THE UNDERLYING ENERGY DEMAND TREND
AND SEASONALITY:
AN APPLICATION OF THE STRUCTURAL TIME SERIES MODEL
TO ENERGY DEMAND IN THE UK AND JAPAN

Yasushi Ninomiya
Surrey Energy Economics Centre
Department of Economics
University of Surrey
Guildford
UK

A Thesis Submitted to the University of Surrey
for the Degree of Doctor of Philosophy in Economics

March 2002
ABSTRACT

Energy demand is essentially a derived demand dependent upon, not only economic variables (such as income and price), but also on the technical efficiency of the energy using appliances and capital stock. This has been accepted by energy economists for some time. In this thesis, it is argued that in addition energy demand is also affected by the way the appliances are used, changes in consumer tastes and economic structure. Moreover, these effects may be aggregated and defined as the Underlying Energy Demand Trend (UEDT). However, since they are normally unobservable or difficult to measure at the aggregated level, these effects have been implicitly ignored in past energy demand studies. At best, the technical progress aspect has been approximated by a deterministic linear time trend. Similarly, when quarterly data is used, deterministic seasonal dummy variables are commonly employed to capture seasonal variations. Very little attention has been paid to the highly probable situation of evolving seasonal patterns in energy demand.

Given this background, this thesis explores the conceptual basis of the UEDT and maintains that it is feasible for it to be positive, negative or zero and likely to change over time. Hence, a flexible and general technique is required to capture these characteristics if they are present. Moreover, if the UEDT is not modelled adequately then the estimated income and price elasticities can be seriously biased. It is also argued that a flexible and general approach is also required for seasonality given the prospect of a changing pattern over time.

The structural time series model which incorporates a stochastic trend and stochastic seasonals is regarded as the optimal methodology in these circumstances. It is shown that this model is very general and encompasses a deterministic trend and/or deterministic seasonals as restricted versions. The structural time series model is therefore applied to energy demand in various sectors and fuels in the UK and Japan using unadjusted quarterly data 1972q1–1998q4 or annual data 1965–1999. For all but one of the quarterly and the annual data sets, some form of the stochastic trend is preferred on a whole range of criteria. Moreover, it is found that the UEDTs are highly non-linear and can have phases where they are both negative and positive. Similarly, for all the quarterly data sets, stochastic seasonality is preferred on a whole range of criteria. These results clearly illustrate the importance of using the approach adopted in the thesis when attempting to model energy demand.
Chapter 1. Introduction

1.1. Introduction

1.2. Background to the energy situations in the UK and Japan
   1.2.1. The UK
   1.2.2. Japan

1.3. Sectors and fuels analysed in this thesis

Chapter 2. Overview of past energy demand modelling

2.1. Introduction
   2.1.1. General overview of the theoretical approach to
           modelling energy demand

2.2. The log-linear model
   2.2.1. The log-linear models in reduced form
   2.2.2. The log-linear models within the cointegration
           technique
       2.2.2.1. Concept of a cointegration relationship
       2.2.2.2. Engel and Granger two step procedure and
                 Error correction model
       2.2.2.3. Multivariate cointegration system
       2.2.2.4. Strengths and weaknesses of the cointegration
                 technique

   2.2.3. Irreversible price response specification in the
           log-linear model
   2.2.4. The log-Linear model in structural form
   2.2.5. Strengths and weaknesses of the log-linear model

2.3. Translog function modelling
   2.3.1. Translog function specification
   2.3.2. Dynamic translog model
   2.3.3. Strengths and weaknesses of the translog model

2.4. Summary and conclusion

Chapter 3. Modelling underlying energy demand trend and stochastic
         seasonality

3.1. Introduction

3.2. Review of modelling technical progress in the log-linear model
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.2.1. Technical progress and a deterministic linear time trend in past studies</td>
<td>81</td>
</tr>
<tr>
<td>3.2.2. Review</td>
<td>82</td>
</tr>
<tr>
<td>3.3. Underlying Energy Demand Trend (UEDT)</td>
<td>100</td>
</tr>
<tr>
<td>3.3.1. Concept of the UEDT</td>
<td>100</td>
</tr>
<tr>
<td>3.3.2. Technical energy efficiency</td>
<td>102</td>
</tr>
<tr>
<td>3.3.2.1. Embodied technical progress</td>
<td>102</td>
</tr>
<tr>
<td>3.3.2.2. Disembodied technical progress</td>
<td>104</td>
</tr>
<tr>
<td>3.3.2.3. Factors driving endogenous technical progress</td>
<td>107</td>
</tr>
<tr>
<td>3.3.3. Consumer tastes</td>
<td>108</td>
</tr>
<tr>
<td>3.3.4. Economic structure</td>
<td>109</td>
</tr>
<tr>
<td>3.4. Ignoring the UEDT and biased elasticity estimates</td>
<td>110</td>
</tr>
<tr>
<td>3.5. Modelling of the UEDT</td>
<td>115</td>
</tr>
<tr>
<td>3.6. Modelling of seasonality in energy demand</td>
<td>117</td>
</tr>
<tr>
<td>3.6.1. Deterministic seasonal dummy variables</td>
<td>120</td>
</tr>
<tr>
<td>3.6.2. Seasonal difference in the Box and Jenkins approach</td>
<td>123</td>
</tr>
<tr>
<td>3.6.3. Seasonal unit root and seasonal cointegration</td>
<td>125</td>
</tr>
<tr>
<td>3.6.4. Stochastic seasonal dummy variables</td>
<td>130</td>
</tr>
<tr>
<td>3.7. Summary and conclusion</td>
<td>134</td>
</tr>
</tbody>
</table>

**Chapter 4. Model and methodology**

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1. Introduction</td>
<td>142</td>
</tr>
<tr>
<td>4.2. Basic modelling framework</td>
<td>146</td>
</tr>
<tr>
<td>4.3. The structural time series model</td>
<td>148</td>
</tr>
<tr>
<td>4.3.1. Trend Component</td>
<td>150</td>
</tr>
<tr>
<td>4.3.2. Seasonal Component</td>
<td>157</td>
</tr>
<tr>
<td>4.3.3. Various combinations of the trend and the seasonal components</td>
<td>158</td>
</tr>
<tr>
<td>4.3.4. State space from and the Kalman filter</td>
<td>160</td>
</tr>
<tr>
<td>4.4. Estimation strategies in the empirical chapters</td>
<td>162</td>
</tr>
<tr>
<td>4.5. Data</td>
<td>170</td>
</tr>
<tr>
<td>4.6. Summary and conclusion</td>
<td>174</td>
</tr>
<tr>
<td>Appendix 4.1. State space form and the Kalman filter</td>
<td>176</td>
</tr>
<tr>
<td>A4.1.1. State space form</td>
<td>177</td>
</tr>
<tr>
<td>A4.1.2. The Kalman filter</td>
<td>181</td>
</tr>
<tr>
<td>A4.1.3. Smoothing</td>
<td>186</td>
</tr>
<tr>
<td>Appendix 4.2. Data</td>
<td>189</td>
</tr>
<tr>
<td>A4.2.1. UK</td>
<td>189</td>
</tr>
<tr>
<td>A4.2.2. Japan</td>
<td>191</td>
</tr>
</tbody>
</table>

**Chapter 5. Application of the structural time series model to UK energy demand**

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1. Introduction</td>
<td>195</td>
</tr>
<tr>
<td>5.2. Aggregated final energy demand in the UK</td>
<td>196</td>
</tr>
<tr>
<td>5.2.1. Aggregated whole economy final energy demand</td>
<td>197</td>
</tr>
<tr>
<td>Section</td>
<td>Page</td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>7.1. Summary of the analysis: Answers to the primary research questions</td>
<td>320</td>
</tr>
<tr>
<td>7.2. The estimates: Answers to the sub-research questions</td>
<td>328</td>
</tr>
<tr>
<td>7.3. Conclusion and further research areas</td>
<td>332</td>
</tr>
</tbody>
</table>

References 334
# LIST OF TABLES

<table>
<thead>
<tr>
<th>List of Tables</th>
<th>Page number</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1. Summary UK Energy Balance 1999</td>
<td>9</td>
</tr>
<tr>
<td>1.2. Summary Energy Balance of Japan 1999</td>
<td>17</td>
</tr>
<tr>
<td>2.1. Energy demand studies using the log linear model</td>
<td>41</td>
</tr>
<tr>
<td>2.2. Energy demand studies using the cointegration technique</td>
<td>53</td>
</tr>
<tr>
<td>2.3. Energy demand studies using the translog model</td>
<td>72</td>
</tr>
<tr>
<td>3.1. Recent studies including a deterministic linear time trend as UEDT for the UK, Japan and OECD</td>
<td>93</td>
</tr>
<tr>
<td>3.2. Underlying Energy Demand Trend (UEDT)</td>
<td>101</td>
</tr>
<tr>
<td>3.3. Four types of technical progress affect technical energy efficiency</td>
<td>107</td>
</tr>
<tr>
<td>4.1. Classification of possible stochastic trend models</td>
<td>150</td>
</tr>
<tr>
<td>4.2. Possible combination of deterministic and/or stochastic trend and seasonals</td>
<td>159</td>
</tr>
<tr>
<td>5.1. Estimated results for the UK whole economy energy demand 1972q1 – 1995q4</td>
<td>199</td>
</tr>
<tr>
<td>5.2. Recent energy demand studies for the UK whole economy aggregated energy demand</td>
<td>208</td>
</tr>
<tr>
<td>5.3. Estimated results for the UK residential energy demand</td>
<td>213</td>
</tr>
<tr>
<td>5.4. Recent energy demand studies for the UK residential sector energy demand</td>
<td>218</td>
</tr>
<tr>
<td>5.5. Estimated results for the UK manufacturing sector final energy demand 1972q1 – 1995q4</td>
<td>221</td>
</tr>
<tr>
<td>5.6. Recent energy demand studies for the UK manufacturing sector energy demand</td>
<td>227</td>
</tr>
<tr>
<td>5.7. Estimated results for the UK transportation oil demand 1972q1 – 1995q4</td>
<td>231</td>
</tr>
<tr>
<td>5.8. Recent energy demand studies for the UK transport oil demand</td>
<td>237</td>
</tr>
<tr>
<td>5.9. Estimated results for the UK electricity demand 1972q1 – 1995q4</td>
<td>243</td>
</tr>
<tr>
<td>5.10. Recent energy demand studies for the UK electricity demand</td>
<td>248</td>
</tr>
<tr>
<td>6.1. Estimated results for the whole economy energy demand in Japan 1965 – 1996</td>
<td>259</td>
</tr>
<tr>
<td>6.2. Recent energy demand studies for the whole economy energy demand in Japan</td>
<td>268</td>
</tr>
<tr>
<td>6.3. Estimated results for the residential-service sector energy demand in Japan 1965 – 1996</td>
<td>271</td>
</tr>
<tr>
<td>6.4. Recent energy demand studies for the residential-service sector in Japan</td>
<td>278</td>
</tr>
<tr>
<td>6.5. Estimated results for the manufacturing sector energy demand in Japan 1965 – 1996</td>
<td>281</td>
</tr>
<tr>
<td>6.6. Recent energy demand studies for the manufacturing sector in Japan</td>
<td>289</td>
</tr>
<tr>
<td>6.7. Estimated results for the transport oil demand in Japan 1972q1 – 1995q4</td>
<td>293</td>
</tr>
<tr>
<td>6.8. Recent energy demand studies for the transport oil demand in Japan</td>
<td>300</td>
</tr>
</tbody>
</table>
6.9. Estimated results for the electricity demand in Japan 1972q1 – 1995q4
6.10. Recent energy demand studies for the electricity demand in Japan
7.1. Deterministic restriction on the stochastic trend/seasonals and problems occurred
7.2. Summary of the estimated elasticities, UEDT and seasonality
<table>
<thead>
<tr>
<th>Figure Number</th>
<th>Description</th>
<th>Page Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1.</td>
<td>Primary energy consumption in 1998</td>
<td>8</td>
</tr>
<tr>
<td>1.2a.</td>
<td>Volume of UK final energy consumption 1960 – 1998 by sectors</td>
<td>12</td>
</tr>
<tr>
<td>1.2b.</td>
<td>Shares of UK final energy consumption 1960 – 1998 by sectors</td>
<td>12</td>
</tr>
<tr>
<td>1.3a.</td>
<td>Volume of UK final energy consumption 1960 – 1998 by fuels</td>
<td>13</td>
</tr>
<tr>
<td>1.3b.</td>
<td>Shares of UK final energy consumption 1960 – 1998 by fuels</td>
<td>13</td>
</tr>
<tr>
<td>1.4.</td>
<td>Volume of UK industrial sector energy consumption by fuels</td>
<td>14</td>
</tr>
<tr>
<td>1.5.</td>
<td>Volume of UK residential sector energy consumption by fuels</td>
<td>14</td>
</tr>
<tr>
<td>1.6.</td>
<td>Volume of UK transportation sector energy consumption by fuels</td>
<td>15</td>
</tr>
<tr>
<td>1.7a.</td>
<td>Volume of final energy consumption 1961 – 1997 in Japan by sectors</td>
<td>19</td>
</tr>
<tr>
<td>1.7b.</td>
<td>Shares of final energy consumption 1961 – 1997 in Japan by sectors</td>
<td>19</td>
</tr>
<tr>
<td>1.8a.</td>
<td>Volume of final energy consumption 1961 – 1997 in Japan by fuels</td>
<td>20</td>
</tr>
<tr>
<td>1.8b.</td>
<td>Shares of final energy consumption 1961 – 1997 in Japan by fuels</td>
<td>20</td>
</tr>
<tr>
<td>1.9.</td>
<td>Volume of industrial sector energy consumption in Japan by fuels</td>
<td>21</td>
</tr>
<tr>
<td>1.10.</td>
<td>Volume of residential-service sector energy consumption in Japan by fuels</td>
<td>21</td>
</tr>
<tr>
<td>1.11.</td>
<td>Volume of transportation sector energy consumption in Japan by fuels</td>
<td>22</td>
</tr>
<tr>
<td>3.1.</td>
<td>Possible biases in estimated price elasticities of energy demand</td>
<td>112</td>
</tr>
<tr>
<td>3.2.</td>
<td>Possible biases in estimated income elasticities of energy demand</td>
<td>113</td>
</tr>
<tr>
<td>5.1.</td>
<td>UK whole economy aggregated final energy consumption, real GDP, real energy price and GB air temperature</td>
<td>197</td>
</tr>
<tr>
<td>5.2.</td>
<td>Estimated UEDT, slope of UEDT, estimated seasonal variations and individual seasonal variations in the UK whole economy aggregated final energy demand</td>
<td>205</td>
</tr>
<tr>
<td>5.3.</td>
<td>UK residential sector aggregated final energy consumption, household real disposable income, real energy price and GB air temperature</td>
<td>211</td>
</tr>
<tr>
<td>5.4.</td>
<td>Estimated UEDT, slope of UEDT, estimated seasonal variations and individual seasonal variations in the UK residential sector final energy demand</td>
<td>215</td>
</tr>
<tr>
<td>5.5.</td>
<td>UK manufacturing sector aggregated final energy consumption, manufacturing output, real energy price and GB air temperature</td>
<td>230</td>
</tr>
<tr>
<td>5.6.</td>
<td>Estimated UEDT, slope of UEDT, estimated seasonal variations and individual seasonal variations in the UK manufacturing sector final energy demand</td>
<td>224</td>
</tr>
<tr>
<td>5.7.</td>
<td>UK road transportation oil consumption, real GDP, real price of road transportation oil and GB air temperature</td>
<td>230</td>
</tr>
<tr>
<td>5.8.</td>
<td>Estimated UEDT, slope of UEDT, estimated seasonal variations and individual seasonal variations in the UK transportation oil demand</td>
<td>235</td>
</tr>
<tr>
<td>5.9.</td>
<td>UK electricity consumption, real GDP, real electricity price and GB air temperature</td>
<td>241</td>
</tr>
</tbody>
</table>
5.10. Estimated UEDT, slope of UEDT, estimated seasonal variations and individual seasonal variations in the UK electricity demand 247
6.1. Whole economy final energy demand, real GDP, real aggregated energy price and the Heating Degree Days in Japan 257
6.3. The estimated UEDT and its slope (by Stochastic Trend Model) 263
6.4. Residential-service sector final energy demand, real GDP, real aggregated energy price and the Heating Degree Days in Japan 269
6.6. The estimated UEDT by Stochastic Trend Model 274
6.7. Manufacturing sector final energy demand, real GDP, real aggregated energy price and the Heating Degree Days and the Cooling Degree Days weighted by the diffusion of air conditioner in Japan 279
6.9. The estimated UEDT and its slope in the manufacturing sector 285
6.10. Transportation oil demand, real GDP, real transportation oil price, higher air temperature deviations in Japan 291
6.11. Estimated UEDT, slope of UEDT, estimated seasonal variation and estimated individual seasonal pattern in the transportation oil demand in Japan 297
6.12. Electricity demand, real GDP, real electricity price, cooler air temperature deviations and higher air temperature deviations in Japan 301
6.13. Electricity demand, real GDP and real electricity price in Japan 1973q1 – 1979q4 305
6.14. Estimated UEDT, slope of UEDT, estimated seasonal variation and estimated individual seasonal pattern in the electricity demand in Japan 307
ACKNOWLEDGEMENTS

First of all, with great respect, I would like to thank my supervisor, Professor Lester C. Hunt, who has continuously encouraged me to complete this thesis for many years. I have been really impressed not only by his academic and professional supervision, but also his kindness and humanity in supporting my research all the time. Without his supervision, this thesis would have been never completed.

I would like to thank Dr. G. Judge (University of Portsmouth) and Dr. R. Fouquet (Imperial College, London) who gave me insightful guidance and valuable comments on my research. I am also grateful to my Ph.D. colleagues in Surrey, particularly, Dr. L. Babalola, Dr. M. Catenaro, Dr. F. Moraiz, Dr. O. Nyawata and Mr. E. Abdalla with whom I enjoyed academic and ‘non-academic’ discussions in the research room. I should also like to acknowledge the friendly assistance I received from the staff members of the Economics Department in Surrey.

I must express to my gratitude to my current employer, Institute for Global Environmental Strategies (Japan), in particular, Professor A. Morishima, Dr. S. Nishioka Dr. T. Y. Jung and Dr. N. Matsuo for their warm encouragements and for giving me the ‘last’ opportunity to complete this thesis. I am also grateful to Professor K. Tamura (Fukuoka University), Professor N. Goto (Nihon University), Dr. T. Komaki (Sapporo University), Professor H. Kibune (Nagoya Gakuin University), Professor T. Tomita (Bunkyo University) and Professor S. Matsusaka (Kyoto University) who provided me with numerous helpful and constructive comments on my research.

Financial support from University of Surrey and Aichi University Alumni Association for this research is greatly acknowledged. I also wish to thank all the members of University of Surrey Japanese Society who shared my Ph.D. period in the UK.

Lastly, but not least, I would like to thank my family for their mental support and understanding.

As always, I am solely responsible for any errors remaining in this thesis.

Yasushi Ninomiya
CHAPTER 1. INTRODUCTION

1.1. Introduction

The aim of econometric studies of energy demand study is to estimate values for the key parameters; income and price elasticities of energy demand. These elasticities are integrated parameters that convey valuable information about the characteristic and structure of energy demand. Energy demand studies are generally conducted by the practical requirement, rather than for the satisfaction of pure intellectual interest. The estimated price and income elasticities are vital for governmental policy makers, consultant agencies, economists and scientists. Therefore, it is important that accurate values for these elasticities of energy demand are available, given they are utilised in various ways for policy formulation and analysis.

The estimated elasticities are critical parameters needed to forecast energy demand in the future. With an increasing concern about global warming, energy consumption has re-appeared recently as one of the highest policy priority issues across the globe. This is particularly true for so-called ‘Annex I countries’ who promised that the CO$_2$ emissions from each country at 2008 – 2012 will be reduced by certain amount specified in the Kyoto Protocol in 1997\(^1\). In November 2001, in Marrakech (Morocco), the detailed

---

\(^1\) See United Nations Framework Convention on Climate Change (UNFCCC, 1992) and Kyoto Protocol to the UNFCCC (UNFCCC, 1997) for the details. In fact, there are other greenhouse gas emissions such as CH$_4$, N$_2$O, HFCs, but around 60% of them are CO$_2$, 80% of which are generated by combustion of fossil energy. Most of the developed countries are included in the Annex I of the UNFCCC. The emissions reduction targets are 12.5% for the UK and 6% for Japan compared to the 1990 emissions levels.
regulations of the Kyoto Protocol have been agreed\textsuperscript{2} and the Protocol is expected to be come into force within 2002. Therefore, in order to avoid the non-compliance of the protocol, each ‘Annex I country’ has now began to consider seriously how to reduce energy demand toward the first commitment period, 2008 - 2012. This further emphasises the importance of accurate estimates of energy demand elasticities and forecasts of future energy demand.

Estimated elasticities of energy demand are also necessary parameters needed to evaluate potential impacts of energy policies on energy demand. Given the commitment to CO\textsubscript{2} emissions reduction, it is a great concern for policy makers on how much a reduction in energy demand can be made through pricing policies. Estimated elasticities are often incorporated into large scale of macroeconomic models to examine the impact of energy policies on a global level. The evaluation of the results is sensitive to the estimated elasticity values of energy demand. Therefore, accurate estimates of energy demand are essential for effective policy analysis.

An extensive number of energy demand studies has been conducted over the decades. During the late 1970s and the early 1980s, the main focus of energy demand studies was estimating on the substitution elasticities between energy and other inputs such as capital, labour, material, or between various energy products, especially oil versus other fuels. Since depletion of oil was a key factor, society’s main concern was these substitution possibilities, represented by these substitution elasticities. The framework

\textsuperscript{2} See the Marrakech Accord (UNFCCC, 2001), which includes, for instance, the modalities of accounting and the assigned amount of emissions, the Kyoto mechanism, the legally binding penalties for non-compliance countries.
of the translog function was extensively employed for estimation of these substitution elasticities\(^3\).

However, as mentioned, towards the late 1990s, the main stream of energy issues has gradually moved to environmental issues, particularly global warming, away from energy depletion issues. As a result, relatively lesser attention was been paid to substitution elasticities between production inputs and fuels recently and, instead, the principal concerns of energy economists have become income and price elasticities of energy demand. This is because global warming is not solely caused by a particular single fuel, but the result of use of aggregated whole types of fuels\(^4\). Consequently, the log-linear framework model is now more frequently employed for energy demand studies than that of the translog framework model. An introduction and development of the unit-root test and cointegration technique in econometrics during the 1990s also have further enforced the use of the log-linear model in energy demand study\(^5\). Currently, the vast majority of energy demand studies employ the log-linear modelling framework.

Energy demand is essentially a derived demand, rather than direct demand. Through energy appliances as capital, energy only can produce various type of services for which consumer is willing to pay. Therefore, energy demand is inevitably affected by energy efficiency embodied in energy appliance or way of using energy appliance. In other

\(^3\) This will be explained in detail in Chapter 2.

\(^4\) Although there is a issue of substitution for coal, which is higher carbon content fuel, by other fuel such as gas, it may be considered as a political issue rather than economics, particularly for the UK. See Robinson (1995, 1998) for the political issues in the energy market in the UK.

\(^5\) The log-linear model and cointegration technique will be explained in Chapter 2.
words, embodied and/or disembodied technical change of the appliance stock should impact on the amount of energy consumed. Although there has been some debate about the best way to model the technical change (see Chapter 3 about the debate), this impact has been generally accepted by applied energy economists. The history of energy demand modelling incorporating technical progress within the log-linear framework has been problematic, since there is no data representing it in aggregated level. As a result, technical progress has been virtually ignored or, at the best, approximated by a deterministic linear time trend. Less active discussion about modelling of technical progress have been made and a choice of whether using of a deterministic time trend or ignoring technical progress have been arbitrary determined by each modeller.

However, in this thesis, additional important factors that impact on energy demand, holding prices and income constant are also considered. For example, a consumer sometimes changes her/his tastes on energy use which is led by neither income nor price changes. In the case of petrol demand, rapid increases in the demand in the UK and Japan are not only led by its relative cheaper price than other alternative fuels, but perhaps more importantly, it is because that the service provided by petrol use (car transportation) is simply more comfortable than other fuels can provide. Another additional factor is change in economic structure which can also affect energy demand. These effects, changes in technical progress, consumers tastes and economic structure are generally unobservable and difficult to be measured particularly at the aggregated level. Hence, they can be aggregated and are re-defined as the Underlying Energy Demand Trend (UEDT) for this thesis.
Similarly, little attention has been paid for modelling of seasonality inherent in quarterly energy demand data. Although deterministic seasonal dummy variables have been used in energy demand studies as if they are mandatory treatment, there is no ground to believe that seasonal pattern of energy demand remains constant over time as assumed by the deterministic seasonal method. Rather, a number of recent studies have pointed out that seasonal pattern of many macro data, including energy demand data, series are not deterministically fixed, but evolving over time.

Given these background, this thesis is concerned with econometric modelling of the UEDT and seasonality inherent in energy demand within the log-linear framework. The reasons for adopting the log-linear framework are explained fully in Chapter 2 but it is worth highlighting the key factors here:

- The log-linear model is currently the most extensively employed for energy demand studies (Berndt, 1991, p.326). Since 1990, at least more than 60% of articles I have found on econometric energy demand modelling, reviewed in Chapter 2, use the log-linear model as the general framework.
- Dynamic specification of the log-linear model is simple and straightforward.
- Required data for the log-linear model is less costly and, therefore, the model can be consistently applied to various sectors and fuels.
- Models used for policy formulation such as that used at the UK DTI, are based upon the log-linear model.
- Many theoretical justifications have been given for using the log-linear model by distinguished applied energy economist and econometricians: For example, see Pesaran et al. (1998, p.57 – 58) and Berndt (1991, Ch.7).
Finally, as Pesaran et al. (1998, p.100) discuss, the log-linear model often better fits the actual data than the theoretically more sophisticated model such as the translog model.

Using this framework, this thesis covers many aspects of energy demand modelling, but the main thrust of it can be summarised by three main research questions:

- **What is the conceptual basis for attempting to estimate the underlying energy demand trend (UEDT) when estimating energy demand functions?**

- **In a log-linear functional framework, what is the optimal methodology for modelling the UEDT inherent in energy demand?**

- **In a log-linear functional framework with quarterly time series data, what is the optimal methodology for modelling seasonality inherent in energy demand?**

This thesis attempts to answer the above research questions by a detailed analysis of the issue surrounding the UEDT and by empirical examination. Moreover, through the process, this thesis also answers the following sub-questions for various sectors in the UK and Japan:

- What are the shape and direction of the UEDTs?
- What are the patterns of the seasonality?
- What is the best estimate of the long-run income elasticity?
• What is the best estimate of the long-run price elasticity?

Before proceeding to the main part, it is useful to set the scene by describing the energy situations and important energy issues in the UK and Japan. This is therefore done in the next section which also identifies the sectors and fuels analysed in the empirical applications, later in this thesis. A final section of this introduction details the sectors and fuels analysed in the thesis and outlines the structure of the remaining chapters.

1.2. Background to the energy situations in the UK and Japan

Figure 1.1 shows the top ten highest primary energy consuming countries in primary basis in 1998. The UK consumed 225.7 m.t.o.e. occupying 2.6% of the total primary energy which was the eighth largest consumption as a single countries marginally after France. Canada consumed 221.9 m.t.o.e. which was almost the same amount as the UK. Japan ranks the forth largest energy consuming country in the world after the U.S., the Former Soviet Union (FOS) and China. In 1998, Japan consumed 225.7 m.t.o.e. of primary energy which occupied 5.9% of the whole world consumption.

As stated earlier, the principal concern of this thesis is the conceptual basis of the UEDT and the appropriate methodology for estimating it and seasonality, if applicable. Therefore, data from two main energy consuming countries (the UK and Japan) are used to undertake the analysis although any country or countries could have been used6.

---

6 This is primarily due to the pragmatic reason in that I am from Japan and this thesis has been written in the UK although in principal the methodology in this thesis could be applied to any country.
1.2.1 The UK

Table 1.1 is the UK energy balance table in 1999. It can be seen in Table 1.1, the UK’s energy supply is characterised by substantially higher indigenous production of energy compared to primary energy demand. As a result, the UK is one of the few developed countries who are self-sufficient in energy supply. This high indigenous energy supply can be achieved thanks to the gas and oil productions in the North Sea and coal production in the main land. Note the UK is a net exporter of petroleum. The primary energy demand in 1999 was divided into gas (38.2%), petroleum (35.6%), coal (15.1%) and nuclear and others (11.1%). Among them, 88% of coal and 37% of gas were used for energy transformation to be changed into mainly electricity.

---

7 Canada is another country who is self-sufficient in energy supply.
Table 1.1. Summary UK Energy Balance 1999

<table>
<thead>
<tr>
<th>Source</th>
<th>Coal</th>
<th>Petroleum</th>
<th>Gas</th>
<th>Primary Electricity</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Indigenous Production</td>
<td>23.54</td>
<td>150.31</td>
<td>98.93</td>
<td>25.59</td>
<td>298.37</td>
</tr>
<tr>
<td>2 Imports</td>
<td>14.40</td>
<td>62.74</td>
<td>1.11</td>
<td>1.25</td>
<td>79.50</td>
</tr>
<tr>
<td>3 Exports</td>
<td>-0.58</td>
<td>-124.18</td>
<td>-7.26</td>
<td>-0.02</td>
<td>-132.04</td>
</tr>
<tr>
<td>4 Marine bunker</td>
<td>0</td>
<td>-2.47</td>
<td>0</td>
<td>0</td>
<td>-2.47</td>
</tr>
<tr>
<td>5 Stock change</td>
<td>-0.58</td>
<td>0.67</td>
<td>-0.52</td>
<td>0</td>
<td>-0.43</td>
</tr>
<tr>
<td>6 Primary Supply</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7 Statistical Difference</td>
<td>0.45</td>
<td>1.30</td>
<td>0.22</td>
<td>0.14</td>
<td>2.11</td>
</tr>
<tr>
<td>8 Primary Demand</td>
<td>36.34</td>
<td>85.77</td>
<td>92.03</td>
<td>26.68</td>
<td>240.82</td>
</tr>
<tr>
<td>9 Transformation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 Energy Industry Use</td>
<td>-32.15</td>
<td>1.29</td>
<td>-26.99</td>
<td>6.64</td>
<td>-51.21</td>
</tr>
<tr>
<td>11 Losses</td>
<td>-0.01</td>
<td>-7.69</td>
<td>-6.59</td>
<td>-2.40</td>
<td>-16.69</td>
</tr>
<tr>
<td>12 Final Consumption</td>
<td>4.19</td>
<td>79.20</td>
<td>58.07</td>
<td>28.49</td>
<td>169.94</td>
</tr>
<tr>
<td>13 Non-Energy use</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14 Final Energy Consumption</td>
<td>4.19</td>
<td>67.18</td>
<td>56.93</td>
<td>28.49</td>
<td>156.78</td>
</tr>
<tr>
<td>14a Industrial sector</td>
<td>1.92</td>
<td>7.75</td>
<td>15.92</td>
<td>9.87</td>
<td>35.45</td>
</tr>
<tr>
<td>14b Transportation sector</td>
<td>0</td>
<td>53.04</td>
<td>0</td>
<td>0.73</td>
<td>53.77</td>
</tr>
<tr>
<td>14c Residential sector</td>
<td>2.05</td>
<td>3.72</td>
<td>30.62</td>
<td>9.72</td>
<td>46.11</td>
</tr>
<tr>
<td>14d Other final consumers</td>
<td>0.22</td>
<td>2.66</td>
<td>10.40</td>
<td>8.17</td>
<td>21.45</td>
</tr>
</tbody>
</table>

Source: DUKES 2000 Table 1.1, p.24

The final energy consumption consisted of petroleum (42.8%), gas (36.3%), electricity (18.2%) and coal (2.7%). Petroleum was the most consumed energy by final users, 79% of which was used in the transportation sector and 62% of which was used for road transportation usage. Therefore, road transportation oil was the largest consumed single fuel for a single sector in 1999. 54% and 28% of gas was used in the residential and the industrial sectors. Electricity was used evenly in the industrial, the residential and other final consumers, except the transportation sector. The use of coal as the final energy was almost negligible in 1999.
As Figure 1.2a illustrates, the UK final energy consumption rose by around 25% over the past 40 years with an overall average growth of about 0.5% p.a.. However, the growth was not steady. Fairly rapid growth up to the early 1970s turned into significant reduction and stagnant trend over the late 1970s and the early 1980s. The demand resumed to rise after the mid-1980s, this increasing trend continued towards the late 1990s. Figure 1.2b show the proportions of the four main sectors against the whole final energy consumption over the same period. A reduction in the energy consumption in the industrial sector brought considerable changes in the picture. The dominant position of the industrial sector during the 1960s and the early 1970s was completely replaced by the expanded transportation sector. As a result, the proportion of the industrial sector against the whole energy consumption diminished to 22.6% in 1999. In contrast, the transportation sector had the top share of 34.3% in and the residential sector took the second largest share of 29.4% in 1999, although the share of the residential sector was relatively stable over the period.

The breakdown of the final energy consumption by fuels over the same period is shown in Figure 1.3a. The decline of coal consumption over the period is dramatic. The corresponding share of coal consumption in the total consumption dropped from 65% in 1960 to less than 3% in 1999 as seen in Figure 1.3b. In contrast, the expansion of gas over the late 1970 was very substantial, but it was relatively stable over the rest of the period. Similarly, the rapid expansion of petroleum was made over the 1960s and it marginally increased after then. But, petroleum still took the top share of 43% in 1999 as already mentioned. The electricity consumption and its share increased almost
steadily over time, having 18% of its share in the total energy consumption in 1999.

Figure 1.4 shows the details of energy consumption in the industrial sector over the past 40 years. The growing demand for energy in this sector terminated at 1974 and it almost continuously decreased over the rest of period. In particular, a sharp drop during the late 1970s and the early 1980s is remarkable, which was mainly a result of a massive decrease in the petroleum demand during the period after its rapid expansion up to 1974. Coal consumption consistently declined over the period changing its position from the most consumed energy to the least important energy for this sector. The demand for gas increased very rapidly during the 1970s, but it has been stable after then. Electricity demand in this sector increased not dramatically, but steadily by 50% over the past 40 years.

As illustrated in Figure 1.5, the energy consumption in the residential sector increased over the past decades with some fluctuations. The main driver of the growth is a huge expansion of the consumption of gas over the period. In 1999, the share of gas was nearly 70% of total energy use in this sector. Electricity also increased by 43% over the period whose present share in this sector is 21%. In contrast, the share of coal drastically shrunk from 78% in 1960 to just 4% in 1999. The petroleum consumption in this sector has been almost stable over time.
Figure 1.2a. Volume of UK final energy consumption 1960 - 1998 by sectors

Source: DUKES (various issues)

Figure 1.2b. Shares of UK final energy consumption 1960 - 1998 by sectors

Source: DUKES (various issues)
Figure 1.3a. Volume of UK final energy consumption 1960 - 1998 by fuels

Figure 1.3b. Shares of UK final energy consumption 1960 - 1998 by fuels

Source: DUKES (various issues)
Figure 1.4. Volume of UK Industrial sector energy consumption by fuels

![Graph showing energy consumption by fuels for the UK Industrial sector from 1960 to 1996. The categories include Petroleum, Electricity, Gas, and Coal & Other solid.]

Figure 1.5. Volume of UK Residential sector energy consumption by fuels

![Graph showing energy consumption by fuels for the UK Residential sector from 1960 to 1996. The categories include Petroleum, Electricity, Gas, and Coal & Other solid.]

Source: DUKES (various issues)
Energy consumption in the transportation sector has been entirely characterised by petroleum throughout the period as seen in Figure 1.6, except during the 1960s when coal was consumed by steam locomotive for rail transport. The expansion of energy consumption in this sector is very substantial and sustainable over the past 40 years. The demand for petroleum in this sector increased by nearly 3 times over the period. Among the petroleum consumption, nearly 80% of them are for road transport use and around 20% of them are for air transport.

The principal issue related to energy in the UK is integrated to the environmental issues, in particular global warming. In the Kyoto Protocol, the EU umbrella group agreed on a reduction in the green house gas (GHG) emissions\(^8\) in 2008 - 2012 by 8% compared to the base of 1990. The UK not only undertakes to reduce its GHG emission by 12.5% by

---

\(^8\) Again, the most important of these are CO₂, which contribute more than 80% of the global warming
2008 - 2012 as a member of the EU, but also has their own reduction target of 20% reduction by 2020. In fact, CO₂ emissions in the UK have already reduced by 7.5% since 1990. However, most of this reduction were achieved by the substantial drop in the coal consumption over the past decades and, as already seen in above, there will be much smaller room to be left for further reductions in the coal consumption. Therefore, the emission reduction in the future probably has to be made elsewhere, rather than simply escaping from coal use. In addition, there are the steady growing tendencies of the energy demand in the transportation and the residential sectors. An increase in the CO₂ emissions already observed between 1999 and 2000 despite it was not substantial amount (DUKES, 2001, p.229).

Having these circumstances, a further reduction in CO₂ emissions seems to be uneasy task for the UK. Although the UK government has already proposed a range of the UK national climate change plans. This includes the introduction of the climate change levy combined with the UK emissions trading scheme, an increase in the fuel taxation on the road transportation oil. However, at present, there is little sign that the demand for energy end to rise. A actual reduction of energy demand, rather than fuel switching from coal to its substitution, seems to be the critical energy issue in the UK. Particular considerations may be required for the aggregated demand in the residential sector and the individual demands for the growing fuels (transportation oil, gas and electricity).

effect (DUKES, 2001, p.229).

9 See the recent Energy Review by the Cabinet Office (2002) for the details.
1.2.2. Japan

Table 1 summarises the energy balance of Japan in 1999.

Table 1.2. Summary Energy Balance of Japan 1999

<table>
<thead>
<tr>
<th>Source</th>
<th>Coal</th>
<th>Petroleum</th>
<th>Gas</th>
<th>Primary electricity</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Indigenous Production</td>
<td>2.16</td>
<td>0.68</td>
<td>2.27</td>
<td>98.36</td>
<td>103.79</td>
</tr>
<tr>
<td>2 Imports</td>
<td>93.17</td>
<td>284.55</td>
<td>67.48</td>
<td>0</td>
<td>445.20</td>
</tr>
<tr>
<td>3 Exports</td>
<td>-1.61</td>
<td>-17.37</td>
<td>0</td>
<td>0</td>
<td>-18.97</td>
</tr>
<tr>
<td>4 Marine bunkers</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>5 Stock change</td>
<td>-0.03</td>
<td>4.47</td>
<td>0</td>
<td>0</td>
<td>4.44</td>
</tr>
<tr>
<td>6 Primary Supply</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Source</td>
<td>Coal</td>
<td>Petroleum</td>
<td>Gas</td>
<td>Primary electricity</td>
<td>Total</td>
</tr>
<tr>
<td>1 Indigenous Production</td>
<td>69.75</td>
<td>24.03</td>
<td>84.96</td>
<td>371.89</td>
<td></td>
</tr>
<tr>
<td>2 Imports</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Exports</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Marine bunkers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Stock change</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 Primary Supply</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Source</td>
<td>Coal</td>
<td>Petroleum</td>
<td>Gas</td>
<td>Primary electricity</td>
<td>Total</td>
</tr>
<tr>
<td>1 Indigenous Production</td>
<td>0.92</td>
<td>36.27</td>
<td>14.87</td>
<td>45.01</td>
<td>97.07</td>
</tr>
<tr>
<td>2 Imports</td>
<td>0</td>
<td>90.76</td>
<td>0</td>
<td>1.88</td>
<td>92.64</td>
</tr>
<tr>
<td>3 Exports</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Marine bunkers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Stock change</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 Primary Supply</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: EDMC (2001)

In contrast to the UK, the indigenous energy production is poor; only 103.79 m.t.o.e. against the total 534.12 m.t.o.e. of the primary energy consumption. Most of the indigenous production was nuclear power for which the original energy resource is imported uranium. Therefore, if nuclear is not counted as a indigenous energy
production, less than 10% of primary energy was supplied by domestic production. This high dependence on imported energy resources is key character of energy supply in Japan\textsuperscript{10}. More than 50% of the primary energy consumption is dominated by petroleum, and coal and primary electricity (hydro and nuclear) contribute 18% of each. Gas has the least share of only 13% in contrast of the UK where gas is the most consumed primary energy as already seen.

48% of coal and 65% of gas were consumed through the energy transformation being changed into electricity and town gas\textsuperscript{11}, which are different from the UK where 90% of coal and 40% of gas were used for the energy transformation. The final energy consumption is also strongly dominated by petroleum which has 62% share of the whole. Petroleum consumption can be further divided into heavy fuel (30%), petrol (25%), diesel oil (20%) and kerosene (12%), in which most of petrol and diesel oil are used for road transportation.

Electricity is the second largest share of 23% followed by coal with the share of 11% of the whole final energy consumption. Gas has the least share of 7% which is completely different from the UK where gas occupies 34% of the whole final energy consumption. In terms of sector, the industrial dominates nearly a half of the final energy consumption, and the rest of energy is equally divided into the residential-service and the transportation sectors. The largest share of the industrial sector is another difference

\textsuperscript{10} Italy and Germany also depend on imported energy resources for 83% and 62% of their primary energy in 1998.

\textsuperscript{11} In Japan, ‘town gas’ does not exactly mean ‘gas originated from coal’. Rather, it includes any types of gases supplied through pipelines networks regardless of the original resources, since almost all of gas is supplied to the final-users after energy transformation process.
from the UK energy demand structure where the industrial sector currently has the least share.

**Figure 1.7a. Volume of final energy consumption 1961 - 1997 in Japan by sectors**

![Diagram showing energy consumption by sectors from 1961 to 1997 in Japan.]

**Figure 1.7b. Shares of final energy consumption 1961 - 1997 in Japan by sectors**

![Diagram showing energy share by sectors from 1961 to 1997 in Japan.]

Source: *Energy Balance Table in Japan* (various issues)
Figure 1.8a. Volume of final energy consumption 1961 - 1997 in Japan by fuels

Figure 1.8b. Shares of final energy consumption 1961 - 1997 in Japan by fuels

Source: Energy Balance Table in Japan (various issues)
Figure 1.9. Volume of Industrial sector energy consumption in Japan by fuels

Figure 1.10. Volume of Residential-Service sector energy consumption in Japan by fuels

Source: Energy Balance Table in Japan (various issues)
Figure 1.11. Volume of Transportation energy consumption in Japan by fuels

Source: Energy Balance Table in Japan (various issues)

Figure 1.7a illustrates the trend of the final energy consumption between 1961 - 1997. The energy consumption expanded very substantially (by about 4.5 times) over the period. The expansion before the mid-1970s was mainly led by the industrial sector which was replaced by the other two sectors over the rest of the period. As a result, the consumption in the industrial sector little increased after the mid-1970 and other two sectors showed marked expansions. The shares of the each sector in the final energy consumption over the same period are shown in Figure 1.7b. Although the dominant position of the industrial sectors is still kept, the share of the industrial sector shrank from more than 65% in 1961 to 47% in 1999. In contrast, the shares of the residential-service sector and the transportation sectors increased considerably after the mid-1970s.

