984	1991			
	LGDP	4	1984	1989	1996	2004	
	LIND	2	1983	1995			
	LK	1	1997				
	LR	2	1984	1989			
	LN	1	1986				
	LCO	1	1983				
	LOIL	2	1985	1999			
	LNG	2	1982	1989			
Poland	LF	2	1989	1996			
	LGDP	3	1982	1989	1994		
	LIND	4	1985	1989	1992	2001	
	LK	2	1987	1995			
	LR	1	1987				
	LN	2	1984	1998			
	LCO	1	1983				
	LOIL	2	1987	1992			
	LNG	2	1986	1993			
Portugal	LF	2	1985	1999			
	LGDP	3	1987	1991	2003		
	LIND	4	1986	1989	1994	2001	
	LK	1	1982				
	LR	1	1989				
	LN	2	1980	1996			
	LCO	2	1985	1990			
	LOIL	1	1986				
	LNG	2	1989	1991			
Spain	LF	3	1987	1990	1998		
	LGDP	2	1989	1993	2001		
	LIND	2	1984	1998			
	LK	3	1982	1986	1997		
	LR	2	1988	1993			
	LN	2	1983	1989			
	LCO	1	1990				
	LOIL	3	1985	1989	1996		
	LNG	1	1993				
Sweden	LF	2	1984	1996			
	LGDP	4	1982	1987	1994	2003	
	LIND	2	1983	1998			
	LK	1	1983				
	LR	1	1997				
	LN	1	1984				
	LCO	2	1984	1989			

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LOIL	1	1986				
	LNG	2	1982	1987			
Switzerland	LF	3	1987	1991	2002		
	LGDP	2	1986	1999			
	LIND	4	1987	1997	2000	2004	
	LK	2	1986	1991			
	LR	2	1983	1993			
	LN	2	1986	1994			
	LCO	1	1991				
	LOIL	2	1986	1998			
	LNG	2	1985	1998			
Turkey	LF	2	1989	1997			
	LGDP	3	1984	1989	1994		
	LIND	2	1984	2000			
	LK	2	1986	1989			
	LR	2	1981	2000			
	LN	2	1989	1998			
	LCO	2	1982	1986			
	LOIL	2	1983	1983			
	LNG	2	1982	1989			
UK	LF	2	1983	1988			
	LGDP	3	1987	1993	2001		
	LIND	2	1980	1991			
	LK	1	1986				
	LR	1	1989				
	LN	2	1989	1997			
	LCO	2	1984	1997			
	LOIL	2	1982	1988			
	LNG	1	1986				
US	LF	2	1989	1996			
	LGDP	2	1984	1997			
	LIND	2	1989	2000			
	LK	2	1993	1998			
	LR	2	1987	1996			
	LN	3	1982	1993	2002		
	LCO	2	1984	1992			
	LOIL	4	1981	1985	1997	2001	
	LNG	2	1985	1989			

CHAPTER 4

THE DETERMINANTS OF DISAGGREGATED ENERGY CONSUMPTION

4.1 Introduction

In Chapter 3, the effects of different types of energy sources on economic growth were investigated. This chapter tries to identify and analyse the determinant factors of energy consumption in OECD countries.

More than half of the world's population now live in cities, implying the world is urbanising rapidly. Urbanisation, as the relative concentration of population, also concentrates economic activities in urban areas. As a result of migration from rural to urban areas, the labour force is in fact transferred from the agricultural sector in the rural areas to the industrial and service sectors in the urban areas. This structural transformation of the economy causes many fundamental changes in natural resources and energy use as well. Although the transformation of production from the low-energy intensive agricultural sector to the high-energy intensive industrial sector is affected by the introduction of new technologies and industrialisation, urbanisation is also one of the key factors. Due to growing urbanisation rates, the volume of production and the market range increase over the past decades. On the other hand, urban living as compared to rural life is expected to require more energy as a result of travelling to work by fuel-using vehicles, and also constructing, operating, and maintaining urban infrastructure and services including housing, water supply, roads and bridges (Jones 1989, 1991, 2004; Parikh and Shukla 1995; Madlener and Sunak 2011). Growing dependency on fossil fuels as a result of concentration of people in cities has led to efforts by policy makers to substitute clean energy resources for fossil fuels. For example, some major cities, particularly in developed countries, have begun to link homes and offices to renewable energy in order to create a fossil-fuel free district in the near future.

The urbanisation–energy use relationship has been studied extensively in recent years, and while some researchers show that urbanisation increases energy consumption, some others argue that urbanisation can improve the efficient use of public infrastructure, resulting in less energy use. However, it is still less clear what sort of energy is more likely to be affected by urbanisation. Recently, with the new approach to using more renewable energy, particularly for generating electricity in large cities, the question arises as to whether urbanisation can expand the use of renewable energy. Therefore, it is important to study the impact of urbanisation on disaggregated energy consumption as knowing more about how urbanisation affects energy use, in terms of renewable and non-renewable, can give some ideas about where energy policy makers could focus their attention.

So far, despite the number of studies that have looked at the urbanisation–energy relationship, the influences of urbanisation on renewable and non-renewable energy consumption has not been investigated. To address this issue, this chapter investigates the effects of urbanisation along with total population size, population density, economic growth, industrialisation and tertiarisation on both types of energy sources, renewable and non-renewable, separately. This is the first time a study has examined the renewable energy–urbanisation nexus as well as non-renewable energy–urbanisation nexus.

The organisational structure of the rest of the chapter is as follows: Section 4.2 provides review of empirical work and hypotheses. Section 4.3 describes the empirical model and data used in this study. The empirical results are performed in Section 4.4. Finally, Section 4.5 concludes the chapter.

4.2 Review of Empirical Work and Hypotheses

4.2.1 Review of Empirical Work

There are a number of studies analysing the relationship between energy consumption and urbanisation. This sub-section reviews the previous studies on this issue.

Using cross-section data for 59 developing countries in 1980, Jones (1991) examines the link between energy use and urbanisation and concludes that a 10% increase in the proportion of the population living in cities increases modern energy consumption per capita by 4.5% to 4.8%, holding constant per capita income and industrialisation. The finding by Jones (1991) may be subject to some limitations. For instance, the coefficients are estimated only based on a single year (1980) which might yield unreliable results due to using a very small sample size of data.

Parikh and Shukla (1995) also provide an early analysis of the relationship between energy use and urbanisation over the period 1965 to 1987 for a sample of developing countries. Their results, obtained from a panel data fixed-effects model, indicate that a 10% increase in a country's urban population leads to a 4.7% rise in its per capita total energy consumption. The authors imply that urbanisation influences energy consumption in three ways: first, by shifting energy use from traditional fuels to modern fuels, second, by increasing embodied energy consumption through goods and service demands, and third, via direct household and transport consumption.

In a similar study, Imai (1997) employs a weighted least square method for the years 1980 and 1993 and finds a positive relationship between energy consumption and urbanisation in Thailand, China, India, Iran, Japan, Turkey, USA and Germany. However, using a bivariate model in this study can increase the likelihood of reaching incorrect conclusions due to the omitted variables.

York et al. (2003b) are the first to develop and use the STIRPAT (STochastic Impacts by Regression on Population, Affluence, and Technology) model to study the impact of urbanisation on energy use. Their results indicate that population is a major driver of the energy consumption; and urbanisation, as an indicator of modernisation, monotonically increases energy use.

In contrast, Liddle (2004) finds that urbanisation and population density negatively affect energy use in OECD countries from 1960 to 2000. However, it is noteworthy to mention that he considers road transport energy use in this study and implies that more densely populated and urbanised societies have less demand for personal transport. In a similar study by Poumanyvong et al. (2012) on road transport energy use, the authors obtain evidence opposite to that of Liddle (2004). They find that urbanisation increased road transport energy consumption in high income countries over the period 1975 to 2005. Poumanyvong et al. (2012) claim that the findings of Liddle (2004) need more scrutiny due to omitted variables of economic activity and small sample dataset.

Focusing on fourteen European Union Nations over the period 1960 to 2000, York (2007) proves that demographic factors including population size, age structure and urbanisation along with economic development affect energy consumption positively. However, predicting energy consumption for the year 2025, based on demographic and economic projections, shows that low fertility and thereby decline in population size in Europe can help restrict expansion in energy consumption.

There are a number of studies dealing with the relationship between urbanisation and energy consumption in China (Zhang and Zhao 2001; Wei et al. 2003; Shen et al. 2005; Liu 2009; O'Neill 2012; Zhang and Lin 2012), of which Liu (2009) provides Granger causality test as well as long-run structural estimates for the relationship between energy consumption, population, urbanisation and economic growth from 1978 to 2008. The findings show the presence of a unidirectional causality running from urbanisation to total energy consumption both in the long run and in the short run. He points out that improvement in urbanisation quality in China would lead to the progress of energy efficiency in the long term.

Using a similar approach for a single country Turkey, Halicioglu (2007) finds a Granger causality running from urbanisation and GDP to energy consumption.

Mishra et al. (2009) also test for Granger causality and reveal that there is a unidirectional relationship from urbanisation to energy consumption in the short run for a panel of nine Pacific Island countries. In the long run, it is found that energy consumption and urbanisation cause economic growth (GDP).

It appears that Liddle and Lung (2010), after Liddle (2004) and York (2007), is the only recent research investigating the effect of urbanisation on energy consumption exclusively for a panel of developed countries. Employing a STIRPAT method for 17 developed countries covering the period from 1960 to 2005, Liddle and Lung (2010) reveal that urbanisation has a positive and fairly large effect on both residential energy consumption and residential electricity consumption.

Considering different development stages in 99 countries from 1975 to 2005, Poumanyvong and Kaneko (2010) investigate the relationship between urbanisation and energy use, controlling for population size, GDP per capita, share of industry and service sectors in GDP. They indicate that while urbanisation increases energy use in the middle- and high-income countries, it decreases energy use in the low-income countries. The authors point out that this finding is supported by the view of the urban environmental transition theory that consumption-related environmental issues are dominant in developed countries.

Shahbaz and Lean (2012) examine the impact of urbanisation and industrialisation on energy consumption in Tunisia from 1971 to 2008. The findings prove the existence of bidirectional causality between industrialisation and energy consumption in the long run and unidirectional causality from urbanisation to energy consumption in the short run.

As seen above, a considerable number of studies have assessed the energy consumption and urbanisation nexus. However, there is still no consensus in the literature on how urbanisation affects energy consumption. Furthermore, there are only a few studies that have investigated this issue for OECD countries.

There are a few studies that focus on population/urban density. Although the density of urban areas is closely related to urbanisation, their measures are different, implying that their effect on energy consumption and pollutant emissions can be different as well. In addition, increased urbanisation does not necessarily result in increases in urban density because cities can expand horizontally (Poumanvong and Kaneko 2010).

Newman and Kenworthy (1989) measure per capita transport energy consumption and population densities in a range of large cities in high-income countries and find that high population density decreases per capita transport energy use. However, Newman and Kenworthy's study is criticised for not using a multivariate analysis that can affect the research result. Their results are also said to be limited due to using 1980s data, which is suspected as not being accurate and consistent (Mindali et al. 2004).

Larivière and Lafrance (1999) find that in Canada, more urbanised areas have lower energy consumption per capita. They explain that high density cities use less gasoline than low density cities because the distances travelled are smaller and inhabitants are more likely to use public transport. They also add that the electricity needed for street lighting seems to be largely invariant to city density, so larger cities reduce electricity consumption per capita.

Using data for 45 Chinese cities, Chen et al. (2008) reveal that urban density has a negative effect on household energy consumption. The authors argue that this effect is caused by compactness of residential structure. It is expected that compact housing (with higher density or taller buildings) needs less heating or cooling loads because of less exposed wall areas and less heat-loss through the roof or floor. Furthermore, they are potentially using less material as flats share foundations, roofs and partition walls.[12]

Finding a negative relationship between population density and energy consumption in all the limited number of studies implies that population density can play an important role in energy use reduction and should be considered as a policy by decision makers. As seen above, the relationship between population density and energy consumption has not been studied much in recent years. Therefore, further study and gathering more empirical evidence on this issue is imperative.

The present study differs from the existing works in a number of ways. First, it estimates the impact of urbanisation on non-renewable and renewable energy consumption employing a STIRPAT model. Second, it controls for population density which is a key factor that influences energy consumption, and has been rarely considered in previous studies. Third, it takes into account statistical concerns over the presence of heterogeneity and cross-section dependence that can result in misleading inference and inconsistent estimates, and has been ignored by previous researchers.

4.2.2 Hypotheses

So far, despite mixed empirical findings in the existing literature, most analyses suggest that urbanisation increases energy use for different reasons. First, the direct 'running costs' of cities are high for functions like space heating, air conditioning and lighting in buildings. Second, transporting goods and services now accounts for 30% of global energy consumption, a share that increases with the spatial and functional differentiation of economies and the shift from rural to urban lifestyles (Schurr et al. 1979). Third, cities are also centres of indirect energy consumption including most obviously those resources required to produce food and other biomass. With lower percentages of the population engaged in agricultural activities and the need to supply food to larger non-agricultural populations, primary sector activities become more resource and energy intensive (Jones 1991). Finally, due to increases in travel distances and mobility of passengers and freight in urban areas more energy is likely to be consumed (Jones 2004; Rodrigue et al. 2006; Hankey and Marshall 2010;

[12] A summary of literature is provide in Appendix A Table 4.1

Poumanyvong et al. 2012). These reasons lead to the hypothesis that urbanisation positively affects total energy use.

The lack of studies on the interaction of urbanisation and disaggregated energy raises the question of how urbanisation influences renewable energy sources. Most of the world's energy comes from non-renewables and fossil fuels including oil, coal and gas. However, energy efficiency in the urban environment has become an important issue particularly for solving the problem of pollution in cities (Larivière and Lafrance 1999). Some cities and regions have undertaken the provision and production of renewable energy, in addition to pursuing goals of increasing renewable energy consumption through land-use zoning, transportation, natural resource and building policies. Some cities in the OECD own and operate power generating facilities, which provide them with more options for increasing local use of renewable energies. Local governments also develop their own sources of renewable energy by capturing and converting energy from one or more renewable energy sources that exist in many cities and towns (IEA 2009).

Therefore, based on this evidence, it can be said that if urbanisation could increase renewable energy use, the consequence would be a substantial reduction in fossil fuels consumption which in turn results in less pollutant emissions.

Considering the relationship between energy consumption and population density, there is a popular view suggesting the existence of a strong negative correlation between population density and energy consumption. This implies that increasing density will result in a reduction in energy consumption (Cities and Automobile Dependence 1989).

There is also evidence indicating a negative association between the total energy consumption of a city and its overall density, that is, the higher the density, the lower energy consumption. For instance, Japan's urban areas are around five times denser than Canada's, and the use of energy per capita (as measured by total primary energy supply) in Japan is around 40% that of Canada's. The link is still visible for countries in the same geographical context with similar heating needs, such as Denmark and Finland: Denmark's urban areas are denser than Finland's by a factor of four and people in Denmark consume 2.5 times less energy than the Finns (Kamal-Chaoui and

Robert 2009). Thus, it can be hypothesised that increasing density is likely to reduce energy use.

4.3 Empirical Model and Data Description

4.3.1 Empirical Model

The IPAT identity is a widely recognised formula for analysing the effects of human activities on the environment (Stern et al. 1992; Harrison and Pearce 2000). Ehrlich and Holdren (1971), Holdren and Ehrlich (1974) introduced the IPAT identity based on the principle driving forces of anthropogenic environmental impacts in the early 1970s. It has come to be widely utilized as a framework for analysing the driving forces of environmental change (Harrison 1993; Raskin 1995; York et al. 2002). IPAT specifies that environmental impacts (*I*) are the multiplicative product of three key driving forces: population (*P*), affluence (*A*) (per capita consumption or production) and technology (*T*) (impact per unit of consumption or production), hence I = PAT (Commoner 1971, 1992; Ehrlich and Holdren 1972; Ehrlich and Ehrlich 1990; Harrison 1993; Raskin 1995; York et al. 2003b).[13] The strengths of the IPAT are that it specifies key driving forces behind environmental change with parsimony and, further, it determines mathematically the relationship between the driving forces and impacts (Dietz and Rosa 1997, York et al. 2003b).

Following the IPAT identity, Waggoner and Ausubel (2002) introduce another approach namely ImPACT. In the ImPACT model, *T* is disaggregated into consumption per unit of GDP (*C*) and impact per unit of consumption (*T*) so that I = PACT. Another extension of IPAT has been suggested by Schulze (2002) who adds the factor, behaviour (*B*) into this identity renaming it I = PBAT. However, Diesendorf (2002) and Roca (2002) point out that behaviour is already included in each factor in the right-hand side of the equation of I = PAT. In addition, behaviour is not a simply measurable term.

Despite the fact that the IPAT and ImPACT are parsimonious and flexible and also easily indicate the effect of driving forces on environmental conditions, they suffer from some limitations. IPAT and ImPACT consider proportionality between the key

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[13] In the IPAT, technology (*T*) is generally determined with the ration of I/GDP; $A = GDP/P$, so that $PA = P\ (GDP/P) = GDP$. Thus, by definition, $T = I/(PA)$ or $T = I/GDP$ (York et al. 2003b).

determinant factors; meaning that by changing one factor, the others should be held constant. Furthermore, they do not allow for non-monotonic or non-proportional effects from the driving forces (York et al. 2003b).

