Modelling the Demand for Energy in the OECD Countries Using Three Econometric Approaches

by

Arqam Al-Rabbaie

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Surrey Energy Economics Centre (SEEC)
Department of Economics
School of Human Sciences
University of Surrey
UK

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Abstract

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Over the last three decades of the twentieth century considerable empirical research was undertaken in the field of energy demand modelling in order to obtain accurate and reliable estimates of the two key elasticities: income and price. This challenge for energy economists remains and has an even greater importance today given the vital global environmental agenda.

There have been numerous attempts to estimate energy demand relationships for the OECD counties either individually or collectively. This thesis contributes and extends this literature in a number of ways. Firstly, two data sets for the most affluent countries are utilised; and secondly, three different estimation techniques are explored: (a) panel data models (b) structural time series models and (c) panel data cointegration. Throughout the thesis, while applying these different methodologies, an attempt is made to answer the questions: what is the 'best' technique? And hence what are the long run price and income elasticities for the OECD countries.

The structural time series approach is found to be the preferred approach where a stochastic trend is incorporated that reflects not only technical progress but other factors such as changes in consumer tastes, and economic structure, unlike the panel approaches where it is not possible to incorporate a trend in its stochastic form. The structural time series approach is therefore applied to estimate energy demand parameters for 17 OECD countries using data over the period 1960-2000. These estimated parameters are preferred and provide the price and income elasticities for the OECD countries.

Dedication

To my Parents

Who have supported me throughout
God Bless them……..

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Chapter 1

Introduction

1.1 Background

The demand for energy has been a cornerstone in the study of energy markets over the last three decades. This is due to two main reasons: the first, the significant movements in oil prices in 1973-74, 1979 and 1985-86, and the second, greater environmental pressures in recent times and the increasing concerns about global warming. For the first reason, Nordhaus (1977)[1] argued that "the industrialised world is attempting to cope with a radical change in energy price levels and with the world recession and to restructure the balance of payments disequilibrium induced by price changes'' (p. 239). For the second reason, most countries have international commitments towards a specific target to reduce their emissions. During the last decade, governments around the globe have shifted the focus of their concern from supply shocks to concern about the environmental consequences of energy use. On December 11 1997, representatives of 150 nations participated in the United Nations Conference on Climate Change (UNFCCC). The purpose of this conference was to reach an agreement on limiting global emission of greenhouse gases, primarily Carbon Dioxide (CO_2) from the combustion of fossil fuels. The countries were listed as 'Annex I countries' and each committed to reduce CO_2 emissions by the amount specified in the Kyoto Protocol by the year 2012.

[1] The argument is not totally valid for developed countries in recent times given the global warming issues for these countries.

Most scientists now agree that emissions of CO_2 and other greenhouse gases contribute to global warming. In the OECD[2] CO_2 emissions increased by 13% over the period 1990-2001 compared to an increase of 3.4% over the period 1973 to 1990 (IEA 2003). This represents an important challenge, to reduce CO_2 emissions and combat climate change. Adopting and implementing policies for reducing CO_2 emissions needs a good understanding of the factors that affect energy consumption such as income, prices, economic structure, lifestyle, climate, and energy efficiency. A report by the International Energy Agency (IEA) in Paris shows that the IEA-11[3] countries all experienced significant reductions in CO_2 emissions per unit of GDP between 1973 and 2001 while they experienced an increase by 12% between 1990 and 2001, but such development is in contrast to what was agreed for the Kyoto targets.

In the past a wide variety of energy models has been explored at various levels of aggregation, on various time periods, and using various models for all types of energy products. These models have a variety of uses including policy analysis, evaluating structural changes, understanding adjustment processes, and forecasting. However, different models may be appropriate given, the availability of data and the purpose for building the model.

The developments in energy demand modelling have taken place as various circumstances have changed. For instance the energy demand modelling work undertaken during 1970s and 1980 was primarily conducted as a result of the two oil

[2] More details about the history and structure of the OECD are given in Chapter 2.
[3] The IEA-11 consists of Australia, Denmark, Finland, France, Germany, Italy, Japan, Norway, Sweden, the UK, and the USA.

and energy price hikes of the 1970s. Therefore, studies were conducted on the question of interfuel and factor substitution using the trans-log function (see Hunt (1986) and (1984) for a summary of these studies.)

More recently the emphasis has been on the effect of energy production and consumption on the environment hence the need for answers about how energy will develop as income and GDP continues to grow and what would be the effect of higher prices, etc. Therefore energy demand models are more concerned with estimating the short and long run income and price elasticities to try and enlighten policy makers about past behaviour and how environmental targets may be achieved in the future. Moreover, the effect of other factors such as technical progress/energy efficiency and socio-economic factors are also important in such circumstances hence models need to be developed that encompass these effects as well, such as those in Hunt et al 2003b).

Energy demand studies are conducted in the light of the need to produce reliable and consistent estimates of the key parameters of interest: namely, income and price elasticities. Energy economists have put a lot of time and effort into searching for the most appropriate specification of energy demand functions and the appropriate econometric techniques to estimate the key parameters of these functions. Using historical data they have attempted to understand the past and the present, but arguably more importantly, to also give a vision of the future.

Energy demand studies are normally based on econometric studies to estimate the key elasticity parameters. These elasticities are crucial tools for governmental policy makers, consultant agencies, economists and scientists who are concerned with economic and energy issues. For example, policy makers require reliable elasticity estimates to help understand and predict the impact of energy policies such as carbon and energy taxes: this is prevalent at the present time given the general acceptance and considerable concern about global warming caused, to a large extent, by energy production and consumption. Therefore, searching for accurate and reliable values for these elasticities remains an important objective for energy economists. Thus, it is crucial that the appropriate specification and estimation technique should be used in order to evaluate accurately the relationships between energy consumption, energy prices and the level of economic activity. In addition, it is as relevant to obtain reliable forecasts of future energy consumption and emissions trends. However, there is no unique approach for modelling the energy demand function, and some researchers may rely on the advantages of different econometric techniques over others. Watkins (1992) stated that "there is no one technique for all seasons. It is a matter of selecting the methodology whose strengths best match the task at hands'' (p. 29).[4]

A number of previous studies, similar to this thesis, have estimated energy demand models using aggregate data for whole economies and at the sectoral level. However, it is possible to disaggregate further in order to analyse distributional effects of energy policies or improve the short runt forecast see Fouquet et al.(1993) for example. This disaggregation can go even further with a microeconomic approach taken, such as that by Henley and Pierson (1998). And in an ideal world the price and income elasticities for all fuels at the much disaggregated level would be desirable for policy makers –

[4] Throughout this thesis econometric energy models are confined to demand side behaviour as opposed to other models such as econometric market models and econometric process models.

although arguably this would actually give too much information. However, such studies require many variables and large quantities of data in contrast to aggregate studies. Such data on a consistent basis across a large number of OECD countries is almost impossible to obtain hence it is not feasible to take such approach when focussing on the OECD. Furthermore, any attempt to compare and contrast the various OECD countries would be misleading since it is very unlikely that the data would be collected and collated on a consistent basis across all countries. Therefore given the aim in this research is to analyse a large number of OECD countries, aggregate energy for the whole economy (the sum of energy consumption for all economic sectors) is used. Moreover, despite the data problems of a disaggregated/microeconomic approach discussed above, arguably the global problem of global warming requires a global analysis, and modelling aggregate energy across the various OECD countries allows such an analysis.

A number of writers have surveyed the literature on energy demand and conclude that econometric studies on energy demand dominate the applied work in this area: see for instance Madlener (1996), Taylor (1975) and Bohi and Zimmerman (1984). Hunt and Manning (1989) describe such literature by stating that there "has been a plethora of energy price- and income- elasticity studies which cover various sectors of the economy and employ numerous modelling and estimation techniques"(p. 183). Despite a large literature on energy demand studies, there is still a need for more studies that explore the appropriateness of different estimation techniques. For the OECD countries, as far as is known, very little effort has been made to estimate the parameters of aggregate energy demand. The literature review in the next section - to a large extent – is therefore limited in terms of the econometric techniques, the number of the OECD countries included in a single study and the estimation period used.

The outline for the rest of this Chapter is as follows: Section 1.2 presents a brief review of the literature for aggregate energy demand for OECD countries. Section 1.3 offers a brief summary of the estimation techniques used in this thesis. Section 1.4 states the aims of the thesis and the research questions; whilst the final section outlines the structure of the remainder of the thesis.

1.2 Previous Literature on Estimating Aggregate Energy Demand Functions

The rapid increase in world oil prices during the 1970s stimulated numerous studies to estimate energy demand income and price elasticities, but as noted by Atkinson and Manning (1995) "following the oil crisis of the early 1970s there have been numerous studies on energy elasticities at the national level but rather fewer at the international level" (p. 47). This thesis therefore concentrates on modelling aggregate energy demand for the OECD countries, but before detailing the aims of the thesis and the research questions, this section briefly reviews past OECD (and EU) aggregate energy demand studies, and the resultant estimated income and price elasticities.

Table (1-1) presents a summary of previous aggregate energy demand studies for OECD countries.[5] It highlights that there are only a few studies at this particular level and limited econometric techniques have been used. Furthermore, the majority of cited studies aggregated data across a number of OECD countries into a single time series to estimate average parameters of aggregate energy demand. In addition, a long debate has taken place about the inclusion of the deterministic time trend as proxy for technical progress. This thesis therefore considers this issue. It explores the effect of technical progress on energy consumption for 17 OECD countries using the concept of the 'Underlying Trend' (see Chapter 4). Furthermore, it could be argued that the panel data techniques are not adequately represented in estimating aggregate energy demand for the OECD countries; therefore, this thesis estimates the energy demand parameters using traditional panel data models and their heterogeneous counterparts for a large number of the countries (see Chapter 3). In addition, the cointegration issue in the panel data context is explored in this thesis because the estimation in Chapter 3 does not allow for the existence of a long run relationship. As a result, Chapter 5 explores whether a valid long-run cointegration can be found in the panel context, and hence the energy demand parameters. A brief outline for the three econometric techniques utilised in this thesis follows.

[5] Of course there have been numerous individual country studies, but Table (1-1) includes all aggregate/multiple country studies for the OECD. In addition, the details of the cited studies are presented in Chapters 3 and 4.

Table (1-1) Energy Demand Studies for OECD Countries

Study /(years)	Sector analysed	Model used and technique	Data used	Estimated linear time trend and LR elasticities	Remarks
Kouris (1976)	Aggregate primary energy	Static log linear reduced form OLS model (Pooled)	EEC annual data 1955-70	η_y =0.84 η_P = - 0.77	Individual country results are reported.
Kouris (1983)	Aggregate energy	Dynamic log linear reduced form (aggregate time series model)	Aggregated OECD annual data (1961-81)	η_y = 1.07 η_p = -0.43	Overlapping 13 years period results are presented
Welsch (1989)	Aggregate energy	Dynamic log linear model and five other different specifications in log linear (aggregate time series model)	OECD annual data 1970-1984	T=Included but results not reported η_y = 0.70 – 2.30 η_P = -0.10 - -0.90	The rejection of the time trend for some countries implied that improvements of energy efficiency are price induced.
Beenstock and Willcocks (1981)	Aggregate energy	ECM (aggregate time series model) in log linear	OECD annual data 1950 -1970	T= -0.04 η_y = 1.80 η_P = -0.06	Commercial energy consumption results show slightly smaller absolute values; this suggests that the aggregation affects the estimates. An attempt to restrict income elasticity to unity is rejected.
Jones (1994)	Aggregate energy	ADL (aggregate time (series model)	OECD annual data (1960-90)	T = -0.05 η_y = 2.19 η_P = -0.32	The finding is consistent with Kouris's view regarding the inclusion the time trend.
Prosser (1985)	Aggregate energy	Dynamic log linear reduced form (different specifications) aggregate time series model	OECD annual data (1960-82)	η_y = 1.02 η_P = -0.40	Specifies one static model and 4 dynamic models. Koyck model is preferred.
Nordhaus (1977)	Aggregate energy	log linear LSDV (Almon) model	Seven OECD countries annual data 82 observations	η_y = 0.79 η_P = -0.85	Results for each sector and each country are presented

η_p and η_y are price and income elasticities respectively and T the coefficient of the time trend.

1.3 Background to Techniques Used in this Thesis

1.3.1 Panel Data Estimation

The two studies in Table (1-1) by Kouris (1976) and Nordhaus (1977) both used a traditional panel approach; namely the fixed effects model. These two studies do not incorporate the effect of technical progress in the specifications. In this thesis the issue of what is the appropriate 'pooling' technique to use in such circumstances is discussed and analysed in some detail in Chapter 3; in particular the issue of whether to use 'homogeneous' or 'heterogeneous' panel data estimators.

At the outset of the research a dataset was assembled that included 23 OECD countries for the period 1978 to 1998. Hence the initial work (detailed in Chapter 3) is confronted with the data restriction that the number of observations for each country is relatively small, and hence it is not possible to estimate separate models for each country. Therefore, pooling the data in such circumstances is an attractive idea, since arguably it yields more efficient estimates. However, this technique (like any other) has numerous advantages and disadvantages (as discussed in Chapter 3). Although this technique has been used to some extent, as highlighted in Table 1-1, it has not been that widely used in estimating aggregate energy demand for the OECD countries, and moreover it has not, as far as is known, been used to estimate aggregate energy demand for a large number of countries, as undertaken in Chapter 3 of this thesis.

1.3.2 Time Series Estimation

Within the studies cited in Table (1-1) there exists a debate around the importance of modelling technical progress in energy demand function and whether a deterministic time trend is appropriate or not as a proxy for technical progress. More recently, in an individual country context, this debate has been continued in the context of estimating energy demand functions with a stochastic trend rather than a deterministic trend as a way of capturing the effect of technical progress (and other exogenous effects) using the Structural Time Series Model (see for example Hunt et al, 2003b). This issue is discussed and analysed at some length in this thesis and extends the work of Hunt and his colleagues to 17 OECD countries in Chapter 4.

Most OECD countries have experienced more efficient energy use in that the intensity of utilisation of energy has been declining over time. Sun (2002) investigates the energy intensity across OECD countries and shows that energy intensity is declining rapidly for OECD countries. The energy intensity concept reflects the economic structure, fuel mix and the level of technology in a country. This is not informative unless there is an adequate way to incorporate it in the specification of the energy demand relationship in order to produce reliable and accurate price and income elasticities. Therefore, Chapter 4 examines the issue of incorporating a simple time trend as a proxy for technical progress in energy demand functions for 17 OECD countries using data for 1960-2000.[1] Moreover, Hunt et al (2003b) argue that in addition to technical progress other economic and socio-economic factors need to be

[1] Following the initial research in Chapter 3 it became possible to extend the data set backwards for a subset of the original countries.

allowed for - separate from standard economic influences of price and income. Following the work of Hunt et al (2003a, 2003b, 2005), the structural time series model is employed given the flexibility of the stochastic trend in capturing the relevant effects.

1.3.3 Panel Cointegration Estimation

Despite the wide range of panel estimators that are employed in Chapter 3, ranging from homogeneous estimators to heterogeneous estimators, the existence of a valid long-run statistical relationship between the energy variables can not be established using such techniques. Therefore, this issue is discussed and analysed in Chapter 5 where there is a need initially to test for the order of integration of the energy variables and then estimate the long run relationship for the energy demand function. This is, as far as is known, the first attempt to obtain cointegrating vector for energy demand estimates in the panel data context.

Therefore Chapter 5 investigates the issue of the non-stationarity of the variables incorporated in the energy demand functions and the cointegration between them in a panel data context using the Data Set used in Chapter 4. The energy demand literature has considered this matter in a number of studies for individual countries in the time series context, for instance, Hunt and Manning (1989), Hunt and Lynk (1992) and Fouquet (1995).

1.3.4 Functional Form

Table (1-1) shows that there is a consensus about the functional form, in that the log-linear model has been employed in estimating all the energy demand functions cited. This means that the estimated price and income elasticities are constant throughout the estimation period. An alternative approach would be to use the translog model approach based on cost functions and the derived cost share equations, which, as discussed above, dominated energy demand studies during the late 1970s and 1980s following the sharp increases in oil prices. However, translog models have their theoretical basis in microeconomic theory, hence a number of restrictions, based on consumer theory, need to be imposed. Arguably, this is a too restrictive approach and moreover, some of the restrictions that are often not satisfied by the data (see Hunt, 1994 for example). Furthermore, there are a large number of estimated parameters in the model that results in a lack of degrees of freedom in many cases. Moreover as Jones (1996) points out, often such models suffer from a problem of finding a positive own price effect. Similarly, estimated cross price elasticities between some fuels are often negative, indicating those fuel are complements, rather than substitutes – which in the majority of cases is not in line with expectations and intuition.

That said one advantage of the translog approach is that the estimated elasticities are not constant throughout the estimation period as with the log-linear model. Therefore, an alternative might be to estimated a translog demand function instead of the log-linear model. However, this would involve a number of additional squared and interactive terms resulting in a loss of degrees of freedom and moreover would not allow an easy comparison with past studies and across the OECD countries. And as

Hunt and Ninomiya (2005) argue "because the [log linear] model structure is quite simple, the interpretation of the estimated parameters is straightforward and the required data for estimation is less costly than other complex theoretical models'' (p. 1409), Berndt (1991) makes a similar argument. In addition, Pesaran et al (1998) argue that "a number of empirical studies have shown that the log-linear specification fits actual energy data better than models which have a tighter link to the utility maximisation theory" (p.100). Furthermore, Pesaran et al argue that the "log-linear specification is a convenient forecasting device". (p.84). Therefore this functional form is maintained throughout this thesis.

1.4 Aims of the Thesis

The overriding aim of this thesis is to obtain accurate and reliable estimates of the income and price elasticities of energy demand models for the OECD. But in order to achieve this, as alluded to above, this thesis adopts and evaluates three different techniques, which are: panel data models, single country time series models (structural time series and cointegration) and panel data cointegration models. A major reason for using such a diverse range of estimation techniques in this thesis is to investigate the most appropriate way for modelling aggregate energy demand for a large number of OECD countries and then derive the most informative estimates for price and income elasticities. Given this, the Research Questions for this thesis are detailed below.

1.4.1 Research Questions

Given the aims above, the research questions are set out with a main overriding question and a number of sub-questions that follow from the main question in terms of the analysis of the different techniques:

The Main research question

This thesis attempts to answer the main following question:

Question M) What are the long run income and price elasticities for the OECD countries?

Through the substantive parts of the thesis: Chapters 3, 4 and 5 the main question is answered using different econometric techniques as discussed above. But within each econometric technique there are a number of sub questions that need to be answered first in order to answer the main question as follows:

The Sub-questions

In the context of panel data estimation:

Question P1) What are the most preferable estimators: the homogenous or the heterogeneous estimators?

Question P2) What is the most appropriate specification?

Question P3) Should an allowance be made for technical progress (and or other exogenous variables)?

In the context of time series:

Question C1) What is the appropriate modelling technique, cointegration or STSM?

Question C2) Is a deterministic trend or a stochastic trend the most appropriate way to allow for technical progress and other underlying exogenous factors?

Question C3) If the STSM approach with a stochastic trend is preferred, what is the shape of the trend for each country?

In the context of panel data cointegration:

Question E1) Does a statistically acceptable long-run cointegrating relationship exist?

Finally in the context of all estimation techniques:

Question T1) Do the long run income and price elasticities vary across the techniques and what is the best technique?

1.5 The Structure of the Thesis

It should be noted that normally a PhD thesis in economics will include a standard literature review chapter and a standard methodology chapter. However, given that the research for this thesis entails three different econometric techniques, the literature review and the methodology aspects are encompassed with each substantive Chapter (3, 4 and 5). Therefore, the rest of the thesis is organised as follows:

Chapter 2: Analyses the trends in the energy time series and energy intensity trends.

Chapter 3: Presents a variety of panel data estimators and different model specifications. It incorporates the time trend in the specifications as a proxy for technical progress.

Chapter 4: Discusses and presents the underlying trend issues and the cointegration approach.

Chapter 5: Discusses and presents the non-stationarity issues in panel data context.

Chapter 6: Remarks, conclusion and future research.

Chapter 2

Data Analysis and Energy Intensities

2.1 Introduction

The empirical work undertaken in this thesis is applied to a group of countries within the framework of the Organisation for Economic Co-operation and Development (OECD). This group was established in Paris on 14th December 1960 and came into existence on 30th September 1961. The original member countries of the OECD were Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom (UK), and the United States of America (USA). The following countries became members (hereafter) at the dates indicated: Japan (1964), Finland (1969), Australia (1971), New Zealand (1973), Mexico (1996), the Republic of Korea (1996), and Slovakia (2000). Within the framework of the OECD, the International Energy Agency (IEA) was established in November 1974. The basic aims of the IEA are:

- To deal with oil supply disruptions and operate information systems on the international oil market;
- To encourage rational energy policies in a global context through arrangements with non-members' countries;

- To improve the efficiency of energy use and assist the integration of environmental and energy policies (IEA 2003).

The IEA provides the main source of the data to be used in this thesis, therefore this and the other data sources are detailed in Section 2.2, in addition to discussion on the construction of the data and variables utilised. This is followed in Section 2.3 by a description of the data and a brief discussion of the trends over time of the key variables: energy consumption, the real energy price and economic activity. Section 2.4 explores the energy intensities of the countries analysed in the thesis. The final section presents a summary.

2.2 The Sources of Data Sets

This research undertaken for this thesis utilises two data sets which have been named 'Data Set 23A' and 'Data Set 17B'. A brief description of both sets is given below.

2.2.1 Data Set 23A

Data Set 23A covers the time span 1978 to 1998 for 23 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Ireland, Italy, Greece, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US.[7] This set gives a balanced data set because

[7] Germany is excluded from the sample due to its unification and the Czech Republic and Slovakia due to their division, while other countries are excluded due to missing many observations.

each country has the same number of time series observations. This data set includes three series for each country:

(i) Aggregate energy consumption (E) data are taken from the Energy Balances of OECD countries (IEA/OECD), in million tonnes oil equivalent (mtoe).

Aggregate energy consumption consists of different types of fuel usually with different units of measurement units; therefore, it is essential to convert the original units to a single measurement unit such as mtoe and then sum to give the aggregate energy series. One problem with such a conversion is that might result in distortions since there is a wide spread in the calorific values between types of fuel in different countries. Therefore, the IEA (1991) adopted specific conversion factors for different fuels to deal with such a circumstance. Exact details of the conversion factors for individual countries can be found in IEA (2004), but the following gives an example:

Natural gas in terajouls (gross);	multiply by 0.0002149 to give mtoe
Motor gasoline in thousand tonnes	multiply by 0.0010700 to give mtoe
Heat in terajoules (net)	multiply by 0.00002388 to give mtoe

(ii) Economic activity (Y) data defined as GDP measured in constant US$ at 1995 prices using exchange rates are taken from the National Accounts of OECD countries, available in the electronic version of the IEA publication entitled Economic Indicators. This is the common units used in a large number of energy demand studies, for e.g. the studies cited in Table (1-1) usually represent the economic activity variable using an exchange rate conversion. That said, one possible alternative would have been to use GDP in constant US$ at 1995 prices using Purchasing Power Parity indices (PPP) with a fixed set of quantity weights. However, one problem with this is the choice of index to be used; Laspeyre or Paasche (although Pindyck (1980) has suggested a geometric mean of the two indexesis used). However, to avoid this problem and consistency with previous studies, the definition outlined above is used in this study.

Another possibility would have been to utilise per-capita income and per-capita consumption rather than working in levels; the argument being that this would help to capture the structural differences in the different OECD economies. However, when undertaken panel data estimation the techniques, such as the fixed effect method, should capture these effects through the different intercepts. Furthermore, when undertaking time series estimation the changes in population of the developed world over the estimation period is relatively small and hence not seen as a key driver of energy consumption – unlike for developing countries. Therefore, the levels of consumption and GDP have been used in this study.

(iii) Aggregate real energy price (P) indices in (1995=100) are taken from various issues of Energy Prices and Taxes (IEA/OECD).

The methodology used by the IEA to calculate these indexes is summarised as follows:

For the products where more than one price is available, a representative series is created for each country. The representative heavy fuel oil price is a combination of high sulphur fuel oil and low sulphur fuel oil. The representative motor gasoline price is a combination of the most consumed unleaded gasoline for recent time periods and leaded gasoline for earlier time periods. For oil, the industry index includes representative heavy fuel oil, light fuel oil and automotive diesel but not fuels used for electricity generation. The household index includes representative gasoline and light fuel oil.

Indices with the base year for instance 1995 = 100 are computed for each price series from price in national currencies and then aggregated over products groups, sectors, and countries. The paasche formula is used for index computation. The weights used are the physical quantities consumed. To calculate the real price index, the nominal prices are deflated by with country specific producer price indices (1995 = 100) for the industry sector and with country specific consumer price indices (1995 =100) for the household. The aggregate is calculated as the weighted averages of country specific indices, using consumption quantities as the weights, IEA (2004).

Although this consists of a relatively large number of countries (23) the time period is relatively short. Therefore, in such circumstances applied economists generally prefer to use panel data techniques. This is therefore undertaken in Chapter 3 to estimate the parameters of an aggregate energy demand function for the 23 OECD countries.

2.2.2 Data Set 17B

The initial empirical work was undertaken using the short time series Data Set 23A. However, given the way the research progressed it was felt necessary to get a data set with a longer time period in order to explore the time series dimension of the data. As a result, Data Set 17B was constructed. This covers the period 1960-2000 for 17 OECD countries: Austria, Belgium, Canada, Denmark, France, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US. This data set has the advantage that it covers 41 observations for each country compared to the 21 observations for each country in Data Set 23A. However, due to the unavailability of consistent and accessible price data prior to 1978, the number of countries falls from 23 to 17.

For each of the 17 countries in Data Set 17B, Data Set 23A is encompassed over the period 1978-1998. As in Data Set 23A, Data Set 17B includes three series:

(i) Aggregate energy consumption (E): definition and source as above but for the period 1960 – 2000.

(ii) Economic activity (Y): definition and source as above but for the period 1960 – 2000.

(iii) Aggregate real energy price indices (P): from 1978 to 2000 the definition and source is as above, but for the period 1960 to 1977 the indices are calculated from data in Baade (1981).[8] The aggregate real price indices are calculated from different fuel price indices: the price of gas in households and industry, a price index for coal in households and industry, a price index of electricity in households and industry, a price index of gasoline, a price index of diesel fuel and a price index of kerosene.

[8] This was used in a similar way by Prosser (1985).

These indices are weighed by their fuel consumption share in order to construct the aggregate real energy prices index in 1972 prices (1972 = 100) over the period 1960 to 1980. The two series (1960 – 1980, 1972=100) and (1978 – 2000, 1995=100) are then spliced using the average ratio from the overlap period to obtain the series for the whole period 1960 to 2000 at 1995 prices.

Given the longer time period, Data Set 17B is more compatible with both the time series techniques and the recently developed panel cointegration approach, which are used to estimate aggregate energy demand parameters in Chapters 4 and 5 respectively.

2.3 Description of the Data

This section undertakes a brief descriptive analysis for both data sets (23A and 17B) that are used in the empirical work in Chapters 3, 4 and 5. The data analysis focuses mainly on two strands: firstly, a descriptive analysis for the entire sample in both data sets in terms of the mean, standard deviation, and minimum and maximum values for LE, LP and LY series; and secondly, a graphical analysis for LE, LP and LY.

Where: LE is the natural logarithm of energy consumption.

LY is the natural logarithm of income (GDP).

LP is the natural logarithm of the real energy price.

2.3.1 Descriptive Statistics

Summary statistics for energy demand variables LY, LP and LE are displayed in Table (2-1) for Data Set 23A. The overall mean of LY, LP and LE are 5.4, 4.7 and 10.6 respectively.

The variation in LY and LE is much larger when looking at between rather than within country variation; this is expressed by the value of the standard deviations from the overall mean, which are 1.41 and 1.37 for the between country variation and 0.19 and 0.16 for the within variation respectively. While the variations in LP are larger within the countries than between countries, as indicated by the value of standard deviation from the overall mean of LP are 0.30 and 0.18 respectively.

Table (2.1) Descriptive Statistics for Data Set 23A

Variable		Mean	Std. Dev	Min	Max
LY	Overall	5.4	1.39	1.87	8.86
	Between		1.41	2.25	8.56
	Within		0.19	4.74	6.13
LP	Overall	4.7	0.35	1.34	5.47
	Between		0.18	4.1	4.97
	Within		0.30	2.0	5.49
LE	Overall	10.6	1.35	7.73	14.18
	Between		1.37	7.95	14.10
	Within		0.16	9.89	11.36

The descriptive statistics for Data Set 17B are displayed in Table (2-2); the overall means of LE and LP are the same as in Data Set 23A, while the overall mean of LY increases by 5.5%.[9] The variation in the price is almost the same between and within countries, which is contrary to the results from Data Set 23A. While the within variation in LY and LE is increased compared to Data Set 23A.

Table (2.2) Descriptive Statistics for Data Set 17B

Variable		Mean	Std. Dev	Min	Max
LY	Overall	5.7	1.34	2.7	9.1
	Between		1.32	3.6	8.5
	Within		0.39	4.2	6.8
LP	Overall	4.7	0.26	3.8	5.5
	Between		0.16	4.3	5.0
	Within		0.20	4.2	5.2
LE	Overall	10.6	1.42	7.6	14.2
	Between		1.41	8.7	14.0
	Within		0.37	9.1	11.5

2.3.2 Graphical Analysis for Individual Countries

To avoid repetition, given that Data Set 23A is contained within Data Set 17B, the discussion of the trends of the variables for the 6 countries included in Data Set 23A only covers the period 1978 – 1998, whereas the discussion of the trends of the variables for the other 17 countries included in both data sets covers the period 1960 – 2000. However, for completeness the charts for all counties for both periods are displayed as follows:

[9] Calculated by the author

Figure (2.1) Energy Consumption Trends, 1978-1998.

Figure (2.2) Energy Consumption Trends, 1960-2000.

Figure (2.3) Energy Price index Trends, 1978-1998.

Figure (2.4) Energy Price Index Trends, 1960-2000.

Figure (2.5) GDP Trends, 1978-1998.

Figure (2.6) GDP Trends, 1960-2000.

2.3.2.1 Energy Consumption Trends

1978 - 1998

For Australia: energy consumption increased rapidly with some fluctuations but surprisingly in 1979 there was no breakdown despite there being some blips in 1983, 1985 and 1990.

For Finland: energy consumption increased up to 1979 and then dropped continuously to the mid 1980s. The rest of the period shows a dramatic increase reaching 25000 mtoe compared to19000 mtoe in 1960.

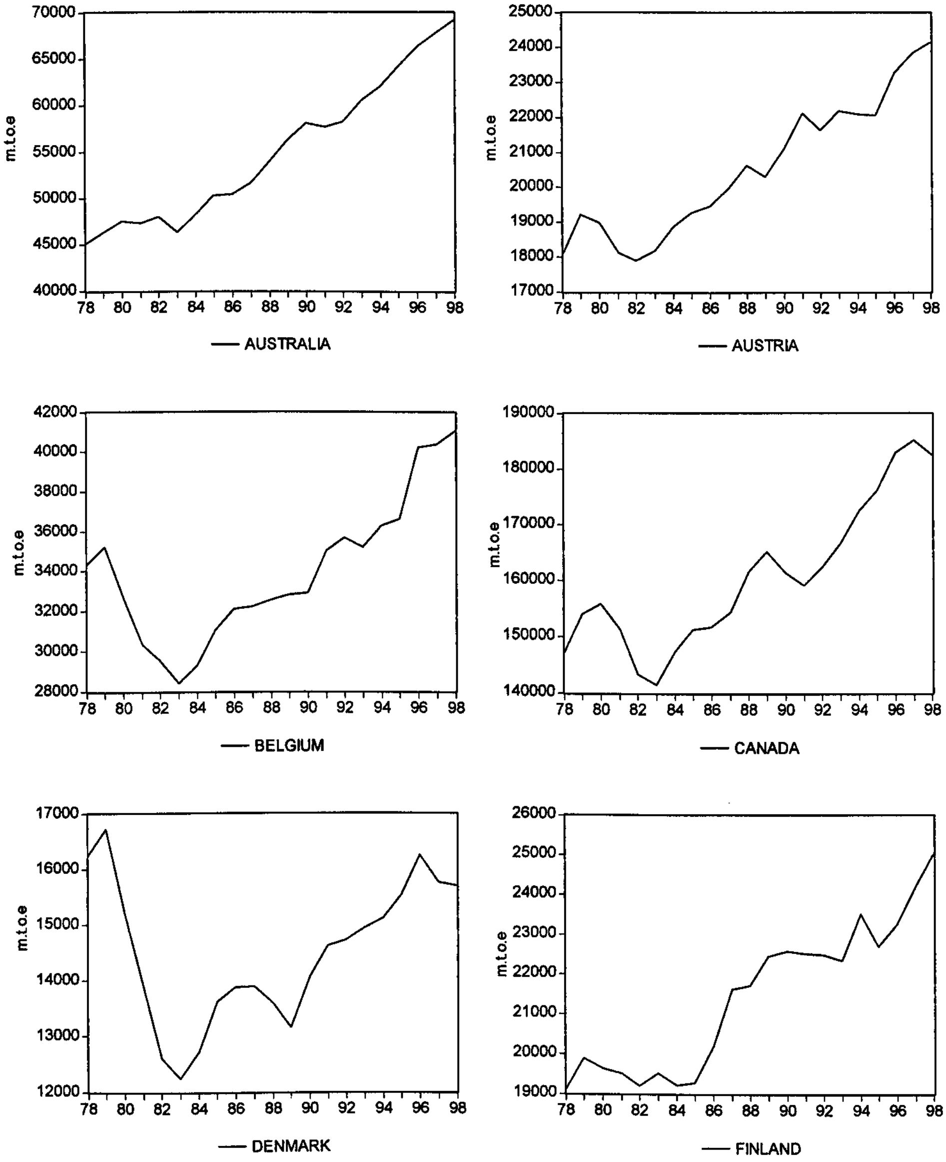
For Korea: energy consumption increased steadily up to 1997 with minor blips. It decreased in 1998. In 1997 it reached 120000 mtoe, which was around four times the amount consumed in 1978.

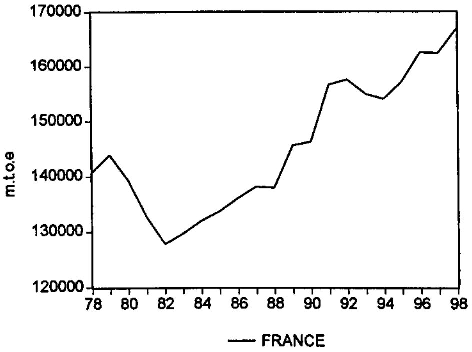
For Luxembourg: energy consumption dropped from 3100 mtoe in 1961 to 2300 mtoe in 1983. Then it increased rapidly over the period 1983 to 1993 with some fluctuations. Over the period 1993 to 1995 it dropped but was followed by an increase for the rest of the period.

For Mexico: energy consumption increased steadily over the period 1978 to 1983. It kept an increasing over the rest of the period, with some fluctuations, reaching 95000 mtoe in 1998 compared to 60000 in 1978.

For New Zealand: energy consumption decreased between 1978 and 1979. Then it was increasing up to 1996 with some variations. This trend levelled off during the last two years reaching the peak of 12000 mtoe in 1998, compared to 7000 mtoe in 1978.

Figure (2.1) Energy Consumption Trends in OECD Countries over the Period 1978-1998 (mtoe)

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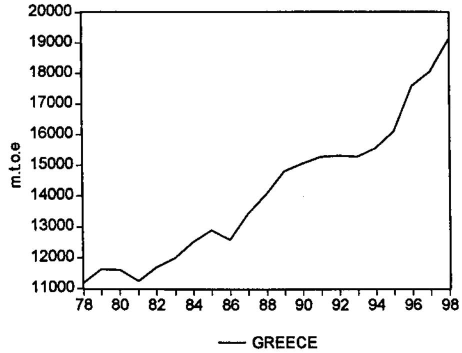
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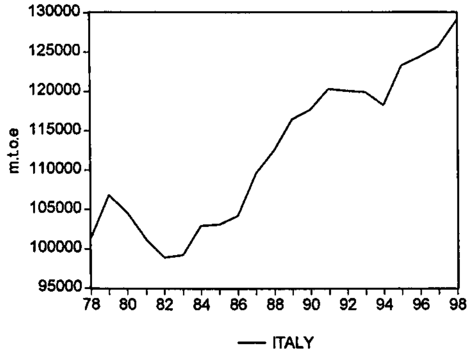
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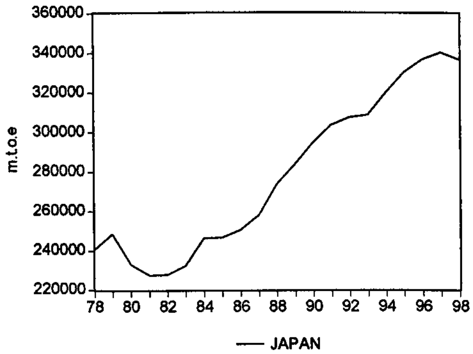
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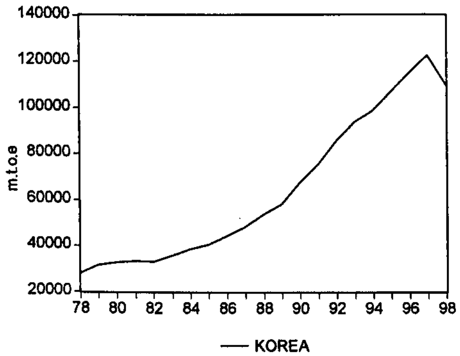
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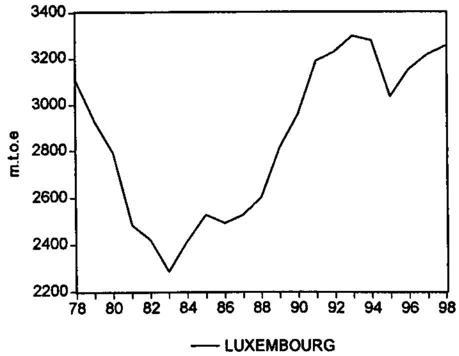
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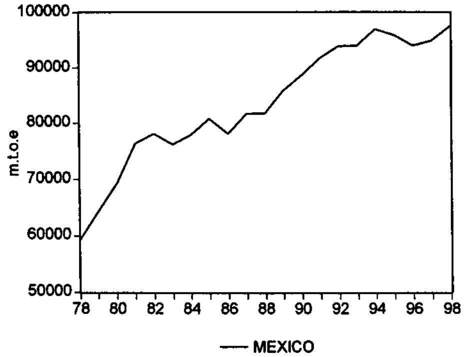
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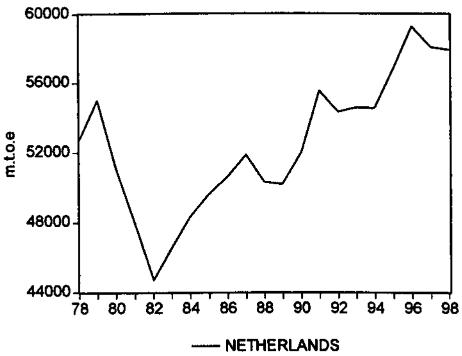
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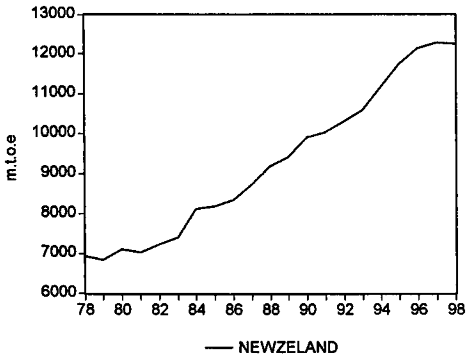
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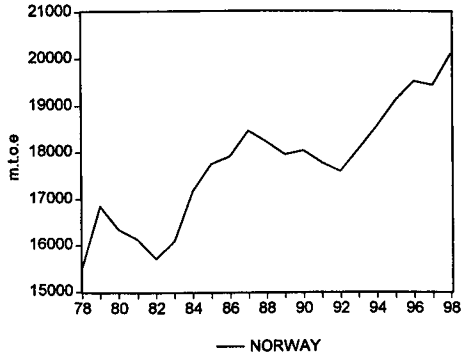
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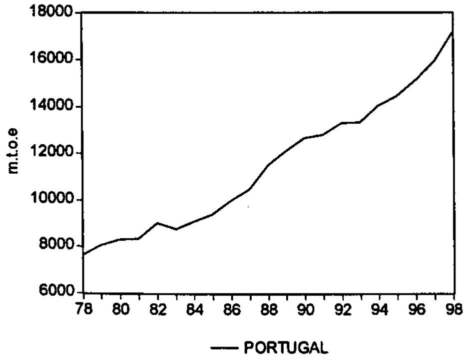
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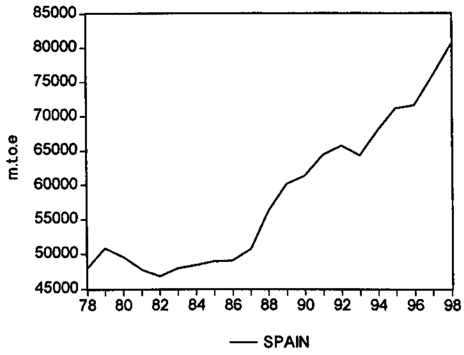
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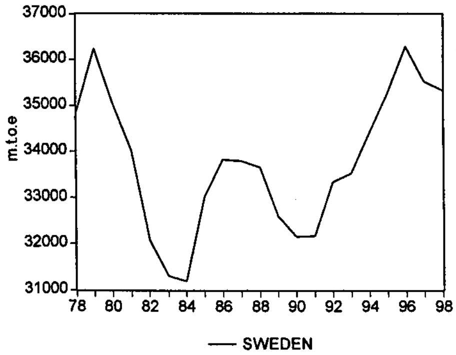
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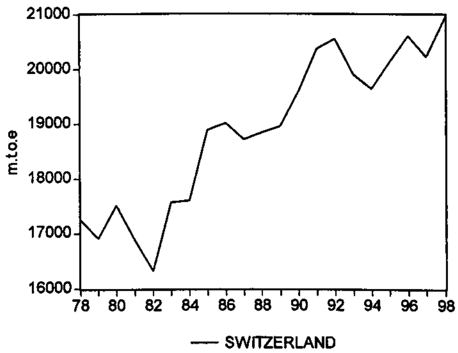
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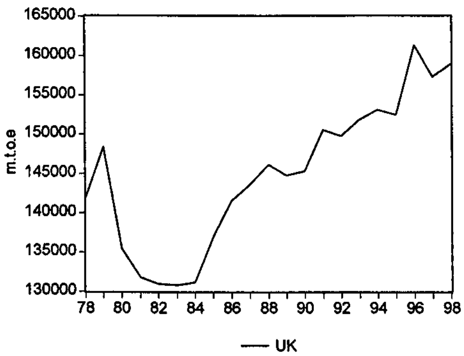
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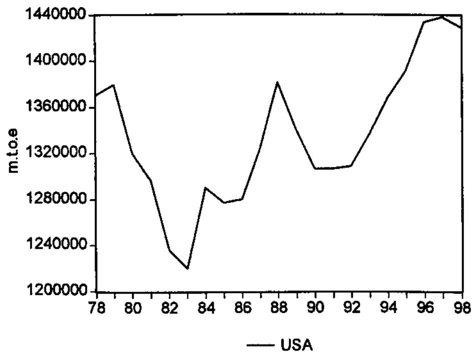
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1960-2000

For Austria: energy consumption shows a steady increase over time. In 1960, energy consumption was about 9000 mtoe, while the consumption at the end of the period reached at 24000 mtoe. The two oil price shocks caused only slight reductions in energy consumption.

For Belgium: The trend in energy consumption shows three main phases. First: a steady increase in consumption during the period 1960 to 1973. Second: large fluctuations during the period 1974 to 1984. Third: a dramatic rise during the period 1985 to 2000.

For Canada: energy consumption increased steadily during the period 1960 to 1974, before stagnating. During the period 1975 to 2000 the consumption trend fluctuated, but was generally on an upward trend and at the end of the period energy consumption had increased by approximately three times.

For Denmark: energy consumption increased during the period 1960 to 1970, and was then followed by remarkable fluctuations occurred over the period 1971 to 1984. The energy consumption peak was in 1978. After 1985, the energy consumption trend flattens and consumption decreased especially during the late 1980s.

For France: energy consumption increased rapidly. In 2000 energy consumption was approximately 170000 mtoe, compared to 60000 in 1960.

For Greece: energy consumption increased rapidly, apart from some relatively minor fluctuations. In 2000 energy consumption was over five times the amount in 1960.

For Ireland: energy consumption increased with some minor fluctuations. It reached its peak in 2000 which was around four times the amount in 1960.

For Italy: energy consumption in 1960 was 30000 mtoe and continuously increased over the period, reaching 130000 mtoe in 2000.

For Japan: energy consumption increased rapidly with some fluctuations during the period 1974 to 1984. The amount of consumption was 350000 mtoe in 2000, which was almost seven times the amount consumed in 1960.

The Netherlands: energy consumption increased steadily over the period, reaching 55000 mtoe in 2000. In 1979 there was a sharp drop in consumption due to the second oil price shock.

For Norway: the energy consumption pattern increased rapidly with some fluctuations during the two oil price hikes, and reached its peak in 2000.

For Portugal: energy consumption increased intensively over the time with minor fluctuations. The amount of consumption in 2000 was almost six times the amount in 1960.

F*or Spain*: energy consumption increased rapidly during the period 1960 to 1979, and then it fluctuated during the period 1980 to 1990. It reached its maximum in 2000.