Figure 1.8a shows the final energy consumption in Japan by fuels over the same period.
The growth of the petroleum consumption before the mid-1970s is massive. The expansion of the whole energy consumption for this period seemed to be solely led by the increase in the petroleum consumption. After the mid-1970s, the electricity consumption rose rapidly, although petroleum consumption was re-boosted powerfully after the mid-1980s. The dominant share of petroleum remained over the past 40 years as seen in Figure 1.8b. The share of coal sharply dropped during the 1960s and gradually diminished after then. Electricity steadily, but not quickly, expanded its shares over the period. In contrast to the UK, the share of gas just marginally increased and still remains to be the least consumed fuel.

The details of the energy consumption in the industrial sector are illustrated in Figure 1.9. The very rapid growth of the petroleum consumption up to 1973 followed by the sharp reduction during the late 1970s and early 1980s represents the fluctuated movement of the whole energy consumption in this sector. On the other hand, the electricity consumption in this sector almost steadily increased. Coal has kept its relatively constant share over the period. The share of petroleum, coal and electricity in 1999 were 50%, 23% and 21% respectively. Gas only had 5% of its share in this sector.

Figure 1.10 shows the final energy consumption in the residential-service which soared almost by 6 times sector over the past 40 years. Similar to the case of the industrial sector, the rapid growth up to 1973 was caused by an expansion of the demand for the petroleum which occupied 38% share in 1997. After the mid-1970s, electricity took over the fastest growing fuel in this sector. In 1997, electricity had the largest share of 42% in this sector. Although the town gas consumption also increased over time, it still
had only 15% of share.

The energy consumption in the transportation sector had the fastest growing record over the same period which increased by 7 times from 12.81 m.t.o.e. in 1961 to 90.24 m.t.o.e in 1997. The consumption is almost entirely dominated by petrol, particularly the road transportation oil throughout the period except the coal consumption during the very early 1960s. In 1998, the shares of petrol and diesel oil in this sector were 52% and 34%.

The current important issue on energy in Japan is, before everything, the global warming problem. In Japan, it is almost equal to the energy problem since 90% of greenhouse gas generated from fossil fuel consumption. As the fourth largest energy consumer in the world, Japan agreed on the Kyoto Protocol to reduce its CO$_2$ emissions in 2008 – 2012 by 6% compared to its 1990 emissions level. However, the CO$_2$ emissions in Japan increased by about 7% between 1990 and 1998 making a clear contrast to the UK situation, where CO$_2$ emissions was already reduced by 7.5% during the 1990s. Moreover, CO$_2$ emissions associated with the energy demand are expected to further increase by around 8% in 2010 under the BAU (“Business as usual”) scenario (Ministry of Environment, Japan, 2001). Therefore, in order to meet the emission reduction target in the Kyoto Protocol, Japan has to reduce its energy demand by at least 13% or nearly 20% at the worst case, over the next 10 years. This kind of the energy demand management is obviously very difficult task for policy makers in the Japanese Government since a required amount of the reduction is considerably large whereas energy demand is likely to further rise.
Japan is likely to ratify the Kyoto Protocol within 2002 by which the protocol would come into effect. Then, a substantial reduction in energy demand will be unavoidable by all means. The government considers a package plan to tackle this matter which includes an introduction of carbon taxation on energy use, domestic and international emissions trading, and even tougher energy standards. However, at present, everything is under discussion and no clear energy policy for the next decade has been decided. It has been repeatedly pointed out in the governmental committee that knowledge about energy demand is still not enough, particularly empirical research on energy demand have been poorly conducted. The concerns specially focus on the faster growing sector and fuels: the residential-service sector, the road transport oil and electricity.

1.3. Sectors and fuels analysed in this thesis

As outlined earlier, this thesis will consider the modelling of the underlying energy demand trend and seasonality in the log-linear functional framework. In order to address the key research questions, also introduced earlier, a number of sectors and fuels are chosen for empirical examination. The most significant sectors and fuels are chosen for both countries as highlighted in the previous section. They are:

- Aggregated final energy demand in the UK
  - Whole economy
  - Residential sector
  - Manufacturing sector
- Individual fuel demand in the UK
As shown in the previous section, in Japan, gas is relatively less used in the final sectors compared to other fuels. In addition, it is mainly used as town gas in the residential-service sector after energy transformation process in Japan, rather than directly used as natural gas like in the UK. Therefore, to keep the consistency between the UK and Japan, the demand for gas will not be considered individually in this thesis.

The remaining chapters of this thesis are as follows:

Chapter 2: Reviews past energy demand studies
Chapter 3: Discusses on the issues of the underlying energy demand trend and the seasonality in depth
Chapter 4: Describes of the proposed model in detail used to estimate the underlying energy demand trend and the seasonality
Chapter 5: Presents the results for the UK
Chapter 6: Presents the results for Japan
Chapter 7: Gives a summary and conclusion
CHAPTER 2. OVERVIEW OF PAST ENERGY DEMAND MODELLING

2.1. Introduction

In this chapter, econometric energy demand modelling employed in past studies will be overviewed. The aim of this chapter is to present the general issues on energy demand modelling which have been extensively researched in this field. The review also provides a rationale of the functional form adopted in this thesis.

Considerable amount of empirical studies for energy demand have been performed over the past decades. Among them, econometric estimations have dominated and its technique has progressed considerably in the last twenty years. Hunt and Witt (1995) give a number of reasons why estimating of energy demand modelling is important.

"Firstly, it provides information necessary for the calculation of future energy demand. Secondly, knowledge of the strength of energy demand responses assists in the evaluation and design of macroeconomic policy given the relative importance of energy sectors in many national economies. Finally, the need for accurate estimates is more prevalent than ever given the environmental agenda will become more closely aligned to the energy policy agenda." (p.1)

There are numerous types of functional models that have been introduced and developed for energy demand modelling. Amongst them, two models have been
extensively employed: the log-linear and the translog models\textsuperscript{2}. This chapter, therefore, focuses on these two important functional models and the estimation techniques associated with them. However, it is useful to consider the general overview of the theoretical approach to modelling energy demand based on the traditional economic theory, before going into each specific model.

2.1.1. General overview of the theoretical approach to modelling energy demand\textsuperscript{3}

Traditional economic theory indicates that the demand for goods can be expressed as optimal solutions to cost minimisation and/or utility maximisation problems given a budget constraint and the price of goods. Energy is not only demanded by households but also demanded by producers as an input factor of production. Therefore, energy demand in the manufacturing sector can be explained as a solution to a cost minimisation problem or a profit maximisation problem. On the other hand, energy demand in the residential sector can be represented by a solution to a utility maximisation problem. However, using the duality theorem, both the profit maximisation problem and the utility maximisation problem can be treated as a reverse process of a cost minimisation problem by which the demand function for energy can be derived in a similar manner for both cases as shown below.

Assume that a representative firm using three inputs, capital, labour and energy (\(K, L,\))

\textsuperscript{2} Pindyck (1979) also identifies the multinomial logit functional form, for example used by, Durbin and McFadden (1984). Although this may have been used frequently during the 1970s and 1980s, there are very few recent applications. Given this and its lack of development in the 1990s, this model is not considered here.

\textsuperscript{3} This section relies heavily on Watkins (1992).
and output level $Q$, wishes to maximise profit, $\pi$. This problem can be written as:

Max. $\pi = P_Q Q - C$ \hfill (2.1)

subject to $Q = Q (K, L, E)$ \hfill (2.2)

where $P_Q$ = price of output product $Q$

$P_Q Q$ = revenue

$C$ = costs $(P_K K + P_L L + P_E E)$

$P_i$ = the price of input $i$ \hfill $i = K, L, E.$

The duality theorem suggests that this problem can be considered as the exact reverse process of the following cost minimisation problem given output level $Q$:

Min. $C = P_K K + P_L L + P_E E$ \hfill (2.3)

subject to $Q = Q (K, L, E)$ \hfill (2.4)

The optimal solutions of both problems are identical and given by:

$D_i = D (P_i, Q)$ \hfill (2.5)

where $D_i$ is the demand for input factor $i$ \hfill $i = K, L, E.$

Therefore, the demand for energy can be presented by:

$D_E = D (P_E, P_K, P_L, Q)$ \hfill (2.6)
In addition, there are a number of other factors that affect the demand for energy over time. They are, for example, air temperature, improvements in technical progress in energy usage, environmental pressure and regulations, energy efficiency standards, and changes in tastes leading to a shift in consumption towards goods and services that are less energy intensive (Jones, 1994, p.245).

Therefore, $X$ which is the vector of these other factors can be included in (2.6) which gives the following energy demand function:

$D_E = D (P_E, P_K, P_L, Q, X)$

(2.7)

where $X = \text{vector of variables other than price and output}$

For energy demand in the residential and transportation sectors, assume that a representative consumer wants to maximise her/his utility $V(q)$ consuming the set of goods and services which are $q_i$ with associated price $p_i$, given her/his budget constraint $M$. This problem can be expressed as:

Max. $u = V(q)$

(2.8)

subject to $\Sigma p_i q_i = M \quad i = 1, \ldots, n.$

(2.9)

Similar to the case of the manufacturing sector, this maximisation problem also has a dual cost minimisation problem as follows:

---

4 This energy demand function can equally apply to the aggregate energy demand for the whole economy, since the cost minimisation problem for the whole economy also can be written as (2.3) and (2.4). In this case, national output ($Q$) is considered as a function of capital ($K$), Labour ($L$) and energy ($E$).
Min. \( M = \Sigma_i p_i q_i \quad i = 1, \ldots, n \) \hfill (2.10)

subject to \( V(q) = u \) \hfill (2.11)

The optimal solutions of both of these problems are again the identical and given by:

\[ D_i = D(p_1, \ldots, p_n, M) \quad i = 1, \ldots, n \] \hfill (2.12)

Demand for energy in the residential and the transportation sectors can therefore be expressed as:

\[ D_E = D(p_1, \ldots, p_{E}, \ldots, p_n, M) \quad i = 1, \ldots, n \] \hfill (2.13)

where \( p_E = \text{price of energy} \)

In parallel to the case of the manufacturing sector, other factors such as air temperature, technical energy efficiency also give certain impacts on the energy demand. Therefore, the vector of these other factors \( X \) can be included in (2.13) which gives:

\[ D_E = D(p_1, \ldots, p_{E}, \ldots, p_n, M, X) \quad i = 1, \ldots, n \] \hfill (2.14)

where \( X = \text{vector of variables other than price and output} \)

(2.14) is the energy demand function in the residential and the transportation sectors, which corresponds to that of the manufacturing sector of (2.7). They imply that demand for energy can be derived as the solutions of the cost minimisation problems. In both
cases, the demand for energy is described with somewhat similar elements i.e. they are the functions of its own price, price of other inputs or other goods and income (budget) or output.

The critical problem of empirical demand modelling (not only for energy demand), is that traditional economic theory says little about the actual form and specification of the demand functions such as (2.7) or (2.14). Therefore, in empirical studies, the exact functional forms of the demand function are somehow arbitrarily chosen (Thomas, 1993, p.198). In other words, the true form of the demand function is rarely known by researchers and, in empirical studies the estimated function is, at best, just an approximation of the true function. This creates uncertainty with need for an approximated function used for empirical estimation.

The remainder of this chapter considers the two main approaches adopted for specifying the functional form of energy demand: the log-linear model specification in section 2.2 and the translog model specification in section 2.3.
2.2. The Log-linear model

2.2.1. The Log-linear models in reduced form

Up to the present time, the overwhelming majority of energy demand modelling has been dominated by the so-called log-linear specification which originates from Houthakker's (1951) paper. Recent empirical application of this specification to energy demand can be found, for example, in Pesaran et al. (1998).

The previous section illustrated that the demand function for the manufacturing sector could be given by:

\[ D_E = D(P_E, P_K, P_L, Q, X) \]  \hspace{1cm} (2.15)

Similarly, for the residential and the transportation sectors, the energy demand function was presented as:

\[ D_E = D(p_1, \ldots, p_i, \ldots, p_n, M, X) \quad i = 1, \ldots, n \]  \hspace{1cm} (2.16)

In aggregation, or when not enough data is available, (2.15) and (2.16) can be rewritten in a general form as illustrated in Weyman-Jones (1986, p.13) which is:

---

5 The other form of the log-linear model which is the structural form will be considered in the later section.

6 This demand function can equally apply to the aggregated whole economy (see footnote 4).

7 However, Weyman-Jones (1986, p.13) does not include X for the other factors.
\[ E = k \left( P_{\text{no}}, P_{\text{nE}}, M, X \right) \]  

where  

\[ E = \text{total aggregated energy demand} \]  

\[ P_{\text{nE}} = \text{nominal price of aggregated energy} \]  

\[ P_{\text{no}} = \text{nominal price of all other goods} \]  

\[ M = \text{nominal income}^8 \]  

\[ X = \text{vector of variables other factors (temperature, energy efficiency etc.)} \]  

Equation (2.17) is a reduced form of demand for energy. Assuming that each variable enters multiplicatively, rather than additively, then equation (2.17) can be written as:

\[ E = a P_{\text{no}}^\psi P_{\text{nE}}^\alpha M^\delta e^X e^{u_i} \]  

where  

\[ u_i = \text{residuals term satisfying the classical assumptions} \]  

Taking natural logs on the both sides of Equation (2.19) yields:

\[ \ln E = a + \psi \ln P_{\text{no}} + \alpha \ln P_{\text{nE}} + \delta \ln M + X + u_i \]  

To avoid the money illusion problem, imposing the restriction of homogeneous of degree zero in price and income \((\psi + \alpha + \delta = 0)\) on equation (2.19) gives (Weyman-Jones, 1986, p.18):

\[ \ln E = a + \alpha (\ln P_{\text{nE}} - \ln P_{\text{no}}) + \delta (\ln M - \ln P_{\text{no}}) + X + u_t \]  

---

8 As illustrated, \( M \) is used here, although this would be \( Q \) for the manufacturing sector and the aggregated whole economy.
\[ \ln(P_{nE}/P_{no}) \text{ is the log of the energy price relative to all other prices, hence it is a real price, and } \ln(M/P_{no}) \text{ is effectively the log of real income}. \]

Therefore equation (2.20) can be written as:

\[ \ln E = a + \alpha \ln P + \delta \ln Y + X + u_t \]  

(2.21)

where

- \( P \) = real price of energy
- \( Y \) = real income or output
- \( \alpha \) = the price elasticity of energy
- \( \delta \) = the income elasticity of energy
- \( X \) = vector of variables other factors (temperature, energy efficiency etc.)

Equation (2.21) is the log-linear energy demand model in a single reduced form. The coefficient \( \alpha \) represents the price elasticity and coefficient \( \delta \) represents the income elasticity of energy. This model assumes implicitly that the adjustment of the endogenous variables complete within one period. This means that, if the adjustment takes more than one period, then, this model fails to capture such lagged movements. This is the reason why this model is often called static log-linear model. However, sometimes the model is considered as the long-run equilibrium model since, when all adjustment process has been completed, the long-run relationship may be explained this static form.

---

\[ ^9 \text{ Or for the manufacturing sector this would be real output, and for the whole economy real income/GDP.} \]
In order to evaluate the long-run effect, a number of studies during the 1970s employed cross-section or pooled data. Studies at that period generally suffered from shortage of number of observations and the sample period was characterised by stable energy prices. Therefore, it was claimed that estimates from cross-section and pooled data were likely to reflect long-run effects since capital stock adjustment takes place over long across countries and regions. On the other hand, estimates from time-series data are likely to reflect only short-run effects (Stapleton, 1981) (Pindyck, 1979). However, Atkins and Manning (1995) show with 1960 – 89 pooled data that cross-section results does not always produce long-run elasticities and conclude that cross-section studies using post-1973 data may produce results which are neither short-run nor long-run estimates, but rather they are biased due to omitted dynamic factors. Moreover, Welsch (1989), and Hall (1986) argue that pooled estimation would lead to misleading results due to highly heterogeneous nature of pooled data.

An alternative approach of distinguishing between short and long-run effects is incorporating lagged dynamic process in the static model. One of the earliest and most widely used of dynamic process in energy demand study is the partial adjustment process. These process hypotheses that the demand for energy cannot adjust to an equilibrium or desirable level mainly due to inflexibility in the stock of appliance and capital. It is argued that the adjustment process of energy demand towards the equilibrium level takes the form of:

\[ \ln E_t - \ln E_{t-1} = \lambda (\ln E_t^* - \ln E_{t-1}) \]  

(2.22)
where  \( E_t^* \) = unobservable equilibrium level of demand

\[ \lambda = \text{speed of adjustment; } 0 < \lambda \leq 1 \]

\( t \) = indication of period \( t \)

If \( \lambda < 1 \), the adjustment is not complete within one period and if \( \lambda = 1 \), then, demand adjusts to the equilibrium level immediately without any lag. Now, given equation (2.21), suppose that the equilibrium level of demand is given by\(^{10}\):

\[
\ln E_t^* = a + \alpha \ln P_t + \delta \ln Y_t + u_t
\]  

(2.23)

Substituting Equation (2.22) into Equation (2.23) and rearranging gives:

\[
\ln E_t = \lambda a + \lambda \alpha \ln P_t + \lambda \delta \ln Y_t + (1 - \lambda) \ln E_{t-1} + \lambda u_t
\]  

(2.24)

Note that, since the error process \( \lambda u_t \) is not serially correlated, consistent estimates can be obtained by OLS (Stewart, 1991). Equation (2.24) can be expressed as simple form as:

\[
\ln E_t = a + \alpha \ln P_t + \delta \ln Y_t + \phi \ln E_{t-1} + u_t
\]  

(2.25)

This looks just like Equation (2.21) including the lagged dependent variable \( \ln E_{t-1} \) in the RHS. Equation (2.25) is sometimes called the dynamic log-linear model which has been

---

\(^{10}\) This can be thought of as equation (2.22) with X is omitted at this stage for simplicity.
popular in energy demand studies. The short-run own price-elasticity and income elasticity are shown by $\beta$ and $\delta$ respectively. The long-run price elasticity and income elasticity are given by $\beta/(1 - \phi)$ and $\delta/(1 - \phi)$ respectively.

Equation (2.25) can be further generalised to be the $m^{th}$ order autoregressive distributed lag (ARDL) model, that is:

$$\ln E_t = a + \alpha_0 \ln P_t + \alpha_1 \ln P_{t-1} + \ldots + \alpha_m \ln P_{t-m} + \delta_0 \ln Y_t + \delta_1 \ln Y_{t-1} + \ldots + \delta_m \ln Y_{t-m} +$$

$$\phi_1 \ln E_{t-1} + \phi_2 \ln E_{t-2} + \ldots + \phi_m \ln E_{t-m} + u_t$$  \hspace{1cm} (2.26)

where

$$\frac{(\alpha_0 + \alpha_1 + \ldots + \alpha_m)/(1 - \phi_1 - \ldots - \phi_m)}{1} = \text{long-run price elasticity}$$

$$\frac{(\delta_0 + \delta_1 + \ldots + \delta_m)/(1 - \phi_1 - \ldots - \phi_m)}{1} = \text{long-run income elasticity}$$

$\alpha_0, \alpha_1, \ldots, \alpha_m$ = short-run price elasticities for period $t = 0, \ldots, m$

$\delta_0, \delta_1, \ldots, \delta_m$ = short-run income elasticities for period $t = 0, \ldots, m$.

The ARDL model was developed by Professor D. F. Hendry and the LSE group as a part of the general to specific approach. This approach starts with an ARDL model with sufficiently number of lagged variables (eg. equation (2.26)) and it is successively tested down to the most parsimonious model. Note that equation (2.25) is restricted model of (2.26). Hence, the former is encompassed by the latter. With the development of the general to specific approach during the early 1980s, the ARDL model also has been employed by energy demand modellers.

Moreover, equation (2.26) can be re-parameterised as follows:
\[ \Delta \ln E_t = a + \alpha_0 \Delta \ln P_t + \alpha_1 \Delta \ln P_{t-1} + \ldots + \alpha_{m-1} \Delta \ln P_{t-m+1} + \delta_0 \Delta \ln Y_t - \delta_1 \Delta \ln Y_{t-1} + \ldots + \]
\[ \delta_{m-1} \Delta \ln Y_{t-m+1} - \theta (\ln E_{t-1} - \alpha^* \ln P_{t-1} - \delta^* \ln Y_{t-1}) \]  
(2.27)

where  
\[ \alpha^* = (\alpha_0 + \alpha_1 + \ldots + \alpha_m)/(1 - \phi_1 - \ldots - \phi_m) = \text{long-run price elasticity} \]
\[ \delta^* = (\delta_0 + \delta_1 + \ldots + \delta_m)/(1 - \phi_1 - \ldots - \phi_m) = \text{long-run income elasticity} \]
\[ \theta = \text{error-correction term} \]
\[ \alpha_0, \alpha_1, \ldots, \alpha_m = \text{short-run price elasticities for period } t = 0, \ldots, m \]
\[ \delta_0, \delta_1, \ldots, \delta_m = \text{short-run income elasticities for period } t = 0, \ldots, m. \]

This model is known as an error-correction model (ECM) of (2.26), which has been widely used not only in energy demand modelling but also in econometric analysis in general since its successful application to the UK income-consumption function (Davidson, et al., 1978). Note, equation (2.27) is simply a different expression of the disequilibrium relationship in equation (2.26). Therefore, the estimated parameters for elasticities are exactly identical as shown above. In this regard, (2.27) is sometimes called a 'restricted ECM', whereas (2.26) is called an 'unrestricted ECM'. The attraction of this ECM is that it can accommodate the short-run disequilibrium as well as the long-run equilibrium within the same equation. During the late 1980s, the ECM modelling seemed to be successfully married with the concept of cointegration technique associated with the unit root tests. This marriage brought about so-called 'unit root revolution', which also had a substantial impact on energy demand modelling within the log-linear model as explained in the next section.
Table 2.1 shows a selection of the past empirical applications for UK and OECD energy demand using the log-linear model, prior to the introduction of the cointegration technique which is discussed in the next section.
### Table 2.1. Energy demand studies using the log-linear model (selected)

<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Sector / area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated coeff. remarked</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kouris (1976)</td>
<td>Aggregated primary energy</td>
<td>Static log-linear reduces from by OLS</td>
<td>EEC annual data 1955 - 70 (16 obs.)</td>
<td>$\eta_r = 0.32$ to $0.47$ (for UK) $\eta_p = 0$ to $-0.17$ (for UK)</td>
</tr>
<tr>
<td>Pindyck (1979)</td>
<td>Transportation sector (petrol demand)</td>
<td>Dynamic log-linear structural form by OLS</td>
<td>11 countries pooled data with country intercept terms 1955 - 73 (19 obs.)</td>
<td>$\eta_r = 0.90$ (for UK) $\eta_p = -1.77$ (for UK)</td>
</tr>
<tr>
<td>Kouris (1981)</td>
<td>Aggregated primary energy</td>
<td>Static/dynamic log-linear reduced form by OLS</td>
<td>UK annual data 1960 - 79 (20 obs.)</td>
<td>$\eta_r = 0.52$ to 1.00 $\eta_p = -0.12$ to $-0.54$</td>
</tr>
<tr>
<td>Common (1981)</td>
<td>Aggregated deliver energy to final user</td>
<td>Static/dynamic log-linear reduced form by OLS</td>
<td>UK annual data 1968 - 79 (12 obs.)</td>
<td>$\eta_r = 0.42$ to 0.48 $\eta_p = -0.21$ to $-0.28$</td>
</tr>
<tr>
<td>Kouris (1983b)</td>
<td>Aggregated energy</td>
<td>Dynamic log-linear reduced form by OLS</td>
<td>Aggregated OECD annual data 1961 - 81 (21 obs.)</td>
<td>$\eta_r = 1.08$ $\eta_p = -0.43$</td>
</tr>
<tr>
<td>Wigley (1983)</td>
<td>Useful energy for industrial sector</td>
<td>Static/dynamic log-linear reduced form by OLS</td>
<td>UK annual data 1954 - 79 (26 obs.)</td>
<td>$\eta_r = 0.62$ $\eta_p = -0.22$</td>
</tr>
<tr>
<td></td>
<td>Useful energy for domestic sector</td>
<td>Static/dynamic log-linear reduced form by OLS</td>
<td>UK annual data 1954 - 79 (26 obs.)</td>
<td>$\eta_r = 0.89$ $\eta_p = -0.43$</td>
</tr>
<tr>
<td>Westoby and Pearce (1984)</td>
<td>Aggregated energy</td>
<td>Static/dynamic log-linear reduced form by OLS</td>
<td>UK annual data 1954 - 73 (30 obs.)</td>
<td>$\eta_r = 0.60$ to 1.00 $\eta_p = -0.01$ to $-0.29$</td>
</tr>
<tr>
<td>Prosser (1985)</td>
<td>Aggregated final energy</td>
<td>Static/dynamic/Almon/Koyck lag by OLS</td>
<td>OECD countries annual data 1960 - 82 (23 obs.)</td>
<td>$\eta_r = 1.02$ $\eta_p = -0.40$ (results for Koyck)</td>
</tr>
<tr>
<td>Beenstock and Dalziel (1986)</td>
<td>Aggregated energy industrial sector</td>
<td>Log-linear by 3SLS within system equations</td>
<td>UK annual data 1953 - 82 (30 obs.)</td>
<td>$\eta_r = 1.10$ $\eta_p = -0.29$</td>
</tr>
<tr>
<td></td>
<td>Aggregated energy household sector</td>
<td>Log-linear by 3SLS within system equations</td>
<td>UK annual data 1953 - 82 (30 obs.)</td>
<td>$\eta_r = 0.26$ $\eta_p = -0.47$</td>
</tr>
<tr>
<td>Welsch (1989)</td>
<td>Aggregated energy</td>
<td>Static/dynamic log-linear reduced form by OLS</td>
<td>eight OECD countries annual data 1970 - 84 (15 obs.)</td>
<td>$\eta_r = 0.71$ (for UK) $\eta_p = -0.11$ (for UK)</td>
</tr>
</tbody>
</table>

Note: $\eta_r$ = the long-run income elasticity, $\eta_p$ = the long-run price elasticity

2.2.2. Log-linear model within the cointegration technique

For a long time, the issue of stationarity in time series was not considered in energy demand modelling. However, in the 1980s, the cointegration technique was introduced in the field of econometrics and subsequently employed in energy demand modelling as a new estimation technique mainly within the log-linear functional framework. Given its popularity in energy demand modelling, this sub-section describes this technique in detail.

2.2.2.1. Concept of a cointegration relationship

The introduction and application of cointegration technique in time series econometric analysis has affected significantly energy demand modelling for the past decade. The first application of this method on energy demand study was Nachane et al. (1988) followed by Hunt and Manning (1989) both of which are based on the log-linear model. Since then, the cointegration technique and error correction model have been popular tools for analysing energy demand.

It was already pointed out in the early 1970s that many time series variables in macroeconomic studies actually exhibit consistent trends, either upwards or downwards (i.e. they are non-stationary variables), and standard static linear regressions with these non-stationary variables are likely to result in unreliable statistical inference (Granger and Newbold, 1974). However, until the late 1980s, very little attention was actually
paid by researchers to non-stationarity variables and spurious regression problems in
time-series data analysis.

Today, it is well known that classical regression techniques are invalid when applied to
stochastic non-stationary time-series variables. In this case, the OLS estimators have
sampling distributions with very different properties from those in the classical case,
and regression coefficients tend to appear spuriously significant (Thomas, 1993).
Suppose, for instance, that time series variable $A_t$ and its autoregressive (AR) process is
represented by:

$$A_t = \alpha A_{t-1} + u_t, \quad u_t \sim iid(0, \sigma^2)$$  \hspace{1cm} (2.28)

If $\alpha = 1$, this process is non-stationary and known as a random walk model which is an
example of a unit root process. Rearranging of Equation (2.28) gives:

$$\Delta A_t = A_t - A_{t-1} = u_t$$  \hspace{1cm} (2.29)

This means that the non-stationary process of $A_t$ can be transformed into stationary
process by first differencing. In such a case, $A_t$ is said to be integrated of order 1 or
denoted I(1). By definition, a time series which requires $d^{th}$ differencing to achieve
stationarity is integrated of order $d$, or I ($d$). Thus, a stationary variable can be said to be
I(0). Testing stationarity of time-series variable, which is a test for unit root of its AR
process, is normally carried out by the Dickey-Fuller (DF) test (for AR(1) case) and the
Augmented Dickey-Fuller test (ADF) test (for a higher order AR case) or the
Phillips-Perron (PP) test (Dickey and Fuller, 1979) (Phillips-Perron, 1988). The Durbin-Watson (DW) test is also suggested to use the test for the unit root by Sargan and Bhargava (1983), but it seems to be less popular than others in energy demand studies. Note that, because of potential non-stationarity of the variable, standard $t$-test cannot be used for this unit root test.

Once non-stationarity is found, handling of such a variable should be careful. Now, consider an OLS regression of two non-stationary variables, $E_t$ and $Y_t$, integrated in the same order one. In an energy demand study, $e_t$ and $y_t$ can be natural log of energy consumption and the log of income respectively, which can be in the log-linear function as follows:

$$e_t = \beta + \delta y_t + u_t \quad u_t \sim iid(0, \sigma^2)$$

Granger and Newbold (1974) show by simulation methods that this regression is likely to be spurious and characterised by a very high $R^2$ and significant estimate of $\delta$ associated with a very low $DW$ value. However, if the error term $u_t$ has a stationary process and, hence, is I(0), then, $y_t$ and $e_t$ are said to be cointegrated and the regression is no longer spurious. In order to test for a cointegration relationship between non-stationary variables, the DF tests can be applied on the OLS residuals $u_t$ from a static regression. Engel and Granger (1987) suggest to use different critical values form the standard DF test since $u_t$ is based on estimated parameters. Therefore, this test is also known as Engel-Granger (EG) test. An alternative test is the Cointegrating Regression Durbin-Watson (CRDW) test proposed by Sargan and Bharagava (1983).
Cointegration suggests that there is a long-run relationship between variables and the coefficient $\delta$ represents the long-run equilibrium value. Short-run fluctuations departing from the long-run path are corrected automatically within the system (Engel and Granger, 1987). Moreover, the OLS estimators in the cointegrated regression are sometimes refereed as “superconsistent” if the sample size is sufficiently large (Stock, 1987). Superconsistent means that the equilibrium relationship will be consistent regardless of whether or not there is a correlation between the explanatory variable and the disturbance in the equation. In addition, they converge to the true values at a very faster rate gaining higher asymptotic efficiency as sample size increases. (Thomas, 1993).

### 2.2.2.2 Engle and Granger two-step procedure and Error correction model

Engle and Granger (1987) show that every cointegrated system can always be represented by a valid dynamic error correction model, in which the short-run disequilibrium relationship between two cointegrated variables is represented. Consider that two I(1) variables, $e$, and $y$, are cointegrated and cointegration relationship is illustrated as:

$$u_t = e_t - \beta - \delta y_t$$

(2.31)

Corresponding a simple error correction presentation is given by:
\[ \Delta e_t = \beta_0 + \delta_0 \Delta y_t + \gamma u_{t-1} + v_t \]  \hspace{1cm} (2.32)

\( \delta_0 \) is a short-run parameter and \( \gamma \) represents the speed of an adjustment process by which the deviation from the equilibrium relationship is corrected each period. Note equation (2.32) corresponds to equation (2.27) with more lagged variables. Since all variables appearing in Equation (2.32) are stationary, the standard OLS procedures are valid for large samples. Through these two steps, both of the short- and long-run in addition to the speed of adjustment process parameters are obtained relatively easily. This procedure is called the Engel-Granger two-step procedure (Engel and Granger, 1987).

A majority of energy demand studies which takes into account cointegration has employed the Engel-Granger two-step procedure within the log-linear model framework. This single equation approach is simple and easy to use. However, there are three main problems with this procedure. First, this equation involves arbitrary assumption about the direction and timing of causal linkages between variables. This is based on Sim’s (1980) critics that restrictions on the direction of causality and on the parameters could not be made to models of the data generating process (Fouquet, 1996). Moreover, the Engel-Granger two-step procedure is sensitive to the choice of the dependent variable of the cointegrating regression. Furthermore, this single equation approach ignores the possibility of multiple cointegrating relationships when more than two variables involved. Finally, estimated parameters by OLS are still biased in small samples and this bias can be substantial. Banerjee et al. (1993) and Inder (1993) show that the bias could often be substantial. In which case, it is preferable to estimate an over-parameterised dynamic model and derive the long-run parameters by solving the
estimated ARDL model (e.g. equation (2.26)) since this reduces any bias, giving precise estimates of the long-run parameters. Inder (1993) also shows that this procedure provides valid t-tests and hence tests of significance on the long-run parameters may be undertaken. In addition, it is possible to carry out a unit root test of no cointegration since the sum of the coefficients on the distributed lag of the dependent variable must be less than one for the dynamic model to converge to a long-run solution (Harris, 1995, pp.60 - 61).

2.2.2.3. Multivariate cointegration system

Because of these deficiencies, the multivariate maximum likelihood approach to cointegration proposed by Johansen (1988, 1991) and Johansen and Juselius (1990) has begun to replace the single equation approach in recent energy demand studies. This so-called the Johansen procedure analyses cointegration relationship within a more general framework based on a vector autoregressive (VAR) model. Recent applications are Hunt and Witt (1995), Masih and Masih (1996), Chan and Lee (1997)(1996), Silk and Joutz (1997), Madlener (1996b), Clements and Madlener (1999), almost all of which are based on the log-linear functional form in the sense that the log of energy demand is a linear function of the log of income and energy prices.

Consider a VAR model of a set of variables $\Phi$ as:

$$\Phi_t = \pi_1 \Phi_{t-1} + \ldots + \pi_k \Phi_{t-k} + u_t \quad t = 1, \ldots, T$$ (2.33)
where $\Phi_t$ is a $(N \times 1)$ vector of I(1) variables. For example, in the three dimensional VAR case, $\Phi_t = (\ln E, \ln P, \ln Y)_t$ where $E$ = energy consumption, $P$ = energy price, $Y$ = income. $\pi_1, ..., \pi_k$ are $(N \times N)$ coefficient matrices, $k$ is the maximum lag length, and $u_t$ is a $(N \times 1)$ vector of error terms under the classical assumptions. It can be seen that there is no prior assumption about the exogeneity or endogeneity of some of the variables and, hence, all variables are treated equally. Equation (2.33) may be reparameterised into vector error correction from (VECM) as:

$$
\Delta \Phi = \Gamma_1 \Delta \Phi_{t-1} + \ldots + \Gamma_{k-1} \Delta \Phi_{t-k} + \Pi \Phi_{t-k} + u_t
$$

(2.34)

where $\Gamma_i = -I + \pi_1 + \ldots + \pi_i$ : for all $i = 1, \ldots, k - 1$

$\Pi = -I + \pi_1 + \ldots + \pi_k$

$I$ = the identity matrix

If there is no cointegration within the system, rank of $\Pi$ will be zero. However, if there are any cointegrating relationships among the variables in $\Phi$, reduced rank of $\Pi$, $r$, will be equal to the number of cointegrating vectors in the system. Then, the matrix $\Pi$ can be decomposed into two matrices $\alpha$ $(N \times r)$ and $\beta$ $(N \times r)$ as follows:

$$
\Pi = \alpha \beta'
$$

(2.35)

$\beta$ is the matrix of cointegration vectors representing long-run relations and $\alpha$ is the matrix of corresponding factor loading representing error correction parameters. Maximum likelihood estimation of the cointegrating vectors $\beta$ can be obtained by two
different likelihood ratio tests for the number of possible cointegrating vectors, \( r \). The first is a test of the null hypothesis of \( r \) cointegrating vectors against the alternative of \( r + 1 \) cointegrating vectors which is based on the trace statistic, and the second is the same test but is based on the maximal eigenvalue statistics. In general, the maximal eigenvalue test is generally regarded as the more powerful (Pierse, 1997).

### 2.2.2.4. Strengths and weaknesses of the cointegration technique

As mentioned, application of the cointegration technique associated with the log-linear functional form has become a major estimation procedure in energy demand studies. A number of reasons can be given for popularity of the methods. First, many researches have found that the majority of time series data appeared in energy demand studies are estimated as non-stationary. Unlike the differencing of the variables, which is the traditional way to treat non-stationary time series, the cointegration technique does not lose the long-run information between these variables. Second, it does not require any particular type of functional form, providing one can believe the long-run equilibrium relationship between variables is represented in model. Therefore, the cointegration technique can be directly applied to the log-linear energy demand model which easily can be expanded to be an error correction model. Third, the VECM enables us to analyse the direction of Granger-causality and the Granger-exogenerty or endogeneity of each of the variables which are cannot detected by the standard Granger test (Masih and Masih, 1996).

There are, arguably, a number of drawbacks with this estimation technique. Firstly, a
critical problem is that the unit root test for non-stationarity has only low power, particularly when the number of observations is not large. Therefore, rejection or acceptance of the null hypothesis of a unit root in the case of marginal significance is a sensitive issue (Maddala, 1992). Harvey (1997, p.199) states that cointegration tests and the unit root tests based on autoregressive models have very poor statistical properties, and it is in practice even more serious when a variable is actually I(2).

Secondly, in practice, cointegration does not always occur and often cointegration cannot be found. Then, the extent of the analysis with this method can be limited. Conversely, in the case of the multivariate cointegration system, when more than one cointegrating vectors are found in the system, there is an identification problem which can be difficult to solve and interpret (Madlener, 1996a).

Thirdly, in the multivariate cointegration approach, a choice of the order of the VAR and the treatment of the constant variables can affect the test for cointegration considerably (Hall, 1991). In addition, the VAR model specification requires a large number of coefficients leading to a rapid exhaustion of degrees of freedom. The maximum lag length of the VAR model is often severely limited, therefore, causing potentially biased estimators. Hence, the small sample problem is potentially quite serious.

Finally, some econometricians question the VECM model and the cointegration technique themselves. Harvey (1997) says that:

"Although they are easy to fit, and can be used as a crude forecasting device,
vector autoregressions tell us little about economics. ... The situations in which VECMs can be usefully employed are therefore limited and I feel very uneasy with the idea that they provide a general vehicle for modelling economic time series. However, casing these technical considerations aside, what have economists learnt from fitting such models? The answer is very little. I cannot think of one article which has come up with a co-integrating relationship which we did not know about already from economic theory” (p.199).

Then, he concludes that “The recent emphasis on unit roots, vector autoregressions and co-integration has focused too much attention on tackling uninteresting problems by flawed methods” (p.200)\textsuperscript{11}.

Despite the problems outlined above, the cointegration technique remains a valid approach to modelling energy demand, in certain circumstances. However, given Harvey’s critical views of this technique and problem mentioned above, in my view, it is perhaps better not to employ the cointegration technique. Instead, non-stationarity in time series data should be addressed in an alternative way as proposed by Harvey (1997)\textsuperscript{12}.

Table 2.2 shows the past energy demand studies using the cointegration technique with the log-linear functional form as their basic framework. It can be seen that the estimated

\textsuperscript{11} Harvey (1997) also points out the poor treatment of seasonality by the cointegration technique. This issue will be considered in Chapter 3.