To overcome these limitations, Dietz and Rosa (1994, 1997) present a new model, namely STIRPAT (STochastic Impacts by Regression on Population, Affluence, and Technology). This model is no longer an accounting equation, and therefore can be used to test hypotheses empirically. STIRPAT basically has the following form:

$$I_i = \alpha \; P_i^b \, A_i^c \, T_i^d \, e_i \qquad (4.1)$$

Taking the natural logarithm of both sides:

$$ln\, I_{it} = ln\, \alpha + b\, ln(P_{it}) + \; c\, ln(A_{it}) + d\, ln(T_{it}) + ln\, e_{it} \qquad (4.2)$$

where α represents a constant, *b*, *c*, and *d* are the exponents of *P*, *A*, and *T*, which indicate respectively population elasticity of impact, affluence elasticity of impact, and technology elasticity of impact. *e* is the error term and *t* denotes the year. The subscript *i* illustrates the differences between the quantities of *I, P, A, T,* and *e* across observational units.

According to York et al. (2003b), additional factors can be entered into the basic STIRPAT model as components of the technology (*T*). However, the authors note that it is important to ensure that the additional factors are conceptually consistent with the multiplicative specification of the model. For instance, while Shi (2003) uses the share of industry and services in GDP as a proxy for *T* in an investigation on emissions, Martínez-Zarzoso (2007) employs the share of industry in GDP and energy intensity as a proxy. In a study of national energy use, York (2007) uses urbanisation to express *T*. Similar to Shi (2003), Poumanyvong and Kaneko (2010) represent *T* with the share of industry and service sectors in GDP in an analysis of energy use and emissions. In this study, following Shi (2003) and Poumanyvong and Kaneko (2010), *T* is considered as the share of the industry and service sectors in GDP. As the main aim of this study is to estimate the impact of urbanisation and population density on energy use, the basic model is modified by adding these two factors. While there are several studies that add urbanisation into the STIRPAT model (Cole and Neumayer 2004; York et al, 2003a, 2003b; York 2007; Liddle and Lung 2010; Poumanyvong and Kaneko 2010; Poumanyvong et al. 2012), to the best knowledge of the author, this study is the first time that population density is included in the model. Therefore, the empirical models for non-renewable and renewable energy consumption can be written as:

$$ln\, N_{it} = ln\, \alpha + b\, ln(P_{it}) + c\, ln(A_{it}) + \; d\, ln(IND_{it}) + \; e\, ln(S_{it}\,) + \\ f\, ln(PD_{it}\,) + \; g\, ln(U_{it}\,) + \; ln\, e_{it} \tag{4.3}$$

$$ln\, R_{it} = ln\, \alpha + b\, ln(P_{it}) + c\, ln(A_{it}) + \; d\, ln(IND_{it}) + \; e\, ln(S_{it}\,) + \\ f\, ln(PD_{it}\,) + \; g\, ln(U_{it}\,) + \; ln\, e_{it} \tag{4.4}$$

In Equation 4.3, *N* is non-renewable energy consumption, *P* is total population size, *A* is GDP per capita, *IND* is the share of the industry sector in GDP (industrialisation), *S* is the share of the service sector in GDP, *PD* is population density and *U* is urbanisation. In Equation 4.4, R is renewable energy consumption and the variables on the right hand side remain the same as in Equation 4.3.

4.3.2 Data Description

As mentioned above, the variables used in this study include total population, GDP per capita, industrialisation, share of service sector in GDP, population density, urbanisation, and renewable and non-renewable energy consumption. Total population is measured by midyear population size, and GDP per capita (US$ in PPP, year 2000 prices) is gross domestic product divided by midyear population. Urbanisation is generally measured as the percentage of population living in urban areas. Therefore, urban population (% of total) is applied as a reliable proxy for urbanisation. As the measure of industrialisation is constructed as the value of gross domestic production created in the industrial sector, industrial value added (% of GDP) is considered as a proxy for industrialisation. It comprises value added in mining, manufacturing (also reported as a separate subgroup), construction, electricity, water, and gas. Services sector value added as the percentage of GDP is considered as a proxy for the share of the services sector in GDP. Services include value added in wholesale and retail trade (including hotels and restaurants), transport, and government, financial, professional, and personal services such as education, health care, and real estate services. Also included are imputed bank service charges, import duties, and any statistical discrepancies noted by national compilers as well as discrepancies arising from rescaling. According to World Development Indicators, population density is defined as the number of people living per square km. of land area. All the data are sourced from the World Bank's World Development Indicators.[14]

All the variables are converted into natural logarithms prior to conducting the analysis. The summary statistics on the variables are presented in Appendix A Table 4.2 describing the number of observations, mean, variation (standard deviation) and bounds (minimum and maximum). To test for multicollinearity between independent variables, the variance inflation factors (VIF) for each predictor is calculated. The results, presented in Appendix A Table 4.3, indicate no existence of multicollinearity between independent variables as all the VIF values are less than 10.

This research estimates long-run panel elasticities of renewable and non-renewable energy consumption in terms of demographic and economic factors and also identifies dynamic causal relationship between the variables. For this purpose, first the results of unit root and cointegration tests are provided in the next subsection.

4.4 Empirical Results

4.4.1 Panel Unit Root Test

Similar to the previous chapter, five different unit root tests are performed. The tests include augmented Dickey and Fuller (1979) (ADF) test, the Phillips and Perron (1988) (PP) test, Breitung (2000), Levin et al. (2002) (LLC) test, and Im et al. (2003) (IPS) test. Individual trends and constants are included in the tests. The results of all these tests are reported in Table 4.1. The test statistics for the level of variables are statistically insignificant with the exception of the PP test for the share of services in GDP and the IPS test for GDP per capita which are significant at 10% levels. Therefore, it can be said that all the series are non-stationary at their levels. However, all the statistics of the first differences of the variables are significant, suggesting that there is no any unit root in each series.

Taken as a whole, the statistics significantly confirm that the level values of all series, including total population, GDP per capita, share of the industry sector in GDP, share of the service sector in GDP, urbanisation and population density are non-stationary and all the variables are stationary at their first difference levels.

[14] The definitions and sources of the renewable and non-renewable energy consumption data are those used in Chapter 3.

As the previous unit root tests do not control for structural breaks, the panel stationarity test with structural breaks following Carrion-i-Silvestre et al. (2005) is provided here to prevent achieving invalid results. Table 4.2 provides the results of the panel stationarity test with structural breaks. These results indicate that the null hypothesis of stationarity is rejected for the total population, GDP per capita, industrialization, share of the service sector in GDP and urbanization at 5% level and for most of the variables at 2.5% and 1% by both the homogeneous and heterogeneous long-run versions of the test.

Table 4.1: Panel unit root tests without structural breaks for the variables used in non-renewable and renewable energy use models

Method	LP	LA	LIND	LS	LU	LPD
ADF						
Level	4.271	70.889	52.890	47.070	62.787	44.106
	(1.000)	(0.119)	(0.665)	(0.847)	(0.310)	(0.911)
First	-4.739	164.514	288.792	221.686	80.649	136.584
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.026)**	(0.000)***
PP						
Level	16.738	33.266	31.542	38.933	0.318	31.097
	(1.000)	(0.996)	(0.998)	(0.074)*	(1.000)	(0.998)
First	-2.542	178.791	332.740	384.467	97.195	78.324
difference	(0.005)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.038)**
Breitung						
Level	5.636	4.629	0.395	1.608	5.079	0.274
	(1.000)	(1.000)	(0.653)	(0.946)	(1.000)	(0.608)
First	-1.150	-2.740	-9.394	-8.232	-15.262	-1.586
difference	(0.024)**	(0.003)***	(0.000)***	(0.000)***	(0.000)***	(0.056)*
LLC						
Level	1.005	-0.997	-0.323	-0.325	3.377	3.661
	(0.842)	(0.159)	(0.373)	(0.372)	(0.999)	(0.999)
First	5.502	-5.221	-15.189	-9.343	-3.774	-3.478
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
IPS						
Level	4.355	-1.289	1.910	1.142	0.374	6.971
	(1.000)	(0.098)*	(0.971)	(0.873)	(0.646)	(1.000)
First	4.735	-7.629	-14.701	-10.833	-18.540	-5.408
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***

Note: Probabilities of the test statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels, respectively. The Schwarz Information Criterion (SIC) has been used to determine the optimal lag length.

In conclusion, the results of the unit root tests indicate that all the variables are non-stationary at their levels even when allowing for structural breaks. The number of breaks and their position for each country and variable are also calculated by means of Monte Carlo simulations based on 20,000 replications. The results are provided in Appendix A Table 4.4.

Overall evidence from the panel stationarity tests in first differences show that all variables are integrated of order one, consequently panel cointegration tests can be employed to study the long-run equilibrium process.

Table 4.2: Panel unit root tests with structural breaks for the variables used in non-renewable and renewable energy use models

Variables	Bartlett Kernel	Quadratic Kernel	Bootstrap critical values		
			5%	2.5%	1%
LP					
Homogeneous	6.744***	6.514**	6.323	6.510	6.711
Heterogeneous	6.918*	7.131*	6.891	7.452	7.859
LA					
Homogeneous	11.428***	11.888***	9.781	9.979	10.163
Heterogeneous	9.639***	9.519***	7.508	8.631	8.357
LU					
Homogeneous	10.249***	10.021**	8.363	9.472	10.236
Heterogeneous	9.381***	9.415***	7.501	8.993	9.303
LPD					
Homogeneous	5.326	5.461	5.513	5.815	6.012
Heterogeneous	4.964*	5.433*	4.959	5.572	5.630
LIND					
Homogeneous	9.316***	9.322***	7.703	8.110	8.741
Heterogeneous	8.120***	8.121***	5.504	6.823	7.330
LS					
Homogeneous	13.391*	13.731**	12. 831	13.555	13.789
Heterogeneous	12.097	12.280	13.561	13.829	13.995

Note: The number of structural breaks is up to 5. The long-run variance is estimated using both the Bartlett and the Quadratic spectral kernel with automatic spectral window bandwidth selection as in Sul et al. (2005). Furthermore, all bootstrap critical values allow for cross-sectional dependence. ***, ** and * indicate that the test statistic is significant at 1%, 2.5%, and 5% levels, respectively.

4.4.2 Panel Cointegration Test

Having identified that all the variables contain a panel unit root and are integrated of order one, the next step is to determine whether there is a cointegration relationship between the variables. Panel cointegration tests of Westerlund (2007), Pedroni (2004), Kao (1999), and Johansen Fisher as proposed by Maddala and Wu (1999) are used for both non-renewable and renewable energy use models. The results of the Kao (1999) test, reported in Table 4.3, suggest evidence of cointegration between variables at a 1% level of significance. The results of Pedroni's (2004) heterogeneous panel tests (Table 4.4) reveal that for the non-renewable energy-use model the null of no cointegration can be rejected at the 1% significance level in panel PP and panel ADF statistics under the within-dimension approach and in group PP and group ADF under the between- dimension approach.

Table 4.3: Kao cointegration test for non-renewable and renewable energy use models

	t-statistic	Prob.
Non-renewable energy-use model		
ADF	-2.397	0.008***
Renewable energy-use model		
ADF	3.377	0.000***

Note: *** indicates rejection of the null hypothesis at the 1% significance level.

The results of Pedroni's (2004) tests for the renewable energy-use model are similar to the results for the non-renewable energy-use model. The panel PP, panel ADF, group PP and group ADF statistics reject the hypothesis of no cointegration at the 1% significance level (Table 4.4). The results of the Johansen panel cointegration test from both a trace test as well as a maximum eigen-value test indicate the existence of cointegration at 1% significance level for both non-renewable and renewable energy use models (Table 4.5).

Table 4.4: Pederoni cointegration test for non-renewable and renewable energy use models

	Statistic	Prob.	Weighted	
			Statistic	Prob.
Non-renewable energy-use model				
Alternative hypothesis: common AR coefs. (within-dimension)				
Panel v-Statistic	-1.956	0.974	-3.391	0.999
Panel rho-tatistic	3.529	0.999	2.234	0.987
Panel PP-Statistic	-5.191	0.000***	-9.943	0.000***
Panel ADF-Statistic	-5.295	0.000***	-9.094	0.000***
Alternative hypothesis: individual AR coefs. (between-dimension)				
Group rho-Statistic	4.468	1.000		
Group PP-Statistic	-12.650	0.000***		
Group ADF-Statistic	-9.866	0.000***		
Renewable energy-use model				
Alternative hypothesis: common AR coefs. (within-dimension)				
Panel v-Statistic	-6.037	1.000	-6.780	1.000
Panel rho-tatistic	5.248	1.000	3.960	1.000
Panel PP-Statistic	-9.268	0.000***	-12.952	0.000***
Panel ADF-Statistic	-5.102	0.000***	-9.979	0.000***
Alternative hypothesis: individual AR coefs. (between-dimension)				
Group rho-Statistic	4.971	1.000		
Group PP-Statistic	-18.924	0.000***		
Group ADF-Statistic	-10.680	0.000***		

Note: Intercept and deterministic trend are included. The optimal lag length is selected by Akaike Information Criterion. *** indicates that the test statistic is significant at 1% level.

Table 4.5: Johansen Fisher cointegration test for non-renewable and renewable energy use models

Model	Fisher statistic (from trace test)	Fisher statistic (from max-eigen test)
Non-renewable energy-use model		
None	1123.0 (0.000)***	607.1 (0.000)***
At most 1	648.6 (0.000)***	323.7 (0.000)***
At most 2	393.6 (0.000)***	210.7 (0.000)***
At most 3	234.7 (0.000)***	152.5 (0.000)***
At most 4	139.2 (0.000)***	120.0 (0.000)***
At most 5	98.53 (0.000)***	98.53 (0.000)***
Renewable energy-use model		
None	1145.0 (0.000)***	587.2 (0.000)***

Model	Fisher statistic (from trace test)	Fisher statistic (from max-eigen test)
At most 1	680.2 (0.000)***	351.4 (0.000)***
At most 2	397.4 (0.000)***	217.8 (0.000)***
At most 3	227.6 (0.000)***	138.7 (0.000)***
At most 4	145.2 (0.000)***	121.4 (0.000)***
At most 5	106.7 (0.000)***	106.7 (0.000)***

Note: The Schwarz Information Criterion (SIC) has been used to determine the optimal lag length.
*** indicates that the test statistic is significant at 1% level.

The results of the Westerlund (2007) cointegration test are reported in Table 4.6. It can be seen that group-t and panel-a reject the null hypothesis of no cointegration at 1% and 5% significance levels respectively in both non-renewable and renewable energy use models. Therefore, overall evidence from the Kao (1999), Pedroni (2004), Johansen Fisher (Maddala and Wu 1999), and Westerlund (2007) tests for cointegration show that there is a long-run relationship between the dependent variables (non-renewable and renewable energy use) and the independent variables (total population, GDP per capita, share of the industry sector in GDP, share of service sector in GDP, urbanisation and population density) in selected OECD countries.

Table 4.6: Westerlund cointegration test for non-renewable and renewable energy use models

Statistic	Value	*P*-value
Non-renewable energy-use model		
Group-t	-2.973	0.000***
Group-a	-3.547	1.000
Panel-t	-12.743	0.016**
Panel-a	-3.858	0.998
Renewable energy-use model		
Group-t	-3.163	0.000***
Group-a	-2.114	1.000
Panel-t	-12.522	0.025**
Panel-a	-1.811	1.000

Note: *** and ** indicate that the test statistics are significant at 1% and 5% levels, respectively. Following Westerlund (2007) maximum lag length is selected according to $4(T/100)^{2/9}$. The null hypothesis of the test is “no cointegration”.

Given the presence of a panel cointegration relationship between the variables, the next step is estimation of the long-run structural coefficients.

4.4.3 Panel Long-Run Estimates

Before moving to formal modelling, the diagnostic tests including cross-sectional dependence, heteroskedasticity and serial correlation are checked. The results of the diagnostic tests for non-renewable and renewable energy use models are presented in Appendix A Table 4.4. The results of the different cross-section dependence tests under both random and fixed effects estimations show that the null hypothesis of no cross-sectional dependence is rejected in both non-renewable and renewable energy use models under all of the used tests —Friedman, Frees, and Pesaran— meaning the residuals of the two models are correlated. The results of heteroskedasticity based on a modified Wald test indicate the existence of the problem of heteroskedasticity at a 1% level of significance in both models. Finally, the findings of serial correlation test based on Wooldridge suggest that the two models suffer from a positive serial correlation. In the case of the existence of cross-section error dependence, in addition to heteroskedasticity and serial correlation, conventional panel estimators (such as fixed or random effects) can result in misleading inference and even inconsistent estimators (Phillips and Sul 2003). Pesaran (2006) proposes an estimation method, called Common Correlated Effects (CCE), which allows for unobserved factors to be correlated with exogenous regressors and idiosyncratic components to be independent across countries. Furthermore, this estimator holds under different situations such as serial correlation in errors, unit roots in the variables and possible contemporaneous dependence of the observed regressors with the unobserved factors (Coakley et al. 2006; Kapetanios and Pesaran 2007; Kapetanios et al. 2011; Pesaran and Tosetti 2011). Therefore, in this study, to account for the cross-sectional dependence in the data, the common correlated effects (CCE) estimator by Pesaran (2006) is employed[15]. A brief review of the structure of this approach is provided in Appendix B.