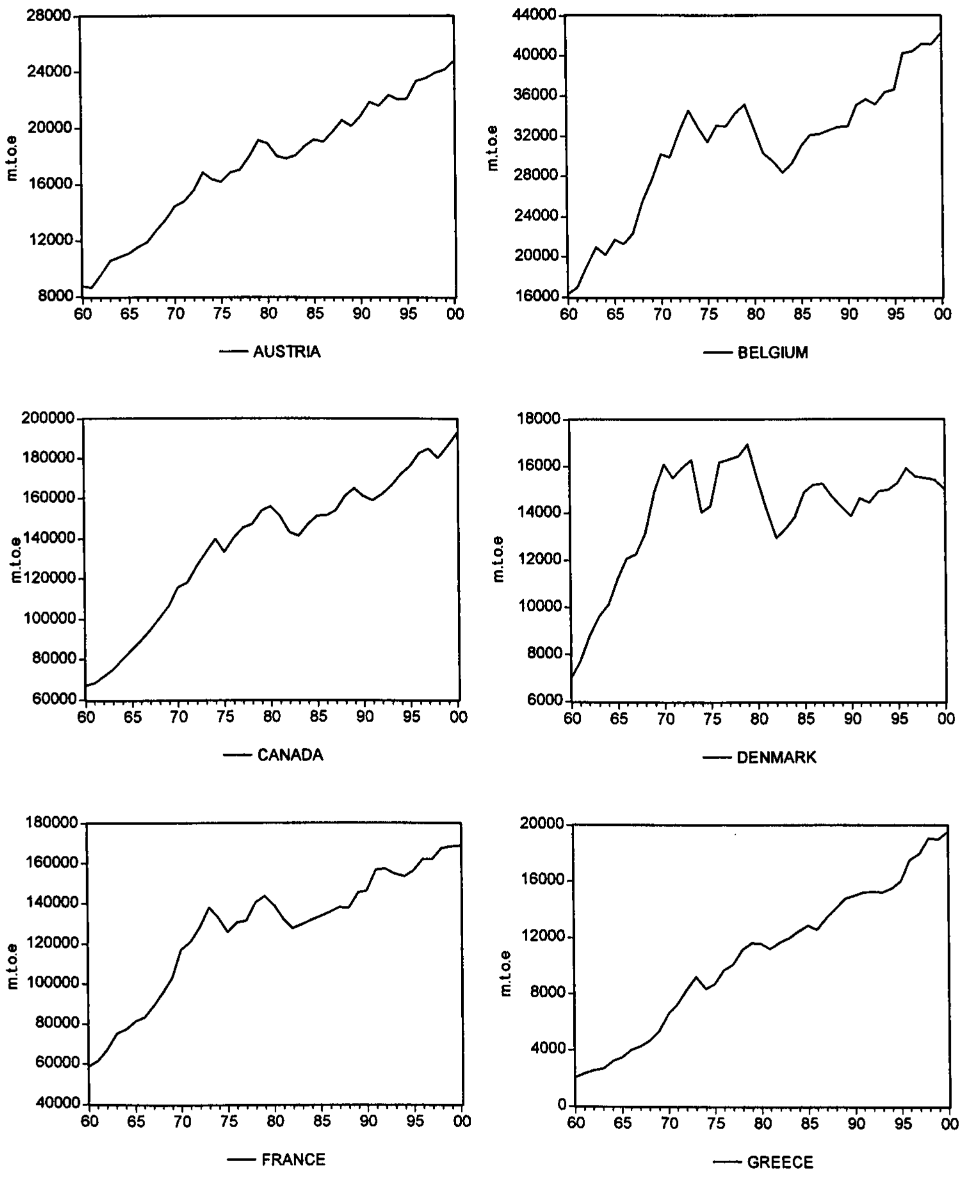
For Sweden: the energy consumption pattern increased rapidly over the period 1960 to 1976, reaching its peak at the end of that period. In contrast, during the period 1977 to 1995, it fell with some fluctuations. Over the last five years it was stable compared to the previous two periods.

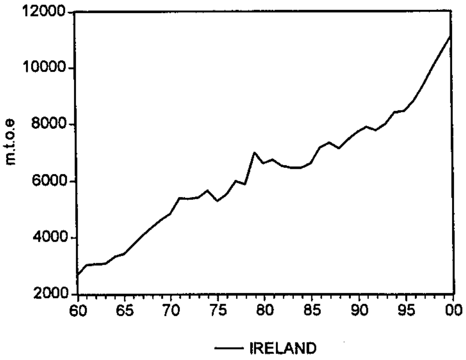
For Switzerland: energy consumption generally increased rapidly over the period 1960 to 2000, with some fluctuations. It reached a peak in 2000 of three times the amount consumed in 1960.

For the UK: energy consumption increased rapidly over the period 1961 to 1973, whilst during the period 1974 to 1985 the consumption trend fluctuated enormously and then reached its peak in 1999.

For the USA: energy consumption increased steadily during the period 1960 to 1973 while it dropped remarkably in 1974 and 1979. After 1985 the consumption increased up to 2000, with some fluctuations and a drop in consumption in 1990.

Figure: (2.2) Energy Consumption Trends in OECD Countries over the Period 1960-2000 (mtoe)

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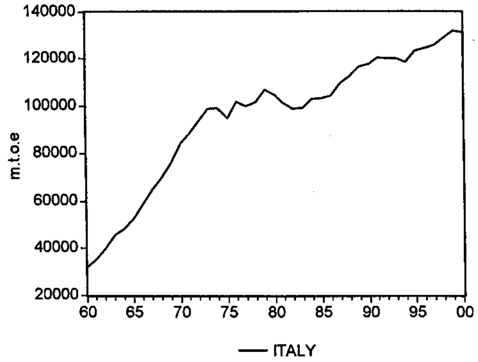
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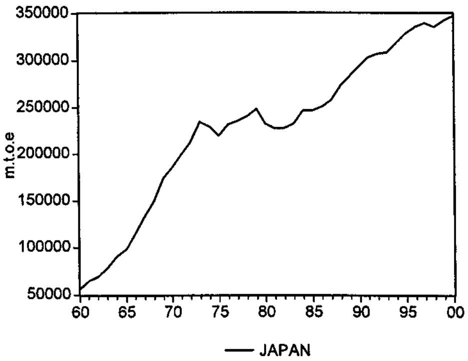
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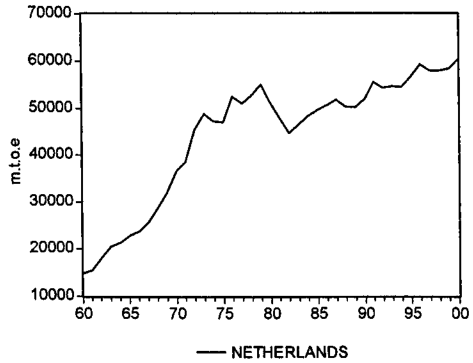
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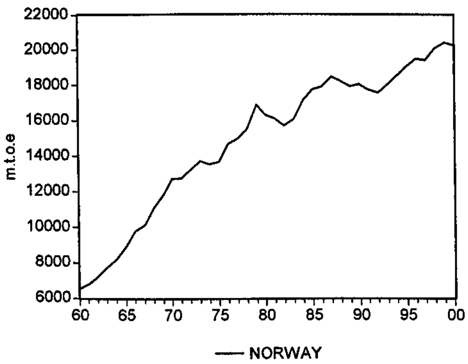
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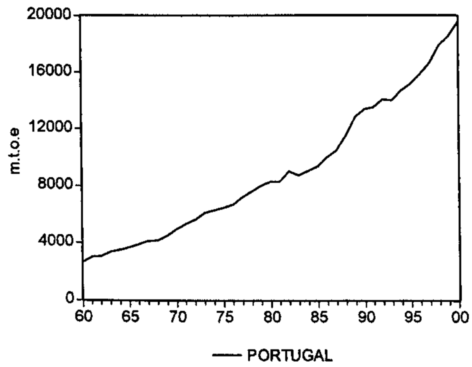
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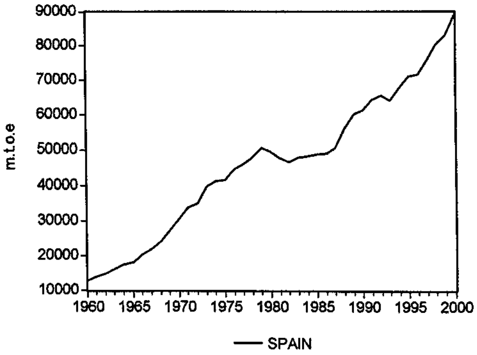
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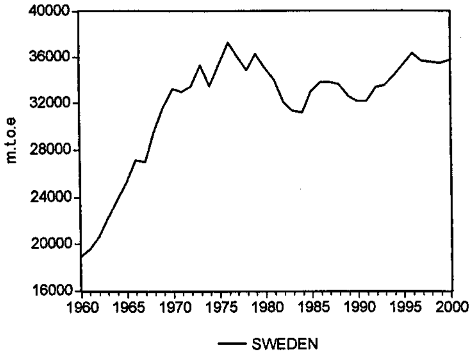
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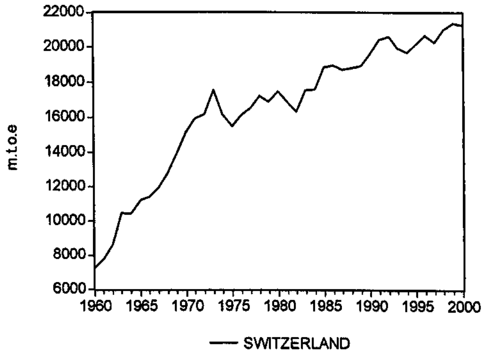
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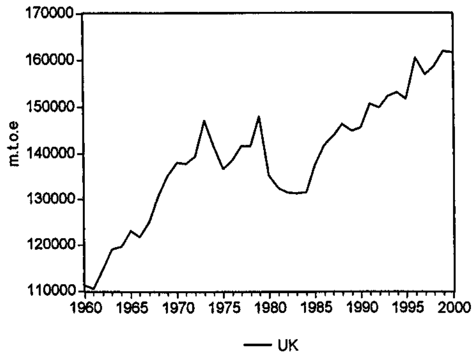
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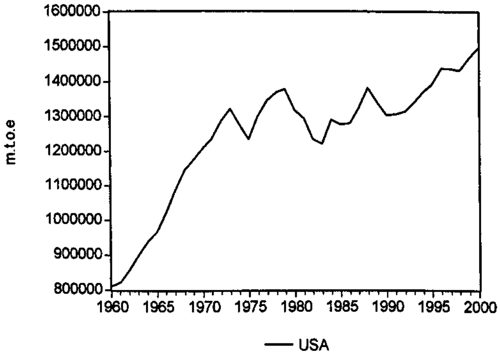
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In summary, the energy consumption trend for the OECD countries all generally experienced an increase over the period 1960 to 1973; whereas up to end of the period there was greater fluctuation. However, the OECD could be divided into two groups:

First: for the countries, Belgium, Denmark, France, the Netherlands, Sweden the UK and the USA, these countries experienced large fluctuations over the period 1974 to 1990.

Second: for the countries, Austria, Canada, Greece, Ireland, Italy, Norway, Portugal, Spain and Switzerland, these experienced less fluctuation during the period 1974 to 1990 and generally energy consumption increased in a slight pattern.

2.3.2.2 Energy Price Index Trends

1978-1998

For Australia: the energy price increased rapidly up to 1984 then dropped dramatically until the late 1980s. During the rest of the period it increased moderately with some variations.

For Finland: the energy price increased steadily up to 1983, when it reached its peak. Then over the period 1983 to 1988 it decreased dramatically, reaching its lowest level in 1988. For the rest of the period it increased with some variations.

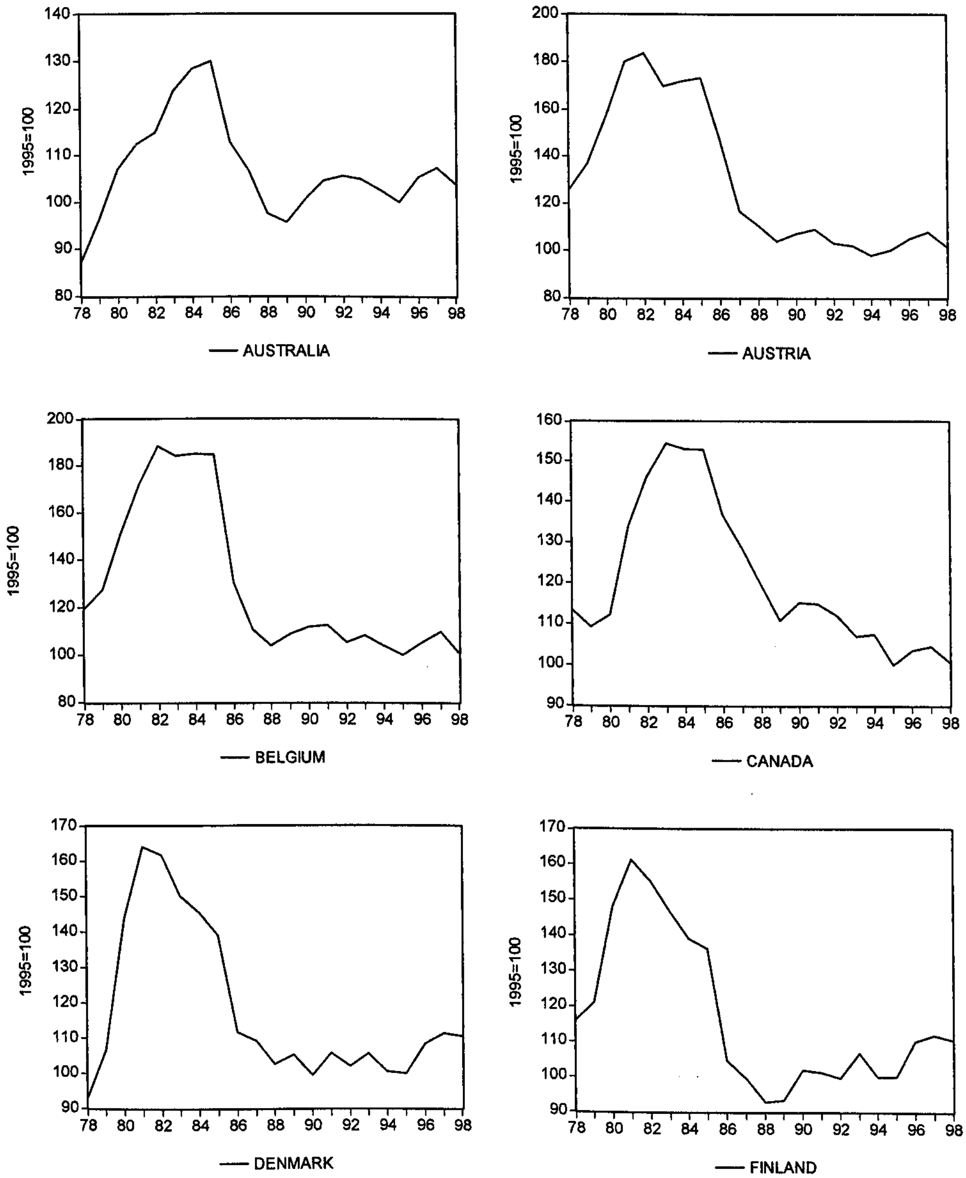
For Korea: the energy price increased up to 1981, when it reached its peak. It dropped continuously up to 1991 with some variations, then was followed by a moderate increase during the rest of the period.

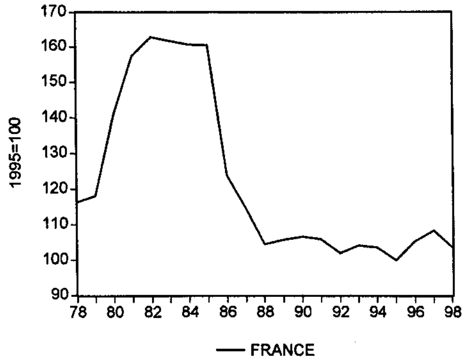
For Luxembourg: the energy price dropped sharply between 1978 and 1979. Then it increased over the period 1979 to 1982, followed by a moderate decrease up to 1985. It diminished sharply from 1985 to 1988, while over the period 1988 to 1997, it increased with some variations, before falling again in 1998.

For Mexico: the energy price increased dramatically up to 1986 with minor variations. Then the price trend flattened with moderate fluctuations over the period 1986 to 1998.

For New Zealand: the energy price increased rapidly over the period up to 1982. Then it dropped continuously with some blips over the period 1982 to 1995 before it started increasing again at the end of the period.

Figure (2.3) Energy Price Index Trends in OECD Countries over the Period 1978-1998 (1995=100)

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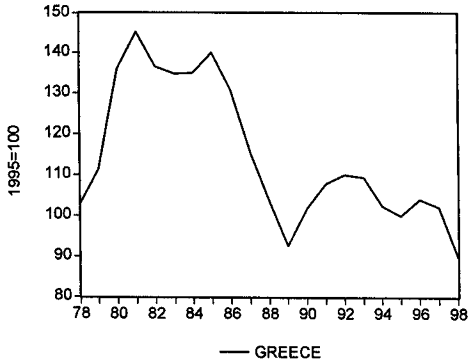
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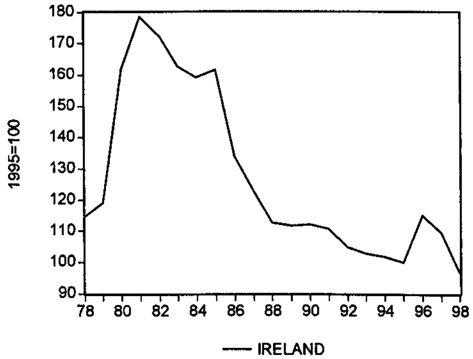
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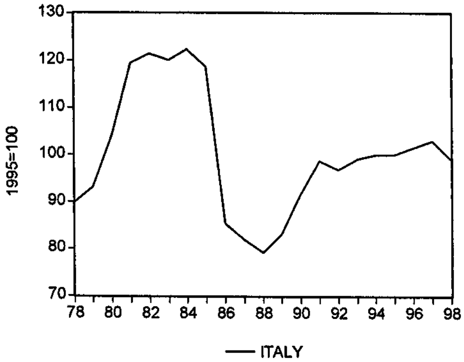
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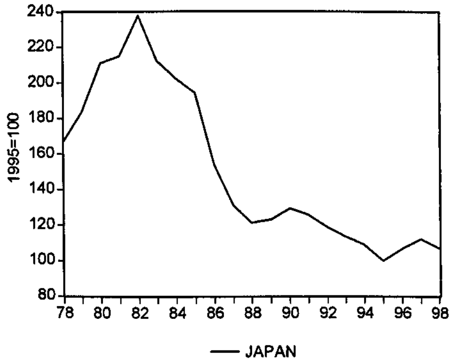
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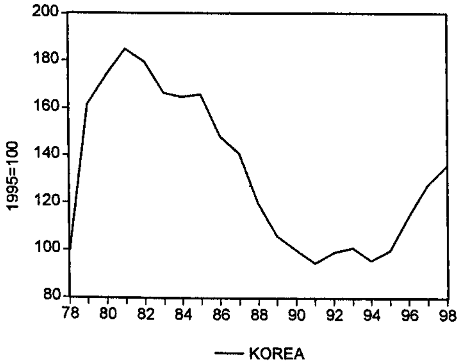
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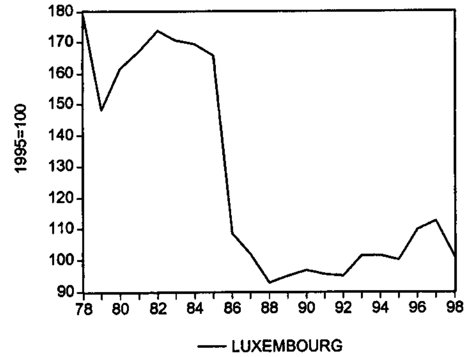
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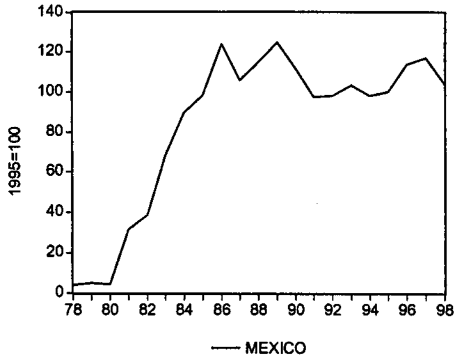
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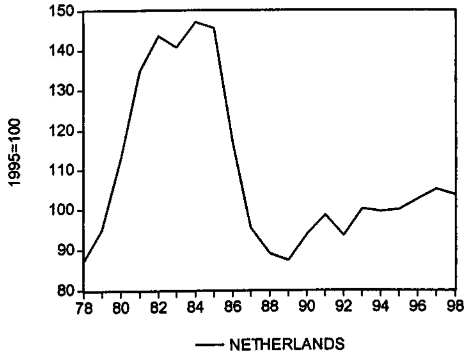
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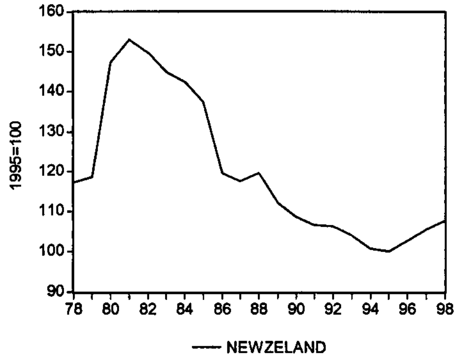
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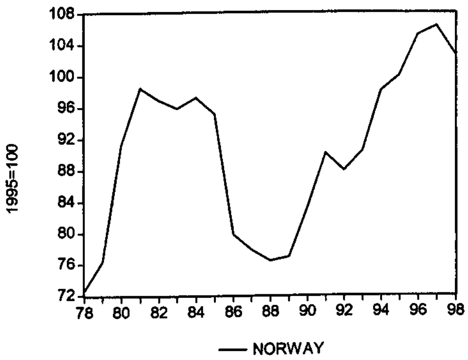
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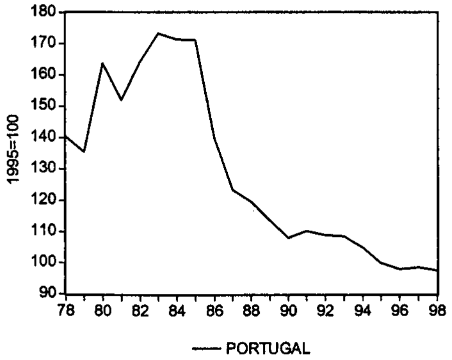
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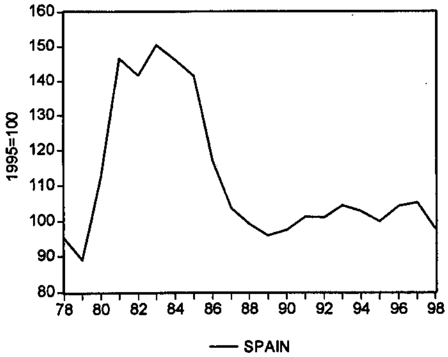

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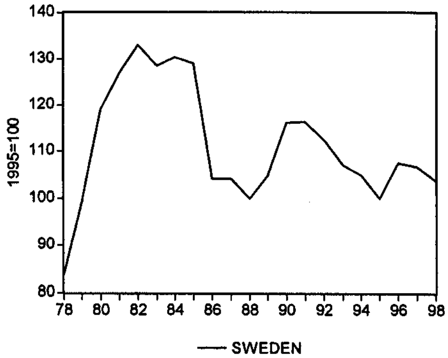

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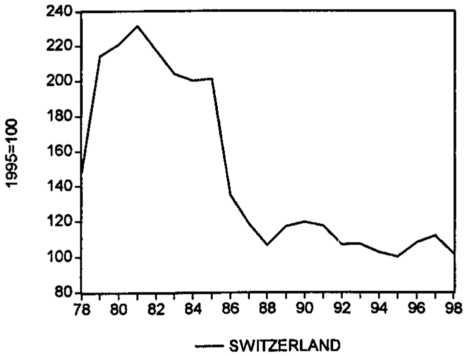

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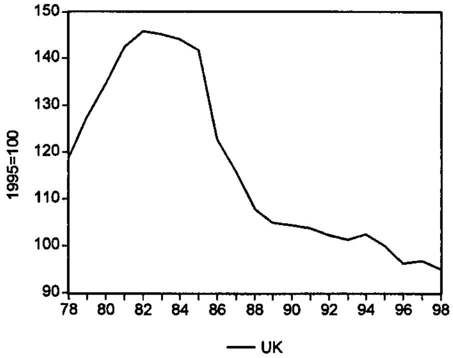

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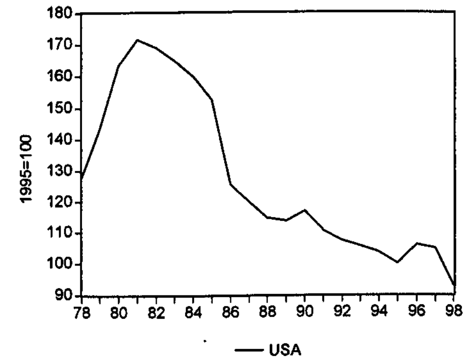

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90
78 80 82 84 86 88 90 92 94 96 98
USA

1960-2000

For Austria: the energy price declined steadily over the period 1960 to 1973, whereas during the period 1974 to 1982 the price rose with some fluctuations and a remarkable drop in 1979. Then during the mid 1980s the price dropped dramatically before the price trend flattened with minor fluctuations during the final years of the last century.

For Belgium: over the period 1960 to 1973 the energy price experienced a remarkable reduction. It rose substantially during the period 1979 to 1982. The price slipped quickly during the period 1985 to 1989 before rising during the 1990s.

For Canada: the energy price decreased continuously over the period 1960 to 1972, followed by a sharp increase over the period 1973 to 1983, then the price decreased continuously up to 1998. The last two years witnessed an increase in the price.

For Denmark: A reduction in the energy price over the period 1960 to 1973 with some fluctuations was followed by a steady increase up to 1976, then a decrease. Over the period 1979 to 1981 the price increased quickly, and then the price decreased continuously up to 1990, before it started increasing up to 2000.

For France: the energy price decreased considerably at the start of the period, reaching its lowest in 1973. Then the price steadily increased up to 1982 with some variations. There was a sharp reduction in the price over the period 1982 to 1988 before the price trend flattened.

For Greece: the energy price diminished up to 1973, followed by a sharp increase over the period 1974 to 1982, while in the mid 1980s to 1990 the price decreased, before fluctuating over the rest of the period.

For Ireland: the energy price increased between 1960 and 1963. In contrast, the period over 1964 to 1973 witnessed fairly large decreases in the price. A sharp increase in the price took place over the period 1974 to 1982, followed by a reduction up to 2000.

For Italy: the energy price diminished considerably over the period 1960 to 1972. After 1973 a continuous increase in the price with some fluctuations up to 1984 was followed by a rapid decrease up to 1988 before the price rose towards the end of the period.

For Japan: the energy price decreased steadily over the period 1960 to 1973. The period 1974 to 1983 witnessed large increases in the price. Over the rest of the period the price fell continuously reaching its minimum in 1995.

For the Netherlands: the energy price reached its lowest in 1972 followed by a continuous increase up to 1984 with some minor variations. From the mid 1980s, the price decreased rapidly up to 1990 followed by an increase during the last decade.

For Norway: the energy price generally increased up to 1980. In the 1980s the price diminished with some variations, whereas the price increased over the period 1990 to 1998, then a reduction over the last two years took place.

For Portugal: the energy price diminished over the period 1960 to 1970, then it kept increasing up to 1983. Then it decreased rapidly over the rest of the period with some small fluctuations.

For Spain: the energy price decreased over the period 1960 to 1973 with some variation, followed by sharp variations over the period 1974 to 1990 before the price flattened during the 1990s.

For Sweden: the energy price decreased rapidly with some fluctuations up to 1970 followed by a remarkable fluctuation up to 1979. Then it increased rapidly reaching it maximum in 1982. Then it dropped continuously during the period 1983 to 1989. There was less fluctuation during 1990s.

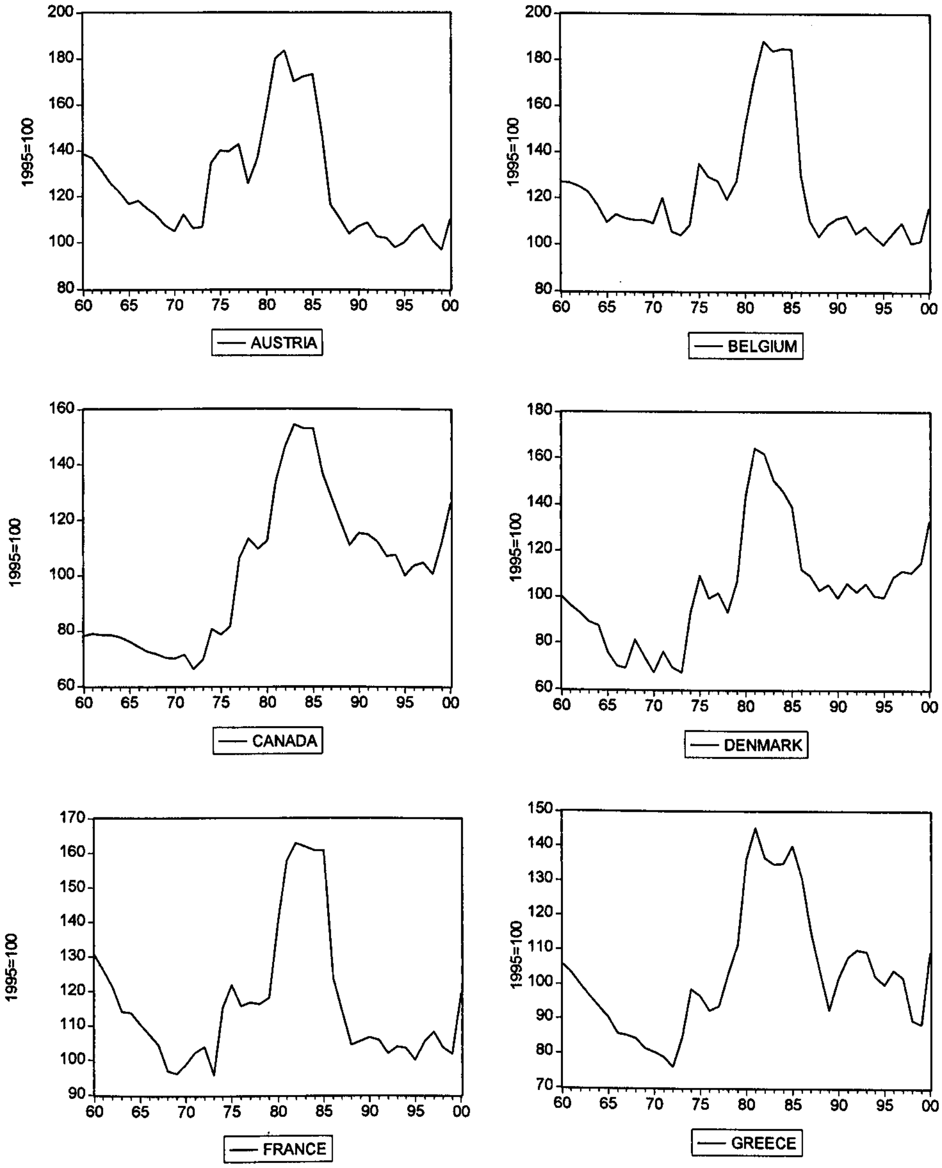
For Switzerland: the energy price decreased with some fluctuation up to 1974, and then it fluctuated remarkably during the period 1974 to 1981. Over the period 1982 to 1988 it dropped continuously before it flattened during 1990s.

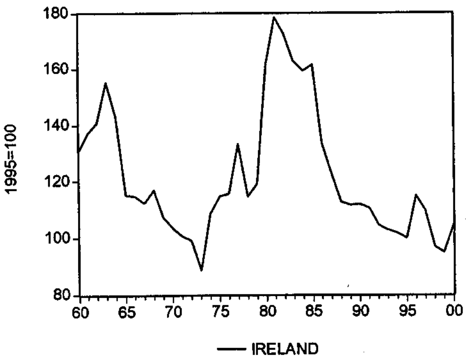
For the UK: the energy price decreased over the period 1960 to 1973 with some fluctuations. Then it increased rapidly with some variability up to 1983, whereas for the rest of the period it diminished continuously reaching its minimum in 1999 before a slight increase in 2000.

For the USA: the energy price diminished up to 1973, then it started to increase rapidly over the period 1974 to 1982. Then for the rest of the period it declined with some fluctuations before it achieved an increase in 1999 and 2000.

To sum up, the trend of the real energy price is very similar for most of the countries in the sample. For Austria, Belgium, Canada, Denmark, France, Greece, Italy, Japan, Portugal, Spain, Sweden, the UK, and the USA, the price decreases over the period 1960 to 1973, generally increases during the period 1974 to the mid 1980s following the two oil crises followed by a general fall in the price again before rising slightly towards the end of the period. The two countries with slightly different trends are Ireland and Norway. For Ireland the real energy price increased up to mid 1960s and then followed the general trend of the countries described above, whereas for Norway the real energy price trend during the 1960s is similar to the majority of the OECD countries above but thereafter generally increased up to 1980 before it dropped during 1980s, but contrary to other OECD countries the energy price continued increasing up to the end of the period.

Figure: (2.4) Energy Price Index Trends in OECD Countries over the Period 1960-2000 (1995=100)

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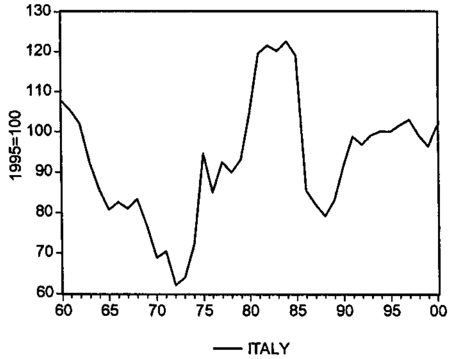
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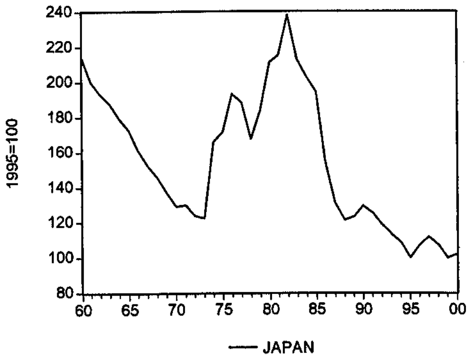
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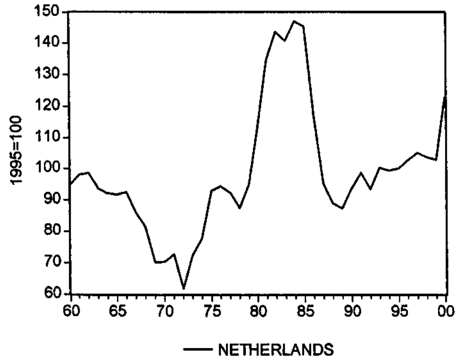
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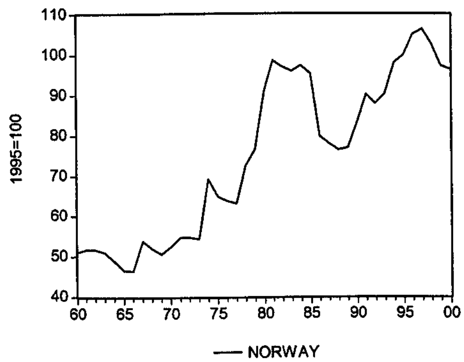
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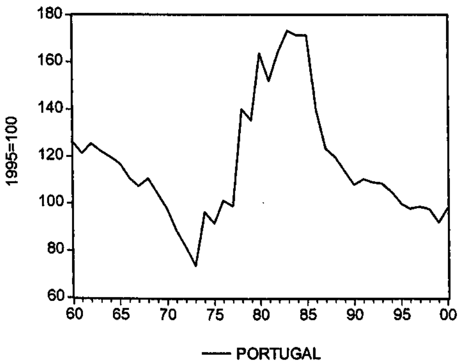
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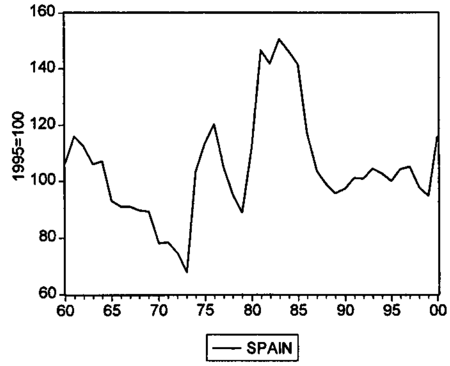
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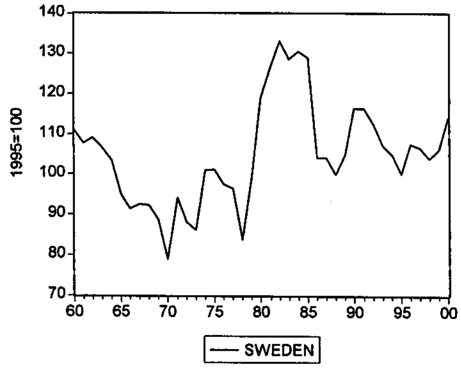
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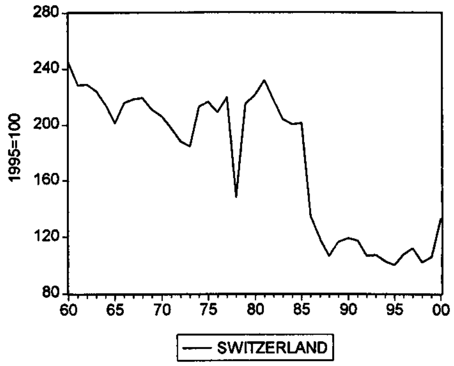
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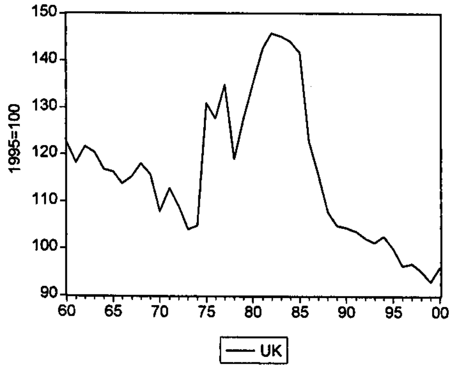
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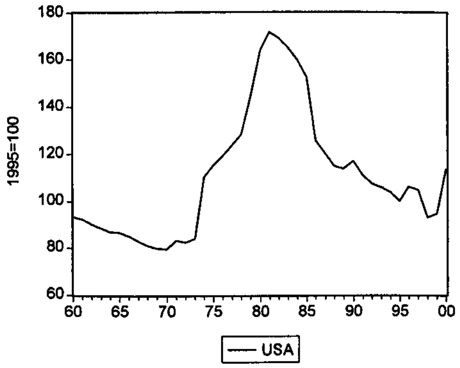
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80
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1995=100
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USA

2.3.2.3 GDP Trends

1978-1998

For Australia: GDP increased steadily over the period, reaching its peak of US$ 380 billion in 2000. However, it dropped slightly during the periods of 1981 to 1983 and 1989 to 1991.

For Finland: GDP increased constantly up to 1989, then it dropped sharply over the period 1989 to 1993 before rising steadily up to the end of the period, reaching its peak at US$150 billion in 1998.

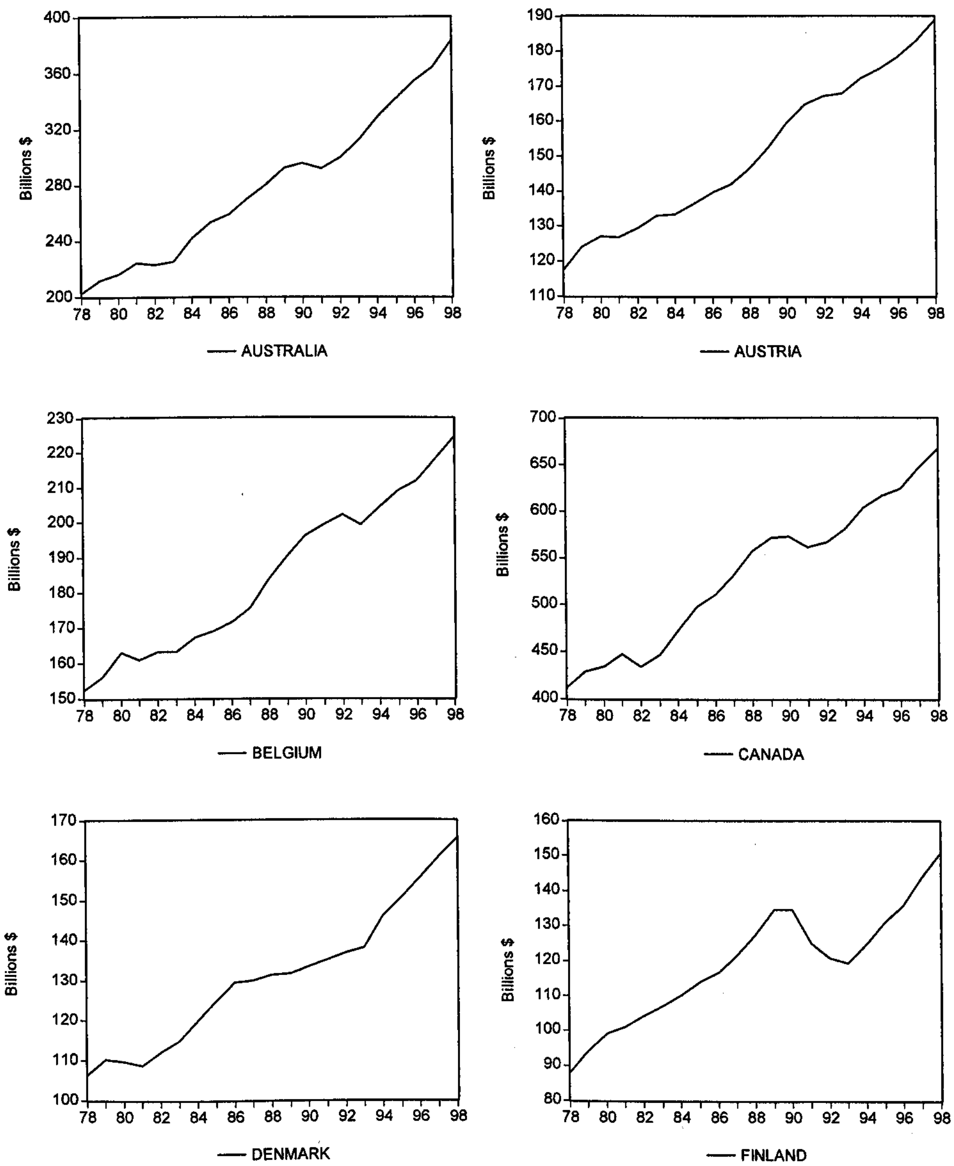
For Korea: GDP increased at a rapid rate up to 1997 with little variation, reaching its peak at US$ 400 billion in 1996. It decreased between 1997 and 1998.

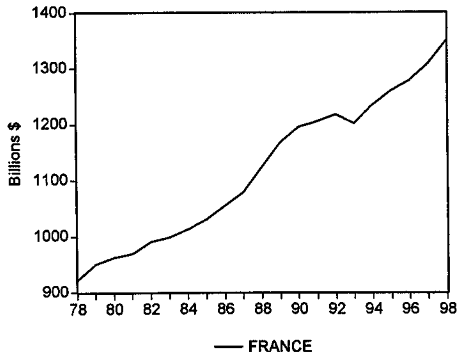
For Luxembourg: GDP increased rapidly over the whole period reaching its peak at approximately US$ 16 billion in 1998.

For Mexico: GDP increased steadily up to 1981, then it continued increasing but with some fluctuations up to 1994, followed by a drop between 1994 and 1995. Then it increased reaching its peak at US$ 330 billion in 1998.

For New Zealand: from 1978 to 1992 GDP increased moderately. Then it rose steadily up to 1997, reaching its peak at approximately US$ 52 billion before a minor drop between 1997 and 1998.