\textsuperscript{12} The alternative approach will be proposed in the later chapter.
long-run price and income elasticities are generally rather lower than the estimated elasticities from other models such as the log-linear or the translog model in the past studies shown in Table 2.1 and 2.3. Although this difference may partly come from an explicit treatment of non-stationary variables within the model (Eltony and Al-Mutairi, 1995), it is more likely to be a result of the difference estimation periods used by the studies. Since the cointegration is a relatively new technique, studies utilising it tend to use the data covering the period of price fluctuations, whereas other studies are likely to use the data that only covers the pre-oil shock period in which energy price steadily declined. Note that the number of observations in the majority of studies is between 20 and 40. Some of them have less than 20 observations which are clearly not sufficient to obtain unbiased estimators (Kennedy, 1992, p.19). Thus, generalising these results should be considered with caution.
<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Sector/area covered</th>
<th>Technique/model used</th>
<th>Data used</th>
<th>estimated coeff. ECM adj. remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nachane et al. (1988)</td>
<td>Aggregated energy</td>
<td>Log-linear EG type single equation model (without ECM)</td>
<td>16 countries annual data 1950/51 - 1984/85 (35 obs.)</td>
<td>cointegration between energy demand and GDP is found in 16 countries out of 25 countries</td>
</tr>
</tbody>
</table>
| Hunt and Manning (1989)| Aggregated energy                  | Log-linear EG 2-step                          | UK annual data (final user demand) 1967 - 86 (20 obs.) | $\eta_p = 0.38$ to $0.49$  
$\eta_p = -0.30$ to $0.33$  
$\gamma = -0.67$ (significant) |
| Boone et al. (1992)  | Aggregated energy                  | Log-linear Johansen                           | 9 OECD countries quarterly data 1978 - 89 | $\eta_p = -0.09$ to $-0.62$  
$\eta_T = -0.01$ |
| Hunt and Lynk (1992) | Industrial sector only             | Log-linear EG 2-step                          | UK annual data 1948 - 88 (41 obs.) | $\eta_p = 0.68$  
$\eta_p = -0.29$  
$\gamma = -0.80$ (highly significant) |
| Dargay (1993)        | Transportation (petrol) only       | Log-linear EG 2-step (Structural form)        | UK annual data 1950 - 1991 (42 obs.) | $\eta_T = 1.5$  
$\eta_p = -1.4$ |
| Bentzen and Engsted (1993)| Aggregate energy                | Log-linear EG 2-step                          | Danish annual data 1948 - 90 (43 obs.) | $\eta_T = 1.21$  
$\eta_p = -0.47$  
$\gamma = -0.24$ (significant) |
| Fouquet et al. (1993)| Disaggregated (oil, coal, gas,    | Log-linear EG 2-step                          | UK annual data 1950 - 1992 (43 obs.)    | $\eta_T = -2.02/-0.19/1.15/0.72$  
$\eta_p = -2.02/-0.90/-1.37/-1.26$ coal/oil/gas/electricity |
| Engsted and Bentzen (1993)| Aggregated energy                | Log-linear EG 2-step / Johansen / LQAC model | Danish annual data 1900 - 91 (92 obs.) | $\gamma = -0.27$ (significant) |

$\eta_T = $ Long-run income elasticity.  
$\eta_p =$ long-run own price elasticity.  
$\gamma =$ an adjustment term in ECM.  
$\eta_T =$ time elasticity.
<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Sector / area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated coeff. ECM adj. remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atkinson and Manning (1995)</td>
<td>Industrial sector aggregated energy</td>
<td>Log-linear Johansen</td>
<td>OECD annual data 1960 - 89 (30 obs.)</td>
<td>( \eta_p = 1.04 ) ( \eta_r = -0.41 ) ( \gamma = -0.67 )</td>
</tr>
<tr>
<td>Bentzen (1994)</td>
<td>Transport sector (petrol) only</td>
<td>Log-linear EG 2-step</td>
<td>Danish annual data 1948 - 91 (44 obs.)</td>
<td>( \eta_p = -3.22/1.17/1.55/0.43 ) ( \eta_r = -0.73/1.02/0.92/0.39 ) ( \gamma = -0.37/-0.82/-0.71/-0.94 )</td>
</tr>
<tr>
<td>Fouquet (1995)</td>
<td>Residential sector only (coal, petroleum, gas, electricity)</td>
<td>Log-linear EG 2-step</td>
<td>UK quarterly data 1974Q1 - 94Q1 (84 obs.)</td>
<td>( \eta_p = 0.23 ) ( \eta_r = -0.29 ) ( \gamma = -0.65 ) (highly significant)</td>
</tr>
<tr>
<td>Hunt and Witt (1995)</td>
<td>Aggregated energy</td>
<td>Log-linear Johansen</td>
<td>UK annual data 1967 - 94 (28 obs.)</td>
<td>( \eta_p = 0.17 ) to 0.73 ( \eta_r = -0.06 ) to 0.65 ( \gamma = -0.01 ) to -0.70</td>
</tr>
<tr>
<td>Barker (1995)</td>
<td>Disaggregated each sector</td>
<td>Log-linear EG 2-step</td>
<td>UK annual data 1970 - 90 (21 obs.)</td>
<td>( \eta_p = -0.05 ) (for UK) ( \eta_r = 1.0 ) (imposed) ( \eta_T = -0.0258 ) (for UK)</td>
</tr>
<tr>
<td>Boone et al. (1995)</td>
<td>Aggregated fossil fuel</td>
<td>Log-linear Johansen</td>
<td>OECD countries quarterly data (interpolated from annual data 1978 - 90, but detail not reported)</td>
<td>( \eta_p = 0.92 ) ( \eta_r = -0.46 ) ( \gamma = 0.52 )</td>
</tr>
<tr>
<td>Eltony and Al-Mutairi (1995)</td>
<td>Transport sector (petrol) only</td>
<td>Log-linear EG 2-step</td>
<td>Kuwait annual data 1970 - 89 (20 obs.)</td>
<td>( \eta_p = 0.52 ) ( \eta_r = -0.12 ) ( \gamma = -0.38 )</td>
</tr>
<tr>
<td>Samimi (1995)</td>
<td>Transportation (petrol) only</td>
<td>Log-linear EG 2-step</td>
<td>Australia quarterly data 1980Q1 - 1995Q2 (54 obs.)</td>
<td>( \eta_p = -0.05 ) (for UK) ( \eta_r = 1.0 ) (imposed) ( \eta_T = -0.0258 ) (for UK)</td>
</tr>
<tr>
<td>Smith et al. (1995)</td>
<td>Aggregated fossil fuel</td>
<td>Log-linear Johansen</td>
<td>OECD countries quarterly data (interpolated from annual data 1978 - 90, but detail not reported)</td>
<td>( \eta_p = -0.05 ) (for UK) ( \eta_r = 1.0 ) (imposed) ( \eta_T = -0.0258 ) (for UK)</td>
</tr>
</tbody>
</table>
Table 2.2. (continued)

<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Sector/ area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated coeff. ECM adj. remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bentzen and Engsted (1996)</td>
<td>Aggregated petroleum demand</td>
<td>Log-linear Johansen</td>
<td>US annual data 1947 - 89 (43 obs.)</td>
<td>No cointegration is found between demand, price and real GDP</td>
</tr>
<tr>
<td>Madlener (1996b)</td>
<td>Aggregated residential energy</td>
<td>Log-linear Johansen</td>
<td>Austrian annual data 1970 - 93 (14 obs.)</td>
<td>( \eta_y = 1.13 ) ( \eta_p = -0.02 ) ( \eta_{temp} = 0.77 )</td>
</tr>
<tr>
<td>Chan and Lee (1996)</td>
<td>Aggregated energy</td>
<td>Log-linear Johansen</td>
<td>China annual data 1953 - 93 (31 obs.)</td>
<td>( \eta_y = 0.71 ) ( \eta_p = -0.91 ) ( \gamma = 0.77 )</td>
</tr>
<tr>
<td>Masih and Masih (1996)</td>
<td>Aggregated energy</td>
<td>Log-linear Johansen</td>
<td>6 South Asian countries annual data 1955 - 90 (36 obs.)</td>
<td>Cointegration is found in 3 countries out of 6 countries. Granger causality test only.</td>
</tr>
<tr>
<td>Chan and Lee (1997)</td>
<td>Aggregated coal demand only</td>
<td>Log-linear Johansen</td>
<td>China annual data 1953 - 1994 (42 obs.)</td>
<td>( \eta_y = 0.84 ) ( \eta_p = -0.82 ) ( \gamma = -0.67 ) (significant)</td>
</tr>
<tr>
<td>Silk and Joutz (1997)</td>
<td>Residential electricity demand only</td>
<td>Log-linear Johansen</td>
<td>US annual data 1949 - 93 (45 obs.)</td>
<td>( \eta_y = 0.82 ) ( \eta_p = -0.60 ) ( \gamma = -0.37 ) (significant)</td>
</tr>
<tr>
<td>Cheng and Lai (1997)</td>
<td>Aggregated energy</td>
<td>Log-linear EG 2step type single equation model</td>
<td>Taiwanese annual data 1955 - 93 (49 obs.)</td>
<td>No cointegration is found between energy demand and GDP, emproy-ment.</td>
</tr>
<tr>
<td>Clements and Madlener (1999)</td>
<td>Aggregated energy</td>
<td>Log-linear Johansen</td>
<td>UK quarterly data 1975Q4 - 1996Q3 (87 obs.)</td>
<td>( \eta_y = 0.36 ) ( \eta_p = 0 )</td>
</tr>
</tbody>
</table>

Source: Clements and Madlener (1999), Fouquet (1996) with modification
2.2.3. Irreversible price response specification in the log-linear model

The irreversible price response specification is a rather special case of the log-linear model, but it has been occasionally applied to energy demand, in particular oil demand modelling since Dargay's attempts (1992a and b) to oil demand in the UK. Other applications of this model to energy demand are found in Haas and Schipper (1998), Haas et al. (1998), Gately (1993) and Hogan (1993)\textsuperscript{13}. The issues of irreversible price response was realised when crude oil consumption did not increase in response to the sharp drop in the crude oil price in 1985 - 1986 period as much as expected by the estimated price elasticity which is normally assumed to be symmetric. In other words, the oil demand seemed to respond by far smaller amount for the price drop compared to the case of price rise.

Although this irreversible price response model is still based on the log-linear model, it includes a number of extra price terms each of which represents unidirectional price change: the maximum price (always positive and non-decreasing), price cut (negative and non-increasing), price recovery (non-negative and non-decreasing) (Gately, 1993, p.167). The results in the empirical applications generally suggest that the energy demand irreversibly responds to the price changes, although Hogan (1993, p.125) concludes that price irreversibility in the long-run seems to be ambiguous.

Despite the model appearing attractive, there are a number of issues with this approach worthy of discussion. First, some of the estimated key parameters in the model tend to

\textsuperscript{13} These models are estimated using OLS.
be statistically insignificant even at the 10% level (Dargay, 1992) (Haas et al., 1998). This implies there are some specification errors in the model. Second, it seems to be rather extreme that the estimated result by this model often suggests that the energy demand only responds to price changes if the price increases beyond the historical maximum price level, otherwise there is no response whatsoever (Haas and Schipper, 1998) (Haas et al., 1998). There are also some questions about the irreversibility of demand. For example, Pesaran et al. (1998, p.173) claim that the irreversibility price response in aggregated energy may be less than the case of oil demand as an individual fuel demand and the irreversible price response in Non-OECD area seems to be even unlikely. Given these circumstances, this approach is arguably still underdeveloped.

2.2.4. The log-linear model in structural form

This is special case of the log-linear model can also be expressed as a multi-equation system rather than the single-reduced form explained above. Energy demand is conceptually a derived demand rather than final demand (Nordhaus, 1977). Therefore, energy demand depends on the stock of the appliance and its capacity utilisation. This relationship can be illustrated by the following identity (Bohi and Zimmerman, 1984) (Bohi, 1981):

\[ E = f(A, R) \]  

(2.36)

where \( E \) = total demand for aggregated energy

\( A \) = stock of appliance for aggregated energy
\[ R = \text{capacity utilisation rate of the appliance} \]

\[ A \text{ and } R \text{ can also be represented separately as:} \]

\[ A = h(P_E, Y, X) \tag{2.37} \]

where \( P_E = \text{real price of aggregated energy} \)

\( Y = \text{real income} \)

\( X = \text{vector of other variables}^{14} \)

\[ R = g(P_E, Y, X) \tag{2.38} \]

where \( X = \text{vector of other variables} \)

Equations (2.37) and (2.38) show respectively that the number of the appliance stock for energy and its capacity utilisation rate are determined by energy price, income and other relevant variables. If information on stock of appliance and capacity utilisation rate is available, these equations can be estimated separately. In addition, using the identity equation (Equation (2.36)), price and income effects on the demand can be obtained (Pindyck, 1979) (Griffin, 1979). This modelling approach is called log-linear structural form model and sometimes referred to as the Fisher-Kaysan (1962) model.

In the structural form model, the short-run effect is captured by Equation (2.38) (changing in capacity utilisation rate of the appliance) and the long-run effect is captured by Equation (2.37) (changing in stock of the appliance). Thus, in contrast to

\[ ^{14} \text{Similar to (2.21), this vector includes temperature, improvement of energy efficiency,} \]
the reduced form model, the structural form model can explicitly distinguish between short- and long-run effects. Bohi and Zimmerman (1984) survey energy demand studies comprehensively and conclude that "the structural models perform better than the reduced form models; they provide more information, produce statistically significant results, and exhibit greater consistency across the separate studies" (p.150).

However, in reality, data availability of number of stock and capacity utilisation rate, which is necessary to construct the structural form model, is very limited in the energy field. The only exception is the transportation sector, particularly the petrol demand sector where stock of appliance (registered number of vehicle) and capacity utilisation rate (vehicle miles) as well as other relevant information may be recorded in some developed countries such as the U.S. Hence, apart from petrol demand, the structural form model has been applied to empirical studies much less than the reduced form mainly due to data limitations.

2.2.5. Strengths and weaknesses of the log-linear model

Thus far, as a one of the most popular functional forms in energy demand modelling, the log-linear model and the cointegration technique associated with the log-linear framework have been reviewed. The characteristics of this model can be summarised as follows\textsuperscript{15}.

First, this log-linear model is simple, therefore interpretation of estimated parameters

\textsuperscript{15} Some of them have been already presented in Chapter 1 without analysis.
are straightforward i.e. the estimated coefficients are directly interpretable as short-run elasticities of demand. In addition, long-run elasticities are easily calculated from the short-run elasticities and the estimated standard errors of the coefficients provide a valid measurement of the estimated elasticities. Although a constant elasticity assumed by this model is criticised as unrealistic, it may still provide useful parameters for simplicity of the model. As seen in Table 2.2, an extensive number of the actual applications of this model, including the DTI model in the UK government, may indicate its usefulness in practice. Pesaran et al. (1998, p.57 – 58) also support this view on a practical basis.

Second, it is easy to estimate by almost any type of estimation technique. In addition, because of its simplicity, required data is less costly. Therefore, the model can be applied to a wide range of sectors and fuels for which detailed data set are unavailable. This is particularly important for energy demand modelling since a lack of detailed energy data series is a common problem.

Third, the model can be easily extended to be a dynamic model such as the ARDL model. Therefore, Hendry’s general to specific approach can be directly adopted to the estimation of this model. In addition, the model can also easily be expressed as an error correction model, which offers a better understanding of the equilibrium levels of energy consumption and the adjustment process to reach them.

Forth, a number of empirical studies show that the log-linear model fits the actual energy series better than the models which have a tighter link to the utility maximisation
theory (Pesaran et al., 1998, p.83 – 88, and p.100). Since data coherency is one of the model selection criteria in the general to specific approach, the log-linear model may be more accessible to the approach. Although it is sometimes pointed out that the specification of the log-linear model is essentially *ad hoc* and is not based on the economic theory of consumer's optimising behaviour, the basic stance of the general to specific approach, that data informs a modeller as well as the theory, further supports the use of the log-linear model in energy demand modelling.

2.3. Translog function modelling

2.3.1. Translog functional specification

After the oil crisis, during the late 1970s, substitution possibility between energy and other production factors, particularly capital, occupied the interest of economists. This is because sustainable development of the economy highly depends on substitution possibility of capital for energy under energy shortage. At least, a three-input function which includes capital, labour, aggregated energy (e.g. \( Y = f(K, L, E) \)) is required for this estimation. The CES (constant elasticity of substitution) function including Cobb-Douglas function as well as log-linear function is too restrictive to estimate substitution elasticities between inputs when they are more than two which is \( Y = f(K, L, E) \) case. For example, when the CES production is applied for three inputs case, Allen's substitution elasticity \( \sigma_{ij} \) is restricted to be equal for all pairs of inputs. Hence, substitution elasticity \( \sigma_{i} \) is already very restricted (Uzawa, 1962). Needless to say, the Cobb-Douglas function is even more restricted so that Allen's substitution elasticities
are always unitary.

Berndt and Wood (1975) is the first and the most influential study employing the translog function. Since then, the translog function has been widely used in energy demand studies for estimation of cross-price elasticities between different energy as well as energy-capital substitutability/complementary. This functional form has far less prior restrictive substitution elasticities between production factors than the CES or the Cobb-Douglas functions. The translog function, which was initially introduced by Christensen et al., (1973), is a second-order approximation to an arbitrary production function and estimated elasticities are free from any prior restrictions. One of the main characters of the translog function is its application of the duality theorem between production function and cost function. Diewert (1974) pointed out that cost function is generally easier to be estimated than production function.

Suppose that production function is given by:

\[ Y = f(K, L, E) \]  

(2.39)

where  

- \( Y \) = total output  
- \( K \) = total capital  
- \( L \) = total labour  
- \( E \) = total energy.

By the duality theorem, there is a cost function corresponding to Equation (2.39), which

\[ \text{16 Some studies such as Berndt and Wood (1975) include 'material' as a 4th factor. However, it is ignored} \]
\[ C = C(Y, P_K, P_L, P_E) \]  

where  
\[ P_K = \text{real price of capital} \]
\[ P_L = \text{real price of labour} \]
\[ P_E = \text{real price of energy} \]

Assume that exogeneity of output and factor prices, a twice-differentiability of the cost function, and constant returns to scale. Then, the Taylor expansion of a log second order approximation of Equation (2.40) is:

\[
\ln C = \ln \alpha_0 + \alpha_Y \ln Y + \alpha_K \ln P_K + \alpha_L \ln P_L + \alpha_E \ln P_E \\
+ \left(\frac{1}{2}\right) \ln \left(\beta_{YY} \ln Y + \beta_{K} \ln P_K + \beta_{KL} \ln P_L + \beta_{KE} \ln P_E \right) \\
+ \left(\frac{1}{2}\right) \ln P_K \left(\beta_{YY} \ln Y + \beta_{K} \ln P_K + \beta_{KL} \ln P_L + \beta_{KE} \ln P_E \right) \\
+ \left(\frac{1}{2}\right) \ln P_L \left(\beta_{KL} \ln Y + \beta_{KL} \ln P_L + \beta_{LE} \ln P_E \right) \\
+ \left(\frac{1}{2}\right) \ln P_E \left(\beta_{KE} \ln Y + \beta_{KE} \ln P_K + \beta_{LE} \ln P_L + \beta_{EE} \ln P_E \right)
\]  

The \( \alpha_i \) are first-order parameters and the \( \beta_{ij} \) are second-order parameters. Then, let us impose a number of restrictions on Equation (2.41) which are derived from the economic theory as follows:

1) The cost function is homothetic which means that \( Y \) and \( P_i \) is separable, implying

---

Chapter 2

63
\[ \beta_{H} = 0. \]

2) The symmetry restrictions, implying \( \beta_{ij} = \beta_{ji} \) for \( i \neq j \).

3) Homogeneity of a constant degree in output (\( \partial \ln C / \partial \ln Y \) is constant) indicating \( \beta_{YY} = 0 \) and \( \alpha_{Y} = 1 \).

4) Homogeneous of degree one in input prices, implying:

   \[ \begin{align*}
   \alpha_{K} + \alpha_{L} + \alpha_{E} &= 1 \\
   \beta_{KK} + \beta_{KL} + \beta_{KE} &= 0 \\
   \beta_{KL} + \beta_{LL} + \beta_{LE} &= 0 \\
   \beta_{KE} + \beta_{LE} + \beta_{EE} &= 0
   \end{align*} \]

These restrictions can reduce the number of independent parameters in Equation (2.42) to be estimated and save the degrees of freedom. Note that if \( \beta_{ij} = 0 \), then, the translog function returns to the Cobb-Douglas function, implying the former can be regarded as the second-order of expansion of the latter.

Differentiate \( \ln C \) with respect to one of the factor prices, say, \( \ln P_{K} \) using Shepherd's Lemma (\( \partial C / \partial P_{K} = K \)), gives:

\[ \frac{\partial \ln C}{\partial \ln P_{K}} = \frac{P_{K}}{C} \frac{\partial C}{P_{K}} = \frac{P_{K}K}{C} = \alpha_{k} + \beta_{YK} \ln P_{K} + \beta_{YL} \ln P_{L} + \beta_{YE} \ln P_{E} = M_{K} \quad (2.43) \]

Equation (2.43) looks surprisingly concise. The left hand side is a simple cost share and right hand side is a linear function of factor prices, which are obtainable. Under the restrictions listed above, the parameters \( \alpha_{i} \) and \( \beta_{ij} \), \( \beta_{ii} \) can be estimated using the maximum likelihood method. Since the cost shares sum to unity, two of the three share
equations are independent. Therefore, exclusion of one equation is necessary to ensure non-singularity of covariance matrix of disturbance vector. The parameters in the excluded equation can be obtained from the remaining parameters in the model (Watkins, 1992) (Bohi, 1981).

Having estimated parameter values, calculations of elasticities are relatively straightforward. A general form of Allen's elasticities of substitution between $i$ and $j$ is given by (Uzawa, 1962):

$$\sigma_{ij} = \frac{CC_{ij}}{C_i C_j}$$  \hspace{1cm} (2.44)

where $C_i = \frac{\partial C}{\partial P_i}$ and $C_j = \frac{\partial^2 C}{\partial P_i \partial P_j}$.

Using this formula and the estimates from the translog, Allen's elasticities of substitution is expressed as (Berndt, 1991):

$$\sigma_{ij} = \frac{\beta_{ij} + M_i M_j}{M_i M_j}$$  \hspace{1cm} (2.45)

and Allen's own-price elasticities are:

$$\sigma_{ii} = \frac{\beta_{ii} + M_i^2 - M_i}{M_i^2}$$  \hspace{1cm} (2.46)
Moreover, the cross-price elasticity of substitution \( E_{ij} \) (\( = \frac{\partial \ln X_i}{\partial \ln P_j} \) when \( Y \) and \( P_i \) is constant, and \( X_i = K, L, E \)) can be presented as:

\[
E_{ij} = M_j \sigma_{ij} \tag{2.47}
\]

and the own-price elasticities are

\[
E_{ii} = M_i \sigma_i \tag{2.48}
\]

Allen’s elasticities of substitution are guaranteed to be symmetric. Hence, \( \sigma_{ij} = \sigma_{ji} \). In contrast to this, generally, \( E_{ij} \neq E_{ji} \). With regard to the choice of these different measures of elasticities, Watkins (1992) says that, although no clear theoretical preference exists for one over the other, there is a clear preference for using \( E_i \) rather than \( \sigma_i \) measures. This is because that, when the cost share \( M_j \) is small, Allen’s elasticities \( \sigma_i \) tend to be large and its volatility may lead to complications in comparison between studies.

It is useful to recall the cost function is given by Equation (2.40) where the price of energy is expressed as an aggregated basis. In this case, therefore, only substitution between energy and non-energy inputs can be estimated. Then, two-stage modelling assuming separability of aggregate energy cost function allows for the estimations of both of substitution elasticities within the same model. Suppose that the cost function is presented as (Denny and Fuss, 1977):

\[
C = C(Y, P_K, P_L, P_E(P_C, P_O, P_G, P_EL)) \tag{2.49}
\]
where \( P_C \) = price of coal

\( P_O \) = price of oil

\( P_G \) = price of gas

\( P_{EL} \) = price of electricity.

\( P_E (\cdot) \) is a sub-function of four fuels which is assumed to be homothetic and weakly separable from other non-energy inputs. This implies that the marginal rates of substitution between each fuel are independent of the quantities of capital and labour. The two-stage modelling process is, firstly, optimising the mix of fuels that make up energy input, and secondly, optimally choosing quantities of capital, labour and energy (Pindyck, 1979).

In order to capture the effect of technical progress, a linear time trend variable can be added to Equation (2.41) and this gives (Moroney and Trapani, 1981):

Equation (2.41) + \( \gamma t + \sum_i \gamma_i t \ln P_i \)  \hspace{1cm} (2.50)

where \( t = \) a linear time trend variable

\( i = K, L, E. \)

If technological progress is assumed to be Hicks-neutral and to occur at a constant proportional rate, then \( \gamma \neq 0 \) and \( \gamma_i = 0 \). Hence, \( \gamma \neq 0 \) suggests that Hicks non-neutral technical change occurs. In this case, differentiation (2.50) with respect to \( \ln P \) to obtain the share equations, which is an equivalent of Equation (2.43), gives:
\[ M_i = \alpha_k + \sum_i \beta_{ij} \ln P_i + \gamma_i t \]  

(2.51)

where \( i = K, L, E \).


2.3.2. Dynamic translog model

One of main drawbacks of the translog model is its static specification, which is unable to capture the intertemporal properties of demand. Therefore, as in the log-linear model case, the cross-sectional and pooled-data were preferred in the 1970s’ studies, since estimations with these data were often interpreted as a long-run values (See, Pindyck (1979), Griffin and Gregory (1976)).

An alternative approach to capture the long-run effect is incorporating a dynamic optimisation process in the static translog model. Pindyck and Rotemberg (1983) combine rational expectations in a variable cost function which adjusts optimally over time. Capital and labour are assumed to be quasi-fixed factors of production, and adjustment costs of these factors are explicitly modelled. Through the estimation of this model, changes in capital stock as the dynamic adjustment of energy demand towards
the equilibrium level can be traced. This representation of adjustment process is a highly desirable property of energy demand modelling. This model, however, severely suffers from a lack of adequate data, model misspecification and capital value measurement problems, which result in rather disappointing outcomes such as insignificant, counter-intuitively signed variables, and common statistical problems (Hunt and Lynk, 1992). Furthermore, because of difficulties in solving stochastic optimal control problems, the dynamic adjustment path can only be simulated for deterministic price scenarios, limiting its use as a prediction device (Griffin, 1993). This is why, despite its theoretical appealing, this dynamic translog model has not been widely employed in empirical studies.

2.3.3 Strengths and weaknesses of the translog model

The translog model has a number of considerable advantages. First of all, in contrast to the log-linear specification, the model specification is rigorously tied to consumer utility maximisation behaviour in economic theory. This means that the economic theory can be tested by the estimated parameters. For instance, through the symmetry conditions, the assumption of homogeneity of degree one in input prices can be tested. In addition, concavity of the cost function can be checked to see if or not the Hessian matrix based on the parameter estimates is negative semi-definite (Atkinson and Manning, 1995). A second advantage is that minimum prior restrictions are imposed on own and cross-price elasticity of demand, allowing these elasticities to vary over the sample period. With regard to other flexible functional forms, Diewert and Wales (1987) show that the translog form is empirically more vigorous than the generalised Leontief or the
generalised Cobb-Douglas forms.

However, there are several critical problems with the translog model. First of all, as mentioned above, it is not easy to expand to the translog specification to a dynamic version to capture the adjustment process to its long-run equilibrium level. Therefore, it is often pointed out that the estimated values from the translog model are likely to be short-run values. Second, many restricted assumptions are required in order to reduce the number of parameters to be estimated. Among them, the concavity condition for negative own-price elasticities and non-negativity condition in input levels for positive cost shares may be satisfied only at the sample mean, but not over other price regions. These conditions are satisfied globally only if the translog collapses to the special case of the Cobb-Douglas form. In fact, violation of these conditions commonly occurs in many empirical studies (Considine, 1989). Third, a large number of estimated parameters in the model results in a lack of degrees of freedom. Fourth, the model is often too sensitive to the data sample and country chosen, and to whether data is time series or cross-sectional (Madlener, 1996a). Fifth, unlike the CES and the Cobb-Douglas production function, the translog production function is not “self-dual”. This implies that the translog cost function is not a “true” cost function but is just a second-approximation (Murota, 1984). Finally, it is often questioned that the appropriateness of weak separatability assumption between production inputs.

Table 2.3 shows past major studies using the translog function and their estimated results. Sample periods and sectors are different from study to study, and estimated results are difficult to compare. However, one can observe that the estimated elasticities
are not consistent and there is a great disparity between them. The 1980s classic controversial issue of the substitution or complementary relationship between energy and capital seems to be not clear since the estimated cross-elasticities between energy and capital do not show consistently neither positive nor negative sign.

In conclusion, although the translog model is theoretically more elegant than others, there are still considerable problems which prevent the model from becoming a universal modelling form.
<table>
<thead>
<tr>
<th>Study</th>
<th>Sector analysed</th>
<th>Data period</th>
<th>Model and estimation technique</th>
<th>$E_{EE}$</th>
<th>$E_{EL}$</th>
<th>$E_{EK}$</th>
<th>$E_{EM}$</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>Berndt and Wood</td>
<td>Time series for US manufacturing</td>
<td>1947-71 annual</td>
<td>KLEM translog by I3SKS</td>
<td>-0.45</td>
<td>0.16</td>
<td>-0.17</td>
<td>0.46 to 0.49</td>
<td></td>
</tr>
<tr>
<td>Griffin and</td>
<td>Pooled manufacturing data for nine nations</td>
<td>1955-69 annual</td>
<td>KLE translog by IZEF</td>
<td>-0.79</td>
<td>0.48</td>
<td>0.31</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td>Gregory (1976)</td>
<td>Pooled cross-section time series for Canadian manufacturing</td>
<td>1961-71 annual</td>
<td>KLEM translog by iterative minimum distance estimation</td>
<td>-0.49</td>
<td>0.55</td>
<td>-0.05</td>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td>Berndt and Wood</td>
<td>Time series for US manufacturing</td>
<td>1947-71 annual</td>
<td>KLEM translog by I3SLS</td>
<td>-0.13</td>
<td>n.a.</td>
<td>0.13</td>
<td>n.a.</td>
<td>Results for 1971</td>
</tr>
<tr>
<td>(1979)</td>
<td></td>
<td></td>
<td>(gross)</td>
<td></td>
<td></td>
<td>(gross)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(net)</td>
<td>-0.57</td>
<td></td>
<td>(net)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pindyck (1979a)</td>
<td>Pooled industrial time series for ten nations</td>
<td>1963-73 annual</td>
<td>KLE translog by IZEF</td>
<td>-0.84</td>
<td>0.02</td>
<td>0.02</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td>Pindyck (1979b)</td>
<td>Pooled residential time series for ten nations</td>
<td>1960-74 annual</td>
<td>Translog by IZEF</td>
<td>-1.05</td>
<td>n.a.</td>
<td>n.a.</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>to</td>
<td>1.15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field and Grebenstein (1980)</td>
<td>Pooled cross-section for US manufacturing</td>
<td>1971</td>
<td>KLE translog</td>
<td>-0.54</td>
<td>-0.32</td>
<td>-1.76</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>to</td>
<td>1.65</td>
<td>1.21</td>
<td></td>
<td>0.89</td>
<td></td>
</tr>
<tr>
<td>Tumovosky et al. (1982)</td>
<td>Time series for Australian manufacturing</td>
<td>1946-75 annual</td>
<td>KLEM translog by FIML</td>
<td>-0.22</td>
<td>-0.64</td>
<td>0.44</td>
<td>0.42</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** $E_{EE}$ = own price elasticity of energy, $E_{EL}$ = labour elasticity of energy demand, $E_{EK}$ = capital elasticity of energy demand, $E_{EM}$ = material elasticity of energy demand, IZEF = Zellner-efficient estimation and iterative seemingly unrelated regression, FIML = full-information maximum likelihood.
<table>
<thead>
<tr>
<th>Study</th>
<th>Sector analysed</th>
<th>Data Period</th>
<th>Model and estimation technique</th>
<th>$E_{EE}$</th>
<th>$E_{EL}$</th>
<th>$E_{EK}$</th>
<th>$E_{EM}$</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pindyck and Rotemberg (1983)</td>
<td>Time series for US manufacturing</td>
<td>1948-71 annual</td>
<td>KELM dynamic translog by 3SLS</td>
<td>-0.36 (SR)</td>
<td>-1.37 (SR)</td>
<td>0.47 (SR)</td>
<td>0.36 (SR)</td>
<td>Capital and labour quasi-fixed case</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.58 (MR)</td>
<td>1.07 (MR)</td>
<td>0.46 (MR)</td>
<td>0.13 (MR)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.58 (LR)</td>
<td>1.03 (LR)</td>
<td>-1.34 (LR)</td>
<td>1.31 (LR)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.66 (SR)</td>
<td>0.88 (SR)</td>
<td>0.35 (SR)</td>
<td>-0.22 (SR)</td>
<td>Capital Quasi-fixed case</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.93 (LR)</td>
<td>0.70 (LR)</td>
<td>-1.01 (LR)</td>
<td>1.15 (LR)</td>
<td></td>
</tr>
<tr>
<td>Westoby and McGuire (1984)</td>
<td>UK electricity supply industry</td>
<td>1955/56 - 79/80 annual</td>
<td>KLE translog cost function by IZEF</td>
<td>-0.13</td>
<td>0.29</td>
<td>0.00</td>
<td>n.a.</td>
<td>Hicks-neutral technical progress assumed.</td>
</tr>
<tr>
<td>Hunt (1984)</td>
<td>UK industrial sector</td>
<td>1960 -80 annual</td>
<td>KLE translog cost function by IZEF</td>
<td>-0.58</td>
<td>0.72</td>
<td>-0.13</td>
<td>n.a.</td>
<td>Hicks-neutral technical progress assumed.</td>
</tr>
<tr>
<td>Hesse and Tarkka (1986)</td>
<td>Pooled cross-section time series of electricity for nine nations</td>
<td>1960-72 annual</td>
<td>KLE translog by FIML</td>
<td>0.09</td>
<td>0.69</td>
<td>-0.39</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hunt (1986)</td>
<td>UK industrial sector</td>
<td>1960 -80 annual</td>
<td>KLE translog by FIML</td>
<td>-0.28</td>
<td>0.06</td>
<td>0.21</td>
<td>n.a.</td>
<td>Allows for non-neutral technical progress</td>
</tr>
<tr>
<td>Apostolakis (1987)</td>
<td>Aggregated energy for five Southern European nations</td>
<td>1953-84 annual</td>
<td>KLE translog</td>
<td>-0.11 to</td>
<td>0.05 to</td>
<td>0.16 to</td>
<td>n.a.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.60 to</td>
<td>0.53 to</td>
<td>0.33 to</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Study</td>
<td>Sector analysed</td>
<td>Data Period</td>
<td>Model and estimation technique</td>
<td>$E_{EE}$</td>
<td>$E_{EL}$</td>
<td>$E_{EK}$</td>
<td>$E_{EM}$</td>
<td>Note</td>
</tr>
<tr>
<td>---------------</td>
<td>-----------------------------------------</td>
<td>-------------------</td>
<td>--------------------------------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
<td>--------------------------------------------------------</td>
</tr>
<tr>
<td>Lynk (1989)</td>
<td>Time series for the UK manufacturing sector</td>
<td>1948-81 annual</td>
<td>KLE translog by FIML</td>
<td>-0.23</td>
<td>0.20</td>
<td>-0.26</td>
<td>n.a.</td>
<td>Dynamic maximizing model with costs of adjustment used</td>
</tr>
</tbody>
</table>

Source: Atkinson and Manning (1995), Hunt and Lynk (1992) with modifications
2.4. Summary and conclusion

This chapter has reviewed the two important functional forms: the log-linear model and the translog model which have been extensively employed in energy demand modelling. First of all, the theoretical background of the log-linear model was outlined. It was shown that the model can be easily extended to the dynamic model, particularly the ARDL and the ECM models which are closely related to the general to specific approach developed by Professor D. F. Hendry.

During the 1980s, the ECM model was successfully combined with the concept of cointegration and this brought about the so-called ‘unit root revolution’ which also substantially influenced the estimation technique of energy demand function in the log-linear framework. Therefore, in connection with the log-linear framework, the detail of the cointegration technique was also outlined. It was discussed that, although the technique has been popularised, there are a number of serious problems with which Professor A. C. Harvey, one of the most distinguished econometricians, strongly opposes the use of the technique to empirical applications. On the other hand, the log-linear model is found to be a useful functional form on the grounds of simplicity, easy handling, less costly data requirement, data coherency and dynamic specification feature. These last two points indicates its accessibility to the general to specific approach.

Finally, the translog model was described. It was found that, although the model closely links to economic theory, there are a number of considerable problems. Many
applications of the model to energy demand were found in the 1970s and 1980s, whereas it is far less frequent in recent literature.

In conclusion, it is reasonable to employ the log-linear model as a basic functional framework in application to energy demand, which is particularly useful when the general to specific approach is adopted.
CHAPTER 3. MODELLING UNDERLYING ENERGY DEMAND TREND AND
STOCHASTIC SEASONALITY

3.1. Introduction

In the previous chapters, energy demand modelling was broadly reviewed. This chapter investigates and reviews two further important aspects of energy demand modelling central to this thesis:

- Underlying energy demand trend (UEDT)
- Evolving seasonality.

Since energy demand is derived demand, technical progress does affect the level of demand for energy. It is well acknowledged that efficiencies of many energy appliances have been significantly improved over past decades. For example, in Japan, the average electricity consumption of a 19/20 inch colour television was 140W in 1973 whereas it had fallen to 80W in 1994. Another Japanese example is that an average electricity consumption of 170 Litre-class refrigerator decreased into 27.0kWh/month in 1994 from 79.6kWh/month in 1973 (EDMC, 2001). For a given income level and energy price, the energy demand required to satisfy the same utility level should fall when an increase in energy efficiency, from technical progress, occurs.

The increasing concern about global warming has highlighted the important role of technical progress in energy usage as a potential element to reduce energy demand in
the long run. Almost all global CO2 simulation models such as the Edmonds and Reilly model (Edmonds and Reilly, 1983), the GREEN model (see, Burniaux et al., 1991) and Whalley and Wigle model (Whalley and Wigle, 1991) include deterministic fixed rate of technological progress in their simulations\(^1\). However, the econometric estimation of the rate of the technical progress rate is still unexplored, and there is non agreement about the exact rate. Therefore, the rates of exogenous technical progress assumed by the global models are criticised as rather arbitrary (Hogen and Jorgenson, 1991, p.78). It is desirable, therefore, to explicitly take into account such technical progress effect within energy demand modelling and estimate its effect as accurately as possible.

The general review of previous energy demand studies illustrated that in the 1970s and the early 1980s the translog model was often employed. The review also illustrated that there was a simultaneous development of the log-linear specification. The log-linear specification became the dominant specification in the late 1980s and 1990s, in part due to the ‘unit root-cointegration revolution’. Both the translog and log-linear specification have been estimated with and without explicitly modelling technical progress. If modelled within a translog framework, technical progress has a fairly tightly defined and measured. See Hunt (1984, 1986), Binswanger (1974) for detailed discussion. This is not true, however, in the log-linear framework. Many studies of energy demand introduce the idea of ‘technical progress’, but in an \textit{ad hoc} fashion with an inadequate explanation of what is being modelled exactly. Therefore, the concern here concentrates on the log-linear model where we will attempt to clearly clarify what is being measured

\(^1\) The rate of technological progress is assumed to be fixed at 1.3/1.75\% p.a. in the Edmonds and Reilly model, 1.0\% p.a. in the GREEN model, 0.3/2.7\% p.a. in Whalley and Wigle (1991) model. These rates are called an autonomous energy efficiency improvement which will be discussed in the latter section.
by ‘technical progress’ in energy demand functions.

When econometric models of energy demand are formulated, with a view to obtaining estimates of price and income elasticities, it is important that such models are flexible enough to allow for any evolving patterns in these factors that may be present in the series. Not only will this reduce the risk of unnecessary biases in the elasticity estimates, but it will also enable a careful examination of trend and seasonal factors once they have been separated from the direct economic influences on energy demand.

To define the nature and sources of trends and technical progress, the concept of the **Underlying Energy Demand Trend (UEDT)** is introduced. The UEDT encompasses the variables in X (see equations (2.7) (2.14) and (2.21) in Chapter 2) that cannot be measured adequately for time series estimation. It is distinct from the economic factors of income, price and other measurable exogenous variables in X such as temperature. In an ideal situation, adequate data on all the elements of the UEDT would be available and the appropriate variables could be included in the energy demand function. However, given the data is unavailable for many of these factors, the UEDT is a second best approximation. However, as illustrated later in the thesis, it is, in my opinion, still far superior to previous attempts to capture some of these effects.

The majority of previous energy demand studies that have recognised the importance of trends in energy demand have focused mainly on the contribution of technical progress which typically leads, ceteris paribus, to a reduction in energy demand through
improved efficiency. The review will show that they have modelled it in a very simple way, either ignoring it completely or, at best, using as a proxy a simple deterministic time trend. The potential biases in the estimated price and income elasticities of energy demand that will arise if the UEDT is not modelled adequately will also be shown.

Similar arguments apply to the modelling of seasonality. It is well known that energy demand is highly seasonal. Although this may be partially due to seasonal patterns in temperature which cause fluctuations in the exogenous sources, seasonal movement sometimes cannot be fully explained by temperature changes. Usually these seasonal fluctuations are captured by deterministic seasonal dummy variables. However, there has been growing concern about the capability of deterministic seasonal dummies for stochastic evolution of seasonal patterns over time which were detected by a number of empirical evidences. (See Hunt and Judge, 1996). Therefore, as well as modelling of the UEDT, appropriate modelling of stochastic seasonal movement should also be required and this issue will be discussed in the latter section.

The main aim of this chapter are to illustrate the importance of appropriate modelling of the UEDT and stochastic seasonality in energy demand function in a flexible way rather than the restrictive deterministic procedures which have employed in past energy studies. The outline of the rest of this chapter is as follows. Section 3.2 reviews the past empirical studies to attempt modelling of technical progress, rather than the UEDT which was not well defined in the past, within the log-linear functional form. The full description of the UEDT is given in Section 3.3, and the biased estimated elasticities as a result of ignoring the UEDT are explained in Section 3.4. Then, Section 3.5 outlines
modelling of the UEDT. Section 3.6 discusses the issue of modelling evolving seasonality in energy demand function when quarterly data is used. The section includes a brief review of the methodologies used in the past empirical studies. A summary and conclusion of this section is given at end.

3.2. Review of modelling technical progress in the log-linear model

3.2.1. Technical progress and a deterministic linear time trend in past studies

In past energy demand studies, the concept of the UEDT was not well defined. The focus in the past has been purely 'technical progress' since the impact of energy efficiency improvement on energy consumption may be more directly and intuitively realised by final energy users. Apart from ignorance of impact of technical progress, the most popular approach to measure such impact on energy demand is using a deterministic linear time trend as an approximation of technical progress. This simple approach has been widely accepted in past. Within the log-linear model, this approach is in the form of:

\[
\ln E_t = a \ln Y_t + b \ln P_t + ct + u_t. \tag{3.1}
\]

where \( E_t \) = energy demand

\( Y_t \) = real income

\( P_t \) = real energy price

\( t \) = deterministic linear time trend
\[ u_t = \text{residuals term}. \]

\[ u_t \text{ is expected to satisfy classical assumptions, namely } u_t \sim N(0, \sigma^2). \] Equation (3.1) is simply a familiar log-linear model which was described in Chapter 2 plus an additional term of \( ct \). In this formulation, the rate of technical progress is numerically explained by the parameter \( c \), which is simply the partial derivative of the energy demand with respect to time:

\[ c = \frac{\partial \ln E_t}{\partial t}. \tag{3.2} \]

What we measure here is the rate of change in the deterministic time trend which cannot be fully explained by the movement of economic activity, energy price and air temperature.

In order to understand the issues behind modelling technical progress with a deterministic linear time trend, the next section reviews previous empirical studies that have to attempt modelling ‘technical progress’ in this way. The review particularly concentrates on the studies which at least have explanations for the use of a deterministic linear time trend in their model.

3.2.2. Review

Beenstock and Wilcocks (1981, 1983) is one of the earliest studies which discuss the appropriateness of a linear time trend as a proxy of technical progress in the log-linear
model framework. They openly admit that a linear time trend is not a satisfactory measure but it is better than just ignoring since, in their opinion, there is undoubtedly technical progress in energy usage. Therefore, they argue that excluding the time trend would be mis-specification leading to under-estimation of the long-run income elasticity (p. 227). Using OECD aggregated energy data between 1950 and 1978, the estimated coefficient on the linear time trend was –0.0357, suggesting ‘autonomous technical progress’ occurred at the rate of 3.6% p.a.. The estimated long-run price elasticity was –0.06 and the long-run income elasticity was 1.78. They are considerably lower and larger respectively than commonly estimated results. It is also reported that the same model excluding the linear time trend produced the long-run price elasticity of –0.13 and the long-run income elasticity of 0.88.