The results of the long-run estimates of the variables are reported in Table 4.7. The estimated coefficients of total population are positive and statically significant at 10% level for non-renewable energy use and renewable energy use. While the elasticity of

[15] For a detailed discussion of this approach refer to Pesaran (2006), and Pesaran and Tosetti (2011).

non-renewable energy use to population size is 1.763, the elasticity of renewable energy use to population size is 0.710. This result indicates that population growth increases energy consumption in terms of both non-renewables and renewables. However, the magnitude of the long-run elasticity of non-renewable energy use with respect to the population is much greater than the elasticity of renewable energy use with respect to the population. The positive relationship between population and energy use can be seen in some previous studies (York 2007; Liddle and Lung 2010; Poumanywong and Kaneko 2010; Liddle 2011; Poumanywong and Kaneko 2012).

Liddle (2011) concentrates on the effects of total population and age structure on residential energy consumption for a panel of OECD countries and finds a positive linkage between population size and energy consumption. He also concludes that age structure has a U-shaped impact on energy consumption: while the youngest and oldest groups have positive coefficients, the middle ones have negative coefficients.

Growth in energy use is linked to population growth through increases in housing, commercial floor space, transportation, and goods and services. Generally, it can be said that population growth expands energy demand, which in turn leads to an increase in energy consumption.

Table 4.7: Coefficients of CCE estimates for non-renewable and renewable energy use models

Dependent Variables	Non-renewable energy use	Renewable energy use
LP	1.763 (1.82)*	0.710 (1.75)*
LA	0.537 (3.18)***	0.268 (1.72)*
LIND	0.389 (2.99)***	0.125 (1.91)**
LS	0.536 (1.95)*	0.294 (2.12)**
LU	0.821 (2.15)**	1.154 (0.24)
LPD	-0.482 (-1.42)*	-0.437 (-0.80)

Note: Related-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels, respectively.

GDP per capita has a positive and statistically significant effect on both non-renewable and renewable energy use at 1% level and 10% level, respectively. The results indicate that a 1% increase in GDP per capita increases non-renewable energy use by 0.537% and renewable energy use by 0.268% in the long run. The relationship between industrialisation and both non-renewable and renewable energy use is positive and significant at 1% and 5% levels, respectively. The estimated coefficients indicate that an increase in industrialisation increases non-renewable energy use by 0.389%, and renewable energy use by 0.125%. The effect of the share of services in GDP on non-renewable energy use and renewable energy use is positive and significant at 10% and 5% levels, respectively. The estimated coefficients suggest that an increase in the share of services in GDP is associated with 0.536% increase in the non-renewable energy use and 0.294% increase in the renewable energy use. It is worth noting that the impacts of economic growth, industrialisation and the share of services in GDP on non-renewable energy consumption are greater than that on the renewable energy use. It appears that, although the benefits of clean and renewable energy are evident, yet the displacement of fossil fuel usage by renewable energy resources has occurred at a very low rate. Finding a positive relationship between GDP per capita, the share of industry and services in GDP and energy consumption, is also found in previous studies that have investigated these three factors simultaneously, controlling for urbanisation (Poumanywong and Kaneko 2010; Zhang and Lin 2012). The relationship between urbanisation and energy consumption is as expected: positive but significant only for non-renewable energy consumption. Similarly, the effect of population density on both non-renewable and renewable energy use are negative, however, significant only for non-renewable energy use. It appears that, although the use of renewable energy sources (hydropower, biomass, biofuels, wind, geothermal, and solar), particularly for electricity generation, has increased recently in developed countries, the main energy source used by humans is still non-renewable fossil fuels. The use of renewable sources is also limited by the fact that they are not always available —cloudy days reduce solar power; calm days reduce wind power; and droughts reduce the water available for hydropower. An increase in non-renewable energy use due to urbanisation can also be explained based on the findings of Poumanyvong et al. (2012) who reveal that the impact of urbanisation on transport and road energy use is high in high income group countries (higher than the low and middle income groups). On the one hand, while energy consumption in motorised individual passenger traffic is up to 10 times as high as consumption in a well-organised and demand-oriented public transport system, people in developed countries depend heavily on the individual automobiles for their daily trips (Weiler 2006; poumanyvong et al. 2012). On the other hand, transport is heavily dependent on fossil fuels (97% of transport energy is based on oil (Weiler 2006)). Therefore, all the evidence supports the positive association between urbanisation and non-renewable energy consumption in OECD countries.

The results obtained in this study may not be exactly comparable with those of other studies that use aggregate energy consumption. However, considering energy consumption regardless of energy type, the findings can be compared with previous studies. The positive link between urbanisation and energy consumption is supported by York (2007), Liddle and Lung (2010) and Poumanywong and Kaneko (2010) who also find that urbanisation influences energy consumption positively in developed countries. Likewise, Jones (1991), Parikh and Shukla (1995), Imai (1997), York et al. (2003b), and Mishra (2009) achieve similar results for different countries.

As mentioned earlier, the linkage between population density and non-renewable energy use is significant, while the relationship between population density and renewable energy use is insignificant. The long-run relationship between population density and non-renewable energy use shows that the effect of population density on non-renewable energy use is negative and statistically significant at 10% level. The results indicate that a 1% increase in population density leads to 0.482% decrease in non-renewable energy consumption in the long run. This result supports the hypothesis implying that increasing density reduces energy use. This finding is consistent with an early study by Newman and Kenworthy (1989) and Larivière and Lafrance (1999) who find a negative relationship between population density and energy use in high income countries and Canada, respectively. The finding is also in line with Chen et al. (2008) who reveal that urban density has a negative effect on household energy consumption in Chinese cities. Population density can reduce environmental impact through clustering a mixture of residential, office, retail, and outdoor recreational uses together, thereby shrinking travel distances and encouraging walking, cycling and public transport that reduces the use of fossil fuels. Despite urbanisation, greater density improves the economics of public transport systems, and thereby results in lower energy use per passenger-kilometre of travel in such places. Furthermore, another attribute of high population density is through its effect on building sectors. Multi-family housing allows for more efficient energy use than single-family homes. For instance, energy use in places like New York City or Philadelphia is significantly less than that in Dallas or Phoenix, which have dispersed settlement patterns (Darmstadter 2001).

Although the limited number of studies so far shows that population density decreases energy consumption in general, the results of this study indicating that population density reduces non-renewable energy consumption in particular, can shed further light on the existing literature. Moreover, this finding helps policy makers to improve not only urban planning but also rural planning that can finally make a substantial contribution to climate change mitigation.

4.4.4 Panel Causality Test

In this section short-run and long-run Granger causality, using the dynamic panel system generalised method of moments (GMM) estimator proposed by Blundell and Bond (1998) is analysed. In order to examine the dynamic error-correction model, the residuals are first obtained from estimating the long-run relationship between the variables. The Granger causality is tested based on the following equations, considering each variable in turn as a dependent variable for each model (non-renewable and renewable energy use models):

$$\Delta LN_{it} = c_0 + \sum_{j=1}^{m} \beta_{11ij} \Delta P_{it-j} + \sum_{j=1}^{m} \beta_{12ij} \Delta A_{it-j} + \sum_{j=1}^{m} \beta_{13ij} \Delta IND_{it-j} + \sum_{j=1}^{m} \beta_{14ij} \Delta S_{it-j} + \sum_{j=1}^{m} \beta_{14ij} \Delta U_{it-j} + \sum_{j=1}^{m} \beta_{14ij} \Delta PD_{it-j} + \lambda_{it} e_{it-1} + u_{1it} \tag{4.5}$$

$$\Delta LR_{it} = d_0 + \sum_{j=1}^{m} \theta_{11ij} \Delta P_{it-j} + \sum_{j=1}^{m} \theta_{12ij} \Delta A_{it-j} + \sum_{j=1}^{m} \theta_{13ij} \Delta IND_{it-j} + \sum_{j=1}^{m} \theta_{14ij} \Delta S_{it-j} + \sum_{j=1}^{m} \theta_{14ij} \Delta U_{it-j} + \sum_{j=1}^{m} \theta_{14ij} \Delta PD_{it-j} + \gamma_{it} e_{it-1} + u_{1it} \tag{4.6}$$

In Equation 4.5, *N* is non-renewable energy consumption and in Equation 4.6, *R* is renewable energy consumption. In both above equations, *P* is total population size, *A* is GDP per capita, *IND* is the share of the industry sector in GDP, *S* is the share of the service sector in GDP, *PD* is population density and *U* is urbanisation.

Table 4.8 and Table 4.9 display the results of the panel error correction for non-renewable and renewable energy use models, respectively. The short-run results of the explanatory variables effects on non-renewable energy use indicate that from the demographic variables, including total population, urbanisation and population density, only total population has a significant impact on non-renewable energy consumption. The impact of GDP per capita on non-renewable energy use is positive and significant at the 1% level in the short run. The relationship between the share of services in GDP and non-renewable energy use is positive and significant, whereas the relationship between the share of industry in GDP and non-renewable energy use is insignificant.

The effects of the same explanatory variables on renewable energy use (Table 4.9) indicate that none of the studied independent factors has a significant impact on renewable energy consumption in the short term.

In relation to the short-run effects of non-renewable and renewable energy consumption on the other variables, the results from Table 4.8 and Table 4.9 respectively, illustrate that while non-renewable energy use has a statistically significant impact on total population and population density, renewable energy use does not show any significant relationship with any of the variables. The short run causality directions show that there is bidirectional causality between non-renewable energy use and total population, unidirectional causality from GDP per capita to non-renewable energy use, unidirectional causality from the share of services in GDP to non-renewable energy use, and unidirectional causality from non-renewable energy use to population density.

Finding a neutral relationship between urbanisation and energy consumption (for both renewable and non-renewable) in this study is consistent with Halicioglu (2007) who also finds no Granger causality between urbanisation and energy consumption for Turkey in the short term. However, this result contrasts with the unidirectional causality running from urbanisation to energy consumption found by Liu (2009) and Mishra (2009) for China and for the Pacific Island countries, respectively. In contrast, Shahbaz and Lean (2012) demonstrate a unidirectional causality running from energy consumption to urbanisation for Tunisia.

In relation to the long-run causality results, the error correction terms in both non-renewable and renewable energy use equations are negative and significant, revealing that there is Granger causality from total population, GDP per capita, the share of industry in GDP, the share of services in GDP, urbanisation and population density to non-renewable energy use and to renewable energy use in the long run. The coefficients of the error correction terms also suggest that the deviation of non-renewable and renewable energy consumption from short run to the long run is corrected by 91% and 92% respectively each year; and convergence to equilibrium after a shock to both non-renewable and renewable energy consumption takes one year (Table 4.8 and Table 4.9).

The short-run Granger causality relationship between the other variables—other than non-renewable and renewable energy consumption variables—shows that briefly there is: i) unidirectional causality from total population to GDP per capita; ii) unidirectional causality from GDP per capita to industrialisation; iii) bidirectional causality between GDP per capita and the share of services in GDP; iv) unidirectional causality from total population to industrialisation v) bidirectional causality between total population and population density vi) bidirectional causality between industrialisation and the share of services in GDP; vii) bidirectional causality between industrialisation and urbanisation; viii) bidirectional causality between industrialisation and population density; ix) unidirectional causality from the share of services in GDP to urbanisation; x) bidirectional causality between the share of services in GDP and population density xi) no causality between urbanisation and GDP per capita (Table 4.8 and Table 4.9). Finding a unidirectional causality from GDP per capita to industrialisation contrasts with the unidirectional causality running from industrialisation to GDP per capita found by Shahbaz and Lean (2012) in Tunisia. A neutral relationship between GDP per capita and urbanisation is in line with Halicioglu (2007) and Mishra (2009) for Turkey and for the Pacific Island countries, respectively.

Table 4.8: Panel causality test for non-renewable energy use model

Dependent Variables	Source of causation (independent variable)							
	Short run							Long run
	ΔLN	ΔLP	ΔLA	ΔLIND	ΔLS	ΔLU	ΔLPD	ECT
ΔLN	_	2.207 (1.67)*	0.137 (2.78)***	0.044 (0.67)	0.190 (1.69)*	0.680 (0.44)	0.215 (0.37)	-0.914 (-12.61)***
ΔLP	0.004 (1.88)**	_	-0.003 (-1.49)	0.003 (1.25)	-0.005 (-0.99)	0.081 (0.93)	0.054 (1.87)**	-0.006 (-1.73)*
ΔLA	0.002 (0.10)	0.919 (1.79)*	_	0.183 (4.00)***	0.168 (3.03)***	0.735 (1.19)	0.374 (0.93)	0.248 (4.49)***
ΔLIND	0.003 (0.08)	1.021 (1.84)*	0.250 (4.47)***	_	1.088 (15.05)***	2.429 (1.86)*	1.09 (2.52)*	-0.019 (0.33)
ΔLS	-0.011 (-0.83)	0.200 (0.63)	0.208 (6.49)***	0.401 (16.50)***	_	0.863 (1.13)	0.765 (3.10)***	-0.006 (-0.19)
ΔLU	0.002 (1.62)	0.02 (0.47)	-0.001 (-0.56)	0.004 (1.96)**	0.007 (2.05)**	_	0.016 (0.69)	0.001 (0.62)
ΔLPD	0.004 (2.15)**	0.101 (2.17)**	-0.003 (-1.19)	-0.005 (-1.72)*	-0.014 (-2.74)***	0.025 (0.44)	_	0.004 (0.85)

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels respectively. The optimal lag length for the variables is two and determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

Table 4.9: Panel causality test for renewable energy use model

Dependent Variables	Source of causation (independent variable)							
	Short run							Long run
	ΔLR	ΔLP	ΔLA	ΔLIND	ΔLS	ΔLU	ΔLPD	ECT
ΔLR	_	0.166 (0.04)	-0.014 (-0.06)	0.196 (0.79)	0.294 (0.72)	-2.382 (-0.53)	1.270 (0.43)	-0.922 (-13.22)***
ΔLP	-0.000 (-0.45)	_	-0.004 (-1.17)	0.003 (1.32)	-0.005 (-0.90)	0.080 (0.89)	0.062 (2.14)**	0.000 (0.10)
ΔLA	-0.001 (-0.21)	0.746 (1.78)*	_	0.204 (4.06)***	0.204 (3.33)***	0.347 (0.49)	0.472 (1.07)	0.001 (0.15)
ΔLIND	0.003 (0.89)	0.995 (1.82)*	0.235 (4.55)***	_	1.082 (15.00)***	3.075 (2.35)**	0.931 (2.18)**	0.004 (0.41)
ΔLS	0.000 (0.24)	0.274 (0.88)	0.180 (6.11)***	0.385 (15.83)***	_	0.996 (1.30)	0.766 (3.13)***	0.003 (0.52)
ΔLU	0.004 (1.77)*	0.02 (0.55)	-0.001 (-0.89)	0.003 (1.97)**	0.004 (1.71)*	_	0.003 (0.15)	0.000 (0.55)
ΔLPD	-0.000 (-0.66)	0.109 (2.35)**	-0.002 (-0.70)	-0.005 (-1.69)*	-0.012 (-2.36)**	0.020 (0.35)	_	0.000 (0.73)

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels respectively. The optimal lag length for the variables is two and determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

Although the results of the short-run causality for the variables total population, GDP per capita, the share of industry in GDP, the share of services in GDP, urbanisation and population density are the same in both non-renewable and renewable energy use models (Table 4.8 and Table 4.9), the long-run causal relationship by the error correction terms are different. While the error correction terms for total population and GDP per capita are significant in the non-renewable energy use model, none of the error correction terms for any of the mentioned variables are significant in the renewable energy use model. This finding is not surprising because the Granger causality nexus is very sensitive to choice of different models or using additional variables in the model (Stern 2011).

4.5 Conclusion

In this chapter the influence of urbanisation on non-renewable and renewable energy consumption is examined for OECD countries between 1980 and 2011. Besides urbanisation, the relationship between population density and non-renewable and renewable energy use, controlling for population size, GDP per capita, the share of industry and services in GDP, is also investigated. The results of the long-run relationship based on the STIRPAT model indicate that urbanisation has a positive and significant impact on non-renewable energy use, whereas the effect of urbanisation on renewable energy use is insignificant. In relation to the effect of population density, a significant negative relationship is found between population density and non-renewable energy consumption. On the other hand, Granger causality results indicate that there is unidirectional causality from non-renewable energy use to population density in the short term. However, no causal linkage is found between urbanisation and non-renewable energy use. Likewise, no causal direction is seen between renewable energy use and any of the demographic factors in the short run. The coefficients of the dynamic error correction terms in both non-renewable and renewable energy use models are negative and significant, implying that the variables adjust towards a long run equilibrium level, after a shock occurs.

The absence of a significant association between renewable energy use and urbanisation and also between renewable energy use and population density illustrate that although the use of renewable energy sources has increased recently in developed countries, the main energy source available for people to use is still non-renewable fossil fuels. In the case of the positive relationship between urbanisation and non-renewable energy use, it can be said that economic development and increasing incomes which are followed by urbanisation, leads to changes in consumer needs, which in turns results in an increasing energy consumption. Moreover, urbanisation through its increasing effect on transport energy demand increases the use of non-renewable sources. However, population density that seems to have negative impact on non-renewable energy consumption (found in this study) might be able to offset the effects of urbanisation on this type of energy to some extent. Therefore, overall evidence derived from the main findings of this study imply that the policy makers should focus more on urban planning as well as clean energy development both in the short term and long term to make a substantial contribution not only to non-renewable energy use reduction but also to climate change mitigation.