Figure: (2.5) GDP Trends in OECD Countries over the Period 1978-1998 (US$ Billion in 1995 prices)

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1000
900
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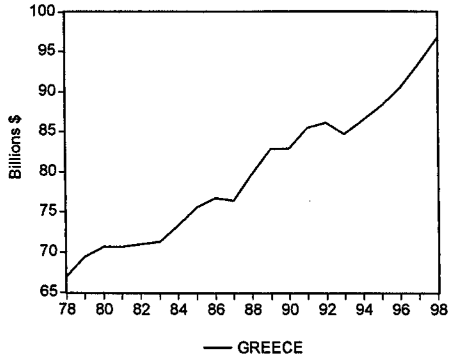
FRANCE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75
70
65
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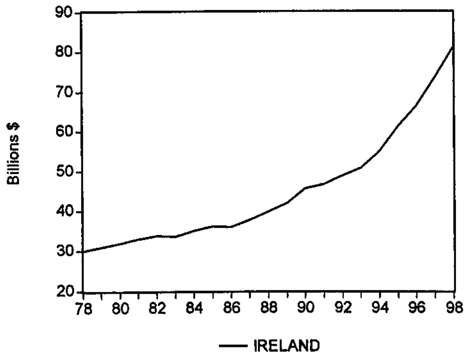
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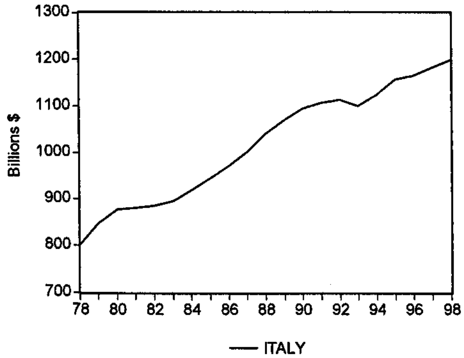
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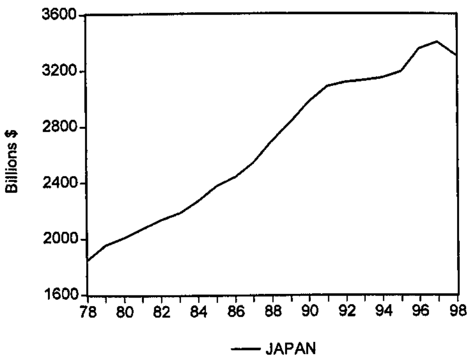
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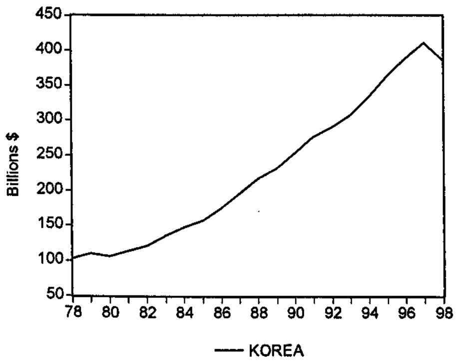
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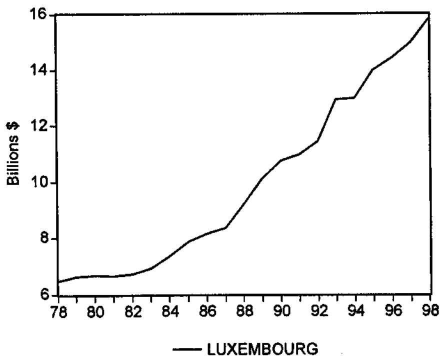
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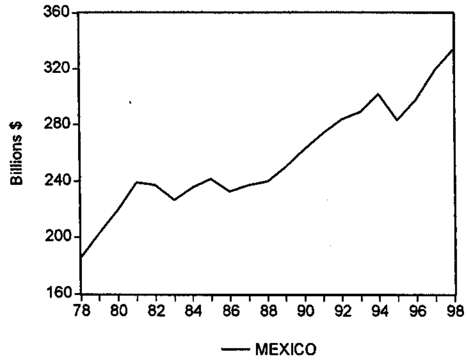
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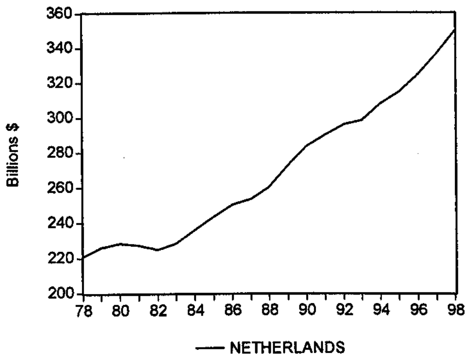
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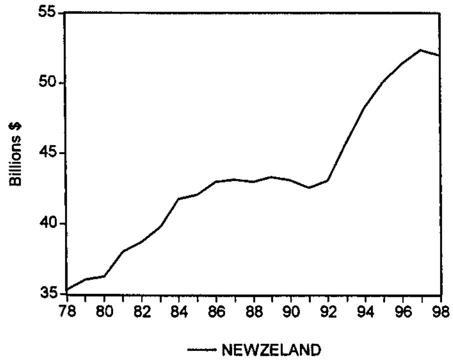
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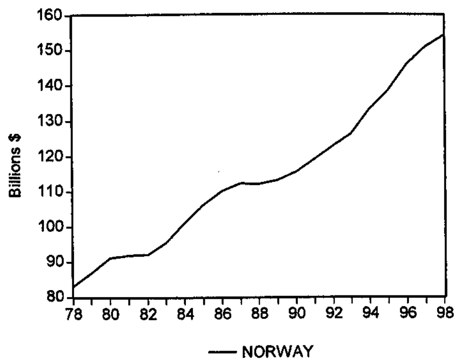
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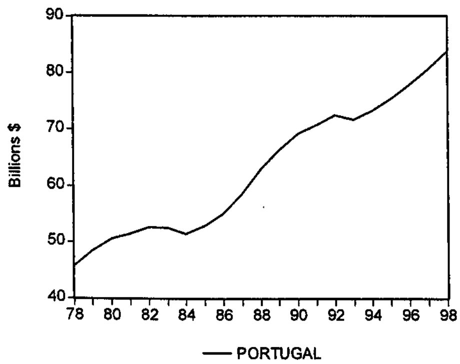
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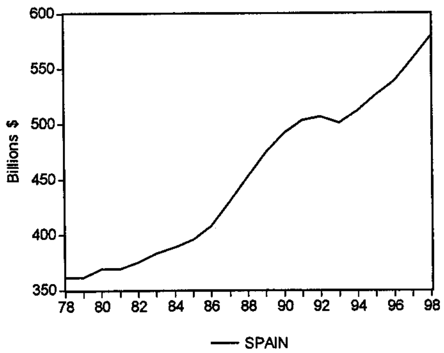
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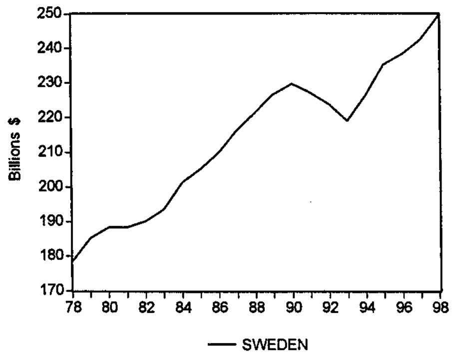
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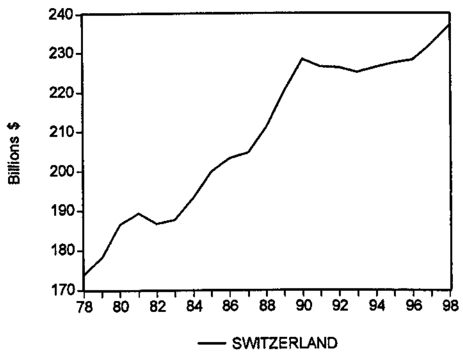
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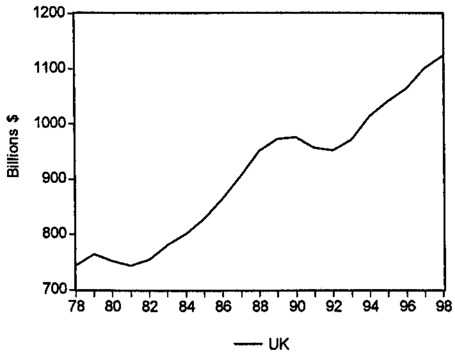
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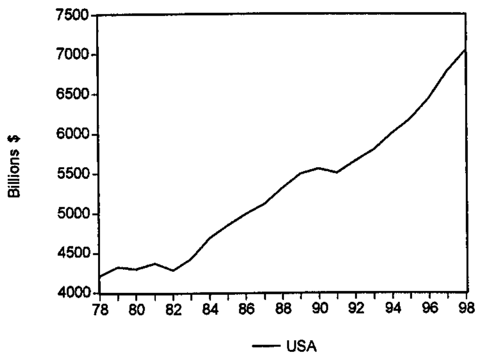
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5000
4500
4000
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USA

1960-2000

For Austria: GDP increased up to 1974 before it decreased slightly over the period 1974 to 1975. Then it resumed increasing with some fluctuations over the rest of the period, reaching its peak of US$ 260 billion at the end of the period. It has increased more than tripled compared to 1960.

For Belgium: GDP increased rapidly up to 1975 before falling in this year. Then it increased rapidly up to the end of the period, reaching its peak of US$ 320 billion in 2000.

For Canada: GDP increased consistently before it dropped in 1984. Then it continued increasing apart from a decline during the period 1990 to 1991. It reached a peak of US$700 billion at the end of the period.

For Denmark: GDP generally increased over the period, reaching its peak of US$ 210 at the end of the period.

For France: GDP increased up to 1974 before it decreased over the period 1974 to 1975. Then it resumed increasing with some fluctuations up to the end of the period, reaching its peak of US$ 1700 billion in 2000.

For Greece: GDP increased rapidly up to 1973 before it dropped during the period 1974 to 1975. Then it fluctuated on an upward trend up to 1989 before it increased steadily up to the end of the period, reaching its peak of US$ 140 billion in 2000.

For Ireland: GDP increased steadily up to 1991 before the trend mostly flattened during the period 1991 to 1994. Then it increased sharply up to the end of the period, reaching its peak of US$ 110 billion in 2000.

For Italy: GDP increased up to 1974 before it dropped in 1975. Then it increased again during the period 1976 to 1990. Then it increased continuously up to the end of the period, reaching its peak of US$ 1200 billion in 2000.

For Japan: GDP increased up to 1973 before dropped in 1974. Then it increased on an upward trend up to 1990 before it fluctuated on an upward trend until the end of the period, reaching its peak of US$ 5800 billions.

For the Netherlands: GDP increased up to 1973 before it dropped in 1974, then it dropped during the period 1979 to 1983. During the rest of the period it fluctuated reaching its peak of US$500 billion in 2000.

For Norway: GDP increased steadily up to 1978, then it has dropped during the period 1979 to 1982. For the rest of the period it generally increased, reaching its peak of US$ 170 billion.

For Portugal: GDP increased rapidly at the start of the period rapidly before it dropped in 1974. Then during the period 1975 to 1995 it fluctuated upwards before it increased steadily at the end of the 1990s, reaching its peak of US$ 130 billion in 2000.

For Spain: GDP increased rapidly at the start of the period before it dropped in 1974. Between 1975 and 1985, there was a relatively small rise before it increased steadily up to the end of the period, reaching its peak of US$ 700 billion in 2000.

For Sweden: GDP increased during the period 1960 to 1989 with some fluctuations. Then a sharp drop over the period 1989 to 1993 before it resumed increasing up to the end of the period. It reached its peak of US$ 280 billion in 2000.

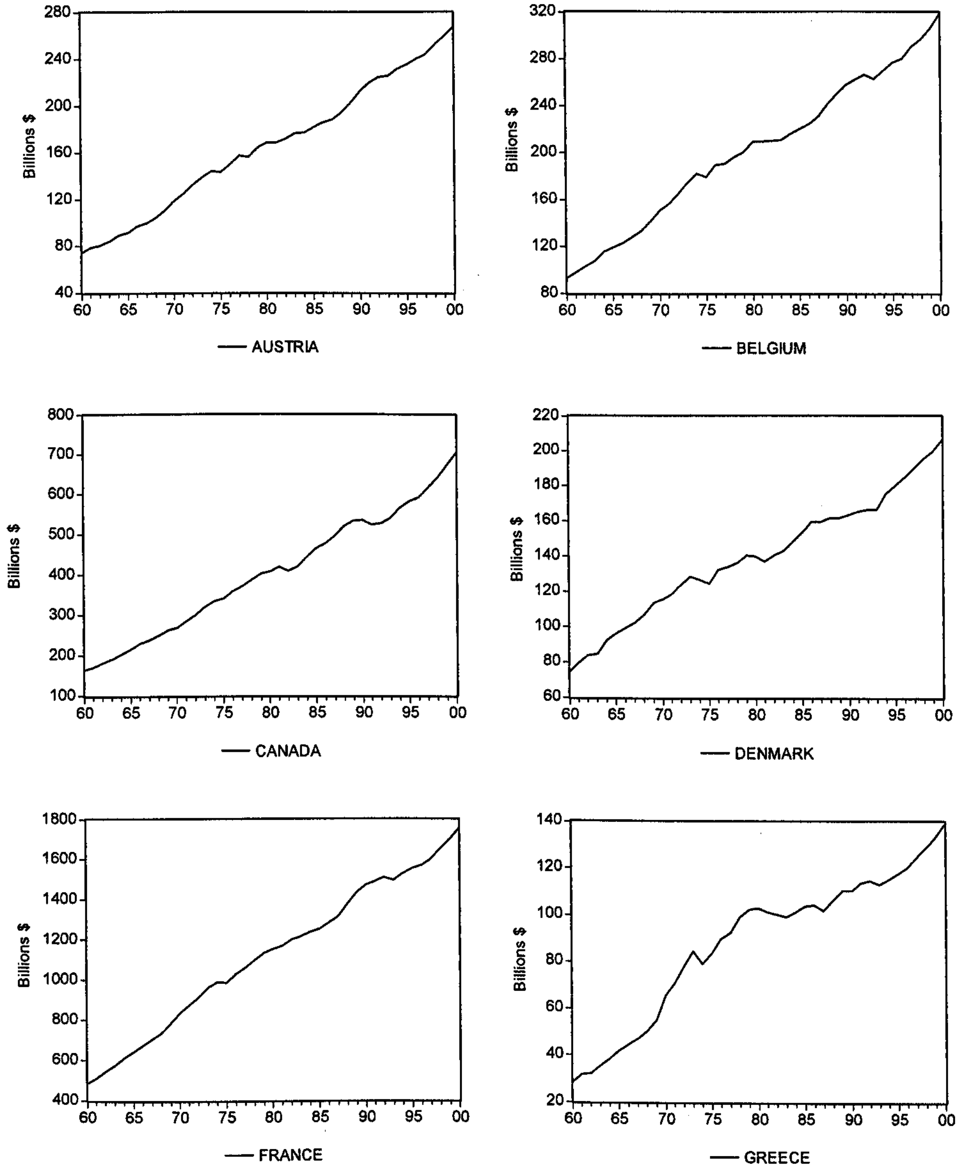
For Switzerland: GDP increased rapidly up to 1974 before it dropped during the period 1974 to 1977. Then it resumed increasing with some fluctuations up to 1990. For the rest of the period it continued increasing, reaching its peak of US$ 340 billion in 2000.

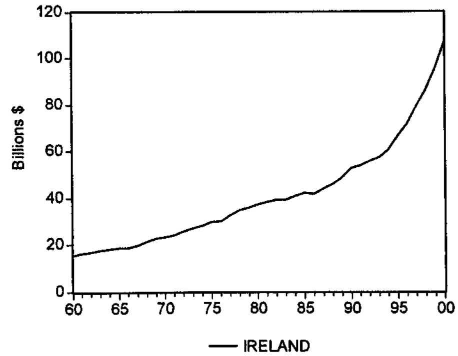
For the UK: GDP increased steadily up to 1973 before it decreased during the period 1973 to 1975. Then it resumed increasing with some fluctuations up to 1992. For the rest of the period it increased rapidly before reaching its peak of US$1300 billion in 2000.

For the USA: GDP increased rapidly up to 1973 before it decreased during the period 1973 to 1975. Then it continued increasing with some fluctuations up to 1992 before it increased steadily over the end of the period, reaching its peak of US$ 9000 billion in 2000.

In summary the trends of GDP for all the OECD countries in the sample are very similar; upward sloping but with some fluctuations after 1974.

Figure: (2.6) GDP Trends in OECD Countries over the Period 1960-2000 (US$ Billion in 1995 Price$)

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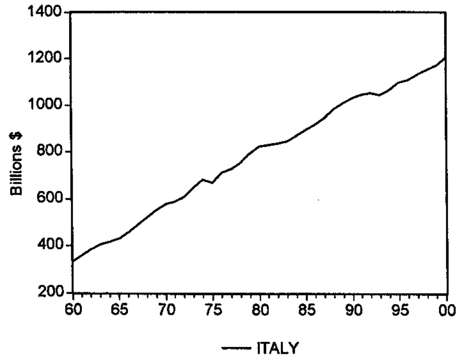
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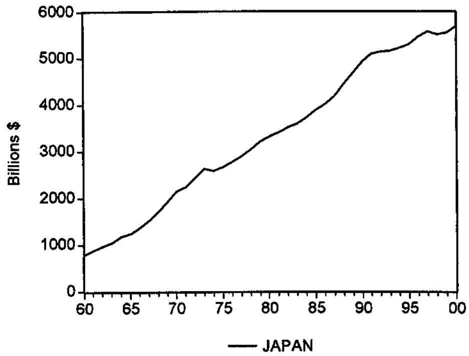
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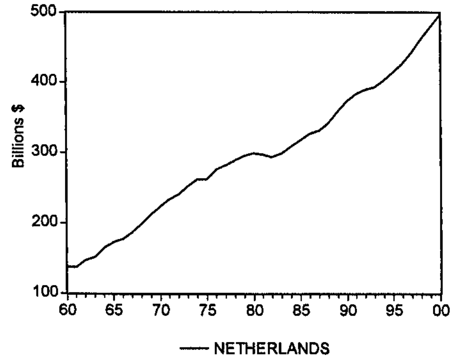
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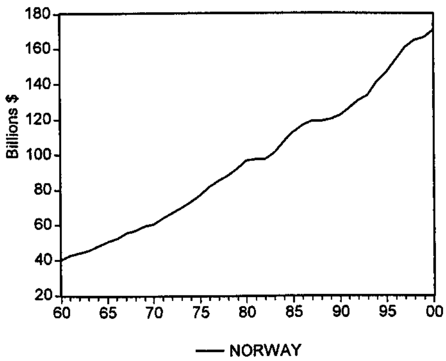
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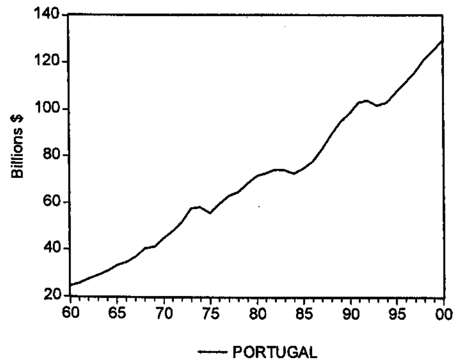
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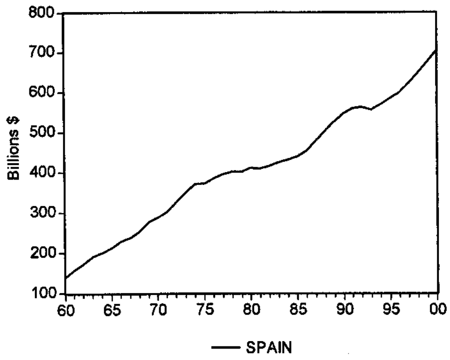

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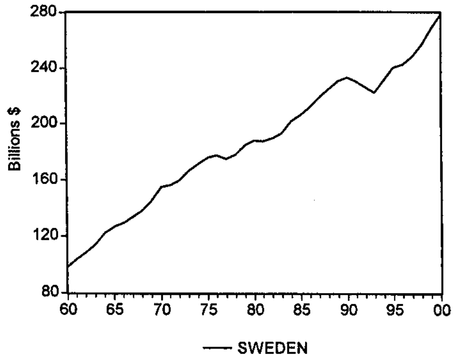

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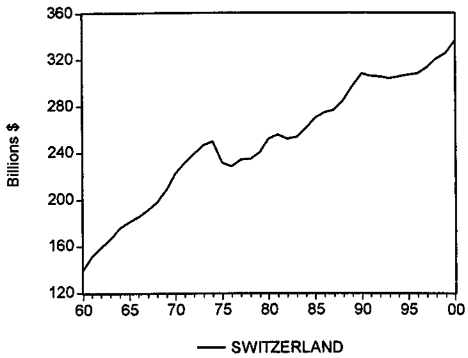

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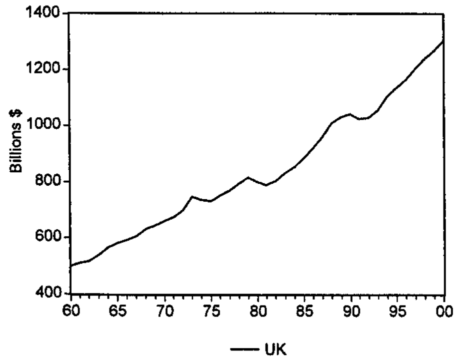

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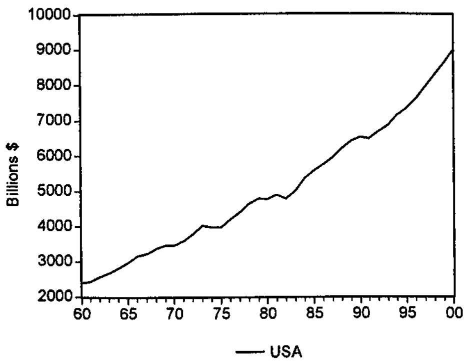

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USA

2.4 Energy Intensity Trends

Energy intensity is a useful way of expressing the relationship between energy consumption and economic activity. In year t, the aggregate energy intensity is simply the ratio of total energy consumption (E) to gross domestic product (Y), the lower the ratio, the less energy intensive the economy (Sun 2002).

$$I_t = E_t / Y_t$$

Where I_t is energy intensity. E_t is the actual energy consumption in mtoe. Y_t is the actual Gross Domestic product (US$ billion) in 1995 prices.

Furthermore, Sun (2002) argues that "energy intensity reflects the economic structure, fuel mix and the level of technology in a country" (p. 631). It can be argued that the change in energy intensity over time is related to different factors, such as the consumer preference for less energy intensive products and the emergence of new improved materials and better technology that reduces the energy embodied in finished goods.[10]

In this section energy intensity is calculated for each country using Data Set 17B and is graphically illustrated in Figure (2.7).

For Austria: energy intensity declined between 1960 and 1961, then it reached its peak in 1963. It dropped continuously up to 2000 with some fluctuations. There were

[10] These factors and others are proxied in energy demand function via a stochastic trend using the Structural Time Series framework in Chapter 4.

two sharp drops were during the periods 1973 to 1977 and 1979 to 1983. The use of energy dropped from 125 mtoe/ US$ billion in 1963 to 91 mtoe/US$ billion in 2000.

For Belgium: energy intensity dropped between 1960 and 1961 then it shot upwards reaching its peak in 1970. It declined dramatically over the period 1970 to 1983 before generally flattening up to 2000. The use of energy declined from 200 mtoe/US$ billion in 1970 to 135 mtoe/US$ billion in 2000.

For Canada: energy intensity dropped over the period 1960 to 1965 followed by an increase up to 1971. It decreased fairly steadily up to 2000. Energy use declined tremendously form 420 mtoe/US$ billion in 1971 to 270 mtoe/US$ billion in 2000.

For Denmark: energy intensity rose steadily at the start of the period, reaching its peak in 1970. It then turned downwards up to 2000 with major drops over the periods 1970 to 1973 and 1979 to 1982. Energy use fell from 140 mtoe/US$ billion in 1970 to 73 mtoe/US$ billion in 2000.

For France: energy intensity fell between 1960 and 1961, but then generally rose over the period 1961 to 1973, followed by a continuous decline with sharp reductions during the two oil hikes before energy intensity trend flattened over the period 1990 to 2000. Energy use fell from 145 mtoe/US$ billion in 1973 to 95 mtoe/US$ billion in 2000.

For Greece: energy intensity increased considerably over the period 1960 to 2000 with some minor variations. Energy use increased from 72 mtoe/US$ billion in 1960 to 145 mtoe/US$ billion in 1998 before it fell between 1998 and 2000.

For Ireland: energy intensity rose continuously at the start of the period, reaching its peak in 1970. Then it decreased up to 2000 with some fluctuations. Energy use was reduced from 225 mtoe/US$ billion in 1970 to 105 mtoe/US$ billion in 2000.

For Italy: energy intensity rose steadily over the period 1960 to 1971. Then it dropped dramatically up to 1982 before energy intensity trend flattened over the period 1983 to 2000. Energy use dropped from 155 mtoe/US$ billion in 1973 to 105 mtoe/US$ billion in 2000.

For Japan: energy intensity increased up to 1970 with some fluctuations. Then it dropped continuously from the mid 1970s to 1984 before it began to decline moderately. Energy use decreased from 90 mtoe/US$ billion in 1970 to 60 mtoe/US$ billion in 1990 before it started to increase slightly in the last ten years of the period.

For the Netherlands: energy intensity increased almost steadily over the period 1960 to 1973 followed by a continuous decrease up to 2000. Energy use declined from 190 mtoe/US$ billion in 1973 to 125 mtoe/US$ billion in 2000.

For Norway: energy intensity decreased between 1960 and 1961 followed by an increase up to 1970. After 1973 it dropped continuously up to 2000. Energy use declined from 210 mtoe/ US$ billion in 1973 to 115 mtoe/US$ billion in 2000.

For Portugal: energy use increased between 1960 and 1961 followed by some drops, reaching its minimum in 1968. Then it shot upwards continuously up to 2000 with some variations. Energy use increased from 105 mtoe/US$ billion in 1968 to 150 mtoe/US$ billion in 2000.

For Spain: energy intensity dropped between 1960 and 1965 followed by a tremendous increase up to 1979. Then it dropped steadily during the period 1979 to 1987, after which it was followed by an increase with minor variations up to 2000. Energy use increased from 90 mtoe/US$ billion in 1960 to 125 mtoe/US$ billion in 2000.

For Sweden: energy intensity decreased between 1960 and 1961. Then it increased, reaching its peak in 1969 followed by a continuous decrease with some variations up to 2000. Energy use dropped from 215 mtoe/US$ billion in 1969 to 125 mtoe/US$ billion in 2000.

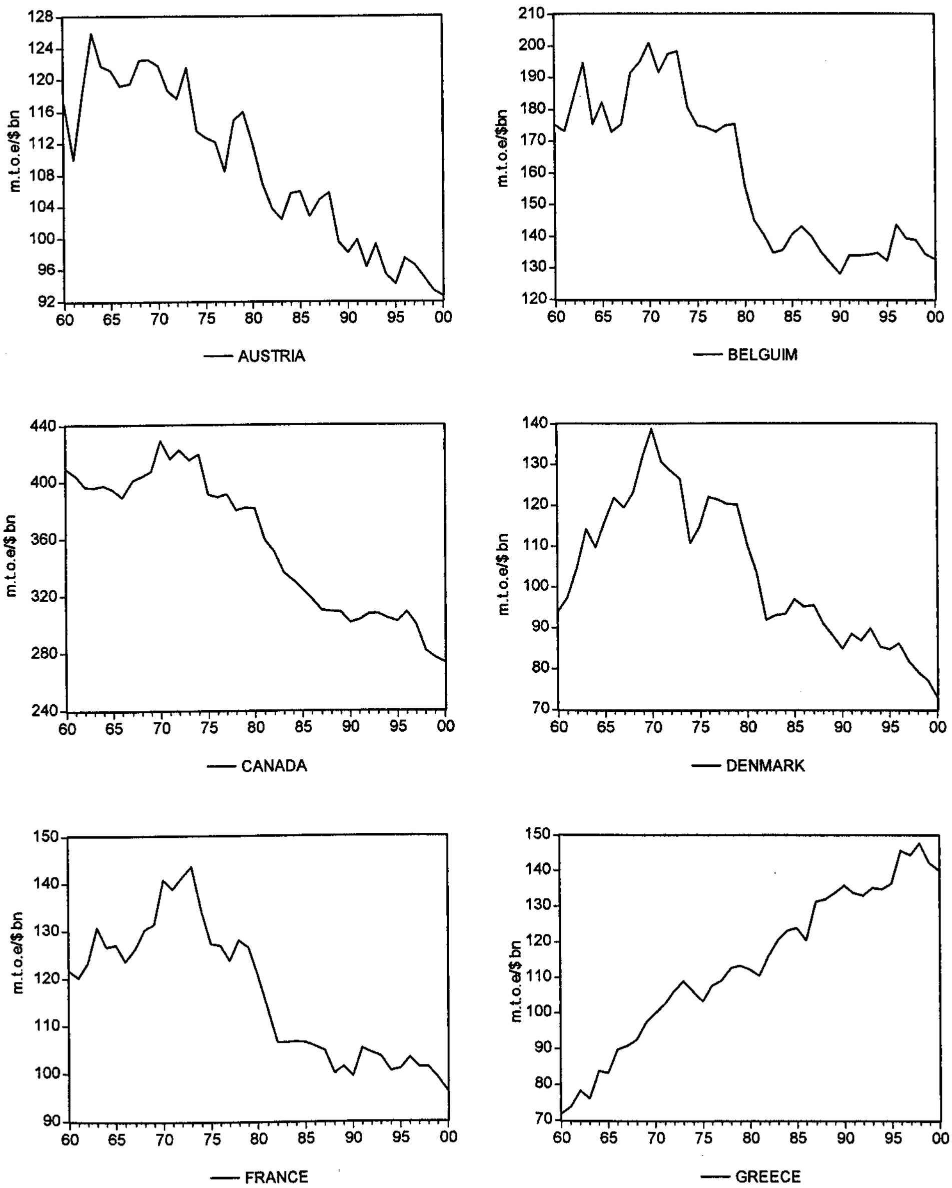
For Switzerland: energy intensity diminished between 1960 and 1961 followed by a dramatic increase up until 1973. It then reached its peak in 1978. Then it dropped sharply in the periods 1979 to 1983 and 1985 to 1989 before it fluctuated until the end of the period. Energy use increased nearly from 52 mtoe/US$ billion in 1960 to 72 mtoe/US$ billion in 1978 before it dropped to 64 mtoe/US$ billion in 2000.

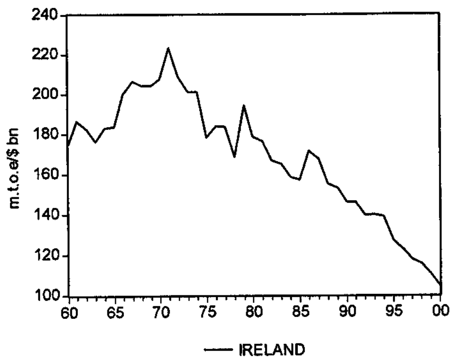
For the UK: energy intensity generally fell over the entire period, with energy use falling from 225 mtoe/US$ billion in 1960 to 125 mtoe/US$ billion in 2000.

For the USA: energy intensity declined over the period 1960 to 1965, followed by an increase over the late 1960s, reaching its peak in 1970. Then it decreased continuously up to 2000. Energy use dropped from 340 mtoe/US$ billion in 1960 to 170 mtoe/US$ billion in 2000.

To sum up, energy intensity in Greece, Spain, Switzerland and Portugal shows a steady increase during the period 1960 to 2000. The USA energy intensity has fallen considerably since the mid 1970s although it started from a very high level. The UK energy intensity trend also shows a decline over the whole period, although the UK economy started with a lower energy intensity ratio. A general feature is the energy intensity trends fell dramatically over the period (1960-2000) for most of the countries after reaching a peak in the mid 1970s. However, there are differences in the energy use per unit of output across the countries. It can be seen that Canada and the USA were the most energy intensive economies amongst all of the countries. Moreover, during the period 1990 to 2000 most OECD countries showed less fluctuation in energy intensity.

Figure (2.7) Energy Intensity Trends in OECD Countries 1960-2000 (mtoe/US$ Billion)

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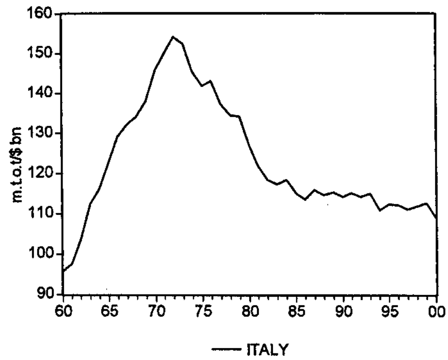
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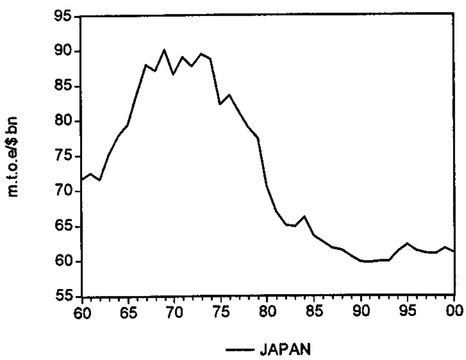
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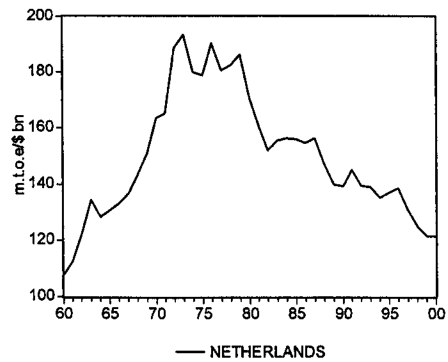
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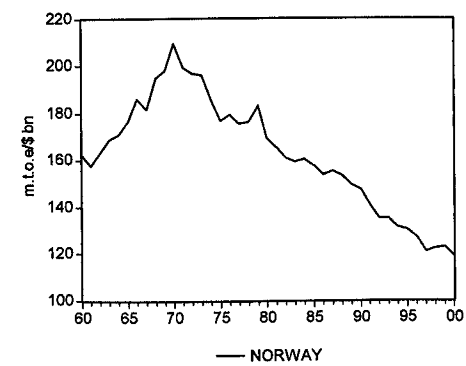
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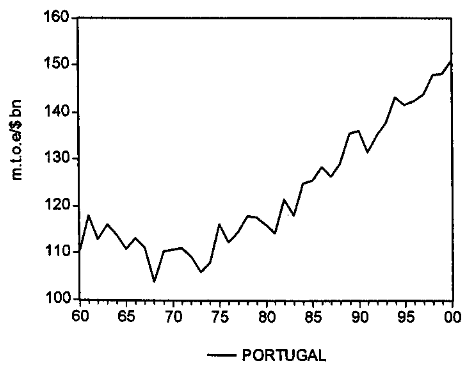
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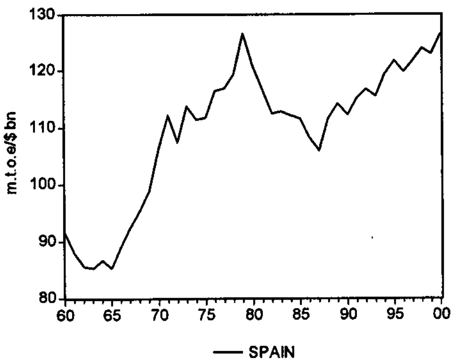
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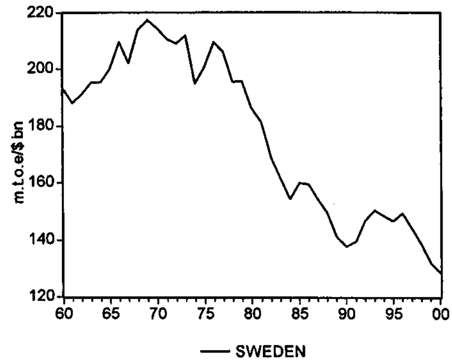
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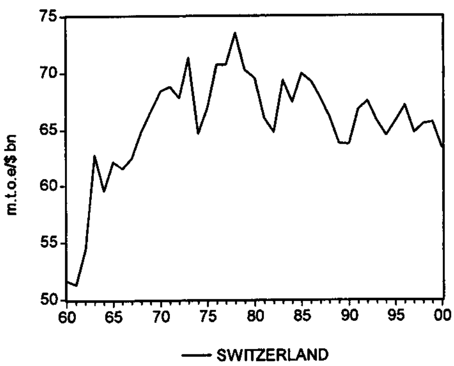
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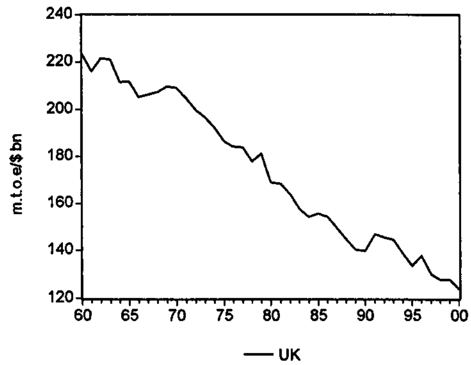
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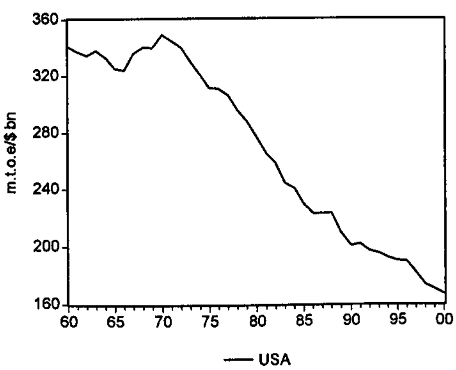
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2.5 Summary and Conclusion

This chapter has outlined the data sources and how the two data sets used in this thesis have been constructed. It has described the general characteristics of the variables used in the energy demand analysis later in the thesis. The descriptive statistics in a panel data context show that there are variations between and within countries. This is important since the panel approach for estimating aggregate energy demand parameters (used in Chapter 3) requires the presence of such types of variation.

Furthermore, a brief analysis and discussion of the evolving energy intensities of the 17 countries in Data Set 17B has been conducted. This shows a dramatic fall in energy intensity trends (for the majority of countries) but with some variations across the countries in the data set. This highlights the importance of correctly specifying and estimating the energy demand price and income elasticities as well as the way technical progress (or an improvement in energy efficiency) is incorporated in such models. This is an issue that is discussed in some depth later in Chapter 4.

Chapter 3

Panel Data Estimation

3.1 Introduction

The term panel data[1] refers to the pooling of observations on individual units (country, industry, and region)[2] over numerous time periods. Therefore, it utilises both the time series and cross-sectional variation in the data. The availability of data sources for a number of countries such as the OECD and the successive increase in the numbers of OECD countries enhances the potential for empirical research. However, the number of existing studies estimating aggregate energy demand parameters for OECD countries is limited (see Chapter 1). This implies the need for a study using panel data techniques to estimate energy demand parameters.

In part, the motivation for using panel data lies in the small number of time series observations that are often available when considering pure time series techniques. Pooling the data identifies aggregate relationships for a group of countries,[3] with the obtained relationship implying that these relationships are similar for all countries. However, it could be argued that this relationship is not appropriate because the average estimate for all countries may not be the ideal method for explaining what is happening in a particular country.

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[1] Other terms used to describe panel data are longitudinal, space-time data and repeated measure data.
[2] Given the focus of this thesis the individual units will normally be referred to as countries hereafter.
[3] As an average of the entire sample set.

Furthermore, panel data techniques are employed to benefit from the added variability of the data, but there is a question about the appropriateness of the pooling methods, in particular about the generality of the implied average relationship for a group of countries. Moreover, neither the underlying causal relationship nor the adjustment path to long run equilibrium is likely to be the same for all countries.[4] The aggregate energy consumption relationship with respect to the main economic variables: income and price may differ among countries, in addition to the technical relationship between energy consumption and stock of appliances. It is therefore necessary to investigate the effect of the presence of heterogeneity in the panel estimation and to model the effect of technical progress in energy demand function. Thus this chapter utilises various panel estimation techniques ranging from homogenous panel estimators to heterogeneous estimators with the aim of obtaining reliable and consistent estimates of income and price elasticities of aggregate energy demand across the 23 OECD countries incorporated in Data Set 23A.

It is worth noting that panel data models vary in the degree of parsimony. The pooled OLS is very parsimonious, but it ignores the cross section differences. The fixed effects model is less parsimonious compared to the pooled OLS. Whereas the random effects model is the most parsimonious, hence it considers the influence of the omitted variables as a part of the error term, Balestra (1996).

Furthermore, it is worth mentioning that the dynamic panel data specification usually leads to correlation between the lagged dependent variable and the error term, which, according to Baltagi (2000) renders the pooled OLS, fixed effects and random effects

[4] The issue of causality in panel data analysis is a potentially fertile research area.

estimator biased and inconsistent. Moreover, the possible endogeneity of the right-hand regressors, causes inconsistency of the panel estimators' thus two stage least squares may be required to obtain the consistent estimators, see Baltagi (2001). In addition, for energy demand it might sometimes be necessary to investigate the possible endogeneity of the energy demand drivers in order to investigate whether the price and income variables need to be instrumented. For this study, it assumed that the aggregate energy price is pre-determined since although local taxes and practices differ the aggregate energy price is primarily driven by international markets. It was also assumed that income is not endogenous on the grounds that the data set involves the most developed countries and on the whole it is unlikely that energy (the production/consumption is a relatively small proportion of total income) will affect income. That said, an attempt was made to instrument the lagged dependent variable and the key variables for energy demand, but the results showed that that the instruments variables were not informative.

This chapter makes three main contributions to the energy demand literature.

Firstly, it investigates a wide variety of panel data estimators, ranging from the homogenous estimator to the heterogeneous estimator and a shrinkage estimator.

Secondly, it covers a large number of OECD countries including the main consumers of energy in the developed world. It is believed that this is the first attempt to use panel data techniques to estimate aggregate energy demand relationships across such a large number of OECD countries.

Thirdly, it addresses the idea of an underlying trend as a proxy for technical progress that has been ignored in the panel data studies.

The structure of this chapter is as follows. The next section presents the advantages and disadvantages of panel data techniques. Section 3.3 discusses the previous aggregate OECD energy demand studies. Section 3.4 describes the homogeneous models and estimators utilised. Section 3.5 describes the results from the homogeneous models. Section 3.6 describes the heterogeneous estimators. Section 3.7 presents the results from the heterogeneous estimators. Section 3.8 provides a comparison of the heterogeneous and homogeneous estimators. Section 3.9 provides a summary and conclusion.

3.2 Advantages and Disadvantages of Panel Techniques

The literature on panel data estimation is voluminous. For example, Chamberlain (1984) and Hsaio (1985, 1986) discuss the major advantages and limitations of panel data and the specification of panel data models. Maddala (1987) introduces the debate between using fixed effects vs. random effects models. Baltagi and Raj (1992) survey some recent developments in panel data analysis. Furthermore, there are also several papers on the theory and application of panel data in Matyas and Sevestre (1995).

The interest in panel data estimation reflects the fact that it offers researchers more possibilities than either pure time series or cross-sectional estimation. According to Hsaio (1986) and Baltagi (1995), panel data models allow inter-country differences to be identified from intra-country differences and controlling for unobservable variables that may vary across the countries, whereas in time series and cross section estimation these effects are absorbed into the unobservable components (error term) of the model, which may cause statistical difficulties. In panel data estimation, on the other hand, one can differentiate the country-specific effects from random unobserved heterogeneity. Furthermore, panel data provides more variability, less collinearity among the variables and more degrees of freedom.

Baltagi and Griffin (1983) argue that "the theoretical justification given for pooling rests on the finding that the estimators from a pooled model will be in general be more efficient than those based on individual time series. Questions of bias do not arise, as both individual time series and pooled cross section/ time series model yield unbiased estimators" (p. 117).

Pooling as an idea implies that all the countries are similar, but such an idea is unappealing to those who consider the structural differences such as - the institutions and social conditions, energy policies, pricing policies, and the availability and security of energy supply are causes rather than effects. These are important issues when modelling the energy demand. However, despite these differences, Houthakker (1965) argues that "structural differences among countries can to a large extent be taken care of by randomly distributed error terms and similar devices, provided the number of the countries is not too small. In fact there is no reason to postulate that differences among countries are of a more fundamental type than differences among aggregates for the same country" (p. 277).

In the context of the energy demand literature, panel techniques have not been used as intensively as time series estimation techniques. There are some studies which have estimated energy demand parameters for a group of OECD countries using aggregate time series models: see for instance, Beenstock and Willcocks (1981), Kouris (1983), Welsch (1989) and Jones (1994). These studies do not exploit the advantages of panel data since the data was aggregated in a single time series while the panel data structure consists of a number of equations equal to the number of cross sections. In addition, the structure of the error term in panel data models differs from the time series models in that the former consists of unobservable individual and /or time specific effects as well as remainder disturbances (Baltagi, 2001).

Most importantly, Griffin (1979) argues that the adoption of panel data techniques is required, given that the variation in energy prices in time series data tends to be small and/or there are a small number of observations. He argues that a "time series ending in 1973 or even 1977 is not long enough to elicit the full effect" (p. 33). However, it could be argued that using a period from the early 1970s until the present day means that the time series variation in energy prices has changed significantly, thereby making time series techniques more appropriate.

Furthermore, researchers' interests lay in the fact that inter-country (between countries) and intra-country (within a country) price and income variation provide more information than the aggregate time series, this can be utilised through adding the cross-section dimension to the time dimension. In the energy demand context, Griffin (1991) argues "as energy consumption dropped sharply in the mid 1980s, researchers recognised that the large price elasticities implied by the panel data sets provided better forecasts" (p. 191). Therefore, panel data provides energy demand modellers with a set of data that exhibits more variations; which is necessary for modelling.

The panel data literature generally splits into two types of estimators: homogeneous and heterogeneous estimators. In empirical work, Baltagi and Griffin (1997) compare the forecast performance of homogeneous and heterogeneous estimators obtained from dynamic demand equations for gasoline in OECD countries. They show that homogeneous estimators outperform their heterogeneous counterparts for out of sample forecasts. Another study by Baltagi et al (2002) uses the prediction performance criteria to compare forecast performances for homogenous, heterogeneous and shrinkage estimators for US electricity and natural gas consumption. Again the results show homogeneous estimators perform better than heterogeneous and shrinkage estimators.

Kouris (1983) suggests that the time span is crucial for obtaining elasticities as statistical theory suggests that desirable asymptotic properties of the estimate need a long time period. Kouris supports Beenstock and Willcocks (1981) in pooling data for a group of OECD countries, since he argues that "the only viable way to pick meaningful price elasticities from pre-1973 is to pool time series from various cross-sections'' (p. 209).