However, Kouris (1983a, 1983b) argued strongly against using a linear time trend as an approximation for technical progress. He argues that technical progress is an important factor that has always been very difficult to quantify unless a satisfactory way of measuring this phenomenon can be found. Therefore, a simple linear time trend is hardly able to capture its dynamic impact (1983a, p.91 and 1983b, p.207). Moreover, according to his arguments, most of technical progress is induced by price changes rather than exogenous autonomous technical progress, and, thus, technical progress cannot be separated from the long-run price elasticity (1983a, p.91). Although Kouris (1983b) also admits that there are a number of factors inducing technology in energy usage such as energy policies, inter-factor substitution, fuel-switching, changes in economics structure which do not necessarily relate to price change (1983b, p.207), he implicitly rejects to the use of a linear time trend to capture these factors for the same
reason. In a word, his argument is that the most of technical progress is price induced which can be captured by a long-run price elasticities and an inclusion of a linear time trend causes unwilling bias in estimates. According to Kouris (1983b, p.208), an inclusion of a linear time trend would lead to price elasticity being biased downwards and income elasticities being biased upwards.

Welsch (1989, p.286), however, points out that Kouris' argument leads to *negative* technical progress if the price of energy falls, which he argues is counterintuitive. In other words, if Kouris' argument is correct that technical progress is price induced and hence is accounted by long-run price elasticity, energy efficiency will *worse* as a result of a decrease in energy price. However, as discussed earlier, once energy efficient technology is embedded in capital, it is unlikely to be removed to revert into energy inefficient capital corresponding to decline in energy price.

Based on the argument between Kouris (1983b) and Beenstock and Wilcocks (1983), Welsch (1989) reconsiders the appropriateness of including a linear time trend to account for autonomous technical progress. Using annual data between 1970 and 1984 for a number of OECD countries using several different model specifications, the answer for the question was inconclusive when the aggregated OECD is examined. However, if each single country is separately considered, an inclusion of a linear time trend is clearly preferred for the UK, Germany and France, but not for US, Italy and the Netherlands. In comparison between them, the latter have much higher price elasticities and lower income elasticities than the former. These results imply that all improvements
of energy efficiency are induced by price changes in the US, Italy and the Netherlands. On the other hand, in the UK, Germany and France, clear tendencies of autonomous improvement of energy efficiency can be identified, and price elasticities are lower since they mostly measure the pure substitution effect (p.290). Moreover, since pure income effect and technical progress is isolated, income elasticities would be higher in this case (p.290). Due to the considerable dispersion between the countries, he argues that energy demand should be modelled in a country-by-country basis rather than imposing a single model (p.291). Finally, for Japan, the appropriateness of a linear time trend is inconclusive.

Similarly, Jones (1994) empirically re-examines the argument between Beenstock and Wilcocks (1981, 1983), Kouris (1983b) using the OECD energy data used in Beenstock and Wilcocks (1981, 1983) but up-dated between 1960 and 1990 within an ARDL model framework. His findings show that an inclusion of a linear time trend improves the model's fit and gives a more plausible long-run price elasticity being in line with previous estimates. According to the preferred model, an annual rate of technical progress is −1.5% which is substantially lower than Beenstock and Wilcocks' finding. The long-run price and income elasticities are estimated as −0.70 and 1.23 respectively. Without the linear time trend, the price elasticity becomes −1.73 which is rather implausible and considerably larger than the case without the linear trend. In contrast, an inclusion of the trend does not affect the estimated income elasticities.

---

2 However, again, these results implicitly suggest that a decline in energy price would result in negative technical progress. In other words, these results predict significant dis-improvement of technical energy efficiency would occur after 1986 in these countries, which has not actually happened. Since the most of the estimation period (1970 - 1984) used in Welsch (1989) is characterised by a drastic increase in energy price, the estimated results may only reflect demand response against a price rise.
Jones (1994) points out that 'technical progress' in energy demand, or the improvement in the 'productivity' of energy use over time, will come about by the improved 'efficiency' of the appliance and capital stock, and hence shift the energy demand curve to the left. Jones goes on, stating that "price increases, if sustained, can ... provide the necessary incentive for energy users to find new ways to increase energy's productivity" (p. 245). However, as Jones also points out, many other non-price factors contribute to improvements in the technical progress of energy. These include environmental pressures and regulations, energy efficiency standards, substitution of labour, capital or raw materials for energy inputs, and changes in tastes leading to a shift in consumption towards goods and services that are less energy intensive. Jones (1994) goes on to argue that the "reductions in aggregate energy demand due to technical progress are distinct from the standard long-run adjustments to price increases that energy consumers make as they gradually replace their energy using capital stock and slowly change their energy consumption habits and patterns" (p. 245). It is important, therefore, to distinguish between the 'price' effects and the 'technical progress' effects. In the short-run, with a fixed appliance and capital stock, a rise in the energy price is likely to bring about a modest fall in energy consumption. Energy consumption will fall further in the long-run as the price rise induces the installation of more energy efficient appliances and capital stock.

For the manufacturing sector in the UK between 1948 and 1988, Hunt and Lynk (1992) include a linear time trend "as a proxy for technical progress since an alternative adequate measure is not available although the time trend is deterministic it is preferable
to the assumption that no technical progress occurs” (p.148). The trend was estimated to be around $-0.01$ i.e. an autonomous 1% reduction in energy demand in the sector. The estimated long-run equilibrium income$^3$ and price elasticities are $0.70$ and $-0.29$ respectively. These results can be directly compared to Lynk (1989) whose does not attempt to estimate a trend or a technical progress effect for the same sector in the UK using slightly shorter sample period 1948 – 1981; he estimates a long-run income elasticity of $0.44$ and long-run price elasticity of $-0.69$ which are clearly higher for income elasticity and lower for price elasticity than Hunt and Lynk (1992).

Hogan (1993) is an interesting case which considers the role of a linear time trend as a proxy of technical progress in comparison between an irreversible demand model and a symmetric demand model. Using oil demand data for OECD countries between 1966 – 1990, the parameter of the linear time trend appears to be significant to capture the evident downward bias in the oil demand intensity (p.151) and a symmetric demand model without trend is clearly rejected by the LR test against the model with trend. In addition, the estimated output (income) elasticity by the symmetric model without trend is estimated as $0.55$ (for the aggregated OECD), which, according to Hogan, seems to be too low and can be a result of mis-specification due to exclusion of the technology trend variables (p.150). It is also found that a symmetric model with trend may be preferred to an asymmetric model with/without trend so that it produces favourable projection of future oil demand intensity (p.154). While Hogan found a necessary important role of a linear time trend in a log-linear symmetric demand model, he

---

$^3$ Although this is referred as output elasticity in Hunt and Lynk (1992), income elasticity is used here for consistency and clarity.
remains sceptical about the importance of the asymmetric price effect on the demand in the long-run (Pesaran et al. 1998, p.173).

Bentzen (1994) uses a linear time trend to capture the effect of increasing fuel efficiency in his empirical analysis of petrol demand in Denmark. The estimated value of the linear time trend, \(-0.0135\), indicates that over the period between 1948 and 1991 an exogenous improvement of petrol efficiency occurred at the rate of 1.35% p.a. which is a "plausible" value (p.142). Similarly, in the application to petrol demand in Australia, Samimi (1995) describes that, in theory, technical progress is assumed disembodied and neutral which can be represented by a linear time trend to reflect the technical change. However, he also claims that, in practice, measuring technical progress cannot be tackled until a proper way of measurement is available. Therefore, along with Kouris’ (1983a, 1983b) argument, Samimi (1995) discards to use a linear time trend and prefers to estimated income and price effects without explicit allowance for technical progress due to the presence of multicollinearity between a linear time trends and income or price variables (p.336).

For the various sectoral energy demand in the UK between 1970 and 1990, Barker (1995) employs a linear time trend ‘to present improvements in energy efficiency’ (p.234) using a log-linear model within a co-integration framework. In the long-run cointegration equation, the estimated linear time trend varies from \(-3.7\) p.a. for iron and steel sector to 3.8% p.a. for air transport sector⁴. Each sector has a different trend tendency: all sub-sectors in the industrial sector have negative time trend, whereas most

⁴ Note that this positive rate of ‘technical progress’ seems not to reflect improvement of energy efficiency.
of the sub-sectors of the transport sector have a positive time trend except rail transport which has no time trend, and the domestic sector which also has no time trend. This means that energy efficiency improvement over the past decades occurred solely in the industrial sector, whereas other sectors lost energy efficiency or at the most remained constant. Since the estimated price and income elasticities are imposed at ‘consensus’ values, they are not directly comparable to others.

Boone et al. (1995) use a linear time trend as a proxy for technical progress in their model for fossil fuel demand in nine OECD countries between 1978 and 1990. The dependent variable in their model is not energy demand itself, but it is the fossil fuel intensity defined as fossil fuel consumption per unit of GDP implying an unit income elasticity. Then, the fossil fuel intensity is modelled as a function of a relative fossil fuel price and a linear time trend which is expected to continue to decline. They consider that this declining rate of the intensity is critical to the predictions concerning greenhouse gas emission (p.193). Therefore, it is important to separate the factors leading to declining energy intensity between those which relate to changes in energy prices and those that do not, namely, autonomous technical change (p.194). They emphasise this point by referring to contradicting findings in the past studies for the rate of autonomous technical progress\(^5\). The estimated linear time trends vary from \(-5.67\%\) p.a. for France to \(-1.61\%\) p.a. for the Netherlands which are somewhat larger than often assumed (p.223). They are negative for all the countries implying the universal existence of autonomous technical progress to reduce fossil fuel consumption. The

\(^5\) For instance, Williams (1990) claims that the potential for the autonomous decline in energy intensity should not be underestimated, whereas Hogan and Jorgenson (1991, p.782-82) report that most the
estimated long-run price elasticities also vary from \(-0.045\) for the UK to \(-0.159\) for the US but within a much smaller range and they are in general considerably smaller than the estimated result given by the above studies.

The dispersion patterns of the estimated values for linear time trends and the price elasticities between the countries seem to be similar to the findings in Welsch (1989) discussed above. For example, the lower price elasticities associated with higher values for linear time trends for the UK and Germany, and the relatively higher price elasticities associated with smaller trend for Italy are consistent in both studies. Therefore, Boone et al. (1995) lends support to the Welsch argument that a large part of improvement of energy efficiency was brought about by autonomous technical progress in the UK and Germany in contrast to the case of Italy where energy efficiency improvement was mainly induced by price movement. Using the estimated parameters in their simulation, they show that stabilisation of fossil fuel consumption critically depend on the rate of technical progress as well as price elasticity of the demand (p.223). However, in addition to a rather arbitrary imposition of unit income elasticity, there are a number of critical problems with Boone et al. (1995) which will be discussed.

Erdogan and Dahl (1997) include a linear “time trend as a proxy for technology” (p.178) in their log-linear model with the Almon lag structure for the residuals for estimation of the final energy demand in the aggregated economy and the industrial sector in Turkey during the period between 1970 and 1992. The trends are estimated as positive values for all cases. This negative technical progress suggests that there is a sectors in the US autonomously became energy intensive rather than energy saving.
significant tendency towards more energy using economy over the sample period. The estimated values are 0.03 for the aggregated economy and 0.16 for the industrial sector associated with somewhat lower income elasticities of 0.56 and 0.50 respectively. Since an omission of the linear time trend does not affect the estimated income elasticities, the linear time trend may not pick up some of the income effect (p.180). The estimated trend of 0.16 for the industrial sector implies the energy demand increased by 16% p.a. even when income and price remain constant, that seems to be rather implausible.

Table 3.1 summarises the estimated values for the linear time trend, the long-run income and price elasticities given by the above studies for UK, Japan and OECD. As can be seen, there are considerable variations of the estimated results for the time trend from 4% reduction p.a. (Boone et al., 1995) to 13% increase p.a. (Erdogan and Dahl, 1997). However, except Erdogan and Dahl (1997) which consider the developing economy and the road transport sector in Barker (1995), most of them have negative sings and fall into a relatively narrow range between 1% and 3% reduction p.a.. Therefore, it is not unreasonable that many of the global simulation model such as Manne and Richards (1990) and Edmonds and Barns (1990) assume that energy demand will decline by between 1% and 2.5% due to improvement of energy efficiency as mentioned at the beginning of this chapter.

Table 3.1 also illustrates that the estimated long-run income elasticities appear to be higher when a linear time trend is included than when it is not included. It is particularly clear to see in the comparison between Beenstock and Wilcocks (1981),

---

6 In the later section, it will be discussed in depth that biased elasticities may be estimated when the
Kouris (1983b), Jones (1994) and Hogan (1993) which use quite similar data series for the OECD aggregated energy over the past decades. When a time trend is included the estimated long-run income elasticities are 1.20 (Hogan, 1993), 1.23 (Jones, 1994) and 1.78 (Beenstock and Wilcocks, 1981), while if it is not included the elasticities decrease to 0.45 (Hogan, 1993) and 0.70 (Kouris, 1983b)

Similar comparison can be made between Hunt and Lynk (1992) and Lynk (1989) for the manufacturing sector in the UK as already mentioned. Moreover, the results in Welsch (1989) can also be compared to Hunt and Manning (1989) and Hunt and Witt (1995) who consider the same sector (the UK aggregated energy) and period but do not include a linear time trend. The latter two studies estimate the long-run income elasticities as 0.44 (an average value) and 0.23 respectively which are obviously much lower than the formers estimate of 0.71.

\(^7\) See Footnote 18 for the debate about the long-run income effect on energy demand.
<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated linear time trend and LR elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beenstock and Wilcocks (1981)</td>
<td>Aggregated energy</td>
<td>ECM</td>
<td>OECD annual data 1950 - 78</td>
<td>$T = -0.0357$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 1.78$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.06$</td>
</tr>
<tr>
<td>Kouris (1983b)</td>
<td>Aggregated energy</td>
<td>Dynamic log-linear with Koyck-lag</td>
<td>OECD annual data 1950 - 78</td>
<td>$T = 0$ (Explicitly imposed)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 0.70$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.43$</td>
</tr>
<tr>
<td>Welsch (1989)</td>
<td>Aggregated energy</td>
<td>Dynamic log-linear model and other various specifications</td>
<td>UK annual data 1970 - 84</td>
<td>$T = \text{Included but details are not reported}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Japan annual data 1970 - 84</td>
<td>$\eta_y = 0.71$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.11$</td>
</tr>
<tr>
<td>Jones (1994)</td>
<td>Aggregated energy</td>
<td>ADRL</td>
<td>OECD annual data 1960 - 90</td>
<td>$T = -0.015$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 1.23$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.86$</td>
</tr>
<tr>
<td>Hunt and Lynk (1992)</td>
<td>Manufacturing sector</td>
<td>Dynamic log-linear EG 2-step co-integration</td>
<td>UK annual data 1948 - 88</td>
<td>$T = -0.009$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 0.70$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.29$</td>
</tr>
<tr>
<td>Hogan (1993)</td>
<td>Aggregated Oil</td>
<td>Dynamic log-linear</td>
<td>OECD annual data 1966 - 90</td>
<td>$T = -0.0234$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 1.20$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.91$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$T = 0$ (Explicitly imposed)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 0.45$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.96$</td>
</tr>
<tr>
<td>Bentzen (1994)</td>
<td>Petrol</td>
<td>Dynamic log-linear EG 2-step co-integration</td>
<td>Denmark annual data 1948 - 91</td>
<td>$T = -0.0135$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 1.04$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.41$</td>
</tr>
<tr>
<td>Source</td>
<td>Sector</td>
<td>Model</td>
<td>Data</td>
<td>Results</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------------------------</td>
<td>----------------------------------------</td>
<td>-------------------------------</td>
<td>--------------------------</td>
</tr>
<tr>
<td>Kuninori and Miyagawa (1993)</td>
<td>Aggregated energy</td>
<td>Static log-linear</td>
<td>UK annual data 1970 - 89</td>
<td>$T = -0.018$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 1.00$ (Imposed)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.003$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Japan annual data 1970 - 89</td>
<td>$T = -0.029$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 1.00$ (Imposed)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.061$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 0.64$ (Imposed)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.65$ (Imposed)</td>
</tr>
<tr>
<td></td>
<td>Road transport sector</td>
<td>Dynamic log-linear EG 2-step co-integration</td>
<td>UK annual data 1960 - 88</td>
<td>$T = 0.021$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 0.24$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.30$ (Imposed)</td>
</tr>
<tr>
<td></td>
<td>Domestic final use sector</td>
<td>Dynamic log-linear EG 2-step co-integration</td>
<td>UK annual data 1960 - 88</td>
<td>$T = 0$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 0.35$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.30$ (Imposed)</td>
</tr>
<tr>
<td>Boone et al. (1995)</td>
<td>Fossil fuel</td>
<td>VAR Johansen</td>
<td>UK quarterly data 1978 - 1990 (Details are not reported)</td>
<td>$T = -0.0258$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 1.00$ (Imposed)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.045$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>VAR Johansen</td>
<td>Japan quarterly data 1978 - 1990 (Details are not reported)</td>
<td>$T = -0.0406$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 1.00$ (Imposed)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.133$</td>
</tr>
<tr>
<td>Erdogan and Dahl (1997)</td>
<td>Aggregated energy</td>
<td>Dynamic log-linear with Almon lag</td>
<td>Turkey annual data 1970 - 1992</td>
<td>$T = 0.03$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 0.56$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.11$</td>
</tr>
<tr>
<td></td>
<td>Manufacturing sector</td>
<td>Dynamic log-linear with Almon lag</td>
<td>Turkey annual data 1970 - 1992</td>
<td>$T = 0.13$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_y = 0.69$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.21$</td>
</tr>
</tbody>
</table>

Note: $T =$ Linear time trend, $\eta_y =$ the long-run income elasticity, $\eta_p =$ the long-run price elasticity.
In terms of the estimated price elasticity, it is difficult to see such an obvious tendency. Nonetheless, the estimated long-run price elasticities with a linear time trend sometimes, if not very often, are found to be lower (in absolute term) than without a time trend\(^8\). Using the same data for the aggregated OECD, Beenstock and Wilcocks (1981) found much smaller price elasticity of \(-0.06\) with a time trend compared to Kouris (1983b) of \(-0.43\) without a time trend. Similarly, once again, Hunt and Lynk (1992) and Lynk (1989), and Welsh (1989), Hunt and Manning (1989) and Hunt and Witt (1995) show the similar contrast. However, the case studies in Hogan (1993) and the comparison between Kouris (1983b) and Jones (1994) do not show the same tendency.

Even though a linear time trend has been widely used and accepted, the assumptions of fixed rate of technical progress implied by the trend is criticised by a number of recent new studies. In their insightful analysis, Azar and Dowlatabadi (1999) repeatedly emphasise that “we cannot rely on technological change as an autonomous driver of improved energy efficiency or reduced energy intensity in the economy” (p.528) and “by making technical change an endogenous process we gain insights about the dynamics of technological change” (p.538). The same comment is offered by Smith et al. (1995) who say that “technological improvement and increasing energy productivity provide the possibility of reducing energy use in the long term ... expressing this rate as an exogenous factor severely limits the model’s ability to represent how policy or macroeconomic changes may affect technological development” (p.135).

---

8 The possibilities of estimated bias of price elasticities when the UEDT is ignored will be further discussed in the later section.
Smith et al. (1995), Boone et al. (1995), Boone et al. (1996) and Mabey et al. (1997) are interesting studies. Instead of including an exogenous time trend variable, they attempt to estimate endogenous technical progress effect on energy demand in a number of OECD countries. They found that the trend is not a simple linear time trend, but is a function of other exogenous variables such as energy price, share of manufacturing output in GDP. Since a stochastic trend is included to represent an autonomous improvement of technology, the model was estimated by the Kalman filter. Their findings show that the trend is negatively and positively related to the real energy price and the share of manufacturing output in GDP in the cases for the UK. While the former indicates that the trend moves towards less energy consume driven by a higher energy price, the latter means that an increase in energy demand is associated with a rise in industrial production ratio against GDP. The results imply that using exogenous deterministic time trend variable as proxy technical progress in energy demand model may lead to misleading. Hence, the role of technological progress to control energy demand would be important.

Another feature of Smith et al. (1995), Boone et al. (1995), Boone et al. (1996) and Mabey et al. (1997) are that the estimated price elasticities are considerably smaller for both the UK and Japan. They report the long-run price elasticities of -0.045 for the UK and -0.016 for Japan. The income elasticities are imposed to be unitary in a rather arbitrary fashion which will be discussed shortly. The coefficients of the price in the

---

9 Boone et al. (1995 and 1996) consider the UK and France respectively, but not other countries.
10 However, only in France, it was found that the trend development is explained by mainly the change in nuclear and hydroelectricity consumption relative to fossil-fuel consumption (p.148).
trend equations are \(-0.00515\) for the UK and \(-0.00199\) for Japan (Mabey, 1997, p.91). Smaller magnitudes of the estimated price elasticities for both countries are in the same line with the linear time trend cases. Alongside the 'normal' price elasticities, they report the 'implied' elasticities calculated by 5 years simulation by a 1% energy price increase which are \(-0.126\) for the UK and \(-0.095\) for Japan. It is noteworthy that not only the 'normal' price elasticities, but also 'implied' price elasticities only small even after 5 years.

Although Smith et al. (1995), Boone et al. (1995), Boone et al. (1996), and Mabey et al. (1997) are interesting works in this field, there are a number of substantial drawbacks with the studies as follows.

- They use fossil fuel consumption/GDP ratio which called a fossil fuel intensity as a dependant variable in their model instead of consumption itself. This is equivalent to imposing the income elasticity of unitary. For this restriction, Mabey et al. (1997) argue that this “allows the proportion of energy use which can be influenced by policy to be identified by estimation; not applying this restriction allows energy intensity to be determined by output level, which 'black boxes' important influences which need to be simulated in a meaningful policy analysis” (p.87). However, given the fact that unit income elasticity is not empirically supported, at least, for the UK by a number of studies (See Hunt and Witt, 1995, Hunt and Manning, 1989), this restriction can be very arbitrary and the estimated result may be biased. It is worthy noted that Nagata (1997) shows that fossil fuel intensity as a indicator of energy efficiency is too
approximate and is misleading since it does not really represent 'real' intensity in energy usage (p.683).

- The data series they use seems to be crudely constructed. In fact, it is very unclear what data actually used\textsuperscript{11}. The detail descriptions of the data are not well explained in Boone \textit{et al.} (1995), Smith \textit{et al.} (1995) and Mabey \textit{et al.} (1997). For instance, in Boone \textit{et al.} (1995, p.199 – 201) say that fossil fuel consumption and prices, taxes of coal, gas and oil are annual data. However, the latter analysis seems to be based on quarterly data series. There is no description about this inconsistency. In addition, although Mabey \textit{et al.} (1997, p.87) and Smith \textit{et al.} (1995) report that the data used is 1978 – 90 (quarterly data), there is no explanation for inherent seasonality issues or the data may be seasonally adjusted. Only Boone \textit{et al.} (1996, Footnote 1, p.148) briefly say that the data used was interpolated from annual to quarterly. Therefore, it is anticipated that Smith \textit{et al.} (1995), Boone \textit{et al.} (1995) and Mabey \textit{et al.} (1997) also use the similar "transformed" quarterly data series\textsuperscript{12}. Although the issue of the transformed data from lower (annual) to higher frequency (quarterly) data is out of scope of this thesis, the pictures of the data series seen in Boone \textit{et al.} (1995, p.207 – 211) appear to be curious enough\textsuperscript{13}.

\textsuperscript{11} An undergraduate econometrics textbook states that "In any research, the researcher should clearly state the sources of the data used in the analysis, their definitions, their methods of collection" (Gujarati, 1995, p.27).

\textsuperscript{12} This has been confirmed by the personal correspondence from Dr. C. Smith although the exact details of the data are still unknown. It was also informed by the personal corresponding with Professor S. Hall and Dr. C. Smith that, unfortunately, the data set used in their studies no longer exists.

\textsuperscript{13} For example, it is clearly observed in Boone \textit{et al.} (1995, p.207 – 211) that the movement of the fossil intensity and the price are folded systematically every four quarters corresponding annually change in the
• Thirdly, data sample period used (1978 – 1990) in them is not sufficiently long enough to analyse the evolution of the technological progress in the long-run. This is not only because the number of observation is not large enough, but also because that this particular sample period is known as an unusual period in which energy demand substantially declined for the first time in majority of OECD countries after the World War II reflecting a dramatic increase in energy prices. This generalisation of the result given by the observation in this period would need caution.

• The models used in their studies are poorly described. For example, it can be seen in Smith et al. (1995) the dependent variables in equations (1) (2) and (3) are inconsistently different. Similarly, in Boone et al. (1995), the inconsistency between equation (8.7) and the estimated measurement equation in p.221 creates another confusion. In addition, their model might have more fundamental problem in terms of specification. Their model defined as fossil fuel intensity is a function of the real fossil fuel price and the trend, i.e. $E/Y = f(p, t)$, and the trend is assumed to be a function of real fossil fuel price and the share of manufacturing output in GDP i.e. $t = g(p, m/y)$. The latter function can be substituted into the former, then, $E/Y = f(p, p, m/y)$ is obtained. If the models are simultaneously estimated, a perfect multicollinearity problem arises between $p$ and $p^{14}$.

---

original data series, which certainly creates artificial 'seasonality'.

14 This kind of problem within a state space form seems to be still unexplored and no clear answer may be given at the present.
Finally, it is useful to mention briefly Harvey and Marshall (1991) and Morana (2000) despite their models not being in a log-linear framework. Both of the studies employ a stochastic trend model within the translog framework to analyse technical bias of energy inputs for the UK and Italian economy respectively. Both of them found significantly important roles of stochastic trends in the econometric models which are far more preferable to the conventional linear time trend approach. These results seem to have direct implication of usefulness the stochastic trend model within the log-linear framework.

3.3. Underlying Energy Demand Trend (UEDT)

Thus far, the past attempts of modelling technical progress have been reviewed. This section formally introduces the Underlying Energy Demand Trend (UEDT). After the concept of the UEDT is explained, the components of the UEDT are also described in full.

3.3.1. Concept of the UEDT

The concept of ‘technical progress’, when incorporated in energy demand functions, is an important one. It is vital that it is clearly defined and understood. Energy is a derived demand, not demanded for its own sake, but for the services it produces in combination with the capital and appliance stock in place at any particular point in time. Therefore, the amount of energy actually consumed in order to obtain the desirable level of services depends on the given level of technology embodied in energy appliances.
Moreover, the level of technology embedded will have come about through a combination of endogenous and exogenous factors (which are expanded upon below). However, it is not only ‘technical progress’ that influences the energy demand trends; other factors will also influence energy usage, both positively and negatively. Therefore, the more general concept of the Underlying Energy Demand Trend (UEDT) is introduced here, which is illustrated in Table 3.2 and described in more detail below. Given this concept, it is important that the method employed to capture the UEDT is sufficiently flexible to incorporate all of these effects and ensure that potential biases are not introduced into the price and income elasticity estimates\(^5\).

<table>
<thead>
<tr>
<th>Underlying Energy Demand Trend (UEDT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical energy efficiency</td>
</tr>
<tr>
<td>Brought by Embodied technical progress</td>
</tr>
<tr>
<td>Endogenous</td>
</tr>
<tr>
<td>Consumers Tastes</td>
</tr>
</tbody>
</table>

The term ‘technical progress’ which has been used in past empirical studies with the log linear energy function is ambiguous. Table 3.2 shows that the ‘technical progress’ in a

\(^5\) Howarth et al. (1993, p.43) say “It is tempting but misleading to assume that energy demand is a simple function of energy prices and the level of aggregate economic activity..... both activity levels and their related energy intensities are driven in large part by changes in lifestyle, technologies and the structure of the economy”.

Chapter 3 101
such context includes not only numerous non-price and -income factors\textsuperscript{16} which interact themselves, but also changes in consumer tastes and economic structure, that are not really true ‘technical progress’. In this thesis, hereafter, a distinction will be made between them. ‘Technical progress’ in the context of the UEDT will be used only when it is necessary.

3.3.2. Technical energy efficiency

As seen in Table 3.2, the UEDT consists of at least three components. A change in energy efficiency through development of engineering technology is a prominent factor determining the direction and magnitude of the UEDT. Technology is a certain kind of knowledge concerning scientific human activity such as industrial, agricultural and medical art. Part of this knowledge is embedded in machines and also in the knowledge of people, in organisational structures and in behavioural patterns. The former is normally referred to as embodied technology and the latter as disembodied technology. Moreover, both embodied and disembodied technology can be endogenous or exogenous.

3.3.2.1. Embodied technical progress

It is important to recall that energy demand is not direct demand for energy itself. Energy is never directly consumed by users. Instead, energy demand is derived from the services provided by energy appliances. Therefore, attainable output level (in the case of

\textsuperscript{18} And non-temperature factor in the case of heating energy.}
a firm) or utility level (in the case of a consumer) provided by consuming energy critically depends on the level of technology currently available which can be embodied in the energy appliances. An innovation of the technologies can bring about higher output and utility level using the same amount of energy. Since new technologies are normally embodied in up-dated energy appliances, technical progress is realised when the energy appliances are replaced by new appliances embedding new technology. This is the case of an improvement of technical energy efficiency brought by embodied technical progress. The embodied technical progress is endogenous if it is induced by price and income changes as often expected (Pesaran et al., 1998, p.73). It was witnessed that the efficiency of energy appliances significantly improved in OECD countries during the late 1970s and 1980s after the substantial and sustainable rise in energy price. This event was a typical example of endogenous embodied technical progress in energy usage (Walker and Wirl, 1993). It is worth noting that embodied technical progress does not necessary move smoothly over time (Berndt et al., 1993, p.34)

Nevertheless, new appliance is generally expected to be more energy efficient than older one since development of technology is likely to occur autonomously as time passes. Therefore, a part of the embodied technical progress can be exogenous. In this case, a change in technology embodied in energy appliance does not depend on other factors and, hence, it is sometimes called autonomous technical progress.17

---
17 Manne and Riches (1991) define the autonomous energy efficiency improvement as a rate of a decline in energy consumption required per unit of output.
3.3.2.2. Disembodied technical progress

Technical progress can also occur by an improvement of disembodied technology. In contrast to the embodied technology, disembodied technology is not in capital, but in labour or user as knowledge. The knowledge here means engineering technique regarding efficient usage of existent capital stock. In the manufacturing sector, for example, it includes how to operate machines more efficiently and how to maintain them to be efficient conditions. Another example is changes in a way of driving an existing car can improve the fuel efficiency of the car. New discovery and the adoption of more efficient ways of energy usage is disembodied technical progress. Once adopted, cost minimising firms and utility maximisation consumers given her/his budget constraint are likely to keep these techniques. That is these improvements are in irreversible way unless they 'unlearned'. Disembodied technical progress does not particularly require replacement of energy appliances although it is likely to be accelerated by new capital installations.

Like embodied technical progress, disembodied technical progress can be endogenous. It is naturally expected that a very rapid and sustainable increase in energy price encourages the firm to seek the most efficient way to use energy without replacement of capital. For instance, an improvement of production management may lead to an increase in output given the same amount of energy input. Again, endogenous disembodied technical progress does not necessary move at a constant rate over time. Therefore, is this case, a simple linear time trend may be an inappropriate way to measure it.
The argument for endogenous *embodied* technical progress can be equally applied to endogenous *disembodied* technical progress. However, one very important distinction between them is that, in terms of response to a change in other factors such as price changes, the former should be much slower than the latter. This is because the former requires replacement of capital stock whereas the latter does not necessarily need it. Therefore, if technical energy efficiency improvement is dominated by *disembodied* endogenous technical process, it would instantaneously occur in responding to the endogenous factors (Watkins, 1992, p.49).

Disembodied technological change can also be exogenous. Knowledge, if not all, is expected to develop autonomously as time passes like 'free manna from heaven'. Thus, irrespective of any changes in energy prices, a certain part of technical energy efficiency is expected to increase through new knowledge without replacement of capital stock. In contrast to endogenous technical progress, no matter if it is embodied or disembodied, exogenous technical progress may be appropriately treated as a simple linear function of time with a certain fixed rate. It has been mentioned earlier that a number of the global models adopts this rate determined arbitrary. In contrast to the endogenous technical progress case, a distinction of adjustment processes between *embodied* exogenous technical progress and *disembodied* exogenous technical progress is very subtle, since both of them are expected to develop at a constant rate over time and difficult to separate the two movements.

In general, endogenous embodied technical progress seems to dominate an
improvement of technical energy efficiency since new technology can be more directly realised in new capital and price change may be a main driver of technology development (Berndt et al, 1993, p.35). However, a number of studies suggest find their empirical results not necessary support this common intuition. For instance, Ingham et al. (1992, p.133) show that half of the improvement of technical energy efficiency taken place in the UK manufacturing sector during the 1970s and 1980s may have come about through exogenous (embodied and disembodied) technical progress. Their finding suggests that exogenous technical progress is important at least as much as endogenous technical progress. Moreover, in the empirical study for US, Canada and France manufacturing sectors, Berndt et al. (1993) found that little portion of energy efficiency was induced by embodied technical progress and they admit the difficulty to interpret this results.

Finally, exogenous technical progress in energy usage can also result from a number of factors such as environmental pressures and regulations, and mandated energy efficiency standards. It should be emphasised that all of these technical progress discussed in this section result in a shift in the energy demand curve to the left, thus reducing energy consumption at a given level of income and price (Kouris, 1983b)\textsuperscript{18}. This shift of the energy demand curve led by changes in the technical energy efficiency brings about substantial impact on the consequences of energy demand estimation, as we will discuss in the later section. The characters of the four types of technical progress considered here are summarised in Table 3.3.

\textsuperscript{18} Kouris (1983b) actually identifies consumer tastes as another exogenous factor that leads to less energy consumed (for a given level of income and prices). However, it may be preferred that to separate this out from 'technical progress' given the ambiguous expected sign, as discussed later.
Table 3.3. Four types of technical progress affect technical energy efficiency

<table>
<thead>
<tr>
<th></th>
<th>Endogenous</th>
<th>Exogenous</th>
</tr>
</thead>
</table>
| Embodied technical progress | - Slow response  
|                        | - Not fixed rate change                         | - Fixed rate change                           |
| Disembodied technical progress | - Instantaneous response  
|                        | - Not fixed rate change                         | - Fixed rate change                           |

3.3.2.3. Factors driving endogenous technical progress

As mentioned, it is often argued that endogenous technical progress is induced by sustainable price rises or induced by price ‘shocks’ above the ‘normal bounds’ of price changes (Walker and Wirl, 1993, p.187). Either way, as Jones (1994, p.245) emphasises, it is important to distinguish between the normal ‘price’ effects (as measured by the price elasticity of demand) and the ‘endogenous technical progress’ effect. Moreover, it is important that the irreversibility nature of the ‘technical progress’ effect is recognised and not allowed to bias the (symmetric) price elasticities. Therefore, the endogenous technical progress referred to in Table 3.2 will be price induced resulting in a (permanent) shift of the energy demand curve to the left, but is distinct from the normal price effect represented by the price elasticity of demand.

However, the induced changes in ‘technical progress’ can also come about as a result of increases in income or output\(^\text{19}\). In the short-run, this will bring about an increase in

\(^{19}\) There is also some debate in the literature as to whether income has a distinct role in energy demand functions (see Kouris, 1983b, p.209, Beenstock and Wilcocks, 1983, p.212, Welsh, 1989, p.287). This thesis takes the view, in agreement with Beenstock and Wilcocks and Welsh, that income should be included in the general specification and only omitted if accepted by the data.
energy demand with the given appliance and capital stock (and could be quite significant before households and firms have time to adjust their stock of appliances). Over time however, new and more efficient appliances will be installed and existing appliances replaced faster than would be otherwise. Hence, similar to the price effect, a distinction needs to be made between the long-run income effect and the technical progress effect. The increase in income will, in the long run, bring about an increase in the demand for energy (as new appliances and stock are acquired) which represents the long-run income effect. Furthermore, the increase in income may also induce the replacement of the existing stock of capital with 'upgraded' more efficient models and hence an irreversible improvement in energy efficiency (and a shift to the left of the (income) energy demand curve).

3.3.3. Consumer tastes

It is important to capture the other exogenous factors identified in Table 3.2. The first is consumer tastes. As mentioned above, change in consumer tastes could, ceteris paribus, result in a reduction in the demand for energy\textsuperscript{20}. However, it is equally plausible that it could result in an increase in energy demand and hence works in the opposite direction to the traditional 'technical progress' effect. For example, it is well known that the efficiency of cars have improved over the last couple of decades. This will reduce, ceteris paribus, the consumption of energy in the transportation sector. However, this is outweighed by an increase in demand brought about an underlying increase in transportation demand. This has been caused by the growth in car size and engine power

\textsuperscript{20}For example, it is as a result of governmental advertising campaign encouraging energy conservation.
and a worsening of traffic conditions in urban areas. Consequently, car fleet fuel intensity has hardly changed. In addition, there has been a shift from public transport to (more energy intensive) private cars (Schipper et al., 1992, p. 123). Another example, at the disaggregated level, is the significant switch in energy for space heating from coal to gas that occurred during the 1960s and 1970s in many industrial countries. The reason why consumers switched from coal is not fully explained by economic factors such as the relative prices, but by the desire to use the cleaner and more convenient alternative energy source. Clearly, in this case the effect on the UEDT for gas was operating in the opposite direction to any legitimate technical improvements also taking place.

The problem with consumer tastes in aggregated energy demand modelling is that it is very difficult to measure numerically and virtually no data is available in aggregated level. Therefore, changes in consumer’s taste have implicitly been included in ‘technical progress’ even though it is certainly not technical progress. In this thesis, UEDT does include consumer’s taste and, again, it is not the same as pure technical energy efficiency. A change in consumer tastes is assumed to be exogenously determined.

3.3.4. Economic structure

When estimating energy demand functions, whether at the whole economy or sectoral level, the UEDT will be affected by a change in the economic structure. At the whole economy level, a switch from, say, manufacturing to services will affect the aggregate demand for energy. This change is not induced by changes in aggregate output and/or prices but the switch from a sector with a certain level of energy intensity to another
sector with a different level of intensity. If therefore, the UEDT is not included, or modelled inadequately, these changes will be forced to be picked up by the activity and price variables resulting in biased estimates of the income and price elasticities. This equally applies to a change in structure within sectors, for example, the changes over time of the sub-sectors of manufacturing. Therefore, if variables indicating the proportion of the output generated by energy intensive sector, typically manufacturing sector, against the aggregated output is available, it is worth checking whether an inclusion of the variables in a model affects the estimated result. Howarth et al. (1993) found that the substantial reductions in energy intensities of five OECD countries between 1973 and 1988 may have been led by changes in the economic structure of these countries which were unrelated to ‘pure’ technical energy efficiency (p.27). Similarly, Boone et al. (1995) also report that the share of manufacturing output is significant impact on the energy consumption in the case of the UK (p.221). However, if no variable is included, this effect will also be captured by the UEDT, in addition to technical progress and consumer tastes.

3.4. Ignoring the UEDT and biased elasticity estimates

In the review section, it was shown that the studies including a linear time trend to proxy UEDT tend to find larger long-run income elasticities than the studies using model without a trend. Similarly, the estimated long-run price elasticities given by the models with a trend sometimes results in a smaller magnitude compared to the case without a trend. Therefore, this section is concerned with the possible biases which can be generated by ignoring or inadequate modelling of the UEDT.
First, let us consider possible biases in estimated price elasticity. The failure to model UEDT adequately could result in an over-estimate of the ‘true’ (absolute) price elasticity of demand when generally price increases and the UEDT is downward. This can be clearly seen in Figure 3.1a.\(^{21}\) Point A represents the initial equilibrium point given the long run demand curve \(D_0\), price level of \(P_0\), and energy consumption \(E_0\). When the price increases to \(P_1\), energy demand falls to \(E_1\), represented by point B. It is this reduction in demand that represents the ‘true’ long-run price effect that would come about by changing consumption patterns given the existing energy appliance stock.

For example, reducing travel by private car, switching off lights more frequently, lowering central heating temperature etc. (all of which could be reversed if prices fell again). If the UEDT is negative (possibly induced by an ‘abnormal’ or ‘substantial price rise but also possibly by any combination of the other exogenous factors discussed above) then the demand curve shifts to the left at \(D_1\). Hence, the new equilibrium is represented at point C with energy demand reducing further to \(E_2\). The ‘true’ UEDT effect is the fall from \(E_1\) to \(E_2\). However, if the estimation procedure ignores the UEDT, the estimated price effect will be from \(E_0\) to \(E_2\) and hence over-estimate the price elasticity of demand.

\(^{21}\) Figure 3.1 is similar to that in Walker and Wirl (1993, p.188).
Figure 3.1. Possible biases in estimated price elasticities of energy demand

(a) Negative UEDT (downward sloping) and price rise

E₀ – E₁ = Price effect
E₁ – E₂ = UEDT effect
E₂ – E₃ = Estimated price effect if UEDT is not modelled

Therefore, price elasticity may be over-estimated if UEDT is not incorporated in the model.

(b) Positive UEDT (upward sloping) and price rise

E₀ – E₁ = Price effect
E₂ – E₃ = UEDT effect
E₃ – E₄ = Estimated price effect if UEDT is not modelled

Therefore, price elasticity may be under-estimated if UEDT is not incorporated in the model.

(c) Negative UEDT (downward sloping) and price decline

E₁ – E₀ = Price effect
E₁ – E₂ = UEDT effect
E₂ – E₃ = Estimated price effect if UEDT is not modelled

Therefore, price elasticity may be under-estimated if UEDT is not incorporated in the model.

(d) Positive UEDT (upward sloping) and price decline

E₁ – E₀ = Price effect
E₂ – E₃ = UEDT effect
E₃ – E₄ = Estimated price effect if UEDT is not modelled

Therefore, price elasticity may be over-estimated if UEDT is not incorporated in the model.
Figure 3.2. Possible biases in estimated income elasticities of energy demand

(a) Negative UEDT (downward sloping) and income rise

\[ E_1 - E_0 = \text{Income effect} \]
\[ E_1 - E_2 = \text{UEDT effect} \]
\[ E_0 - E_2 = \text{Estimated income effect if UEDT is not modelled} \]

*Therefore, income elasticity may be under-estimated if UEDT is not incorporated in the model.*

(b) Positive UEDT (upward sloping) and income rise

\[ E_1 - E_0 = \text{Income effect} \]
\[ E_2 - E_1 = \text{UEDT effect} \]
\[ E_2 - E_0 = \text{Estimated income effect if UEDT is not modelled} \]

*Therefore, price elasticity may be over-estimated if UEDT is not incorporated in the model.*

(c) Negative UEDT (downward sloping) and income decline

\[ E_0 - E_1 = \text{Income effect} \]
\[ E_1 - E_2 = \text{UEDT effect} \]
\[ E_0 - E_2 = \text{Estimated income effect if UEDT is not modelled} \]

*Therefore, price elasticity may be over-estimated if UEDT is not incorporated in the model.*

(d) Positive UEDT (upward sloping) and income decline

\[ E_0 - E_1 = \text{Price effect} \]
\[ E_1 - E_2 = \text{UEDT effect} \]
\[ E_0 - E_2 = \text{Estimated price effect if UEDT is not modelled} \]

*Therefore, price elasticity may be under-estimated if UEDT is not incorporated in the model.*
It is important, however, to recognise that this is only one source of bias and it depends on the assumption that the price is rising and that the UEDT is negative as conventionally assumed. Whereas, the price elasticity can be both negatively and positively biased depending on whether the price is rising or falling and the UEDT is negative or positive. Figure 3.1 also illustrates the alternative biases that may exist for the price effects. Figure 3.1b shows that if the price rises but the UEDT is positive (upward sloping) then the price elasticity will be under-estimated if the UEDT is ignored\(^\text{22}\). Figure 3.1c shows that if the price falls but the UEDT is negative (downward sloping) then the price elasticity will be under-estimated if the UEDT is ignored\(^\text{23}\). Finally, Figure 3.1d shows that if the price falls but the UEDT is positive (upward sloping) then the price elasticity will be over-estimated if the UEDT is ignored.