Given the importance of the effects of urbanisation and population density on energy consumption, this question arises: how can these factors influence environmental pollutant emissions in developed countries? The next chapter will address this issue and also compare the impacts of non-renewable and renewable energy sources on pollution emissions.

Appendix A to Chapter 4

Appendix A Table 4.1: Summary of Literature on Energy Consumption-Urbanisation Nexus

Study	Country (Period)	Methodology	Main Variables	Finding
Jones (1991)	59 developing countries (1980)	OLS	energy consumption per capita and urbanisation	Positive relationship between energy consumption per capita and urbanisation.
Parikh and Shukla (1995)	44 developing countries (1965-1987)	Fixed effects	energy consumption per capita and urbanisation	Positive relationship between energy consumption per capita and urbanisation.
York et al. (2003b)	146 countries (1996, 1999)	STIRPAT model and OLS	GNP and energy consumption	Positive relationship between energy consumption per capita and urbanisation.
Liddle (2004)	OECD countries (1960-2000)	Fixed effects	road transport energy consumption and urbanisation	Negative relationship between road transport energy consumption and urbanisation
Poumanyvong et al. (2012)	92 (low, middle and high income) countries (1975-2005)	STIRPAT model and Fixed effects	road transport energy consumption and urbanisation	Positive relationship between road transport energy consumption and urbanisation
York (2007)	14 European Union Nations (1960-2000)	STIRPAT model and Prais–Winsten regression with panel-corrected standard errors	urbanisation and energy consumption	Positive relationship between urbanisation and energy consumption
Liu (2009)	China (1978-2008)	Cointegration and Granger causality	urbanisation and energy consumption	Unidirectional causality from urbanisation to total energy consumption in the short run and long run.

Halicioglu (2007)	Turkey (1968-2005)	Autoregressive distributed lag (ARDL) and Granger causality	urbanisation and energy consumption	Unidirectional causality from urbanisation to energy consumption in the short run and long run.
Mishra et al. (2009)	9 Pacific Island countries (1980-2005)	Cointegration, DOLS and Granger causality	urbanisation and energy consumption	Unidirectional causality from urbanisation to energy consumption in the short run.
Liddle and Lung (2010)	17 developed countries (1960-2005)	STIRPAT model and two-way fixed effects	urbanisation, residential energy and residential electricity consumption	Positive relationship between urbanisation, residential energy consumption and residential electricity consumption.
Poumanyvong and Kaneko (2010)	99 countries (1975-2005)	STIRPAT model, pooled OLS, fixed ffects, Prais–Winsten and first differenced	urbanisation and energy consumption	Positive relationship between urbanisation and energy use in the middle- and high-income countries and negative relationship between urbanisation and energy use in the low-income countries.
Shahbaz and Lean (2012)	Tunisia (1971-2008)	Cointegration and Granger causality	Industrialisation, urbanisation and energy consumption	Bidirectional causality between industrialisation and energy consumption in the long run and unidirectional causality from urbanisation to energy consumption in the short run.
Larivière and Lafrance (1999)	Canada (1991)	OLS	urban density and energy consumption	Negative relationship between urban density and energy consumption.
Chen et al. (2008)	45 Chinese cities	Pearson product–moment correlation coefficient and Best-to-fit analyses	urban density and household energy consumption	Negative relationship between urban density and household energy consumption.

Appendix A Table 4.2: Summary statistics of the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
LN	928	0.6131858	1.562073	-3.79691	4.45892
LR	928	-2.034407	1.991509	-8.4684	1.5453
LP	928	4.024885	4.343143	-1.47771	19.55721
LA	928	9.645223	0.724376	7.6758	10.9442
LIND	928	3.410728	0.1976116	2.521543	3.91421
LS	928	4.155072	0.1439641	3.48931	4.46899
LU	928	4.293364	0.160268	3.75654	4.579703
LPD	928	4.134103	1.461466	0.6483842	6.223514

Appendix A Table 4.3: Multicollinearity test

Variable	VIF	1/VIF
LS	4.60	0.217387
LIND	2.97	0.336490
LA	2.12	0.471891
LP	1.31	0.764511
LU	1.30	0.767854
LPD	1.20	0.833617
Mean VIF	2.25	

Note: The VIF values are all below than 10, implying that there is no multicollinearity.

Appendix A Table 4.4: Estimated breaks for individual countries

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
Australia	LP	2	1981	1998			
	LA	4	1985	1989	1994	2001	
	LIND	3	1982	1996	2000		
	LS	2	1983	1994			
	LU	2	1986	1993			
	LPD	1	1981				
Austria	LP	3	1982	1989	1993		
	LA	4	1982	1991	1998	2002	
	LIND	2	1983	1992			
	LS	1	1987				
	LU	3	1980	1987	1999		
	LPD	2	1981	1998			
Belgium	LP	2	1983	1989			
	LA	3	1988	1996	2001		
	LIND	2	1989	2003			
	LS	2	1983	1997			
	LU	1	1991				
	LPD	2	1988	1998			
Canada	LP	2	1984	1999			
	LA	2	1981	1997			

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LIND	3	1984	1995	2002		
	LS	2	1986	1998			
	LU	3	1986	1996	2000		
	LPD	1	1987				
Chile	LP	2	1984	1993			
	LA	2	1986	1999			
	LIND	3	1983	1994	2003		
	LS	4	1980	1989	1993	2004	
	LU	2	1985	1998			
	LPD	2	1987	1994			
Denmark	LP	2	1987	1994			
	LA	3	1982	1994	2000		
	LIND	3	1984	1992	1999		
	LS	1	1988				
	LU	2	1986	1995			
	LPD	1	1983				
Finland	LP	2	1985	1996			
	LA	3	1984	1997	2001		
	LIND	2	1983	1998			
	LS	3	1980	1989	1996		
	LU	2	1991	2002			
	LPD	1	1989				
France	LP	2	1982	1998			
	LA	2	1983	1999			
	LIND	2	1989	2001			
	LS	2	1988	2002			
	LU	3	1981	1988	1995		
	LPD	2	1983	1991			
Germany	LP	2	1985	1997			
	LA	4	1984	1992	1998	2003	
	LIND	3	1985	1996	2001		
	LS	1	1989				
	LU	2	1984	1993			
	LPD	2	1984	1992			
Greece	LP	1	1986				
	LA	3	1983	1997	2002		
	LIND	3	1984	1996	2001		
	LS	3	1982	1991	2000		
	LU	2	1983	1994			
	LPD	2	1983	1996			
Hungary	LP	2	1985	1994			
	LA	1	1985				
	LIND	2	1983	1994			
	LS	2	1982	1998			
	LU	3	1982	1997	2000		

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LPD	2	1982	1997			
Iceland	LP	1	1994				
	LA	3	1984	1992	1999		
	LIND	2	1987	1997			
	LS	2	1984	1996			
	LU	2	1983	1992			
	LPD	1	1993				
Ireland	LP	2	1985	1997			
	LA	4	1982	1989	1996	2001	
	LIND	3	1985	1997	2003		
	LS	2	1984	1997			
	LU	3	1981	1987	1998		
	LPD	2	1988	1995			
Italy	LP	1	1991				
	LA	4	1983	1990	1998	2003	
	LIND	3	1983	1989	1999	2001	
	LS	2	1984	1994			
	LU	3	1982	1989	1994		
	LPD	2	1982	1987			
Japan	LP	3	1981	1988	1991		
	LA	2	1984	1998			
	LIND	3	1986	1995	2002		
	LS	2	1988	2000			
	LU	2	1989	1996			
	LPD	1	1989				
South Korea	LP	3	1985	1991	1997		
	LA	2	1988	2000			
	LIND	3	1987	1997	2001		
	LS	2	1984	1994			
	LU	1	1994				
	LPD	2	1989	1995			
Luxembourg	LP	2	1986	1996			
	LA	3	1981	1989	1998		
	LIND	2	1987	2000			
	LS	2	1983	1999			
	LU	2	1987	1994			
	LPD	1	1992				
Mexico	LP	2	1981	1997			
	LA	2	1991	2002			
	LIND	2	1995	2001			
	LS	2	1984	1995			
	LU	2	1989	1994			
	LPD	2	1989	1997			
Netherlands	LP	3	1984	1988	1992		
	LA	2	1983	1997			

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LIND	2	1983	1999			
	LS	2	1993	2000			
	LU	1	1997				
	LPD	2	1987	1997			
New Zealand	LP	2	1989	1994			
	LA	3	1983	1997	2000		
	LIND	2	1986	1994	2002		
	LS	2	1983	1991			
	LU	2	1981	1986			
	LPD	1	1982				
Norway	LP	2	1984	1991			
	LA	4	1984	1989	1996	2004	
	LIND	2	1983	1995			
	LS	1	1997				
	LU	2	1984	1989			
	LPD	2	1982	1989			
Poland	LP	2	1989	1996			
	LA	3	1982	1989	1994		
	LIND	4	1985	1989	1992	2001	
	LS	2	1987	1995			
	LU	2	1987	1992			
	LPD	2	1986	1993			
Portugal	LP	2	1985	1999			
	LA	3	1987	1991	2003		
	LIND	4	1986	1989	1994	2001	
	LS	2	1985	1990			
	LU	1	1986				
	LPD	2	1989	1991			
Spain	LP	3	1987	1990	1998		
	LA	2	1989	1993	2001		
	LIND	2	1984	1998			
	LS	3	1982	1986	1997		
	LU	2	1988	1993			
	LPD	1	1993				
Sweden	LP	2	1984	1996			
	LA	4	1982	1987	1994	2003	
	LIND	2	1983	1998			
	LS	2	1983	1997			
	LU	1	1986				
	LPD	2	1982	1987			
Switzerland	LP	3	1987	1991	2002		
	LA	2	1986	1999			
	LIND	4	1987	1997	2000	2004	
	LS	2	1986	1991			
	LU	2	1983	1993			

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
	LPD	2	1985	1998			
Turkey	LP	2	1989	1997			
	LA	3	1984	1989	1994		
	LIND	2	1984	2000			
	LS	2	1986	1989			
	LU	2	1983	1983			
	LPD	2	1982	1989			
UK	LP	2	1983	1988			
	LA	3	1987	1993	2001		
	LIND	2	1989	1997			
	LS	2	1984	1997			
	LU	2	1986	1994			
	LPD	1	1986				
US	LP	2	1989	1996			
	LA	2	1984	1997			
	LIND	2	1989	2000			
	LS	2	1993	1998			
	LU	1	1983				
	LPD	2	1985	1989			

Note: the maximum number of structural breaks is 5. The number of break points is estimated by using the Bay and Perron (2003) procedure.

Appendix A Table 4.5: Diagnostic tests for non-renewable and renewable energy use models

	FE Estimation	RE Estimation
Non-renewable energy use model		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.000***	0.000***
Frees (*Q*)	8.616***	8.565***
Friedman (*P*-value)	0.000***	0.000****
Heteroskedasticity		
Modified Wald (*P*-value)	0.000***	
Serial Correlation		
Wooldridge (*P*-value)	0.000***	
Renewable energy use model		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.000***	0.000***
Frees (*Q*)	6.679***	6.574***
Friedman (*P*-value)	0.000***	0.000****

	FE Estimation	RE Estimation
Heteroskedasticity		
Modified Wald (*P*-value)	0.000***	
Serial Correlation		
Wooldridge (*P*-value)	0.000***	

Note: FE and RE denote fixed effects and random effects estimations. *** indicates that the *P*-value or test statistic is significant at the 1% level.

Appendix B to Chapter 4

A Brief Review on the Structure of Common Correlated Effects (CCE) Estimator

Pesaran (2006) considers the heterogeneous panel data model with y_{it} as the observation on the *i*th panel member at time *t* for *i* = 1, …, *N* and *t* = 1, ..., *T*

$$y_{it} = \alpha'_i d_t + \beta'_i x_{it} + e_{it} \tag{4.1}$$

where d_t represents a (n × 1) vector of observed common effects including deterministic components such as intercepts or seasonal dummies. The observed cross unit specific regressors are denoted by the (k × 1) vector x_{it}, while the error term e_{it} is specified by a multifactor structure:

$$e_{it} = \gamma' f_t + \varepsilon_{it} \tag{4.2}$$

where f_t denotes the (m × 1) vector of unobserved common factors and ε_{it} are the cross unit-specific (idiosyncratic) disturbance terms, which are assumed to be independently distributed of $(d_t,\ x_{it})$. Since the unobserved factors f_t could be correlated with (d_t, x_{it}), a general specification of the cross unit-specific regressors is adopted:

$$x_{it} = A'_i d_t + \Gamma'_i f_t + v_{it} \tag{4.3}$$

where A_i and Γ_i denote (n × k) and (m × k) factor loading matrices with fixed omponents, and v_{it} are the specific components of x_{it} distributed independently of the common effects and across *i*, but assumed to follow general covariance stationary processes.

Combining Equations 4.1 to 4.3 yields the system:

$$\underset{(k+1)\times 1}{z_{it}} = \begin{pmatrix} y_{it} \\ x_{it} \end{pmatrix} = \underset{(k+1)\times n}{B'_i} \ \underset{n\times 1}{d_t} + \underset{(k+1)\times m}{C'_i} \ \underset{m\times 1}{f_t} + \underset{(k+1)\times 1}{u_{it}} \tag{4.4}$$

where

$$u_{it} = \begin{pmatrix} \varepsilon_{it} + \beta'_{it} v_{it} \\ v_{it} \end{pmatrix}, B_i = (\alpha_i \quad A_i) \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix}, C_i = (\gamma_i \quad \Gamma_i) \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix}$$

with I_k as the identity matrix of order k. The rank of C_i is determined by the rank of the (m × (k + 1)) matrix of the unobserved factor loadings $\widetilde{\Gamma_i} = (\gamma_i \quad \Gamma_i)$.[16]

Pesaran (2006) suggests the use of cross-section averages of the dependent variable, y_{it}, and the regressors, x_{it}, as proxies for the unobserved common factors. For illustration purposes of the elimination of those factors, consider the simple cross-section averages of the Equations B4.4[17].

$$\bar{z}_t = \bar{B}'d + \bar{C}'f_t + \bar{u}_t \tag{4.5}$$

where $\bar{z}_t = 1/N \sum_{i=1}^{N} z_{it}$, $\bar{v}_t = 1/N \sum_{i=1}^{N} u_{it}$, $\bar{B} = 1/N \sum_{i=1}^{N} B_i$ and $\bar{C} = 1/N \sum_{i=1}^{N} C_i$.

Assume that Rank ($\bar{C}$) = m ≤ k+1 for all N, so that

$f_t = (\bar{C}\bar{C}')^{-1}\bar{C}\,(\bar{z}_t - \bar{B}'d - \bar{C}'f_t - \bar{u}_t)$. If $u_t \to 0$ and $\bar{C} \to C$ as $N \to \infty$ then

$f_t - (\bar{C}\bar{C}')^{-1}\bar{C}\,(\bar{z}_t - \bar{d}) \to 0$.

This suggests that it is valid to use $\bar{h}_t = (d'_t,\ z'_t)$ as observable proxies for the unobservable common factors f_t, and justified the basic idea of the common correlated effects (CCE) estimators.

[16] For more details on the underlying assumption refer to Pesaran (2006).

[17] Although Pesaran (2006) uses more general weighted cross-section averages, this study restricts the discussion about the CCE estimator to simplify the illustration, (see Kapetanios et al. 2011).

CHAPTER 5

NON-RENEWABLE, RENEWABLE ENERGY CONSUMPTION AND CO_2 EMISSIONS: A COMPARATIVE ANALYSIS

5.1 Introduction

Carbon dioxide (CO_2) is the most important anthropogenic greenhouse gas (GHG). Increased CO_2 emissions from fossil-fuel use is certain to be the dominant influence on the trends in atmospheric CO_2 concentration that eventually resulted in rising global temperatures (IPCC 2005). According to the International Energy Agency (IEA), most CO_2 emissions come from energy production, with fossil fuel combustion representing two-thirds of global CO_2 emissions. Human activities are also influencing the environment. Activities, in particular those involving combustion of fossil fuels and biomass burning, produce GHGs that affect the composition of the atmosphere and global climate (IPCC 2001). Energy consumption and the resulting greenhouse gas effect is thought to have led to a series of natural disasters. Furthermore, industrialisation and urbanization, as the two major factors of economic growth, lead to environmental degradation through energy consumption. In addition, expansion in services industries, which is the result of economic development, can increase energy demand and consequently leads to pollutant emissions. Environmental degradation, declining natural resources and climate change have become important concerns to the world.

It appears that the most significant increase of energy consumption and CO_2 emissions is taking place in urban areas, where rapidly expanding populations enjoy higher living standards and material affluence (Fong et al. 2007a, 2007b). Therefore, governments should consider the importance of promoting sustainable development and combating climate change particularly in urban sectors, when setting out their energy policies. As renewable energy technologies generate far lower or near-zero emissions of GHGs compared with fossil fuels, one way to reduce greenhouse gas emissions is to replace energy from fossil fuels with energy from renewables. Thus, it seems increasing use of renewable energy slowly can help prevent pollutant emissions.