In spite of the advantages of panel data techniques, a problem may arise from the fundamental assumption underlying homogeneous models, that of the homogeneity of the slope parameters. In the context of the energy demand literature Hunt and Lynk (1992) argue that "the pooled time series cross-section model imposes the restriction of homogenous values. This is highly questionable given that industrial sectors vary in terms of capital vintages and energy using ratios" (p. 144). Moreover, in the same way, E-GDP ratios vary across OECD countries, implying that the assumption of the homogeneous slopes needs to be investigated. Maddala (1991) suggests "a preliminary test of significance to test the equality of the coefficients across the cross-section units, and decide not to pool if this hypothesis is rejected and to pool if the hypothesis is not rejected" (p. 255). More recently, Maddala et al (1997) argued against imposing homogeneity stating that "the homogeneity of the slope coefficients is often an unreasonable assumption, and one can allow for cross-sectional heterogeneity and/or heterogeneity over time" (p. 90). It is worth mentioning that this thesis takes into account the heterogeneity over the countries, whereas the heterogeneity over time is a different concept as Maddala and Hu (1995) state "heterogeneity over time is a matter of technical change and could fruitfully be handled by a model slowly changing parameters, or switching regressions (which imply pooling over sub-periods)" (p. 307).

In a separate applied literature, Robertson and Symons (1992) question imposing the homogeneity of slopes in the estimation. They argue that "the (false) imposition of the equality constraint leads to mistaken description of the dynamics and the response of the parameters" (p. 176).

In the same way, Pesaran and Smith (1995) argue that "the average effects in a dynamic model where the slope coefficients differ over groups cannot be consistently estimated from a pooled regression" (p. 84). They suggest running individual regressions for each country and averaging the estimates, this estimator being called the Mean Group (MG) estimator. These individual regressions may be performed by using different estimation techniques, for instance, OLS or two stage least squares (2SLS).[5] However, Baltagi and Griffin (1997) conclude that average estimators capture the short run responses but they are not appropriate for long run forecasts. Moreover, they found pooled 2SLS estimators performed worse than their counterparts such as the traditional pooled OLS, within and Generalised Least Squares (GLS) estimators.

The main argument is about the dilemma of whether 'to pool or not to pool'. In order to answer such a question, a test for the homogeneity of the coefficients across the cross-section units such as the F test must be implemented before the pooling decision; and decide not to pool if this hypothesis is rejected and to pool if this hypothesis is not rejected. The appropriate significance level of the test has been argued in the literature, and a 50% significance level has been suggested (see Maddala (1991), this indicates an unusual level for economists to use.

Furthermore, researchers using panel data techniques need to specify the method of pooling, depending on the problem in hand. Most commonly in panel data analysis, either a fixed or random effect model is estimated. These models assume the slope coefficients do not vary across the cross sectional units, whereas they do account for heterogeneity in the intercept term.

Pesaran and Smith (1995) summarise four categories for identifying the average long run effect of exogenous variables on an endogenous variable. They are:

[5] Pesaran and Smith (1995) report the MG estimator based on the existence of cointegrating relations.

1- *Mean group estimator*: a separate estimation for each country and then averaging the estimated parameters across countries.

2- *Fixed or random effects*: the countries are pooled to form common slopes, but allowing for fixed or random effects on the intercepts of each country. There is a special case where common intercept is assumed e.g. a simple pooled estimator.

3- *Group average*: averages the data across countries for each period and an aggregate time series model run on the group means.

4. *Time average estimator*: The data is averaged over time and then estimates are found using a cross-country regression. This estimator is known as the between estimator in the panel literature (p. 81-88).[6]

This chapter applies a number of panel data estimators to energy demand models because the available literature (see below) on aggregate energy demand for OECD countries mostly lies under category 3 in the above listing, and also because some studies were undertaken when the OECD group only had 7 members. In response to the previous energy demand studies for the OECD, this chapter extends the estimation methods to include both traditional estimators (homogeneous) and heterogeneous estimators in order to compare the estimates that are obtained from energy demand function. That is:

(a) The traditional panel data estimators:

- Pooled Ordinary Least Square (POLS) estimator
- Fixed Effects (FE) estimator
- Random Effects (RE) estimator.

[6] The categories 2, 3 and 4 provide unbiased estimates for the average effect when the regressors are exogenous, but this does not extend to dynamic models including a lagged dependent variable. Therefore, this issue is considered in the heterogeneous panel estimator section in this chapter.

(b) The heterogeneous panel data estimators:

- Mean (MG) estimator

- Stein Rule (SR) estimator

- Random coefficients model.

3.3 Previous Aggregate OECD Energy Demand Studies

Before introducing these different methodologies, this section reviews the literature on aggregate energy demand studies for OECD countries (see Table (1-1). This literature, according to Pesaran and Smith's (1995) classification, falls into category 3, except the studies by Kouris (1976) and Nordhaus (1977), which fall into category 2. It is apparent within the cited studies that there is an absence of heterogeneous estimators of OECD aggregate energy demand. In addition, the issue of whether to, and how to, incorporate the effect of technical progress on energy demand consumption is generally ignored; this will also be explored in this chapter. Below there follow a review for the studies from categories 2 and 3.

Kouris (1976) estimates the parameters of an energy demand model for *EEC* countries (Italy, Netherlands, France, Denmark, Germany, Belgium and the UK) over the period 1955 to 1970 using a pooled time series -cross section model. The specified model is a static fixed effects model; the estimated income and price elasticities obtained were 0.840 and -0.768 respectively. Given a static model is utilised, these elasticities may be interpreted as long run elasticities.

Nordhaus (1977) estimates a fixed effects energy demand[7] function for a number of OECD countries: Belgium, France, Germany, Italy, the Netherlands, the UK and the USA over various sub-samples during the period 1959-1972. The reason put forward by Nordhaus for using the pooling technique is to reduce the chaos of the individual country results and to obtain more accurate estimates. For the sake of comparison, he estimates the energy demand function using two specifications, the geometric lag and the Almon lag. He argues that "the geometric lag and Almon lag complement each other, if their messages are strong and similar, then we can have some confidence in the results" (p. 250). The estimated long run income and price elasticities obtained from the fixed effects model are 0.79 and –0.85 respectively.[8]

Welsch (1989) suggests that the disparity of income and price elasticities across OECD countries motivates the use of group averages over the period 1970-1984. Among the five specifications estimated; the preferred model is a dynamic model with a lagged dependent variable and the time trend included, applied to eight OECD countries. The estimated long run price and income elasticities are –0.338 and 0.634 respectively. These elasticities are relatively low compared to single country estimates. Furthermore, Welsch suggests it may be inappropriate to impose a single model on all countries. In addition, he suggests that energy demand elasticities should be modelled in a 'country-by- country' framework.

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[7] Energy consumption, as considered by Nordhaus (1977), is net energy instead of gross energy consumption.

[8] The reported elasticities are obtained from Almon lags, while results from geometric lag are not reported.

The study by Beenstock and Willcocks (1981)[9] averages the data for a group of OECD countries over the period 1950 to 1978. An error correction model is specified to estimate the price and income elasticities. In contrast to Welsch (1989), they do not present single country regression results; however, the estimation period allows for a time series regression for each country.[10] The estimated long run income and price elasticities are 1.78 and -0.06 respectively.

Using the same data set as Beenstock and Willcocks, Kouris (1983)[11] estimates energy demand parameters for a group of OECD countries over the period 1950 to 1978 using a dynamic log linear equation with Koyck lags. The data for OECD countries are averaged for each period and an aggregate time series model is estimated. The estimated income elasticity is 0.70 whereas the long run price elasticity is -0.43.

Prosser (1985) estimates aggregate energy demand parameters for a group of OECD countries over the period 1960 to 1982. Four models are estimated, which are static, dynamic, Almon and Koyck lag. The Koyck model with the lag structure assumed to relate only to the price variable is the preferred model. The estimated long run income and price elasticities are 1.02 and -0.40 respectively.

The studies reviewed above show that aggregate energy demand for OECD countries in a panel data context appear less frequently than aggregate time series models in the energy demand literature. The exception is the studies by Kouris (1976) and Nordhaus

[9] The number of the countries is not reported.
[10] They do not provide any arguments for averaging the data over the groups.
[11] The number of the countries is not reported.

(1977) that utilised the simple panel models, namely the fixed effects model. The inclusion of the time trend as a proxy for technical efficiency is also absent from both studies, whereas the other studies estimate the aggregate time series models for OECD countries.

Given that the number of aggregate energy demand studies for OECD countries is relatively small, it is important to estimate income and price elasticities with different model specifications and different panel estimators ranging from homogeneous to heterogeneous, especially given that most of these panel estimators have never been applied to aggregate energy demand for OECD countries.

One issue that runs through the above literature (and elsewhere) either explicitly or implicitly is whether or not to include a time trend to proxy technical progress. It is useful therefore to expand on some of the arguments concerning this issue. According to Kouris (1983), the inclusion of a linear time trend would lead to the price elasticity being biased downwards and the income elasticity being biased upwards. Whereas Beenstock and Willcocks (1981) state that an inclusion of a time trend is better than ignoring it, but they admit it is not a satisfactory measure. Furthermore, Welsch (1989) argues that "given the diversity of results obtained for different countries, in particular with respect to the inclusion of a time trend, the question is whether there are models which describe energy demand of all countries in a uniform fashion. To examine this question the 40 models considered were fitted to pooled data of the eight countries" (p. 290). The results show that only one model is accepted, therefore, he concludes that it might be inappropriate to impose a single model for all countries. However, the two studies above include the effects of technical progress on aggregate energy demand for the OECD countries by estimating aggregate time series models, and there was a long debate about the inclusion of a deterministic time trend as proxy for technical progress in OECD energy demand models. This issue requires further investigation in the panel data context.

Consequently, this chapter addresses the appropriateness of incorporating the effect of technical progress on energy consumption in a panel data context and in both homogeneous and heterogeneous panel estimators. In addition, it attempts to explore both homogeneous and heterogeneous estimators using different model specifications.

3.4 Description of Homogeneous Models and Estimators

3.4.1 Homogeneous Model Specifications

Given that the parameters of an aggregate energy demand function for OECD countries has not been extensively estimated using panel data techniques (and in order to allow a comparison of the obtained results), this chapter specifies three dynamic pooled energy demand models: a Partial Adjustment (PA) model, an Almon (ALN) model and Autoregressive Distributed Lag (ADL) model. Each of these models is then associated with three panel estimators: the Pooled Ordinary Least Squares (POLS) estimator, the Fixed Effect (FE) estimator and the Random Effect (RE) estimator. Furthermore each set of models is estimated with and without a time trend to proxy technical progress.

The homogeneous models estimated below are classified as follows:

Specification I) PA (estimated by POLS, FE and RE)

Specification II) ALN (estimated by POLS, FE and RE)

Specification III) ADL (estimated by POLS, FE and RE)

Furthermore, given the discussion above about the inclusion of a time trend, there are two versions of specifications I to III, the first *without* a time trend (denoted by A) and the second *with* a time trend as a proxy for technical progress (denoted by B).

The underlying assumption of a homogeneous panel model is that the parameters are the same for all countries and the heterogeneity is captured through an intercept in either a fixed or random fashion. This assumption is highly questionable (see section 3.6).

The discussion below gives different model specifications and types of estimator used for the analysis in this chapter. The definitions of the variables are defined in Chapter 2 except T, which represents a linear time trend.

Model I: PA Model

The basic specification of the PA model is as follows:

$$\lambda(L)LE_{it} = \alpha_i + \delta LP_{it} + \rho LY_{it} + \omega_{it} \qquad i = 1, \ldots, 23; t = 1, \ldots, 21. \qquad \text{(IA)}$$

$$\lambda(L)LE_{it} = \alpha_i + \delta LP_{it} + \rho LY_{it} + \gamma T + \omega_{it} \qquad i = 1, \ldots, 23; t = 1, \ldots, 21. \qquad \text{(IB)}$$

α_i [12] represents the country specific effects, $\lambda(L) = 1 - \lambda L$ is the first order distributed lag function; this term represents the lagged dependent variable lagged one period, $1-\lambda$ represents the coefficient of adjustment which measures how fast the response to exogenous changes takes places - the larger the coefficient estimates λ, the slower the adjustment.

In this formulation, the common short run price elasticity is given by δ, the common short run income elasticity is given by ρ and the common long run price and income elasticities are calculated as $\delta/(1-\lambda)$ and $\rho/(1-\lambda)$ respectively. The long run time trend is $\gamma/(1-\lambda)$. This specification is of specific interest in the log-linear model in energy demand studies, see for instance Houthakker et al (1974), Lakshmanan and Anderson (1980), Dunstan and Schmidt (1988), Parhizgari and Davis (1978), Kwast (1980), Berzeg (1982), Chern and Bouis (1988).[13]

However, these models must be treated with some caution since Robertson and Symons (1992) argue that this specification produces an overestimate of the coefficient of the lagged dependent variable with it being biased towards one and consequently biases the calculation of the long run estimates. They questioned the pooled estimates of such dynamic panels and refer to them as strange estimates of dynamic panel data because the lagged dependent variable estimate is biased upward while other exogenous variables are biased downward (see section 3.6).

[12] This does not apply in the POLS estimator.
[13] These studies are related to USA gasoline and electricity demand.

Model II: ALN Model

The basic specification of the ALN model is as follows:

$$LE_{it} = \alpha_i + \delta(L)LP_{it} + \rho(L)LY_{it} + \omega_{it} \qquad i = 1, \ldots, 23; t = 1, \ldots, 21. \qquad \text{(IIA)}$$

$$LE_{it} = \alpha_i + \delta(L)LP_{it} + \rho(L)LY_{it} + \gamma T + \omega_{it} \quad i = 1, \ldots, 23; t = 1, \ldots, 21. \qquad \text{(IIB)}$$

This model allows a more general lag structure using only lagged exogenous explanatory variables, therefore, it provides a useful comparison with the PA model. As Baltagi and Griffin (1983) argue "the advantage of this [Almon] approach is the allowance for a more general lag structure and the use of only exogenous explanatory variables" (p. 121).

The length of the lag structure of the variables for both ALN and ADL models (see below) is assumed to be three years for each explanatory variable, given the number of observations is 21 for each country (and the prior knowledge of estimating energy demand models in the context of time series data). $\delta(L)$ is the polynomial lag operator on prices $\theta_0 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3$ and $\rho(L)$ is the polynomial lag operator on income $\psi_0 + \psi_1 L + \psi_2 L^2 + \psi_3 L^3$. The summation of $\theta_0 + \theta_1 + \theta_2 + \theta_3$ and $\psi_0 + \psi_1 + \psi_2 + \psi_3$ represent the long run elasticities for price and income respectively.

Nordhaus (1977) uses this formulation to estimate the parameters of the FE model for a group of OECD countries. In addition, Baltagi and Griffin (1983) estimate the gasoline demand parameters in OECD countries using an ALN model as one of the dynamic specifications.

Model III: ADL Model

The basic specification of ADL model is as follows:

$$\lambda(L)LE_{it} = \alpha_i + \delta(L)LP_{it} + \rho(L)LY_{it} + \xi_{it} \qquad i = 1, \ldots, 23; t = 1, \ldots, 21. \quad \text{(IIIA)}$$

$$\lambda(L)LE_{it} = \alpha_i + \delta(L)LP_{it} + \rho(L)LY_{it} + \gamma T + \xi_{it} \qquad i = 1, \ldots, 23; t = 1, \ldots,21. \quad \text{(IIIB)}$$

Here, $\delta(L)$ is the polynomial lag operator on prices $\pi_0 + \pi_1 L + \pi_2 L^2 + \pi_3 L^3$, $\rho(L)$ is the polynomial lag operator income $\mu_0 + \mu_1 L + \mu_2 L^2 + \mu_3 L^3$ and $\lambda(L)$ is the polynomial lag operator on energy consumption $1 - \psi_1 L + \psi_1 L^2 + \psi_3 L^3$. $\delta(L)/\lambda(L)$ and $\rho(L)/\lambda(L)$ represent the long run price and income elasticities. The long run time trend is $\gamma/\lambda(L)$.

The ADL model includes the lags of endogenous and exogenous variables, Pesaran and Smith (1995) specify an ADL model of order (1,1,1) to estimate energy demand parameters for ten Asian countries and Jones (1994) estimates aggregate energy demand parameters for OECD countries using an ADL model of order (1,1,1).

One would expect there to be a different lag structure for each cross-section, but when the model is pooled it is difficult to determine different lags for each cross-section structure unless there is a rule to specify such lags.[14] For both models II and III the estimation strategy is estimating the general models and testing down to the specific preferred model, see Thomas (1993).

3.4.2 Traditional Pooled Estimators

Using annual time series data over the period 1978 to 1998 for each of the twenty-three countries (Data Set 23A), the three models specified in section 3.4 are estimated by the different alternative estimators explained below; the aim being to compare and contrast the results from these estimators. The study therefore considers the three following traditional pooled estimators:

(i) The POLS: This estimator is obtained from pooling the data through a full homogeneous model for the entire group of countries. The main assumption of this estimation method is that the regression coefficients, both the slope and the intercept are equal for all countries. This estimation method ignores any form of heterogeneity across the countries. Arguably this could be considered as a benchmark model (Balestra, 1996). In the models (I), (II) and (III) the intercepts are common across countries and take the form α. Therefore, whatever the model specification, the disturbances have the standard properties i.e. $\omega_{it} \sim \text{i.i.d.}(0, \sigma^2)$.

[14] Professor Ron Smith states "there is not a simple rule in the literature because it is a rather difficult problem. It is certainly a good research issue''. Personal email communication 17 Aug 2004.

(ii) The FE estimator (within): This specification of panel data models differs in the treatment of the unobserved country specific effects; it assumes country specific effects to be fixed parameters to be estimated. This model should not include too many country dummies so that the dummy variable trap can be avoided. A simple transformation can wipe out unobserved country specific effects by subtracting out the time series means of each variable for each country: this transformation creates the within estimator (Baltagi 2001). The importance of presenting the FE estimates depends on: 1) if they are policy variables, 2) if they help to understand the nature of the energy demand function across countries. This might be considered to be reasonable if the cross section in the sample represents a comprehensive sample of the population of economic agents (OECD countries), as might be the case in this study. Therefore, this study captures an advantage from this model in that it allows for this limited heterogeneity which is represented in the intercepts (level heterogeneity) but not in the slopes of the energy demand model for OECD countries. Again the disturbance term in this model has the standard properties $\omega_{it} \sim \text{i.i.d.}(0, \sigma^2)$.

(iii) RE model:[15] This assumes country effects α_i are random; therefore the model avoids the loss of the degrees of freedom compared with fixed effects model. A GLS approach is required to deal with the complex error term in equations I, II, III. This approach yields a GLS estimator that is a combination of between group and within group variations, whereas the fixed effects model ignores the between countries variations and the only effect would be α_i (Greene, 2002). This model introduces country specific effects in the disturbances term; therefore the disturbances term has

[15] Sometimes is called the variance components or random components model.

two components: an individual component and overall remainder as follows: $\omega_{it} = \alpha_i + \nu_{it}$, the two components are assumed to be: $\alpha_i \sim \text{i.i.d}(0, \sigma^2{}_\alpha)$ and $\nu_{it} \sim \text{i.i.d.}(0, \sigma^2{}_\nu)$.

In order to examine the suitability of the homogeneous estimators the following questions are considered:

- Is pooling beneficial compared to individual country regressions?
- Given the specified models (PA, ALN and ADL), what are the long run price and income elasticities obtained from different estimators?
- Do the long run elasticities from the POLS, FE and RE estimators differ between different model specifications?
- What are the appropriate pooling estimators, in light of results obtained from specific tests?

The first question is answered by comparing the individual country estimates with their counterpart (homogeneous) estimators. The second and the third questions are answered using long run income and price elasticities within the different homogeneous estimators and model specifications. The last question is answered through adopting different specific tests which are explained below.

The presence of individual effects in either the FE or RE as part of the error term can be tested. A test for the presence of country specific effects may be conducted under the null hypothesis that the estimated parameters $\hat{\alpha}_i$ are equal. The joint significance of country specific effect can be tested with a Fisher test (F1).[16] The null hypothesis is that the POLS estimator with an overall constant is efficient, that is the country specific effect dummies are not necessary for estimating the model. If the null is rejected, this indicates the validity of a fixed effects model. If the null cannot be rejected then dummies are jointly insignificant.

The RE model can be tested with a Lagrange Multiplier (LM) test, proposed by Breusch and Pagan (1980). Under the null hypothesis there are no random effects, given the value of Chi-squared distribution for this test, if the null hypothesis is rejected, this favours the RE estimator over the POLS estimator.

In applied work there is another possible test – whether FE or RE model is more appropriate? Hausman (1978) provides a test for model specification. The null hypothesis is that the residuals in the RE model are uncorrelated with the regressors and that the model is correctly specified. Thus under the null hypothesis, the estimated coefficients by the RE estimator should be statistically equal to those estimated by FE estimator, otherwise the RE estimator is inconsistent. If the null hypothesis is rejected, this means that the models are not correctly specified and/or the country specific effects are correlated with the regressors although the regressors are correctly inserted in the equation, (Baltagi, 2001).

[16] Baltagi (1999), Chapter 12

3.5 Results for Homogeneous Models

3.5.1 Without A Time Trend

Table (3.1) reports the estimated parameters for Model IA, which utilises the PA model. The POLS estimate for the short run price elasticity is statistically significant, whereas the estimated coefficient of income is insignificant. The coefficient of the lagged dependent variable is 0.990; intuitively this value is unreasonable for the OECD group as the larger the coefficient estimate, the slower the adjustment.

The FE short run estimators of the price and income elasticities are -0.030 and 0.120 respectively, which are both statistically significant and have the expected signs. The coefficient on the lagged dependent variable is 0.850, a little lower than the POLS estimate, confirming the importance of including the country specific effects in panel models as a potential source for the heterogeneity of energy demand across the OECD countries. Furthermore, the F1 test rejects the equality of the country specific effects. The long run income and price elasticity are of -0.200 and 0.800 respectively, hence the estimated long run impact is greater than the short run impact.

The RE short run estimates of price and income elasticities are statistically significant and have the expected signs with values of -0.034 and 0.030 respectively. The lagged dependent variable is 0.960 which lies between the POLS and FE estimators. The long run price and income elasticities are -0.850 and 0.750 respectively, the price elasticity being somewhat larger (in absolute terms) than that obtained from the FE estimator.

However, the LM test indicates that RE estimator is preferred over the POLS estimator and the H test indicates that the FE estimator is preferred to the RE estimator. This could be expected since the estimation sample represents almost the whole of the OECD population, which it is not drawn randomly. Hence, out of the three, the FE results are preferred.

The POLS, FE and RE estimators for model IA show the short run elasticities do not vary considerably but there are some differences in the long run impacts. Overall the POLS estimator produces unreliable long run elasticities due to imposing complete homogeneity on the intercepts and slopes. Whereas allowing the heterogeneity via a fixed component as in FE estimates or random component via RE estimates is more desirable.

Table (3-1): Model IA Parameter Estimates

	POLS	FE	RE
Estimated coefficients			
LP_{it}	-0.030 (-5.2)	-0.030 (-5.1)	-0.034 (-6.2)
LY_{it}	0.004 (0.80)	0.120 (8.3)	0.030 (3.9)
LE_{it-1}	0.990 (202.6)	0.850 (48.9)	0.960 (108.4)
α	0.190 (4.9)	1.10 (8.4)	0.380 (6.8)
Long run price elasticity	-3.000	-0.200	-0.850
Long run income elasticity	0.400*	0.800	0.750
No. of observations	460	460	460
Test of Restrictions			
R^2	0.999	0.960	
F1	$F(22,434)=7.600^{**}$		
F2		$F(66,391)=2.400^{**}$	
F3		$F(88,368)=5.000^{**}$	
LM			$\chi^2(1)=100.72\,0^{**}$
H		$\chi^2(3)=63.100^{**}$	

Estimation conducted using the STATA software package version 7.0.
t statistics in parentheses.
* Based on insignificant short-run coefficient.
F1 = Country specific effects test.
F2 = Homogeneity of slopes test.
F3 = Overall homogeneity test.
LM = Lagrange Multiplier test for random effects.
H = Hausman test for fixed or random effects.
** indicate that the null hypothesis is rejected at 1% significance level.

Table (3.2) reports the parameter estimates of model IIA, which utilises the ALN model after eliminating insignificant lags. For prices: the POLS estimator suggests that energy consumption responds to the first difference in prices, whereas the FE and the RE estimators suggest that it is the first and third lags, which are important. For income: the POLS and FE estimators both suggest that energy consumption is determined by the current level and the third lag, whereas the RE estimator suggests the first and third lag are most important. The long run price elasticities for the three specified estimators; POLS, FE and RE are 0.000, -0.030 and -0.020 respectively, whereas the long run income elasticities are 0.950, 0.800 and 0.820 respectively. Furthermore, the ALN model seems to produce very inelastic long run price elasticities which differs from the PA model, whereas the long run income elasticities are comparable, apart from the POLS estimator, which now produces more reasonable estimates. Again, the homogeneity assumption of the intercepts is rejected by the F1 test, the RE estimator is preferred to the POLS estimator as indicated by the LM test. The FE is the preferred estimator for model IIA as denoted by the H test. So once again, as with the PA model, the FE estimator is the preferred estimator out of the three.

Table (3-2): Model IIA Parameter Estimates

	POLS	FE	RE
Estimated coefficients			
ΔLP_{it}	-0.070 (-2.1)		
$LP_{i,t-1}$		-0.060 (-2.8)	-0.050 (-2.3)
$LP_{i,t-3}$		0.030 (3.1)	0.030 (1.9)
LY_{it}	1.880 (6.7)	0.470 (5.2)	
$LY_{i,t-1}$			0.480 (5.3)
$LY_{i,t-3}$	-0.930 (-3.3)	0.330 (3.6)	0.340 (3.7)
α	5.930 (20.5)	6.400 (39.0)	6.300 (37.7)
Long run price elasticity	0.000	-0.030	-0.020
Long run income elasticity	0.950	0.800	0.820
No of observations	414	414	414
Test of Restrictions			
R^2	0.930	0.820	
F1	$F(22,387)=512.9^{**}$		
F2			
F3			
LM			$\chi^2(1)=2376.600^{**}$
H		$\chi^2(4)=8.2500^{**}$	

Estimation conducted using the STATA software package version 7.0.
t statistics in parentheses
F1 = Country specific effects test.
F2 = Homogeneity of slopes test.
F3 = Overall homogeneity test.
LM = Lagrange Multiplier test for random effects.
H = Hausman test for fixed or random effects.
** indicate that the null hypothesis is rejected at 1% significance level.

Table (3.3) reports the parameter estimates from model IIIA, which utilises the ADL specification, again after eliminating insignificant lags. The first lag of the dependent variable is significant for all three estimators. The estimated coefficients for the POLS, FE and RE estimators are found to be 0.990, 0.860 and 0.970 respectively, which are very similar to the estimates obtained from the PA model. The FE and RE estimators both include the current price level and second lag of price and both also include the current income level and its first lag. The POLS estimator includes the first and second lags of prices and the current and first lag of income. The long run price elasticities for the three estimators; POLS, FE and RE are –2.000, -0.640 and -0.670 respectively. These results indicate a much higher price elasticity (in absolute value) than found in the ALN model, whereas the long run income elasticities are 2.000, 0.860 and 1.000 respectively as with the PA model the long run elasticities from POLS estimator appears implausibly large.

Table (3-3) also reports for the ADL model, similar to the PA and ALN models that the homogeneity assumption of the intercept is rejected. Moreover, also similar to the PA and ALN models, the RE estimator is preferred to POLS model as shown by the LM test and the H test indicates that the FE is preferred to the RE estimator. So for all three models the FE estimator is the preferred estimation technique.

Table (3-3): Model IIIA Parameters Estimates

	POLS	FE	RE
Estimated coefficients			
$LE_{i,t-1}$	0.990 (22.2)	0.860 (47.7)	0.970 (123.8)
$LP_{i,t}$		-0.050 (-5.1)	-0.050 (-6.1)
$LP_{i,t-1}$	-0.050 (-3.9)		
$LP_{i,t-2}$	0.030 (3.0)	0.020 (3.5)	0.030 (3.8)
$LY_{i,t}$	0.630 (10.0)	0.460 (7.8)	0.560 (9.3)
$LY_{i,t-1}$	-0.610 (-10.2)	-0.340 (-5.4)	-0.530 (-8.8)
α	0.110 (3.4)	0.930 (7.0)	0.270 (5.2)
Long run price elasticity	-2.000	-0.640	-0.670
Long run income elasticity	2.000	0.860	1.000
No of observations	437	437	437
Test of restrictions			
R^2	0.990	0.970	
F1	$F=(22,409)=7.400^{**}$		
F2			
F3			
LM			$\chi^2(1) = 63.700^{**}$
H		$\chi^2(5) = 55.2\,00^{**}$	

Estimation conducted using the STATA software package version 7.0.
t statistics in parentheses
F1 = Country specific effects test.
F2 = Homogeneity of slopes test.
F3 = Overall homogeneity test.
LM = Lagrange Multiplier test for random effects.
H = Hausman test for fixed or random effects.
** indicate that the null hypothesis is rejected at 1% significance level.

In summary, the following can be seen from Tables (3-1) to (3-3):

- For all three estimators the lagged coefficient on the dependent variable in the PA model is biased towards one, producing unstable long run elasticity estimates across the different estimators;
- In each of the models, allowing for heterogeneity by inserting country specific effects implicitly or explicitly reduces the bias of the lagged dependent variable;
- The FE model is preferred given the statistical tests for each model, suggesting a long run income elasticity of between 0.800 to 0.860 and a long run price elasticity which ranges between -0.030 and -0.640. Hence there is some consistency in the estimated income elasticity estimate but not so much in the price elasticities.
- Furthermore, for the PA model, the overall homogeneity test is rejected, which requires further investigation (see below).

3.5.2 *With* A Time Trend

Before considering the heterogeneity issue, the importance of including a time trend is first investigated. The above estimation omitted a time trend, whereas the following three tables repeat the above estimation procedures but now with a time trend included to proxy for technical progress.

Table (3-4) reports the results obtained from model IB for the POLS, FE and RE estimators. For the POLS estimator, the estimated short run price elasticity is statistically significant and has the expected sign, whereas the short run income elasticity is insignificant. Similar to model IA, the lagged consumption estimate would appear to be biased upwards at 0.995, which produces a long run price elasticity estimate of -4.800, which again appears to be unreasonable, and the long coefficient for the time trend is significant and suggests that energy consumption increases by 14%.p.a, (which is obtained from 0.0007/ (1-0.995).

For the FE estimator, both the short run price and income elasticities are statistically significant and have the expected signs. The estimated coefficient for lagged consumption is 0.850. Therefore, the long run price and income elasticities are -0.200 and 0.870 respectively. The estimated trend parameter in this case is negative but statistically insignificant. Moreover, the F1 test denotes the importance of the country specific effects.

The RE estimator indicates that the short run price and income elasticities are statistically significant and have the expected signs. The estimated lagged consumption coefficient is a little lower than the POLS estimator but higher than the FE estimator; this produces long run price and income elasticities of -1.100 and 1.000 respectively. The coefficient on the time trend is again positive but statistically insignificant. Furthermore, as in model IA, the RE estimator is preferred to POLS estimator, whereas the H test indicates that the FE estimator is preferred over the RE estimator.

It can be seen by comparing Table (3-4) with Table (3-1) that for IB model, the inclusion of the time trend does not greatly alter the POLS and FE long run income and price elasticities but it does change the RE long run elasticities somewhat. This may be explained by the fact that the RE estimator takes into account the variation within and between countries.

Table (3-4): Model IB Parameter Estimates

	POLS	FE	RE
Estimated coefficients			
$LP_{i,t}$	-0.024 (-4.3)	-0.030 (-5.1)	-0.032 (-5.5)
$LY_{i,t}$	0.002 (0.39)	0.130 (5.8)	0.030 (3.4)
LE_{it-1}	0.995 (201.3)	0.850 (48.7)	0.970 (105.9)
T	0.0007 (2.2)	-0.000005 (-0.01)	0.0003 (1.3)
α	0.160 (3.7)	1.100 (7.6)	
Long run price elasticity	-4.800	-0.200	-1.100
Long run income elasticity	0.400 [1]	0.870	1.000
Long run trend	0.140	-0.000033 [1]	0.010 [1]
No. of observations	460	460	460
Tests of restrictions			
R^2	0.999	0.960	
F1	$F(22,433)=8.900^{**}$		
F2		F(88,368)= 10.7**	
F3		F(110,345)=9.2**	
LM			$\chi^2(1)=93.700^{**}$
H		$\chi^2(4)=61.400^{**}$	

Estimation conducted using the STATA software package version 7.0.
t statistics in parentheses
[1] Based on an insignificant short-run coefficient
F1 = Country specific effects test.
F2 = Homogeneity of slopes test.
F3 = Overall homogeneity test.
LM = Lagrange Multiplier test for random effects.
H = Hausman test for fixed or random effects.
** indicate that the null hypothesis is rejected at 1% significance level.

Table (3-5) presents the estimated results from model IIB for the POLS, FE and RE estimators. The FE and RE estimators include the first and the third lag for both income and price, whereas the POLS includes the third lag of price and current level and third lag income. The long run price elasticities for the POLS, FE and RE estimator are -0.190, -0.030 and -0.024 respectively, whereas the estimated long run income elasticities for the POLS, FE and RE are 1.020, 0.820 and 0.830 respectively. The coefficient for the trend for the POLS estimator is -0.008 implying that there is a significant tendency toward energy saving by 0.8% p.a, while the estimated trend for FE estimator is negative but statistically insignificant. For the RE estimator the estimated coefficient for the time trend is –0.002 that implies a reduction in aggregate energy demand by 0.2% p.a. Furthermore, the FE estimator for model IIB is preferred over the RE estimator as the H test indicates. Nevertheless, it can be seen by comparing Table (3-5) with Table (3-2) that for model IIB, the inclusion of the time trend slightly alters the long run parameter estimates and its coefficients vary among the estimators.

Table (3-5): Model IIB Parameter Estimates

Variables	POLS	FE	RE
Estimated coefficients			
$LP_{i,t-1}$		-0.060 (-2.9)	-0.064 (-2.8)
$LP_{i,t-3}$	-0.190 (-4.2)	0.030 (2.1)	0.040 (2.3)
LY_{it}	2.030 (7.3)		
$LY_{i,t-1}$		0.470 (5.2)	0.490 (5.4)
$LY_{i,t-3}$	-1.010 (-3.9)	0.350 (3.7)	0.380 (4.1)
T	-0.008 (-2.5)	-0.0008 (-0.65)	-0.002 (-2.1)
α	6.3 (26.9)	6.3 (27.6)	6.1 (31.2)
Long run price elasticity	-0.190	-0.030	-0.024
Long run income elasticity	1.020	0.820	0.830
Long run trend	-0.008	- 0.0008 [1]	-0.002
No. of observations	414	414	414
Tests of restrictions			
R^2	0.940	0.820	
F1	$F(22,386)=511.5^{**}$		
F2			
F3			
LM			$\chi^2(1)=278.600^{**}$
H		$\chi^2(5)=3.370^{**}$	

Estimation conducted using the STATA software package version 7.0.
t statistics in parentheses
[1] Based on insignificant short-run coefficient
F1 = Country specific effects test.
F2 = Homogeneity of slopes test.
F3 = Overall homogeneity test.
LM = Lagrange Multiplier test for random effects.
H = Hausman test for fixed or random effects.
** indicate that the null hypothesis is rejected at 1% significance level.

Table (3.6) reports the estimated results from model IIIB for POLS, FE and RE estimators. The estimated coefficients on lagged of energy consumption are 0.995, 0.860 and 0.980 for the POLS, FE and RE estimators respectively. The estimated long run price and income elasticities are found to (-2.000 and 2.000), (-0.140, 0.780) and (-0.550, 1.000) for the POLS, FE and RE estimators respectively. The estimated long run time trend coefficients for the POLS and RE estimators are 0.200 and 0.05 respectively, while the estimated trend coefficient for the FE estimator is statistically insignificant. The F1 test rejects by the equality of the intercepts, in addition the LM test indicates that the RE estimator is preferred over the POLS estimator and the H test indicates that FE estimator is preferred to the RE estimator.

By comparing Table (3-6) and (3-3) for model IIIB, it can be seen that the inclusion of the time trend does not alter the POLS long run parameter estimates, but it substantially alters the long run price elasticities obtained from FE and RE estimators, and the long income elasticities are less affected.

Table (3-6): Model IIIB Parameters Estimates

	POLS	FE	RE
Estimated coefficients			
$LE_{i,t-1}$	0.995 (224.7)	0.860 (47.8)	0.980 (122.7)
$LP_{i,t}$		-0.040 (-4.5)	-0.041 (-3.3)
$LP_{i,t-1}$	-0.040 (-2.73)		0.030 (2.8)
$LP_{i,t-2}$	0.030 (2.3)	0.020 (3.1)	
$LY_{i,t}$	0.610 (10.0)	0.460 (7.8)	0.570 (9.4)
$LY_{i,t-1}$	-0.600 (4.1)	-0.350 (-5.5)	-0.550 (-9.0)
T	0.001 (3.8)	0.0007 (1.4)	0.001 (3.5)
α	0.060 (1.6)	1.010 (7.0)	0.170 (3.2)
Long run price elasticity	-2.000	- 0.140	- 0.550
Long run income elasticity	2.000	0.780	1.000
Long run trend	0.200	0.005 [1]	0.050
No. of observations	437	437	437
Tests of restrictions			
R^2	0.999	0.970	
F1	$F(22,408)=7.100^{**}$		
F2			
F3			
LM			$\chi^2(1)=45.800^{**}$
H		$\chi^2(6)=65.100^{**}$	

Estimation conducted using the STATA software package version 7.0.
t statistics in parentheses
[1] Based on an insignificant short-run coefficient
F1 = Country specific effects test.
F2 = Homogeneity of slopes test.
F3 = Overall homogeneity test.
LM = Lagrange Multiplier test for random effects.
H = Hausman test for fixed or random effects.
** indicate that the null hypothesis is rejected at 1% significance level

In summary therefore the following can be seen from Tables (3.4) to (3.6):

- For all three estimators the coefficient on the lagged dependent variable in the PA model are biased towards unity, producing unstable long run elasticity estimates;
- In all three models, allowing for heterogeneity by inserting country specific effects implicitly or explicitly reduces the bias of the lagged dependent variable;
- In all three models the FE estimator is preferred on the basis of the statistical tests, suggesting a long run income elasticity of between 0.780 and 0.870 and a long run price elasticity ranging between -0.030 and -0.200. Hence as before there is some consistency in the income elasticity estimates but also now more consistency in the price elasticity estimates;
- Furthermore, the F3 test rejects the overall homogeneity of coefficients which requires further investigation (see below).
- The introduction of the technical progress term in these homogeneous models does not change the elasticity estimates substantially (although there is less variation in the long-run price elasticity for the preferred FE specification). In addition, technical progress coefficients appear to be rather unstable producing positive to negative effects, and they are consistently insignificant in the preferred FE specification.

The next section attempts to address the upward biases found in the lagged dependent variable and also price and income elasticities in homogeneous models. These issues will be tackled by estimating heterogeneous panel estimators.

3.6 Heterogeneous Estimators

The previous estimation process maintained the assumption that the slope coefficients (i.e. the elasticities and, if included, the technical progress effect) are homogeneous. The only heterogeneity was accounted for by either the individual country fixed effects or through the individual specific error term in the RE model. However, as discussed earlier in section 3.2, this may be not be a valid assumption because there are differences in socio-economic structures and energy policies across countries implying that the response parameters may show variation across countries.

Therefore, it is crucial to assess the impact of imposing homogeneity on the key parameters of the energy demand model, namely income and price elasticities, and the rate of energy productivity across all countries in the sample. Pesaran, Smith and Im (1996) argue that "while it is widely recognised that parameters heterogeneity can have important consequences for estimation and inference, most attempts at dealing with it have focused on allowing for intercept variation, and in comparison little attention has been paid to the implications of variation in slopes"(p.145). Furthermore, it has been illustrated that when estimating dynamic panel models, the coefficient on the lagged dependent variable is 'over estimated' and is very close to one, see the argument by Robertson and Symons (1992) below. Therefore, this section extends the analysis of Data Set 23A by estimating heterogeneous panel data estimators that allow for heterogeneity across countries.

These heterogeneous estimators are: the Mean Group (MG) estimator, the Stein Rule (SR)[17] estimator (shrinkage estimator) and the Random Coefficients (RC) estimator. The choice of these estimators is to construct a succession of panel data estimators in addition to the homogeneous estimators: POLS, FE and RE, in order to make a comparison. This is a necessary step in assessing the impact of ignoring the coefficient heterogeneity when the estimated model is dynamic. A common characteristic of these estimators is that they all consider the heterogeneity across cross sections but not heterogeneity over time.[18]

3.6.1 The Mean Group (MG) Estimator

Robertson and Symons (1992) argue that "the coefficient on the lagged dependent variable is overestimated while the mean effect of the regressors is underestimated. The false imposition of the equality constraint leads to a mistaken description of the dynamics and the response to the regressors. The long run response is overestimated by between 0 and 5 percent'' (p. 176). Furthermore, Pesaran and Smith (1995) investigate the homogeneity assumption and the nature of pooled parameters. They show the heterogeneous estimators are less biased than the traditional homogenous estimators. They propose the MG estimator, which relies upon average responses

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[17] The SR estimator is considered among the heterogeneous estimators hence it is obtained by different weights and relies on an individual regression for each country similar to the MG and RC estimators. However, the estimates are supposed to shrink toward the POLS estimator.

[18] Heterogeneity over time is not considered in this chapter. This is a potential fertile area in energy demand modelling in panel data context.

from individual country regressions and then takes the unweighted arithmetic average of them. They show that the MG estimator produces consistent estimates of the average of the parameters. This estimator relies on the assumption that the between country disturbance covariances are zero. The disadvantage of the MG estimate is that it does not take into account the possibility that certain parameters may be the same across groups.

As opposed to the specifications for the homogenous models in Section 3.4, only the PA model is used in this section to obtain the heterogeneous estimators because the other two models, ADL and ALN models involve testing down, but it is not possible to apply this on individual country regressions to obtain the heterogeneous estimators. Therefore, for this reason, and also to ensure adequate degrees of freedom for each country, the PA model is extended to the heterogeneous estimators. As before, two versions are estimated, one *without* a time trend and one *with* a time trend, the first being denoted by IVA and the second by IVB.

Model IV

$$\lambda_i(L)LE_{it} = \alpha_i + \delta_i LP_{it} + \rho_i LY_{it} + \upsilon_{it} \qquad i=1, \ldots, 23; t=1, \ldots, 21. \quad \text{(IVA)}$$

$$\lambda_i(L)LE_{it} = \alpha_i + \delta_i LP_{it} + \rho_i LY_{it} + \phi_i T + \upsilon_{it} \qquad i=1, \ldots, 23; t=1, \ldots, 21. \quad \text{(IVB)}$$

Here, $\lambda_i(L) = 1 - \lambda L$ is the distributed lag function of the first order, this term represents the lagged dependent variable; lagged one period for each country regression. The un-weighted average long run elasticity coefficients can be obtained by two ways:

First: from the mean of the long run country specific coefficients as below:

With respect to the real energy price, $\hat{\gamma}_i = \hat{\delta}_{1i} /(1-\hat{\lambda}_{1i})$

With respect to income, $\hat{\varphi}_i = \hat{\rho}_{1i}(1-\hat{\lambda}_{1i})$

With respect to the time trend, $\hat{\psi}_i = \hat{\phi}_{1i}(1-\hat{\lambda}_{1i})$

The mean of the long run (in Table 3-9) for price, income and the time trend are computed respectively as:

$$\hat{\gamma} = \sum_{i=1}^{N} \gamma_i / N$$

$$\hat{\varphi} = \sum_{i=1}^{N} \varphi_i / N$$

$$\hat{\psi} = \sum_{i=1}^{N} \psi_i / N$$

Second: The long run elasticity estimates are calculated from the average of country specific short run coefficients as below:

With respect to the price, $\overline{\delta} = \sum_{i=1}^{N} \delta_{1i} / N$

With respect to income, $\overline{\rho} = \sum_{i=1}^{N} \rho_{1i} / N$

With respect to the time trend, $\overline{\phi} = \sum_{i=1}^{N} \phi_{1i} / N$

Then the long run elasticity estimates are calculated from the mean of country short run estimates for price, income and the time trend respectively as follow:

$$\overline{\gamma} = \overline{\delta}/(1-\overline{\lambda})$$

$$\overline{\varphi} = \overline{\rho}/(1-\overline{\lambda})$$

$$\overline{\psi} = \overline{\phi}/(1-\overline{\lambda}).$$

3.6.2 Stein Rule (SR) Estimator

Maddala et al. (1997) in a study of USA gas and electricity demand investigate whether to estimate the separate models for each state or whether to estimate the model by pooling the entire data set. They note that this choice depends upon the extreme assumptions of either homogeneity of the estimates across cross-sectional units or complete heterogeneity, whereas the truth probably lies somewhere in between. Therefore, they suggest applying the SR estimator instead, which 'shrinks' towards the POLS estimator.

Furthermore, Maddala et al. (1997) estimate the short run and long run parameters of residential electricity and natural gas demand using a panel of 49 states over the period 1970-1990 using different approaches. They propose the shrinkage estimators as a compromise between heterogeneous estimators and homogeneous estimators.[19]

In addition, Baltagi et al. (2002) investigate the performance for homogenous, heterogeneous and shrinkage estimators using the electricity and natural gas data sets

[19] Details of different shrinkage estimators can be found in Maddala et al.(1997).

used by Maddala et al. (1997) and use the out-of-sample criteria to compare the different estimators. The results show that homogeneous estimates give the best out-sample forecasts.

Furthermore, Baltagi and Griffin (1997) investigate the pooled estimators vs. their heterogeneous counterparts for the dynamic demand of gasoline using a set of data for 18 OECD countries over the period 1960-1990. They find that the homogenous estimators perform well compared to the heterogeneous and shrinkage estimators based on out-sample forecast criteria.