As well as price elasticity, it is equally important to recognise that similar biases will occur when estimating the income elasticity of demand. Figure 3.2 illustrates the possible biases if the UEDT is not modelled adequately. Figure 3.2a shows that if the income is rising and the UEDT is negative (downward sloping) then the income elasticity will be under-estimated if the UEDT is ignored. Figure 3.2b shows that if income is rising and the UEDT is negative (downward sloping) then the income elasticity will be over-estimated if the UEDT is ignored. Figure 3.2c shows that if income is falling and the UEDT is negative (downward sloping) then the income elasticity will be over-estimated if the UEDT is ignored. And Figure 3.2d shows that if

\(^{22}\) If the rise in the UEDT is sufficiently large, but ignored, then the resultant estimated price elasticity could be positive.

\(^{23}\) If the fall in the UEDT is sufficiently large, but ignored, then the resultant estimated price elasticity
income is falling and the UEDT is positive (upward sloping) then the income elasticity will be under-estimated if the UEDT is ignored.

The above discussion illustrates the importance of adequately modelling the UEDT that encompasses the ‘technical progress’ effect. Given the various influences underpinning the UEDT and hence its expected non-linear (positive and/or negative) nature it should be modelled in the most ‘general’ or ‘flexible’ way possible. Moreover, given that in addition prices (and sometimes income) will be falling as well as rising, the resultant biases will vary throughout the estimation period if the UEDT is excluded or modelled inadequately.

3.5. Modelling of the UEDT

Given above argument on the UEDT, it is now clear modelling the UEDT must be in flexible way as possible since the UEDT can move any directions and can be non-linear, in contrast to the approximation by the deterministic linear time trend. Let consider the following general function of energy demand:

\[ E = f(Y, P, \mu) \]  

(3.3)

where \( E \) = energy demand, \( Y \) = real income \( P \) = real energy price, and \( \mu \) = UEDT. Equation (3.3) indicates that energy demand is a function of output and energy price as well as the UEDT. As shown in equation (3.1), equation (3.3) also can be shown as the could be positive.
log-linear form of:

\[ \ln E_t = a \ln Y_t + b \ln P_t + \mu_t + u_t. \]  \hspace{1cm} (3.4)

\( u_t \) is expected to satisfy classical assumptions, namely \( u_t \sim N(0, \sigma^2) \). Equation (3.4) is identical to equation (3.1) except the UEDT term of \( \mu_t \). Again, \( \mu_t \) should not be a deterministic linear time trend since it has been argued that the UEDT is not necessary linear and can move in any direction. Moreover, inappropriate modelling of the UEDT can result in biased estimated elasticities. Therefore, subscript of \( t \) associated with \( \mu_t \) indicates \( \mu_t \) is no longer a constant trend at a fixed rate of change, but is in the form of a stochastic trend which is a time-variant time trend.

This formulation of trend term introduces substantial differences between equations (3.1) and (3.4). That is, since \( \mu_t \) is much more flexible than the deterministic time trend in equation (3.1), \( \mu_t \) can fully capture the effect of the UEDT, thereby equation (3.4) can be completely free from the biased elasticities problem explained above. In contrast, equation (3.1) is clearly inflexible model since the effect of the UEDT cannot be effectively captured by the trend.

It should be emphasised that the stochastic trend of \( \mu_t \) in equation (3.4) encompasses the deterministic linear trend in equation (3.1) as a restricted special case. Therefore, equation (3.4) is a more general model than equation (3.1). It means that, in estimation of energy demand function, as also suggested by Hendry's general to specific philosophy, it is clearly better to start with the general model of equation (3.4) with a
stochastic trend, rather than with the restricted model of equation (3.1) with a deterministic trend. Harvey et al. (1986), when analysing the employment-output relationship, argue 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).

The detailed discussion about the required estimation technique for the stochastic trend is given in Chapter 4 at length.

3.6. Modelling seasonality in energy demand

Thus far, we have extensively explored the issue of modelling of the UEDT\textsuperscript{24}. This section is concerned with another important aspect of energy demand modelling that is seasonality. When using quarterly data\textsuperscript{25}, modelling of seasonal variations in time series has been a growing area of research in econometrics, particularly, seasonal unit-root, seasonal integration and seasonal co-integration for non-stationary seasonality (see Hylleberg, 1992, and Franses, 1996 for the recent development in these techniques). It is, however, rather surprising that the seasonality issue seems to be of little interest for energy demand modellers since the vast majority of the empirical energy demand studies deal with annual data (Clements and Madlener, 1999, p.186). This is partly due to a poor availability of accurate and consistent data series in higher frequency time series in longer term. It is generally even worse in developing countries. Therefore, the

\textsuperscript{24} This implicitly applies to annual and higher frequency models.

\textsuperscript{25} This also applies to monthly, weekly, daily data, but the quarterly data is used in the thesis. Therefore, discussion concentrates on quarterly data.
use of annual data may be unavoidable in many cases.

Unfortunately, annual data often suffers from a lack of number of observation and of degree of freedom, which tends to be around 20 – 30 in a majority of the studies (see Table 1 in Clements and Madlener, 1999, p.187 and Table 5.7 in Hunt and Lynk, 1992, p.154 – 157). In fact, it is also rather curious that while the bias due to the non-stationary and the spurious regression problems are considered as critical in the literatures (for example, see Eltony and Hoque, 1997, p.296 – 297)\(^{26}\), very little attentions are paid for the another bias on the estimated parameter arise from the maximum likelihood procedure (see, Thomas, 1993, p.51), and the Engle-Granger two-step procedure pointed out by Banarjee, \textit{et al.} (1986) due to small sample size. In this regard, whenever available, higher frequency data is preferred to annual in order to increase in a number of observations and gain the necessary asymptotically efficiency for unbiased estimation when, for instance, the ML procedure is employed for the estimation\(^{27}\). Therefore, where feasible, this thesis attempts to use quarterly data whenever the appropriate data is available.

Energy demand is inherently characterised by seasonal variations when it is expressed in higher frequency than annually. This is because, a large extent, the energy used for heating and air conditioning purposes, and energy usage often corresponds to level of economic activities which also exhibits systematic seasonal fluctuations. If all of

\(^{26}\) This may create recent extreme disposition among energy demand modellers that everything will be fine so long as co-integration is found, and, sometimes, their main purpose seems to be seeking co-integration rather than 'econometric analysis'.

\(^{27}\) For example, the number of the annual observation of just twenty used in Eltony and Hoque (1997) is clearly insufficient to gain the desirable asymptotic property (Kennedy, 1992, p.19).
seasonal fluctuations are attributed to these known factors, adding temperature variable and GDP in the model, seasonality can be effectively removed. However, there is an enormous variety of unidentifiable factors generating seasonal variations in energy demand such as people's habits, seasonal events (e.g. Christmas season, summer holiday, school days cycle and so on). Thus, introducing possible attributed factors in the model often fails to eliminate the seasonal variations thoroughly. If any remaining of seasonal variation is ignored, it normally causes strong autocorrelation in residuals (Greene, 2000, p.788). Therefore, energy demand modelling using higher frequency data than annual is almost inevitably subject of seasonality issues, suggesting an appropriate modelling of seasonal fluctuations are as important as modelling the UEDT.

To explore better modelling of seasonal variation for the empirical part of this thesis, this section reviews how the past energy demand studies attempted to model seasonal variations in energy demand when higher frequency data than annually were used. There are various ways to address seasonal variations in time series such as deterministic seasonal dummy variable, the Box-Jenkins type seasonal difference, the seasonal unit root and the seasonal co-integration technique, and stochastic seasonal dummy variables. It is often considered as the easiest option to use seasonal adjusted data (Gujarati, 1995, p.517). However, the recent studies argue the seasonal adjustment process not only can distort some of important underlying properties (Davison and MacKinnon, 1993, section 19.6), but also it may remove valuable information from economic time series for characterising the behaviour of economic agents (Franses, 1996, p.306). Moreover, economic relationship between the series may be distorted if the series are seasonally adjusted by difference metrologies which are often 'black-box'
processes (Wallis, 1974). As a result, the recent trend in seasonality modelling is toward explicitly describing seasonality instead of removing it by seasonal adjustment (Franses, 1996. p.301). Therefore, this thesis treats seasonal adjustment as an unfavourable process, and not considered.

3.6.1. Deterministic seasonal dummy variables

General aspects of the seasonality issues are well described in the standard econometrics textbooks and, in such cases, they are not repeated here in greater details. Instead, the chapter looks into the empirical aspects of them, particularly focusing on the currently available energy demand studies.

One of the most popular procedures to capture seasonal variation has been deterministic seasonal dummy variables. This has been widely accepted in many areas of econometric modelling and empirical applications as well as energy demand modelling. Deterministic seasonal dummy variables capture seasonal variation through by shifting the intercept term vertically from quarter to quarter. Similar to a linear time trend, they are easy to be handled and to be interpreted directly. The use of deterministic seasonal dummy variables based on the assumption that the model is subject to a deterministic seasonality, which is parallel to the case of a linear time trend which corresponds to the assumption of the deterministic trend.

---

28 For instance, see Stewart (1991, p.97 - 109) for the deterministic seasonal dummy variable; Stewart (1991, p.214 - 217) and Charemza and Deadman (1997, Ch.3) for the seasonal differencing; and Pindyck and Rubinfield (1998, p.478 - 485) for the seasonal adjustment.
Empirical applications of the deterministic seasonal dummy variables for energy demand are, however, far less common than anticipated, despite its popularity of the procedure. In the recent literatures, there are three log-linear studies: Clements and Madlener (1999) and Fouquet (1995) who analyse the UK residential energy demand, and Yokoyama et al. (2000) who examine the demand for the various oil products in Japan with quarterly data.

Fouquet (1995) is in line with the traditional use of the deterministic seasonal dummy variables. He does not discuss the evolving seasonal issues and the deterministic seasonal dummy variables are used. Therefore, the possibility of changing in seasonal patterns in energy consumption is virtually ignored. Using the unadjusted quarterly data 1974q1 – 1994q1, the various fuel consumption in the UK are modelled as the log-linear function of the real disposable income and the real fuel prices together with the deterministic seasonal dummy variables. None of discussion is given for the seasonality. The estimated elasticities for the electricity demand, for instance, are 0.24 for income and -0.39 for price.

Yokoyama et al. (2000) also use the deterministic seasonal dummy variables in the usual way, but, in parallel, they also use “the seasonal adjustment procedure built into the computer software ‘Economate’” (p.10). There is no further description about the seasonality issues in the estimation. Using the quarterly data 1985q2 – 1998q1, they estimated the demand function for the various oil products such petrol, kerosene and jet fuel in Japan. The estimated results are statistically very poor. Very significant autocorrelation of the residuals arise in the almost all models, suggesting the models are
clearly mis-specified. It may be curious enough that the authors claim “the estimated result is comparatively excellent considering that the function form is simple” (p.10). No clue is given for whether or not the autocorrelations relate to the seasonality modelling adopted. In any case, the estimated elasticities for the petrol demand are 0.85 for income and -0.2 for price.

Using quarterly data 1975q4 – 1996q3, Clements and Madlener (1999) firstly applied seasonal unit root test\(^{29}\) which indicates that only the domestic energy demand in the UK seems to have a unit root at the bi-annual frequency, which means that its seasonality is non-stationary, whereas other variables do not have any seasonal unit root (p.192). Then, the deterministic seasonal dummy variables were incorporated in ECM model (p.194) suggested by Pesaran, Shin and Smith (1996) and the Hendry type dynamic model (p.198) as a log-linear function of the real disposable income, the real energy price and the temperature variable. Although detailed discussion about the deterministic seasonal dummy variables are not given, they seem to effectively capture seasonal variation. However, it may be questionable how the deterministic seasonal dummy variables can capture the non-stationary seasonality found in the energy demand by the seasonal unit root test. Moreover, no clear answer is given for the consideration for “the usefulness for annual as opposed to quarterly data for empirical modelling” (p.186) questioned by themselves. The estimated elasticities are around 0.3 and nearly zero for income and price respectively.

The critical problem of the deterministic seasonal dummy variables arises from its

\(^{29}\) This will be described later.
fundamental assumption that seasonality in the model is deterministic, that is seasonal fluctuations are fixed and stationary (deterministic) over time. A number of the recent empirical studies in non-energy area provides plenty of evidence that seasonal patterns in macro economics data are changing and their seasonal variations are stochastic non-stationary rather than deterministic (see, for example, Osborn, 1990). The stochastic seasonal variations in energy demand are also empirically shown by Hunt and Judge (1996). These findings raise the question about the autonomous assumption of deterministic seasonality which can lead to serious misleading results (Osborn, 1990, p.334). Harvey and Scott (1994) critically attack the deterministic seasonal dummy because that “if seasonal effects change gradually over time, this approach leads to dynamic mis-specification and there is no general agreement on how this problem should be tackled” and suggest “treating seasonality as an unobserved component which changes slowly over time” (p.1324) which will be considered in the later chapter of this thesis. Finally, Harvey (1997, p.198) strongly states that it should not be assumed that seasonality can be adequately modelled by a set of deterministic seasonal dummies.

3.6.2. **Seasonal difference in the Box and Jenkins approach**

Seasonal difference is a popular way to remove seasonal variation in time series econometrics, in particular known within univariate time series modelling framework developed by Box and Jenkins (1976) as the seasonal autoregressive-moving average (SARMA) model\(^{30}\). Very few applications of the SARMA model to energy demand analysis are found in existing literature. Clements and Madlener (1999), again, employ

\(^{30}\) The model also known as the 'Airline model' named after the successful application to monthly UK
the SARMA model for the same data described in the previous section in order to assess its forecasting ability for some three years in comparison to the econometric model with exogenous variables of income and temperature. Another study employing the SARMA model for energy demand is Darbellay and Slama (2000) for forecasting the short-term electricity demand hourly data in the Czech Republic. The focus of the study is to find out a better fitted univariate time series model for the hourly load curve in the electricity demand, rather than estimation of the demand function with explanatory variables. Therefore, the scope of the study is somewhat different from that of this thesis.

Unlike the deterministic seasonal dummy variables, stochastic as well as deterministic seasonal variations can be removed by this method (Clements and Hendry, 1997). The major drawback of the seasonal difference is that it can remove valuable information for long-run relationship between the variables in the model and, therefore, only explain a short-run relationship. Thus, the process seems to be against the recent manner of seasonality modelling which is, again, explicit modelling of seasonality itself rather than removing. Furthermore, a long-run relationship is more often of interest of energy demand modellers, the seasonal difference has not been widely used except for a short-run forecasting analysis.

In addition, another problem of the seasonal difference within the SARMA model is that it is normally constructed excluding any explanatory variables. However, as well as the long-run forecasting, the important purpose of traditional energy demand modelling has been policy evaluations and demand structure analysis through the estimated parameters

airline passenger time series data.
for the exogenous variables. Thus, from the view of an energy demand modeller, the SARMA model tends to be of little interest, unless the main purpose of the modelling is the short-run forecast without changes in policy.

3.6.3. Seasonal unit root and seasonal cointegration

As an extension of the cointegration technique associated with the unit root tests and non-stationary at zero frequency, which is normally annual data series, a series of the seasonal unit root tests and co-integration technique have also been introduced and developed by Dickey et al. (1984), Hylleberg et al. (1990), Engle et al. (1993). The concept of seasonal unit root is based on the assumption that seasonal variations in, say, quarterly time series may be non-stationary so that the seasonal pattern does not remain constant over time. It parallels the assumption that the trend in annual time series may be non-stationary. The assumption of varying and changing their pattern over time is contrasted to fixed deterministic seasonal pattern which implicitly assumed by the deterministic seasonal dummy variable procedure. To test for the seasonal unit root tests, a number of test procedures have been introduced. Among them, the HEGY test (Hylleberg et al. 1990) and the test proposed by Osborn (1990) seem to appear frequently. These tests attempt to detect potential unit roots at a number of different frequencies; zero, half-annual, and annual. The possible presence of these unit roots makes the seasonal unit root test far more complex compared to the conventional unit root tests. Consider a quarterly time series \( y_t \). 4th difference can be written as \((1 - L^4) y_t\). By the factorisations, \((1 - L^4) y_t\) is can be re-written as:
\[(1 - L^4)y_t = (1 - L)(1 + L)(1 + L^2)y_t = (1 - L)(1 + L)(1 - iL)(1 + iL)y_t \quad (3.5)\]

where \(L\) is the lag operator and \(i\) is an imaginary part of a complex number such that \(i^2 = -1\).

Equation (3.5) shows that a quarterly stochastic seasonal unit root process has four unit roots corresponding to different frequencies. \((1 - L)\) is the unit root at zero frequency, which is a familiar unit root at a non-seasonal case. \((1 + L)\) is the unit root at bi-annual (half-yearly) frequency, and a pair of complex conjugate root \((1 - iL)(1 + iL)\) corresponds to the four-quarter (annual) frequency unit root process. What the seasonal unit root test actually does is to detect whether any of these roots are on the unit circle. See Hylleberg et al. 1990 for the details of the test, or more intuitive descriptions are given in Harris (1995, p.42 - 43) and Charemza and Deadman (1997, p.107 - 109). Exactly corresponding the concept of the integration of non-stationary time series, if any seasonal unit roots are found by the seasonal unit root test, then the series is called seasonal integrated. That is the series becomes stationary after appropriate seasonal difference to remove non-stationary seasonal component.  

When two time series have seasonal unit roots, their seasonal pattern are said to be non-stationary. If these non-stationary seasonal patterns move together, they are said to be seasonally co-integrated. Therefore, seasonal cointegration can be considered as an expanded concept of the well-known co-integration at seasonal frequencies. However, the testing for the seasonal co-integration and the estimation of cointegrating vector is

\[\text{An additional first difference may be required to be stationary when the series also contains stochastic}\]
more problematic than the for annual data and this is still underdeveloped area (Charemza and Deadman, 1997, p.130), and as far as I have known, there are only two articles found in the energy demand literatures. They are Clements and Madlener (1999) and Beenstock et al. (1999).

Clements and Madlener (1999) investigate whether or not the UK quarterly residential energy demand, real disposable income, real energy price and air temperature series 1975q4 – 1996q3 have unit roots at the seasonal frequencies using the HEGY test. The test statistics indicate that only the energy demand series has unit root at the bi-annual frequency and the rest of the series have unit root at the zero frequency, but not at any seasonal frequency. Since the frequency of the unit root is different between the energy demand and other variables, implicitly suggesting that there is no possibility of seasonal co-integration, they conclude that the seasonal unit root model cannot characterise the seasonality in the series. This implies that the modeller may face the problem when the seasonal unit roots are found but at the different order in each series because, in the case, the series inevitably have to be differenced at certain order to remove the seasonality and may lose important properties underling in the series. In this study, the seasonal unit root analysis does not seem to contribute significantly to the aim of the study.

Beenstock et al. (1999) is another study in energy demand area which attempt to model electricity demand quarterly series 1973q1 – 1994q4 in Israel in the framework of the seasonal unit root and the seasonal cointegration. Their concern is whether the seasonal pattern of electricity demand is stochastic or deterministic, and if it is stochastic, the trend.
seasonality varies over time and the conventional deterministic seasonal dummy variables cannot capture the seasonal variations (p.169). Therefore, they initially applied the HEGY test to find that the electricity demand and other explanatory variables have seasonal unit roots as well as the zero frequency unit root. Given the presence of the seasonal unit roots, the seasonal co-integration test proposed by Engle et al. (1989) was conducted. The test indicates there is no seasonal co-integration vector at any seasonal frequencies (p.175). Subsequently, they immediately abandon the quest for the seasonal cointegration and take the forth differencing to remove the stochastic seasonality from the series. Then, they move onto the familiar Johansen co-integration test and the Hendry's dynamic regression model with the seasonal differenced series. Hence, in the finally preferred model, the stochastic seasonality is simply removed by a classical seasonal differencing approach.

The consequences of the seasonal unit root test and the seasonal cointegration technique in Beenstock et al. (1999) also highlight the issue behind of these procedures addressing the stochastic seasonality in the energy demand. That is, although the presence of the seasonal unit roots are found by the seasonal unit root test, once seasonally co-integration is not found, there is no way but the stochastic seasonality is simply removed by seasonal differencing. Again, removing seasonality in such a way is far from desirable since the seasonal pattern may contain important information and is better to be kept rather than simply removing from the view point of the current seasonal modelling. Similar to Clements and Madlener (1999), it is reasonable to say that the seasonal unit root test and the seasonal cointegration technique do not take important roles in Beenstock et al. (1999).
Another problem of the seasonal unit root test and the seasonal cointegration technique may be the difficulty of an intuitive interpretation for the presence of the unit root at the seasonal frequency. Neither of Clements and Madlener (1999) nor Beenstock et al. (1999) gives an explanation for the economic implication of the presence of the unit root, for example, at the bi-annual frequency found in the studies. By the same token, the difficulty of the interpretation also can be applied to the seasonal cointegration, although very little energy demand literatures have found the seasonal cointegration. In this regard, Osborn (1993) says "the presence of seasonal unit roots begs the question of what sort of economic mechanism would give rise to this failure of cointegration" (p.300) and "I am still left with the nagging problem that it as no obvious underlying economic rationalisation" (p.302). The lack of an intuitive awareness of the seasonal unit root and the seasonal cointegration, in addition to the mathematical complexity behind the processes, seem to prevent the procedures from common applications to the energy demand analysis.

Finally, as mentioned in Clements and Madlener (1999, p.192), it is known that the test is very sensitive to the choice of the augmented lagged order which is often difficult to be chosen an appropriate order. Harvey (1997, p.198) points out that the seasonal unit root test has a very poor statistical property since the autoregressive approximation fitting stationary process is often a disaster unless a large number of the augmented lags are included32. Therefore, Harvey (1997, p.198) strongly advises not to use the seasonal

32 Note that an inclusion of a large number of lags is likely to reduce the power of the test statistics, causing an increasing probability of an occurrence of the type I error (Clements and Madlener, 1999, p.192).
unit root test as well as the standard unit root test.

3.6.4. Stochastic seasonal dummy variables

An empirical application of the stochastic seasonal dummy approach was introduced by Harvey and Scott (1994) for the UK income-consumption function. This approach assumes that the seasonality evolves stochastically over time and explicitly models them by simply including a stochastic seasonal component. (See Chapter 2 in Harvey, 1989, for the details of the model). This approach can be distinguished from other approaches for a number of reasons as follows.

Firstly, it does not have any prior assumption of a deterministic seasonality, as obviously the deterministic seasonal approach does and the seasonal unit root approach also implicitly does since it has the alternative hypothesis of the stationary seasonality, which is the deterministic seasonality, against the null hypothesis of the non-stationary seasonality. Instead, the stochastic seasonal approach assumes the seasonality in the series may be stochastic, rather than deterministic. The stochastic assumption can be much safer since it can be shown that the deterministic seasonal dummies are restricted versions of the stochastic seasonal dummies. In other words, the stochastic seasonals are more general model than the deterministic seasonals. Harvey and Scott (1994, p.1341 – 1342) show that very little is lost by starting with the assumption of the seasonality is stochastic, even if the true seasonality is deterministic.

---

33 The detailed of this model will be described in Chapter 4.
Second, in contrast to the seasonal unit root and the seasonal cointegration technique, an application and interpretation of the stochastic seasonality are straightforward. The stochastic seasonal dummies do not intend to model the seasonality within the 'stationary' framework, in which a distinction between stationary or non-stationary processes is crucial and, therefore, no statistical test is needed prior to the seasonal modelling. In short, the stochastic seasonal dummies do intend to model the seasonality directly within the structural time series framework\textsuperscript{35}. Moreover, the procedure also does not face the 'dead-end' problem often found in the literatures using the seasonal unit root and the seasonal cointegration technique, unless the seasonal co-integration is identified which rarely seems to occur.

Third, the computation technique required for an estimation of the stochastic seasonal dummies is not as complex as that of the seasonal unit root and the seasonal cointegration technique since the underlying mathematics are relatively simple and easily understandable to applied economists. Finally, the stochastic seasonal dummies can be easily incorporated in the model including the UEDT as a form of a stochastic trend\textsuperscript{36}, as well as any type of normal regression model.

However, there is a minor drawback of the stochastic seasonal dummy model which is the model cannot be estimated by the familiar OLS type regression model since the model directly models the stochastic components. Although the model can be efficiently estimated by the Kalman filtering instead as explained in the later chapter, the limited

\textsuperscript{34} This will be proved in Chapter 4.
\textsuperscript{35} The detailed of the structural time series model will be discussed in Chapter 4 in depth.
\textsuperscript{36} Ditto.
availability of the estimation procedure may be a disadvantage of the stochastic seasonal model.

One of the earlier applications of the stochastic seasonal dummies to the energy demand is Harvey and Marshall (1991) who examine the quarterly UK data 1971q1 – 1986 q4 for the various energy demand within the framework of the translog cost function. In any cases, the seasonality in the energy demand is turned out to be stochastic, implying deterministic seasonal modelling for the energy demand is likely to be questionable. Hunt and Judge (1996) who also explores the evolution of seasonal patterns in various energy demand series in the UK. Their finding shows that the seasonal patterns in the series evolve overtime and the assumption of a deterministic seasonal pattern is clearly inappropriate. More recent application is found in Morana (2000) who analysis the energy demand in Italy using the quarterly data 1978q1 – 1994q4. His result also shows the seasonal pattern in the series changes stochastically. It is interesting that he compare this approach to the seasonal unit root (HEGY) approach. According to his result, stochastic seasonality is preferred to the seasonal unit root test, because the stochastic seasonal model can allow for a flexible modelling of any instability in the seasonal pattern, which is not necessary always generated by the presence of the seasonal unit root (p.81). This finding suggests the stochastic seasonal model is more general than the seasonal unit root model.

The findings in Harvey and Marshall (1991), Hunt and Judge (1996) and Morana (2000) suggest that the seasonal pattern in energy demand series is more likely to be stochastic rather than deterministic. They also indicate a prior assumption of deterministic
seasonality may be not only unreasonable but also misleading. Hence, it is clearly safe to start with as general a model as possible. Given these circumstances and the discussion we have made, it is reasonable to conclude that the stochastic seasonal dummies are the most appropriate method to address the seasonality in energy demand function compared to other procedures.

The flexible modelling of the seasonality as stochastic seasonals can also directly link to the flexible modelling of the UEDT discussed in the earlier part of this chapter. In other words, the model incorporating both stochastic seasonals and a stochastic trend as a flexible form of the UEDT can be the most suitable model. Such a model can provide the most general framework to formulate the UEDT and evolving seasonality. Clearly the model is more flexible than the deterministic seasonal formulation, and more straightforward to apply than the seasonal unit root and the seasonal cointegration technique. Furthermore, the model does not require seasonal differencing to remove seasonality and can avoid any loss of information underlying the series. The flexible modelling of the seasonality can also minimise the possibility of biased estimate generated by an improper modelling of seasonality as well as the UEDT. Therefore, in empirical application in the later section, the model including stochastic seasonals and stochastic trend will be employed, which will be described at length in Chapter 4.
3.7. Summary and conclusion

This chapter has been concerned with the two important aspects of energy demand modelling. One is the Underlying Energy Demand Trend (UEDT), which is a newly defined concept encompassing pure technical progress, changes in consumers taste and economic structure. The other is evolving seasonality which changes its seasonal pattern over time. Although experience suggests that these two aspects are very likely to affect energy demand, the modelling of these factors within the log-linear energy demand function have been poorly treated. However, in order to obtain unbiased estimates of price and income elasticities, it is important that the model should be flexible enough to allow for any evolving pattern in these factors which may present in the demand series.

The first section of this chapter reviewed how the past energy demand literature approached model technical progress, rather than the UEDT, in the log-linear functional framework expressed in a form in the equation (3.1). The vast majority of the past studies attempted to model technical progress using a deterministic linear time trend which were summarised in Table 3.1.

On the whole, except Erdogan and Dahl (1997) for the application to the Turkish economy, the estimated deterministic trend parameters appeared to be negative values, suggesting the linear trend is generally a downward sloping, although the estimates varied for technical progress from -4.06% (Boone et al., 1995) to 0% (Barker, 1995). In

37 Of course, when annual data is used, seasonality issue becomes irrelevant. However, even in that case,
spite of the differences between the studies, there are some common characteristics in
the estimated results. First, the studies concerning the oil and fossil fuel demand
estimated larger values of technical progress compared to the application to the
aggregated energy. This may reflect the substantial increase in energy efficiency in oil
use (an improvement of energy efficiency) and switching other type of fuels (a change
in consumers tastes) after the oil crisis. Second, focusing on the case of the aggregated
energy demand, the estimated technical progress was somewhat around –2% p.a.
indicating the aggregated energy demand may be reduced by around 2% p.a. even
without income and price changes, which is not negligible amount. Third, the model
including a linear time trend tends to produce a relatively higher value of the income
elasticities and, conversely, a lower value (in absolute term) of the price elasticities
compared to the model excluding the time trend.

It was reviewed that there was an intense debate whether or not a linear time trend can
appropriately capture the effect of technical progress between mainly Kouris (1983b)
and Beenstock and Wilcocks (1983). The debate highlights a number of issues
underlying the modelling the UEDT. First, there are substantial differences between the
estimated income and price elasticities with or without a linear time trend in the model.
In other words, the estimated values can be significantly affected by the modelling of
the UEDT. However, it was not accepted which is a biased elasticity compared to the
other. Second, there is a general agreement that a linear time trend is not a satisfactory
measure of the UEDT. However, it was not agreed at all which is better between an
inclusion of the ‘unsatisfactory’ linear time or simple ignorance of technical progress.
Although a clear-cut conclusion was not drawn from the debate, the issues highlighted by them provide an important orientation for a better way of modelling the UEDT.

A number of recent studies have attempted to model technical progress in flexible way, one of which is an endogenous technical progress model. Although the model opens the door to a flexible modelling of technical progress, there are considerable drawbacks of their empirical application to the energy demand. Nonetheless, it is interesting that the estimated price elasticities of the fossil fuel demand in several OECD countries are substantially smaller (in absolute term). Another attempt of a flexible modelling of the technical progress is the stochastic trend model formulated in the structural time series model developed by Harvey (1989). Although so far the stochastic trend model has been applied to the energy demand with the translog model framework, the results seems to have direct implication of substantial benefit to apply the stochastic trend model to the energy demand within the log-linear model framework. The stochastic trend is much more flexible than the deterministic linear trend, and therefore, it is expected to be a much more satisfactory way to model technical progress. Given the importance of flexible modelling of the UEDT, an application of the stochastic trend model is likely to be the most sensible.

The UEDT was then formally introduced which encompasses ‘technical progress’ in past empirical studies used in rather ambiguous fashion within the log-linear energy demand function. Hence, the UEDT is divided into three main parts which are change in technical energy efficiency, consumers tastes and economic structure. Technical energy efficiency can be brought about by embodied technical progress and disembodied
technical progress both of which can be endogenous and exogenous. It has shown that the realisation of embodied technical progress can be slower than that of disembodied technical progress.

It was also argued that exogenous technical progress, both of embodied and disembodied, is more likely to move at a constant rate, whereas endogenous technical progress, both of embodied and disembodied, would not necessarily develop at a constant fixed rate, implies that the fixed rate of deterministic linear trend as the UEDT may be inadequate. It was noted that an improvement of the technical energy efficiency, no matter if it is endogenous or exogenous, embodied or disembodied, leads to a shift in the energy demand curve to the left, which reduces energy consumption at a given level of income and price. This also emphasises the importance to separate out between the technical energy efficiency effect and the normal price and income effects represented by the symmetric price and income responses along with the demand curve.

It was argued that change in consumer tastes, which is another component of the UEDT, can lead to the demand curve either way to the left and the right. In the case of the latter, the effect of an improvement of technical energy efficiency can be largely offset, causing an ultimate increase in energy demand even if income and price remain constant. In this case, the demand curve is shifted to the right. A number of empirical studies have pointed out the effect of changes in consumer tastes on energy demand is not negligible. However, numerical measuring of changes in consumer taste in aggregated level is practically unattainable. Hence, it was noted that the UEDT takes into account the effect of changes in consumer tastes, which is assumed to be exogenous.
A change in economic structure also affects the energy demand, hence it is included in a part of the UEDT.

The theoretical section briefly described that the UEDT is can easily be incorporated in the right hand side of the log-linear energy demand function as shown in equation (4.6). It was theoretically presented that biased income and price elasticities are likely to be obtained when the UEDT is ignored or inadequately modelled. Both of an underestimation and an overestimation may equally occur for income and price elasticities depending on the conditions such as the ‘true’ direction of the UEDT, and the general tendencies of income and price series.

Figure 3.1 and 3.2 illustrate all the possible biased elasticity estimates for income and price changes. The findings in the review for the UEDT modelling, that is for instance relatively lower income elasticities were estimated when the model does not include any trend to capture the UEDT effect, are generally consistent to what the theoretical argument suggests. The possibility of biased estimate further emphasises the significance of flexible and proper modelling of the UEDT.

It became clear that modelling the UEDT must be in flexible way as possible since the UEDT can move any direction and can be non-linear, in contrast to an approximation by a deterministic linear time trend. Then, as a preferable modelling of the UEDT, a stochastic trend, in place of a deterministic linear time trend, was presented within the log-linear functional framework. It was stressed that a stochastic trend is flexible and general which encompasses a deterministic time trend as a special restricted case.
Therefore, the UEDT modelling with a stochastic trend can have a direct linkage to the general to specific approach in the estimation process.

Modelling of evolving seasonality in energy demand was considered in length in the second half of this chapter. Seasonality issue has seem to be of little interest for energy demand modellers since the vast majority of empirical energy demand studies deal with annual data series, rather than quarterly or monthly data series, mainly due to a poor availability of higher frequency energy data series. However, in terms of statistical efficiency, the higher frequency data is clearly preferred to annul data which sometimes consists of only 10 to 20 observations. The problem of higher frequency data series is that, since the energy data is almost always subject of systematic seasonal variations, modellers have to handle the seasonality in an appropriate way.

Then, various ways of the seasonality modelling were examined keeping application to the energy demand in mind. Deterministic seasonal dummy variables were the most popular way to handle seasonality. However, the model assumes \textit{a priori} the seasonal pattern remain constant over time. There is plentiful evidence in many time series that the seasonal pattern of the series is not only unnecessarily constant, but perhaps more like to be stochastic. Hence, this procedure may be improper to model seasonality in energy demand.

Seasonal differencing was also considered. However, this method is not ideal since it completely removes seasonality in the series, which may contain valuable information underlying the series. This is not in line with the recent seasonality modelling, which
explicitly modells seasonality rather than removing it. Seasonal unit root and seasonal cointegration is arguably also not the most suitable model for energy demand estimation. This is because:

- When the seasonal unit root test detects any seasonal unit root in the series and if the seasonal cointegration is not found, there is no other way but a simple seasonal differencing, losing a long-run information underlying the series;
- The outcomes, in particular the seasonal cointegration, given by the model are difficult to interpret;
- The statistical property of the test for seasonal unit root and the seasonal cointegration is poor, and is heavily criticised by Harvey (1997).

Finally, the stochastic seasonal dummy model was examined. The model has a number of advantages which seem to be particularly suited to the energy demand estimation within the log-linear model framework, which are:

- The model directly models the stochastic seasonals as they are, and does not require seasonal differencing at any cases;
- It does not have any prior assumption of the deterministic seasonality;
- The flexible modelling of the stochastic seasonality can directly link to the flexible modelling of the UEDT considered in the first half part of this chapter;
- An application and interpretation of the stochastic seasonality is fairly straightforward;
- Computation technique required for an estimation of the model is not as complex as that of the seasonal unit root and the seasonal cointegration model.
Taking into account these advantages of this model compared to other procedures, it is reasonable to conclude that the stochastic seasonal model is the most appropriate for the application to the energy demand.

In conclusion, it can be stressed again that the most important issue for the energy demand estimation within the log-linear model framework is that the model should be as flexible as possible to accommodate the UEDT and seasonality. A failure of appropriate modelling of the UEDT and the seasonality is likely to result in obtaining unfavourable biased income and price elasticities of energy demand. Therefore, given these circumstances, the structural time series model which includes a stochastic time trend and stochastic seasonal dummies can be considered as the optimal methodology. This is introduced and discussed in detail in the next chapter.
CHAPTER 4. MODEL AND METHODOLOGY

4.1. Introduction

This chapter considers the model and methodology as well as the estimation strategies that will be employed in the latter empirical part of this thesis. The previous chapter highlighted, in the past, how the UEDT has been ignored or modelled, at best, by a linear time trend which has began to be questioned by a number of recent studies as it is based on too restrictive exogenous assumption. It was also shown that ignoring or inadequate modelling the UEDT, is likely to result in biases of estimated price and income elasticities. Therefore, it is vital to model the UEDT in as flexible form as possible.

In addition to the UEDT, it was also discussed that seasonality in energy demand, which is often observed in higher than annual frequency data, have been commonly modelled by deterministic seasonal dummy variables. Similar to the deterministic trend, deterministic seasonal dummies can be criticised as being too restrictive considering the fact that a number of studies found seasonal movement in energy demand are in fact not stationary or stochastic. Seasonal differencing and seasonal cointegration techniques tackling non-stationary seasonality have not widely been used due to both lack of long-run perspective, the very complex estimation process and the difficulty of using in applied economic research. Therefore, flexible modelling of seasonal fluctuation is required as well as flexible modelling of the UEDT.
In order to model the UEDT and seasonality in a general and flexible way, it was proposed that the structural time series approach is an ideal vehicle for estimation in these circumstances. In addition, Chapter 2 indicated that the log-linear model is still useful model, particularly in connection to the general to specific approach developed by Professor D. F. Hendry. The structural time series model also has a direct linkage to the general to specific approach, since a stochastic trend and stochastic seasonals incorporated in the model are more general than the deterministic trend and deterministic seasonals. Therefore, the framework adopted for the empirical analysis in this thesis combines the structural time series model and the log-linear model with an ARDL dynamic modification allowing for both a stochastic trend and stochastic seasonality. This general to specific approach can be adopted and is the most general model which will be tested down to the specific preferred model.

The cointegration technique, which has dominated time-series empirical modelling for the past decade as seen in Chapter 2, can be critically compared to the structural time series model based on the argument in Harvey (1997). Cointegration is led by a common trend in more than one series which must move together in the long-run (Harvey, 1989, p.9). However, an existence of a co-integration relationship between series does not necessary prove that the relationship is a long-run and often support is needed from relevant economic theory (Charemza and Deadman, 1997, p.133). As discussed in the previous chapter, because energy demand is essentially derived demand, an existence of technical progress in energy usage brings about the question whether energy demand, economic activity and energy price have a stable relationship in the long-run. For instance, the comment by Bentzen and Engsted (1996) on Jones (1993)
points out that petroleum consumption, the real oil price and real GNP in the US all appear to be non-stationary but they do not cointegrate, suggesting there does not exist a long-run relationship between them. The authors claim that the reason for the non cointegration is that energy efficiency or technical progress is likely to exert a strong influence on the level of energy consumption (Bentzen and Engsted, 1996, p.786). This implies that technical progress in energy usage can be the source of non-stationary (Hendry and Juselius, 2000, p.4) and, therefore, in my opinion, it is better to model it as a stochastic trend rather than assuming there is a common trend between energy demand, economic activity and real energy price\(^1\). This is contrast to the cointegrated relationship between aggregated income and consumption in the UK, for example, which is theoretically strongly supported (Charemza and Deadman, 1997, p.133)

Furthermore, the so-called ‘unit-root revolution’ often implied that, if working with time series data, modellers were not undertaking legitimate econometric modelling unless they were using co-integration. This is the case with energy economics, as in other areas, where a substantial amount of time and effort has been employed seeking a cointegrating vector for energy demand relationships. However, the reliance on the cointegration technique has been questioned (for example see Maddala and Kim, 1998, p. 487 – 488). In particularly, as already mentioned in Chapter 2, Harvey (1997, p196) heavily criticises the unit-root test and the cointegration methodology as unnecessary and/or a misleading procedure due to, amongst other things, its poor statistical properties. This is equally applicable, in my view, to energy demand modelling.

---

\(^1\) Hendry and Juselius (2000) say that “There are many plausible reasons why economic data may contain stochastic trends. For example, technology involves the persistence of acquired knowledge, so that the
Therefore, this thesis follows Harvey’s (1997) modelling procedure “to combine the flexibility of a time series model with the interpretations of regression” which is “exactly what is done in the structural time series approach” (p. 200). It should be stressed again that this approach does not ignore possible non-stationary processes in series unlike conventional modelling before ‘unit-root revolution’ occurred. Rather, the model explicitly or directly forms non-stationary or stochastic component as the UEDT.

The structure of this chapter is as follows. The next section presents the basic modelling framework which is followed by Section 4.3 of a full description of the structural time series model. Section 4.4 outlines the estimation strategies adopted in the empirical chapters. After a brief note for the data in section 4.5, the last section presents a summary and conclusion. Appendix 4.1 provides the technical details of a space state form and the Kalman filter which are used for estimation of the structural time series model. Finally, Appendix 4.2 explains the data sources.

present level of technology is the cumulation of past discoveries and innovations. Economic variables depending closely on technological progress are therefore likely to have a stochastic trend” (p.5).
4.2. Basic modelling framework

Throughout this study, it is assumed that energy demand is defined by the following function:

\[ E = f(Y, P, \mu, \gamma, TEMP) \]  \hspace{1cm} (4.1)

where

- \( E \) = aggregated energy demand
- \( Y \) = level of economic activity in real terms
- \( P \) = aggregated real energy price
- \( \mu \) = UEDT (technical progress, change in tastes etc.)
- \( \gamma \) = seasonal component^2
- \( TEMP \) = temperature variable.