So far, numerous studies have dealt with the relationship between energy consumption and pollutant emissions, in different countries and with various modelling methods, approaches and findings. However, only a few studies have investigated the relationship between disaggregated energy consumption and CO_2 emissions. Therefore, the main objective of this study is to fill this gap in the literature by using disaggregated energy consumption including renewable and non-renewable energy to compare their impacts on CO_2 emissions. Moreover, for the first time, this research investigates the effects of renewable and non-renewable energy consumption simultaneously on CO_2 emissions based on a statistical model, namely STIRPAT. Additionally, this chapter looks at the relationship between urbanisation and CO_2 emissions by emphasising on the Environmental Kuznets Curve (EKC) hypothesis.

The rest of the chapter is organized as follows: Section 5.2 provides the related literature review. Section 5.3 presents methodology including model specification and estimation strategy. The empirical results are reported in Section 5.4. Finally, Section 5.5 presents the conclusion.

5.2 Literature Review

5.2.1 CO_2 Emissions, Energy Consumption and Economic Growth

The relationship between growth and environment and between growth and energy has been investigated extensively. However, a new line of research has arisen recently that combines the approach of the two nexus in a single framework.

Soytas et al. (2007) investigate the effect of energy consumption and income on CO_2 emissions, including gross fixed capital formation and labour in the US for the period 1960 to 2004. The results indicate no evidence of a causal relationship between income and CO_2 emissions, whereas energy consumption causes CO_2 emissions in the long run. Considering population growth, urbanisation, energy consumption, economic growth and CO_2 emissions for Pakistan during the period 1971 to 2005, Alam et al. (2007) find that population growth, urbanisation, energy consumption and economic growth have positive and significant effect on CO_2 emissions in the long run.

Employing a multivariate vector error-correction model for France over the period 1960–2000, Ang (2007) estimates a dynamic link between CO_2 emissions, energy consumption and output. The empirical findings reveal the existence of a long-run relationship between the variables. The results also indicate that output growth causes CO_2 emissions in the long run. In another study by Ang (2008) for the case of Malaysia during the period 1971 to 1999, the author reveals that CO_2 emissions is positively related to economic growth in the long term. However, no causality is found between CO_2 emissions, energy consumption and output.

Soytas and Sari (2009) examine the long run causality link between economic growth, CO_2 emissions and energy consumption in Turkey for the period 1960 to 2000, controlling for investment per capita and labour. They find a unidirectional causality running from CO_2 emissions to energy consumption. Zhang and Cheng (2009) examine the inter-temporal relationship in an income–energy–environment nexus and also investigate the effect of urbanisation on the latter variables for China over the period 1960 to 2007. They conclude that energy consumption causes the CO_2 emissions.

Sadorsky (2009a) analyses the relationship between renewable energy consumption, economic growth, pollution emissions, and oil prices for the period 1980 to 2005 in the G7 countries. Panel cointegration estimates show that in the long term, real GDP per capita and CO_2 emissions per capita have positive effects on renewable energy consumption; and oil price has a negative impact, although small, on renewable energy consumption. The author explains that the latter result may be due to using a relative short sample period.

In the case of Turkey during the period 1960 to 2005, Halicioglu (2009) empirically investigates the dynamic causal correlation between carbon emissions, energy consumption, income and foreign trade. Econometric evidence suggests that energy consumption, income, and foreign trade have positive and statistically significant effects on CO_2 emissions in the long run. However, the author shows that income has a more significant impact in explaining the CO_2 than the energy consumption. Moreover, Granger causality tests indicate a bidirectional causality relationship between CO_2 emissions and income both in the short term and long term.

Acaravci and Ozturk (2010) test the long-run and casual relationship between economic growth, carbon emissions, and energy consumption for the selected nineteen European countries from 1960 to 2005. The econometric method used in this study is an ARDL bounds testing approach of cointegration as well as error-correction based Granger causality models. The results yield evidence of a long-run relationship between the variables in Denmark, Germany, Greece, Iceland, Italy, Portugal and Switzerland. Furthermore, the results of Granger causality models are as follows: i) there is evidence of a long-run unidirectional causal relationship from energy consumption per capita, real GDP per capita and the square of per capita real GDP to carbon emissions per capita in Denmark, Germany, Greece, Iceland, Italy, Portugal and Switzerland. ii) There is evidence of a short-run unidirectional causal relationship from real GDP per capita and the square of per capita real GDP to carbon emissions per capita in Denmark and Italy.

Focusing attention on six Central American countries covering the period 1971 to 2004, Apergis and Payne (2009b) employ a panel vector error-correction model to test for causality between CO_2 emissions, energy consumption, and real GDP. The findings show that in the long run energy consumption has a positive and statistically significant impact on emissions while real output exhibits the inverted U-shape pattern associated with the Environmental Kuznets Curve (EKC) hypothesis. Moreover, the results confirm the existence of causality from energy consumption and real output, respectively, to emissions. In the long run there is bidirectional causality between energy consumption and emissions.

Apergis and Payne (2010f) study a dynamic relationship between CO_2 emissions, energy consumption, and real GDP in the case of eleven countries of the Commonwealth of Independent States covering the period 1992 to 2004. The results observed from a vector error-correction model point to a positive and statistically significant impact of energy consumption on CO_2 emissions and an inverted U-shape pattern for real output in the long run. In addition, the short run results illustrate unidirectional causality from energy consumption and real GDP to emissions. In the long run there is bidirectional causality between energy consumption and emissions.

Employing a panel error-correction model, Apergis et al. (2010) analyse the causal relationship between CO_2 emissions, nuclear energy consumption, renewable energy consumption, and economic growth for a group of 19 developed and developing countries for the period 1984 to 2007. The long-run tests indicate that there is a statistically significant negative link between nuclear energy consumption and emissions, while there is a statistically significant positive relationship between emissions and renewable energy consumption. The evidence from the panel Granger causality tests reveal that in the short run nuclear energy consumption plays an important role in reducing CO_2 emissions whereas renewable energy consumption does not contribute to reductions in emissions. The authors point out that the latter result may be due to the limited proportion of renewable energy in total energy consumption.

Lean and Smyth (2010) study the relationship between economic growth, energy consumption and pollutant emissions for a panel of five countries in the Association of South East Asian Nations (ASEAN) consisting of Indonesia, Malaysia, the Philippines, Singapore and Thailand for the period 1980 to 2006. In this paper, the authors show that there is a statistically significant positive association between electricity consumption and emissions and a non-linear relationship between emissions and real output, consistent with the environmental Kuznets curve. The results obtained from the Granger causality tests indicate a unidirectional causality running from emissions to economic growth in the long run. The results also point to unidirectional causality running from emissions to electricity consumption in the short run.

In the case of the US, Menyah and Wolde-Rufael (2010a) investigate the causal relationship between CO_2 emissions, renewable and nuclear energy consumption and real GDP for the period 1960 to 2007. The results suggest a unidirectional causality running from nuclear energy consumption to CO_2 emission. While the findings indicate no causality running from renewable energy consumption to CO_2 emissions, there is a unidirectional causality running from CO_2 emissions to renewable energy consumption. At the end, the authors point out increasing nuclear energy consumption can result in reducing CO_2 emissions in the US.

Using the cointegration approach developed by Pesaran et al. (2001) and using the modified version of the Granger causality test proposed by Toda and Yamamoto (1995), Menyah and Wolde-Rufael (2010b) analyze the long run and the causal association between economic growth, energy consumption, and pollutant emissions, controlling for labour and capital variables for South Africa covering the period 1965 to 2006. The empirical results demonstrate a short-run and a long-run relationship between the variables with a positive and a significant relationship between pollutant emissions and economic growth. Furthermore, Granger causality tests indicate that there is a unidirectional Granger causality running from pollutant emissions to economic growth and from energy consumption to CO_2 emissions.

Pao and Tsai (2010) study a dynamic causal relationship between economic growth, energy consumption, and pollutant emissions for a panel of four countries—Brazil, Russia, India, and China—for the period 1971 to 2005. The results indicate that there is a statistically significant positive relationship between energy consumption and CO_2 emissions, while there is an inverted U-shape significant relationship between real output and CO_2 emissions in the long run. The results of the Granger causality tests indicate that there is bidirectional causality between energy consumption and CO_2 emissions; finally, there is a unidirectional causality from CO_2 emissions to output in the short run.

Salim and Rafiq (2012) investigate the relationship between CO_2 emissions and renewable energy consumption, controlling for income and oil prices. The long run results obtained from dynamic OLS and fully modified OLS methods show that CO_2 and income are the major determinants of renewable energy consumption in Brazil, China, India, and Indonesia. For these countries, a bidirectional causal relationship is also found between renewable energy consumption and CO_2 emissions in the short run. The results also indicate that there is bidirectional relationship between income and CO_2 emissions in Brazil, China and Turkey.

In the case of India, Alam et al. (2011) show that there is bidirectional Granger causality between energy consumption and CO_2 emissions, whereas there is no causality relationship between CO_2 emissions and income in any direction in the long run. This implies that India can contribute significantly to global climate mitigation by energy conservation and reducing CO_2 emissions without forgoing their economic growth. The same results are obtained for the long run by Hossain (2011) in a panel of newly industrialised countries during 1971–2007. However, Hossain provides evidence of unidirectional causal relationship from economic growth to CO_2 emissions in the short run.

Using the Toda-Yamamoto procedure over the period 1949 to 2009 for the US, Payne (2012) reveals that real GDP, CO_2 emissions, and real oil prices do not have a causal effect on renewable energy consumption. However, unexpected shocks to real GDP and CO_2 emissions positively affect renewable energy consumption over time.

Focusing on Middle East and North African countries from 1981 to 2005, Arouri et al. (2012) find that energy consumption has a long-run positive impact on CO_2 emissions. Despite finding poor evidence of the existence of the EKC hypothesis, they claim that CO_2 emissions might be reduced at the same time as GDP per capita grows. Hamit-Haggar (2012) examines the long-run and the causal relationship between greenhouse gas emissions, energy consumption and economic growth for Canadian industrial sectors from 1990 to 2007. The results indicate that while energy consumption has a positive and statistically significant impact on greenhouse gas emissions, an inverted U-shaped relationship is found between greenhouse gas emissions and economic growth. The short-run causality results show that there is a unidirectional Granger causality running from energy consumption to greenhouse gas emissions; and from economic growth to greenhouse gas emissions.

5.2.2 Review of Empirical Work Based on the STIRPAT Model

The STIRPAT method has been applied by some scientists in order to investigate the effects of driving forces on pollutant emissions. For instance, York et al. (2003a) study a non-linear relationship between emissions and the factors such as population, urbanisation and economic growth for 142 nations and find a positive relationship between emissions and the independent variables. In a similar study by York et al. (2003b), they authors analyse the effects of population and economic growth on CO_2 emissions, controlling for urbanisation and industrialisation, and conclude that the elasticity of CO_2 emissions with respect to population is close to unity.

Shi (2003) investigates the impact of population changes on CO_2 emissions in 93 countries over the period from 1975 to 1996 and finds a direct relationship between population changes and emissions. He shows that the elasticity of emissions with respect to population change varies with per capita income levels; the impact of population on emissions is more pronounced in lower-income countries than in higher-income countries.

Considering 86 countries during the period from 1971 to 1998, Cole and Neumayer (2004) study the effects of population size and some other demographic factors including age composition, the urbanisation rate and the average household size on CO_2 and sulphur dioxide (SO_2) emissions. The results indicate a U-shaped linkage between population size and SO_2 and a positive linkage between the urbanisation rate and CO_2 emissions. Moreover, a higher average household size is found to decrease emissions.

In contrast, a negative relation between urbanisation and CO_2 emissions is found by Fan et al. (2006) for developed countries over the period 1975 to 2000. The same result is obtained by Martínez-Zarzoso (2008). He analyses the determinants of CO_2 emissions during the period 1975 to 2003 and demonstrates that while the elasticity of emission-urbanisation is positive in low income countries, it is negative in upper and highly developed countries.

Lin et al. (2009) add urbanisation and industrialisation factors to the basic model and name the new model, STIRPUrlnAT. They use this revised model to analyse environmental impacts in China from 1978 to 2006 and find population has the largest potential effect on environmental impact, followed by urbanisation level, industrialisation level, GDP per capita and energy intensity.

Similar to the study of Fan et al. (2006), Poumanyvong and Kaneko (2010) consider different development stages and provide evidence of positive effects of population, affluence and urbanisation on CO_2 emissions for all the three low, middle and high income groups.

Considering aggregate CO_2 and CO_2 from transport for 17 developed countries covering the period from 1960 to 2005, Liddle and Lung (2010) reveal that total population and economic growth positively influence the two types of emissions. However, urbanisation has a positive and significant impact only on CO_2 emissions from transport. Improving this study by checking unit root and cointegration tests, Liddle (2011) finds a positive linkage between GDP per capita and CO_2 emissions from transport, and between total population and CO_2 from transport.

Using a panel of 29 provinces of China from 1995 to 2010, Zhang and Lin (2012) show that population, affluence, industrialisation and energy intensity increase CO_2 emissions for the whole sample, whereas the results are different across the regions.

5.2.3 CO_2 Emissions, Urbanisation and Income: Environmental Kuznets Curve (EKC) Hypothesis

The empirical articles relating to the link between environmental degradation and economic activities usually refer to the so-called Environmental Kuznets Curve (EKC) hypothesis, which reflects an inverted-U shape relationship between pollutant emissions and income per capital. The conjecture of the EKC hypothesis is that environmental quality initially intensifies as per capita income increases and subsidies after a certain level of economic growth. So far, a large number of studies have tested the economic growth and environmental pollution nexus (Shafik and Bandyopadyay 1992; Selden and Song, 1994 Grossman and Krueger 1995; Galeotti and Lanza 1999; Galeotti et al. 2006; Wagner 2008; Kearsley and Riddel 2010).[18] Some of the studies have focused on developed countries. For instance, Dijkgraaf and Vollebergh (2001) show a statistically significant turning point and confirm the inverted-U EKC pattern for 11 out of 24 OECD countries. Martínez-Zarzoso and Bengochea-Morancho (2004) analyse 22 OECD countries using a pooled mean group estimator and support the evidence of an N-shaped relationship for the majority of countries.

In contrast, Liu (2005) studies 24 OECD nations using panel data and finds that the EKC exists for CO_2 emissions. Similarly, the evidence of the EKC is found by Galeotti et al. (2006) for the OECD countries from 1950 to 1998. Canas et al. (2003) also find an inverted U-shaped EKC relationship for16 industrialised countries for the period 1960 to 1998.

Considering nuclear power generation, Richmond and Kaufman (2006) investigate the EKC for CO_2 using the panel data of OECD countries and point out that there is limited support of the EKC in the case of OECD countries. Iwata et al. (2010) also take into account nuclear energy and find poor evidence in support of the EKC hypothesis in the cases of 11 OECD countries.

Recently, a few studies have examined the EKC hypothesis in terms of the relationship between pollutant emissions and urbanization. For instance, York et al. (2003b) find that there is no evidence of the EKC for total CO_2 emissions and urbanization in 142 nations in the year 1996.

For developing countries during the period 1975 to 2003, Martínez-Zarzoso and Maruotti (2011) analyse the EKC hypothesis based on the STIRPAT method. They confirm the existence of an inverted U-shaped relationship between CO_2 emissions and urbanisation indicating urbanisation in higher levels contribute to environmental damage reduction.

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[18]For early empirical studies on the EKC hypothesis, refer to Grossman and Krueger (1993, 1995) and Selden and Song (1994); and for other recent studies on the EKC hypothesis, see, for example, Halicioglu (2009), Musolesi et al. (2009) and Kearsley and Riddel (2010).

Using a semi-parametric model, Zhu et al. (2012) find little evidence in support of an inverted U-shaped curve between CO_2 emissions and urbanisation in a sample of 20 emerging countries over the period 1992 to 2008.[19]

The general observation from the literature is that although the relationships between emissions, energy and economic growth are widely discussed, the results are still inconclusive. Most studies are criticised over the validity of the estimated coefficients and elasticities because their tests are not based on an appropriate quantitative framework. For example, they fail to take into account the diagnostic statistics and specification tests which are necessary for obtaining non-biased and consistent regression results.

The present research differs from the existing studies in a number of ways. First, it estimates the long-run and short-run impacts of renewable and non-renewable energy consumption simultaneously with CO_2 emissions. Second, it investigates the relationship between CO_2 emissions and urbanisation under the EKC hypothesis that has not been carried out for the OECD countries up to now. Third, it controls for diagnostic and specification tests that have been seldom considered in previous works. Finally, it makes use of recent panel data techniques that allow for the heterogeneous unobserved parameters and cross-sectional dependence.

5.3 Methodology

5.3.1 Model Specification

Similar to the previous chapter, this chapter also employs the STIRPAT method to analyse the impact of demographic and economic factors on CO_2 emissions.[20] Three different models are considered to estimate the effects of different variables (based on the objectives of this study) on CO_2 emissions. In the first model (Model I), the relationship between CO_2 emissions and renewable and non-renewable energy consumption is investigated. As mentioned in Chapter 4, Section 4.3, according to York et al. (2003b), additional factors can be entered into the basic STIRPAT model as components of the technology (*T*). Since *T* is basically considered as the environmental impact per unit of economic activity, in this study, *T* is disaggregated

[19] A summary of the literature is provided in Appendix Table 5.1.