Maddala et al. (1997) define the SR (shrinkage) estimator as:

$$b_{s,i} = \left(1 - \frac{c}{F_3}\right)\hat{b}_i + \frac{c}{F_3}\hat{b}_p \qquad \text{(V)}$$

Where $b_{s,i}$ represents the SR estimator for individual country, $\hat{b}_i$ represents the OLS estimator for the parameter estimates of interest: price, income, lagged consumption and the time trend - if it is included - in the separate regression for each country,[20] $\hat{b}_p$ is the POLS estimator,[21] and $(1 - c/F_3)$ is the shrinkage factor.[22] F_3 is the test statistic for complete homogeneity of the demand parameters across countries, the

[20] In the results section the individual country estimates without the inclusion of the time trend are shown in model VA while with the time trend in model VB.
[21] In the calculation of the SR estimator, the POLS estimator obtained from a PA model with and without the time trend.
[22] (1-c/F3) is equal to 0.988.

constant c is given by $c = \frac{(N-1)K-2}{NT-NK+2}$, where N is a number of cross-sections, T number of observations for each cross section and K is the number of regressors.

Model V shows that the individual country OLS parameter estimates shrink toward the POLS estimator. However, this is dependent on the shrinkage factor, if this term is close to one then the SR estimator hardly shrinks towards POLS instead it may shrink to individual OLS. Furthermore, model V shows that the SR estimator combines both the POLS estimator and individual OLS (unpooled) estimator.

3.6.3 Random Coefficients (RC) Estimator

The RC estimator was developed by Swamy (1970). It assumes that the parameters are allowed to vary randomly over the cross sectional units. The specification of the RC estimator seems appropriate since aggregate energy demand functions are most likely affected differently by random disturbances such as energy policies and the utilisation of the capital stock. In the energy the demand context, this model has a particular interest, for instance; Mehta, Narasimaham and Swamy (1978) use the RC estimator to examine the demand for gasoline, whilst Kraft and Rodekoher (1978) also investigate the demand for gasoline across nine regions in the USA using the RC specification.

The basic specification of the RC model is as follows:

Model VI

$$\lambda_i(L)LE_{it} = \alpha_i + \delta_i LP_{it} + \rho_i LY_{it} + u_{it} \qquad i = 1, \ldots, 23;\ t = 1, \ldots, 21. \qquad \text{(VIA)}$$

$$\lambda_i(L)LE_{it} = \alpha_i + \delta_i LP_{it} + \rho_i LY_{it} + \phi_i T + \upsilon_{it} \qquad i = 1, \ldots\ldots, 23;\ t = 1, \ldots, 21. \qquad \text{(VIB)}$$

The specifications above allow the parameters of aggregate energy demand to vary randomly across countries but are constant over time, and require that the distribution of the coefficients is independent of the regressors. The parameters of interest are the weighted averages, over countries, of the coefficients.

The above two specifications, with their coefficients $\lambda_i, \alpha_i, \delta_i$ and ρ_i vary across countries according to the following RC estimators which presume that parameter heterogeneity can be viewed due to stochastic variation as follow:

$$\lambda_i = \lambda_i + \eta_{1i},\ \alpha_i = \alpha_i + \eta_{2i},\ \delta_i = \delta_i + \eta_{3i},\ \rho_i = \rho_i + \eta_{4i} \text{ and } \phi_i = \phi_i + \eta_{5i}.$$

Where $\eta_{1i}, \eta_{2i}, \eta_{3i}, \eta_{4i}$ and η_{5i} are assumed to have zero means and constant covariances. For more details, see Greene (2002).

Here, $\lambda_i(L) = 1 - \lambda L$ is the distributed lag function of the first order. This term represents the lagged dependent variable, lagged one period for each country regression. In this case the weighted average long run elasticities estimates are calculated from the average short run estimates for price, income and time respectively as:

$$\overline{\gamma} = \overline{\delta}/(1-\overline{\lambda})$$

$$\overline{\varphi} = \overline{\rho}/(1-\overline{\lambda})$$

$$\overline{\psi} = \overline{\phi}/(1-\overline{\lambda}).$$

3.7 Results for the Heterogeneous Estimators

Table (3-7) presents the OLS time series results for the 23 individual countries. There appears to be implausible parameter estimates for some individual countries. For instance, the estimated coefficients of lagged consumption for Greece and Ireland have negative values which mean a positive depreciation for stock appliances and/or there is an unusual dynamic path. The estimated price elasticity is insignificant for 11 countries, whereas the income elasticity is insignificant for only five countries.

Table (3-8) reports the OLS individual country time series estimates when a deterministic time trend is included. Again some of the individual parameter estimates either have unexpected signs or are statistically insignificant, for instance, the estimated lagged consumption coefficient for Austria, Greece, Netherlands, Switzerland and UK is statistically insignificant and for Norway it has negative sign. The estimated price elasticities are insignificant for thirteen countries and have a positive sign for three countries. The estimated income elasticities are insignificant for twelve countries and have a negative sign for two countries. The estimated coefficients of the time trend are insignificant for sixteen countries. In addition, the country regressions show that the estimates vary across countries. Therefore, the variation of the estimates across the countries implies that the income and price elasticities are not homogeneous.[23]

[23] Remember in the earlier estimation of the homogeneous model the reason was to gain efficiency from pooling.

Table (3.7) Parameter Estimates for Individual Country Time Series without a Trend

Country	Lagged consumption	Price	Income
Australia	0.53	-0.74	0.35
	4.70	**-1.81**	**4.40**
Austria	0.33	-0.06	0.35
	1.51	**-1.40**	**2.40**
Belgium	0.71	-0.052	0.24
	5.40	**-0.87**	**1.91**
Canada	0.42	-0.17	0.19
	2.90	**-3.30**	**3.00**
Denmark	0.73	-0.16	0.06
	7.50	**-2.40**	**0.68**
Finland	0.69	-0.076	0.14
	5.30	**-1.74**	**1.65**
France	0.65	-0.08	0.19
	5.50	**-1.70**	**2.10**
Greece	-0.012	-0.09	1.5
	-0.04	**-1.42**	**3.00**
Ireland	-0.03	-0.14	0.36
	-0.14	**-2.91**	**4.60**
Italy	0.66	-0.08	0.24
	4.41	**-2.10**	**2.10**
Japan	0.62	-0.10	0.17
	6.40	**-2.10**	**1.90**
Korea	0.72	-0.19	0.21
	7.90	**-2.90**	**1.90**
Luxembourg	0.67	-0.07	0.11
	6.50	**-1.30**	**1.90**
Mexico	0.47	0.009	0.36
	3.50	**0.90**	**3.60**
Netherlands	0.49	-0.06	0.22
	2.90	**-1.10**	**2.60**
New Zealand	0.75	-0.11	0.35
	5.9	**-1.20**	**2.10**
Norway	0.13	-0.13	0.34
	0.60	**-2.20**	**3.90**
Portugal	0.40	-0.006	0.8
	1.50	**-0.07**	**2.10**
Spain	0.67	-0.11	0.36
	6.30	**-2.42**	**3.10**
Sweden	0.63	-0.19	-0.02
	4.50	**-2.50**	**-0.30**
Switzerland	0.22	-0.007	0.60
	0.92	**-0.13**	**3.02**
United Kingdom	0.25	-0.28	0.03
	1.30	**-2.00**	**0.21**
United States	0.61	-0.05	0.06
	4.00	**-0.70**	**0.61**

Estimation conducted using the STATA software package version 7.0.
Figures in bold are t statistics

Table (3.8): Parameter Estimates for Individual Country Time Series with a Trend

Country	Lagged consumption	Price	Income	Trend
Australia	0.60	-0.52	0.49	-0.006
	4.34	**-1.10**	**2.92**	**-0.95**
Austria	0.32	-0.06	0.47	-0.0023
	1.37	**-1.25**	**1.13**	**-0.30**
Belgium	0.76	-0.06	-0.29	0.0097
	5.50	**-1.00**	**-0.56**	**1.1**
Canada	0.41	-0.17	0.19	0.000023
	2.60	**-3.03**	**1.09**	**0.0053**
Denmark	0.73	-0.16	0.45	-0.009
	7.42	**-2.40**	**1.24**	**-1.10**
Finland	0.55	-0.08	0.071	0.0034
	3.05	**-1.81**	**0.65**	**1.10**
France	0.65	-0.07	0.38	-0.0033
	5.40	**-1.20**	**0.94**	**-0.47**
Ireland	0.055	-0.2	0.51	-0.011
	0.35	**-4.21**	**5.70**	**2.60**
Italy	0.67	-0.094	0.043	0.0035
	4.40	**-1.93**	**0.13**	**0.61**
Greece	0.032	-0.11	1.08	0.005
	1.00	**-1.62**	**1.66**	**0.88**
Japan	0.62	-0.069	0.15	0.00056
	5.32	**-2.03**	**0.98**	**0.11**
Korea	0.91	0.021	1.03	-0.073
	13.10	**0.35**	**5.70**	**-4.92**
Luxembourg	0.46	-0.07	0.7	-0.03
	2.90	**-1.31**	**1.95**	**-1.70**
Mexico	0.49	0.009	0.37	-0.00051
	3.02	**0.85**	**2.82**	**-0.142**
Netherlands	0.22	-0.046	1.15	-0.021
	0.98	**-0.84**	**2.07**	**-1.70**
New Zealand	0.14	-0.12	0.13	0.024
	0.66	**-1.71**	**0.90**	**3.30**
Norway	-0.12	-0.19	1.20	-0.021
	-0.81	**-4.62**	**6.44**	**-4.80**
Portugal	-0.58	-0.021	1.14	0.03
	-2.62	**-0.42**	**5.01**	**6.00**
Spain	0.67	-0.11	0.33	0.0008
	6.1	**-1.9**	**0.98**	**0.11**
Sweden	0.58	-0.22	-0.38	0.006
	4.11	**-2.9**	**-1.6**	**1.6**
Switzerland	0.19	-0.0082	0.503	0.002
	0.75	**-0.151**	**1.8**	**0.46**
UK	0.25	-0.29	0.009	0.0004
	1.20	**-1.83**	**0.032**	**0.08**
USA	0.38	-0.044	0.66	-0.015
	2.20	**-0.66**	**2.30**	**-2.20**

Estimation conducted using the STATA software package version 7.0.
Figures in bold are t statistics.

Table (3-9) presents the estimates obtained from model IV. In both versions A and B the estimates have the expected signs and are statistically significant. The short run income and price elasticities vary slightly between the two models. The estimated lagged consumption coefficient is 0.471 for version A and is 0.391 for version B. The long run price elasticities are quite similar, whereas for income there is a large difference between versions A and B on the income elasticities, which are 0.577 and 1.080 respectively. The coefficient on the time trend is negative and statistically significant indicating a reduction in the energy use by 3.8% p.a. In general, the results show two things: (1) the MG estimator appears to reduce the bias of the lagged consumption coefficient; (2) the inclusion of the deterministic time trend leads to downward bias in the long run price elasticity (not serious) and to an upward bias in the long run income elasticity. However, the bias in the latter is more prominent when compared to the former.

Table (3-9): Model IV (A&B): MG Parameter Estimates:

	IVA	IVB
Estimated coefficients		
LP_{it}	-0.123 (1.90)	-0.117 (2.10)
LY_{it}	0.310 (2.43)	0.452 (3.50)
LE_{it}	0.471 (3.10)	0.391(4.30)
T		-0.0046 (2.30)
Long run price elasticity	-0.272	-0.229
Long run income elasticity	0.577	1.080
Long run time trend		-0.038

Estimation conducted using the STATA software package version 7.0.
t statistics are in the parenthesis.
The long run elasticities and the long run trend coefficient are calculated by averaging the long run estimates.

Table (3-10) presents the estimated income and price elasticities for model V. In both versions A and B the estimated elasticities are statistically significant and have the correct signs. The short run income and price elasticities vary slightly between the two versions, the estimated lagged consumption coefficients are 0.504 and 0.404 for versions A and B respectively. The long run price elasticities vary slightly between the two versions, whilst the estimated long run income elasticities display greater variation. Thus, the inclusion of the deterministic time trend biases the long run income elasticity, which is similar to the result found for model IVB. The coefficient on the time trend is negative and statistically significant suggesting a reduction in energy use by 4.9% p.a.

Table (3-10) Model V (A &B): SR Parameter Estimates

	VA	VB
Estimated coefficients		
LP_{it}	-0.120 (2.10)	-0.115 (2.30)
LY_{it}	0.303 (3.30)	0.442 (3.30)
LE_{it}	0.504 (4.10)	0.404 (4.10)
T		-0.0045 (2.70)
Long run price elasticity	-0.226	-0.267
Long run income elasticity	0.588	1.100
Long run time trend		-0.049

Estimation conducted using the STATA software package version 7.0.
t statistics are in the parentheses.
The long run elasticities and long run trend coefficient are calculated by averaging the long run estimates.

Table (3-11) reports the estimated income and price elasticities obtained from model VI. The test of parameters constancy rejects the equality of the estimates across the countries in both versions. The coefficients on the lagged dependent variable are 0.960 and 0.830 for version A and B respectively, which are much higher than the estimates from the MG and SR estimators. Version A of this model shows that the price elasticity is insignificant and long run income elasticity is large, with a value 1.880. In version B, the estimated long run income and price elasticities are 2.180 and -0.188 respectively. The income elasticity is larger than what the MG and SR estimators yield but the long run price elasticity is in the same range. The trend coefficient is -0.041 suggesting a reduction in energy use by 4.1% each year.

Table (3-11) Model VI (A &B) RC Parameter Estimates

	VIA	VIB
Estimated coefficients		
LP_{it}	-0.013(-0.90)	-0.032 (-1.80)
LY_{it}	0.075 (2.00)	0.37 (3.90)
LE_{it}	0.96 (40.10)	0.83 (17.20)
T		-0.007 (-3.00)
Long run price elasticity	-0.330*	-0.188
Long run income elasticity	1.880	2.180
Long run time trend		- 0.041
Test of parameter constancy	$Chi^2(66) = 154.3$	$Chi^2(88) = 390.9$

Estimation conducted using the STATA software package version 7.0.
t statistics are in the parentheses.
* based on insignificant short run estimate.
The long run elasticities and the long run trend coefficient are calculated from the means of the short run coefficients.

In summary, without the inclusion of a time trend both the MG and SR estimators yield almost the same long run income and price elasticities but the RC model yields insignificant price elasticity and very large long run income elasticity. The inclusion of the time trend has biased the long run income estimate upward for both the MG and SR estimators, whereas for the RC estimator the long run income elasticity yields large long run income elasticities in both cases; with the trend and without the trend.

3.8 Comparison of the Heterogeneous and Homogeneous Estimators

Table (3-12) summarises the estimated short run and long run elasticities for the PA model using different estimators -homogeneous and heterogeneous- *without* the time trend. There is variability in the short run and long run elasticities between homogenous and heterogeneous approaches but the variability in the price elasticities is more than found in the income elasticities.

For the heterogeneous estimators (MG, SR and RC), the short run and long run price elasticity estimates are (-0.123, -0.120) and (-0.272 and -0.226) for the MG and SR respectively. The estimates are quite similar since the SR estimator presumes to shrink individual country estimates towards the POLS, and the shrinkage factor was very close to 1. Thus, each country estimates were hardly shrunk towards the overall POLS estimate. Therefore, the SR estimates were only slightly different from the MG estimates. In contrast, the RC estimator displays insignificant price elasticity.

The short run and long run income elasticity estimates are (0.310, 0.557) and (0.303, 0.558) for the MG and SR estimator respectively but the RC estimator gives short run and long run income elasticity estimates of 0.075 and 1.880 respectively, which are not comparable with the MG and SR estimates.

For the homogeneous estimators (POLS, FE and RE), the price elasticity estimates lie in the interval -0.034 to -0.030 in the short run and -3.000 to -0.850 in the long run. The separate OLS regressions show more variability, ranging from - 0.620 to 0.009 in the short run and -2.440 to 0.017 in the long run. While the income elasticity estimates for the homogeneous estimator range from 0.004 to 0.120 in the short run and 0.400 to 0.800 in the long run. The separate OLS regressions again show more variability, ranging from 0.022 to 1.450 in the short run and 0.060 to 1.430 in the long run.

Table (3-12) Comparison of the Elasticity Estimates: Heterogeneous vs. Homogeneous Estimators without a Trend*

Approaches	Short run elasticities		Long run elasticities	
	Price	Income	Price	Income
POLS	-0.030	0.004	-3.000	0.400[1]
FE	-0.030	0.120	-0.200	0.800
RE	-0.034	0.030	-0.850	0.750
MG [a]	-0.123	0.310	-0.272	0.557
Maximum	0.009	1.450	0.017	1.430
Minimum	-0.620	0.022	-2.440	0.060
Median	-0.090	0.230	-0.220	0.520
MG [b]	-0.123	0.310	-0.233	0.586
SR [a]	-0.120	0.303	-0.226	0.558
Max	0.008	1.410	0.016	1.390
Min	-0.600	-0.210	-2.400	0.060
Median	-0.090	0.220	0.220	0.500
SR [b]	-0.120	0.303	-0.242	0.611
RC [b]	-0.013	0.075	-0.330 [1]	1.880

* All the reported estimates obtained from Partial Adjustment model (PAM).

[1] Based on an insignificant short run estimate.

[a] Calculated based on the individual elasticity for each country. The same is the case for the maximum, minimum and median values.

[b] Calculated by first taking the mean of individual parameter estimates. Then the elasticities are calculated from this mean. The elasticities marked by [a] and [b] are the same in the short run but not for the long run.

Table (3-13) summarises the short run and long run price and income elasticities for the PA model using different estimators (homogeneous and heterogeneous) with the time trend. The obtained results will be compared to the results in Table (3-12).

For heterogeneous estimators (MG, SR and RC), the short run price and income elasticity estimates for the MG, SR. The MG, SR and RC estimators give elasticities of (-0.117, 0.452), (-0.115, 0.442) and (-0.032, 0.370) respectively. These short run estimates are fairly similar to those in Table (3-12).

The long run price and income elasticity estimates for the MG, SR and RC estimators are (-0.229, 1.080), (-0.267, 1.100) and (-0.188, 2.180) respectively. For the MG and SR estimators the income elasticity is larger than found in Table (3.12). The RC estimator yields an income estimate of 2.180, which is outside the circle for OECD countries estimates, but it gives a significant price estimate, though it was insignificant without the inclusion of the time trend. The trend coefficients for the MG, SR and RC estimators are of -0.038, -0.049 and -0.041 respectively, these estimates are higher than the short run estimates and show less variability compared to homogeneous estimators.

It is also useful to compare the long run price and income elasticity estimates in Table (3-12) with the long run elasticity estimates in Table (3-13) since the short run estimates do not vary considerably. The long run income elasticity estimates for the MG and SR estimators are higher in the case when the time trend included, but the RC estimator yields a large elasticity estimate with and without the trend inclusion. Therefore, for the MG and SR estimators, the inclusion of the trend biases the income elasticity estimates upwards. Therefore, the simple deterministic trend may not be capable of capturing the underlying trends in the energy demand function.

The long run price elasticity estimates for homogeneous estimators range widely from -4.800 to -0.200. The long run income elasticity estimates show narrower range than the price estimates with the POLS estimate found insignificant. The trend coefficient estimates show mixed results- remember the FE estimator is the preferred estimator but without the time trend.

The discussion above reveals some important points:

- The homogeneous estimators are incapable of picking up the effect of technical progress in the energy demand function, since it imposes the same rate of technical progress for all countries, which in all probability is unrealistic.
- The heterogeneous estimators are seemingly picking up the effect of technical progress, but it seems the inclusion of the trend biases the elasticity estimates; again such a simple trend may not be capable to capture all the underlying trends in the energy demand function.

Therefore, Chapter 4 estimates the energy demand parameter estimates for each country incorporating a stochastic trend that may be better in capturing the underlying trends in the energy demand function.

Table (3.13) Comparison for the Elasticity Estimates: Heterogeneous vs. Homogeneous Estimators with a Trend*

Approaches	Short run elasticities			Long run elasticities		
	Price	Income	Trend	Price	Income	Trend
POLS	-0.024	0.002	0.0007	-4.800	0.400[1]	0.140
FE	-0.030	0.130	-0.000005	-0.200	0.870	-0.000033 [1]
RE	-0.032	0.030	0.0003	-1.100	1.000	0.010[1]
MG [a]	-0.117	0.452	-0.0046	-0.229	1.080	-0.038
Max	0.020	1.200	0.030	0.230	11.440	0.040
Min	-0.520	-0.380	-0.073	-1.3	-1.21	-0.810
Median	-0.080	0.450	0.000023	-0.178	0.720	0.00004
MG [b]	-0.117	0.452	-0.0046	-0.192	0.742	-0.008
SR [a]	-0.115	0.442	-0.0045	-0.267	1.100	-0.049
Max	0.020	1.170	0.030	0.190	11.200	0.000023
Min	-0.510	-0.370	-0.070	-1.300	-1.200	-0.0005
Median	-0.08	0.440	0.000031	-0.220	0.720	0.00000023
SR [b]	-0.115	0.442	-0.0045	-0.193	0.742	-0.0076
RC [b]	-0.032	0.370	-0.007	-0.188	2.180	-0.041

[*] All the estimates obtained from PA model.

[1] Based on an insignificant short run estimate.

[a] Calculated based on the individual elasticity for each country. The same is the case for the maximum, minimum and median values.

[b] Calculated by first taking the mean of individual parameter estimates. Then the elasticities are calculated from this mean. The elasticities marked by [a] and [b] are the same in short run but not for the long run.

3.9 Summary and Conclusion

This chapter attempts to estimate the key parameters of aggregate energy demand for OECD countries using various panel data approaches. In particular, the homogeneous estimators, POLS, FE and RE are estimated using different models specifications: the PA, ALN and ADL. The PA model experienced the problem that the coefficient on the lagged dependent variable is biased towards one, and therefore biases the long run estimates due to imposing homogeneous estimates across the countries. In addition the inclusion of the time trend as a proxy for technical progress showed an inability of picking up the heterogeneity of the underlying trends variables across the countries. However, the restriction tests preferred the FE estimator for all the estimated models without the inclusion of the time trend.

Therefore, the analysis proceeded to introduce the heterogeneous estimators: MG, SR and RC. These estimators were just estimated the PA model. Again the time trend as a proxy for technical progress was incorporated in the model specifications. The MG and SR estimator yielded more plausible coefficients of the lagged dependent variable as well as the long run estimates but the RC estimator yielded very large long run income elasticity with and without the time trend. However, the inclusion of the time trend biases the long run income estimates for the MG and SR estimator.

Given the problems incorporated in the panel estimation the solution is to estimate the energy demand function country by country and incorporating a stochastic trend which may be capable of capturing the underlying trends, since the overriding aim of this thesis is to obtain accurate and reliable estimates of the income and price elasticities. An issue discussed in Chapter 4.

Chapter 4

Time Series Modelling

4.1 Introduction

This chapter focuses on the important issue when modelling energy demand, that of its Underlying Trend. As discussed in earlier chapters, a primary aim for applied energy economists is to estimate the two key elasticities of energy demand: income and price. Therefore, it can be argued that is essential that such models are flexible enough to allow for any evolving patterns in the underling trend or unobserved variables. Not only for the sake of reducing any potential biases in the elasticity estimates but also to ensure that the direct effect of the economic variables are separated from the effect of the unobserved variables on energy demand.

The concept of the Underlying Energy Demand Trend (UEDT) is used in this chapter which acts as a proxy not only for technical progress which usually produces improved energy efficiency, but also other factors such as changes in consumer tastes and the economic structure that may be working in the same or opposite direction. Therefore, by allowing for the UEDT in its stochastic form to capture as much information as possible from the past this should, as discussed below, lead to a better understanding of the past and therefore improve the accuracy of future projections.

As shown below, the Structural Time Series Model (STSM) suggested by Harvey (1989 and 1997) is a useful and convenient tool allowing the UEDT to evolve over time (stochastically). Since the traditional formulations with a linear time trend (or maybe no trend at all) become limiting cases within this framework, then the validity of these restrictions can be tested and consequently gauge the effect of imposing restrictions that may not be supported by the data. Furthermore, this chapter also compares the STSM/UEDT energy demand results with those obtained from using the cointegration estimation approach that incorporates the deterministic time trend as a proxy for technical progress, hence exploring any potential biases in the elasticity estimates.

The layout of this chapter is as follows: Section 4.2 reviews the relevant literature. Section 4.3 outlines the two methodologies: STSM and cointegration approaches. Section 4.4 presents the estimation results. And the final Section presents a summary and conclusion.

4.2 Literature Review

Chapter 1 briefly discussed some aggregate energy demand studies for OECD countries, focusing on the estimated elasticities. In a time-series context, this chapter focuses on the issue of how technical progress is or is not incorporated into modelling OECD energy demand. Energy demand is a derived demand rather than a final demand: it is not demanded for its own sake, but for the services it produces in combination with the capital and appliances stock in place at any particular point of time (Hunt et al., 2003b).

This section therefore reviews the energy demand literature that discusses the issue of modelling technical progress. Within this literature there is a common argument as to whether or not a simple deterministic time trend is an adequate proxy for technical progress in an energy demand function. Furthermore, this section reviews the more recent studies in modelling the effect of technical progress on energy demand; these studies introduce the concept of the UEDT in its stochastic form.

Beenstock and Willcocks (1981) observe the rise of energy productivity in developed market economies and thus assume it is appropriate to consider these productivity improvements upon energy consumption using a linear time trend as a proxy for technical progress (energy productivity). However, they suggest "proxying technical progress in this way is never satisfactory although it is common in practice" (p. 227). Moreover, they argue that ignoring the time trend in the energy demand function would result in the underestimation of the long run income elasticity. Using OECD aggregated energy data from 1950 to 1978, the estimated coefficient on the linear time trend is -0.036, indicating that autonomous technical progress occurs at 3.6% p.a. The estimated long run price elasticity is -0.06 and the long run income elasticity is 1.78. They state that these are considerably lower and larger respectively than common estimated results, whereas excluding the linear time trend result the long run elasticity of -0.13 and long income elasticity of 0.88.

In contrast to Beenstock and Willcocks, Kouris (1983) argues strongly against including a linear time trend as an approximation for technical progress. He states that "a variable ... which takes the clumsy values 1, 2, 3... etc will not do the trick" (p. 207). Moreover, according to his argument, part of the technical progress is induced by price changes rather than exogenous autonomous technical progress, and, thus, the cause of technical progress in total is related to two elements: the price induced element and autonomous element. Thus technical progress cannot be separated from long run price elasticity unless there is a proper way to measure the autonomous technical progress. In addition, Kouris realised that there are a number of elements inducing technical progress in energy usage such as energy policies, inter-factor substitution, fuel switching and changes in economic structure. Using this approach (i.e. with no trend), Kouris finds the estimated long run price and income elasticities are -0.43 and 0.70 respectively using OECD countries aggregated data from 1950 to 1970.

Welsch (1989) reconsidered the issue of including a linear time in aggregate energy demand function to account for autonomous technical progress. He points out that Kouris' argument leads to negative technical progress in the case of energy price falls which Welsch argues counterintuitive. Using eight OECD countries, (USA, Germany, Japan, France, the UK, Italy, Netherlands and Canada) data over the period 1970 to 1984, aggregate energy demand is estimated for different specifications and a set of criteria are applied to the estimated models.[34] In particular he investigates whether including a time trend is appropriate or not. He concludes that it is appropriate to include a time trend as far as the set of all countries is considered. Within the results for each country, an inclusion of a linear time trend is preferred for the UK, France, Canada and Germany, but not for the USA, Italy and the Netherlands. In comparison between them, the latter have much higher price elasticities and lower income elasticities than the former. The results imply that the improvements of energy

[34] Model 4 and 5 in his specification, the income is split into a cyclical and a trend component beside a simple trend. The Cyclical component of the trend is a fertile area to study in the context of STSM.

efficiency in the latter countries are induced by price changes, whereas for the former countries, there are clear tendencies of autonomous improvement of energy efficiency that can be identified, and price elasticities are lower because the predominately measure pure substitution effect, Welsch (p. 290). Furthermore, because pure income effect and technical progress are separated, then income elasticities may be higher in this case (p. 290). Due to variant results between the countries, he suggested that energy demand should be modelled on a country by country basis rather than imposing a single model (p. 291)

Jones (1994) re-examined the accounting for technical progress in the aggregate energy demand in seven OECD countries.[35] He argues that an increase in the price of energy leads to a movement along the energy demand curve (short run effect) but if the increase in the price is sustained, this motivates the energy users to replace their current equipment with more efficient stock, therefore shifting the energy curve to the left over time such that price driven technical progress has long run effects. Jones agreed with Kouris about other non-price factors contributing to improvements in the technical progress of energy as a response to environmental regulations, efficiency standards of the stock, substitution between factor of production and a structural shift toward less energy intensive usage. Jones (1994) goes on to argue that "reductions in aggregate energy demand due to technical progress are distinct from the standard long-run adjustments to price increases" (p. 245). Therefore, using aggregated data for OECD countries over the period 1960 to 1990, Jones finds that the estimated coefficient of the linear time trend is -0.015 which implies an autonomous reduction

[35] Jones realised the complication of estimating aggregate energy elasticities is the presence of technical progress, in addition to aggregation across countries and various types of energy.

of energy consumption in OECD by 1.5 % p.a; and the estimated long run price and income elasticities are -0.70 and 1.23 respectively.

Many researchers agree that there is an important role for of the effect of technical progress determining the consumption of energy. Moreover, they are aware that it is not (usually) observable and therefore there is less agreement on how this effect should be incorporated when trying to estimate energy demand functions in order to avoid any bias that might be introduced if ignored. Improvements in technology take place in the economy over time but not necessarily at a fixed rate. Moreover, there are times when improvements in technology (and hence improved energy productivity) may occur very rapidly, whereas at other times it might be very slow. In other words, it is unlikely to occur at a steady continuous rate.

But in addition to the important technical progress effect, Hunt et al (2003b) have argued that there are other important influences (distinct from income and price) that will impact on energy demand. For instance, a restructuring of the economy from energy intensive industries to less energy intensive sectors, changes in consumer taste and the pressures from environmental issues, all of which can have an important impact on energy consumption at various times, but are unlikely to happen at an even and constant rate. Arguably, therefore, there is a need for a broad concept to capture not only technical progress in an energy demand function but also other unobservable factors that might produce energy efficiency.[36] Recently, the concept of the Underlying Energy Demand Trend (UEDT) proposed by Hunt et al (2003a and

[36] Or possibly inefficiency

2003b) has been introduced which is stochastic in form, and has been incorporated in recent energy demand studies.

Hunt et al (2003b) state that "the level of technology embedded will have come about through a combination of endogenous and exogenous factors" (p. 141). Thus their statement enlarges the concept of technical progress - as a factor influencing energy consumption trends - to include other factors such as consumer tastes and economic structure. It is this enlargement of the technical progress concept that they call the UEDT.

Table (4-1) below shows the factors (usually unobservable) that might affect energy consumption (other than price, income, etc.) which according to Hunt et al (2003b) will bias the estimated energy demand elasticities if they are ignored or not encompassed adequately in an estimated energy demand function. Therefore, they argue that it is crucial to encompass these factors when estimating an energy demand function in order to capture the underlying changes in energy efficiency, and other (usually unobservable) factors (Hunt et al 2003b).

Table (4-1) Underlying Energy Demand Trend (UEDT)

(Pure) Technical energy efficiency		Consumer tastes	Economic structure
Endogenous	Exogenous	Exogenous	Exogenous

Source: Hunt et al (2003b: p. 141)

Given these different factors it is, according to Hunt et al. (2003b), unreasonable to expect the UEDT to be linear. Therefore, a technique is needed that allows the

UEDTs to be modelled adequately, such as Harvey's STSM that allows the unobservable trend to vary stochastically over time.

Hunt and Ninomiya (2003c) investigate the nature of the trend (stochastic or deterministic) in transport oil demand functions for the UK and Japan. The results for both countries confirm that the STSM is the preferred technique to model the UEDTs. Given, restrictions of the deterministic trend and seasonal component are rejected, that would suggest technical progress and other factors are evolving over time and so a stochastic formulation of the trend is preferred. Moreover, Hunt and Ninomiya state that "the STSM framework is arguably a superior technique, it produces unbiased estimates of the long run income and price elasticity, even when it is not possible to capture all the underlying influences explicitly'' (p. 91). Using a quarterly data set over the period 1971q1 to 1997q4 for both the UK and Japan, they find for the both countries that the stochastic seasonal trends are preferred to the conventional deterministic dummies. The estimated underlying trends at the end of the estimation period are 0.56% and 1.73% p.a for the UK and Japan. This indicates, holding income and price constant, the underlying use of transportation oil is growing in both countries at the end of the estimation period. For the UK the shape of the UEDT is generally upward sloping with small fluctuations and contains stochastic level and fixed slope whereas for Japan the shape of the UEDT moves in a nonlinear fashion and involves both stochastic trend and slope. The estimated long run income and price elasticities are 0.801, -0.123 and 1.080, -0.083 for the UK and Japan respectively.

Furthermore, Hunt et al (2003a) estimate UK aggregate energy demand functions for the whole economy, the residential sector, the manufacturing sector and the transportation sector using quarterly data over the period 1971q1 to 1997 q4. For the whole economy and the residential and manufacturing sectors the stochastic trend (and stochastic seasonals) is the preferred formulation instead of the deterministic trend (and seasonal dummy variables). The estimated whole economy UEDT declines almost continuously, implying that the UK economy has become more energy saving after holding the effects of income and price over the estimation period; the estimated long run income and price elasticities for the whole economy are 0.56 and -0.23 respectively. For the manufacturing sector the estimated UEDT is generally downward sloping with estimated long run income and price elasticities of 0.72 and -0.20 respectively; whereas for the transportation sector the estimated UEDT is generally upward sloping with estimated long run income and price elasticities of 0.79 and -0.13 respectively. For the residential sector however the estimated UEDT is flat with estimated long run income and price elasticities of 0.30 and -0.22 respectively.

The results from Hunt et al. (2003a) have been confirmed by Dimitropoulos, et al. (in press). Using UK annual data for the period 1967 to 2002 they re-estimate aggregate energy demand functions for the whole economy, the residential sector, the manufacturing sector and the transport sector and conclude, similar to Hunt et al. (2003a), that it is important to adopt the STSM/UEDT approach. Moreover, they show that using this approach the direction and slopes of the UEDT and the estimated long run elasticities are robust to a different frequency of data.

This brief review has shown that there has been some debate about how to model technical progress and other underlying exogenous factors when modelling energy demand. Therefore, this issue is addressed in the context of OECD demand in the remainder of this chapter. In particular estimates of time series energy demand functions are explored for the 17 OECD countries in Data Set 17B by estimating STSM and cointegration in an attempt to try to ascertain what the appropriate technique is and what is the direction and shapes of the UEDTs for each country.

4.3 Methodology

The cointegration technique has had a considerable influence on energy demand studies and has been widely used. However, these studies either ignored or approximated the effect of technical progress on energy consumption. This technique allows modelling technical progress in the energy demand function via a simple deterministic trend; see for instance (Hendry and Juselius, 2000 and 2001) for a discussion of cointegration methodology.

Harvey (1997) criticises the concept of cointegration as being unnecessary or misleading or both, arguing that there is nothing to keep individual series moving together in the long run. Moreover, Harvey (1997) asserts that this is a general shortcoming of pure time series techniques and in general such models are likely to have poor statistical properties.

Using the idea introduced by Harvey, Hunt et al (2003b) argue that "modelling the underlying energy demand trend ensures that as much information as possible from the past is employed to fully understand the past and hence to enhance future projections" (p. 140). Furthermore, they argue that the form of the trend involved in energy demand functions should be flexible enough to incorporate, in addition to pure technical progress, the other exogenous factors outlined in the previous section. Hence according to the arguments in Hunt (2003a and 2003b), cointegration is an inadequate technique. This follows from the work by Harvey et al (1986) who argue that "technical progress has traditionally been modelled by a deterministic trend. However, we believe that a stochastic trend offers an intuitively more appealing way of modelling variables like productivity and technical progress, and offers a way out of the problems caused by constraining them to be deterministic" (p. 975).

Hunt et al (2003b) suggest that "it is feasible to expect that the underlying energy demand trend (UEDT) will be non-linear with periods when it could be upward sloping and/or when it could be downward sloping" (pp. 143 - 144). Furthermore, a simple deterministic time trend is present only if statistically accepted by the data. The specification of technical progress via the UEDT concept therefore ensures that the model captures the underlying trend effects and avoids biases of the long run income and price elasticities, as identified in Figure (9.1) in Hunt et al (2003b), if the UEDT is not modelled in an appropriate way. Furthermore, given the unobservable trend has both a level and slope component, then the shape of the estimated trend model depends upon their variances, known as hyperparameters.[37] Hunt et al (2003b) classify numerous possibilities of the stochastic trend models as in Table (4-2) below.

[37] These are explained in details in the following section.

Table (4-2) Classification of Possible Stochastic Trend Models

	LEVEL		
SLOPE	Lvl = 0, $\sigma_{\eta}^2 = 0$	Fixed Level Lvl ≠ 0, $\sigma_{\eta}^2 = 0$	Stochastic Level Lvl ≠ 0, $\sigma_{\eta}^2 \neq 0$
No Slope Slp = 0, $\sigma_{\xi}^2 = 0$	**(i)** Conventional regression but with no constant and no time trend	**(ii)** Conventional regression with a constant but no time trend.	**(iii)** Local Level Model (random walk plus noise).
Fixed Slope Slp ≠ 0, $\sigma_{\xi}^2 = 0$	**(iv)**	**(v)** Conventional regression with a constant and a time trend.	**(vi)** Local Level Model with Drift.
Stochastic Slope Slp ≠ 0, $\sigma_{\xi}^2 \neq 0$	**(vii)**	**(viii)** Smooth Trend Model.	**(ix)** Local Trend Model.

Source: Hunt et al (2003b, p. 151).

Therefore, as stated above, this chapter utilises the STSM approach to estimate the energy Demand functions for the 17 countries in Data Set 17B.[38] The following section therefore outlines this technique.

4.3.1 STSM Approach

Drawing on Hunt et al (2003a & 2003b) this study combines the structural time series model with an Autoregressive Distributed Lag (ADL) to estimate the OECD energy demand functions. This structure allows for a stochastic trend in which the level and slope are allowed to evolve over time when estimating price and income elasticities of an aggregate demand function. In the present context, the study postulates the model to be:

[38] It should be noted that there is also a growing literature on asymmetric price (and income) elasticity modelling which also attempts to address some of the issues of induced technical progress, etc (see for example, Dargay and Gately, 1995).

$$A(L)LE_t = \mu_t + B(L)LY_t + C(L)LP_t + \varepsilon_t \tag{4.1}$$

LE_t,, LY_t, LP_t are as defined in Chapter 2. Where $A(L)$ is the polynomial lag operator $1-\phi_1 L-\phi_2 L^2 ....\phi_p L^p$, $B(L)$ is the polynomial lag operator $\delta_0+\delta_1 L+\delta_2 L^2 ....\delta_p L^p$ and $C(L)$ is the polynomial lag operator $\pi_0+\pi_1 L+\pi_2 L^2 .....\pi_p L^p$. $B(L)/A(L)$ and $C(L)/A(L)$ represent the long run income and price elasticities, respectively. The trend component μ_t is assumed to have the following stochastic process:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{4-2}$$

$$\beta_t = \beta_{t-1} + \zeta_t \tag{4-3}$$

Where $\eta_t \sim NID(0,\sigma_\eta^2)$ and $\zeta_t \sim NID(0,\sigma_\zeta^2)$. Equations (4-2) and (4-3) represent the level and the slope respectively. The effect η_t is to allow the level of the trend to shift up and down, while ζ_t allows the slope to change; this specification is contrary to a simple deterministic time trend. The shape of the underlying trend depends upon the variances σ_η^2 and σ_ζ^2, (also known as the hyperparameters); the larger the variances the greater the stochastic movements in the trend. In the limiting case when the variances are equal to zero the model collapses to a conventional deterministic time trend regression. There are a number of alternatives to estimate the stochastic trend depending on the values of the hyperparameters, as illustrated in Hunt et al (2003b) and reproduced as Table (4-2). This specification may even pick up the effects of large and/or asymmetric price and income effects (which appears to be the case with Ireland below).

The initial model to be estimated therefore consists of equation (4-1) with (4-2) and (4-3). All the disturbances are assumed to be independent and uncorrelated with each other. The estimation is carried out by maximum likelihood and the hyperparameters are obtained from a smoothing algorithm using the Kalman filter. For model selection, equation residuals are estimated (similar to those from ordinary regression), in addition to a set of auxiliary residuals. The auxiliary residuals include irregular residuals, level residuals and slope residuals. Of course, level and slope residuals are estimated if the trend components are non-zero. The final preferred specifications for each individual country are found by testing down from the initial general model by eliminating insignificant variables, provided that the equation passes an array of diagnostic tests which are described in more detail in the results section below.

In addition, a Likelihood Ratio (LR) test is undertaken to test the restriction of a deterministic trend against the estimated stochastic trend. However, the LR test cannot be used in some cases. This is because in the structural time series framework, unlike the conventional Maximum Likelihood Estimation, the likelihood function of the Kalman filter is a function of hyperparameters only (Harvey, 1989, p. 126). During the maximisation, other parameters are treated as constant which are automatically given by the linear recursive algorithm system in the Kalman filter (Harvey, 1989, pp 105-106). In other words, the final estimators for the coefficient parameters are not directly generated through the maximisation procedure of likelihood function, but are calculated by the Kalman filter associated with the hyperparameters with which the likelihood function yields the maximum value. Consequently, the LR test may be invalid when the coefficient parameters in the tested models are not the same, since such differences are not reflected in the likelihood function, so that the comparison between the log-likelihood values is not legitimate in order to construct the restriction test. However, it is still valid to test the deterministic restrictions against stochastic components using the LR statistic, since these restrictions can correspond to the maximisation of the likelihood function through changes in the hyperparameters. The software package STAMP 5.0 (Koopman et al, 1995)[39] is used to estimate the demand function for the 17 OECD countries.

4.3.2 Cointegration Approach

For the sake of facilitating the comparison of the STSM results, aggregate energy demand parameters for OECD countries are also estimated using the cointegration approach developed by Engle and Granger (1987). This approach is well documented in many places (see for instance, Henry and Jueslius, 2001 and Madalla and Kim, 1998). Two forms of the E-G approach are taken: the first is the original E-G two-step method (denoted by 'Static E-G'). This approach depends on running a static cointegrating regression, for instance, LE_t on LY_t, LP_t, a constant and a deterministic trend using OLS. This approach yields a consistent estimate of the long run steady state relationship between the variables due to the 'superconsistency' of the OLS estimator. (However, in a finite sample it has been shown that the bias is a problem.

[39] During the latter part of the research STAMP6.3 became available so all results have been cross checked with the later version.

Banerjee et al. (1993) and Inder (1993) show the bias could be often substantial). In addition, the residuals are used to test for cointegration using Dickey-Fuller and augmented Dickey-Fuller tests.

The second approach (given the bias problem highlighted by Banerjee et al (1993) and Inder (1993)) is the dynamic Engle-Granger procedure (denoted by 'Dynamic E-G'). For this procedure an overparameterised ADL model of LE_t on, LY_t, LP_t, a constant and a deterministic trend is estimated by OLS, and the long-run cointegrating vector is derived as the long run solution to the dynamic model. Inder (1993) shows that this procedure provides valid t-tests and thus tests on the significance on the long run parameters may be undertaken. Therefore, it is possible to carry out a test of no cointegration, hence the sum of the coefficients on the distributed lag of LE_t must be less than one for the dynamic model to converge to a long run solution. Thus dividing this sum by the sum of the associated standards errors provides the PcGive unit test, which is a t-type test that can be compared against the critical values given in Banerjee et al (1993).

Furthermore, for both the Static E-G and Dynamic E-G methods the errors from the long-run solutions are used as the Error Correction (EC) term in a second short run ADL equation of ΔLE_t on ΔLY_t, ΔLP_t and EC_{t-1}. The preferred dynamic model is found by testing down from the initial general model by eliminating insignificant variables but ensuring the model passes an array of standard diagnostic tests.[40]

[40] These tests are given in the results section below. In addition the description of this methodology heavily depends on Harris and Sollis (2003).

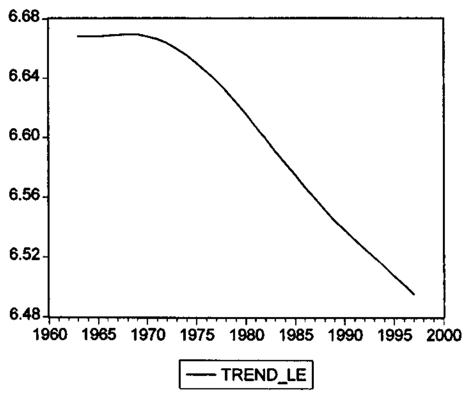
4.4 Results

4.4.1 STSM Results

The aggregate energy demand functions for the 17 OECD countries are estimated using time series Data Set 17B (1960-1997) with three observations (1998-2000) saved for the purpose of the post sample prediction test. Table (4-3) represents the results. Generally, they reveal that the models fit the data well with some exceptions. For all countries the LR test rejects the null hypothesis of the restriction of a deterministic trend, hence supporting the idea of utilising the STSM approach. More detailed discussions for each country follow.