The experience suggests air temperature very often affects the energy demand and therefore \( TEMP \) variable is included. This additional variable does not have a major impact on the discussion below^3.

To allow for flexible dynamics, the function is specified as a log-linear autoregressive distributed lag (ARDL) model as follows:

\[ A(L)e_t = \mu_t + \gamma_t + B(L)y_t + C(L)p_t + \epsilon_t \] \hspace{1cm} (4.2)

where

- \( e_t \) = log of aggregated energy demand
- \( y_t \) = log of economic activity
- \( p_t \) = log of aggregated energy price

---

^2 The seasonal component is ignored when annual model is considered.
\[ A(L) = \phi_0 - \sum_{i=1}^{p} \phi_i L^i, \phi_0 = 1 \]
\[ B(L) = \sum_{i=0}^{q} \psi_i L^i \]
\[ C(L) = \sum_{i=0}^{r} \delta_i L^i \]
\[ L^i = \text{the lag operator for } i^{th} \text{ order} \]
\[ \varepsilon_t = \text{residuals}^4. \]

Beginning with a fairly generous lag length, the model will be successively tested down until the most parsimonious model is obtained. This will be guided by a battery of diagnostic tests, which will be explained in the section on estimation strategy. The solved static long-run equation is given by:

\[ e_t = \mu_t + \gamma_t + \Gamma^* y_t + \Pi^* p_t + \varepsilon_t \quad (4.3) \]

where the long-run income elasticity of the energy demand \( \Gamma^* \) is given by:

\[ \Gamma^* = \frac{\sum_{i=0}^{q} \hat{\psi}_i}{1 - \sum_{i=1}^{p} \hat{\phi}_i} = \frac{B(L)}{A(L)} \quad (4.4) \]

Similarly, the long-run price elasticity of the energy demand \( \Pi^* \) is given by:

\[ \Pi^* = \frac{\sum_{i=0}^{r} \hat{\delta}_i}{1 - \sum_{i=1}^{p} \hat{\phi}_i} = \frac{C(L)}{A(L)} \quad (4.5) \]

\[ ^3 \text{For simplicity, } TEMP \text{ is excluded in the model description section.} \]

\[ ^4 \text{The smoothed estimator of the residual is called as the irregular component, which will be described in a later section.} \]
To model the UEDT and seasonality in as flexible form as possible, the log-linear ARDL model is combined with the structural time series model described below.

4.3. The structural time series model

The structural time series model has been developed by Professor A. C. Harvey at the University of Cambridge and his associates. The structural time series model treats a time series as a composition of trend, seasonal and irregular components. The central model used in this study is a regression model combined together with the structural time series model allowing for the unobservable trend and seasonal components that are permitted to vary stochastically over time. This approach was originally introduced by the pioneer work of Harvey et al. (1986) for the employment - output model in the UK.

To look into the structural time series model, consider the following quarterly model which corresponds to equation (4.2) but the explanatory variables are in the matrix form:

\[ e_t = \mu_t + \gamma_t + Z_t'\delta + \epsilon_t. \]

\[ (4.6) \]

\( Z_t \) is a \( k \times 1 \) vector of explanatory variables in logs (price, income and temperature), \( \delta \) is a \( k \times 1 \) vector of unknown parameters. The irregular component \( \epsilon_t \) is an equivalent of

---

5 The technical parts of this section rely on Harvey (1989), Harvey (1997) and Harvey et al. (1986).
6 Although a cyclical component can also be added in the equation, a number of empirical results to energy demand series demonstrated by Harvey (1989, Chapter 2) suggest it is unlikely to exist in the series and therefore not included.
the residuals in the conventional equation model reflecting non-systematic movements and is assumed to be white noise, i.e. \( \varepsilon_t \sim \text{NID}(0, \sigma^2) \). \( Z_t \) may include lagged values of the dependent variable as well as lagged values of explanatory. The lag structure of \( Z_t \) is assumed to be ARDL as explained in the previous section. The key feature of the structural time series model concentrates on the explicit modelling of the stochastic trend and the seasonal components, while the explanatory variables take the same role as in the conventional model and can be interpreted as usual.

The structural time series model can be estimated by the Kalman filter which is conceptually an extension of the recursive least estimation\(^7\). Therefore, the estimated values are sequentially estimated as a one-step-ahead predictors using the information available at time \( t \) in the same fashion of the recursive least square. These filtered estimators are smoothed using the information available after \( t \), giving the smoothed estimator\(^8\). The smoothed estimators of \( \varepsilon_t \) (which is denoted as \( \varepsilon_{t|T} \)) are called the auxiliary residuals of the irregular component. They are serially uncorrelated white noise disturbance term, which may be considered as an equivalent of the residuals of the conventional OLS type model\(^9\).

The modelling of the trend and the seasonal components in the structural time series model are explained below.

---

\(^7\) The technical details of the Kalman filter will be given in Appendix 4.1.
\(^8\) The technical details of the smoothing within the Kalman filtering process will be explained in Appendix 4.1.
\(^9\) The useful role of the irregular component will be discussed shortly.
4.3.1. Trend component

The trend component \( \mu_t \) is assumed to have the following stochastic process:

\[
\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \quad (4.7)
\]

\[
\beta_t = \beta_{t-1} + \xi_t \quad (4.8)
\]

where \( \eta_t \sim NID(0, \sigma_\eta^2) \) and \( \xi_t \sim NID(0, \sigma_\xi^2) \).

Equations (4.7) and (4.8) represent the level and the slope of the trend respectively. This process can be interpreted as the trend this period is the trend last period plus a growth term plus some unpredictable noise, in which the growth term is the slope and is time-varying. The variances \( \sigma_\eta^2 \) and \( \sigma_\xi^2 \) are called the hyperparameters. They have an important role in that they govern the basic properties of the model. Table 4.1 illustrates the various models that can be estimated from this process according to whether the values of the hyperparameters are zero, or whether the slope component exists.

Table 4.1 Classification of possible stochastic trend models

<table>
<thead>
<tr>
<th>SLOPE</th>
<th>LEVEL No Level</th>
<th>Fixed Level</th>
<th>Stochastic Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Slope</td>
<td>Lvl = 0, ( \sigma_\xi^2 = 0 )</td>
<td>Lvl ( \neq 0 ), ( \sigma_\eta^2 = 0 )</td>
<td>Lvl ( \neq 0 ), ( \sigma_\eta^2 \neq 0 )</td>
</tr>
<tr>
<td>Fixed Slope</td>
<td>(iv) Conventional regression but with no constant and no time trend</td>
<td>(v) Conventional regression with a constant and a time trend</td>
<td>(vi) Local Level Model with Drift.</td>
</tr>
</tbody>
</table>

10 The seasonal component is ignored in section for simplicity and clarity.
Cell (ix) of Table 4.1 represents the most general model, the local trend model, when

\[ \sigma_n^2 \neq 0 \] and \[ \sigma_z^2 \neq 0 \] so that both the level and slope of the trend change stochastically over the sample period. The model implies that the growth in the trend \( \Delta \mu_t \) is assumed to be equal to a stochastic growth parameter \( \beta_{t-1} \), which evolves as a random walk, associated with a random disturbance term \( \eta_t \). In this case, the first difference of equation (4.6) becomes:

\[ \Delta e_t = \Delta \mu_t + (\Delta Z_t) \delta + \Delta \epsilon_t \] (4.9)

where \( \Delta \) is the first-difference operator.

Substituting (4.7) into (4.9) gives:

\[ \Delta e_t = \beta_{t-1} + \eta_t + (\Delta Z_t) \delta + \Delta \epsilon_t \] (4.10)

where, \( \beta_{t-1} \) has a unit-root process. Thus, it is clear that the trend is still non-stationary even after the first-differencing. However, taking second-differencing, (4.10) becomes:

\[ \Delta^2 e_t = \Delta^2 \mu_t + (\Delta^2 Z_t) \delta + \Delta^2 \epsilon_t \] (4.11)

where \( \Delta^2 \) is the second-difference operator.

Substituting (4.7) into (4.11) gives:
\[
\Delta^2 e_t = \Delta \beta_{t-1} + \Delta \eta_t + (\Delta^2 Z_t)\delta + \Delta^2 \epsilon_t. \tag{4.12}
\]

Using (4.8), (4.12) can be written as:

\[
\Delta^2 e_t = \xi_{t-1} + \Delta \eta_t + (\Delta^2 Z_t)\delta + \Delta^2 \epsilon_t \tag{4.13}
\]

By the assumption, the trend component in (4.13), which consists of \(\xi_{t-1}\) and \(\Delta \eta_t\) are now both purely random. Therefore, after the trend is differenced twice, it becomes stationary, indicating it is integrated of order two or I(2).

The remaining cells of Table 4.1 represent possible restricted alternatives, depending upon the estimates of the level and slope of the trend and the hyperparameters, \(\sigma_{\xi}^2\) and \(\sigma_{\eta}^2\). Cells (iii), (vi) and (viii) are restricted versions of the general stochastic trend model but still involve some form of stochastic trend in the level or slope. For example, if \(\sigma_{\eta}^2 = 0\) but \(\sigma_{\xi}^2 \neq 0\) it is the Smooth Trend which is in cell (viii). In this case, the trend is associated with fixed level and stochastic slope, exhibiting a slowly changing direction of the trend. As seen the local trend model, this trend is also I(2). The first-differencing of this type of the trend becomes:

\[
\Delta e_t = \beta_{t-1} + (\Delta Z_t)\delta + \Delta \epsilon_t. \tag{4.14}
\]

However, from (4.8), \(\beta_{t-1} = \beta_{t-2} + \xi_{t-1}\), which shows that (4.14) still contains

\[\text{cells (iv) and (vii) of Table 4.1 are ignored since it is not possible to estimate models of this type.}\]
non-stationary unit-root process. Then, second-differencing gives:

\[ \Delta^2 e_i = \xi_{i-1} + (\Delta^2 Z_t) \delta + \Delta^2 \epsilon \]  

(4.15)

where there is no longer a stochastic element in (4.15). Therefore, like the local trend, the smooth trend is I(2). Harvey (1997) particularly emphasises that unit root tests are likely to fail to detect that the smooth trend is I(2), since if it differenced twice, it is close to non-invertibility, and real macroeconomic time series in fact can be modelled as the smooth trend and I(2) on the contrary to economists' common recognition (p.197)\(^{12}\).

If \( \sigma_y^2 \neq 0 \) but \( \sigma_{\xi}^2 = 0 \) the trend is called the *Local Level with Drift* provided the slope is non-zero (slp \( \neq 0 \)) or cell (vi), and it is called as the *Local Level (random walk with drift)* if the there is no slope (slp \( = 0 \)) or cell (iii). In these two cases, the stochastic trends are I(1). To illustrate this, taking first-difference (5.6) in the case of the local level with drift (cell (vi)) gives:

\[ \Delta e_i = \Delta \mu + (\Delta Z_t) \delta + \Delta \epsilon_i. \]  

(4.16)

which can be shown as:

\[ \Delta e_i = \beta_{i-1} + \eta_i + (\Delta Z_t) \delta + \Delta \epsilon_i \]  

(4.17)

\(^{12}\) This is equally true in some energy series, as explained in later chapters.
Although (4.17) seems to be synonymous with (4.10), $\beta_{-1}$ is no longer stochastic but fixed over time since $\sigma^2 = 0$. In other words, the trend component $\beta_{-1}$ and $\eta_t$ are both stationary. Thus, in this case, a first-differencing of (4.6) becomes the trend stationary i.e. the local level with drift is $I(1)$.

Similarly, when the trend is the local level model (cell (iii)), the first-differencing of (4.6) provides:

$$\Delta \epsilon_t = \eta_t + (\Delta Z_t) \delta + \Delta \epsilon_t \quad \quad (4.18)$$

Again, there is no stochastic element. Hence, the local level is $I(1)$.

It has been shown that the stochastic trend modelled in (4.7) and (4.8) are either $I(1)$ or $I(2)$\(^3\). This implies that if these stochastic trends are not appropriately modelled, for instance, by a linear time trend or just ignored, the non-stationary component still remains in the residuals. Therefore, a linear combination of energy demand, economic activity and real energy price (and temperature in some cases) will also be non-stationary. As a result, they are not co-integrated and the likely result is a spurious regression. In contrast, within the structural time series model framework, the trend is explicitly modelled as non-stationary element which can be interpreted as the UEDT in the energy demand function. In this case, the residuals are stationary white noise processes by which the model is completely free from the ‘non-stationary problem’.

\(^3\) However, in fact, within the structural time series model framework, it is not critical to examine the degree of integration (Harvey, 1997, p.196). It is presented here to make an intuitive linkage between the structural time series model and the ‘familiar unit-root’ model for a comparison purposes.
This is one of the distinct advantages of the structural time series model. In the conventional cointegration model, unless the series are actually co-integrated, the model unavoidably suffers from the 'non-stationary problem'. Then, researchers tend to spend enormous time and energy, which may be unnecessary, to seek 'possible cointegration' which must be found by all means in the modelling framework. It is worth re-emphasises that, in the energy demand function, co-integration is unlikely to occur due to an existence of UEDT in energy use as discussed in the previous chapter.

As special cases of the general stochastic trend models, cells (i), (ii) and (v) illustrate the conventional regression models (ignoring evolving seasonals) which can be estimated by OLS. When both of the hyperparameters are zero, namely \( \sigma^2_\eta = 0 \) and \( \sigma^2_\zeta = 0 \), equation (4.6) reverts to a conventional deterministic linear trend model, cell (v), as follows (Harvey, 1989, p.37):

\[
e_t = \alpha + \beta t + Z_t \delta + \epsilon_t
\]  

(4.19)

In this case, the trend is characterised by a trend-stationary process where non-stationary elements are fully explained by a linear time trend. Note that the conventional models (cell (i), (ii) and (v)) are the deterministic restricted cases of the general local trend model (cell (ix)) and other stochastic trend model (cell (iii), (vi) and (viii)). These deterministic restrictions can be formally tested by an appropriate restriction test, provided the restricted model is nested by the general model\(^{14}\). In

\[^{14}\] The restriction test employed in the later empirical chapters will be outlined shortly.
contrast, a linear time trend is normally used in a rather arbitrary fashion in the conventional model. Concerning this point, Harvey (1997) argues that “very little, if anything, is lost by starting off with a general stochastic trend model which has the deterministic slope and level as special cases” (pp.196–197).

As mentioned for the irregular component in equation (4.6), the smoothed estimators of $\eta$ and $\xi$ are also called the auxiliary residuals for the level and the slope components respectively. One of the attractions of the structural time series model is that the auxiliary residuals for the level and slope as well as the irregular components can be used to identify possible structural break and outliers in the series. This is because they may be able to separate out the relevant information which are often mixed up in the normal equation residuals. As demonstrated by Harvey and Koopman (1992), excess estimated values of auxiliary residuals for irregular component by a correctly specified model can be indications of outliers of the series. Similarly, structural break of series, such as a permanent shift in the level of a series, can be detected by excess values of auxiliary residuals for level component estimated by correctly formulated model.

In practice, the tests for excess kurtosis and skewness combined with the Bowman – Shenton test for normality of the auxiliary residuals can be used for a formal check of their excess values (Harvey and Koopman, 1992, p.381). In terms of the auxiliary residuals for the slope component, although it also may be used for to identify a sudden change in the slope, Harvey and Koopman (1992) say it is more difficult for a number of technical reasons. Nonetheless, non-existence of excess values of the auxiliary residuals for the slope indicates that, at least, there is no sudden change in the slope and
therefore it is still a meaningful indicator.

Therefore, in the application sections, the Bowman–Shenton test statistics (for normality, kurtosis and skewness) for the auxiliary residuals will be reported along with the ‘traditional’ diagnostic test statistics, which will be explained in the later section. If no significantly large statistics appears, it implies there is not substantial structural break or/and outlier in the series.

4.3.2. Seasonal component

Following the pioneer work by Harvey and Scott (1994), the ‘general’ seasonal model allows the component $y_t$ to have the following stochastic process for the quarterly model (4.6):

$$S(L)y_t = \omega_t,$$  \hspace{1cm} (4.20)

where $\omega_t \sim NID(0, \sigma_\omega^2)$, $S(L) = 1 + L + L^2 + L^3$ and $L$ = the lag operator.

This is called as the dummy variable form of stochastic seasonality, since the seasonal pattern can change stochastically in this formulation. The well-known conventional seasonal dummies represent seasonal effect by shifting the regression equation vertically upward and downward by fixed amounts for each season so that the seasonal effects sum to zero in each seasonal cycle. In contrast, the stochastic seasonal dummies shift vertically freely for each season and the sum of the stochastic seasonal dummies
do not necessary need to sum to zero, but some value of $a_t$ with the variance of $\sigma_{o}^2$. Since $a_t$ is purely random process, its mean value over one cycle period will be zero. In the same fashion as the stochastic trend, this variance $\sigma_{o}^2$ is also called the hyperparameter, which determines the nature of the seasonal component. The conventional case (ignoring the stochastic trend) is again a restricted version of the general stochastic seasonal dummies when $\sigma_{o}^2 = 0$ with $\gamma$ reducing to the familiar deterministic seasonal dummy variable model. The restriction can therefore be statistically tested. If this restriction is not accepted, seasonal components are moving stochastically over time and have to be modelled by the general stochastic seasonal model. This general (stochastic) to specific (deterministic) process will be consistently adopted throughout the later empirical analysis sections. Again, Harvey and Scott (1994) show that even if the true seasonal pattern is deterministic, very little is lost regarding estimation efficiency (p.1342).

4.3.3. Various combinations of the trend and the seasonal components

The previous sections describe how the structural time series model incorporates stochastic trend and seasonal components, and they also can be modelled as deterministic trend and seasonal components if the deterministic restrictions are accepted by appropriate statistical tests. This means that, in practice, there are a number of possible combinations of trend and seasonals both/either of which are deterministic and/or stochastic. For example, a model with a stochastic trend may not necessarily have stochastic seasonal component, but, instead, it may have deterministic seasonal

---

15 This section relies on Harvey and Scott (1994).
component. Conversely, it is also possible that a model has stochastic seasonal component and a deterministic trend. The six possible combinations are summarised in Table 4.2.

Table 4.2. Possible combinations of deterministic and/or stochastic trend and seasonals

<table>
<thead>
<tr>
<th>Deterministic Seasonals</th>
<th>II: Deterministic Linear Trend (cell (v))</th>
<th>III: Stochastic Trend (cell (iii)(vi)(ix)(viii))</th>
</tr>
</thead>
<tbody>
<tr>
<td>I: No Trend (cell (i)(ii))</td>
<td>Model (1): No Trend and Deterministic Seasonals</td>
<td>Model (5): Stochastic Trend and Deterministic Seasonals</td>
</tr>
<tr>
<td>I: No Trend (cell (i)(ii))</td>
<td>Model (3): Deterministic Trend and Deterministic Seasonals</td>
<td>Model (5): Stochastic Trend and Deterministic Seasonals</td>
</tr>
</tbody>
</table>

Note: Cell numbers (i) to (viii) correspond to those in Table 4.1.

Model (6) of Table 4.2 is the most general model possible in which both of trend and seasonal components are stochastic. On the other hand, Model (1) is the most restricted model which has no trend and deterministic seasonal component. Model (1) and (3) are conventional models which can be efficiently estimated by OLS.

When annual data is considered, since seasonal components disappear, only the first row of Table 4.2 becomes applicable. In this case, the possible models are limited to:

Cell I: No Trend Model

Cell II: Deterministic Trend Model

Cell III: Stochastic Trend Model.

Similar to the case of quarterly data, Cell III is the most general model and Cell I and Cell II are the restricted versions of Cell III. Cell I and Cell II can be estimated by OLS.
In Chapter 5 and 6, the estimated results will be compared between the models categorised in Table 4.2. In the empirical sections of this thesis, the estimated results will be compared between the models categorised in Table 4.2. i.e. models (1) to (6) will be compared in quarterly data case, and No Trend (Cell I ), Deterministic Trend (Cell II) and Stochastic Trend (Cell III) will be compared in annual data case.

4.3.4. State space form and the Kalman filter

Thus far, we have seen the modelling framework featuring the structural time series model which will be adopted in the later empirical chapters of this thesis. This section considers how the model is actually estimated. The structural time series model is an unobservable components model since the trend and seasonal components are not directly observed. The unobservable components model is 'non-standard' which cannot employ familiar 'least squares' procedures. However, once the equations (4.6) with (4.7) (4.8) and (4.20) are re-set out in the following state space form as two separate equations, one is the transition equation and the other is the measurement equation, then the Kalman filter\(^\text{16}\) can produce a batch of recursive equations which can be used to estimate unknown parameters through the maximum likelihood procedures (Cuthbertson et al., 1992, p.192).

In the state space form, unobserved parameters such as the trend, the seasonal components are treated as state variables.

\(^{16}\) For the detail of the Kalman filter, see Appendix 4.1.
A transition equation is defined as:

\[
\alpha_t^* = \begin{bmatrix}
\mu_t \\
\beta_t \\
\gamma_t \\
\gamma_{t-1} \\
\gamma_{t-2} \\
\delta_t
\end{bmatrix} =
\begin{bmatrix}
1 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & -1 & -1 & -1 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & I
\end{bmatrix}
\begin{bmatrix}
\alpha_{t-1} \\
\beta_{t-1} \\
\gamma_{t-1} \\
\gamma_{t-2} \\
\gamma_{t-3} \\
\delta_{t-1}
\end{bmatrix} +
\begin{bmatrix}
\eta_t \\
\xi_t \\
\omega_t \\
0 \\
0 \\
0
\end{bmatrix}
\] (4.21)

where \( \alpha_t^* \) = state vector and \( I \) = identity matrix.

An associated measurement equation is:

\[
e_t = (1 \ 0 \ 1 \ 0 \ 0 \ Z'_t) \alpha_t^* + \epsilon_t.
\] (4.22)

The measurement equation (4.22) corresponds to equation (4.6). The role of the measurement equation is to connect the unobservable state vector \( \alpha_t^* \) to the observable scalar values of \( \epsilon_t \), aggregated energy demand. The explanatory variables \( Z_t \) provide additional information of \( k \) observable variables to explain the evolution of the energy demand as well as the trend \( \mu_t \) and seasonal components \( \gamma_t \). If the evolution of the energy demand is fully explained by the explanatory variables (economic activity, real energy price and temperature), the trend component would reduce to a constant term and the seasonal component would be unnecessary (Harvey, 1989, p.366).

The transition equation (4.21) describes the dynamics of the state vector in time domain.

The combination of (4.20) and (4.21) attempts to estimate unobservable variables using
observable variables. Note that \( \delta \), which is the unknown parameters of the explanatory variables, is associated with the identity matrix, indicating the parameters are assumed to be constant. In contrast, the trend and seasonal components are given stochastic movements as defined in the previous sections.

All the disturbances are assumed to be independent and mutually uncorrelated. The hyperparameters \( \sigma^2_n, \sigma^2_x, \sigma^2_\omega, \) and \( \sigma^2_\varepsilon \) are estimated by the Kalman filter recursive equations and the maximum likelihood procedures, and having these parameter values, the optimal estimates of \( \beta_T, \mu_T \) and \( \gamma_T \) are estimated by the Kalman filter, where \( \beta_T, \mu_T \) and \( \gamma_T \) represent the latest estimates of the slope, the level and the seasonal components in each period. Optimal estimates of the trend and seasonal components whole sample period are calculated by smoothing algorithm of the Kalman filter, thereby evolution of the trend and seasonal components can be traced. The software package STAMP 5.0 (Koopman et al., 1995), which implements the above structural time series model is used to estimate the model.

4.4. Estimation strategies in the empirical chapters

The modelling framework and specifications employed in the empirical chapters of this thesis has been described. This section outlines the estimation strategies employed in the empirical chapters of this thesis, where a number of energy demand functions for various sectors and fuel are estimated for the UK and Japan.

Recall that Chapter 3 highlighted that an inappropriate modelling of the UEDT and
seasonality may lead to a biased estimator, suggesting it is vital to model them as flexible form as possible. Therefore, it will be demonstrated that how the structural time series model in the form of equation (4.6) can manage to estimates of income and price elasticities through the proper modelling of the UEDT and seasonality in comparison to the restricted models classified in Table 4.2.

Each model in Table 4.2 is estimated using the general to specific approach i.e. a sequential tested down to parsimonious model guided by a battery of the diagnostics and the post sample prediction failure test. Even if the general model (e.g. Model (6)) is found to be preferred model to the other restricted models (e.g. Model (1)), the latter models are also estimated with the particular restricted from(s) of trend or/and seasonal. The estimated results given by these models are expected to indicate how the different specifications of the trend (the UEDT) and seasonality ultimately affect them.

Whenever available, quarterly data series is used for the estimation. However, due to the data availability, annual data series inevitably will be used for some cases in Japan. Therefore, the estimation process for the annual data series will differ from the quarterly data case, since the annual data series does not show a seasonal pattern and seasonality is not therefore an issue. This means that, when annual data series is considered, the classification of Table 4.2 is simplified to the first row only; No Trend Model, Deterministic Linear Trend Model and Stochastic Trend Model.

For all of the UK energy demand, and the oil transportation and the electricity demand in Japan, the set of the quarterly data series is available. The data set for the sectors
consists of unadjusted data from 1971q1 to 1997q4 except the electricity demand in Japan which is ended at 1997q1 due to the data availability. Each model starts with four quarterly lags and insignificant variables are sequentially dropped from the equation taking into account the omission effects on the diagnostics. Hence, the equation is estimated from 1972q1 for all models categorised in Table 4.2. They ended in 1995q4 in order to save the two-year 1996 and 1997 (8 observations) for the post-sample prediction test\textsuperscript{17}, which will be explained shortly. Only if the preferred model is found to be one of the restricted model in Table 4.2 (e.g. some models other than Model (6)), the more general model than the preferred model is not considered since such comparison my not be very useful.

Only annual data is available for the aggregated energy whole sector, manufacturing sector, and the residential sector in Japan. For the sector, annual data set from 1965 to 1999 holding 3 observations 1996 to 1999 for the post-sample prediction test. The models estimated are three models shown in the first row of Table 4.2. Due to a limited number of the observations, the each model begins with two annual lags and it is tested down keeping the trend specifications remain constant.

For the testing down procedure under the general to specific approach, a number of criteria listed below will be applied to a model selection (Thomas, 1993, p.148 – 149).

- Data coherency: the residuals of the preferred models should be entirely random and white noise. In other words, the residuals of the preferred model should be, at least, free from autocorrelation and heteroscedascity. In addition, the normality of

\textsuperscript{17} For the electricity demand in Japan, 1996q4 – 1997q1 (5 observations) is used for the test.
the residuals should be ensured.

- Consistency with theory: the model should have reasonable economic sense and the estimated results conform to the norms of conventional economics. For example, the model estimates positive price elasticity for normal goods should not be acceptable.

- Parsimony: the preferred model should contain as little explicit variables as possible. In other words, a simpler model is always preferred to a complex model under the same conditions.

- Encompassing: the preferred model should encompass all or at least most of the rival models.

- Parameter consistency: the parameters values of the preferred model should remain stable and constant over time including post-sample period.

The preferred model will be selected through the testing down procedure on the ground of these criteria. In order to examine whether or not the models satisfy these criteria, a battery of diagnostic statistics are presented, which are (Koopman et al., 2000, p.119):

- Standard error of estimate which is standard deviation of dependent variable values about the estimated regression line.

- The Bowman-Shenton normality test statistic based on third and forth moments of the residual. which is approximately distributed as distributed as $\chi^2(2)$.

- Skewness statistics of the residuals is approximately distributed as $\chi^2(1)$.

- The heteroscedasticity test statistics, $H(h)$ is the ratio of the square of the last $h$ residuals to the squares of the first $h$ residuals where $h$ is set to the closest integer of $T/3$ were $T$ is number of observations. It is centred around unity and should be
treated as having and $F$ distribution with $(h, h)$ degrees of freedom.

- The serial correlation coefficients $r(j)$ at lag $j$ which are approximately distributed as $N(0, 1/T)$.
- The Durbin-Watson (DW) test statistic for first-order autocorrelation.
- The Box-Ljung statistic $Q(p,q)$ based on the first $p$ autocorrelations which is tested against a $\chi^2$ distribution with $q$ degrees of freedom.
- $R^2$ is the coefficient of determination.
- $R_s^2$ is the coefficient of determination based on the differences around the seasonal mean (see Harvey, 1989, p.269) which is applied for quarterly model.
- $R_d^2$ is the coefficient of determination based on the first differences (see Harvey, 1989, p.268) which is applied for annual model.
- The post sample prediction failure test for which the test statistics ($pft$) is given by (Koopman et al., 2000, p.184):

$$pft = \sum_{j=1}^{L} v_{T+j}^2$$

(4.23)

where $v$ is the standardised residuals (see koopman et al., 2000, p.156) and $L$ is the number of the ‘post-sample’ observations reserved for the test. The total number of the observations are $t = T + 1, \ldots, T + L$. $pft$ is approximately distributed as $x_L^2$.

- The cumulative sum of the standardised prediction errors (Cusum) $t$-test statistic is given by (koopman et al., 2000, p.184):

$$\text{Cusum } t = L^{-1/2} \sum_{j=1}^{L} v_{T+j}$$

(4.24)

where $v$ is the standardised residuals and $L$ is the number of the ‘post-sample’ observations reserved for the test. Cusum $t$ is approximately distributed as a $t$
distribution with \(T - L\) degrees of freedom.

In addition to these diagnostics, where applicable, the Log likelihood test (LR test)\(^{18}\) will be further conducted to examine the validity of the deterministic restrictions on the stochastic trend and/or the stochastic seasonals. In the case of quarterly data case, the test restrictions are as follows:

(a) deterministic seasonal dummies;
(b) a deterministic time trend;
(c) a deterministic time trend with deterministic seasonal dummies;

Test (a) is applicable to Models (2), (4) and (6) of Table 4.2. Test (b) is applicable only for Models (5) and (6). Finally, test (c) is only for Model (6) which is the most general model. Of course, the test is not applied to Model (1) which is the most restricted model already. For annual data case, the LR test is applied to the two restrictions. One is the deterministic restriction, which is only applicable to the Stochastic Trend Model. The other test is the No trend restriction which can be applied to the Stochastic Trend Model and the Deterministic Trend model. For annual data case, a deterministic restriction can only be imposed to a stochastic trend, for which test (b) can be applied to this restriction (cell II in Table 4.2). In addition, in only a particular case, test (d) for the no trend restriction on a stochastic trend (cell I in Table 4.2) is applied where applicable in annual data case. These tests acted as a check to ensure whether the deterministic restrictions were accepted by the data and allowed for a comparison of the estimated

\(^{18}\) For the LR test in general, see Thomas (1993, p.71 – 73) and Stewart (1991, p.132 – 133).
long-run price and income elasticities.

However, practically, in some cases, the LR test cannot be used. This is because that, in the structural time series framework, unlike conventional Maximum Likelihood Estimation, the likelihood function of the Kalman filter is a function of the hyperparameters only (Harvey, 1989, p.126). During the maximisation, other parameters such as the coefficient parameters are treated as constant which are automatically given by the linear recursive algorithm system in the Kalman filter (Harvey, 1989, p.105-106). In other words, the final estimators for the coefficient parameters are not directly generated through the maximisation procedure of the 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 a comparison between the log-likelihood values is not legitimate in order to conduct the restriction test. However, it is still valid to test the deterministic restrictions against stochastic components (such as the fixed slope restriction or the deterministic seasonal dummies restriction) using the LR statistic since these restrictions can correspond to the maximisation of the likelihood function through changes in the hyperparameters. In this thesis, the LR test results are reported only when the test is valid.

Furthermore, the auxiliary residuals for the irregular, level and slope components, which have been explained already, are also examined by the Bowman-Shenton test.
statistics for normality, kurtosis and skewness in order to identify outliers and structural breaks in energy demand series. The use of this test follows the empirical application by Harvey and Koopman (1992).

When consider annual data series for Japan, due to a lack of seasonality modelling issue, the trend modelling is only a major difference between models estimated. This follows that it may be difficult to choose the most preferred model on the ground of the diagnostics test statistics. In the case, the longer-term post sample prediction test for the period 1985 – 1999 is applied to the models to compare the further robustness. The period was characterised by recovery of the Japanese energy demand after the stagnation era. Therefore, it is of interest whether or not the models are able to predict this transition and evolution. This ‘tough’ post-sample prediction test is not required for the quarterly model, since it is expected that different ways of seasonality modelling, in addition to the modelling UEDT, is significant enough to separate out the robustness of the models.

Two types of the post-sample prediction tests will be employed in this thesis as already mentioned. Amongst them, the Cusum can be visually illustrated with the two boundary lines which are based on a significant level of 10% at both side. When the Cusum does not cross the boundary lines, the parameters of the model can be said to be consistent over the horizon of the prediction period. Systematically underestimation and overestimation can be effectively detected by the Cusum test (Harvey, 1989, p.272). Along with the formal test statistics, whenever necessary, the actual observations are
plotted along with the predicted values associated with the prediction intervals of two root mean square errors (RMSEs). When the actual values lie within the prediction intervals, the model has satisfactory prediction power over the post sample period.

In terms of the diagnostics, there will be minor differences in the diagnostics reports for the autocorrelation of the residuals between the quarterly and the annual cases. For the quarterly case, they are reported at 1st, 4th and 8th orders since the experience suggests the autocorrelation is more likely to occur at these orders when quarterly data series is used. On the other hand, 1st, 2nd, 3rd and 4th orders are selected for the annual data case for the similar reason.

Finally, the estimated average annual rates of the trend growth are the highlights of the differences between the models, as well as the estimated income and price elasticities. Therefore, the growth rates of the estimated UEDT over the whole sample period and for the sub-divided periods will be reported. The sub-divided periods are selected by partition off the whole sample period by every 5 years to see the changes in the trend growth when the models allow the stochastic trend20.

4.5. Data

The details of data used in the empirical chapter are described in Appendix 4.2. In the empirical sections, the following abbreviations are consistently used regardless of

---

20 The selection of the sub-sample periods is rather arbitrary.
sectors and fuel types analysed.

\[ e_t = \log \text{ of energy demand (aggregated energy, transport oil and electricity) at period } t \]

\[ y_t = \log \text{ of economic activity (GDP, output etc.) at period } t \]

\[ p_t = \log \text{ of energy price at period } t \]

\[ TEMP_t = \text{ air temperature at period } t \]

\[ Irr(\ ) = \text{ impulse dummy for period } (\ ) \]

\[ Lvl(\ ) = \text{ level dummy for period } (\ ) \]

\[ HDD_t = \text{ Heating Degree Days at period } t \text{ (only for annual model in Japan)} \]

\[ CDD_t = \text{ Cooling Degree Days at period } t \text{ (only annual model for Japan)} \]

\[ CDDAC_t = \text{ Cooling Degree Days weighted by the diffusion of air conditioner at period } t\]

\[ (\text{only for annual model in Japan)} \]

\[ HotDev_t = \text{ higher air temperature deviation from 24 degrees Celsius at period } t \text{ (only for quarterly model in Japan)} \]

\[ CoolDev_t = \text{ cooler air temperature deviation from 14 degrees Celsius at period } t \text{ (only for quarterly model in Japan)} \]

There are some differences between the UK and Japan in terms of the variables representing the economic activities, the price for energy and the air temperature variations. For the UK, the real GDP, the manufacturing output and the real disposable income are used respectively for the whole economy, the manufacturing, and the residential sectors. In constant, for Japan, the real GDP is consistently used for all the sectors. This is because it is empirically found that the real GDP always shows a better fit for the Japanese energy demand compared to the other alternative variables in

Chapter 4
Japan. For the residential sector, the data series also includes the service sector which occupies nearly half of it, the real GDP is more appropriate and is better fit than the personal disposable income. Similarly, the real GDP appears to fit better than the index of industrial production (IIP) for the manufacturing sector. Hence, the real GDP is used as the economic activity variable.

The variables represented the temperature variation used for the UK and Japan are also not the same. For the UK, the actual air temperature variable is used, whereas some of the deviation variables such as the Heating Degree Days (HDD) and the Cooling Degree Days (CDD) are employed for Japan. The use of the temperature deviation variables rather than the original air temperature series for the Japanese energy demand is an effective way to capture the temperature effect on the demand in the country. This is because that any movement of the temperature between 14°C and 24°C may have little impact on the demand and deviated temperature above and below the range affects it. This is highly contrasted to the case of the UK, where the range of the air temperature fluctuation lies just within the lower end of the range of the Japanese air temperature. In the UK, the impact of the temperature on the demand is merely uni-directional i.e. the lower air temperature the higher electricity demand arises, but not the other way. However, in the Japanese case, the temperature impact is by-directional i.e. the higher air temperature the higher electricity demand arises too. Therefore, the deviation variable is adopted for Japanese energy demand.

---

21 In fact, many of past studies for energy demand in Japan use GDP as approximation of economics activity. Examples are found in Tomita (1994), Franzén and Sterner (1995), Baltagi et al. (1997) and Yokoyama (2000) for individual fuels.

22 Due to the data availability, the slightly different temperature deviation variables are used for the quarterly model for Japan. However, this does not affect the discussion in this section.
In some cases in Japan, the Cooling Degree Days weighted by the diffusion of air conditioner \((CDDAC)\) is found to be better fitting and is used for the estimation. An increase in energy demand associated with higher temperature is almost caused by turning-on of air conditioner. Therefore, the impact of higher temperature on the energy demand should relate to the stock of air conditioner. For example, the diffusion of the air conditioner was only 3% in 1965, whereas it was 208% in 1999, which suggests that the impact of higher temperature on the energy demand can be much smaller in 1965 compared to 1999 and vice versa. Therefore, when the \(CDDAC\) is found to be better fitting to the model, it is included instead of the original \(CDD\).

Since neither of the \(HDD\) nor the \(CDD\) is available at quarterly basis, \(HotDev\) and \(CoolDev\), which are originally constructed by author as quarterly data series, are used instead. The \(HotDev\) indicates only the upper-side deviations of the average quarterly air temperatures from 24°C. The threshold of 24°C was chosen since it is normally expected that air conditioners are turned-on when air temperature exceeds 24°C. The diffusion of air conditioners equipped in the cars is not available, therefore, the modification weighted by the diffusion rate was not made for the \(HotDev\) series. \(CoolDev\) is exactly the same as the \(HotDev\) in reverse, which indicates the lower-side deviations of the average quarterly air temperatures from 14°C. \(HotDev\) and \(CoolDev\) are used only for quarterly models, again, due to data availability.

With regard to the price for energy, the aggregated energy prices for the all sectors are available separately in the UK. However, they are not available for Japan. Therefore,
the aggregated energy price for the whole economy is used for the individual sectors. However, the prices for the transportation oil demand and the electricity demand are available both for the UK and Japan, and used for the estimation.

4.6. Summary and conclusion

This chapter has described the modelling framework and the methodology which will be employed in the latter empirical part in this thesis. Given the need for modelling the UEDT and seasonality in a general and flexible way, the structural time series model is set at the central econometric tool to analyse energy demand. The important features of the model have been highlighted. Firstly, the structural time series model can model both the UEDT as a stochastic trend and seasonality as stochastic components without prior restrictions whether they are deterministic or stochastic. Secondly, the deterministic restrictions on the trend and the seasonality can be statistically tested and, if the restrictions are accepted, the model can easily revert into the conventional deterministic model without any loss of efficiency. Finally, in contrast to the conventional co-integration model, non-stationary elements are explicitly modelled in the structural time series model being completely free from the non-stationary problem.

At the end of the chapter, the estimation strategies employed in the empirical chapters of this thesis was outlined. Each model classified in Table 4.2 is all estimated by general to specific procedure guided by diagnostics test statistics under a number of model selection criteria. Due to the data availability, for the energy demand in the some sectors,

---

23 This is one of the limitations of this thesis due to data unavailability.
annual data series will be used as well as quarterly data series, making a number of the variations in the estimation and test procedures. It was also explained that there are several differences between the variables representing the economic activities and the temperature variations used for the UK and Japan.
APPENDIX 4.1. STATE SPACE FORM AND THE KALMAN FILTER\textsuperscript{24}

The Kalman filter is a systematic filtering process for nonstationary problems in time series data. It was originally introduced by Kalman (1960), Kalman and Bucy (1961) and developed in engineering fields, particularly, process control, space development and space science. Application to economic analysis began in the 1970s but it is still relatively under developed. In terms of energy demand modelling, the Kalman filter, itself, is of little interest since it is simply a statistical algorithm. However, it becomes a powerful tool to computes optimal estimators once the model is put into state space form. (Harvey, 1987, p.285). In other words, the state space form is a necessary formulation to employ the Kalman filter to estimate econometric models. Therefore, in this appendix, firstly, a state space from will be described followed by the estimation process of the Kalman filter within state space form. This technical discussion of the Kalman filter is placed in the appendix since it is the application of the technique, not the technique itself, that is central to this thesis. That said, it is felt some explanation is warranted for those interested in the technical details, but it is worth citing Harvey (1989) that “it should perhaps be stressed that the Kalman filter is simply a statistical algorithm, and it is only necessary to understand what the filter does, rather than how it does it” (p.xi).

\textsuperscript{24} This appendix relies on Harvey (1989, 1987), Tanizaki (1993), Cuthbertson et al. (1992), Engle and Watson (1987). Less formal, but more intuitive explanation for the Kalman filter is given in Bomhoff (1994).
A4.1.1 State space form

A general state space form consists of the following measurement and transition equations. They are linear system equations illustrating dynamics of time series within the framework. Consider a univariate time series $y_t$.

Then, a measurement equation is:

$$y_t = Z_t \alpha_t + d_t + \epsilon_t, \quad t = 1, \ldots, T \tag{A.4.1}$$

where $y_t$ is observable scalar, $Z_t$ is a known $m \times 1$ fixed vector, $d_t$ is a known fixed scalar and $\epsilon_t$ is a scalar disturbance. $\alpha_t$ is a state vector which will be estimated.

A corresponding transition equation is:

$$\alpha_t = T_t \alpha_{t-1} + c_t + \eta_t, \quad t = 1, \ldots, T \tag{A4.2}$$

where $T_t$ is a known $m \times m$ fixed matrix, $c_t$ is a known $m \times 1$ fixed vector, $\eta_t$ is a $m \times 1$ vector of disturbances. Again, $\alpha_t$ is an unknown state vector.