[20] For a review on the background and conceptual aspects of the STIRPAT model refer to Chapter 4, Section 4.3.

into two factors denoting the difference in economic structure of each country in terms of the type of energy used: renewable energy and non-renewable energy. Therefore, *T* is considered as renewable energy use and non-renewable energy use as follows:

$$ln(CO_{2it}) = ln\, a_0 + a_1\, ln(P_{it}) + a_2\, ln(A_{it}) + a_3\, ln(R_{it}) + a_4\, ln(N_{it}\,) + ln\, e_{1it} \tag{5.1}$$

where P, A, R, N denote total population size, GDP per capita, renewable energy consumption and non-renewable energy consumption, respectively. e is the error term. The subscript *i* refers to countries and *t* denotes the year.

In the second model (Model II), the effects of the variables include total population, GDP per capita, industrialisation, the share of the service sector in GDP, population density, and urbanisation. The motivation behind building this model is to explore whether the variables those increase or decrease energy consumption (investigated in previous chapter) have the same effect on CO_2 emissions. For instance, since the population density has a negative impact on non-renewable energy consumption, it is expected to have the same impact on CO_2 emissions. In other words, it is expected that population density contributes to CO_2 emissions mitigation in OECD countries. Thus, the second model is given by:

$$\begin{aligned} ln(CO_{2it}) = ln\, b_0 + b_1\, ln(P_{it}) + b_2\, ln(A_{it}) + b_3\, ln(IND_{it}) + b_4\, ln(S_{it}) \\ + b_5\, ln\,(U_{it}) + b_6\, ln(PD_{it}) + ln\, e_{2it} \end{aligned} \tag{5.2}$$

In this equation, *P* is total population size, *A* is GDP per capita, *IND* is the share of industry sector in GDP (industrialisation), *S* is the share of service sector in GDP, *PD* is population density and *U* is urbanisation.

In the third model (Model III), the purpose is to examine the relationship between CO_2 emissions and urbanisation and income in terms of the EKC hypothesis. Following Martínez-Zarzoso and Maruotti (2011), the squared terms of affluence and urbanisation are added into the basic STIRPAT model and energy intensity is used as a proxy for technology (*T*). The model is presented as follows:

$$ln(CO_{2it}) = ln\,c_0 + c_1\,ln(P_{it}) + c_2\,ln(A_{it}) + c_3\,ln(A_{it}^2) + c_4\,ln(U_{it}) + c_5\,ln\,(U_{it}^2) + c_6\,ln(EI_{it}) + ln\,e_{3it} \quad (5.3)$$

In the above equation, P is total population size, A is GDP per capita, A^2 denotes the squared term of GDP per capita, U is urbanisation, U^2 denotes the squared term of urbanisation, and EI is energy intensity measured as total primary energy consumption in Quadrillion Btu divided by GDP (year 2005 U.S. Dollars, Purchasing Power Parities).

In the above equations, CO_2 refers to total carbon dioxide emissions which come from the consumption of energy in million metric tons.[21] All the variables used in this chapter are converted into natural logarithms prior to conducting the analysis. The summary statistics on the variables are presented in Appendix Table 5.2 describing the number of observations, mean, variation (standard deviation) and bounds (minimum and maximum). To test for multicollinearity between independent variables in each model, the variance inflation factors (VIF) for each predictor is calculated. The results, presented in Appendix Table 5.3, indicate no existence of multicollinearity between independent variables as all the VIF values are less than 10.

5.3.2 Estimation Strategy

To explore the dynamics of the relationship between energy, demographic and economic factors and CO_2 emissions, the following steps are performed. First, the existence of a unit root in each variable is tested. Then, if the variables contain a unit root, the long-run cointegration relationship between the variables in each model is examined. If the variables are cointegrated, the final step is to detect the direction of causality between the variables by applying the panel vector error-correction model.

Before selecting an appropriate estimator to examine the long-run estimates of CO_2 emissions, it is important to check the diagnostic tests including cross-sectional dependence, heteroskedasticity and serial correlation. The results for all the three models (I, II, and III) (provided in Appendix Table 5.4) show the existence of the problem of cross-sectional dependence, heteroskedasticity and serial correlation among the variables in the three models. To deal with this issue, a recently developed

[21] The data of total carbon dioxide emissions and energy intensity are obtained from the U.S. Energy Information Administration, which is available at http://www.eia.gov/environment.html.

approach, namely the Augmented Mean Group (AMG) estimator by Eberhardt and Teal (2010) is applied. This approach is conceptually close to the Common Correlated Effects (CCE) estimator developed by Pesaran (2006).[22] This estimator accounts for the effect of common shocks by the inclusion of a "common dynamic process". The model is estimated in two steps. First step:

$$\Delta y_{it} = b\,\Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + \varepsilon_{it} \tag{5.4}$$

obtaining $c_t = \mu_t^*$. This represents a standard first differences-OLS regression with T - 1 year dummies in first differences, from which the year dummy coefficients are obtained (relabelled as μ_t^*). Second step:

$$y_{it} = a_t + b_i x_{it} + d_i\, \mu_t^* + \varepsilon_{it} \tag{5.5}$$

obtaining $b_{AMG} = 1/N\ \sum_{i=1}^{N} b_i$.[23]

In the end, by employing the GMM method, the long-run and short-run Granger causality of CO_2 emissions with respect to total population, population density, GDP per capita, urbanisation, industrialisation, the share of services in GDP, renewable and non-renewable energy use are examined. The residuals, obtained by the long-run estimates in Model I and Model II, are used as dynamic error correction terms. The causality relationship between the variables is tested based on the following equations, considering each variable in turn as a dependent variable for each model.

$$\Delta LCO_{2it} = f_0 + \sum_{j=1}^{m} \delta_{11ij} \Delta LP_{it-j} + \sum_{j=1}^{m} \delta_{12ij} \Delta LA_{it-j} + \sum_{j=1}^{m} \delta_{13ij} \Delta LR_{it-j} + \sum_{j=1}^{m} \delta_{13ij} \Delta LN_{it-j} + \lambda_{it} e_{it-1} + u_{1it} \tag{5.6}$$

$$\Delta LCO_{2it} = g_0 + \sum_{j=1}^{m} \rho_{11ij} \Delta LP_{it-j} + \sum_{j=1}^{m} \rho_{12ij} \Delta LA_{it-j} + \sum_{j=1}^{m} \rho_{13ij} \Delta LIND_{it-j} + \sum_{j=1}^{m} \rho_{14ij} \Delta LS_{it-j} + \sum_{j=1}^{m} \rho_{15ij} \Delta LU_{it-j} + \sum_{j=1}^{m} \rho_{16ij} \Delta LPD_{it-j} + \lambda_{it} e_{it-1} + u_{1it} \tag{5.7}$$

[22] This estimator was used to examine the long-run relationship between the variables in Chapter 4.

[23] For further information regarding the Augmented Mean Group (AMG) estimator, see Bond and Eberhardt (2009) and Eberhardt and Teal (2010).

In the above equations, CO_2 is total dioxide carbon, *N* is non-renewable energy consumption, *R* is renewable energy consumption, P is total population size, *A* is GDP per capita, *IND* is the share of the industry sector in GDP, *S* is the share of the service sector in GDP, *PD* is population density and *U* is urbanisation.

The next section proceeds to estimating long-run panel elasticities of CO_2 emissions and also identifies dynamic causal relationship between the variables. For this purpose, first the results of unit root and cointegration tests are provided.

5.4 Empirical Analysis and Results

5.4.1 Panel Unit Root and Cointegration Tests

As the most of the variables used in this chapter have been also used in previous chapters and already checked for the unit root test, only the results of unit root test for CO_2 emissions, energy intensity, and quadratic terms of GDP per capita and urbanisation are provided here.[24] The results of the unit root test with and without structural breaks for the variables are reported in Table 5.1. The results of the unit root tests (without structural breaks), including Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP), Breitung (2000), Levin et al. (2002) (LLC), and Im et al. (2003) (IPS), for CO_2 emissions, energy intensity, and the quadratic terms of GDP per capita and urbanisation show that the variables contain a unit root at their levels, implying the variables are not stationary. There is an exception for the variable CO_2 emissions in the Breitung test that indicates that this variable is significant at the 5% level. All the coefficients of the first difference of the variables are significant at the 1% level, implying that all the variables are stationary at their first difference (Table 5.1).

The results of the panel unit root tests with structural breaks following Carrion-i-Silvestre et al. (2005) (Table 5.1) show that the statistics reject the null hypothesis of stationarity for the variables by both the homogeneous and heterogeneous long-run versions of the test. The number of breaks and their position for each country and variable are calculated by means of Monte Carlo simulations based on 20,000 replications. The results are reported in Appendix Table 5.5.

[24] See the results of the panel unit root tests for total population, GDP per capita, industrialisation, the share of services in GDP, urbanisation, population density, renewable and non-renewable energy consumption in Chapter 4, Section 4.4.

Overall, the results of the panel unit root tests with and without structural breaks for all the variables used in this chapter confirm that the level values of all the series are non-stationary and all the variables are stationary at the first difference, that is, all variables are integrated of order one. Consequently, panel cointegration tests can be employed to study the long-run equilibrium process.

The panel cointegration tests of Johansen Fisher proposed by Westerlund (2007) and Maddala and Wu (1999) are applied to the three models. The results of the Johansen Fisher panel cointegration test from both a trace test and a maximum eigen-value test indicate the existence of cointegration at 1% significance level for each of the models (Table 5.2). The results of the Westerlund (2007) cointegration test are reported in Table 5.3. It can be seen that group-t and panel-t reject the null hypothesis of no cointegration in the three models. Therefore, overall evidence from the Johansen Fisher and Westerlund (2007) tests for cointegration show that there is a long-run relationship between the dependent and independent variables. The next subsection addresses this issue.

Table 5.1: Panel unit root tests for the variables used in Models I, II and III

Panel unit root test without structural breaks					
Variable	ADF	PP	Breitung	LLC	IPS
LCO_2					
Level	62.571	63.448	-2.287	-0.010	0.160
	(0.317)	(0.290)	(0.011)**	(0.495)	(0.563)
First difference	436.893	531.591	-9.882	-19.183	-20.152
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
LA^2					
Level	70.905	33.272	4.625	-0.998	-1.289
	(0.119)	(0.996)	(1.000)	(0.115)	(0.986)
First difference	164.650	178.834	-2.744	-5.230	-7.635
	(0.000)***	(0.000)***	(0.003)***	(0.000)***	(0.000)***
LU^2					
Level	62.764	46.878	3.396	-0.618	0.529
	(0.311)	(0.851)	(0.999)	(0.268)	(0.701)
First difference	88.125	97.122	-15.143	-3.642	-4.719
	(0.006)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***
LEI					
Level	67.418	70.900	1.384	-0.248	-0.098
	(0.186)	(0.119)	(0.916)	(0.401)	(0.460)
First difference	220.532	699.758	-3.505	-4.893	-10.764
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Panel unit root test with structural breaks					
	Bartlett	Quadratic	Bootstrap critical values		

	Kernel	Kernel	5%	2.5%	1%
LCO_2					
Homogeneous	7.928**	7.929**	7.062	7.866	8.278
Heterogeneous	8.211	8.271	6.728	7.381	8.021
LA^2					
Homogeneous	15.351*	16.281***	15.348	15.692	16.093
Heterogeneous	16.211*	16.836*	16.203	16.897	17.356
LU^2					
Homogeneous	13.612**	14.549***	12.462	13.112	13.899
Heterogeneous	15.721*	16.723**	15.564	16.714	17.231
LEI					
Homogeneous	18.715***	19.291***	17.348	17.702	18.367
Heterogeneous	20.248***	20.711***	18.826	20.210	21.245

Note: In the panel unit root test without structural breaks, probabilities of the test statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels respectively. Individual trends and constants are included in the tests and the Schwarz Information Criterion (SIC) has been used to determine the optimal lag length. In the panel unit root test with structural breaks, the number of structural breaks is up to 5. ***, ** and * indicate that the test statistic is significant at 1%, 2.5%, and 5% levels, respectively. The long-run variance is estimated using both the Bartlett and the Quadratic spectral kernel with automatic spectral window bandwidth selection as in Sul et al. (2005). Furthermore, all bootstrap critical values allow for cross-sectional dependence.

Table 5.2: Johansen Fisher cointegration test for Models I, II and III

Model	Fisher statistic (from trace test)	Fisher statistic (from max-eigen test)
Model I		
None	626.8 (0.000)***	373.6 (0.000)***
At most 1	333.3 (0.000)***	202.0 (0.000)***
At most 2	182.1 (0.000)***	105.7 (0.000)***
At most 3	124.7 (0.000)***	99.24 (0.000)***
At most 4	105.2 (0.000)***	105.2 (0.000)***
Model II		
None	1543.0 (0.000)***	587.2 (0.000)***
At most 1	1161.0 (0.000)***	351.4 (0.000)***
At most 2	800.0 (0.000)***	217.8 (0.000)***
At most 3	519.9 (0.000)***	138.7 (0.000)***
At most 4	296.7 (0.000)***	121.4 (0.000)***
At most 5	180.7 (0.000)***	106.7 (0.000)***
At most 6	106.1 (0.000)***	106.1 (0.000)***

Model	Fisher statistic (from trace test)	Fisher statistic (from max-eigen test)
Model III		
None	1297.0 (0.000)***	729.4 (0.000)***
At most 1	861.1 (0.000)***	422.9 (0.000)***
At most 2	507.6 (0.000)***	234.0 (0.000)***
At most 3	315.6 (0.000)***	166.4 (0.000)***
At most 4	190.1 (0.000)***	124.3 (0.000)***
At most 5	117.5 (0.000)***	96.27 (0.001)***
At most 6	102.9 (0.000)***	102.9 (0.000)***

Note: The Schwarz Information Criterion (SIC) has been used to determine the optimal lag length. *** indicates that the test statistic is significant at 1% level.

Table 5.3: Westerlund cointegration test for Models I, II and III

Statistic	Value	*P*-value
Model I		
Group-t	-2.939	0.003***
Group-a	-11.387	0.865
Panel-t	-14.610	0.003***
Panel-a	-8.396	0.741
Model II		
Group-t	-3.107	0.064*
Group-a	-1.562	1.000
Panel-t	-9.055	0.000***
Panel-a	-0.843	1.000
Model III		
Group-t	-3.122	0.054*
Group-a	-3.938	1.000
Panel-t	-12.005	0.059*
Panel-a	-4.719	1.000

Note: *** and * indicate that the test statistics are significant at 1% and 10% levels, respectively. Following Westerlund (2007), maximum lag length is selected according to $4(T/100)^{2/9}$. The null hypothesis of the test is “no cointegration”.

5.4.2 Estimation of the Long-Run Elasticities of CO_2 Emissions

Results of the regression analysis of the three Models I, II, and III under an Augmented Mean Group (AMG) estimator are presented in Table 5.4. As the variables total population (*P*) and GDP per capita (*A*) are commonly used in the three models, first the direction and magnitude of these variables with respect to CO_2 emissions in Models I and II are compared.[25] The results show that total population and GDP per capita have positive and significant impact on CO_2 emissions, implying increases in each of total population and GDP per capita lead to increases in CO_2 emissions. Although each model presents different magnitudes of the coefficients of total population and GDP per capita, the coefficient of total population is greater than that of GDP per capita in the three models. This demonstrates that in the long run, total population size contributes more to increased CO_2 emissions than economic growth in developed countries. This finding is consistent with those of Fan et al. (2006), Poumanyvong and Kaneko (2010) and Liddle (2011) who obtain the same results for developed countries. Liddle (2011) points out that environmental impact is more sensitive to changes in population growth than to changes in economic growth. Generally, this phenomenon can be simply explained based on the same result that has been found for energy consumption. Investigating the effects of total population and affluence on energy consumption in this thesis (Chapter 4) and also by Poumanyvong and Kaneko (2010) and Liddle (2011), show that the elasticity of energy consumption with respect to population is greater than the elasticity of energy consumption with respect to affluence. Therefore, it can be said that population growth through accelerating energy consumption speeds up pollutant emissions.

With respect to the renewable energy consumption in Model I (Table 5.4), it is found that this variable has a negative and significant impact on CO_2 emissions, indicating a 1% increase in renewable energy consumption reduces CO_2 emissions by 0.004% in the long run. This outcome is as expected. However, this finding contrasts with the positive relationship between renewable energy consumption and CO_2 emissions found by Menyah and Wolde-Rufael (2010a) for the US and Apergis et al. (2010) for

[25] It is worth noting that in Model III, the coefficients for affluence and urbanisation cannot be interpreted directly as an elasticity coefficient due to the inclusion of their quadratic terms. Thus, in Model III, the focus with respect to the affluence and urbanisation is only on whether the EKC hypothesis exists or not.

a group of 19 developed and developing countries. The result obtained in this study implies that increases in level of renewable energy usage can contribute to reducing pollutant emissions in OECD countries in the long run.

Non-renewable energy consumption has a positive and statistically significant impact on CO_2 emissions at the 1% level. The coefficient of non-renewable energy consumption suggests that increases in this factor increases CO_2 emissions by 1.038%. It is obvious from the estimated coefficients which have a positive effect on CO_2 emissions in Model I, the impact of the non-renewable energy consumption upon CO_2 emissions is much higher than that of population and affluence.