UK

Figure (4-1) The Estimated UEDT for the UK

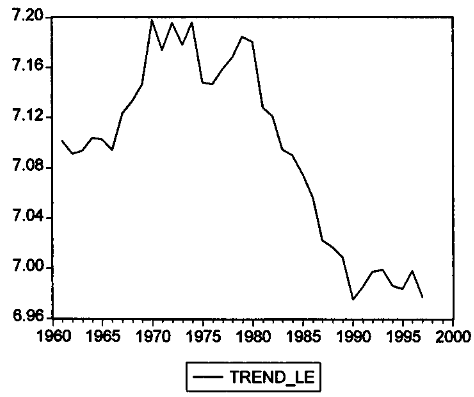


All the diagnostic tests of the estimated model are passed.[41] The estimated model includes the first lagged difference of the price. This was included since the current and the first lagged were insignificant with coefficients of almost equal size but of opposite signs. The estimated long run price and income elasticities are -0.30 and 0.60 respectively. The form of the estimated trend is the smooth trend model that includes a fixed level and stochastic slope. The shape of the UEDT is almost continuously downward sloping, Figure (4-1), which implies a reduction in energy consumption in the UK economy almost continuously after controlling the effects of price and income. The rate of decline of the UEDT is 0.63% p.a. at the end of the period. Hunt et al (2003a) and Dimitropoulos et al (in press) both found a similar shape of the UEDT for the UK economy using quarterly and annual data respectively. In addition, the estimated long run income and price elasticities are also close to those in this study despite a different frequency and length of the data.

[41] See the explanation of the diagnostic tests at the bottom of Table (4-3).

Canada

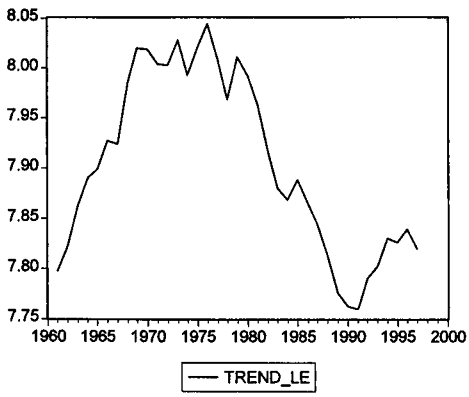
Figure (4-2) The Estimated UEDT for Canada



The model passes all diagnostic tests. In addition, the inside and post sample predictive tests are all passed. The number of lagged variables required is small with just a one year lag on income required. This suggests almost instantaneous adjustment of aggregate energy demand to the price change. The preferred stochastic specification is the local level model with drift – see the estimated UEDT in Figure (4-2). This model consists of a random walk component to capture the underlying level that varies in a particular direction as specified by the fixed slope component; therefore the stochastic movement of the underlying trend is being created by the specific shift in the level component rather than changes in the slope. The estimated long run income and price elasticities are 0.89 and –0.13 respectively. The estimated UEDT effect reduced energy consumption significantly over the period 1980 to 1990 probably through the improvement of technical progress while from 1990 onwards this decline stopped with the estimated UEDT being -0.13% at the end of the period.

Sweden

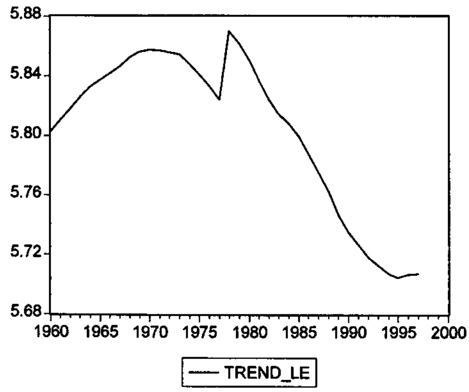
Figure (4-3) The Estimated UEDT for Sweden



All diagnostic tests are passed satisfactorily. The number of lagged variables required is small with only a one year on income required. This suggests almost an instantaneous adjustment of aggregate energy demand to the price change. The estimated UEDT is a local trend model, which consists of a stochastic level and stochastic slope. The estimated UEDT, see Figure (4-3), shows an upward sloping shape over the period 1961 to 1970 suggesting a shift in the energy demand curve to the right , whereas during the during the period 1971 to 1991 the UEDT shows a downward sloping suggesting the demand curve shifted to the left before turning positive again during the 1990s. The estimated UEDT at the end of the period is of – 0.07% p.a; suggesting that after controlling for the income and price the energy consumption fall by 0.07% each year.

Austria

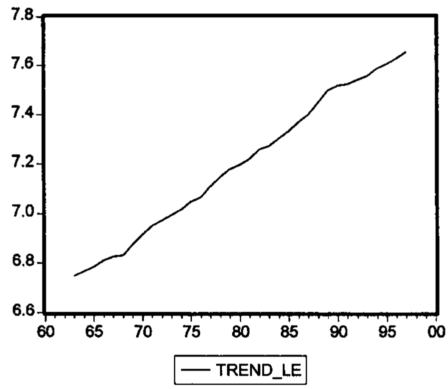
Figure (4-4) The Estimated UEDT for Austria



The estimated model passes all the diagnostic tests. The model adjusts to long run position without any lagged variables in the estimated equation suggesting an instantaneous adjustment of energy demand to both price and income. However, it should be noted that the preferred specification includes irregular dummies for the years 1961 and 1963 and a level dummy for the year 1978 to ensure the auxiliary residuals are normally distributed. The estimated long run income and price elasticities are 0.88 and -0.11 respectively. The estimated model is a local trend model; hence the variations in the UEDT in Figure (4-4) come through the level and the slope. The estimated UEDT trend growth at the end of the period being -0.08% p.a. Therefore, holding income and price constant, energy consumption would autonomously fall by 0.08 each year.

Portugal

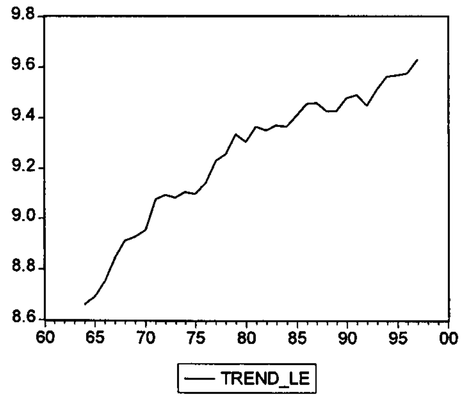
Figure (4-5) The Estimated UEDT for Portugal



All the diagnostic tests for the estimated model are passed. The preferred specification includes the current income variable and it requires the price variable to be lagged three periods. The stochastic trend variation is via the level and the preferred model is the local level model with drift, hence the trend slope is fixed. The estimated UEDT at the end of the period is +2.6% p.a. Therefore, after controlling for the income and price effects, the use of the energy has been increasing rapidly over the estimation period by 2.6% each year. The upward sloping of the UEDT (Figure 4-5) is in line with the energy intensity in Figure 2.7 and reflects a shift in energy demand curve to the right. The estimated long run income and price elasticities are 0.50 and -0.07 respectively.

Ireland

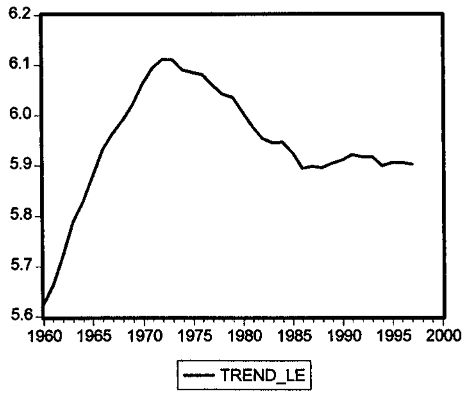
Figure (4-6) The Estimated UEDT for Ireland



The diagnostic tests are all satisfactory. The preferred specification is a local trend model, Figure (4-6), It contains a one year lag of the price variable and the difference on income variable lagged two periods. In addition, it requires the inclusion of the difference between the second and first lagged of the dependent variable. This, this was included since the first and second lags of the dependent variable were needed to ensure the estimated model is not violating the diagnostic tests. Individually, they were insignificant but with the coefficients of almost the same size and opposite signs. Therefore, the two variables LE_{t-2} and LE_{t-4} were replaced by their difference (LE_{t-2} - LE_{t-4}) which is significant at the 5% level. The estimated long run price and income elasticities are -0.12 and zero respectively. The income elasticity is a strange estimate. As a developed countries become saturated with energy, it is expected the income elasticity might decline. However, it would seem implausible that it would fall so close to zero for a country such as Ireland. Thus, one should be cautious when considering this result. The estimated UEDT at the end of the period is +2.43 p.a. Therefore, after controlling for the income and price effects, the use of the energy has been increasing rapidly over the estimation period by 2.43 each, reflecting a shift in the energy demand curve to the right.

Italy

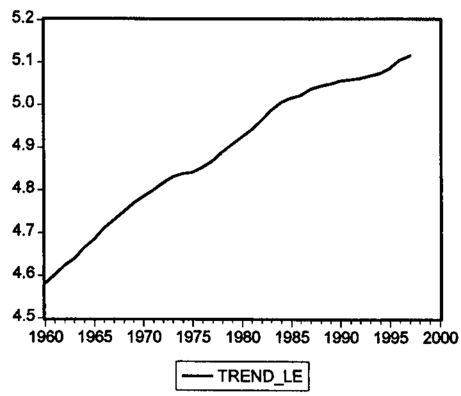
Figure (4-7) The Estimated UEDT for Italy



The model specification appears to fit the data well. The misspecification tests reject the presence of serial correlation, heteroscedasticity and non-normality. In addition, the inside and post sample predictive tests are all passed. There are no lagged variables in the preferred specification suggesting an instantaneous adjustment of aggregate energy demand to price and income. The estimated long run income and price elasticities are 0.90 and –0.1 respectively. The estimated hyperparameters for the level and slope are both non-zero hence the form of the stochastic trend is a local trend model. The estimated UEDT, see Figure (4-7), shows an upward sloping shape over the period 1960 to 1970. While during the 1970s and towards the mid 1980s the UEDT shows a downward sloping shape. The period from 1985 toward late 1990s shows the UEDT flattens out. Moreover, the fluctuation of the UEDT confirms it is non-linear, which indicates that trying to approximate the UEDT by a linear time trend is not appropriate. The estimated UEDT growth rate at the end of the estimation period is of -0.20% p.a, suggesting that after controlling for the income and price the energy use fall by 0.20% each year.

Greece

Figure (4-8) The Estimated UEDT for Greece

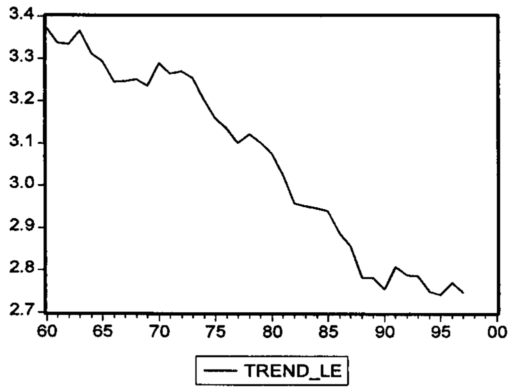


The estimated equation is well specified hence there is no evidence of autocorrelation, heteroscedasticity, and non-normality. In addition, the inside and outside predictive tests are all passed. The model does not include lagged variables implying an immediate adjustment to the long run equilibrium. The estimated UEDT, Figure (4-8), is a local trend model because the hyperparameters for slope and level are non-zero so the trend is stochastic in both the level and slope and is confirmed via the LR test. The estimated long run income and price elasticities are 1.1 and –0.14 respectively. The income elasticity is much lower than the 1.598 obtained by Samouilidis and Mitropoulos (1984) using Greek annual data for the period 1958 to 1980, whereas the price elasticity is lower than their estimate of -0.464 (in absolute terms). These differences might be explained by the arguments in Hunt et al (2003b) about possible biases if the UEDT is ignored, given Samouilidis and Mitropoulos (1984) ignored the effect of technical progress in their energy demand function.

The increase in energy use in Greece might be explained as follows: firstly, after holding income and price constant, energy use increased rapidly during the estimation period so that the effect of other exogenous variables modelled through the stochastic trend show positive effects and shifts the energy demand function to the right. This is reflected in the positive UEDT growth at the end of the period by 1.1% p.a. Secondly, given that the income elasticity is greater than 1 then holding the price effect and other exogenous and endogenous variables modelled via UEDT, the increase in energy use is more than the increase in income. This also implies the economy has become more energy intensive. The upward slope of the UEDT reflects a shift in the energy demand curve to the right. This is all consistent with the calculated energy intensity discussed in Chapter 2, which showed that the Greek economy become more energy intensive even during the two oil price crises (see Figure 2-5). This might suggest that energy sector in Greece might need restructuring if there is any desire to reduce energy consumption.

France

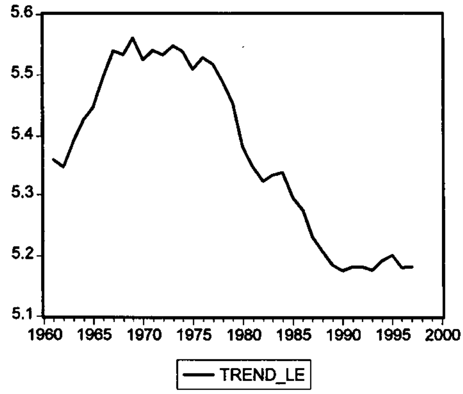
Figure (4-9) The Estimated UEDT for France



The estimated equation passed all the diagnostic tests, in addition to the predictive tests. The long run estimates of income and price elasticities are 1.35 and –0.15 respectively. The estimated UEDT, Figure (4-9), is a local level model with drift, hence the value of the hyperparameter of the slope is equal to zero but not for the level; therefore, the variation in the trend comes through via the level. The shape of the estimated UEDT generally declines at -1.9% p.a. thus after holding income and price effects the energy use falls autonomously by 1.9% each year.

Japan

Figure (4-10) The Estimated UEDT for Japan

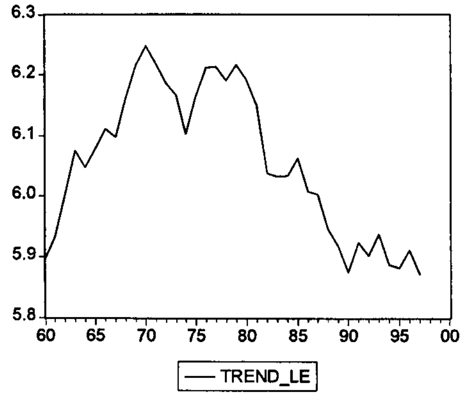


The diagnostics of the model are satisfactory with no sign of autocorrelation, heteroscedasticity, etc. the inside and post sample predictive tests are all passed which indicate the model is stable. The model needs one lag on the price variable to adjust to its long run equilibrium; this indicates almost instantaneous adjustment of aggregate energy demand to the price change. The estimated long run income and price elasticities are 0.95 and –0.14 respectively. The preferred stochastic trend is a local trend model as specified by the hyperparameters of the level and the slope. During the 1970s and 1980s the estimated UEDT, Figure (4-10), shows a rapid decline implying that the Japanese economy became more energy efficient and the amount of energy needs as input is less than before. The UEDT shows an inverse relation to real price index before the oil crisis where the UEDT and real price series drift in a similar direction. It appears other exogenous variables (other than income and price) are responsible for a reduction of energy consumption. The UEDT growth rate at the end of the period is –0.27% p.a., indicating, holding the price and income effects, energy demand would autonomously fall by 0.27% each year.

The estimated elasticities from this study can be compared with the results from a past study which used the STSM approach in modelling aggregate energy demand in Japan. Hunt and Ninomiya (2005) estimate a *primary* energy demand function for Japan using STSM approach over the period 1888 to 2001. The stochastic trend is the preferred model and the long run income and price elasticities obtained are 1.05 and –0.20 respectively, which are only slightly different from the result obtained from in this study, despite analysing *primary* energy demand, and using a different data source and a considerably different estimation period. The shape of the estimated UEDT in Hunt and Ninomiya (2005) has an inverse U shape, the downward sloping part starts in 1950 to the end of the estimation period, whereas in this study the estimated UEDT downward sloping part starts in 1971 and its shape relatively similar to energy intensity trend (Figure 2-7). While they find that the estimated UEDT declined after 1950 unlike the E-GNP ratio between mid 1950 and 1974.

Denmark

Figure (4-11) The Estimated UEDT for Denmark

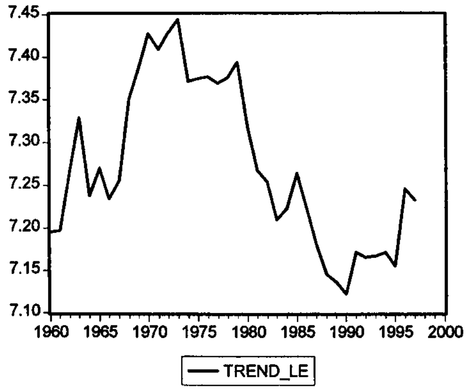


The estimated equation passed all the diagnostic tests. The preferred model is adjusted instantaneously to the long run position. The estimated long run and income and price elasticities are 0.90 and -0.20 respectively. The nature of the trend is the local trend model because the hyperparameter estimates for the slope and level are not zero, indicating that both the level and slope are stochastic. The shape of the UEDT, Figure (4-11), reflects two periods of energy use. The period from 1960 to 1970 shows an increase in the use of energy with a generally upward sloping UEDT, but a general downward sloping UEDT over the period 1971 to 1990 reflecting the improvement of energy efficiency. The estimated UEDT contributes to the reduction in energy use by -1.11% p.a. at the end of the sample period after controlling for the income and price effects. The Danish economy can therefore be described as energy using over the period 1960 to 1970 while over the period 1970 to 1997 it is an energy saving economy.

As mentioned above the long run income and price elasticity obtained from this study are 0.90 and – 0.20 respectively. Bentzen and Engsted (1993) estimate long run income and price elasticities for Denmark aggregate energy demand function using annual data for the period 1948 to 1990, ignoring the effect of technical progress in energy demand function even in its simple form (time trend). Their estimated income and price elasticities are 1.213 and –0.465 respectively. These differences in the obtained elasticities are consistent with the suggestion of Hunt et al (2003b) about the possible biases that may exist if the UEDT is not modelled appropriately. In this case, given the UEDT is downward sloping over the two thirds of the estimation period and the price and income are generally rising, one would expect their long run price elasticity to be overestimated if the UEDT is not included.

Belgium

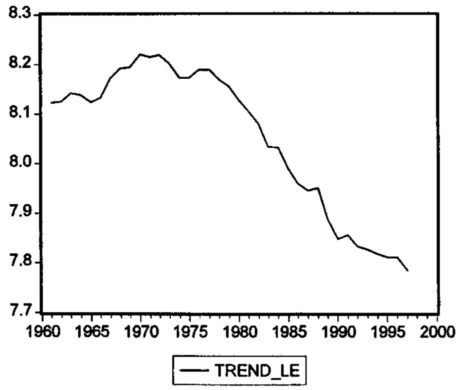
Figure (4-12) The Estimated UEDT for Belgium



The diagnostic tests are satisfactory with no indication of serial correlation, non-normality and heteroscedasticity. In addition, the inside and post sample predictive tests are all passed. The estimated model adjusts to its equilibrium position with no need for any lagged variables. The long run estimates are 0.74 and –0.18 for income and price elasticities respectively. In addition, the estimated UEDT, Figure (4-12), is a local trend model; therefore, the variation in the trend comes from both slope and level components. The estimated UEDT shows a continuous downward slope over the period from the mid 1970s to 1990 but turns up during the period 1990 to 1997 which appears to be inversely linked to real energy price index (Figure 2-4) and almost in line with the energy intensity over the period 1960 to 1997 (Figure 2-7). The estimated UEDT shows a negative impact on energy use at the end of the sample period by -0.16% p.a. after controlling for income and price effects.

USA

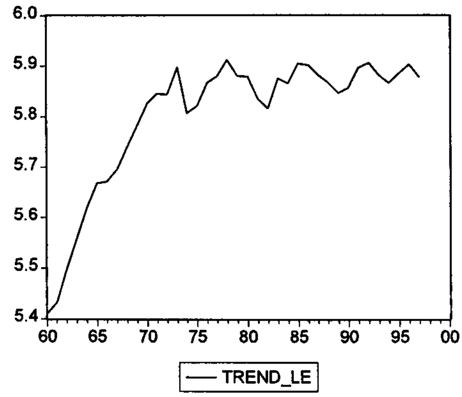
Figure (4-13) The Estimated UEDT for USA



The estimated model passes all the diagnostic tests. It adjusts to the long run position fairly quickly despite the price variable requiring a one year lag. The estimated long run income and price elasticities are 0.77 and –0.12 respectively. The nature of the stochastic trend is a local trend model because the level and slope components are stochastic. The UEDT shape, Figure (4-13) is almost downward sloping over the period from the mid 1970s to 1997. The estimated UEDT growth at the end of the period being -1.42% p.a. Therefore, holding the price and income constant, energy demand would autonomously fall by 1.42 % each year. Furthermore, comparing the UEDT with the real price index series (Figure 2-4); it is worth noticing that the evolution of the UEDT does not follow the fluctuations of the price series. This explains the importance of other exogenous variables modelled by stochastic trend in reducing energy demand.

Switzerland

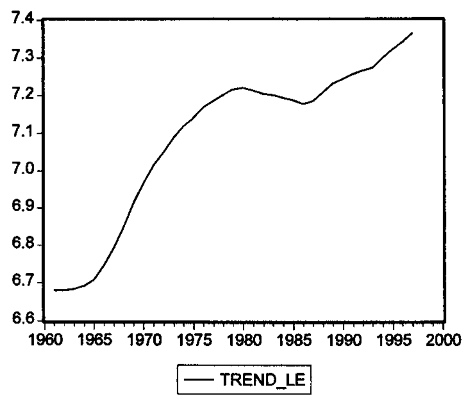
Figure (4-14) The Estimated UEDT for Switzerland



All the diagnostic tests are passed satisfactorily. However, it should be noted that the specification includes an irregular dummy for 1963 and level dummy for 1974 to ensure the auxiliary residuals are normally distributed. The estimated long run income and price elasticities are 0.70 and zero respectively. The preferred specification model is a local trend model with both trend components (level and slope) evolving over time. The UEDT, Figure (4-14), shows a steady upward slope until 1975 but it then flattens out during the rest of the period; the UEDT growth at the end of the period is of -0.06% p.a. Therefore, holding income and price constant, energy demand would autonomously fall by 0.06% p.a. The zero long run price elasticity suggests any attempt by the government to reduce energy consumption through an increase in the energy price is unlikely to achieve the desired objective.

Spain

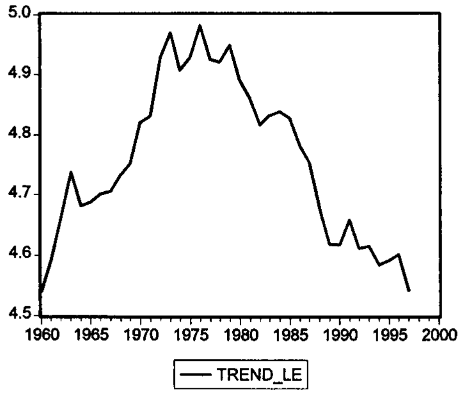
Figure (4-15) The Estimated UEDT for Spain



The diagnostic tests of the estimated model are satisfactory. The estimated energy demand model needs a one year lag of income. The estimated long run income and price elasticities are 0.70 and –0.125. The estimated UEDT, Figure (4-15), is a local level model consisting of a stochastic level and a stochastic slope. It moves in a non-linear pattern, increasing rapidly until 1980 followed by a slight decline during the period 1981 to 1986 before starting to increase again to the end of the period. The pattern of the UEDT in the 1990s is steadily upward sloping, therefore, after controlling for the price and income variables energy use has generally tended to increase.

Netherlands

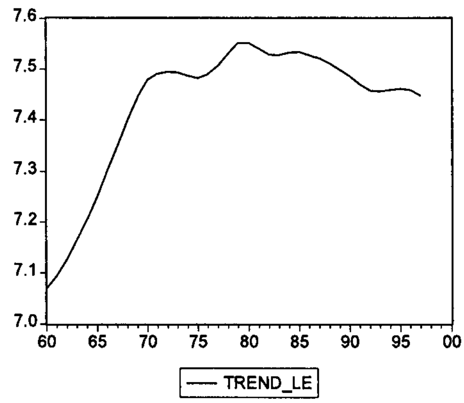
Figure (4-16) The Estimated UEDT for the Netherlands



The estimated model passes all diagnostic tests. The preferred specification gives long run income and price elasticities of 1.2 and -0.16 respectively without any lagged variables in the estimated equation suggesting an instantaneous adjustment of energy demand to both price and income. The preferred stochastic trend is a local trend model hence both trend components (level and slope) vary over time which results in an inverse V shaped UEDT with two stages, see Figure (4-16). The first stage is upward sloping during the period 1970 to mid 1970s indicating that holding income and price constant, the demand curve shifts to the right due to other exogenous variables. The second stage is downward sloping curve indicating that after holding price and income, a shift in the energy demand curve to the left.

Norway

Figure (4-17) The Estimated UEDT for Norway



The estimated model passes all the diagnostic tests. It adjusts to the long run position without a need to lag the variables (income and price) implying an immediate adjustment to the long run position. The estimated long run income and price elasticities are 0.60 and -0.13 respectively. The form of the estimated trend is the smooth trend model which includes a stochastic slope and a fixed level. The estimated UEDT in Figure (4-17) is upward sloping during the 1960s up to 1970; but towards the end of the estimation period it flattens with some fluctuations. This implies that trying to approximate the UEDT by a linear trend is not adequate. The estimated UEDT growth rate at the end of the period -1.04 % p.a., suggesting, after holding price and income constant, the energy demand would autonomously fall by 1.04% each year.

Table (4-3) The Estimated Results for Aggregate Energy Demand Using STSM

	UK	Canada	Sweden
LY_t	0.44*	0.89**	
LY_{t-1}			0.64*
LP_t			-0.18**
LP_{t-1}		-0.12*	
LP_{t-3}	-0.17**		
$LP_t - LP_{t-2}$	-0.18**		
LE_{t-1}	0.26*		
Long-run estimates			
Income (Y)	0.60	0.89	0.64
Price (P)	-0.30	-0.12	- 0.18
Diagnostics equation residuals			
Standard error	0.02	0.02	0.03
Normality	2.20	1.53	1.27
$H_{(11)}$	0.93	0.63	0.83
$r_{(1)}$	0.13	-0.09	- 0.05
$r_{(7)}/r_{(8)}$	$r_{(7)} = 0.04$	$r_{(7)} = 0.06$	$r_{(8)} = 0.07$
DW	1.64	2.07	2.03
Q	$Q_{(7,\ 6)} = 4.70$	$Q_{(7,\ 6)} = 2.64$	$Q_{(9,\ 6)} = 3.33$
R^2	0.92	0.99	0.96
Auxiliary residuals			
Irregular			
Normality	0.61	1.90	1.64
Kurtosis	0.53	0.01	0.17
Skewness	0.07	1.89	1.47
Level			
Normality	0	0.45	1.57
Kurtosis	0	0.29	0.70
Skewness	0	0.17	0.87
Slope			
Normality	1.63	0	0.61
Kurtosis	1.60	0	0.07
Skewness	0.03	0	0.54
Predictive tests (inside sample)			
CHOW	F (3, 30) = 1.45	F (3, 32) = 0.50	F (3, 28) = 0.38
Cusum t	t (30) = -0.31	t (32) = 0.06	t (28) = 0.68
Predictive tests (post sample)			
Failure χ^2 (3)	0.06	6.18	0.77
Cusum t (3)	-0.17	-1.42	- 0.71
Estimated Hyperparameters			
Irregular	0.020	0.002	0.009
Level	0	0.022	0.028
Slope	0.002	0.00	0.006
LR	4.05*	38.1**	45.4**
Nature of the trend	Smooth trend model	Local level model with drift	Local trend model

Table (4-3) continued

	Austria	Portugal	Ireland
LY_t	0.88**	0.50**	
ΔY_{t-2}			0.63*
LP_t	- 0.11**		
LP_{t-1}			- 0.12**
LP_{t-3}		- 0.07*	
$LE_{t-2} - LE_{t-4}$			0.23*
Long-run estimates			
Income (Y)	0.88	0.50	0.00
Price (P)	- 0.11	- 0.07	-0.12
Diagnostics equation residuals			
Standard error	0.020	0.022	0.03
Normality	1.93	0.62	1.64
$H_{(11)}$	3.2	1.01	1.45
$r_{(1)}$	0.04	- 0.034	- 0.07
$r_{(7)}$ / $r_{(8)}$	$r_{(7)} = -0.02$	$r_{(7)} = 0.14$	$r_{(8)} = 0.02$
DW	1.90	2.03	1.97
Q	$Q_{(7,\ 6)} = 8.32$	$Q_{(7,\ 6)} = 3.91$	$Q_{(8,6)} = 7.47$
R^2	0.99	0.99	0.98
Auxiliary residuals			
Irregular			
Normality	1.50	1.57	0.14
Kurtosis	0.15	0.25	0.05
Skewness	1.35	1.32	0.09
Level			
Normality	0.25	0.64	0.79
Kurtosis	0.24	0.35	0.79
Skewness	0.01	0.29	0.01
Slope			
Normality	0.91	N/A	0.33
Kurtosis	0.13	N/A	0.27
Skewness	0.78	N/A	0.06
Predictive tests (inside sample)			
CHOW	F (3, 33) = 2.40	F (3, 30) = 0.16	F (3, 29) = 0.52
Cusum t	t (33) = 1.70	t (30) = - 0.56	t (29) = 0.01
Predictive tests (post sample)			
Failure χ^2 (3)	0.75	0.78	2.44
Cusum t (3)	- 0.50	- 0.60	0.97
Estimated Hyperparameters			
Irregular	0.018	0.013	0.003
Level	0.006	0.02	0.037
Slope	0.003	0	0.002
LR	10.68**	6.70**	25.20**
Nature of the trend	Local trend model Irr 1961,1963.level 1978	Local level with drift model	Local trend model Include level dummy for 1971

Table (4-3) continued

	Italy	Greece	France
LY_t	0.90**	1.10**	1.35**
LP_t	- 0.10*	-0.14**	-0.15**
Long-run estimates			
Income (Y)	0.90	1.10	1.35
Price (P)	- 0.10	- 0.14	-0.15
Diagnostics equation residuals			
Standard error	0.022	0.026	0.029
Normality	0.86	0.007	0.85
$H_{(11)}$	0.98	1.40	1.22
$r_{(1)}$	0.03	- 0.20	-0.04
$r_{(7)}$	0.23	-0.22	0.08
DW	1.90	2.30	2.06
$Q_{(7,6)}$	5.40	5.82	8.64
R^2	0.98	0.95	0.99
Auxiliary residuals			
Irregular			
Normality	0.56	1.07	0.698
Kurtosis	0.51	0.33	0.696
Skewness	0.05	0.74	0.002
Level			
Normality	1.53	0.26	1.18
Kurtosis	0.40	0.26	0.02
Skewness	1.2	0.0003	1.16
Slope			
Normality	0.18	0.55	0
Kurtosis	0.01	0.23	0
Skewness	0.17	0.32	0
Predictive tests (inside sample)			
CHOW	$F(3, 33) = 0.31$	$F(3,33) = 1.70$	$F(3,33)=0.90$
Cusum t	$t(33) = 0.51$	$t(33) = 0.89$	$t(33) = 0.99$
Predictive tests (post sample)			
Failure $\chi^2(3)$	1.41	5.40	0.32
Cusum t (3)	-0.33	- 1.90	- 0.36
Estimated Hyperparameters			
Irregular	0.0085	0.00035	0.002
Level	0.013	0.00013	0.031
Slope	0.0089	0.0000037	0.00
LR	75.98**	10.34**	33.54**
Nature of the trend	Local trend model	Local trend model	Local level model with drift

Table (4-3) continued

	Japan	Denmark	Belgium
LY_t	0.95**	0.90^*	0.74^*
LP_t		-0.20	-0.18^*
LP_{t-1}	- 0.14*		
Long-run estimates			
Income (Y)	0.95	0.90	0.74
Price (P)	- 0.14	-0.20	-0.18
Diagnostics equation residuals			
Standard error	0.03	0.05	0.04
Normality	1.44	0.8767	1.2
$H_{(11)}/H_{(12)}$	$H_{(11)} = 0.29$	$H_{(12)} = 0.90$	$H_{(12)} = 0.56$
$r_{(1)}$	0.027	-0.06	-0.034
$r_{(8)}$	0.061	0.29	- 0.012
DW	1.83	2.01	2.00
$Q_{(8,6)}$	3.95	9.77	6.62
R^2	0.98	0.95	0.96
Auxiliary residuals			
Irregular			
Normality	0.79	0.67	0.89
Kurtosis	0.48	0.47	0.01
Skewness	0.31	0.21	0.88
Level			
Normality	1.43	1.02	0.06
Kurtosis	0.21	0.59	0.04
Skewness	1.22	0.43	0.02
Slope			
Normality	0.78	0.80	0.65
Kurtosis	0.77	0.80	0.64
Skewness	0.01	0.00	0.01
Predictive tests (inside sample)			
CHOW	F (3,32)= 0.38	F (3,33)=0.55	F (3,33)=1.90
Cusum t	t(32)= -0.16	t(33)=0.21	t(33)=0.86
Predictive tests (post sample)			
Failure χ^2 (3)	0.63	0.22	0.53
Cusum t (3)	- 0.09	- 0.40	-0.17
Estimated Hyperparameters			
Irregular	0.0057	0.008	0.005
Level	0.022	0.043	0.044
Slope	0.0084	0.007	0.0042
LR	54.96**	15.42**	26.90**
Nature of the trend	Local trend model	Local trend model.	Local trend model

Table (4-3) continued

	USA	Switzerland	Spain
LY_t	0.77**	0.70**	
LY_{t-1}			0.70**
LP_t			-0.125**
LP_{t-1}	-0.12*		
Long-run estimates			
Income (Y)	0.77	0.70	0.70
Price (P)	- 0.12	0	-0.125
Diagnostics equation residuals			
Standard error	0.02	0.03	0.03
Normality	0.38	0.46	0.08
$H_{(11)}/H_{(12)}$	$H_{(11)}=1.54$	$H_{(12)}= 0.99$	$H_{(11)}= 1.10$
$r_{(1)}$	- 0.017	-0.04	- 0.029
$r_{(8)}$	0.031	0.06	- 0.14
DW	1.98	1.91	2.03
$Q_{(8,6)}$	3.01	9.41	5.40
R^2	0.98	0.99	0.99
Auxiliary residuals			
Irregular			
Normality	0	0.74	2.80
Kurtosis	0	0.69	0.58
Skewness	0	0.06	1.22
Level			
Normality	0.18	1.10	1.53
Kurtosis	0.01	1.01	0.98
Skewness	0.07	0.09	0.55
Slope			
Normality	0.75	0.69	1.30
Kurtosis	0.69	0.53	0.17
Skewness	0.06	0.16	1.13
Predictive tests (inside sample)			
CHOW	$F(3,32) = 0.45$	$F(3,33) = 0.73$	$F(3,32) = 0.46$
Cusum t	$t(32) = 0.17$	$t(33)= 0.14$	$t(32)= 0.22$
Predictive tests (post sample)			
Failure $\chi^2(3)$	1.66	1.09	2.20
Cusum t(3)	- 0.40	-0.12	0.40
Estimated Hyperparameters			
Irregular	0	0.008	0.02
Level	0.02	0.028	0.009
Slope	0.005	0.006	0.012
LR	81.77**	37.60**	34.88**
Nature of the trend	Local trend model	Local trend model Includes irregular dummy for 1963 and level dummy for 1974	Local trend model

Table (4-3) continued

	Netherlands	Norway
LY_t	1.20*	0.60*
LP_t	-0.16**	-0.13*
Long-run estimates		
Income (Y)	1.2	0.60
Price (P)	-0.16	- 0.13
Diagnostics equation residuals		
Standard error	0.04	0.03
Normality	1.5	0.91
$H_{(12)}$	0.80	0.53
$r_{(1)}$	-0.07	0.05
$r_{(7)}/r_{(8)}$	$r_{(8)}$= -0.08	$r_{(7)}$ =-0.21
DW	2.0	1.82
$Q_{(7.6)}/Q_{(8,6)}$	$Q_{(8,6)}$=4.55	$Q_{(7,6)}$ = 6.40
R^2	0.98	0.99
Auxiliary residuals		
Irregular		
Normality	2.50	1.70
Kurtosis	0.36	0.04
Skewness	2.14	1.66
Level		
Normality	0.42	0
Kurtosis	0.29	0
Skewness	0.13	0
Slope		
Normality	0.80	1.20
Kurtosis	0.19	0.02
Skewness	0.61	1.18
Predictive tests (inside sample)		
CHOW	F(3,33)=0.65	F(3,33)=0.55
Cusum t	t (33)=0.004	t (33)= -0.45
Predictive tests (post sample)		
Failure χ^2 (3)	1.8	0.78
Cusum t (3)	-0.007	-0.45
Estimated Hyperparameters		
Irregular	0.007	0.02
Level	0.042	0.00
Slope	0.008	0.014
LR	119.4**	58.68**
Nature of the trend	Local trend model	Smooth trend model

- Estimation conducted using the STAMP 5.0 software package.
- ** indicates significant at 1% level and * indicates significant at the 5%.
- Normality is the Bowman-Shenton statistic, approximately distributed as $\chi^2_{(2)}$.
- Kurtosis statistic is approximately distributed as $\chi^2_{(1)}$.
- Skewness statistic is approximately distributed as $\chi^2_{(1)}$.
- H(h) is the test for heteroscedasticity, distributed approximately F(h,h).
- r(τ) the residual autocorrelation at lag τ, distributed approximately as N(0, 1/T).
- DW-Durbin-Watson statistic, distributed approximately as N(2,4/t);
- Q(p,d)- Box-Ljung Q statistic based on the first P residuals autocorrelations and distributed approximately as χ^2_d.
- R^2 is the coefficient of determination.
- χ^2_p is the post-sample predictive failure test.
- The Cusum t is the test of parameter constancy, approximately distributed as the t distribution.

4.4.2 Cointegration Results[42]

The aggregate energy demand functions were also estimated for 17 OECD countries using time series Data Set 17B (1960-1996) with three observations (1998-2000) saved for the purpose of the post-sample tests. The traditional cointegration or error correction technique was applied to the above Data Set. Initially, the unit root of the key variables, LE_t, LY_t and LP_t, were explored using the ADF test. The results from these tests are given in Table (4-4) and show that generally they may all be regarded as I(1) thus it is reasonable to test for the cointegration between the variables. Furthermore, and as stated in section 4.3.2, this technique was adopted in order to compare the statistical results and the estimated income and price elasticities obtained from STSM. Therefore, one can check the robustness of the results from STSM.

Table (4-4): Unit Root Test Using ADF for Individual Countries

Country	ADF		
	LE	LP	LY
Austria	-3.70*[1]	-2.45	-3.61*[1]
Belgium	-1.74	-1.94	-2.78
Canada	-2.61	-2.51	-2.97
Denmark	-2.03	-1.94	-2.40
France	-2.58	-2.10	-2.94
Greece	-3.98**[4]	-2.11	-2.40
Ireland	-2.60	-2.10	-0.90
Italy	-3.10	-1.80	-1.85
Japan	-3.43	-2.10	-0.60
Netherlands	-3.10	-2.30	-2.20
Norway	-2.30	-1.70	-2.40
Portugal	-2.63	-2.50	-2.90
Spain	-2.50	-1.64	-4.10**
Sweden	-1.81	-2.24	-2.80
Switzerland	-3.98*	-2.28	-3.14
UK	-1.60	-1.86	-2.50
USA	-2.30	-2.60	-3.85*

The individual ADF statistic is calculated with 5 lags on the dependent variable to ensure there is no serial correlation unless the square brackets [ ] denote the number of lags for some series.
Estimation conducted using the PcGive 10.0.0 software package
** reject the null of the unit root at 1%.
* reject the null of the unit root at 5%.

[42] The results for cointegration approach are obtained by using PcGive 10.0.

Table (4-5) presents the results of the cointegration approach as outlined above. The top half of Table (4-5) therefore shows the long run elasticities for both the Static E-G and Dynamic E-G results. In addition, t statistics and diagnostic tests are given for the long-run Dynamic E-G results, but not for the Static E-G results since they are not valid. The bottom half of Table (4-5) summarises the short run dynamic equations, showing the coefficients and t statistics for the error correction terms, equation diagnostics for both the Static E-G and Dynamic E-G results. The Static E-G results confirmed cointegration between the variables for each individual country, as denoted by ADF or DF, with the exception of Ireland. The estimated long run income elasticities give the expected signs for all countries whereas the price variable give the wrong sign for USA, Switzerland, Spain and Netherlands. The coefficient for the deterministic time trends are positive for Sweden, Portugal, Greece, Ireland, Sweden, Ireland and Canada and negative for all other countries. Furthermore, the PcGive test rejects cointegration for all countries for the Dynamic E-G results, although all estimated equations have no problems of serial correlation, heteroscedasticity and functional form misspecification. The estimated long run income and price elasticities take the expected signs for all countries, with the exception of the price elasticity for Ireland. The derived long run coefficients for the deterministic time trends are positive for Portugal, Italy, Ireland and Greece, but negative for all other countries.

In addition, for the *dynamic short run equations*: first, for the ***Static E-G*** model the EC coefficients and the diagnostic tests for most countries are significant and satisfactory respectively with some exceptions as follows:

For the USA: the EC is insignificant but it is free of any problem.

For Sweden: the EC is insignificant but it is free of any problem.

For Canada: the EC is insignificant but free from any problem.

For the Netherlands: the EC is significant but it fails predictive tests.

For Japan: the EC term is significant but it has problems with predictive tests.

For Italy: the EC is insignificant and it is free of any misspecification problem.

For Greece: the EC is significant but it fails the predictive tests.

Second, the ***Dynamic E-G*** model the EC and the diagnostic tests are significant and free from any mis-specification with the following exceptions.

For Sweden, Canada and Denmark: the EC is insignificant but it is free of any problem.

For Greece: the EC is significant but it fails the predictive tests.

The results for individual countries are considered in a little more detail below and mainly focusing on the estimated elasticities and the preferred model.

USA

The estimated long run income elasticity has the expected sign but is rather larger than would normally be expected, and is insignificant in the Dynamic E-G model. The price elasticity has the wrong sign for the Static E-G model and is very insignificant in the Dynamic E-G despite being the expected sign. Both trend coefficients are negative, indicating a similar direction to the UEDT in the STSM - but it is insignificant in the Dynamic E-G model. Thus, given the LR test in Table (4-3) the stochastic formulation is clearly preferred.

UK

The estimated long run income elasticity has the expected sign in both approaches and highly significant in the Dynamic E-G approach. However, they are rather larger than in most previous studies; see Hunt and Manning (1989), and about two and half times larger than that given by the STSM approach above. The estimated long run price elasticities give the expected signs but the Dynamic E-G estimate is insignificant. The trend coefficient is negative in both approaches and significant in the Dynamic E-G – generally consistent with the UEDT from the STSM approach above. However, the stochastic trend is the preferred specification as the LR test indicates.

Switzerland

The estimated long run income elasticity takes the expected sign in both approaches and is highly significant in the Dynamic E-G approach, but it is about double the size of that obtained by the STSM approach above. The estimated long run price elasticity is positive in both approaches and significant in the Dynamic E-G approach. The trend coefficient is negative according to both approaches and significant in the Dynamic E-G approach. Therefore, given these poor results the STSM results are preferred.

Sweden

The estimated long run price and income elasticities have the expected sign in both approaches. The price estimate is significant but the income estimate is insignificant in the Dynamic E-G. The trend coefficient is negative in both approaches but it is insignificant in the Dynamic E-G approach. This is probably due to the linear time trend acting as a very poor proxy for the UEDT. Thus, the STSM results are preferred.

Spain

The estimated long run income elasticity takes the expected sign in both approaches and is very significant in the Dynamic E-G approach, with the estimate much higher than the estimate obtained from STSM in Table (4-3). The estimated long run price elasticity has the wrong sign in the Static E-G approach and is also insignificant in the Dynamic E-G model. The trend coefficient has a negative sign in both models and is insignificant in the Dynamic E-G approach. Therefore, the latter is not consistent with the STSM result in Table (4-3) since the estimated UEDT for most of the period is upward sloping and varies over time. The insignificant deterministic trend coefficient suggests that it is not a good proxy for the UEDT, given the latter is non-linear as found above. Hence, once more the stochastic formulation is preferred.

Portugal

The estimated long run income and price elasticities in the Dynamic E-G approach have the expected signs, with the income elasticity being very significant and the price elasticity is insignificant. The time trend coefficient is positive and appears to act as a reasonable proxy for the non-linear UEDT. Nevertheless, the STSM results are better defined than the Dynamic E-G approach. Hence, yet again, the LR test in Table (4-3) suggests that the STSM is preferred.

Norway

The estimated long run income elasticity has the expected sign in both approaches and is significant in the Dynamic E-G approach, but it is about three times larger than that obtained from the STSM approach. The estimated long run price elasticity takes the expected sign in both approaches but is insignificant in the Dynamic E-G approach. The time trend has a negative coefficient in both cases and is marginally significant in the Dynamic E-G model. Thus in this case the deterministic time trend would appear to be a poor proxy for the UEDT found in the STSM. So again given the LR test in Table (4.3) the STSM results are preferred.

Netherlands

The estimated long run income elasticity takes the expected sign in both approaches and is significant in the Dynamic E-G approach, but it is about two and a half times larger than that from the STSM. The estimated long run price elasticity is positive in the Static E-G model but negative and insignificant in the Dynamic E-G model. The coefficient of the time trend is negative for both approaches and also significant in the Dynamic E-G model. However, the non-linearity of the UEDT in Figure (4-16) suggests that the time trend acts as a poor proxy for the UEDT. Hence, yet again the STSM results are preferred.

Japan

The estimated long run income and price elasticities take the expected signs and are significant in the Dynamic E-G model. The time trend coefficient is negative in both models. The D-G model yields reasonably long run elasticities, but the LR test is in favour of STSM results.

Italy

The estimated long run income elasticity takes the expected signs in both approaches but is insignificant in the Dynamic E-G model. The estimated long run price elasticity is negative in both approaches and significant in the Dynamic E-G model. The time trend coefficient is negative but insignificant in the Dynamic E-G model.