$\epsilon_t$ and $\eta_t$ are serially uncorrelated disturbances with zero mean and covariance matrix $\sigma^2 \epsilon_t$ and $\sigma^2 \eta_t$, respectively, that are:
\[
\begin{bmatrix}
\epsilon_t \\
\eta_t
\end{bmatrix}
\sim N\left[
\begin{bmatrix}
0 \\
0
\end{bmatrix},
\begin{bmatrix}
\sigma^2 h_t & 0 \\
0 & \sigma^2 Q_t
\end{bmatrix}
\right],
\quad t = 1, \ldots, T
\]  

(A.4.3)

\(\sigma^2 h_t\) and \(\sigma^2 Q_t\) may be non-zero values but unknown and are regarded as the hyperparameters.

Moreover, the following two assumptions are required to complete the state space form.

1. The initial value of the state vector has a mean of \(a_0\) and its covariance matrix \(P_0\), that is:

\[E(a_0) = a_0\] and \[\text{Var}(a_0) = P_0.\]  

(A.4.4)

2. The disturbance term \(\epsilon_t\) and \(\eta_t\) are mutually uncorrelated with each other for all \(t\) and \(s\). Moreover, they are also uncorrelated with the initial state, that are:

\[E(\epsilon_t \eta_s') = 0\] for all \(s, t = 1, \ldots, T.\]  

(A.4.5)

and

\[E(\epsilon_t a_0') = 0,\] \[E(\eta_t a_0') = 0\] for \(t = 1, \ldots, T.\]  

(A.4.6)

Note that (A.4.6) means that \(\epsilon_t\) and \(a_t\) in (A.4.1) are uncorrelated with each other. By the same token, \(\eta_t\) and \(a_t\) in (A.4.2) are also uncorrelated with each other, that is:
The assumption of an initial value is important because that, once an initial value and its variance are given, the Kalman filter algorithm recursively calculates values of a state vector for all periods after the initial period. However, it is shown by Tanizaki (1993, p. ii) that, when a sufficiently large value $k$, where $k \to \infty$, is given for variance of initial value (which is $P_0$) predicted values of a state vector after the initial period are hardly affected by the initial value $a_0$ itself.

As can be seen above, important characters of the state space form are that, firstly, it explicitly separates the state vector, which is unobservable, from other observable variables, and, secondly, the dynamics of the state vector $(d\alpha/dt)$ is placed into the transition equation of the linear system.

To see how this form fits in the actual model, consider the case of the local trend described in Chapter 4 (Cell. ix of Table 4.1). The simplest local trend model for an univariate time series $y_t$ is the following the basic structural model (Harvey, 1989, p. 45).

\[
y_t = \mu_t + \xi_t \quad t = 1, \ldots, T \tag{A.4.8}
\]
\[
\mu_t = \mu_{t-1} + \beta_t + \eta_t \quad t = 1, \ldots, T \tag{A.4.9}
\]
\[
\beta_t = \beta_{t-1} + \xi_t \quad t = 1, \ldots, T \tag{A.4.10}
\]

The state space form for this model is expressed as:
\[ y_t = [1 \ 0] \begin{bmatrix} \mu_t \\ \beta_t \end{bmatrix} + \varepsilon_t \quad t = 1, \ldots, T \] : Measurement equation \hfill (A.4.11)

\[ \begin{bmatrix} \mu_t \\ \beta_t \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \xi_t \end{bmatrix} \quad t = 1, \ldots, T \] : Transition equation \hfill (A.4.12)

where \( Z_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \), \( \alpha_t = \begin{bmatrix} \mu_t & \beta_t \end{bmatrix} \), \( T_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \) and \( \eta_t = \begin{bmatrix} \eta_t & \xi_t \end{bmatrix} \) in (A.4.1) and (A.4.2).

Another example of expression in the state space form is given for the well-known AR(2) model, that are:

\[ y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \alpha_t \quad t = 1, \ldots, T \] : Measurement equation \hfill (A.4.13)

\[ \alpha_t = \begin{bmatrix} y_t \\ \phi_2 y_{t-1} \end{bmatrix} = \begin{bmatrix} \varphi_1 & 1 \\ \varphi_2 & 0 \end{bmatrix} \alpha_{t-1} + \begin{bmatrix} \xi_t \\ 0 \end{bmatrix} \quad t = 1, \ldots, T \] : Transition equation \hfill (A.4.14)

There are equivalent to the conventional formula of:

\[ y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \xi_t \quad t = 1, \ldots, T \] \hfill (A.4.15)
A4.1.2 The Kalman filter

When the model is fitted into the state space form, the Kalman filter can recursively calculate the optimal estimator of the state vector $\alpha_t$ at time $t$, using the information available at time $t$. The significance of the Kalman filter is based on (Koopman et al., 2000, p.150);

1. computation of one-step ahead predictions of observation and state vectors, and the corresponding mean square errors;
2. diagnostic checking by means of one-step ahead prediction errors;
3. computation of the likelihood function via the one-step ahead prediction error decomposition and this opens the way for the estimation of any unknown parameters in the model;
4. smoothing to estimate the state vector using all the information in the sample, not just a part of it.

Consider $a_{t-1}$ as the minimum mean square estimator (MMSE) which is an optimal estimator of $\alpha_{t-1}$ based on all the observations up to and including time $t - 1$. Let $P_{t-1}$ be the mean square error (MSE) matrix of $a_{t-1}$ that is the covariance matrix of the estimation error $(a_{t-1} - \alpha_{t-1})$, namely:

$$P_{t-1} = E [(a_{t-1} - a_{t-1})(a_{t-1} - a_{t-1})']$$  
(A.4.16)

Having $a_{t-1}$ and $P_{t-1}$, the MMSE of $\alpha_t$ at the period $t$, which is the optimal estimator of
\( \alpha_t \), and the MSE of \( \alpha_t \) are given by:

\[
a_{t/t-1} = T_t \alpha_{t-1} + c_t \tag{A.4.17}
\]

and

\[
P_{t/t-1} = T_t P_{t-1} T'_t + Q_t \tag{A.4.18}
\]

(A.4.17) and (A.4.18) are called the \textit{prediction equations}. The subscript of \( t/t-1 \) indicates that it is predicted value for the period \( t \) using the information available at \( t-1 \).

When the new observation \( y_i \) becomes available, \( a_{t/t-1} \) (the optimal estimator of \( \alpha_t \)) can be updated as follows:

\[
a_t = a_{t/t-1} + P_{t/t-1} Z_t (y_t - Z'_t a_{t/t-1} - d_t) / f_t \tag{A.4.19}
\]

and

\[
P_t = P_{t/t-1} - P_{t/t-1} Z'_t Z_t P_{t/t-1} / f_t \tag{A.4.20}
\]

where \( f_t = Z'_t P_{t/t-1} Z_t + h_t \) \tag{A.4.21}

(A.4.19) (A.4.20) and (A.4.21) are known as the \textit{updating equations}. Note the subscript \( t \) indicates \( \alpha_t \) and \( P_t \) are the estimators for the period \( t \) given available information at time
rather than $t-1$. Hence, they are *updated*.

The linear recursive algorithm system expressed as a set of equations from (A.4.17) to (A.4.21) is known as the *Kalman filter*. As seen above, the Kalman filter re-estimates the state vector repeatedly every time new information becomes available. In this sense, the Kalman filter is somehow similar to the recursive least square estimation. If $T_t = I_m$, $c_t = 0$ and $\eta_t = 0$ in (A4.2), both of the Kalman filter and the recursive least square produce the identical estimates. In this case, it is obvious that the state vector has no dynamics in time domain.

The starting values for the Kalman filter are specified as (A4.4) (A4.6) and (A4.7). The exact starting value can be zero, that is $a_0 = 0$ and its covariance matrix $P_0$ can be set as $P_0 = kI$ where $k \to \infty$ (see Harvey, 1989, p.121 for the technical details). As mentioned, the initial value little affects the estimates of the state vector so long as its variance is set to be sufficient large value (Tanizaki, 1993, p.ii).

The Kalman filter estimates the mean and covariance matrix of the distribution of $\alpha_t$ conditional on the information available at time $t$. That are:

$$a_t = E(\alpha_t) = E(\alpha_t | y_t) \quad \text{(A.4.22)}$$

and

$$P_t = E\{[\alpha_t - E(\alpha_t)][\alpha_t - E(\alpha_t)]'\} \quad \text{(A.4.23)}$$
Therefore, the conditional mean estimator of \( \alpha_t \) is the minimum mean square estimate of \( \alpha_t \). This follows that \( \alpha_t \) is the MMSE of \( \alpha_t \) based on observations up to and including time \( t \). This applies in the same way to \( \alpha_{t-1} \) and \( P_{t-1} \). Moreover, the conditional mean of \( y_t \) at time \( t-1 \) also can be considered as the MMSE, which is (from (A.4.1)):

\[
y_{t-1} = Z_t \alpha_{t-1} + d_t
\]  

(A.4.24)

Then, the prediction errors, \( v_t \), are defined as:

\[
v_t = y_t - y_{t-1} = Z_t (\alpha_t - \alpha_{t-1}) + \xi_t \quad t = 1, \ldots, T
\]  

(A.4.25)

or

\[
v_t = y_t - E(y_t | y_{t-1}) \quad t = 1, \ldots, T
\]  

(A.4.26)

which are also called innovations. These indicate the divergence between the prediction and the actual value representing the new information which has just been available.

The above output of the Kalman filter is used to construct the log-likelihood (ML) function estimating unknown hyperparameters in the measurement and transition equations. It is known that the log-likelihood in the following function \( L(\theta) \) will be maximised with respect to the unknown hyperparameter vector \( \theta \):
\[
\log L(\theta) = -\frac{T}{2} \log 2\pi - \frac{T}{2} \log \sigma^2 - \frac{1}{2} \sum_{t} \log f_t - \frac{1}{2\sigma^2} \frac{\nu_t^2}{f_t},
\]  
(A.4.27)

where \(\nu_t\) and \(f_t\) are defined above, and \(\sigma^2\) come from (A.4.3) where \(h_t\) and \(Q_t\) depend on the hyperparameter vector \(\theta\) but not on \(\sigma^2\). (A.4.27) is known as the \textit{prediction error decomposition} form of the likelihood. The simple grid search and the scoring method are often employed to maximise the log-likelihood function. The estimated values of the unknown parameters through the ML procedure are substituted into the Kalman filter algorithm to calculate the optimal estimates of the state vector. In practice, this process requires iterated converge calculations explained below. Some arbitrary values are initially substituted into the known parameters and the value of the log-likelihood function is evaluated through the Kalman filter algorithm. This process will be iterated until the particular predicted values of the unknown parameters are found to maximise the log-likelihood. In other words, the values of \(\alpha_t\) which yield the maximum log-likelihood are the optimal estimators.

Finally, the actual estimation process is summarised. Consider, again, the basic structural model shown in equations (A.4.8) to (A.4.10). With some initial values for \(Q_n\), \(a_0\) and \(P_0\) (which is normally \(kI\) where \(k \to \infty\) as explained)\(^{25}\), the series of the Kalman filter ((A.4.17) (A.4.18) (A.4.19) (A.4.20) (A.4.21) and (A.4.25)) is recursively processed to calculate \(a_{1/0}, \ldots, a_{T/T-1}\) where \(T\) observations are available for the whole sample period. At \(t = T\), (A.4.17) and (A.4.18) are calculated to obtain \(a_{T+1/T}\) as a final estimator. The estimated parameters are \(a_{1/0}, \ldots, a_{T+1/T}\). Having \(\nu_1, \ldots, \nu_T\) (from A.4.25)

\(^{25}\) In the estimation in the empirical chapters, the initial values are set at \(\eta_0 = \exp(-2)\) and \(\xi = \exp(-3)\) in \(Q_n, a_0 = 0,\) and \(P_0 = kI\) where \(k = 9999.\) However, again, the choices of these numbers are not critical matter in the process.
and $f_1, ..., f_T$ (from A.4.21), the log-likelihood can be calculated through (A.4.27). Then, using the BFGS (Broyden-Fletcher-Goldfarb-Shanno) quasi-Newton grid-search method (see Koopman, 2000, p.163, for the technical detail) changing the initial values for $Q$, the process of the Kalman filter is iterated, with the same initial values for $a_0$ and $P_0$. The iteration stops when the log-likelihood is found to be maximised by the grid-search method. Then, given the maximised log-likelihood, the final estimator $a_{T+1/T}$ is the optimal estimates of unknown state vector $\alpha_t$. This process can be equally applied to the model including the parameters of the explanatory variables in state vector $\alpha_t$.

A4.1.3. Smoothing

This section briefly outlines the smoothing algorithm. As explained above, the Kalman filter recursively estimates the MMSE of the state vector $\alpha_t$ step-by-step for the each period as the information becomes available. However, once all the information is available at the period $T$, estimation can be made better for all the period rather than using the information available at the period $1, ..., t < T$. The smoothing algorithm is used to re-estimate the state vector taking into account all the information available, once all the Kalman filter estimation have been done for the time being. Put simply, while filtering is to find the expected value of the state vector $\alpha_t$ given the information available at time $t$ which is $E(\alpha_t | y_t)$, smoothing is modifications of the estimates using the information made available after time $t$. This can be mathematically written as follows:

$$E (\alpha_t | \Omega_s) = a_{s|s}$$ where $\Omega_s$ is all the information available at time $s$ i.e. $\Omega_s = \{y_s, y_{s-1},$
..., \( y_0 \), other exogenous variables; \( t = 1, \ldots, T \)

If \( t = s \): filtering

If \( t < s \): smoothing

If \( t > s \): prediction.

The mean of the distribution of \( \alpha_t \) conditional on all the sample is written as \( E(\alpha_t \mid y_T) \) rather than \( E(\alpha_t \mid y_t) \). The former is known as a smoothed estimate and, in contrast, the later is called as a filtered estimate. The MSE (mean square error) of the smoothed estimate must be smaller than that of the filtered estimate since the smoothed estimate is based on more information.

There are three types of smoothing algorithms: fixed-point, fixed lag, and fixed interval smoothing algorithms. Among them, it is known that fixed-interval smoothing may be more useful tool for economic analysis to examine the past trend (Tanizaki, 1993, p.12). Therefore, the fixed-interval smoothing algorithm will be outlined here. The fixed interval smoothing algorithm consists of a number of recursions that begin with the final Kalman filter estimates \( a_T \) and \( P_T \) which is the optimal estimator and its covariance matrix for a particular final one period using all the information available. The smoothing algorithm works backwards from these estimates. Let \( a_{\nu T} \) and \( \sigma^2 P_{\nu T} \) be the smoothed estimator and its covariance matrix conditional on all \( T \) observations respectively, that are:

\[
a_{\nu T} = E(\alpha_t \mid y_T) \quad (A.4.28)
\]
and

\[ P_{t/T} = E \{ (\alpha_t - a_{t/T})(\alpha_t - a_{t/T})' \} \] (A.4.29)

Then, the smoothing equation can be written as:

\[ a_{t/T} = a_t + P_t^*(a_{t+1/T} - T_{t+1} a_t) \] (A.4.30)

and

\[ P_{t/T} = P_t + P_t^* (P_{t+1/T} - P_{t+1/0}) P_t^* \] (A.4.31)

where

\[ P_t^* = P_t P_t' t_{t+1/T} P_{t+1/T}, \quad t = T - 1, \ldots, 1 \] (A.4.32)

The smoothed estimator \( a_{t/T} \) is the optimal estimator of \( \alpha_t \) based on all the information up to and including the final observation \( y_T \). The estimates of the trend and the seasonal components shown in the main chapters are all smoothed estimator obtained by the above described process, unless otherwise stated as a filtered estimate.
APPENDIX 4.2. DATA

A4.2.1. UK

The data set is quarterly seasonally unadjusted for the period 1971q1 to 1997q4.

Energy Consumption

The aggregated energy consumption data refers to UK Final Consumption of aggregate energy in million tonnes of oil equivalent (m.t.o.e) for the whole economy, the residential sector and the manufacturing sector. These were taken from various issues of the UK Energy Trends up to June 1999. Data before 1992 have been converted to m.t.o.e. from millions of therms.

The transportation oil consumption data for the UK refers to UK Final Consumption ‘petroleum’ for the transport sector in million tonnes of oil equivalent (m.t.o.e.) from various issues of the UK Energy Trends up to June 1999. Data before 1992 have been converted to m.t.o.e from millions of therms.

The electricity consumption data for the UK refers to UK Final Consumption ‘electricity’ for the whole economy in million tonnes of oil equivalent (m.t.o.e.) from various issues of the UK Energy Trends up to June 1999. Data before 1992 have been converted to m.t.o.e from millions of therms.

Activity

The nominal and constant prices expenditure estimates of UK Gross Domestic Product
GDP(E) at market prices were kindly supplied by the Office of National Statistics (ONS) since the seasonally unadjusted data are not published. Therefore the activity variable for the whole economy \((Y_t)\) is the constant GDP(E) series re-based and indexed to \(1990 = 100\). The implicit GDP(E) price deflator at \(1990=100\) was calculated from the nominal and constant price series. For the Residential sector, seasonally unadjusted Real Household Disposable Income (RHDY) has been used as the activity variable. This series is published in *Financial Statistics*, Table 14.8B, in 1995 £ million. However, the series (code RVGK) was retrieved electronically from MIMAS in October 1999. For manufacturing, the Index of Output, used as the activity variable, was kindly supplied by the Office of National Statistics (ONS) since the seasonally unadjusted data are not published. This was re-based to \(1990=100\).

**Energy Prices**

The nominal aggregate price series for the residential sector is a weighted average of different fuels from the GB Domestic Fuel Price Index (taken from various issues of the *UK Energy Trends* up to June). The nominal aggregate price series for the manufacturing sector is a weighted average of different fuels from the GB Industrial Fuel Price Index (taken from various issues of the *UK Energy Trends* up to June). For the two sectors, the nominal indexes were deflated by the GDP(E) deflator and re-based to \(1990=1100\). The price index for the whole economy is a weighted average of the price indexes from the three other sectors.

The nominal price index for transport oil was derived by weighting the appropriate Fuel Price Index from various issues of the *UK Energy Trends* up to June 1999. The real
index of oil prices was found by deflating the nominal index by the implicit GDP(E) deflator.

The nominal price index for electricity was derived by weighting the appropriate GB Domestic and Industrial Fuel Price Indices from various issues of the UK Energy Trend up to June 1999. The real index of electricity price was found by deflating the nominal index by the implicit GDP (E) deflator.

Temperature
Temperature refers to the average GB quarterly temperature in degrees Celsius taken from various issues of the *UK Digest of Energy Statistics (DUKES)*.

A4.2.2. Japan

The data set for the aggregated energy consumption for the whole economy, the residential sector and the manufacturing sector is annual data for the period 1965 to 1999. The data set for the transport oil and electricity consumption is quarterly seasonally unadjusted for the period 1971q1 to 1997q4 for transport oil and 1971q1 to 1997q1 for electricity.

Energy Consumption
The aggregated energy consumption data refers to Japan Final Consumption of aggregate energy in $10^{10}$ Kcal for the whole economy, the residential sector and the manufacturing sector. These were directly taken from the *Handbook of Energy & Economic Statistics in Japan 2001* (the Energy Conservation Centre, Japan).
Petrol and diesel consumption (Kilo litres) were taken from various issues of the *Yearbook of Production Supply and Demand of Petroleum, Coal and Coke* (Ministry of International Trade and Industry, Japan (MITI)) (in Japanese). Since a part of diesel oil is consumed for non-transportation use, this part was excluded from the total diesel oil consumption. Diesel oil consumption for non-transportation use was estimated from various issues of the *Energy Balance Tables in Japan* (Agency of Natural Resource and Energy, MITI) (in Japanese). Petrol and diesel consumption for transportation use were converted into $10^{10}$ Kcal basis and added together to give the aggregated total transportation oil consumption.

The electricity consumption data for Japan refers to the aggregated final electricity consumption in $10^6$ kWh from various issues of the *Outlook of Electricity Supply and Demand* (Agency of Natural Resource and Energy, MITI) (in Japanese). Electricity supplied by *Okinawa Electricity Company* was excluded from the data for data consistency.

**Activity**

Both annual and quarterly data series of the real Gross Domestic Products (GDP) (based on Calendar 1990, Billion Yen) were directly taken from the Economic Planning Agency, Japan (EPA) Web site: [http://www.epa.go.jp](http://www.epa.go.jp).

**Energy Prices**

The nominal retail price indices of ‘fuel and energy’ and ‘electricity’ were taken from
various issues of the *Price Index Annual* (The Bank of Japan) (in Japanese). They were divided by the Final Private Consumption Quarterly Deflator (1990 = 100) taken from EPA web site: [http://www.epa.go.jp](http://www.epa.go.jp).

The nominal retail price indices of petrol and diesel oil were taken from various issues of the *Price Index Annual* (The Bank of Japan) (in Japanese). They were divided by the Final Private Consumption Quarterly Deflator (1990 = 100) taken from EPA web site: [http://www.epa.go.jp](http://www.epa.go.jp). The 'real transportation oil price' was derived as a weighted average of the deflated petrol and diesel oil price indices.

**Temperature**

Temperature refers to the quarterly series of average of Tokyo and Osaka air temperature in degree Celsius taken from various issues of the *Meteorological Agency Annual* (Meteorological Agency, Japan) (in Japanese).

Annual series of the Heating Degree Days (*HDD*) and the Cooling Degree Days (*CDD*) were directly taken from the *Handbook of Energy & Economic Statistics in Japan 2001* (the Energy Conservation Centre, Japan).

The *CDD* weighted by the 'diffusion rate of air conditioner' taken from the *Handbook of Energy & Economic Statistics in Japan 2001* (the Energy Conservation Centre, Japan) gives the Cooling Degree Days weighted by the diffusion of air conditioner (*CDDAC*).
*HotDev* is an upper-side deviation of the quarterly series of average of Tokyo and Osaka air temperature in degree Celsius taken from various issues of the *Meteorological Agency Annual* (Meteorological Agency, Japan) (in Japanese) from 24 degrees Celsius.

*CoolDev* is a lower-side deviation of the quarterly series of average of Tokyo and Osaka air temperature in degree Celsius taken from various issues of the *Meteorological Agency Annual* (Meteorological Agency, Japan) (in Japanese) from 14 degrees Celsius.
CHAPTER 5. APPLICATION OF THE STRUCTURAL TIME SERIES MODEL TO UK ENERGY DEMAND

5.1. Introduction

This chapter presents empirical results from applying the structural time series model described in Chapter 4 to energy demand for various sectors and fuels in the UK. The main thrust of this chapter is to demonstrate how the structural time series model can best estimate the UEDT and stochastic seasonality potentially inherent in energy demand. The performance is compared to that of the models where some of the trend and/or seasonal components are restricted to be deterministic as defined in Table 4.2. The comparison highlights the importance of modelling the UEDT and seasonality to obtain sensible estimates of energy demand functions.

Taking into account the stochastic trend and seasonals in the flexible way discussed in the previous chapters, that the structural time series model is more general and less restrictive than the conventional deterministic trend and seasonal models. Therefore, the estimated elasticities given by the structural time series model are less likely to be biased. In addition, the estimated UEDT and stochastic seasonal variations shed light on the complex nature of the energy demand structure in the UK. The comparison of the estimation performances between the structural time series model and the deterministic model also will be of our interest in order to illustrate the distinctions of the structural time series model.
The structure of this chapter is as follows. Section 5.2 considers the demand for aggregated final energy, for various sectors including: the whole economy, the residential sector, and the manufacturing sector. Section 5.3 focuses on two individual fuels, electricity and transport oil. This is followed by Section 5.4, which summarises this chapter.

5.2. Aggregated final energy demand in the UK

Equation (4.6) was estimated for the aggregated final energy in various sectors which are the whole economy, the residential and the manufacturing sectors. The data set consisted of quarterly unadjusted data from 1971q1 to 1997q4 for the final energy consumption in the three sectors, the real aggregated energy price, the average air temperature and economic activity indicators such as real GDP, manufacturing output index and personal disposable income. Since the general model outlined in equation (4.6) consists of four quarterly lags the equations were estimated from 1972q1. They ended in 1995q4 in order to save the two years 1996 and 1997 (8 observations) for the post-sample prediction tests.
5.2.1. Aggregated whole economy final energy demand

5.2.1.1. The data

The data series for the aggregate whole economy energy demand are illustrated in Figure 5.1. It shows that the energy consumption, real GDP and air temperature, as normally expected, exhibit marked seasonal fluctuations over the period. In contrast, the real energy price does not have any particular strong seasonal pattern. GDP has a strong up-ward trend. The energy consumption stagnated up to the mid-1980s, followed by a gradual increase for the subsequent period. The energy price shows dramatic up and
down movement during the 1970s and 1980s. The temperature seems to be, by and large, stable.

5.2.1.2. The estimated results

Equation (4.6) associated with the six types of the combination of deterministic and/or stochastic trend and seasonals classified in Table 4.2 are estimated for the set of the series. Each model is individually tested down guided by a series of diagnostic tests as explained in the previous chapter. Table 5.1 summarises the estimated results by the best-performed models given the specifications of the UEDT and seasonality after the successive testing down process. The numbers of the top row of the table correspond to the cell number in Table 4.2.

For all specifications, the GDP (\(y\) in Table 5.1), the energy price (\(p\) in Table 5.1), and air temperature (\(TEMP\) in Table 5.1) are found to be very significant drivers of the energy demand. In addition, the auxiliary residuals for the irregular component (see Chapter 4) indicate that there is a substantial impulse shock in the energy demand series at 1974q1 reflecting the Arab oil embargo taken place October 1973 and the coal miners strike. To capture this shock effect as an outlier, an impulse dummy variable for 1974q1 is included in the models which appears to be very significant in all cases. No other signs of outliers and/or structural breaks are found.
### Table 5.1. Estimated results for the UK whole economy energy demand 1972q1 – 1995q4

<table>
<thead>
<tr>
<th>Models</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
<th>Model (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Trend and Deterministic Seasonals</td>
<td>No Trend and Stochastic Seasonals</td>
<td>Deterministic Trend and Deterministic Seasonal</td>
<td>Deterministic Trend and Stochastic Seasonal</td>
<td>Stochastic Trend and Deterministic Seasonal</td>
<td>Stochastic Trend and Stochastic Seasonal</td>
</tr>
<tr>
<td><strong>Estimated Coefficients</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( y_t )</td>
<td>0.5234**</td>
<td>0.4705**</td>
<td>0.8096**</td>
<td>0.6847**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.437)</td>
<td>(4.941)</td>
<td>(7.316)</td>
<td>(5.934)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( y_{t-3} )</td>
<td>-0.4032**</td>
<td>-0.3366*</td>
<td>-0.2992**</td>
<td>-0.2256*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.367)</td>
<td>(2.480)</td>
<td>(2.822)</td>
<td>(2.095)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta y_t )</td>
<td>0.4066**</td>
<td>0.2955**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.446)</td>
<td>(3.306)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( y_{t-4} )</td>
<td>0.2960**</td>
<td>0.2340</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.658)</td>
<td>(1.909)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( p_{t-3} )</td>
<td>-0.2673**</td>
<td>-0.2339**</td>
<td>-0.2031**</td>
<td>-0.1963**</td>
<td>-0.2050**</td>
<td>-0.1897**</td>
</tr>
<tr>
<td></td>
<td>(10.877)</td>
<td>(10.196)</td>
<td>(7.457)</td>
<td>(7.549)</td>
<td>(3.979)</td>
<td>(3.880)</td>
</tr>
<tr>
<td>( \epsilon_{t-1} )</td>
<td>0.3111**</td>
<td>0.4137**</td>
<td>0.2731**</td>
<td>0.3269**</td>
<td>0.1124*</td>
<td>0.1848**</td>
</tr>
<tr>
<td>TEMP,</td>
<td>-0.0229**</td>
<td>-0.0221**</td>
<td>-0.0235**</td>
<td>-0.0231**</td>
<td>-0.0242**</td>
<td>-0.0239**</td>
</tr>
<tr>
<td></td>
<td>(8.955)</td>
<td>(9.221)</td>
<td>(10.131)</td>
<td>(10.179)</td>
<td>(12.005)</td>
<td>(12.117)</td>
</tr>
<tr>
<td>Irr1974q1</td>
<td>-0.0987**</td>
<td>-0.0974**</td>
<td>-0.0990**</td>
<td>-0.1001**</td>
<td>0.0761**</td>
<td>-0.0764**</td>
</tr>
</tbody>
</table>

**Long-Run Estimates**
- Income (Y): 0, 0.5725, 0.5465, 0.5750, 0.5632
- Price (P): -0.3879, -0.4036, -0.2794, -0.2917, -0.2309, -0.2327

**Estimated Hyperparameters**
- \( \sigma^2 \times 10^{-4} \)
  - 4.411
  - 3.442
  - 3.606
  - 3.214
  - 1.969
  - 1.489
- \( \sigma^2 \times 10^{-4} \)
  - 0
  - 0
  - 0
  - 0
  - 0.401
  - 0.341
- \( \sigma^2 \times 10^{-4} \)
  - 0
  - 0
  - 0
  - 0
  - 0
  - 0

**Nature of Trend**
- No Trend
  - (Cell ii)
- No Trend
  - (Cell ii)
- A Linear Trend
  - (Cell v)
- A Linear Trend
  - (Cell v)
- Local Level with Drift
  - (Cell vi)
- Local Level with Drift
  - (Cell vi)

**Average Annual Growth rate of the estimated trend**
- 1972q1 – 1995q4
  - 0% 0% -0.82% -0.73% -0.85% -0.76%
  - 0% 0% -0.82% -0.73% -0.44% -0.44%
  - 0% 0% -0.82% -0.73% -0.67% -0.64%
  - 0% 0% -0.82% -0.73% -1.44% -1.26%
  - 0% 0% -0.82% -0.73% -1.07% -0.95%
  - 0% 0% -0.82% -0.73% -0.48% -0.42%

Chapter 5
### Diagnostics

#### Equation Residuals

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>$H(30)$</th>
<th>$r(1)$</th>
<th>$r(4)$</th>
<th>$r(8)$</th>
<th>DW</th>
<th>$Q$</th>
<th>$Q_{(8,8)}$</th>
<th>$Q_{(8,7)}$</th>
<th>$Q_{(8,8)}$</th>
<th>$Q_{(8,7)}$</th>
<th>$Q_{(8,7)}$</th>
<th>$Q_{(8,6)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.00%</td>
<td>1.99%</td>
<td>1.78%</td>
<td>1.82%</td>
<td>1.65%</td>
<td>1.68%</td>
<td>1.99%</td>
<td>1.78%</td>
<td>1.82%</td>
<td>1.65%</td>
<td>1.68%</td>
<td>1.99%</td>
<td>1.78%</td>
<td>1.82%</td>
<td>1.65%</td>
<td>1.68%</td>
</tr>
<tr>
<td>Normality</td>
<td>0.03</td>
<td>0.19</td>
<td>1.60</td>
<td>2.40</td>
<td>0.82</td>
<td>0.35</td>
<td>0.19</td>
<td>1.60</td>
<td>2.40</td>
<td>0.82</td>
<td>0.35</td>
<td>0.19</td>
<td>1.60</td>
<td>2.40</td>
<td>0.82</td>
<td>0.35</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.00</td>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>0.41</td>
<td>0.35</td>
<td>0.41</td>
<td>0.00</td>
<td>0.41</td>
<td>0.35</td>
<td>0.41</td>
<td>0.00</td>
<td>0.41</td>
<td>0.00</td>
<td>0.41</td>
<td>0.35</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.02</td>
<td>0.19</td>
<td>1.54</td>
<td>2.39</td>
<td>0.41</td>
<td>0.00</td>
<td>0.41</td>
<td>0.00</td>
<td>0.41</td>
<td>0.00</td>
<td>0.41</td>
<td>0.00</td>
<td>0.41</td>
<td>0.00</td>
<td>0.41</td>
<td>0.00</td>
</tr>
<tr>
<td>$H(30)$</td>
<td>0.54</td>
<td>0.75</td>
<td>1.28</td>
<td>0.97</td>
<td>1.00</td>
<td>0.91</td>
<td>0.97</td>
<td>0.97</td>
<td>1.00</td>
<td>0.91</td>
<td>0.97</td>
<td>0.97</td>
<td>0.97</td>
<td>0.97</td>
<td>0.97</td>
<td>0.91</td>
</tr>
<tr>
<td>$r(1)$</td>
<td>0.28**</td>
<td>0.24*</td>
<td>0.27**</td>
<td>0.19</td>
<td>-0.03</td>
<td>-0.07</td>
<td>0.19</td>
<td>-0.03</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
</tr>
<tr>
<td>$r(4)$</td>
<td>0.40**</td>
<td>0.28**</td>
<td>0.33**</td>
<td>0.29**</td>
<td>0.12</td>
<td>0.04</td>
<td>0.29**</td>
<td>0.12</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>$r(8)$</td>
<td>0.21*</td>
<td>0.11</td>
<td>0.17</td>
<td>0.14</td>
<td>0.04</td>
<td>0.02</td>
<td>0.04</td>
<td>0.04</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>DW</td>
<td>1.37</td>
<td>1.48</td>
<td>1.42</td>
<td>1.47</td>
<td>2.03</td>
<td>2.12</td>
<td>1.47</td>
<td>2.03</td>
<td>2.12</td>
<td>2.12</td>
<td>2.12</td>
<td>2.12</td>
<td>2.12</td>
<td>2.12</td>
<td>2.12</td>
<td>2.12</td>
</tr>
<tr>
<td>$Q$</td>
<td>51.62**</td>
<td>35.06**</td>
<td>40.62**</td>
<td>34.34**</td>
<td>4.62</td>
<td>6.21</td>
<td>34.34**</td>
<td>4.62</td>
<td>6.21</td>
<td>6.21</td>
<td>6.21</td>
<td>6.21</td>
<td>6.21</td>
<td>6.21</td>
<td>6.21</td>
<td>6.21</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.98</td>
<td>0.98</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>$R_2^2$</td>
<td>0.77</td>
<td>0.77</td>
<td>0.82</td>
<td>0.82</td>
<td>0.84</td>
<td>0.84</td>
<td>0.82</td>
<td>0.82</td>
<td>0.84</td>
<td>0.84</td>
<td>0.84</td>
<td>0.84</td>
<td>0.84</td>
<td>0.84</td>
<td>0.84</td>
<td>0.84</td>
</tr>
</tbody>
</table>

#### Auxiliary Residuals

<table>
<thead>
<tr>
<th></th>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normality</td>
<td>0.04</td>
<td>0.23</td>
<td>0.37</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.02</td>
<td>0.11</td>
<td>0.26</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.03</td>
<td>0.11</td>
<td>0.10</td>
</tr>
</tbody>
</table>

#### Level

<table>
<thead>
<tr>
<th></th>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normality</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Skewness</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

#### Slope

<table>
<thead>
<tr>
<th></th>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normality</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Skewness</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

#### Predictive Tests (1996Q1-1997Q4)

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2(8)$</th>
<th>$\chi^2(8)$</th>
<th>$\chi^2(12)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2(8)$</td>
<td>25.64**</td>
<td>24.15**</td>
<td>25.66**</td>
</tr>
<tr>
<td>$\chi^2(12)$</td>
<td>23.55**</td>
<td>14.06</td>
<td>9.62</td>
</tr>
</tbody>
</table>

#### LR tests

<table>
<thead>
<tr>
<th></th>
<th>Test (a)</th>
<th>Test (b)</th>
<th>Test (c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test (a)</td>
<td>n/a</td>
<td>2.23</td>
<td>n/a</td>
</tr>
<tr>
<td>Test (b)</td>
<td>n/a</td>
<td>n/a</td>
<td>9.67**</td>
</tr>
<tr>
<td>Test (c)</td>
<td>n/a</td>
<td>n/a</td>
<td>33.92**</td>
</tr>
</tbody>
</table>

Note:

- $\Delta y_t$ denotes $y_t - y_{t-3}$.
- $t$-statistics from STAMP 5.0 are given in parenthesis.
- ** Indicates significant at the 1% level and * indicates significance at the 5% level;
- Normality is the Bowman-Shenton statistic, approximately distributed as $\chi^2(\nu)$;
- Skewness statistic is approximately distributed as $\chi^2(\nu)$;
- $H(30)$ is the test for heteroscedasticity, approximately distributed as $F_{30,30}$;
- $r(1), r(4)$ and $r(8)$ are the serial correlation coefficients at the 1, 4th and 8th lags respectively, approximately distributed as $N(0,1/\nu)$;
- DW is the Durbin Watson test for first-order autocorrelation;
- $Q_{30}$ is the Box-Ljung Q-statistics based on the first 30 residuals autocorrelation and distributed as $\chi^2(30)$;
- $R^2$ is the coefficient of determination;
- $H(30)$ is the test for heteroscedasticity, approximately distributed as $F_{30,30}$;
- $r(1), r(4)$ and $r(8)$ are the serial correlation coefficients at the 1, 4th and 8th lags respectively, approximately distributed as $N(0,1/\nu)$;
- $R^2$ is the coefficient of determination based on the differences around the seasonal mean (see Harvey, 1989, p.268);
- $R^2$ is the post-sample predictive failure test;
- The Cusum $t$ is the test of parameter consistency, approximately distributed as the $t$-distribution;
- The restrictions imposed for the LR test are explained in the text.

The results indicate that the stochastic trend models (Models (5) and (6)) clearly...
perform better than other deterministic trend models (Models (1)(2)(3) and (4)). The latter models not only suffer from severe autocorrelation of the residuals at the first order, but also consistently fail the prediction tests even at the 1% level of significance. These signs of mis-specification cannot be removed from the specifications of Model (1)(2)(3) and (4) regardless to the number of the additional lagged variables in higher orders. In addition, the LR tests (test (b) and (c)) for the deterministic restrictions on the stochastic trends in Model (5) and (6) decisively reject such restrictions. These results suggest that the stochastic trend is essential for the appropriate modelling of the UK total energy demand. Although the stochastic seasonal component seems to play a relatively small role when it is associated with a deterministic trend (Model (2) and (4)), the LR test (test (a) for Model (6)) indicates that the deterministic restrictions on the stochastic seasonal component are not acceptable.

The estimated average annual rates of the trend growth are different between the models, as well as the estimated income and price elasticities. The growth of the UEDT in Models (1) and (2) are always restricted to be zero which means the models assume that the UK aggregated energy demand is fully explained by the movement of the GDP, price and temperature. As already mentioned, the poor diagnostics suggest this assumption is clearly wrong and there should be a UEDT which cannot be entirely explained by the movement of the GDP, price and temperature. Models (3) and (4) estimate the average annual growth rate of the UEDT over the whole sample period to be around -0.8% and -0.9% which remain constant throughout the sub-divided sample periods. This suggests that the energy demand constantly declined by the rates over the

---

1 Therefore, the results shown in Table 5.1 are estimated by the models after delating the insignificant
sample period even without income, price and temperature changes. However, these models with fixed rate of a declining UEDT also suffer from the first-order autocorrelation of the residuals. Moreover, the post-sample prediction test detects that these model constantly perform very poor forecasting properties. These are clear warning signals that the models are mis-specified.

Models (5) and (6) are the structural time series models which allow the stochastic trend of the UEDT in the estimations. The difference between two models is that the former has the deterministic seasonals and the later has the stochastic seasonal. Therefore, the model (5) can be considered as a restricted version of model (6). The statistics in Table 6 show that these two models are clearly preferred to others since the residuals are completely white noise without any signs of misspecification. Furthermore, the post-sample prediction test indicates that these models show excellent forecasting ability. Although the estimated annual growth rate of the UEDT are -0.7% and -0.9% respectively, the UEDT growth rates for the sub-divided periods are not constant, but are changing over the sample period, implying that the true shape of the UEDT of the UK whole economy energy demand is certainly not linear. This aspect will be further discussed below.

However, the LR test (a) for Model (6) points out that the deterministic restriction on the stochastic seasonal is invalid. This suggests the preferred model should be Model (6) which includes both the stochastic trend and the stochastic seasonals allowing the estimation of the flexible UEDT and changing seasonal patterns. The hyperparameter

variables at 5% level. Again, the delation little affects the diagnostics, which are consistently poor.
value for the stochastic seasonals is relatively small (0.009) compared to that of the stochastic trend (0.341). This means that the stochastic seasonal fluctuation is relatively moderate. Despite this, the LR test shows the stochastic seasonals should not be restricted to be deterministic.

The estimated elasticities are also considerably different between models shown in Table 5.1. The long-run income elasticities estimated by the models without any trend (Models (1) and (2)) are both zero which are rather implausible. The estimated long income elasticities given by the models with either the stochastic trend or the stochastic trend (Models (3) to (6)) are much higher; around 0.6. They are clear examples of the biased estimated elasticities discussed in Chapter 3 caused by an ignoring UEDT i.e. an exclusion of the UEDT may lead to an under-estimation of the long-run income elasticity when the UEDT is generally downward sloping. Although there are not many divergences between the estimated LR income elasticities given be Models (3)(4)(5) and (6), from the discussion above, the estimated value of 0.56 produced by the model (6) is clearly the most preferable.

The estimated long-run price elasticities are also varying according to the models. There is a tendency for the models without any trend (Models (1) and (2)) to produce larger magnitude of elasticities of around −0.4, and the model with the stochastic trend (Model (5) and (6)) generate relatively lower values of around −0.23. The estimated values of around −0.3 by the model with a linear time trend (Models (3) and (4)) lie between them. However, as seen from a statistical viewpoint, it is now clear that the estimate of Model (6) is the most preferable, which is −0.23. This is another example of biased estimates
caused by inappropriate modelling of the UEDT. In other words, in the case of the UK whole economy energy demand, the models ignoring the UEDT may over-estimate the LR price elasticities. This is in line of the argument which is seen in Chapter 3.

In contrast, the differences between modelling of seasonality, namely either by the stochastic or the deterministic modelling, seem not to affect the estimated income and price elasticities much compared to the case of the trend modelling. This is understandable since, again, the estimated hyperparameters for the seasonals are much smaller (0.009) than those of the trend (0.341) as seen in Table 5.1, suggesting the stochastic seasonal variation is far moderate. Despite this, the stochastic seasonals are still preferable from the statistics viewpoint since the deterministic restriction is rejected by the LR test (a).

It has been shown that the estimated results given by the various different models and it has been shown that Model (6) with the stochastic trend and the stochastic seasonals is the finally preferred model. It is, therefore, worth discussing the shape of the UEDT in detail. The estimated trend in Model (6) is the Local Level with Drift (cell (vi) of Table 4.1) that includes a stochastic trend level with fixed slope\(^2\). The estimated UEDT has a clear ‘downward’ shape over the period mainly driven by the stochastic movement of the level and a negative slope as illustrated in the top charts of Figure 5.2. These imply that the UEDT in the energy demand declined almost continuously even after controlling for the income and price effects taken place on the demand curve.