The coefficients of the variables considered in Model II indicate that industrialisation, the share of services in GDP, and urbanisation all are positively associated with CO_2 emissions. However, the effect of the share of services in GDP on CO_2 emissions is not significant. The coefficient of industrialisation is statistically significant at the 5% level indicating that an increase in industrialisation increases CO_2 emissions by 0.319%. The same result is also found by York et al. (2003b), Shi (2003), Lin et al. (2009), and Zhang and Lin (2012) across different countries. It appears that industrialisation, through the extraction and consumption of raw materials, emissions of industrial pollutants, and increased energy demand, can intensify CO_2 emissions.

With respect to the relationship between urbanisation and CO_2 emissions, it is found that a 1% increase in urbanization increases CO_2 emissions by 0.462% in Model II. This result is consistent with Alam et al. (2007) for Pakistan, Poumanyvong and Kaneko (2010) for high income countries, and Zhang and Lin (2012) for China. Likewise, Liddle and Lung (2010) find a positive linkage between urbanisation and CO_2 emissions from transport in OECD countries. They state that this is a surprising result as it is expected that higher urbanisation leads to more public transport use and then to less emissions. Finding a direct relationship between urbanisation and CO_2 emissions contrasts with those of Fan et al. (2006), Sharma (2011), and Sharif Hossain (2011), who find that urbanisation negatively affects CO_2 emissions for high income and newly industrialised countries. From different studies, it can be seen that the relationship between urbanisation and emissions is complex, even in the countries with the same level of income and development. However, it is obvious that developed and largely urbanised countries are in a better position to achieve low carbon intensity by adopting new energy technologies. Generally speaking, it seems that the relationship between urbanisation and emissions can be better explained under the EKC hypothesis in developed countries. The last variable investigated in Model II is population density which has a negative, but statically insignificant impact on CO_2 emissions.

Table 5.4: CO_2 emissions coefficients of the AMG estimator

	Model I	Model II	Model III
LP	0.543 (4.31)***	2.677 (2.49)**	1.037 (6.69)***
LA	0.119 (13.55)***	0.570 (3.53)***	0.466 (8.10)***
LR	-0.004 (-1.81)*		
LN	1.038 (16.59)***		
LIND		0.319 (2.17)**	
LS		0.434 (1.44)	
LU		0.462 (2.57)**	0.175 (1.80)*
LPD		-0.411 (-.012)	
LA^2			0.237 (10.01)***
LU^2			-0.078 (-1.87)*
LEI			0.683 (11.11)***

Note: Statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels respectively.

Turning to Model III (Table 5.4), the results confirm evidence of the EKC hypothesis between urbanisation and CO_2 emissions because the coefficient of urbanisation is positive and significant and the coefficient of the quadratic term of urbanisation is negative and significant. This indicates that at a higher level of urbanisation, CO_2 emissions decrease. In the other words, when a certain level of urbanisation is achieved, emissions tend to decline in OECD countries. This finding confirms ecological modernisation theory which argues that if the environment and the economy are properly managed, through structural change or modernisation, they can curb emissions. Therefore, as urbanisation is a key indicator of modernisation

(Ehrhardt-Martinez 2002; York et al. 2003a, 2003b), it is expected that at higher levels of urbanisation, environmental impact decreases. In addition, Ehrhardt-Martinez (1998) explains this phenomenon in the way that the urbanisation process in its initial stages depends more on resource extraction. However, advanced urbanisation is accompanied by largely complete urban infrastructure as well as increased use of less polluting fuels. Although Ehrhardt-Martinez (1998) claims that this reasoning might be true only for the relationship between urbanisation and the phenomenon of deforestation, according to the results obtained in this study, it seems it is also true for CO_2 pollutant emissions. This result can also be explained based on observations and experiences in developed countries. The economy in urban areas is primarily service based rather than manufacturing based. Moreover, using nuclear and hydro energy for generating electricity is becoming more common in such areas. In addition, today, in some developed countries, most industrial activities have relocated to other regions far from the cities or even to other countries. Furthermore, strong investment in infrastructure and policies to extend public transport systems have led to increases in levels of public transport usage. Therefore, all these activities can be reasons for the reduction in CO_2 emissions in urbanised areas. The inverted U-shaped relationship between urbanisation and CO_2 emissions is also supported by Martínez-Zarzoso and Maruotti (2011) for developing countries. However, this result is in contrast with those of York et al. (2003b) and Zhu et al. (2012) who find little evidence of the existence of the EKC hypothesis in the urbanisation–CO_2 emissions nexus.

The estimated long-run coefficients of GDP per capita and its square do not satisfy the EKC hypothesis as the coefficients for both GDP per capita and its quadratic term are positive and significant. Unlike the previous result for urbanisation–CO_2 emissions nexus, the result for a affluence–CO_2 emissions nexus contradicts the expectation of the modernisation perspective. It may be concluded that environmental impacts follow an EKC in association with urbanisation, rather than economic development per se (Ehrhardt-Martínez 1998; Ehrhardt-Martinez et al. 2002; York et al. 2003b). Finding no evidence in support of the EKC hypothesis is in line with the results of Martínez -Zarzoso and Bengochea-Morancho (2004), Richmond and Kaufman (2006), and Iwata et al. (2010) for OECD countries. This finding also supports those of York et al. (2003a) and Martínez-Zarzoso and Maruotti (2011) who investigate the

EKC with respect to income and emissions, using the STIRPAT model. However, the latter finding is contrary to those who find an inverted U-shaped association between income and emissions including Dijkgraaf and Vollebergh (2001) and Liu (2005) for OECD countries and also Apergis and Payne (2009b), Apergis and Payne (2010f), Lean and Smyth (2010), Pao and Tsai (2010), and Arouri et al. (2012) for other countries.

The last variable included in Model III is energy intensity which has a positive and significant effect at the 1% level on CO_2 emissions. The related coefficient demonstrates that an increase in energy intensity increases CO_2 emissions by 0.683% in the long run. This finding is as expected and also supported by Cole and Neumayer (2004) for 86 countries and Poumanyvong and Kaneko (2010) for low to high income countries.

5.4.3 Granger Causality

This section provides the results of causality test between the variables used in Model I and Model II.[26] The results of the panel error-correction model for Model I and Model II are reported in Table 5.5 and Table 5.6, respectively. The findings are interpreted only for the relationship between CO_2 emissions and the other variables.[27] Beginning with Model I and the short-run effects (Table 5.5), total population, GDP per capita, and non-renewable energy consumption have positive and significant effects on CO_2 emissions, implying these three variables do Granger cause CO_2 emissions in the short run.

The coefficient of renewable energy consumption is negative; however, it is not statistically significant. This indicates that renewable energy use does not Granger cause CO_2 emissions in the short run. The results also show that CO_2 emissions have a positive effect on total population and a negative effect on GDP per capita in the short run. However, both the coefficients are statistically insignificant. Interesting results are found with respect to the effect of CO_2 emissions on renewable and non-renewable energy consumption. The impact of CO_2 emissions on renewable energy use is positive and statistically significant, suggesting increases in CO_2 emissions can stimulate the use of renewable sources. The coefficient of CO_2 emissions with respect

[26] The variables used in Model III are included in Model II except for energy intensity.

[27] Interestingly, the results of the causality relationship between the independent variables in Equations 5.6 and 5.7 remain the same as those found in Chapter 4, Section 4.4.

to non-renewable energy use is negative and statistically significant, implying increases in CO_2 emissions may contribute to a reduction in the use of non-renewable sources, even in the short term.

Table 5.5: Panel causality test for Model I

Dependent Variables	Source of causation (independent variable)					
	Short run					Long run
	ΔLCO_2	ΔLP	ΔLA	ΔLR	ΔLN	ECT
ΔLCO_2	_	0.145 (1.93)*	0.093 (1.66)*	-0.006 (-0.34)	0.945 (66.57)***	-0.684 (-14.93)***
ΔLP	0.002 (0.53)	_	0.005 (0.13)	-0.002 (-0.94)	-0.003 (-1.76)*	-0.002 (-0.44)
ΔLA	-0.095 (-1.63)	0.884 (2.96)***	_	0.008 (1.24)	0.099 (1.63)	0.037 (0.47)
ΔLR	1.079 (2.20)**	-6.902 (-0.54)	-0.450 (-1.49)	_	-0.339 (-0.68)	-0.550 (-0.82)
ΔLN	-0.737 (-29.74)***	0.063 (1.81)	0.033 (1.92)*	-0.006 (-0.23)	_	-0.610 (-13.29)***

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels, respectively. The optimal lag length for the variables is two and determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

In sum, the empirical results (Table 5.5) indicate that there is unidirectional causality from total population size to CO_2 emissions. Similarly, a unidirectional causality running from GDP per capita to CO_2 emissions is obtained in the short run for OECD countries. This result is consistent with the findings of Apergis and Payne (2009b) for six Central American countries, Acaravci and Ozturk (2010) for European countries, Apergis and Payne (2010f) for countries of the Commonwealth of Independent States, Alam et al (2011) for India, Salim and Rafiq (2012) for the Philippines, and Hamit-Haggar (2012) for Canada. However, this finding contrasts with the unidirectional causality from CO_2 to income found by Menyah and Rufael (2010b) for Southern African countries, Pao and Tsai (2010) for Brazil, Russuia, India, and China, and Salim and Rafiq (2012) for India. This is also contrary to Halicioglu (2009), Apergis et al. (2010), Menyah and Rufael (2010a), and Salim and Rafiq (2012) who find bidirectional causality between income and emissions for a mix of developed and developing countries. Finding unidirectional causality from CO_2 emissions to renewable energy consumption is in line with Menyah and Wolde-Rufael (2010a) for the US. However, this result is contrary to the bidirectional causality between emissions and renewable energy consumption found by Apergis and Payne (2010f) for a group of developed and developing countries, Salim and Rafiq (2012) for Brazil, China, India and Indonesia as well as Menegaki (2011) for European countries. In addition, this finding is also in contrast with Payne (2012) who finds no causal relationship between renewable energy use and CO_2 emissions in the US. Finally, as can be seen from Table 5.5, there is bidirectional causality between non-renewable energy consumption and CO_2 emissions. This finding is not directly comparable to previous studies because they mostly use total energy consumption.

Turning to the long-run causality relationship in Model I (Table 5.5), the coefficients of the lagged error-correction terms (ECT) are negative and significant at the 1% level for the equations in which CO_2 emissions and non-renewable energy use are dependent variables. This means bidirectional causality exists between CO_2 emissions and non-renewable energy consumption in the long run. Further, the coefficients of the error- correction terms also suggest that the deviation of CO_2 emissions and non-renewable energy consumption from the short run to the long run is corrected by 68% and 61% respectively each year; and convergence toward equilibrium after a shock to each of CO_2 emissions and non-renewable energy consumption takes 1.4 and 1.6 years, respectively.

Moving to the short-run effects in Model II (Table 5.6), the causal relationship between total population and CO_2 emissions and between GDP per capita and CO_2 emissions remain the same as those in Model I, that is, unidirectional from total population and GDP per capita to CO_2 emissions. The coefficients of the other variables indicate that effects of industrialisation, urbanisation, and population density on CO_2 emissions are negative, whereas the effect of the share of services in GDP is positive. However, only the coefficients of the share of services in GDP and population density are statistically significant. This implies that while industrialisation and urbanisation do not Granger cause CO_2 emissions, the share of services in GDP and population density do Granger cause CO_2 emissions in the short run. The effect of CO_2 emissions as the independent variable on the other variables as the dependent variables from Table 5.6 shows that CO_2 emissions have a negative and significant impact on the share of services in GDP in the short run, suggesting there is bidirectional causality between CO_2 emissions and the share of services in GDP and unidirectional causality running from population density to CO_2 emissions. A positive effect of the share of services in GDP on emissions in the short run shows that in OECD countries due to increase in services industries, more energy services are required for lighting, heating and cooling, electronics use, and transport mobility.

On the other hand, although the relationship between population density and CO_2 emissions in the long run is not significant, finding negative and significant association between them in the short run indicates that density in population not only decreases energy consumption (as shown and discussed in Chapter 4) but also, through this way, contributes to emissions mitigation. However, it seems that there are some stronger factors that can make ineffective this association in the long run.

The results of the long-run causality presented by the error-correction terms (ECT) in Model II (Table 5.6) reveal that in the equations in which CO_2 emissions and industrialisation are dependent variables, ECTs are -0.811 and -0.227, respectively. This demonstrates that total population, GDP per capita, industrialisation, the share of services in GDP, urbanisation, and population density Granger cause CO_2 emissions in the long run. Moreover, it shows that CO_2 emissions, total population, GDP per capita, the share of services in GDP, urbanisation, and population density Granger cause industrialisation in the long run. Further, the results indicate that the variables adjust towards a long-run equilibrium level after 1.2 and 4.4 years after a shock occurs.

Table 5.6: Panel causality test for Model II

Dependent Variables	Source of causation (independent variable)							
	Short run							Long run
	ΔLCO_2	ΔLP	ΔLA	ΔLIND	ΔLS	ΔLU	ΔLPD	ECT
ΔLCO_2	_	0.412 (1.72)*	0.553 (11.46)***	-0.074 (-1.42)	0.258 (2.98)***	-0.101 (-0.19)	-0.869 (-1.67)*	-0.811 (-12.92)***
ΔLP	0.001 (0.68)	_	-0.002 (-0.91)	-0.001 (-0.34)	-0.005 (-1.50)	-0.030 (-1.16)	-0.235 (-9.99)***	-0.002 (-1.05)
ΔLA	-0.250 (-1.56)	0.998 (2.50)**	_	0.162 (4.77)***	0.512 (9.32)***	-0.604 (-1.06)	-0.275 (-0.77)	-0.227 (-5.92)***
ΔLIND	-0.013 (-0.55)	0.877 (2.11)**	0.139 (3.83)***	_	1.153 (25.99)***	-0.215 (-1.66)*	-0.514 (-2.36)**	0.002 (0.06)
ΔLS	-0.029 (-2.13)**	-0.316 (-1.36)	0.162 (8.07)***	0.400 (27.00)***	_	0.327 (1.65)	0.016 (1.88)*	0.011 (0.49)
ΔLU	0.003 (0.62)	-0.008 (-0.34)	-0.005 (-0.62)	0.003 (1.80)*	0.006 (1.78)*	_	-0.009 (-0.43)	-0.003 (-1.55)
ΔLPD	0.001 (0.62)	-0.297 (-8.17)***	0.001 (0.63)	-0.006 (-2.12)**	-0.008 (-1.66)*	0.002 (0.07)	_	-0.002 (-0.67)

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistic is significant at 1%, 5% and 10% levels, respectively. The optimal lag length for the variables is two and determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

5.5 Conclusion

This chapter attempts to explore the determinants of CO_2 emissions under three different models based on a statistical method, namely STIRPAT for OECD countries over the period 1980 to 2011. First, it compares the impacts of renewable and non-renewable energy consumption simultaneously on CO_2 emissions in the short run and long run. Second, the effects of the variables such as industrialisation, the share of service sector in GDP and population density on CO_2 emissions are investigated. Finally, the relationship between urbanisation and CO_2 emissions is examined in the context of the Environmental Kuznets Curve hypothesis.

The long run results show that renewable energy consumption has a negative and significant impact on CO_2 emissions, whereas non-renewable energy consumption has a positive and statistically significant impact on CO_2 emissions. The results also reveal that total population size, GDP per capita, industrialisation, and urbanisation have positive and significant impacts on CO_2 emissions. Finally, the findings confirm evidence of the Kuznets curve hypothesis between urbanisation and CO_2 emissions in OECD countries in the long run. Granger causality results indicate that there is unidirectional causality from CO_2 emissions to renewable energy consumption, from total population to CO_2 emissions, from GDP per capita to CO_2 emissions, and from population density to CO_2 emissions. Moreover, bidirectional causality is found between non-renewable energy consumption and CO_2 emissions and also between the share of services in GDP and CO_2 emissions.

The evidence from the findings of this study indicates that renewable energy consumption plays an important role in reducing CO_2 emissions. Therefore, in order to achieve a steady and sustainable growth of renewable energy use, governments should design and implement effective support policies to promote investment in new renewables energy capacity. Further, increase in population density seems to be another key strategy for reducing pollutant emissions that should be considered by policy makers. Generally, congestion and spatial density reduces personal vehicle use and also promotes less-motorized travel. Finally, urban planners should take serious action on climate change through improving public transportation systems, improving the energy efficiency in buildings, and increasing the share of renewable sources in energy supplies.

Appendix to Chapter 5

Appendix Table 5.1: Summary of Literature on Energy Consumption-Output-CO_2 Emissions Nexus

Study	Country (Period)	Methodology	Main Variables	Finding
Soytas et al. (2007)	US (1960-2004)	Toda and Yamamoto	GDP, energy consumption, and CO_2 emissions	No causal relationship between income and CO_2 emissions and unidirectional causality from energy consumption to CO_2 emissions in the long run.
Ang (2007)	France (1960-2000)	Cointegration and Granger causality	GDP, energy consumption, and CO_2 emissions	Unidirectional causality from GDP to energy consumption and CO_2 emissions in the long run.
Ang (2008)	Malaysia (1971-1999)	Cointegration, and Granger causality	GDP, energy consumption, and CO_2 emissions	Positive relationship between CO_2 emissions and GDP in the long run and no causality relationship between CO_2 emissions, energy consumption and GDP.
Soytas and Sari (2009)	Turkey (1960-2000)	Toda and Yamamoto and generalized impulse responses	GDP, energy consumption, and CO_2 emissions	Unidirectional causality from CO_2 emissions to energy consumption.
Zhang and Cheng (2009)	China (1960-2007)	Cointegration, and Granger causality	GDP, energy consumption, and CO_2 emissions	Unidirectional causality from energy consumption to CO_2 emissions in the long run.
Sadorsky (2009)	G7 countries (1980-2005)	Cointegration, and Granger causality	GDP per capita, renewable energy consumption, and CO_2 emissions	Positive relationship between both GDP per capita, CO_2 emissions per capita and renewable energy consumption.
Halicioglu (2009)	Turkey (1960-2005)	ARDL and Granger causality	GNI per capita, energy consumption, and CO_2 emissions	Positive relationship between income, energy consumption and CO_2 emissions and bidirectional causality between income and CO_2 emissions in the short run and long run.