The STSM is preferred given the estimated elasticities are significant, and the LR test in Table (4-3) rejects the specification of a linear time trend as a proxy for the UEDT.

Ireland

The estimated long run income elasticity takes the expected signs in both approaches but is highly insignificant in the Dynamic E-G model. The estimated long run price elasticity has the expected negative sign in the Static E-G approach but is positive and highly insignificant in the Dynamic E-G approach. The time trend coefficient is positive in both cases but insignificant in the Dynamic E-G model. The STSM is preferred given the estimates are significant. In addition the LR test in Table (4-3) rejects the specification of a linear time trend as a proxy for the UEDT.

Greece

The estimated long run income and price elasticities take the expected signs in both approaches, with the income elasticity significant in the Dynamic E-G model but the price elasticity insignificant. The trend coefficient takes the positive sign and is significant in the Dynamic E-G approach, which is to be expected given the shape of the estimated UEDT via the STSM framework. However, the STSM estimates in Table (4-3) are preferred, given they are significant and the LR test favours the stochastic trend specification.

Belgium

The estimated long run price and income elasticities take the expected signs in both cases, but both are insignificant in the Dynamic E-G model. The time trend coefficient is negative in both approaches but insignificant in the Dynamic E-G model. The STSM estimates in Table (4-3) are preferred given they are significant and the LR test rejects the linear time trend.

Canada

The estimated long run income and price elasticities all have the expected sign and are both significant in the Dynamic E-G model. The coefficient of the time trend is negative in both cases and significant in the Dynamic E-G model. Furthermore, even the Dynamic E-G model gives significant estimates and all the diagnostic tests are passed but the long run income and price (in absolute value) elasticities are somewhat larger than those obtained from the STSM approach in Table (4-3). In addition, the non linearity of the UEDT in Figure (4-2) suggests that the time trend acts as a poor proxy for the UEDT. Therefore, the STSM yields more reliable long run elasticity estimates. In addition, the LR test favours the stochastic trend formulation.

Denmark

The estimated long run income and price elasticities have the expected signs and are significant in the Dynamic E-G model. However, the estimated long run income elasticity is very high, being a lot higher than that obtained from the STSM approach, whereas the estimated price elasticity is fairly similar to the STSM results. The coefficient on the time trend is negative and significant in the Dynamic E-G model. Again, given the non-linearity of the estimated UEDT, Figure (4-11), it is unlikely that the time trend would be a good proxy. Hence, one would expect the estimated elasticities obtained from the Dynamic E-G approach may be biased; in particular the income elasticity appears to be biased upward and to be outside the expected range of values. Therefore, given this and the LR test result in favour of the stochastic formulation of the trend, the STSM results are again preferred.

France

The estimated long run income and price elasticities are significant in the Dynamic E-G approach. These estimates are reasonable and well defined and the income elasticity from the Dynamic E-G model is similar to the estimate obtained from the STSM approach; however the estimated price elasticity is about double the STSM estimate. The coefficient on the time trend is negative in both cases and significant in the Dynamic E-G approach. The non-linearity of the estimated UEDT in Figure (4-9) suggests that the time trend acts as a poor proxy for the UEDT. Furthermore, the LR test in Table (4-3) is in favour of the stochastic formulation of the trend.

Austria

The estimated long run income elasticity takes the expected sign in both cases and is significant in the Dynamic E-G case. The estimated long run price elasticity is negative in both cases but insignificant in the Dynamic E-G case. The time trend coefficient is negative in both cases and significant in the Dynamic E-G case. However, it is doubtful that the deterministic time trend would be a good proxy for the UEDT, given the shape of the UEDT in Figure (4-4) above. Therefore, given the LR test result in Table (4-3) the STSM estimates are preferred.

4.5 Summary and Conclusion

This chapter has explored the estimation of energy demand functions for the 17 countries in Data Set 17B, focussing on the estimation of the underlying trends. The STSM approach was adopted, since it allows for the estimation of a stochastic trend known as the Underlying Energy Demand Trend (UEDT). This accommodates unobservable variables such as technical progress and changes in consumer taste and economic structure. Furthermore the cointegration approach has also been utilised to estimate energy demand functions for the 17 countries. Using this technique the effect of technical progress (and any other exogenous factors) on energy demand is constrained to be linear, so that these estimates were adopted for a comparison with the STSM results.

The findings for all countries show clear evidence in support of the STSM framework given its more flexible approach to estimating the underlying trends as compared to the overly restrictive cointegration approach, where the underlying trend is linear. The STSM gave more plausible estimates than the cointegration results, and in a number of cases the results suggest that long run elasticities estimated by using cointegration approach are biased by the misspecified linear underlying trend.

Table (4-5) The Estimated Results for Aggregate Energy Demand Using the Cointegration Approach

	USA		UK	
	Static E-G	Dynamic E-G	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities				
Income (Y)	2.30	3.41 (1.87)	1.30	1.49** (3.07)
Price (P)	+0.08	- 0.58 (-0.90)	-0.11	-0.16 (-1.24)
Time	-0.06	-0.10 (- 1.70)	-0.02	-0.03** (-2.70)
Diagnostic tests				
Normality	N/A	0.85	N/A	1.78
DW	N/A	1.78	N/A	1.90
AR 1-3	N/A	F (3,22) = 1.37	N/A	F (3,21)= 0.40
ARCH 3	N/A	F (3,19) = 0.35	N/A	F (3,18)= 0.36
Unit roots test				
DF/ADF (P)	DF= -2.19*	N/A	DF= -2.93*	N/A
PcGive unit root test	N/A	- 1.07	N/A	-2.43
Short run dynamic equations				
EC coefficients	-0.02 (1.11)	-0.03** (7.50)	-0.36** (4.12)	-0.32** (4.20)
Diagnostic tests				
Standard error	0.020	0.030	0.027	0.024
R^2	0.74	0.81	0.65	0.68
Normality	2.23	1.56	0.78	1.64
AR	F(3,23)= 0.04	F(3,23) = 0.02	F(3,28)= 0.42	F (3, 24) = 0.23
ARCH	F(3,17)= 0.83	F(3,21) = 1.14	F(3,26)= 0.57	F (3, 22) = 1.11
Hetero	F(12,13)= 0.34	F(8,16) = 0.25	F(6,23)= 0.50	F(6,19) = 0.56
Reset	F(1,25)= 1.20	F(1,24) = 1.30	F(1,29)= 4.10	F (1, 25) = 4.10
Predictive test				
$\chi^2{(3)}$	4.78	6.30	3.44	5.20
CHOW	F(3, 26) = 1.35	F(3, 23) = 1.14	F(3, 32) = 1.20	F(4,26) = 1.50

Table (4-5) (Continued)

	Switzerland		Sweden	
	Static E-G	Dynamic E-G	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities				
Income (Y)	1.75	1.45** (12.70)	1.66	0.58 (1.27)
Price (P)	+0.08	+0.08 (2.66)	-0.26	-0.62 (-3.10)
Time	-0.01	-0.01 (-2.90)	-0.03	-0.01 (-0.70)
Diagnostic tests				
Normality	N/A	0.51	N/A	2.33
DW	N/A	1.37	N/A	2.13
AR 1-3	N/A	F (3,30)= 2.52	N/A	F (3,26)=1.73
ARCH 3	N/A	F (3,27)=3.38*	N/A	F (3,23)=0.43
Unit roots test				
DF/ADF (P)	ADF (2)=-3.65*	N/A	ADF (1)=-2.51**	N/A
PcGive unit root test		-2.66	N/A	-2.97
Short run dynamic equations				
EC coefficients	-0.05* (3.75)	-0.10** (2.60)	-0.02 (1.19)	-0.17** (2.92)
Diagnostic tests				
Standard error	0.04	0.044	0.03	0.03
R^2	0.55	0.63	0.63	0.46
Normality	4.52	6.03*	2.81	1.82
AR	F(3,26) = 0.76	F(3, 30) = 0.18	F (3,28)= 0.05	F (3,27) = 0.07
ARCH	F(3,23) = 0.21	F(3,27) = 0.49	F (2,25) = 0.08	F (3,24) = 0.80
Hetero	F(8,20) = 0.75	F (4, 28) = 0.17	F(6,24) =1.56	F(6,23) = 1.16
Reset	F(1,26) = 1.40	F (1, 32) = 0.89	F(1,30) = 0.72	F(1,29) = 0.39
Predictive test				
$\chi^2{}_{(3)}$	2.46	1.46	1.00	2.04
CHOW	F(3, 29) =0. 74	F(3,33) = 0.46	F(3, 31) = 0.32	F(3,30) = 0.63

Table (4-5) (Continued)

	Spain		Portugal	
	Static E-G	Dynamic E-G	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities				
Income (Y)	1.47	1.56** (6.34)	0.52	0.54** (8.61)
Price (P)	+0.01	-0.45 (-1.60)	-0.03	-0.03 (-1.30)
Time	-0.01	-0.01 (-1.60)	0.03	0.03** (11.50)
Diagnostic tests				
Normality	N/A	0.66	N/A	2.80
DW	N/A	1.89	N/A	1.91
AR 1-3	N/A	F (3,21)=1.47	N/A	F (3,21)=0.72
ARCH 3	N/A	F(3,18)=0.58	N/A	F(3,18)=0.40
Unit roots test				
DF/ADF (P)	DF=-2.27*	N/A	DF=-3.98**	N/A
PcGive unit root test	N/A	-1.99	N/A	-3.80
Short run dynamic equations				
EC coefficients	-0.21* (2.85)	-0.28** (4.98)	-0.67** (4.35)	-0.68** (4.91)
Diagnostic tests				
Standard error	0.027	0.024	0.022	0.02
R^2	0.70	0.77	0.60	0.65
Normality	3.90	0.68	4.10	8.40*
AR 1-3	F(3,24) = 0.74	F (3,23) = 0.59	F (3,26) = 0.36	F (3,22) = 0.65
ARCH 3	F (3,21) = 1.42	F (3, 20) = 0.29	F (3,23) = 0.66	F (3,19) = 0.44
Hetero	F (10,16) = 1.08	F (8, 17) = 1.41	F (6,22) = 0.53	F (8, 16) = 0.30
Reset	F (1,26) = 0.26	F (1, 25) = 1.64	F (1,28) = 1.02	F (1,24) = 1.24
Predictive test				
χ^2 (3)	2.93	2.70	2.60	3.00
CHOW	F (3,29) = 0.64	F (2, 28) = 0.55	F (3,29) = 0.37	F (3,26)= 0.65

Table (4-5) (Continued)

	Norway		Netherlands	
	Static E-G	Dynamic E-G	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities				
Income (Y)	2.70	1.90* (2.28)	3.11	3.06 (6.49)
Price (P)	-0.33	-0.33 (-1.30)	+0.13	-0.04 (-0.17)
Time	-0.065	-0.04* (-1.80)	-0.064	-0.07 (-4.94)
Diagnostic tests				
Normality	N/A	3.0	N/A	4.90
DW	N/A	1.84	N/A	2.02
AR 1-3	N/A	F (3,21) = 0.66	N/A	F (3,16) =2.37
ARCH 3	N/A	F (3,19) = 0.59	N/A	F (3,19) = 0.85
Unit roots test				
DF/ADF (P)	ADF (7)=-2.07*	N/A	ADF (1)=-2.15*	N/A
PcGive unit root test	N/A	-2.14	N/A	-1.83
Short run dynamic equations				
EC coefficients	-0.36** (3.85)	-0.18** (4.90)	-0.57** (4.67)	-0.48** (4.43)
Diagnostic tests				
Standard error	0.026	0.029	0.038	0.037
R^2	0.66	0.72	0.73	0.78
Normality	2.68	2.23	7.90*	2.20
AR 1-3	F (3,24) = 0.85	F (3,29) = 0.46	F (3,29) = 0.80	F (2,23) = 0.06
ARCH 3	F (3,21) = 0.47	F (3,27) = 0.05	F (3, 29)= 0.62	F (3, 21) = 0.77
Hetro	F (10, 16) = 0.31	F (2,28) = 0.13	F (6, 24) = 0.48	F (8, 16) = 0.31
Reset	F (1,26) = 0.002	F (1,30) = 2.6	F (1,30) = 7.90**	F (1,24) = 1.71
Predictive tests				
$\chi^2_{(3)}$	4.62	1.46	19.81**	2.70
CHOW	F (3,28) = 1.36	F (3, 32) = 0.49	F (3, 32) = 4.0*	F (3, 27) = 1.30

Table (4-5) (Continued)

	Japan		Italy	
	Static E-G	Dynamic E-G	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities				
Income (Y)	1.39	0.81** (2.95)	1.90	0.33 (0.53)
Price (P)	-0.21	-0.54** (-3.14)	-0.33	-0.58 (-3.40)
Time	-0.03	-0.02* (-2.81)	-0.03	0.01 (0.62)
Diagnostics				
Normality	N/A	0.09	N/A	0.19
DW	N/A	2.36	N/A	1.90
AR 1-3	N/A	F(3,21)=1.16	N/A	F (3,22)=0.74
ARCH 3	N/A	F(3,18)=2.60	N/A	F (3,19)=0.29
Unit roots test				
DF/ADF (P)	ADF (3)=-2.14*	N/A	ADF (9)=-2.34*	N/A
PcGive unit root test	N/A	-2.93	N/A	-2.70
Short run dynamic equations				
EC coefficients	-0.49** (5.91)	-0.16** (5.41)	-0.12 (1.47)	-0.13** (6.30)
Diagnostics				
Standard error	0.022	0.02	0.021	0.02
R^2	0.88	0.96	0.88	0.85
Normality	1.67	0.95	0.87	1.24
AR	F(3,22) = 0.40	F(3,23) = 0.71	F(3,25)= 0.64	F(3, 27) = 0.86
ARCH	F (3,19) = 0.83	F (3, 21) = 0.39	F (3, 22) = 0.98	F (3,25) = 1.25
Hetero	F (14,10) = 0.40	F (10, 14) = 0.45	F (8, 19) = 1.40	F (6, 22) = 2.30
Reset	F(1,24) = 2.80	F (1,24) = 0.01	F (1,27) = 2.10	F (1, 28) = 1.01
Predictive tests				
$\chi^2_{(3)}$	11.50**	4.90	2.91	3.16
CHOW	F (3, 27) = 2.89	F (3, 26) = 0.93	F (3, 29) = 0.88	F (3,31) = 0.79

Table (4-5) (continued)

	Ireland		Greece	
	Static E-G	Dynamic E-G	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities				
Income (Y)	0.30	0.10 (0.13)	1.20	1.27** (18.30)
Price (P)	-0.07	0.08 (0.27)	-0.09	-0.018 (-0.17)
Time	0.02	0.02 (0.50)	0.01	0.01* (1.87)
Diagnostic tests				
Normality	N/A	3.90	N/A	1.30
DW	N/A	1.92	N/A	1.88
AR 1-3	N/A	F (3,21) = 1.99	N/A	F (3,22)= 1.10
ARCH 3	N/A	F (3,18) = 0.91	N/A	F (3,19) = 1.09
Unit roots test				
DF/ADF (P)	-2.20	N/A	DF=-2.40*	N/A
PcGive unit root test	N/A	-2.26	N/A	-1.86
Short run dynamic equations				
EC coefficients	-0.18 (1.76)	-0.14** (2.90)	-0.77** (5.41)	-0.40** (4.24)
Diagnostic tests				
Standard error	0.042	0.045	0.024	0.023
R^2	0.67	0.71	0.87	0.92
Normality	5.12	3.96	0.79	2.57
AR 1-3	F(3, 30) = 0.87	F (3, 26) = 0.77	F (3,29) = 1.30	F (3, 274)= 0.16
ARCH 3	F (3, 28) = 0.43	F (3, 24)= 0.45	F (3, 29)= 0.002	F (3,22) = 0.73
Hetero	F (4,27) = 0.62	F (4,23) = 0.30	F (6, 24) = 0.96	F (10, 15) = 0.37
Reset	F (1,32) = 0.03	F (1,27) = 0.02	F (1, 30) = 0.12	F (1, 25) = 0. 21
Predictive tests				
$\chi^2_{(3)}$	1.29	0.61	28.7**	10.20*
CHOW	F (3,32) = 1.20	F (3, 30) = 0.16	F (3, 33) = 6.10**	F (3, 28) = 3.10*

Table (4-5) (Continued)

	Belgium		Canada	
	Static E-G	Dynamic E-G	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities				
Income (Y)	1.59	0.89 (1.01)	1.54	1.46** (8.20)
Price (P)	-0.25	-0.53 (1.35)	-0.13	-0.25** (-3.95)
Time	-0.03	-0.011 (-0.50)	-0.027	-0.03* (-4.57)
Diagnostic tests				
Normality	N/A	1.60	N/A	4.00
DW	N/A	2.13	N/A	1.92
AR 1-3	N/A	F(3,22) = 0.85	N/A	F(3,28) = 0.52
ARCH 3	N/A	F(3,19)= 0.75	N/A	F(3,25) = 0.89
Unit roots test				
DF/ADF (P)	DF= -2.02*	N/A	ADF(3) = -3.09*	N/A
PcGive unit root test	N/A	-1.26	N/A	-3.43
Short run dynamic equations				
EC coefficients	-0.25* (1.98)	-0.21* (2.61)	0.01 (1.70)	0.02 (1.20)
Diagnostics				
Standard error	0.043	0.041	0.02	0.02
R^2	0.69	0.73	0.70	0.71
Normality	0.13	2.65	1.97	2.94
AR 1-3	F(3,30)= 0.22	F (3, 24) = 0.33	F(3,29) = 0.47	F(3,28) = 0.55
ARCH	F(3,28)= 0.01	F(3, 22)= 2.8	F(3,26) = 0.46	F(3, 25) = 0.17
Hetero	F(6,25)= 0.46	F (8, 17) = 0.50	F(8,23) = 1.54	F (6, 24) = 1.97
Reset	F(1,31)=0.29	F(1, 25) = 0.001	F(1,31) = 0.06	F(1,30) = 0.05
Predictive tests				
$\chi^2_{(3)}$	0.74	5.70	5.91	6.11
CHOW	F(3,33) = 0.18	F (3, 28) = 1.30	F(3,32) = 1.90	F (3, 31) = 1.90

Table (4-5) (Continued)

	Denmark		France	
	Static E-G	Dynamic E-G	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities				
Income (Y)	2.58	2.27** (38.4)	2.30	1.45** (7.01)
Price (P)	-0.10	-0.16** (-2.73)	-0.20	-0.30** (-2.5)
Time	-0.044	-0.04** (-25.00)	-0.025	-0.021** (- 3.65)
Diagnostic tests				
Normality	N/A	4.88	N/A	1.49
DW	N/A	1.57	N/A	2.02
AR 1-3	N/A	F(3,33) = 0.76	N/A	F(3,22) = 0.90
ARCH 3	N/A	F(3,30)= 0.22	N/A	F(3,19)= 2.02
Unit roots test				
DF/ADF (P)	DF =-3.00*	N/A	ADF(2) = - 2.51*	N/A
PcGive unit root test	N/A	-2.73	N/A	-2.62
Short run dynamic equations				
EC coefficients	0.03* (2.44)	0.02 (1.48)	-0.47** (3.34)	-0.39** (3.36)
Diagnostic tests				
Standard error	0.041	0.05	0.029	0.030
R^2	0.64	0.51	0.64	0.65
Normality	0.63	0.55	1.96	2.10
AR 1- 3	F(3,23) = 0.40	F(3,29) = 1.13	F(3,26) = 0.44	F(3, 26) = 0.20
ARCH 3	F(3,20) = 0.62	F (3, 26) = 0.92	F(3,24) = 1.4	F(3, 24) = 0.03
Hetero	F(6,13) = 1.32	F (6, 25) = 0.15	F(10,17) = 0.38	F (6, 21) = 0.87
Reset	F (1, 25) = 1. 55	F (1, 31) = 0.29	F(1,27) = 0.02	F(1, 27) = 0.20
Predictive tests				
$\chi^2_{(3)}$	3.70	1.53	1.81	3.92
CHOW	F(3,26) = 1.17	F(3 , 32) = 0.50	F(3,28) = 0.36	F (3, 29) = 0.89

Table (4-5) (Continued)

	Austria	
	Static E-G	Dynamic E-G
Long run equilibrium relationships Coefficients/elasticities		
Income (Y)	1.30	1.17** (9.15)
Price (P)	-0.07	- 0.05 (-0.81)
Time	-0.02	-0.01 (-3.3)
Diagnostic tests	N/A	
Normality	N/A	1.26
DW	N/A	1.90
AR 1-3	N/A	F(3,18)=0.84
ARCH 3	N/A	F(3,18)=0.19
Unit roots test		
DF/ADF (P)	ADF (3)=-3.7**	N/A
PcGive unit root test	N/A	-2.3
Short run dynamic equations		
EC coefficients	-0.70** (4.8)	-0.89* (3.97)
Diagnostic tests		
Standard error	0.022	0.023
R^2	0.59	0.66
Normality	0.53	3.5
AR 1-3	F(3, 29) = 1.15	F(3,20) = 1.07
ARCH 3	F (3, 27) = 0.73	F(3,17) = 0.14
Hetero	F (6, 24) = 0.83	F(4,21)=1.40
Reset	F(1, 30) = 0.06	F(1,22) = 2.10
Predictive test		
χ^2 (3)	1.29	1.79
CHOW	F (3, 31) = 0.27	F(3,33)= 0.65

Notes:

Estimation conducted using the PcGive 10.0.software package

The data set B is used in the estimation of the long run equations and the short run dynamic equations;

t statistics in the parentheses;

** Significant at 1% level and * significant at 5% level.

For static E-G estimation the ADF(p) is augmented Dickey-Fuller test with no constant or trend included, sufficient lagged difference included to make the error white noise, DF is Dickey- Fuller without lagged differences.

The PcGive unit root test is applied for dynamic E-G estimation, see Banerjee et al (1992); Normality is that given in PcGive and is distributed as $\chi^2_{(2)}$;

DW is the Durbin-Watson test for first-order serial correlation;

AR 1-3 is a test of serial correlation up to order 3 and is distributed as $F_{(3,n2)}$;

ARCH is Autoregressive Conditional Hetereoscedastic structure in the residual and is distributed as $F_{(3,n3)}$;

Hetero is a test for heteroscedasticity and distributed as $F_{(n4,\ n5)}$;

Reset is a test for functional form mis-specification and is distributed as $F_{(1,n6)}$.;

$\chi_{(3)}$ is the post-sample predictive failure test;

CHOW is the post sample parameters constancy test and is distributed as $F_{(3,n7)}$.

Chapter 5

Panel Unit Roots and Cointegration

5.1 Introduction

This chapter focuses on the issue of non-stationarity of the key energy demand variables in a panel data context. While it is common practice to test for non-stationarity in single equation time series models, until recently the practical application of panel cointegration and integration tests have not been adopted in energy demand modelling.

Since time series data tend to be non-stationary, determining the order of integration or cointegration of the variables becomes important. Baltagi and Kao (2000) state that "adding the cross section dimension to the time series dimension offers an advantage in the testing for nonstationarity and cointegration. The addition of the cross section dimension, under certain assumptions, can act as repeated draws from the same distribution. Thus as the time and cross section dimension increase panel test statistics, and estimators can be derived which converge in distribution to normally distributed random variables'' (p.8).

In Chapter 3 in this thesis the estimation of energy demand models, using panel data, was conducted without investigating the stationarity of the energy demand series and whether there is a statistically acceptable long run relationship or not. Therefore, these issues are explored in this chapter using Data Set 17B. The tests developed by Levin, Lin and Chu (2002) (hereafter LLC) and Im, Pesaran and Shin (2003) (hereafter IPS) are used to explore the stationarity of the variables: LE, LY, LP which were used in the previous chapter. The two tests represent various degrees of heterogeneity; the LLC test allows for heterogeneity in the intercepts while it restricts the autoregressive coefficient to be the same for all countries, whereas the IPS test allows for a complete heterogeneity across countries. In addition, seven tests for cointegration for energy consumption, price and income are applied for the OECD panel. Finally, a heterogeneous cointegrating demand function is estimated using the Fully Modified OLS (FMOLS) technique suggested by Pedroni (2000), which yields a group mean estimator.

The plan of this chapter is as follows. Section 5.2 sets out the panel unit roots tests, the panel cointegration tests and the way to estimate the cointegrating vector in a panel. Section 5.3 presents the results of these tests and estimation. 5.4 present a summary and conclusion.

5.2 Methodology

5.2.1 Panel Unit Root Tests

Unit root tests, such as the Augmented Dickey-Fuller (ADF) test for unit roots and cointegration, are now well established and easily accessible in a number of time series econometric packages such as PcGive, Eviews etc. In addition, the multivariate Johansen procedure is widely used and also easily accessible in such packages. (see

Hendry and Juselius, 2000 and 2001 for a full explanation of these time series techniques).

However, Maddala and Wu (1999) argue that "it is by now a generally accepted argument that the commonly used unit root tests like the Dickey-Fuller (DF), augmented Dickey-Fuller and Phillips–Perron (PP) tests lack power in distinguishing the unit root null from stationary alternatives, and that using panel data unit root tests is one way of increasing the power of unit root tests based on single time series (p. 631). The panel unit root tests are an attractive idea to those who try to resurrect the purchasing power parity (PPP) theory, for instance, Wu (1996), MacDonald (1996) and MacDonald et al (2002) who find that the conventional unit root test never rejects the null hypothesis. In contrast when the data are pooled and a panel based test is conducted, the null is rejected; MacDonald (1996) states "implementing a unit root test on pooled cross section data set, rather than performing separate unit root test for each individual series, can provide a dramatic improvement in the statistical power" (p. 9). Moreover, Oh (1996) illustrates graphically the significant improvement of a range of unit root tests, suggesting that pooling 2, 10, 51 time series, the power increases 9.7%, 25.3% and 81.7% respectively compared to 6.4% when a single time series of 18 observations is used (p. 409).

Furthermore, in practice, unit root tests have been used for testing the convergence in economic growth for a group of counties that the presence of unit root provides evidence against convergence while the stationarity supports the convergence hypothesis (see Nahar and Inder, 2002).

In the panel data literature, various unit root tests for panel data have been suggested by Breitung and Mayer (1994), Maddala and Wu (1999) and Choi (2001), in addition to - as mentioned above - the Levin, Lin and Chu and (2002) and Im, Pesaran and Shin (2003) tests. See Baltagi and Kao (2000) and Banergee (1999) for a review of this literature.[43] This chapter utilises the LLC (2002) and IPS unit root tests in the panel context, hence the former can be considered a pooled panel unit root whereas the later represent a heterogeneous panel test.

LLC test

LLC (2002) introduced a number of pooled panel unit root tests with a number of different specifications depending upon the treatment of the individual specific intercepts and time trends. The test imposes homogeneity on the autoregressive coefficient that indicates the presence or absence of a unit root while the intercept and the trend can vary across individual series.

The aim of the LLC procedure is to test the unit root hypothesis via an ADF regression. This is done as follows:

1. Implement a separate ADF regression for each country

$$\Delta y_{i,t} = \alpha_i + \gamma_i y_{i,t-1} + \sum_{j=1}^{p_i} b_{i,j} \Delta y_{i,t-j} + \varepsilon_{i,t} \tag{5.1}$$

[43] Baltagi and Kao (2000) and Banerjee (1999) reviewed the working paper by LCC and IPS, which are not different from the published one.

The lag order p_i is permitted to vary across individual countries. The appropriate lag order is chosen by allowing the maximum lag order and then uses the t-statistics for b_{ij} to determine if a smaller lag order is preferred.

2. Run two separate regressions and save the residuals $\widetilde{e}_{it}, \widetilde{v}_{i,t-1}$

$$\Delta y_{i,t} = \alpha_i + \sum_{j=1}^{p_i} b_{i,j} \Delta y_{i,t-j} + e_{i,t} \Rightarrow \widetilde{e}_{it} \tag{5.2}$$

$$y_{i,t-1} = \alpha_i + \sum_{j=1}^{p_i} b_{i,j} \Delta y_{i,t-j} + v_{i,t-1} \Rightarrow \widetilde{v}_{i,t-1}$$

LLC suggest to normalise the errors $\widetilde{e}_{it}, \widetilde{v}_{i,t-1}$ by the regression standard error in the ADF equation above

$$\hat{e}_{it} = \frac{\widetilde{e}_{it}}{\hat{\sigma}_{\varepsilon i}}, \quad \hat{v}_{i,t-1} = \frac{\widetilde{v}_{i,t-1}}{\sigma \varepsilon i} \tag{5.3}$$

3. Run the regression in order to compute the panel test statistics.[44]

$$\hat{e}_{it} = \rho \hat{v}_{i,t-1} + \hat{\varepsilon}_{i,t} \tag{5.4}$$

Therefore, given the equation (5.4), the null hypothesis is:

The null hypothesis is,

$H_0 : \rho = 0$

Thus, under the null hypothesis LLC presumes the panel contains a unit root.

[44] For the details about the test, see LLC (2002).

and the alternative hypothesis is,

$H_A : \rho < 0$

Thus, under the alternative LLC presumes that all the series are stationary.

IPS test

IPS (2003) suggest a panel unit root test in the context of a heterogeneous panel.[45] This basically applies the ADF test to individual series thus allowing each series to have its own short-run dynamics, and the overall t-test statistic is based on the arithmetic mean of all individual countries' ADF statistic. A series (such as LE, LY and LP) can be represented by the ADF (without trend).[46]

$$\Delta y_{i,t} = \alpha_i + \gamma_i y_{i,t-1} + \sum_{j=1}^{p_i} b_{i,j} \Delta y_{i,t-j} + \varepsilon_{i,t} \tag{5.5}$$

When the ADF regression has different augmentation lags for each country in finite samples, the term $E(t_T)$ and $\text{var}(t_T)$ are replaced by the corresponding group averages of the tabulated values of $E(t_T, p_i)$ and $\text{var}(t_T, p_i)$, respectively. The IPS test has the advantage over the LLC test that it allows for the heterogeneity in the value γ_i under the alternative hypothesis. If the data from each country are statistically independent then, under the null, we can reject the average t-value as the average of independent random draws from a distribution with known expected value

[45] This test applies the same principle as that of heterogeneous panel data estimation (i.e. averaging).

[46] Appropriate deterministic variables can be added; in addition the test can be implemented on both raw and demeaned data (The STATA Software version 7.0 facilitates this).

and variance (i.e., those for a non-stationary series). Therefore, given the equation (5.5), the null hypothesis is:

$H_0 : \gamma_i = 0$

Thus, under the null hypothesis IPS presumes that each series in the panel contains a unit root for all i.

and the alternative hypothesis is:

$H_1 = \gamma_i < 0$

Thus, under the alternative IPS presumes γ_i differs across the group.

The form of IPS unit root test is:

$$t_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{i,t}(p_i) \tag{5.6}$$

Where $t_{i,t}$ is the individual ADF t-statistics for the unit root tests and p_i is the lag order in the ADF regression then the test statistic can be calculated as:

$$\Lambda_{\bar{t}} = \frac{\sqrt{N(T)}[\bar{t}_T - E(t_T)]}{\sqrt{\mathrm{var}(t_T)}} \tag{5.7}$$

Where t_{NT} is defined above and values for $E[t_{iT}(p_i,0)]$ and $\mathrm{var}[t_{iT}(p_i,0)]$ are obtained from the results of Monte Carlo simulations carried out by IPS and are available from their Table (2); they have tabulated them for various time periods and lags. When the ADF has different augmentation lags (p_i) the two terms $E(t_T)$ and $\mathrm{var}(t_T)$ in the equation above are replaced by corresponding group averages of the tabulated values of $E(t_T, p_i)$ and $\mathrm{var}(t_T, p_i)$ respectively. Furthermore, in order to remove the impact of the common effect IPS (2003) suggest demeaning by subtracting cross section means from the observed data.[47]

Karlsson and Lothgren (2000) demonstrate the power of panel unit root tests by Monte Carlo simulation. The null of all these tests is that each series contains a unit root and thus is difference stationary. However, the alternative hypothesis is not clearly specified. For the LLC test the alternative is that all individual series in the panel are stationary. For the IPS test the alternative is that at least one of the individual series in the panel is stationary. They conclude that the "presence or absence of power against the alternative where a subset of the series is stationary has a serious implications for empirical work. If the tests have high power, a rejection of the unit root null can be driven by few stationary series and the whole panel may inaccurately be modelled as stationary. If, on other hand, the tests have low power it may incorrectly concluded that the panel contains a common unit root even if a majority of the series is stationary'' (p. 254). The simulation results reveal that the power of the tests (LLC, IPS) increases monotonically with: (1) an increased number (N) of the series in the panel; (2) an increased time series dimension (T) in each individual series; (3) increased proportion of stationary series in the panel. Their Monte Carlo simulations for N=13 and T=80 reveal the power of the test is 0.7 for LLC tests and approaching unity for the IPS tests. Furthermore, Choi (2001) conducts simulation studies for a number of unit root tests to explore the performance of these tests. The major findings therefore are that these tests differ in their power and the inclusion of the time trend in the models leading to decrease all the tests power considerably.

[47] The study does not apply demeaning on LCC test hence the authors argue that this can be relaxed to allow for a limited degree of dependence.

Given this background, this explores the procedure for testing the properties of the energy demand series: the LE, LY and LP are tested using two panel data unit root tests, namely LLC and IPS. Hence the interest of the process involves testing whether there is a statistically acceptable cointegration relationship between the variables of interest. However, extending the estimation and testing procedures for the cointegration is a natural development. Thus, the next section explores these procedures via cointegration tests in a panel data context developed by Pedroni (1999), which arguably represent a significant advancement in addressing the low power of conventional single equation cointegration tests for a single time series by exploiting both the cross-sectional and time series information.

5.2.2 Panel Cointegration Tests

The cointegration literature in a panel data context has so far taken two directions and has its analogue in time series literature. The first specifies a null hypothesis of no cointegration as developed by Pedroni (2000) and Kao (1999) and is analogous to the E-G two step approach. The second specifies a null hypothesis of cointegration developed McKoskey and Kao (1998) and is analogous to the Lagrange Multiplier (LM) test proposed by Harris and Inder (1994). This chapter implements the first approach suggested by Pedroni because it applies heterogeneous panel and allows for both homogeneous and heterogeneous trend, while Kao (1999) tests impose homogeneity on the slope coefficients and only take the DF and ADF forms.[48]

[48] Both approaches based on the residuals.

Pedroni (1997, 1999 and 2001) suggests seven tests for cointegration in a panel context.[49] Four of the tests are *within-dimension* statistics (or panel cointegration statistics) and three are *between-dimension* statistics (or group mean statistics). The four within-dimension statistics are based on pooling the autoregressive coefficients across the different countries for the unit root tests on the estimated residuals, whereas the three between-dimension statistics are based on estimators that simply average the individual estimated coefficients for each country.

Included in the within-dimension category are three non-parametric tests that correct for serial correlation: the first a parametric variance ratio test, the second a test analogous to the Philips and Peron rho-statistic, and the third a test analogous to the Philips and Peron t-statistic. The fourth is a parametric test analogous to the ADF statistic (Harris and Sollis, 2003). Included in the between-dimension category are two non-parametric tests analogous to the Philips and Peron rho- and t-statistics respectively and a parametric test similar to the ADF statistic (Harris and Sollis, 2003).

Pedroni's methodology suggests that in order to conduct these tests in an energy demand context the following models are estimated:

$$LE_{it} = \alpha_i + \delta_i t + \phi_i LP_{it} + \varphi_i LY_{it} + \varepsilon_{it} \qquad t = 1, \ldots, 41; i = 1, \ldots, 17. \tag{5.8}$$

$$LE_{it} = \alpha_i + \delta t + \phi_i LP_{it} + \varphi LY_{it} + \varepsilon_{it} \qquad t = 1, \ldots, .41; i=1, \ldots, 17. \tag{5.9}$$

[49] The mathematical formula for all cointegration statistics can be found in Table (2), see Pedroni (1999).

This has the potential for a considerable amount of heterogeneity through the fixed effects aspect, α_i, the individual country specific effect, $\delta_i t$ or δt and by the different slope coefficients, all of which could vary across individual countries.

From this, the null of no cointegration is based on the regression:

$$e_{it} = \rho_i e_{i,t-1} + \upsilon_{it} \tag{5.10}$$

Given ρ_i represents the autoregressive coefficient of the residuals in the *ith* cross-section, then the specification of the null and alternative hypothesis for the pooled (within-dimension) estimation are the following:

$H_0 : \rho_i = 1$ for all i

$H_A : \rho_i = \rho < 1$ for all i.

Thus, under the alternative the within dimension estimation presumes a common value for $\rho_i = \rho$

Whereas for between dimension they are given by:

$H_0 : \rho_i = 1$ for all i

$H_A : \rho_i < 1$ for all i.

Thus, under the alternative the between dimension estimation does not presume a common value for $\rho_i = \rho$. Therefore, this permits to model an additional source of potential heterogeneity across individual members of the panel.

Pedroni also shows that these tests are distributed as the standard normal distribution given by:

$[\kappa_{N,T} - \mu\sqrt{N}] / \sqrt{\nu} \Rightarrow N(0,1)$ where $\kappa_{N,T}$ is the respective panel/group cointegration statistic, μ and ν are the expected mean and variance of the corresponding statistic (both of which depend upon the number of regressors in the model and whether a constant and/or a time trend is included) and are computed in Table (2), see Pedroni (1999).

The next part of the process involves testing whether there is a statistically acceptable long run relationship between the variables of interest. This issue is ignored in the estimation process in Chapter 3 in this thesis. Therefore, the next two sections discuss the related literature in the heterogeneous panel data context and the estimation method respectively.

5.2.3 Related Literature [50]

With panel data estimation the underlying assumption is that the estimated parameters are homogenous. Roberston and Symons (1992) investigate the bias from pooled parameters when the estimated model is dynamic and homogeneous whereas the true model is static and heterogeneous. Pesaran (1997) argues that "in some cases where the theory predicts the same long run relationship across groups, but does not necessarily require the short run adjustments to be the same, it would be possible to take advantage of the extra power that pooling provides without introducing

[50] This literature is related mainly to heterogeneous panel data.

inconsistencies that arise when the heterogeneity of short run dynamics across groups is ignored" (p. 188). Furthermore, Pedroni (2000) states that "one important advantage to working with a cointegrated panel approach of this type is that it allows researcher to selectively pool the long run information contained in the panel while permitting the short run dynamics and fixed effect to be heterogeneous among different members of the panel". (p. 93-94). In addition, according to Pedroni this method produces asymptotically unbiased estimators. He argues that by doing this "inferences can be made regarding common long run relationships which are asymptotically invariant to the considerable degree of short run heterogeneity [as the theory suggests] that is prevalent in dynamics typically associated with panels that are composed of aggregate national data'' (p. 94). Additionally, he argues that "the group mean panel provides a consistent test of a common values of the cointegrating vector under the null hypothesis against values of the cointegrating vector that not be common under the alternative hypothesis"(p. 96).[51] Finally, he argues that "although the OLS estimator is superconsistent, it is still contains a second order bias in the presence of endogeneity, which is not eliminated asymptotically. Accordingly, this bias leads to size distortions, which is not necessarily eliminated even when the sample size grows large in the panel dimension" (p. 97).

Furthermore, Haque et al. (2000) investigate the effect of neglecting slope heterogeneity in static panel models and argue that imposing slope homogeneity may be reasonable for the analysis of household or firm behavior in a given locality or region, but it is less likely to hold across countries due to the differences of their economic development stages and institutions, customs or social norms. Therefore, it

[51] Pedroni (2000) argues in favour of mean group (FMOLS) but not in favour of pooled within dimension estimators.

would appear sensible to attempt to estimate a heterogeneous cointegrating relationship in these situations. This is particularly true given that theory would suggest a similar long run relationship between energy consumption, economic activity and price (although with slightly different magnitudes).

5.2.4 Panel FMOLS Estimation

Turning to the cointegrating vector estimation and relying on the arguments outlined above by Roberston and Symons (1992) Pesaran (1997), Pesaran and Smith (1995), Haque et al. (2000). Pedroni (2000) suggests a method for estimating and testing hypothesis for cointegrating vectors in dynamic time series panels. This is based on the (FMOLS) which can capture the heterogeneity across countries (slope and intercept heterogeneity).

Furthermore, the Pedroni approach suggests a group mean (FMOLS) estimator which is simply the average of the individual FMOLS for each country. The technique therefore deals with the endogeniety of the regressors and corrects for serial correlation. Thus, the FMOLS estimator depends on the between dimension estimation which allows for heterogeneity of the cointegrating vectors in that it provides a common cointegrating vector under the null hypothesis while under the alternative the cointegrating vector need not be common.

Therefore, the between-dimension or group mean FMOLS, as suggested by Pedroni, is utilised to estimate a cointegrating aggregate energy demand relationship for LE_{it} as a function of LP_{it} and LY_{it}, and thus determine the long-run price and income elasticities for the 17 OECD countries as follows:

$$LE_{it} = \alpha_i + \beta_i LP_{it} + \delta_i LY_{it} + \mu_{it} \quad t = 1 \ldots T; i = 1 \ldots N \qquad (5.11)$$

The time dummies are included in the above equation to capture the effect of technical progress on energy demand consumption. In addition, the above equation is estimated over the whole period (1960-2000) and two sub-periods (1960-1980) and 1981-2000).

5.3 Results[52]

5.3.1 Unit Root

Initially the stationarity of energy series has been investigated country-by-country using ADF (generated in the presence of a time trend and a constant). These results show that it is not possible to reject the unit root hypothesis for individual OECD countries (see Table (4-4)).

Table (5-1) summaries the LLC and IPS unit root tests for the level of each series using the model with and without trend. As mentioned above LLC is applied on the raw data, while IPS is applied on raw and demeaned data.

[52] The unit root tests have been conducted using STATA version 7.0 (Stata corporation, 2001) and the cointegration tests and estimation in RATS version 5.0 (Estima, 2000)

The null hypothesis of a unit root for LE series is rejected at the 1% level in the case of including trend or omitting it and with the demeaned data. For the LP series the null hypothesis cannot be rejected at the 5% level by the IPS test for the model including the time trend, whereas it is rejected by LLC test in the case of omitting and including the trend. In addition, on the demeaned data IPS succeeds to reject the null with and without trend. The result for the LE and LP series suggest that both series are stationary and integrated of order zero. For LY, the LLC test cannot reject the null of unit root while IPS rejects the null for the raw data series but the null cannot be rejected for the demeaned data series.

The results of panel unit root tests might mitigate the concerns about the existence of unit root in energy demand models. However, there are several warnings. One is that the IPS could not reject the null for the LP series when the trend is included. Moreover, it could not reject for demeaned income data. In addition, LLC is sensitive somewhat to including the trend only for the income series.

Table (5-1): Panel Unit Roots Tests (LCC, IPS) over the Period 1960-2000 for 17 OECD countries

Variable		Specification	LCC*	IPS*	No obs LLC	No obs IPS
LE	raw data	const.	-4.04[0.00]	-11.10[0.00]	663	680
		const+trend	-3.98[0.00]	-2.30[0.01]	663	680
	demeaned data	const.	N/a	-2.90[0.002]		680
		const+trend	N/a	-2.20[0.01]		680
LP	raw data	const	-3.55[0.00]	-1.63[0.05]	663	663
		const+trend	-3.30[0.00]	0.15[0.56]	663	663
	demeaned data	const	N/a	-1.74[0.04]		680
		const+trend	N/a	-2.60[0.005]		680
LY	raw data	const	-1.40[0.08]	-1.65[0.05]	663	646
		const+trend	-0.52[0.30]	-1.64[0.05]	663	629
	demeaned data	const	N/a	2.01[0.98]		663
		const+trend	N/a	1.83[0.96]		663

* IPS and LLC tests are asymptotically distributed under the standard normal distribution.
Values in brackets are the significance levels.
Estimation conducted using the STATA software package version 7.0.

5.3.2 Cointegration

The results of the cointegration analysis tests over the period 1960 – 2000 are presented in Table (5-2). This shows that out of all the different tests only the group ADF test rejects the null of no cointegration. (Note: the null rejection is determined by large positive values for Panel Variance statistics while for the six other statistics it is determined by large negative values). Thus, the one test where the null of no cointegration is rejected is where there is a heterogeneous trend specification.

Given the above further investigation was undertaken into the stability of these tests by splitting the sample into two sub-periods, 1960 – 1980 and 1981 – 2000. The results from these tests are given in Tables (5-3) and (5-4). These show that the null hypothesis is now rejected by most of statistics and the specification of the trend (whether it is homogeneous or heterogeneous) does not appear to affect the statistics with both specifications rejecting the null. This instability warrants further investigation. One potential solution is to estimate the model by including explicitly the lagged variables then testing for cointegration. However, since in general cointegration cannot be ruled out completely the next section proceeds to the estimation of the cointegrating relationship and the long-run price and income elasticities.[53]

[53] The author tried to split the 17 countries into two groups regarding to the consumption level in order to test the stability of the results across the two groups but there was no evidence of cointegration which deterred estimating the long run price and income elasticities.

Table (5-2): Panel Cointegration Tests with Heterogeneous and Homogeneous Trends over the Period 1960-2000 for 17 OECD Countries

Heterogeneous trend		Homogeneous trend	
Test	**Value**	**Test**	**Value**
Panel ν stat	-0.56	Panel ν stat	-1.59
Panel rho-stat	0.49	Panel rho-stat	1.93
Panel pp-stat	-0.73	Panel pp-stat	0.76
Panel adf	-0.49	Panel adf	1.09
Group rho-stat	0.51	Group rho-stat	3.12
Group pp stat	-1.28	Group pp stat	1.53
Group adf	-1.73	Group adf	1.80

All tests are asymptotically distributed under the standard normal distribution.
Estimation conducted using RATS software package version 5.0

Table (5-3): Panel Cointegration Tests with Heterogeneous and Homogenous Trends over the period 1960-1980 for17 OECD Countries

Heterogeneous trend		Homogeneous trend	
Test	**Value**	**Test**	**Value**
Panel ν stat	2.25	Panel ν stat	4.11
Panel rho-stat	-1.06	Panel rho-stat	-2.95
Panel pp-stat	-4.62	Panel pp-stat	-4.88
Panel adf	-5.00	Panel adf	-4.16
Group rho-stat	0.28	Group rho-stat	-1.85
Group pp stat	-4.70	Group pp stat	-5.49
Group adf	-5.43	Group adf	-5.36

All tests are asymptotically distributed under the standard normal distribution.
Estimation conducted using RATS software package version 5.0

Table (5-4): Panel Cointegration Tests with Heterogeneous and Homogeneous Trends over the period 1981-2000 for17 OECD countries

Heterogeneous trend		Homogeneous trend	
Test	**Value**	**Test**	**Value**
Panel ν stat	1.71	Panel ν stat	3.36
Panel rho-stat	-1.34	Panel rho-stat	-2.16
Panel pp-stat	-7.16	Panel pp-stat	-5.25
Panel adf	-3.73	Panel adf	-4.20
Group rho-stat	0.03	Group rho-stat	-1.04
Group pp stat	-7.71	Group pp stat	-6.05
Group adf	-4.69	Group adf	-5.11

All tests are asymptotically distributed under the standard normal distribution.
Estimation conducted using RATS software package version 5.0

5.3.3 Panel FMOLS Estimates

Tables (5-5) gives the FMOLS estimates of the long run equilibrium energy demand functions for the 17 individual OECD countries and the panel group mean FMOLS estimates over the period 1960 – 2000. The individual country price elasticity estimates are unreliable given most of the individual country estimates are the wrong economic sign and/or are insignificant whereas the income elasticities for each individual country show the right sign and are generally significant.

The group mean (FMOLS) estimates are given with and without time dummies. The time dummies are included in the regression in order to pick up any important underlying trends as discussed in the previous chapter. The estimated long run income and price elasticities without the time dummies are 0.830 and -0.140 respectively, while with the time dummies the estimated income and price elasticities are 0.910 and -0.080 respectively.

Tables (5-6) and (5-7) give the estimated long run income and price elasticities over the two sub-periods 1960 – 1980 and 1981 – 2000 respectively. The individual country estimates are similar to the whole period results in that all individual country income elasticities are of the right sign and generally significant, but the price elasticities are of the wrong sign for Portugal and Spain. However, the mean group FMOLS gives sensible and statistically significant results. It is worth noting that over the 1960 - 1980 period, the price elasticity is higher (in absolute terms) than over the 1981 – 2000 period. This needs further investigation, but perhaps it is due to the greater fluctuations in the real energy price over the earlier period. However, perhaps the price elasticity is biased upwards in the earlier period given the omission of technical progress or any underlying trend effects.

It can be seen therefore that although the results, in terms of the long run price and income elasticities, are reasonable and consistent with economics priors there is still some instability across the periods.

Table (5-5): FMOLS Estimates over the Period 1960 - 2000 for 17 OECD Countries

Country	Income	Price
Austria	0.79	0.05
	(28.31)	(0.84)
Belgium	0.65	-0.14
	(9.06)	(-1.05)
Canada	0.73	-0.11
	(10.63)	(-1.00)
Denmark	0.55	-0.26
	(3.84)	(1.74)
France	0.73	-0.13
	(11.59)	(-0.89)
Greece	1.46	-0.11
	(37.98)	(-1.16)
Ireland	0.68	-0.09
	(14.36)	(-0.68)
Italy	1.00	-0.52
	(13.72)	(-3.43)
Japan	0.82	-0.07
	(12.30)	(-0.45)
Netherlands	0.98	-0.33
	(7.86)	(-1.54)
Norway	0.78	-0.14
	(4.71)	(-0.55)
Portugal	1.19	-0.01
	(32.59)	(-0.12)
Spain	1.24	-0.05
	(33.10)	(-0.61)
Sweden	0.51	-0.55
	(5.48)	(-2.80)
Switzerland	1.39	0.21
	(17.81)	(3.98)
UK	0.30	-0.13
	(7.37)	(-1.57)
USA	0.34	(0.04)
	(5.35)	(0.44)
Panel group FMOLS without time dummies	0.830 (62.10)	-0.140 (-2.99)
Panel group FMOLS with time dummies	0.910 (21.58)	-0.080 (-3.41)

t statistics are in parenthesis.
Estimation conducted using RATS software package version 5.0

Table (5-6): FMOLS Estimates over the Period 1960 - 1980 for 17 OECD Countries

Country	Income	Price
Austria	0.96	-0.22
	(48.01)	(-5.06)
Belgium	1.01	-0.56
	(19.77)	(-4.25)
Canada	1.04	-0.21
	(44.57)	(-5.55)
Denmark	1.37	-0.33
	(24.31)	(-6.48)
France	1.05	-0.41
	(25.68)	(-3.90)
Greece	1.34	-0.12
	(104.85)	(-3.12)
Ireland	0.94	-0.34
	(19.44)	(-4.06)
Italy	1.30	-0.59
	(39.59)	(-10.86)
Japan	1.03	-0.43
	(38.78)	(-6.46)
Netherlands	1.58	-0.27
	(30.31)	(-3.09)
Norway	1.48	-0.70
	(11.19)	(-3.75)
Portugal	1.00	0.11
	(48.64)	(3.27)
Spain	1.42	0.01
	(38.96)	(0.19)
Sweden	1.01	-0.45
	(27.90)	(-6.55)
Switzerland	1.48	-0.20
	(24.76)	(-2.07)
UK	0.59	-0.35
	(17.80)	(-5.43)
USA	0.97	-0.27
	(28.97)	(-8.70)
Panel group FMOLS without time dummies	1.150	-0.310
	(143.96)	(-18.40)
Panel FMOLS with time dummies	0.670	-0.260
	(35.98)	(-5.56)

t statistics are in parenthesis.
Estimation conducted using RATS software package version 5.0

Table (5-7): FMOLS Estimates over the Period 1981-2000 for 17 OECD Countries

Country	Income	Price
Austria	0.71	-0.02
	(17.25)	(-0.65)
Belgium	1.06	0.06
	(10.60)	(1.11)
Canada	0.52	-0.10
	(10.01)	(-1.87)
Denmark	0.36	-0.14
	(3.70)	(-2.03)
France	0.80	0.00
	(14.06)	(0.04)
Greece	1.29	-0.30
	(17.45)	(-5.89)
Ireland	0.49	-0.07
	(20.14)	(-1.67)
Italy	0.81	-0.01
	(36.20)	(-0.60)
Japan	0.96	0.08
	(8.37)	(1.15)
Netherlands	0.51	-0.04
	(13.20)	(-1.15)
Norway	0.44	-0.15
	(10.58)	(-2.24)
Portugal	1.41	0.03
	(18.38)	(0.40)
Spain	1.37	0.17
	(36.82)	(4.45)
Sweden	0.30	-0.14
	(2.72)	(-1.21)
Switzerland	0.79	-0.02
	(8.04)	(-0.73)
UK	0.30	-0.16
	(5.44)	(-3.29)
USA	0.36	0.07
	(6.82)	(1.32)
Panel group FMOLS	0.700	-0.050
without time dummies	(56.87)	(-3.24)
Panel group FMOLS	0.440	-0.010
with time dummies	(10.11)	(-8.41)

t statistics are in the parenthesis.
Estimation conducted using RATS software package version 5.0

5.4 Summary and Conclusion

In this chapter, an attempt has been made to investigate the statistical properties of LE, LP and LY within a panel context for the 17 OECD countries in Data Set B using the LLC and IPS statistics. Furthermore, a test has been conducted to see if there is a statistically valid cointegrating relationship between these variables using the Pedroni test and an attempt has been made to estimate the long run energy demand elasticities using the group mean FMOLS also suggested by Pedroni. However, it would be worth investigating other functional forms in order to compare the obtained elasticities.

The unit root tests are sensitive to the test used and the inclusion or otherwise of the time trend. Unfortunately, at this stage the theory of these tests has not developed adequately to decide upon which one to use in what circumstances. Similarly, with the cointegration tests just one test rejects the null of no cointegration over the whole period, but given this single test where a heterogeneous trend is included, intuitively this might be the most appropriate test to apply. However, when tested over the two halves of the sample different results emerge with cointegration accepted for the majority of the tests.

Finally the estimated - group mean FMOLS- long run income and price elasticities for the whole period 1960 – 2000 are 0.830 and -0.140 respectively without the time dummies and the income elasticity is slightly higher and price elasticity is slightly lower with the time dummies. However, when estimating over the period 1960-1980 the estimated long run income and price elasticities are 1.150 and -0.310 respectively, while with the time dummies they are 0.670 and -0.26 0. And when estimating over the period 1981-2000 the estimated long run price elasticity is almost similar with and without the time dummies, while the long run income elasticity is 0.730 and 0.390 without and with the time dummies respectively. Therefore, this instability in the estimates over the specified periods which requires further research, but in the meantime, it is comforting that theses numbers are still within the same ballpark as those given in Table (1-1) in Chapter 1 which summarises some previous studies on OECD aggregate energy demand and those obtained in Chapters 3 and 4.

Overall therefore, the application of the panel cointegration technique gives reasonably sensible looking results; although there is still a high degree of uncertainty surrounding them for the applied energy economist to put too much faith in them. Therefore, although this has proved a useful and interesting exercise, it is the author's opinion that the technique has not developed enough, as yet, to allow the applied energy economist to use the results for policy analysis – such as in energy/environmental modelling. That said, the results still provide a useful benchmark against the other results in this thesis summarised in Table (6-1), and the technique, it is contended, will be used in the applied energy modelling once it becomes more established and accepted.

Chapter 6

Remarks, Conclusion and Future Research

6.1 Introduction

This thesis has utilised various econometric approaches in order to estimate the reliable and accurate parameters of aggregate energy demand functions for OECD countries. The summary of these approaches is as follows.

- *Panel data estimation:* this is has been applied to Data Set 23A that includes 23 countries for the period 1978 to 1998. This approach analyses both traditional homogeneous estimators and the more recent heterogeneous estimators. It also investigated whether a time trend can be used as a proxy for technical progress.

For the former methodology, there are two difficulties associated with such estimators: the first: relates to the hypothesis that the coefficients of the explanatory variables included in the model are the same across countries. Arguably, this is an unrealistic hypothesis; moreover it is arguably important to incorporate the effect of technical progress when estimating energy demand functions. The inclusion of a deterministic time trend as a proxy for technical progress is therefore questionable since it imposes the same technical rate over time and for all countries. Another problem is with the dynamic specification since when estimating a panel model it imposes the same lag structure on the endogenous and exogenous variables, which is unlikely to be the case in energy demand modelling because economies may differ in their responses to the change in the price and income, or adjusting to the long run equilibrium. Furthermore, in a dynamic panel specification the ignorance of the heterogeneity across the countries leads to bias in the estimates.

Due to the problems encountered in the dynamic homogeneous specification, Chapter 3 introduces a number of heterogeneous panel estimators which allow the coefficients to vary across countries such as the MG, SR, and RC. However, the inclusion of a deterministic trend as a proxy for technical progress in each country regression remains questionable; as explained in Chapter 4. Thus, in order to overcome the problems encountered in panel data estimation the next approach adopted is in the context of time series estimation as below.

- *Structural Time series Model and Cointegration:* There have been many studies applying the cointegration technique, but the structural time series approach has only recently been applied in this area. These two approaches have been applied to the 17 OECD individual countries for Data Set 17B over the period 1960 to 2000.

This approach was adopted to explore and define the appropriate way of modelling the effect of technical progress on energy consumption. The appropriateness of a deterministic linear time trend as an approximation for technical progress has be questioned by a number of studies, with a long debate on how to model such effect on energy consumption within the log-linear energy demand function framework. As highlighted in Chapter 4 the underlying trends may be nonlinear and reflect not only technical progress but other factors such as changes in the consumer tastes and economic structure etc. Therefore, the structural time series approach allows modelling the underlying trend in its stochastic form. In addition, as discussed in Chapter 4 the cointegration approach is adopted for the sake of comparing the results.

- *Panel data cointegration:* This approach, as far as is known, has never been used in any published energy demand studies, and is also applied to Data Set 17B. This approach investigates properties of the variables and helps to validate whether a long run relationship exists or not.

This final approach was adopted for the sake of completing panel data estimation in Chapter 3, since the order of integration and the existence of a valid long run relationship were not explored. Therefore, as discussed in Chapter 5 the order of integration of energy series was tested using unit root tests in the panel data context and the cointegrating vector was estimated with and without time dummies as a proxy for effect of technical progress on energy consumption. Furthermore, estimation of the cointegrating vector was investigated on the whole sample and two sub-samples in order to explore the stability of the estimation using panel group mean FMOLS method.

The outline of the remainder of this chapter is as follows. Section 6.2 shows how the research has attempted to answer the research questions outlined in Chapter 1. Section 6.3 provides a brief conclusion and some ideas for future research.

6.2 The Estimates: Answers to the Thesis Questions

Table (6.1) presents a summary of the results from the different techniques employed in Chapters 3, 4 and 5. As stated in Chapter 1, in addition to the main research question, there are a number of sub-research questions that need to be addressed before considering the main one. Therefore the sub-questions are considered below prior to returning to the main question.

6.2.1 Panel Data Estimation – Questions P1 to P3

As stated in Chapter 1, the first set of sub-questions in the context of panel data estimation is:

Question P1) What are the most preferable estimators: the homogenous or the heterogeneous?

Question P2) What is the most appropriate specification?

Question P3) Should an allowance be made for technical progress (and or other exogenous variable)?

For P1: The homogeneous panel data estimators: the POLS, FE, and RE showed the coefficient on the lagged dependent variable is biased towards one. The long run estimates showed a wide range between different estimators and unreasonable estimated elasticities, outside the normal expected range. Therefore, they may be considered as unreliable estimators due to an unrealistic assumption of homogeneity. Furthermore, the FE estimator is preferred without including the effect of technical progress in the models that the coefficient of the deterministic time trend was not statistically significant. This may indicate that the underlying trends may not be constant over time and/or differ across countries and the deterministic time trend was incapable of capturing the effect of the underlying trends in this technique.

The heterogeneous panel data estimators: the MG and SR showed a more reliable value of the lagged dependent variable. The long run estimates showed less variability even though they are somewhat similar. However, the SR estimator should be addressed with caution because it was not shrunk towards POLS estimator hence the shrinkage factor was close to one. The RC estimator yields a long run price elasticity fairly close to the estimates obtained from the MG and SR estimators, but the long run income elasticity is large and the lagged dependent variable biased towards one. Given the above the heterogeneous estimators are preferred compared to the homogeneous estimators.

For P2: The FE estimator is the preferred specification in all specified models as indicated by Hausman test (see Chapter 3). However, in this preferred specification the time trend coefficient is statistically insignificant.

For P3: Given the discussion to question P1 above, an allowance should be made for a more flexible trend in order to capture the underlying trends in energy demand function beside the effects of price and income.

6.2.2 Time Series Data Estimation: Questions C1 to C3

The Research Questions outlined in Chapter 1, in the context of time series are:

Question C1) What is the appropriate modelling technique, cointegration, or STSM?

Question C2) Is a deterministic trend or a stochastic trend the most appropriate way to allow for technical progress and other underlying exogenous?

Question C3) If the STSM approach with a stochastic trend is preferred, what is the shape of the trends for each country?

For C1: STSM approach is preferred to the cointegration approach as indicated by the LR tests for all countries estimation and because of the 'poor' cointegration results, (see Table 4-3).

For C2: On statistical and economic grounds the stochastic trend models were always preferred to the deterministic trend models for all countries (see Chapter 4).

For C3: The shapes of the UEDTs differ across the OECD countries even when the estimated elasticities are relatively similar. Therefore, the underlying trend differences between countries are captured by the stochastic formulations of the UEDTs, and, moreover, it is important that they are allowed to differ across countries. However, the shapes of UEDTs exhibit some similarities for different countries and could be classified into three groups as following:

Group A: Generally falling: the UK, France, the USA.

Group B: Generally rising: Portugal, Ireland, Greece, Spain, Switzerland, Norway

Group C: Generally rising during 1970s and generally falling thereafter: Austria, Canada, Sweden, Italy, Japan, Denmark, Belgium, the Netherlands.

These groups show that some OECD countries have similar trend despite the differences in economic structure and energy policy.

6.2.3 Panel Data Cointegration: Question E1

In the context of panel data cointegration:

Question E1) Does a statistically acceptable long-run cointegrating relationship exist?

For E1: The results suggest there might be a statistically acceptable panel cointegrating relationship. However, the results still entail a large amount of uncertainty, hence the estimates show instability over the sub-periods. In addition, the underlying trend was modelled using the time dummies, which is questionable as discussed in question P1.

6.2.4 Overall

In the overall context of all estimation techniques applied, the research question given in Chapter 1 is:

Question T1) Do the long run income and price elasticities vary across the techniques and what is the best technique? Table (6-1) reports the long run income and price elasticities obtained from the different techniques utilised throughout the thesis. It shows that the estimated long run income and price elasticities do vary between the different techniques. The obtained elasticities from the different techniques are discussed below:

For the homogeneous panel estimators, the long run price and income elasticities exhibited a wide variability between estimators and the specified models utilised. However, as shown in Chapter 3 the FE estimator is preferred in all specified models but the trend coefficient is statistically insignificant. Therefore, as mentioned above such specification is incapable of capturing the underlying trends. Moreover, when estimating the dynamic model the lagged dependent variable for all specified models is biased towards one as shown by the results in Chapter 3.

For the heterogeneous panel data estimators, in contrast to the homogenous estimators, the lagged dependent variable is more reliable (see Chapter 3). The long run price elasticity for the MG and SR estimators are -0.272, -0.226 respectively, while the RC model yielded an insignificant estimate. The long run income elasticity for MG and SR show close estimates of 0.577 and 0.588 respectively, whereas RC estimate is very large with a value of 1.880. When the deterministic time trend is included in the specification, the long run price elasticities for the MG and SR estimators are -0.229 and -0.267 respectively, and the long run income elasticities are 1.080 and 1.100, while the RC estimate is 2.180.

For the cointegration approach in a panel data context: the long run relationship between energy demand series is statistically significant. However, the results show instability when the whole period was split into two sub-periods. For the whole period the estimated long run price and income elasticities are -0.080 and 0.910 respectively, and without the inclusion of the time trend they are -0.140 and 0.830. For the two sub-periods (1960 -1980) and (1981- 2000), with the time trend, the estimated long run price and income elasticities are (-0.260, 0.670) and (-0.010, 0.440) respectively, see (Table 6-1).

For the time series approaches: Table (6-1) shows that on average the long run income elasticity for the STSM and cointegration approaches are 0.79 and 1.39 respectively. Whilst the average long run price elasticity for the STSM and cointegration approaches are -0.14 and -0.25 respectively.[54] Therefore, the income and price elasticities obtained from cointegration approach which incorporates the deterministic time trend as a proxy for technical progress in the OECD energy demand functions

[54] The details of the elasticities from the structural time series and cointegration approaches for each country are in Chapter 4. The averages of long run income and price elasticities are presented her in order to ease the comparison. However, these averages should not be taken as the preferred estimates.

biased the estimated elasticities and mainly the income elasticity. This confirms that the STSM estimates are preferred to cointegration estimates.

In summary, the FE estimator is preferred without the inclusion of the time trend. The long run income elasticity obtained from MG and SR estimators is biased upward due to the inclusion of the time trend. In addition, the RC model yields a large income elasticity, which rests outside the ballpark of OECD elasticities as shown in Chapter 3, while the long run elasticities obtained from the cointegration approach show some instability. Therefore, given what is discussed above, it is now possible to respond to the main research question below as stated in Chapter 1.

> Question M) What are the long run income and price elasticities for the OECD countries?

The long run income and price elasticities for OECD countries are the one which estimated for individual countries using *Structural Time Series* approach hence it allows encompassing UEDTs, as shown in Chapter 4. An important policy implication from these results is the low estimated price elasticities of aggregate energy demand for OECD countries indicate that the reliance on market mechanisms may not be efficient enough to reduce the aggregate energy demand and hence the emissions. Therefore, stricter regulation policy may work better and is required. Moreover, when these elasticities are coupled with an upward –sloping UEDT, then energy policy should focus more on changes people's lifestyle, via advertising campaigns and improve the energy equipment standards in order to reduce energy consumption and hence the emissions.

6.3 Conclusion and Future Research

This thesis has shown the importance of incorporating the UEDT when estimating energy demand models. Therefore, it has been argued that the appropriate estimation technique for modelling energy demand function for the OECD countries is the structural time series model hence it incorporates the trend in its stochastic form which incorporates technical progress, consumer tastes and changing economic structure (see Chapter 4).

Moreover, it has been shown that when estimating energy demand parameters using the homogenous panel approach the inclusion of a time trend as a proxy for technical progress is too restrictive and hence incapable of picking up the different UEDTs across countries. However, the homogenous panel approach might still be promising if it were possible to incorporate a stochastic trend to adequately capture the appropriate underlying trends. Furthermore, the cointegration panel data technique is arguably an even more promising technique compared to the simple homogeneous panel approach given that it considers the heterogeneity of the estimates across countries and explicitly confirms or refutes the existence of a valid statistical long run relationship, but it still has limitation to incorporate a stochastic trend. Perhaps, in time it will be possible to incorporate a stochastic trend, and then it is easier to explore the direction of the UEDTs for OECD countries collectively. However, the results may constrain policy makers to decide what happening in individual country.

Although the structural time series approach is found to be the preferred approach in this thesis, there is still an important issue that could be explored within this framework; the combination of the structural time series model and non-linear UEDT with asymmetric price (and income) response models. The argument for this is that the structural time series/UEDT approach assumes symmetric responses and hence may be picking up some price effects – particularly when there are large changes or shocks outside the normal range. By combining the UEDT approach with asymmetric price effects (and/or possibly income effects) it might avoid the UEDT picking up the price (and possibly income) effects and hence further help to separate the 'true' price (and income) effects from the UEDT components.

Previous estimated asymmetric models, however, assume that the response to price rises are greater than price falls (with price rises stimulating energy efficiency improvements that are not reversed when the price falls) but do not include an allowance for other exogenous trend effects like those incorporated in the UEDT. Therefore, a fruitful area of research is to start with a general specification that allows for asymmetric price (and possibly income) elasticities *and* a non linear UEDT and test down to see whether one approach dominates the other or whether there is a role to play for both approaches, and hence the consequences on the estimated price and income elasticities.

Table (6-1): The Estimated Long Run Price and Income Elasticities for OECD Countries

Chapter	Data Set	Approaches			Range of estimated Long run elasticities: Price	Range of estimated Long run elasticities: Income	Trend
Three	23A	Panel Data	Homogenous models with out trend	POLS	-0.070 to -3.000	0.400 to 2.000	
				FE	-0.030 to -0.640	0.800 to 0.860	
				RE	-0.020 to -0.850	0.750 to 1.000	
Three	23A	Panel Data	Homogenous models with trend	POLS	-0.19 to -4.800	0.400 to 2.000	Deterministic
				FE	-0.300 to -0.200	0.780 to 0.870	
				RE	-0.024 to -1.100	0.830 to 1.000	
Three	23A	Panel Data	Heterogeneous models with out time trend	MG	-0.272	0.557	
				SR	-0.226	0.588	
				RC	-0.330[1]	1.880	
Three	23A	Panel Data	Heterogeneous models with time trend	MG	-0.229	1.080	Deterministic
				SR	-0.267	1.100	
				RC	-0.190	2.180	
Four	17B	Structural time series model		Average[1]	-0.140	0.790	Stochastic
				Maximum	-0.30	1.350	
				Minimum	0.00	0.00	
				Median	-0.13	0.77	
Four	17B	Cointegration		Average[1]	-0.250	1.390	Deterministic
				Maximum	0.080	3.410	
				Minimum	-0.580	0.100	
				Median	-0.280	1.450	
Five	17B	Panel Data Cointegration	Heterogeneous model with out trend	Average	-0.140[a]	0.830[a]	
					-0.310[b]	1.140[b]	
					-0.050[c]	0.700[c]	
Five	17B	Panel Data Cointegration	Heterogeneous model with trend	Average	-0.080[a]	0.910[a]	
					-0.260[b]	0.67[b]	
					-0.010[c]	0.440[c]	

POLS: :Pooled Ordinary Least Squares
FE: Fixed Effects estimator
RE: Random Effect estimator
MG: Mean Group estimator
SR: Stein Rule estimator
RC Random coefficient estimator
a, b and c represent the estimation periods (1960-2000), (1960-1980) and (1981- 2000).
* based on insignificant short run estimate.
[1] The estimates obtained in Chapter 4 are averaged by the same fashion as the MG estimator

References:

Atkinson, J. and Manning, N. (1995), 'A Survey of International Energy Elasticities', Chapter 3 in Baker, T., Ekins, P. and Johnstone, N. (eds), **Global Warming and Energy Demand**, Routledge, London, UK.

Badde, P. (1981), **International Energy Evaluation System: International Energy Prices (1955-1980)**, Department of Energy, USA.

Balestra, P. (1996), 'Fixed Effects Models and Fixed Coefficients models', in Matyas, L. and Sevestre, P. (eds), **The Econometrics of Panel Data: A handbook of the Theory and Applications**, 2nd ed, Vol. 33,Kluwer Academic Publisher, London.

Balestra, P. (1996), 'Introduction to Linear Models for Panel Data', Chapter 2 in Matyas, L. and Sevestre, P. (eds), **The Econometrics of Panel Data: A handbook of the Theory and Applications**, 2nd ed, Vol. 33,Kluwer Academic Publisher, London.

Baltagi, B.H. (1983), 'Gasoline Demand in the OECD Countries: An application of Pooling and Testing Procedures', **European Economic Review**, Vol. 22, No. 2, pp. 117-137.

Baltagi, B.H. (1995), **Econometric Analysis of Panel Data**, 1st ed, John Wiley & sons, Ltd, UK.

Baltagi, B.H. (1999), **Econometrics**, 2nd edition, Springer-Verlag Berlin, UK.

Baltagi, B.H. (2001), **Econometric Analysis of Panel Data**, John Wiley & sons, Ltd, UK.

Baltagi, B.H. and Griffin, J.M. (1983), 'Gasoline Demand in the OECD: An application of Pooling and Testing Procedures, **European Economic Review**, Vol. 22, No. 2, pp117-137

Baltagi, B.H. and Griffin, J.M. (1997), 'Pooled estimators vs. their Heterogeneous Counterparts in the Context of Dynamic Demand for Gasoline', **Journal of Econometrics,** Vol. 77, No. 2, pp. 303-327.

Baltagi, B.H. and Kao, C. (2000), 'Nonstationary Panel, Cointegration in Panels and Dynamic Panels: A Survey', in Baltagi, B. H. (ed), **Nonstationary Panels, Panel Cointegration, and Dynamic Panels**, Advance in Econometrics, Vol. 15, The Elsevier Science, Netherlands.

Baltagi, B.H. and Raj, B. (1992), 'A Survey of Recent Theoretical Developments in the Econometrics of Panel Data', **Empirical Economics**, Vol.17, No. 1, pp. 85-109.

Baltagi, B.H., Bresson, G and Pirotte, A. (2002), 'Comparasion of Forecast Performance for Homogeneous, Heterogeneous and Shrinkage Estimators: Some Empirical Evidence from US Electricity and Natural Gas Consumption', **Economic Letters**, Vol. 76, No. 3, pp 375-382.

Banerjee, A. (1999), 'Panel Data Unit Roots and Cointegration: An overview', **Oxford Bulletin of Economics and Statistics**, Vol. 61, Supplement 1, pp. 607- 629.

Banerjee, A. Dolado, J. Galbraith, J and Hendry, D. (1993), **Cointegration, Error-Correction, and the Economic Analysis of Non-stationary Data**, Oxford University Press, Oxford.

Beenstock, M., and Willcocks, P. (1981), 'Energy Consumption and Economic activity in industrialized Countries', **Energy Economics**, Vol. 3, No. 4, pp. 225-232.

Bentzen, J, and Engsted, T. (1993), 'Short-run and Long-run elasticities in Energy Demand', **Energy Economics**, Vol. 15, No.1. pp. 9-16.

Berndt, E.R. (1991), **The Practice of Econometrics: Classic and Contemporary**, Addison-Wesley, New York.

Berzeg, K. (1982), 'Demand for Motor Gasoline: A Generalised Error Components Model', **Southern Economic Journal**, Vol. 49, No.2, pp. 462-471.

Bohi, D. R. and Zimmerman, M. (1984), 'An Update on Econometric Studies of Energy Demand', **Annual Review of Energy**, Vol. 9, No. 1, pp. 105-154.

Breitung, J. and Meyer, W. (1994), 'Testing Unit Roots in Panel Data: Are Wages on Different Bargaining Levels Cointegrated? **Applied Economics**, Vol. 26, No. 4, pp. 353-361.

Breusch, T.S. and Pagan, A.R. (1980) 'The Lagrange Multiplier Test and its application to Model Specification in Econometrics', **Review of Economic Studies**, Vol. 47, No. 146, pp. 239-253.

Chamberlain, G. (1984), 'Panel Data', in Griliches, Z. and Intriligator, M.(eds), **Handbook of Econometrics: Volume II**, Amsterdam, North Holland.

Chern, Wen S. and Bouis, Howarth E. (1988), 'Structural Change in Residential Electricity Demand', **Energy Economics**, Vol.10, No. 3, pp. 213-222.

Choi, In. (2001), 'Unit Root Tests for Panel Data', **Journal of International Money and Finance**, Vol. 20. No. 2, pp. 249-272.

Dargay, J. and Gately, D. (1995), 'The Response of World Energy and Oil Demand to Income Growth and Changes in Oil Prices', **Annual Review of Energy and the Environment**, Vol. 20, pp. 145-178.

Dimitropoulos, J., Hunt, L. C. and Judge, G (2005), 'Estimation Underlying Energy Demand Trends Using UK Annual Data', **Applied Economic Letters**, Vol. 12. No. 4, pp. 239-244.

Doornik, J. A. and Hendry, D. F. (2001), **Modelling Dynamic System Using PcGive**, Timberlake Consultants Ltd, UK.

Dunstan, R.H. and Schmidt, R.H., (1988), 'Structural Changes in Residential Energy Demand', **Energy Economics**, Vol. 10, No. 3, pp. 206-212.

Engle, R. F. and Granger, C. W. J. (1987), 'Cointegration and Error Correction: Representation, Estimation and Testing', **Econometrica**, Vol.55, No. 2, pp. 251-276.

Estima (2000) **RATS Software, Version 5**, Evanston, USA

Fouquet, R. (1993), 'Recent Development in Energy Demand Modelling', in Hawdon, D. (ed), **Recent Studies of the demand for Energy in the UK**, Surrey Energy Economics Centre, UK.

Fouquet, R. (1995), 'The Impact of VAT on UK Residential Energy Demand', **Energy Economics**, Vol.17. No. 3, pp. 237-247.

Greene, W. H. (2002), **Econometric Analysis**, 4th Edition, Prentice Hall, New Jersey. USA.

Griffin, J.M. (1979), **Energy Conservation in the OECD: 1980 to 2000**, Ballinger Publishing Company, USA.

Griffin, J.M. (1991), 'Methodological Advances in Energy Modelling: 1970-1990', **The Energy Journal**, Vol.14, No. 1, pp. 111- 123.

Haque, N.U., Pesaran, M.H., and Sharma, S. (2000), 'Neglected Heterogeneity and Dynamics in Cross-Country Savings Regressions, Chapter 3 in Krishnakumar, J and E, Ronchetti, (eds), **Panel Data Econometrics: Future Directions**, Papers in Honour of Professor Pietro Balestra, North-Holland.

Harris, D. and Inder, B. (1994), 'A Test of the Null Hypothesis of cointegration', In C.P. Hargreaves (ed), **Nonstationary Time Series Analysis and Cointegration**, Oxford University Press, New York.

Harris, R., and Sollis., R. (2003), **Applied Time Series Modelling and Forecasting,** John Wiley & Sons Ltd, Chichester, UK.

Harvey, A. C, 1997. 'Trend, Cycles and Autoregression', **Economic Journal**, Vol. 107, No. 440, pp. 192-201.

Harvey, A. C. (1989), **Forecasting, Structural Time Series Models and Kalman Filter**, Cambridge University Press, Cambridge.

Harvey, A. C., Henry, S.G.B, Peters, S. and Wren-Lewis, S. (1986), 'Stochastic Trends in Dynamic Regression Models: An Application to the Employment-Output Equation', **Economic Journal**, Vol. 96, No. 384, pp. 975-985.

Hausman, J.A. (1978), 'Specification Tests in Econometrics', **Econometrica**, Vol. 46, No. 6, pp.1251-1271.

Hendry, D. and Juselius, K., (2000). 'Explaining Cointegration Analysis: Part I ', **Energy Journal**, Vol. 21, No. (1), pp. 1-42.

Hendry, D. and Juselius, K., (2001). 'Explaining Cointegration Analysis: Part II', **Energy Journal**, Vol. 22, No. 1, pp. 75-120.

Henley, A. and Persion, J. (1998), 'Residential Energy Demand and Interaction of Price and Temperature: British Experimental Evidence', **Energy Economics**, Vol. 20, No. 2, pp 157-171.

Houthakker, H.S. (1965), 'New Evidence on Demand Elasticities', **Econometrica,** Vol. 32, No. 2, pp. 277-288.

Houthakker, H.S., Verleger, P.K., and Sheehan, D. P. (1974), 'Dynamic Demand Analysis for Gasoline and Residential Electricity', **American Journal of Agriculture Economics**, May, pp. 412-418.

Hunt, L. C. (1984), 'Energy and Capital: Substitute or Complements? Some Results for the UK Industrial Sector. **Applied Economics**, Vol. 16, No. 5, pp.783-789.

Hunt, L.C. (1986), 'Energy and Capital: Substitutes or Complements? A note on the importance of testing for Non-neutral Technical Progress', **Applied Economics**, Vol. 18, No.7, pp.729-735.

Hunt, L. C. and Manning, N. (1989), 'Energy Price and Income Elasticities of Demand: Some Estimates for the UK Using the Co-integration Procedure', **Scottish Journal of Political Economy**, Vol. 36, No. 2, pp. 183-193.

Hunt, L.C. and Lynk, E.L.(1992), 'Industrial Energy Demand in the UK: A Cointegration Approach' , in Hawdon, D. (ed), **Energy Demand: Evidence and Expectations,** Academic Press, London.

Hunt, L.C., Judge, G., and Ninomiya, Y. (2003a), 'Underlying Trends and Seasonality in UK Energy Demand: A Sectoral Analysis', **Energy Economics**, Vol. 25, No. 1, pp. 93-118.

Hunt, L.C., Judge, G., and Ninomiya, Y. (2003 b), 'Modelling Underlying Energy Demand Trends', In Hunt, L.C., (ed.), **Energy in a Competitive Market: Essays in Honour of Colin Robinson**, Edward Elgar, UK.

Hunt, L.C., Ninomiya, Y. (2003c), 'Unravelling Trend and Seasonality: A Structural Time Series Analysis of Transport Oil Demand in the UK and Japan', **Energy Journal**, Vol. 24. No. 3, pp. 63-96.

Hunt, L.C., Ninomiya, Y. (2005), 'Primary Energy Demand in Japan: An Empirical Analysis of Long-Term Trends and Future CO_2 Emissions', **Energy Policy**, Vol. 33, No.11, pp. 1409-1424.

Hsaio, C (1985), 'Benefits and Limitations of Panel data', **Econometric Reviews,** Vol.4, No. 1, pp. 121-174.

Hsaio, C. (1986), **Analysis of Panel Data**, Cambridge University Press, Cambridge, USA.

Im, K. S., Pesaran, M. H. and Shin, Y. (2003) 'Testing Unit Roots in heterogeneous panels', **Journal of Econometrics**, Vol. 115, No. 1, pp. 53-74.

Inder, B. (1993), 'Estimating Long-run Relationships in Economics: A Comparison of Different Approaches ', Journal of Econometrics, Vol. 57, No. 1, pp. 53-68.

International Energy Agency, (1991), **Energy Balance of OECD Countries**, OECD, Paris.

International Energy Agency, (2003), **'From Oil Crisis to Climate Change Challenge: Understanding CO_2 Emission Trends in IEA Countries**, OECD, Paris.

International Energy Agency, (2004), **Energy Prices and Taxes, Quarterly Statistics, Third Quarter**, OECD, Paris.

Jones, C. T. (1994), 'Accounting for Technical Progress in Aggregate Energy Demand', **Energy Economics**, Vol. 16, No. 4, pp. 245-252.

Jones, C. T. (1996), ' A pooled Dynamic Analysis of Interfuel Substitution in Industrial Energy Demand by the G-7 Countries, **Applied Economics**, Vol. 28, No. 7, pp. 815-821.

Kao, C. (1999), 'Spurious Regression and Residual- Based Tests for Cointegration in Panel Data', **Journal of Econometrics**, Vol. 90, No.1, pp. 1- 44.

Karlsson, S. and Lothgren, M. (2000), 'On the Power and Interpretation of Panel Unit Roots tests', **Economics Letters**, Vol. 66, No. 3, pp. 249-255.

Koopman, S. J. Harvey, A.C. Doornik, J. A. and Shephard, N. (1995) **STAMP 5.0,** International Thompson Business Press, London.

Koopman, S. J. Harvey, A.C. Doornik, J. A. and Shephard, N.(2004) **STAMP 6.3,** International Thompson Business Press, London.

Kouris, G. (1976), 'The Determinants of Energy demand in the EEC Area', **Energy Policy**, Vol. 6, No. 4, pp. 343- 355.

Kouris, G. (1983), 'Energy Consumption and Economic Activity in Industrialized Economies- A Note', **Energy Economics**, Vol. 5, No. 3, pp. 207-212.

Kraft, J. and Rodekohr, M. (1978), 'Regional Demand for Gasoline: A temporal Cross-Section specification', **Journal of Regional Science**, Vol. 18, No.1, pp.45-55.

Kwast, M. L. (1980), A note on Structural Stability of Gasoline Demand and Welfare Economics of Gasoline Taxation', **Southern Economic Journal**, Vol. 46, No. 4, pp. 1212-1220.

Lakshamanan, T. R. and Anderson, W. (1980), 'Residential Energy Demand in the United State: A Regional Econometric Analysis', **Regional Science and Urban Economics**, Vol. 10, No. 3, pp. 371-386.

Levin, A., Lin, C-F. and Chu, C-S. J. (2002) 'Unit Root tests in Panel Data: Asymptotic and Finite-Sample Properties', **Journal of Econometrics**, 108, No. 1, pp. 1-24.

MacDonald, G., Allen. D., and Cruickshank, S. (2002), 'Purchasing Power Parity-Evidence from A New Panel Test', **Applied Economics**, Vol.34. No. 11, pp. 1319-1324.

MacDonald, R. (1996) 'Panel Unit Root Tests and Real Exchange Rates', **Economics Letters**, Vo.50, No. 1, pp. 7-11.

Maddala, G. S. and Kim, I. (1998), **Unit Roots, Cointegration and Structural Change**, Cambridge University Press, Cambridge, UK.

Maddala, G. S. and Wu. S (1999) 'A Comparative Study of Unit root Tests with Panel Data and a New Simple Test', **Oxford Bulletin of Economics and Statistics**, 61, Supplement 1, pp. 631 – 652.

Maddala, G.S. (1987), 'Recent Development in the Econometrics of panel Data Analysis', **Transportation Research**, Vol. 21, No. 3, pp 303-326.

Maddala, G.S. (1991), 'To Pool or Not To Pool: That is the Question', **Journal of Quantitative Economics**, Vol.7, No 2, pp. 225-246.

Maddala, G.S. and Hu, W. (1995), 'The Pooling Problem', Chapter 13 in Matyas, L., and Sevestre, P. (eds), **The Econometrics of Panel Data: A Handbook of the Theory and Application**, Kluwer Academic Publisher, USA.

Maddala, G.S., Trost, R.P., Li, H., and Joutz, F. (1997), 'Estimation of the Short-run and Long-run Parameters from Panel Data Using Shrinkage Estimators', **Journal of Business and Economic Statistics**, Vol.15, No. 1, pp. 90-100.

Madlener, R. (1996), 'Econometric Analysis of Residential Energy Demand: A Survey', **The Journal of Energy Literature**, Vol. 2, No.2, pp. 3-32.

Matyas, L. and Sevestre, P. (eds), **The Econometrics of Panel Data: A Handbook of the Theory and Applications**, 2nd ed, Vol. 33, Kluwer Academic Puplisher, London.

McCoskey, S. and Kao, C. (1988), 'A Residual-Based Test of the Null of Cointegration in Panel Data', **Econometric Reviews**, Vol. 17, No.1, pp. 57-84.

Mehta, J. S., Narasimham, G. V. L., and Swamy, P. A. B. (1978), 'Estimation of A Dynamic Function for Gasoline With Different Schemes of Parameter Variation', **Journal of Econometrics**, Vol. 7, pp. 263-279.

Nahar, S. and Inder, B. (2002), 'Testing Convergence in Economic Growth for OECD Countries', **Applied Economics**, Vol. 34, No. 16, pp. 2011 - 2022.

Nordhaus, W.D. (1977), 'The Demand for Energy: An International Perspective', Chapter 13 in Nordhaus, W.D (ed), **International Studies of the Demand for Energy**, North Holland.

Oh, K. Y, (1998) 'Purchasing Power Parity and Unit Root Tests Using Panel Data' **Journal of International Money and Finance**, Vol.15, No. 3, pp. 405– 418.

Parhizgari, Am and Davis, PS, (1978), 'The Residential Demand for Electricity: A Variant Parameters Approach, **Applied Economics**, Vol.10, No. 4, pp. 331-440.

Pedroni, P. (1997) 'Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with Application to the PPP Hypothesis: New Results', Working Paper, Department of Economics, Indiana University.

Pedroni, P. (1999) 'Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors', **Oxford Bulletin of Economics and Statistics**, Vol. 61, Supplement 1, pp. 653-670.

Pedroni, P. (2000) 'Fully Modified OLS for the Heterogeneous Cointegrated Panels', In Baltagi, B H. (ed), **Nonstationary Panels, Panel Cointegration, and Dynamic Panels, Advances in Econometrics**, Vol.15, Elsevier Science Inc, USA.

Pedroni, P. (2001) 'Purchasing Power Parity Tests in Conintegrated Panel', **The Review of Economics and Statistics**, Vol. 83, No. 4, pp. 727-731.

Pesaran, H. R, Smith, and Im, K.S.(1996), 'Dynamic Linear Models for Heterogeneous Panels', Chapter 8 in Matyas, L., and Sevestre, P (eds.), **The Econometrics of Panel Data: A Handbook of the Theory with Applications**, Kluwer Academic Publishers, USA.

Pesaran, M.H. and R. Smith. (1995), 'Alternative Approaches to Estimating Long run Energy Demand Elasticities: An Application to Asian Developing Countries', Chapter 2 in Baker, T., Ekins, P. and Johnstone, N. (eds), **Global Warming and Energy Demand**, Routledge, London, UK.

Pesaran, M.H. and R. Smith. (1995), 'Estimating Long-run Relationships from Dynamic Heterogeneous Panels, **Journal of Econometrics**, Vol. 68, No. 1, pp. 79-113.

Pesaran, M.H., (1997), 'The Role of Economic Theory in Modelling the Long run, **Economic Journal**, Vol. 107, No. 440, pp. 178-191.

Pesaran, M.H., R. Smith., and Akiyama, T. (1998), **Energy Demand in Asian Developing Economies**, Oxford University Press, Oxford.

Pindyck, S. R. (1980), **The Structure of World Energy Demand,** The MIT Press, Cambridge, UK.

Prosser, R.D. (1985), 'Demand Elasticities in OECD: Dynamic Aspects', **Energy Economics**, Vol.7, No. 1, pp. 9-12.

Robertson, D. and Symons, J. (1992), 'Some Strange Properties of Panel Data Estimators', **Journal of Applied Econometrics**, Vol. 7, No. 2, pp. 175-189.

Samouilidis, J-E. and Mitropoulos, C. S. (1984), 'Energy and Economic Growth in Industrialised Countries: The Case of Greece', **Energy Economics**, Vol. 6, No. 3, pp. 191-201.

Stata Corporation (2001), **Stata Statistical Software: Release 7.0**, Stata Press: College Station, TX, USA.

Sun, J. W. (2002), 'The Decrease in the Difference of Energy Intensities between OECD Countries from 1971 to 1998', **Energy Policy**, Vol.30, No. 8, pp. 631-635.

Swamy, P A V B. (1970), 'Efficient Inference in a Random Coefficient Regression Model', **Econometrica**, Vol. 38, No. 2, pp. 311-323.

Taylor, L. D. (1975) 'The Demand for Electricity: A Survey', **Bell Journal of Economics**, Vol. 6, No.1, pp. 74-110.

Thomas, R. (1993), **Introductory Econometrics: Theory and Application**, Longman, London.

UNFCCC (1997), Kyoto Protocol to the United Nations Framework Convention on Climate Change Download from: http://unfccc.int/resource/docs/convkp/kpeng.html.

Watkins, G. C. (1992), 'The Economic Analysis of Energy Demand: Perspective of a Practitioner' in, Hawdon. D. (ed), **Energy Demand Evidence and Expectations,** Academic Press Limited, London.

Welsch, H. (1989), 'The Reliability of Aggregate Energy Demand Function: An Application of Statistical Specification Error Tests', **Energy Economics**, Vol.11, No. 4, pp. 285-292.

Wu, Y. (1996) 'Are Real Exchange Rates Stationary? Evidence from a Panel Data Test', **Journal of Money, Credit and Banking**, Vol. 28, No. 1, pp. 54-63.