Apergis and Payne (2009b)	6 Central American countries (1971-2004)	Cointegration, FMOLS and Granger causality	GDP, energy consumption, and CO_2 emissions	Positive relationship between energy consumption and CO_2 emissions and an inverted U-shape relationship between GDP and CO_2 emissions in the long run and bidirectional causality between energy consumption and CO_2 emissions in the long run.
Apergis et al. (2010)	19 developed and developing countries (1984-2007)	Cointegration and Granger causality	GDP, renewable energy consumption, and CO_2 emissions	Positive relationship between renewable energy consumption and CO_2 emissions, bidirectional causality between CO_2 emissions and GDP and between CO_2 emissions and renewable energy consumption in the short run and long run.
Lean and Smyth (2010)	Indonesia, Malaysia, Philippines, Singapore and Thailand (1980-2006)	Granger causality, and dynamic ordinary least squares (DOLS)	GDP, electricity consumption, and CO_2 emissions	Positive relationship between electricity consumption and CO_2 emissions, an inverted U-shape relationship between GDP and CO_2 emissions, unidirectional causality from CO_2 emissions to electricity consumption in the short run and unidirectional causality from electricity consumption and CO_2 emissions to GDP the long run.
Menyah and Wolde-Rufael (2010a)	US (1960-2007)	Cointegration and Granger causality	GDP, nuclear and renewable energy consumption and CO_2 emissions	Unidirectional causality from nuclear energy consumption to CO_2 emission and unidirectional causality from CO_2 emissions to renewable energy consumption.
Menyah and Wolde-Rufael (2010b)	South Africa (1965-2006)	Cointegration, and Toda and Yamamoto causality	GDP, energy consumption, and CO_2 emissions	Unidirectional causality from CO_2 emissions to GDP and unidirectional causality from energy consumption to CO_2 emissions.
Alam et al. (2011)	India (1971-2006)	Toda-Yamamoto	GDP, energy consumption and CO_2 emissions	Bidirectional causality between energy consumption and CO_2 emissions and no causality between CO_2 emissions and GDP in the long run.
Salim and Rafiq (2012)	6 major emerging economies (1980-2006)	Cintegartion, FMOLS, DOLS and Granger causality	GDP, CO_2 emissions and renewable energy consumption	Bidirectional causality between renewable energy consumption and CO_2 emissions in Brazil, China, India, and Indonesia in the short run and bidirectional causality between GDP and CO_2 emissions in Brazil, China and Turkey.

Shi (2003)	93 countries (1975-1996)	STIRPAT model and generalized least squares (GLS)	population and CO_2 emissions	Positive relationship between population changes and CO_2 emissions.
Martínez-Zarzoso (2008)	Developing countries (1975-2003)	STIRPAT model and feasible generalized least squares (FGLS)	urbanisation and CO_2 emissions	Positive relationship between CO_2 emissions and urbanisation in low income countries and negative relationship between CO_2 emissions and urbanisation in upper and highly developed countries.
Liddle (2011)	17 developed countries (1960-2005)	STIRPAT model and FMOLS	GDP per capita, population and CO_2 emissions	Positive relationship between GDP per capita and CO_2 emissions and between total population and CO_2 emissions.
Zhang and Lin (2012)	China (1995-2010)	STIRPAT model and Driscoll–Kraay estimation	GDP per capita, population, industrialisation and energy intensity	Positive relationship between GDP per capita, population, industrialisation and energy intensity.

Appendix Table 5.2: Summary statistics of the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
CO_2	928	4.846126	1.543952	0.4420992	8.702532
LN	928	0.6131858	1.562073	-3.79691	4.45892
LR	928	-2.034407	1.991509	-8.4684	1.5453
LP	928	4.024885	4.343143	-1.47771	19.55721
LA	928	9.645223	0.724376	7.6758	10.9442
LA^2	928	19.29045	1.448752	15.3516	21.8884
LIND	928	3.410728	0.1976116	2.521543	3.91421
LS	928	4.155072	0.1439641	3.48931	4.46899
LU	928	4.293364	0.160268	3.75654	4.579703
LU^2	928	8.586728	0.320536	7.51308	9.159406
LPD	928	4.134103	1.461466	0.6483842	6.223514
LEI	928	8.907721	0.3423855	8.06202	9.75778

Appendix Table 5.3: Multicollinearity test

Variable	VIF	1/VIF
Model I		
LTP	4.77	0.209643
LN	9.99	0.100100
LA	3.16	0.316455
LR	1.94	0.515463
Mean VIF	4.96	
Model II		
LS	4.60	0.217387
LIND	2.97	0.336490
LA	2.12	0.471891
LP	1.31	0.764511
LU	1.30	0.767854
LPD	1.20	0.833617
Mean VIF	2.25	
Model III		
LP^2	1.33	0.751519
LEI	1.22	0.817681
LA^2	1.22	0.821599
LP	1.13	0.882127
Mean VIF	1.23	

Note: The VIF values are all below 10, implying that there is no multicollinearity.

Appendix Table 5.4: Diagnostic tests for Models I, II, and III

	FE Estimation	RE Estimation
Model I		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.000***	0.006***
Frees (*Q*)	3.769***	3.856***
Friedman (*P*-value)	0.001***	0.001***
Heteroskedasticity		
Modified Wald (*P*-value)	0.000***	
Serial Correlation		
Wooldridge (*P*-value)	0.001***	
Model II		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.000	0.000
Frees (*Q*)	9.233***	9.294***
Friedman (*P*-value)	0.000***	0.000****
Heteroskedasticity		
Modified Wald (*P*-value)	0.010**	
Serial Correlation		
Wooldridge (*P*-value)	0.000***	
Model III		
Cross-Sectional Dependence		
Pesaran (*P*-value)	0.000***	0.006***
Frees (*Q*)	4.927***	4.879***
Friedman (*P*-value)	0.002***	0.002***
Heteroskedasticity		
Modified Wald (*P*-value)	0.000***	
Serial Correlation		
Wooldridge (*P*-value)	0.001***	

Note: FE and RE denote fixed effects and random effects estimations. *** and ** indicate that the *P*-value or test statistic are significant at 1% and 5% levels, respectively.

Appendix Table 5.5: Estimated breaks for individual countries

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
Australia	LCO_2	2	1981	1998			
	LEI	2	1985	1989			
Austria	LCO_2	1	1986				
	LEI	1	19882				
Belgium	LCO_2	2	1983	1987			
	LEI	3	1988	1996	2001		
Canada	LCO_2	2	1984	1999			
	LEI	1	1981				
Chile	LCO_2	2	1984	1993			
	LEI	2	1986	1999			
Denmark	LCO_2	1	1987				
	LEI	3	1982	1994	2000		
Finland	LCO_2	1	1985				
	LEI	1	1984				
France	LCO_2	2	1982	1998			
	LEI	2	1983	1999			
Germany	LCO_2	2	1985	1997			
	LEI	1	1984				
Greece	LCO_2	1	1986				
	LEI	2	1983	1997			
Hungary	LCO_2	2	1985	1994			
	LEI	1	1985				
Iceland	LCO_2	1	1994				
	LEI	3	1984	1992	1999		
Ireland	LCO_2	1	1985				
	LEI	2	1982	1989			
Italy	LCO_2	1	1991				
	LEI	3	1983	1990	1998		
Japan	LCO_2	3	1981	1988	1991		
	LEI	2	1984	1998			
South Korea	LCO_2	1	1985				
	LEI	2	1988	2000			
Luxembourg	LCO_2	2	1986	1996			
	LEI	1	1981				
Mexico	LCO_2	2	1981	1997			
	LEI	2	1991	2002			
Netherlands	LCO_2	3	1984	1988	1992		
	LEI	1	1983				
New Zealand	LCO_2	2	1989	1994			
	LEI	3	1983	1997	2000		
Norway	LCO_2	1	1984				
	LEI	2	1984	1989			
Poland	LCO_2	2	1989	1996			
	LEI	3	1982	1989	1994		

Countries	Variables	Number of breaks	Dates of breaks				
			1	2	3	4	5
Portugal	LCO_2	1	1985				
	LEI	3	1987	1991	2003		
Spain	LCO_2	3	1987	1990	1998		
	LEI	2	1989	1993	2001		
Sweden	LCO_2	2	1984	1996			
	LEI	4	1982	1987	1994	2003	
Switzerland	LCO_2	3	1987	1991	2002		
	LEI	2	1986	1999			
Turkey	LCO_2	2	1989	1997			
	LEI	3	1984	1989	1994		
UK	LCO_2	2	1983	1988			
	LEI	1	1987				
US	LCO_2	3	1989	1996	2000		
	LEI	2	1984	1998			

Chapter 6

Conclusion

6.1 Proceedings

Energy plays a fundamental role in economic growth and industrial development. On the other hand, worldwide concern about the impact of energy use on environmental degradation has raised interest in investigating the relationship between energy use, economic growth and the environment. One of the objectives of this research is to investigate the effects of renewable and non-renewable energy consumption on economic growth and industrial output based on a neoclassical economic growth model. In addition, this study makes a comparison between the impacts of the sources of non-renewable energy (coal, oil and natural gas) on economic and industrial output to identify the capability of non-renewable energy sources for replacing with clean energies. Demographic factors, including population, urbanisation and population density, alongside income, industrialisation and tertiarisation are recognised as the major factors that affect energy consumption. Therefore, another aim of this research is to assess the relationship between these factors and renewable and non-renewable energy consumption. Finally, the impacts of the same factors are examined on CO_2 emissions and further the relationship between renewable energy consumption and CO_2 emissions is analysed. This thesis pursues its objectives by applying two well-known models, namely Cobb-Douglas production function and STIRPAT. This study employs panel econometric methods such as unit root and cointegration tests. Before estimating the long-run relationship between the variables, diagnostic tests, including cross-sectional dependence, heteroskedasticity, and serial correlation are investigated to prevent misleading inference and inconsistent estimates. Choosing the proper methods for estimating the long-run relationship is based on the results of the diagnostic tests. Accordingly, the methods such as Dynamic Ordinary Least Square (DOLS), Common Correlated Effects (CCE) and Augmented Mean Group (AMG) are adopted. To determine the direction of causation between the variables that has important policy implications, the Generalised Method of Moments (GMM) technique is used. All the empirical findings are based on data for selected OECD countries over the period 1980 to 2011.

6.2 Key Findings and Policy Implications

The empirical evidence suggests that renewable and non-renewable energy consumption stimulate economic growth in OECD countries. However, comparing the magnitudes of their coefficients confirms that non-renewables are still the dominant type of energy utilised in the process of economic growth. Similar results are obtained for industrial output, indicating that although the share of the use of non-renewable energy is declining compared with the share of renewable sources, non-renewables still play a considerable role in industrial production in developed countries today. The results also indicate that while oil and natural gas consumption positively and significantly influence economic growth, no significant relationship is observed between coal consumption and economic growth. It seems to be due to emerging policies that try to curb pollutant emissions by imposing a cost on higher-carbon fuels that in turn results in declined demand for coal in developed countries. In contrast, even though policies seek to slow consumption growth of oil, it is still the dominant fuel particularly in the transport sector. According to the EIA, since developed countries tend to have higher vehicle ownership per capita, oil consumption within the OECD transportation sector usually accounts for a larger share of total oil consumption than in non-OECD countries. In addition, oil is used in many ways, from the manufacture of goods, to transport of goods and people, to food production, to operating construction equipment, to mining. Therefore, it seems not to be achievable to substitute oil for clean energy in the near future. However, natural gas, which has the second position after oil, has an important feature in that it generates less carbon emissions compared with the other fossil fuels. Thus, fuel transformation at least from coal and/or oil to natural gas should be taken into account by policymakers.

Regarding the direction of causality, the results indicate the existence of bidirectional causality between economic growth and renewable energy consumption as well as between economic growth and non-renewable energy consumption in both the short run and long run. This finding confirms the feedback hypothesis which implies that a high level of economic growth leads to high level of energy consumption and vice-versa. Although non-renewables still have important role in the economic activities, OECD countries should encourage the substitution of renewable energy sources for non-renewable energy sources in order to mitigate pollutant emissions. The same results are achieved for industrial output, suggesting that energy conservation in terms of either renewable or non-renewable may lead to a reduction in industrial production.

Investigating the factors that can affect renewable and non-renewable energy consumption shows that demographic factors including total population, urbanisation and population density are important factors, particularly with respect to non-renewable energy consumption. The results reveal that while total population and urbanisation positively influence non-renewable energy consumption, population density has a negative impact on non-renewable energy consumption. From the demographic factors only total population has a significant impact on renewable energy consumption. In addition to demographic factors, some other factors such as GDP per capita, the share of industry and services in GDP is also found to affect positively and significantly both types of energy consumption.

Granger causality results indicate that there is unidirectional causality from non-renewable energy use to population density in the short term. However, no causal linkage is found between urbanisation and non-renewable energy use. Likewise, no causal direction is seen between renewable energy use and any of the demographic factors in the short run. The lack of existence of a significant association between renewable energy use and urbanisation and also between renewable energy use and population density illustrate that although the use of renewable energy sources has increased recently in developed countries, the main energy source available for people to use is still non-renewable fossil fuels. In the case of the positive relationship between urbanisation and non-renewable energy use, it can be said that economic development and increasing incomes which are followed by urbanisation, leads to changes in consumer needs, which in turns results in an increasing energy consumption. Moreover, urbanisation through its increasing effect on transport energy demand increases the use of non-renewable sources. However, population density that seems to have negative impact on non-renewable energy consumption (found in this study) might be able to offset the effects of urbanisation on this type of energy to some extent. Therefore, policy makers should focus more on urban planning as well as clean energy development both in the short term and long term to make a substantial contribution not only to non-renewable energy use reduction but also to climate change mitigation.

Examining the relationship between CO_2 emissions and renewable and non-renewable energy consumption indicates that renewable energy consumption negatively affects CO_2 emissions, whereas non-renewable energy consumption has a positive impact on CO_2 emissions. The results also reveal that total population size, GDP per capita, industrialisation, and urbanisation have positive and significant impacts on CO_2 emissions. Finally, the findings confirm evidence of the Kuznets curve hypothesis between urbanisation and CO_2 emissions in OECD countries in the long run. Granger causality results indicate that there is unidirectional causality from CO_2 emissions to renewable energy consumption, from total population to CO_2 emissions, from GDP per capita to CO_2 emissions, and from population density to CO_2 emissions. Moreover, bidirectional causality is found between non-renewable energy consumption and CO_2 emissions and also between the share of services in GDP and CO_2 emissions.

Overall evidence from the findings of this thesis implies that renewable energy is an important factor that contributes to economic growth and industrial production On the other hand, given the evidence of the existence of a negative relationship between renewable energy sources and CO_2 emissions, it can be concluded that alternative renewable energy sources are a solution to the climate change crisis without being detrimental to economic growth in OECD countries. Therefore, in order to achieve a steady and sustainable growth of renewable energy use, governments should design and implement effective support policies to promote investment in new renewables energy capacity. Further, increase in population density seems to be another key strategy for reducing pollutant emissions that should be considered by policy makers. Generally, congestion and spatial density reduces personal vehicle use and also promotes less-motorised travel. Finally, urban planners should take serious action on climate change through improving public transportation systems, improving the energy efficiency in buildings, and increasing the share of renewable sources in energy supplies.

6.3 Research Limitations and Direction of Future Research

Although it has been tried to use as many observations as possible and also apply the latest modified econometric techniques and models, this research may still suffers from some limitations. Limited sample size is one of the limitations of this study that was mostly due to unavailability of data on the variable renewable energy consumption. Moreover, this research investigates the relationship between renewable energy consumption and economic activities at an aggregated level. It might be difficult to obtain disaggregated data on renewable energy consumption for a panel of OECD countries. However, if such data could be found, such a project would be a useful topic for future research. Another direction for future research would be to examine the relationship between different sources of energy and output of different economic sectors that can provide policymakers an overview to decide properly regarding the issue of energy substitution.

Energy prices are well recognised as effective factors on energy consumption. However, due to no existence of the prices for the specific energy types, these factors have not been investigated on renewable and non-renewable energy consumption in this research. Population aging is another important factor that can influence energy consumption as well as CO_2 emissions. According to UNPD, it is estimated that the proportion of the elderly (60+) worldwide will more than double from 10% in 2005 to 22% in 2050. Changes in population age cause massive shifts in consumption behaviours and income structure. Therefore they are followed by variations in energy use and carbon emissions. For instance ageing populations may have reduced demands in terms of transportation, but they may on the other hand need and increased energy use for heating and cooling. Overall, further population ageing may reduce labour productivity and therefore energy consumption (Jiang and Hardee 2011). These issues can be considered for potential future research.

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