\(^2\) The estimated UEDT is therefore an I(1) variable that becomes stationary after first-differencing.
Looking more closely at the estimated UEDT in the top right hand chart of Figure 5.2, it can be seen that there was a substantial decline during the early 1980s towards the mid-1980s, but the decline diminished in the late 1980s and the early 1990s. This corresponds to the estimated average annual growth rate of the UEDT for each sub-divided period in Table 6.1 for Model (6). The growth rates of the UEDT are -1.26% p.a. during the early 1980s and -0.95% p.a. during the late 1980s, which are considerably higher declining rate compared of -0.44% p.a. before 1974 and -0.42 after 1990. Thus, the UEDT generally declines, but not at a fixed rate as the conventional
deterministic model assumes. This re-enforces the argument that trying to approximate
the UEDT by a linear time trend or simply an intercept term is not appropriate.

Evolution of the stochastic seasonal component is illustrated in the bottom half of
Figure 5.2. Although its stochastic movement is relatively moderate in contrast to the
estimated UEDT, it is observed that the demand in the 1\textsuperscript{st} and the 2\textsuperscript{nd} quarters gradually
increased and decreased respectively over time, suggesting conventional seasonal
dummies are too restrictive. Not surprisingly, the LR test (a) clearly rejects the
restriction of deterministic dummies in favour of the stochastic formulation as seen in
Table 5.1.

The estimated long-run income and price elasticities are 0.56 and -0.23 respectively.
It is useful to compare these results to those of the recent similar energy demand
studies for the same sector, which are summarised Table 5.2.

Westoby and Pearce (1984) compare a number of different specifications within the
log-linear model using the annual data 1954 – 1980 on the basis of the post-sample
prediction test 1974 – 80. They argue that a time trend is just a crude method to
approximate energy efficiency represented by the energy-GDP ratio (p.236) and,
therefore, is excluded from their models. Instead, a measure of the structural
composition of GDP was used to capture the effect. Hence, they assume the UEDT is
dominated by the structural changes in economy, rather than energy efficiency
improvement led by technical progress. Their preferred model is the dynamic log-linear
model since it can provide the most accurate simulation over the post-sample period
amongst the twelve models they consider. However the critical problem with the preferred model is that, except for income, the rest of the coefficients are all insignificant at even at the 10% level of significance. Therefore, although their estimated long-run elasticities are 0.76 for income and -0.21 for price, these estimates cannot be taken seriously from the statistical viewpoint.

Welsch (1989) examines the unbiasedness of energy elasticity estimates for a number of counties including the UK using the log-linear model. Appropriateness of an inclusion of a deterministic time trend is considered as an important issue. As mentioned in Chapter 3, for the UK, model including a time trend is clear preferred. Although the estimated long-run income and price elasticities are 0.71 and -0.21 which are somewhat different from the estimates here, his finding is still consistent with what we have found i.e. when the trend (deterministic or stochastic) is completely ignored, a lower income elasticity and a higher price elasticity are generated. He claims that the lower price elasticity for the UK compared to the US, Italy and the Netherlands implies that energy efficiency improvement is mostly induced by autonomous technical progress rather than price-induced, and a higher income elasticity is led by the separation between pure income effect and technical progress effect (p.290). This is a case where the deterministic time trend acts as a reasonable approximation of the UEDT.

---

3 This differences may be caused by the significantly different estimation period considered in the studies. Haas et al. (1998) show the estimation using the data covering only before the plummeting in oil prices, around 1985, tends to produce much higher values for both income and price elasticities compared to the estimation using the data including after the period (p.125).
### Table 5.2. Recent energy demand studies for the UK whole economy aggregated energy demand

<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Sector / area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated long-run income and price elasticities</th>
</tr>
</thead>
</table>
| Westoby and Pearce (1984) | Aggregated energy    | Dynamic log-linear (Manufacturing output/GDP ratio included) | Annual data 1954 - 80 (27 obs.) | $\eta_y = 0.760$
|                        |                       |                                             |                                  | $\eta_p = -0.210$
|                        |                       |                                             |                                  | No trend included |
| Welsch (1989)          | Aggregated energy    | Static/dynamic log-linear reduced form by OLS | Annual data 1970 - 84 (15 obs.)  | $\eta_y = 0.71$
|                        |                       |                                             |                                  | $\eta_p = -0.11$
|                        |                       |                                             |                                  | Trend included but no detail shown |
| Hunt and Manning (1989)| Aggregated final energy | Log-linear EG 2-step                     | Annual data 1967 - 86 (20 obs.)  | $\eta_y = 0.38$ to 0.49
|                        |                       |                                             |                                  | $\eta_p = -0.30$ to 0.33
|                        |                       |                                             |                                  | No trend included |
| Hunt and Witt (1995)   | Aggregated final energy | Johansen - VECM                     | Annual data 1967 - 94 (28 obs.)  | $\eta_y = 0.23$
|                        |                       |                                             |                                  | $\eta_p = -0.29$
|                        |                       |                                             |                                  | No trend included |
| Boone et al. (1995)    | Aggregated fossil fuels | Johansen - VECM                     | Quarterly data (interpolated from annual data 1978 - 90, but detail not reported) | $\eta_y = 1.0$ (imposed)
|                        |                       |                                             |                                  | $\eta_p = -0.045$
|                        |                       |                                             |                                  | $t = -0.0258$
| Smith et al. (1995)    | Aggregated fossil fuels | Log-linear - Kalman filter               | Quarterly data (interpolated from annual data 1978 - 90, but detail not reported) | $\eta_y = 1.0$ (imposed)
|                        |                       |                                             |                                  | $\eta_p = -0.045$
|                        |                       |                                             |                                  | $t = \text{stochastic trend}$

Note: $\eta_y$ = the long-run income elasticity, $\eta_p$ = the long-run price elasticity

In contrast, Hunt and Manning (1989) do not include the UEDT at all. The estimated long-run income elasticity of 0.38 to 0.49 are rather lower than our estimate of 0.56, which can be considered as the bias due to an ignorance of the UEDT effect. The long-run price elasticity is also estimated as slightly larger value of around –0.3 (in absolute term) which is consistent with our finding that the models excluding any trend generate the higher price elasticities. However, the sample period used by Hunt and Manning (1989) does not include the period after the energy price dropped in around 1985. Thus, as noted, the estimated values can be larger than the estimation with more recent sample.

In this regard, the estimated values given by Hunt and Witt (1995) using annual data for the period 1967 to 1994 may be more directly comparable to those here. Their estimated long-run income elasticity is much lower, at 0.23 compared to 0.56 estimated by our model. This is a clear example of the bias arguments in Chapter 3 given the generally declining shape of the UEDT. When income increases (as it does over the estimation period) and the UEDT is downward sloping, it is expected that the estimated conventional model will under-estimate the income elasticity as demonstrated here. In contrast, the estimated long-run price elasticity is much closer to their estimate of –0.29 obtained by Hunt and Witt (1995). Given the UEDT is generally down-ward, the biased estimation for the price elasticity is expected based on argument in Chapter 3. However, since the price movement over the sample period includes both up-ward and down-ward (see Figure 6.1), the biased effect seems to be rather obscured, generating the similar estimated values for the price elasticity.
With regards to Boone et al. (1995) and Smith et al. (1995), in Chapter 3, it was already pointed out that a number of critical problems with the studies in spite of their challenging modelling framework. In particular, the impositions of the unitary income elasticity are serious misleading since the long-run income elasticity is estimated to be 0.56 which is far from a unitary.

5.2.2. Aggregated final energy demand in the UK residential sector

5.2.2.1. The data

The data series for the estimation of the aggregate final energy demand in the UK residential sector are illustrated in Figure 5.3. The demand for energy in this sector is characterised by a higher magnitude of seasonal fluctuation, compared to the whole economy final energy demand illustrated in Figure 5.1, implying that most of energy in this sector is used for space heating. In contrast, the real household disposable income (RHDY, here after) and the energy price for this sector do not exhibit any particular strong seasonal pattern. Although the RHDY constantly increased over the sample period except the mid-1970s and the early 1980s, the price exhibits drastic rise in the early 1980s followed by the long-term declining after the mid-1980s. Temperature is the same as that used in the previous section 5.2.1.1.

5.2.2.2. The estimated results

Table 5.3 is the summary table of the estimated results for this sector. $y_t$, $p_t$, $e_t$ and $TEMP_t$ in the table represent the RHDY, the price, the energy consumption and air
temperature respectively. In contrast to the case of the UK whole economy energy and other sector analysed in this chapter, it is found that neither a stochastic nor a deterministic trend exits in this sector as illustrated in the top charts of Figure 5.4. To understand this more intuitively, recall Table 4.1. The estimation began with the most general model (ix) and gradually tested down to the restricted versions guided by appropriate restriction tests, which was finalised by cell (ii) that has only a constant term. However, the seasonality does exhibit a stochastic pattern. Therefore, Table 5.3 shows the two models; Model (1) which has no trend with deterministic seasonals and Model (2) with stochastic seasonals, which correspond to cell (1) and (2) of Table 4.2 in respectively.

**Figure 5.3.** UK residential sector aggregated final energy consumption (LDOMEt), Household real disposable income (LRHDY), Real energy price (LDOMPt) (in log scale) and GB air temperature (TMP)
Non-existence of the trend reflects zero value for the hyperparameter for the trend ($\sigma_n^2$ and $\sigma_x^2$) in the both models, and zero values for the average growth rate of the trend throughout the sample period. The main difference between the models is highlighted by the hyperparameter value for the seasonals (2.403) in Model (2) which is significantly larger than the other sectors analysed, implying the stochastic variation in the seasonals is far from negligible. This is why the LR test (a) categorically rejects the deterministic restriction on the stochastic seasonals. In addition, Model (1) requires a much larger number of the lagged variables to eliminate the autocorrelation of the residuals. Some of the lagged variables included in Model (1) are not statistically significant at 5% level, but the deletion of them immediately causes the autocorrelation, therefore, they are retained\(^4\). Thus, Model (2) is more parsimonious and simpler, which is clearly preferred to the other.

Moreover, it was found that the deterministic seasonal model (Model (1)) suffers from deterioration of the normality and the skewness of the residual distribution, which are much closer to the 5% critical values. Since Model (2) is more parsimonious, simpler, lesser restrictive in modelling the seasonality and better diagnostics, Model (2) is clearly the preferred model to Model (1).

\(^4\) However, they are significant at 10%.
<table>
<thead>
<tr>
<th>Models</th>
<th>No Trend and Deterministic Seasonals</th>
<th>No Trend and Stochastic Seasonals</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Estimated Coefficients</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$y_i$</td>
<td>0.4888</td>
<td>0.2561**</td>
</tr>
<tr>
<td></td>
<td>(1.916)</td>
<td>(9.973)</td>
</tr>
<tr>
<td>$y_{t-1}$</td>
<td>-0.6703*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.340)</td>
<td></td>
</tr>
<tr>
<td>$y_{t-3}$</td>
<td>0.4363</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.934)</td>
<td></td>
</tr>
<tr>
<td>$p_t$</td>
<td>-0.2120**</td>
<td>-0.1873**</td>
</tr>
<tr>
<td></td>
<td>(10.255)</td>
<td>(4.903)</td>
</tr>
<tr>
<td>$e_{t-1}$</td>
<td>0.1674*</td>
<td>0.2688**</td>
</tr>
<tr>
<td></td>
<td>(2.506)</td>
<td>(4.540)</td>
</tr>
<tr>
<td>$e_{t-2}$</td>
<td>-0.2140**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.709)</td>
<td></td>
</tr>
<tr>
<td>$e_{t-4}$</td>
<td>0.1978**</td>
<td>0.1236*</td>
</tr>
<tr>
<td></td>
<td>(2.714)</td>
<td>(2.122)</td>
</tr>
<tr>
<td>$TEMP_t$</td>
<td>-0.0581**</td>
<td>-0.0557**</td>
</tr>
<tr>
<td></td>
<td>(10.144)</td>
<td>(12.962)</td>
</tr>
<tr>
<td><strong>Long-Run Estimates</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income ($Y$)</td>
<td>0.3003</td>
<td>0.2996</td>
</tr>
<tr>
<td>Price ($P$)</td>
<td>-0.2498</td>
<td>-0.2191</td>
</tr>
<tr>
<td><strong>Estimated Hyperparameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2 \times 10^{-4}$</td>
<td>21.333</td>
<td>7.769</td>
</tr>
<tr>
<td>$\sigma^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\sigma^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\sigma^2 \times 10^{-4}$</td>
<td>2.403</td>
<td></td>
</tr>
<tr>
<td><strong>Nature of Trend</strong></td>
<td>No Trend (Cell ii)</td>
<td>No Trend (Cell ii)</td>
</tr>
<tr>
<td>Corresponding cell of Table 4.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Average Annual Growth rate of the estimated trend</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1972q1 – 1995q4</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>1972q1 – 1974q4</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>1975q1 – 1979q4</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>1980q1 – 1984q4</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>1985q1 – 1989q4</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>1990q1 – 1995q4</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td><strong>Diagnostics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Equation Residuals</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Error</td>
<td>4.33%</td>
<td>3.67%</td>
</tr>
<tr>
<td>Normality</td>
<td>4.86</td>
<td>0.62</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>1.24</td>
<td>0.26</td>
</tr>
</tbody>
</table>
The estimated income elasticities given by the both models are almost the same which are around 0.3. Similarly, the estimated price elasticities are not different, although Model (1) (−0.25) is slightly higher (in absolute term) than that of Model (2) (−0.22).

The air temperature is indeed very significant implying the energy demand in this sector is highly influenced by the temperature movement.

Model (2) still requires several lagged variables, despite it is much smaller number than Model (1), implying the demand cannot adjust instantaneously to the long-run position.

As mentioned above, energy demand in the residential sector does not have a trend component at all - neither stochastic nor deterministic as illustrated by the horizontal
line in Figure 5.4. When it is included the equation fails some of the diagnostic tests. The result that there is no significant UEDT for the residential sector might imply that the demand for energy is driven solely by income, price, and temperature.

Figure 5.4. Estimated UEDT (top left), slope of UEDT (top right), estimated seasonal variation (bottom left) and individual seasonal variations (bottom right) in the UK residential sector final energy demand

However, the absence of a UEDT in energy demand could indicate that an improvement in the energy efficiency of residential energy usage is cancelled out by changes in consumer’s taste; that is consumers choosing larger and more comfortable energy appliances such as central heating system, freezers, tumble dryers etc. This result is also
consistent to the findings of Schipper et al. (1992, pp. 175 – 6). On the contrary, the seasonality exhibits a stochastic pattern as seen in the bottom charts in Figure 5.4 which illustrates well the evolution of the stochastic seasonal pattern, with the fluctuations getting larger over the estimation period. Such evolving seasonal pattern certainly cannot be adequately modelled by the conventional deterministic seasonal dummies.

The estimated long-run elasticities are 0.3 for income and –0.2 for price. It is worth noting that the long-run income elasticity of 0.3 is somewhat smaller than those estimated in this paper for the whole economy, manufacturing, and transportation sectors. This is consistent with the view that the energy service for the residential sector is approaching saturation of the residential energy service (Haas and Schipper, 1998, p.438). These estimated values can be compared to the recent energy demand studies for this sector which is reported in Table 5.4.

Barker (1995) estimates the same demand using the log-linear model with annual data 1970 – 1990 including a deterministic time trend. The linear trend is estimated to be zero, which is consistent to the results in this thesis. The estimated long-run income elasticity is 0.35 which is fairly close to our estimate of 0.3. Since the UEDT does not present, this similar elasticity is understandable. On the other hand, the estimated price elasticity by Barker (1995) is –0.3, which is not very different from the estimates here, but it is not being freely estimated, but imposed at, what he refers to as the “consensus” value (p. 234).

---

5 However, there is no description why it is included in his model.
For the estimation of the demand in the same sector using the annual data 1970 – 1993, Haas and Shipper (1998) employ the log-linear model with the irreversible price effect term described in Dargay (1992), as well as the model assuming the normal reversible price response. With the normal reversible price model, the long-run income elasticity is estimated as 0.53 whereas the long-run price elasticity is found to be insignificant even at 25% level. The lagged dependent variable also appears to be insignificant at the 10% level. With the irreversible model, the long-run income price elasticity is estimated as 0.44, but, again, none of price terms appears to be significant even at the 10% level. Only at 20% level, the maximum price term becomes significant value of –0.13. Given the poor statistical properties of the estimated parameters, the model is not robust despite its attractive theoretical properties. Moreover, the implication of the estimated price elasticity by the irreversible model may be rather unrealistic from the economics viewpoint, since it implies that, only when the price rises beyond the historical maximum level, the demand would reduced by 0.13%, otherwise the demand has no response to any change in the price no matter it increases or decreases. This is highly contrasted to our estimate of –0.2 which is reversible price effect.
<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated long-run income and price elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.30$ (imposed)</td>
<td>$t = 0$</td>
</tr>
</tbody>
</table>
| Hodgson and Miller (1995) | Aggregated energy and individual fuels | Log-linear unrestricted ECM                | Annual data 1954 - 88 (35 obs.) | $\eta_y = 0.2$
|                     |                                       |                                            | $\eta_p = \text{n.a.}$         |                                                 |
| Haas and Schipper (1998) | Aggregated energy                     | Dynamic log-linear model                   | Annual data 1970 - 93 (24 obs.) | $\eta_y = 0.53$
|                     |                                       | (Energy intensity included)                |                              | $\eta_p = 0$ (insignificant)                     |
|                     |                                       | Dynamic log-linear Irreversible demand model | Annual data 1970 - 93 (24 obs.) | $\eta_y = 0.44$
|                     |                                       |                                            | $\eta_p = -0.13$ (for the max. price increase, but insignificant at 10%) |                                                 |
| Clements and Madlener (1999) | Aggregated energy                     | Johansen - VECM                            | Quarterly data 1975q4 - 1996q3 (87 obs.) | $\eta_y = 0.36$
|                     |                                       |                                            | $\eta_p = 0$                   | Trend included, but not reported                |
|                     |                                       |                                            |                              | Seasonal dummies included                    |

Note: $\eta_y =$ the long-run income elasticity, $\eta_p =$ the long-run price elasticity

Finally, using quarterly data 1975q4 – 1996q3 for the same sector, Clements and Madlener (1999) estimate the long-run income elasticities of about 0.3. Given the absence of an UEDT, this consistency is to be expected since all three studies have similar model specifications other than seasonality. The estimated long-run price elasticities of zero is, however, different to our result of −0.2. The difference may come from the different sample period considered in their study of 1975 – 1996. This does not include the early 1970s during rapidly rising prices and hence is likely to contribute to the difference. Moreover, they used deterministic seasonal dummies that might also contribute to the different results.

5.2.3. Aggregated final energy demand in the UK manufacturing sector

5.2.3.1. The data

Figure 5.5 illustrates the data series used for the estimation of aggregate final energy demand for the UK manufacturing sector, which includes output, the real energy price and air temperature between 1971q1 and 1997q4. Energy consumption almost steadily declined over the sample, and exhibits a clear seasonal pattern but smaller in magnitude than the residential sector. At the end of the sample, a recovery of the energy consumption is observed. The movement of the manufacturing output is very different from that of real GDP in Figure 5.1 and the RHDY in Figure 5.3. Figure 5.5 illustrates the severe effect of the early 1980s recession on the manufacturing output. Therefore, it shows strong growth at the late 1980s followed by small scale of fluctuations during the 1990s. The energy price exhibits dramatic up and down periods with a continuously
declining period after the mid 1980s. It is also noted that, for this sector only, the energy price has a seasonal pattern which becomes more marked towards the end of the sample period. The air temperature is the same as that used in previous sections.

Figure 5.5. UK manufacturing sector aggregated final energy consumption (LOI Et), Manufacturing output (LMANY), Real energy price (LOIPt) (in log scale) and GB air temperature (TMP)

5.2.3.2. The estimated results

For this sector, both of the UEDT and seasonal variation are found to be stochastic. Therefore, similar to the whole economy, all models (Models (1) to (6)) classified in Table 4.2 are estimated. The results are summarised in Table 5.3.
Table 5.5. Estimated results for the UK manufacturing sector final energy demand 1972q1 – 1995q4

<table>
<thead>
<tr>
<th>Cell number of Table 4.2</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
<th>Model (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Models</strong></td>
<td>No Trend and Deterministic Seasonals</td>
<td>No Trend and Stochastic Seasonals</td>
<td>Deterministic Trend and Seasonal</td>
<td>Deterministic Trend and Stochastic Seasonals</td>
<td>Stochastic Trend and Deterministic Seasonals</td>
<td>Stochastic Trend and Deterministic Seasonals</td>
</tr>
<tr>
<td><strong>Estimated Coefficients</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yt</td>
<td>0.8594**</td>
<td>0.8591**</td>
<td>0.8572**</td>
<td>0.8437**</td>
<td>0.8070**</td>
<td>0.7171**</td>
</tr>
<tr>
<td>Yt-1</td>
<td>-0.7342**</td>
<td>-0.7340**</td>
<td>-0.4453**</td>
<td>-0.4352**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.265)</td>
<td>(5.260)</td>
<td>(2.961)</td>
<td>(2.850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pt</td>
<td>-0.2578*</td>
<td>-0.2529*</td>
<td>-0.3759**</td>
<td>-0.2019**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.550)</td>
<td>(4.032)</td>
<td>(3.437)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pt-1</td>
<td>0.3271**</td>
<td>0.3218**</td>
<td>0.2158*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.191)</td>
<td>(3.088)</td>
<td>(2.247)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔPt</td>
<td>-0.3208**</td>
<td>-0.3207**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.004)</td>
<td>(3.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>et-1</td>
<td>0.4920**</td>
<td>0.4926**</td>
<td>0.2836**</td>
<td>0.2958**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.615)</td>
<td>(6.610)</td>
<td>(3.217)</td>
<td>(3.317)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>et-2</td>
<td>0.2973**</td>
<td>0.2970**</td>
<td>0.1971*</td>
<td>0.1879*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.466)</td>
<td>(3.458)</td>
<td>(2.338)</td>
<td>(2.180)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>et-4</td>
<td>0.2647**</td>
<td>0.2645**</td>
<td>0.2123**</td>
<td>0.2050**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.551)</td>
<td>(3.546)</td>
<td>(3.006)</td>
<td>(2.867)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TEMPt</td>
<td>-0.0112**</td>
<td>-0.0112**</td>
<td>-0.0114**</td>
<td>-0.0125**</td>
<td>-0.0128**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.696)</td>
<td>(2.694)</td>
<td>(2.908)</td>
<td>(2.873)</td>
<td>(3.666)</td>
<td>(3.812)</td>
</tr>
<tr>
<td><strong>Long-Run Estimates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income (Y)</td>
<td>-2.3116</td>
<td>-2.3138</td>
<td>1.3441</td>
<td>1.3236</td>
<td>0.8071</td>
<td>0.7171</td>
</tr>
<tr>
<td>Price (P)</td>
<td>0</td>
<td>0</td>
<td>0.2262</td>
<td>0.2232</td>
<td>-0.1602</td>
<td>-0.2019</td>
</tr>
<tr>
<td><strong>Estimated Hyperparameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>σ_γ^2 x 10^{-4}</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>σ_e^2 x 10^{-4}</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.018</td>
<td>0.017</td>
</tr>
<tr>
<td>σ_γ^2 x 10^{-4}</td>
<td>0.0001</td>
<td>0</td>
<td>0.015</td>
<td>0</td>
<td>0.115</td>
<td></td>
</tr>
<tr>
<td><strong>Nature of Trend</strong></td>
<td>No Trend (Cell ii)</td>
<td>No Trend (Cell ii)</td>
<td>A Linear Trend (Cell v)</td>
<td>A Linear Trend (Cell v)</td>
<td>Smooth Trend (Cell viii)</td>
<td>Smooth Trend (Cell viii)</td>
</tr>
<tr>
<td><strong>Average Annual Growth rate of the estimated trend</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1972q1 – 1995q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.92%</td>
<td>-0.92%</td>
<td>-2.70%</td>
<td>-2.66%</td>
</tr>
<tr>
<td>1972q1 – 1974q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.92%</td>
<td>-0.92%</td>
<td>0.44%</td>
<td>0.47%</td>
</tr>
<tr>
<td>1975q1 – 1979q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.92%</td>
<td>-0.92%</td>
<td>0.03%</td>
<td>0.17%</td>
</tr>
<tr>
<td>1980q1 – 1984q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.92%</td>
<td>-0.92%</td>
<td>-3.85%</td>
<td>-3.80%</td>
</tr>
</tbody>
</table>

Chapter 5 221
<table>
<thead>
<tr>
<th></th>
<th>1985q1 – 1989q4</th>
<th>1990q1 – 1995q4</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
<td>0%</td>
<td>-0.92%</td>
<td>-0.92%</td>
<td>-4.55%</td>
<td>-4.57%</td>
<td></td>
</tr>
<tr>
<td>Diagnostics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equation Residuals</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Error</td>
<td>3.14%</td>
<td>3.39%</td>
<td>2.90%</td>
<td>3.00%</td>
<td>2.93%</td>
<td>3.01%</td>
<td></td>
</tr>
<tr>
<td>Normality</td>
<td>1.47</td>
<td>0.80</td>
<td>0.22</td>
<td>0.17</td>
<td>0.26</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.03</td>
<td>0.06</td>
<td>0.00</td>
<td>0.17</td>
<td>0.19</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>1.44</td>
<td>0.75</td>
<td>0.22</td>
<td>0.09</td>
<td>1.33</td>
<td>1.11</td>
<td></td>
</tr>
<tr>
<td>H(30)</td>
<td>1.15</td>
<td>1.09</td>
<td>1.21</td>
<td>0.97</td>
<td>3.54</td>
<td>1.74</td>
<td></td>
</tr>
<tr>
<td>r(1)</td>
<td>-0.11</td>
<td>-0.11</td>
<td>-0.03</td>
<td>-0.04</td>
<td>0.09</td>
<td>-0.07</td>
<td></td>
</tr>
<tr>
<td>r(4)</td>
<td>-0.16</td>
<td>-0.15</td>
<td>-0.14</td>
<td>0.12</td>
<td>0.04</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>r(8)</td>
<td>0.12</td>
<td>0.13</td>
<td>0.13</td>
<td>0.15</td>
<td>0.23*</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>DW</td>
<td>2.20</td>
<td>2.20</td>
<td>1.42</td>
<td>2.05</td>
<td>2.16</td>
<td>2.00</td>
<td></td>
</tr>
<tr>
<td>Q</td>
<td>Q(8,9) = 8.41</td>
<td>Q(8,7) = 8.50</td>
<td>Q(8,8) = 5.21</td>
<td>5.32</td>
<td>10.73</td>
<td>6.21</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.98</td>
<td>0.97</td>
<td>0.98</td>
<td>0.99</td>
<td>0.97</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>R²²</td>
<td>0.58</td>
<td>0.52</td>
<td>0.65</td>
<td>0.63</td>
<td>0.64</td>
<td>0.62</td>
<td></td>
</tr>
<tr>
<td>Auxiliary Residuals</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Irregular</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Normality</td>
<td>1.52</td>
<td>1.51</td>
<td>0.33</td>
<td>0.26</td>
<td>4.45</td>
<td>4.12</td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.03</td>
<td>0.03</td>
<td>0.00</td>
<td>0.00</td>
<td>0.65</td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>1.50</td>
<td>1.48</td>
<td>0.33</td>
<td>0.26</td>
<td>3.80</td>
<td>3.51</td>
<td></td>
</tr>
<tr>
<td>Level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Normality</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Normality</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>0.39</td>
<td>0.48</td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>0.37</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>0.02</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>Predictive Tests (1996Q1-1997Q4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X² (a)</td>
<td>36.50**</td>
<td>34.77**</td>
<td>58.13**</td>
<td>54.79**</td>
<td>58.83**</td>
<td>50.58**</td>
<td></td>
</tr>
<tr>
<td>Cusum t</td>
<td>3.06**</td>
<td>3.01**</td>
<td>5.23**</td>
<td>5.15**</td>
<td>4.74**</td>
<td>4.36**</td>
<td></td>
</tr>
<tr>
<td>LR tests</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test (a)</td>
<td>n/a</td>
<td>(0)</td>
<td>n/a</td>
<td>0.06</td>
<td>n/a</td>
<td>6.10*</td>
<td></td>
</tr>
<tr>
<td>Test (b)</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>54.24**</td>
<td>58.72**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test (c)</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>60.86**</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: See notes for Table 5.1.

Model (6) is surprising simpler and more parsimonious compared to other rival models, in particular Models (1) (2) (3) and (4) for which the larger number of the lagged variables are necessary to ensure the residuals are white noise. The long-run income elasticities estimated by the models excluding any trend (Model (1) and (2)) are around -2.3, which are peculiar negative values. Similarly, the models including the
deterministic time trend (Models (3) and (4)) produce the price elasticities of around 0.24 which are also curiously positive values. These rather odd estimated values for the elasticities are little changed whether or not including the stochastic seasonals in the models. The average annual growth rates of the UEDT are imposed to be zero by Model (1) and (2), and estimated to be a fixed rate of -0.9% p.a. by Models (3) and (4). The latter value suggests that the UEDT steadily declines at that rate throughout the estimation period. However, since these inflexible and restricted forms of the UEDT cause estimated elasticities not to conform to the norms of conventional economics, Models (1) (2) (3) and (4) are not preferred.

When the model includes the stochastic trend (Model (5) and (6)), the estimated elasticities become far more plausible, around 0.7 - 0.8 for the income and -0.15 - -0.18 for the price. The LR test (b) decisively rejects the deterministic restriction on the stochastic trend, indicating that a simple linear deterministic trend should not be imposed on the stochastic trend. The difference between Models (5) and (6) is the modelling of the seasonality; the former has the conventional deterministic seasonal dummies and the latter has the stochastic seasonal dummies. The diagnostics suggest the autocorrelation occurs in Model (5) at the 8th order and the LR test (a) indicate the deterministic seasonal is unacceptable. In addition, Model (6) is the most parsimonious. Therefore, our ultimate preferred model is Model (6) which includes both the stochastic trend and stochastic seasonals. The model estimates that the LR elasticities are 0.73 for income and -0.18 for price. Only problem with Model (6) is the failure of the post-sample prediction tests, though other rival models equally fail it. This is caused by

---

6 This might imply that energy is an inferior good, but it is rather unrealistic given the relationship
the sudden jump of the energy consumption series taken place at 1996q3 onwards without major changes in other series corresponding it. Therefore, the sudden shift of the energy series is considered as a structural break occurred outside the estimation period. Unlike the case of a structural break arose within the estimation period, it can be hardly predicted by econometric models properly.

Figure 5.6. Estimated UEDT (top left), slope of UEDT (top right), estimated seasonal variation (bottom left) and individual seasonal variations (bottom right) in the UK manufacturing sector final energy demand

The preferred model for the manufacturing sector does not include any lagged variables implying immediate adjustments of the demand to income (output) and price changes to
the long-run position along with the demand curve. The stochastic trend in the preferred model is what is known as, the Smooth Trend\(^7\) which includes a stochastic slope component but a fixed level\(^8\). That has zero hyperparameter value for \(\sigma^2\), but \(\sigma^2\) is non-zero as reported in Table 5.5. Therefore, the estimated UEDT is smoothly changing its direction with generally downward sloping as illustrated in Figure 5.6. The estimated UEDT rises slightly at the start of the estimation period but falls continually from 1977. The slope of the UEDT in Figure 5.6 clearly illustrates that a substantial change in the direction of the UEDT occurred during the early 1980s.

This is also observed in the average growth rate of the UEDT reported in Table 6.5. The positive growth of 0.1% - 0.5% p.a. during the 1970s was followed by considerable negative growth of around -4% p.a. during the rest of the sample period. Note that this substantial downward trend in the energy demand is led by neither the change in the manufacturing output nor the changes in the energy price nor the changes in the temperature. Therefore, the UEDT is introducing in the model and is found to be highly non-linear UEDT which cannot be adequately approximated by a simple deterministic time trend. It is no wonder that the deterministic trend or no trend model (Models (1) to (4)) generates substantially biased estimates for income and price elasticities, as we have already seen.

It is interesting to note that this result is consistent with Unander et al. (1999) using the Divisia decomposition method. They show that the UK manufacturing sector, in line

---

\(^7\) See Chapter 4, Section 3.1 and Table 4.1 for the detail.

\(^8\) Therefore, the estimated UEDT requires second-differencing to be a stationary and is therefore I(2) which can be very problematic when modelled by the conventional OLS type model (See Chapter 4).
with all OECD manufacturing sectors, experienced a fall in energy intensities throughout the period 1971 – 1995. The most rapid decline being between 1979 – 85 followed by slower decline from the mid-1980s. Unander et al. (1999), argue that that the fall in oil prices in the mid-1980s did not bring the decline in energy intensities “to a halt” (p. 776).

The evolving seasonal pattern found in the energy series is also illustrated in Table 5.6. It is observed that the seasonal pattern evolves, in particular, it becomes smaller in magnitude after the early 1980s. The evolution of each of the seasonals indicates that a relative increasing in the third quarter and relative decreasing in the forth quarter. The conventional deterministic seasonal dummies cannot adequately model these evolving seasonal patterns.

The estimated long-run output and price elasticities from the preferred model (6) are 0.72 and –0.20 respectively. It is worth noting that the output elasticity is somewhat larger than the other sectors analysed in this thesis. This is not surprising, reflecting the close link between output and energy demand in the manufacturing sector.
Table 5.6. Recent energy demand studies for the UK manufacturing sector energy demand

<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated long-run income and price elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lynk (1989)</td>
<td>Aggregated final energy</td>
<td>KLE translog by FIML</td>
<td>Annual data</td>
<td>$\eta_Y = 0.44$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1948 - 81 (34 obs.)</td>
<td>$\eta_P = -0.69$</td>
</tr>
<tr>
<td>Hunt and Lynk (1992)</td>
<td>Aggregated final energy</td>
<td>Log-linear EG 2-step</td>
<td>Annual data</td>
<td>$\eta_Y = 0.68$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1948 - 88 (41 obs.)</td>
<td>$\eta_P = -0.29$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$t = -0.009$</td>
</tr>
<tr>
<td>Atkinson and Manning (1995)</td>
<td>Aggregated energy</td>
<td>Log-linear EG 2-step</td>
<td>Annual data</td>
<td>$\eta_Y = 0.42$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(incl. prices of K, L)</td>
<td>1960 - 1989 (30 obs.)</td>
<td>$\eta_P = 0$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(not cointegrated)</td>
<td></td>
<td>trend included, but not reported</td>
</tr>
<tr>
<td>Barker (1995)</td>
<td>Disaggregated energy in several industries</td>
<td>Log-linear EG 2-step</td>
<td>Annual data</td>
<td>$\eta_Y = 0.52$ (averaged)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1970 - 90 (21 obs.)</td>
<td>$\eta_P = -0.51$ (imposed)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$t = -0.01825$ (averaged)</td>
</tr>
<tr>
<td>Hodgson and Miller (1995)</td>
<td>Aggregated energy and individual fuels</td>
<td>Log-linear unrestricted ECM</td>
<td>Annual data</td>
<td>$\eta_Y = 0.48$ (averaged)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1954 - 88 (35 obs.)</td>
<td>$\eta_P = -0.91$ (averaged)</td>
</tr>
</tbody>
</table>

Note: $\eta_Y$ = the long-run income elasticity, $\eta_P$ = the long-run price elasticity

The estimated values can be compared to those of the recent energy demand studies summarised in Table 5.6. Using annual data 1948 – 1988 and a different estimation technique, Hunt and Lynk (1992) estimate very similar results of 0.70 for income and -0.29 for price\(^9\). Note that they include a linear time trend as a proxy for technical progress that is found to be -0.9% p.a.. This growth rate of technical progress\(^10\) is far smaller compared to our result of -3.9% p.a. at the end of sample period or -2.7% p.a. on overall average. This dissimilarity of the UEDT growth rates may be led by the different estimated sample periods of the studies, which are overlapped each other only for 16 years out of 41 years considered by Hunt and Lynk (1992). This implies the income and the price elasticities of this sector are stable over the longer-term, whereas the UEDT changes its direction flat into steeper downward sloping.

However, the results obtained by Lynk (1989) are quite different. With annual data 1948 – 1981 and the KLE translog model not including a trend, hence ignoring the UEDT effect, he estimates a long-run output elasticity of 0.44 and long-run price elasticity of -0.69. Again, these differences are in line with those discussed in Chapter 3. That is, given that the general direction of the UEDT is negative, then a model that does not attempt to allow for the overall effect will result in a downward bias of the output elasticity (in a period of rising output) as discussed in Chapter 3. Similarly, it will result in a positive bias (in absolute terms) of the long-run price elasticity when prices are generally rising.

\(\text{Hunt and Lynk (1992) do explicitly attempt to model the factor substitution/complementarity between energy and other non-energy factors of production.}\)

\(\text{This can be considered as the equivalent to the UEDT.}\)
Atkinson and Manning (1995) employ the log-linear model including a deterministic time trend using the annual data 1960 – 1989 for the estimation of this sector\textsuperscript{11}. The estimated long-run elasticities are 0.42 for income and zero for price. However, for the statistical reason, they admit the estimated long-run elasticities are not encouraging (p.103). The long-run price estimated elasticities given by Barker (1995), and Hodgson and Miller (1995) also differ considerably from zero similar to the estimates here. This also indicates the difficulty of proper modelling of the energy demand of this sector and the estimated result is sensitive to the model specifications. However, since the estimate by Barker (1995) is imposed value, it should be taken with care.

5.3. Individual fuel energy demand in the UK

This section examines the application of the structural time series model to two individual fuel energy demands in the UK; road transportation oil and electricity demands.

5.3.1. Road transportation oil demand in the UK

5.3.1.1. The data

Figure 5.7 illustrates the data used for the estimation of the transport oil demand in the UK. The series consists of consumption, real GDP, real price and air temperature.

\textsuperscript{11} However, reason for the inclusion of the deterministic trend is not given in the study.
The consumption of transportation oil increased almost continuously, by nearly 70%, during the sample period. There is some stagnation during the mid-1970s and the early 1980s. A systematic seasonal pattern is also observed. Real GDP series is the same as that used for the whole economy. The real price of transportation oil is characterised by dramatic fluctuations reflecting the first and second oil shock until the late 1980s, followed by a gradual rising mainly due to an increase in fuel taxation during the 1990s. The air temperature is the same as used before.

5.3.1.2. The estimated results

Table 5.7 reports the estimated results by the six models classified in Table 4.2.
### Table 5.7. Estimated results for the UK transportation oil demand 1972q1 – 1995q4

<table>
<thead>
<tr>
<th>Models</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
<th>Model (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Trend and Deterministic</td>
<td>No Trend and Stochastic</td>
<td>Deterministic Trend and</td>
<td>Deterministic Trend and</td>
<td>Stochastic Trend and</td>
<td>Stochastic Trend and Stochastic</td>
</tr>
<tr>
<td></td>
<td>Seasonals</td>
<td>Seasonals</td>
<td>Deterministic Seasonal</td>
<td>Deterministic Seasonal</td>
<td>Stochastic Seasonals</td>
<td>Stochastic Seasonals</td>
</tr>
<tr>
<td>Estimated Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$y_t$</td>
<td>0.4657** (6.702)</td>
<td>0.4128** (5.937)</td>
<td>0.4757** (5.393)</td>
<td>0.4381** (5.006)</td>
<td>0.5912** (6.031)</td>
<td>0.5634** (5.387)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$y_{t-1}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$y_{t-2}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_t$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1269** (4.120)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_{t-1}$</td>
<td>-0.0487** (2.746)</td>
<td>-0.0429* (2.596)</td>
<td>-0.1120** (4.595)</td>
<td>-0.1042** (4.369)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_{t-2}$</td>
<td>-0.2605** (2.716)</td>
<td>-0.2389** (2.511)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta p_t$</td>
<td>0.1713** (4.618)</td>
<td>-0.1702** (4.717)</td>
<td>-0.1930** (5.575)</td>
<td>-0.1896** (5.576)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_{t-1}$</td>
<td>0.6065** (10.636)</td>
<td>0.6515** (11.401)</td>
<td>0.5391** (7.615)</td>
<td>0.5728** (7.947)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{TEMP}_t$</td>
<td>0.2746** (2.834)</td>
<td>0.2327* (2.266)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long-Run Estimates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income (Y)</td>
<td>1.1835</td>
<td>1.1843</td>
<td>0.4667</td>
<td>0.4662</td>
<td>0.8658</td>
<td>0.7961</td>
</tr>
<tr>
<td>Price (P)</td>
<td>-0.1237</td>
<td>-0.1230</td>
<td>-0.2430</td>
<td>-0.2438</td>
<td>-0.1269</td>
<td>-0.1285</td>
</tr>
<tr>
<td>Estimated Hyperparameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_n^2 \times 10^{-4}$</td>
<td>2.828</td>
<td>2.393</td>
<td>2.315</td>
<td>2.083</td>
<td>1.106</td>
<td>0.736</td>
</tr>
<tr>
<td>$\sigma_T^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.799</td>
<td>0.798</td>
</tr>
<tr>
<td>$\sigma_e^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\sigma_{\alpha}^2 \times 10^{-4}$</td>
<td>0</td>
<td>0.006</td>
<td>0.006</td>
<td>0.030</td>
<td>0</td>
<td>0.039</td>
</tr>
<tr>
<td>Nature of Trend</td>
<td>No Trend (Cell ii)</td>
<td>No Trend (Cell ii)</td>
<td>A Linear Trend (Cell v)</td>
<td>A Linear Trend (Cell v)</td>
<td>Local Level with Drift (Cell vi)</td>
<td>Local Level with Drift (Cell vi)</td>
</tr>
<tr>
<td>Corresponding cell of Table 4.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Annual Growth rate of</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>the estimated trend</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1972q1 – 1995q4</td>
<td>0%</td>
<td>0%</td>
<td>0.65%</td>
<td>0.60%</td>
<td>0.41%</td>
<td>0.54%</td>
</tr>
<tr>
<td>1972q1 – 1974q4</td>
<td>0%</td>
<td>0%</td>
<td>0.65%</td>
<td>0.60%</td>
<td>-0.28%</td>
<td>-0.06%</td>
</tr>
<tr>
<td>1975q1 – 1979q4</td>
<td>0%</td>
<td>0%</td>
<td>0.65%</td>
<td>0.60%</td>
<td>0.92%</td>
<td>1.03%</td>
</tr>
<tr>
<td>1980q1 – 1984q4</td>
<td>0%</td>
<td>0%</td>
<td>0.65%</td>
<td>0.60%</td>
<td>0.57%</td>
<td>0.63%</td>
</tr>
<tr>
<td>1985q1 – 1989q4</td>
<td>0%</td>
<td>0%</td>
<td>0.65%</td>
<td>0.60%</td>
<td>0.61%</td>
<td>0.85%</td>
</tr>
<tr>
<td>1990q1 – 1995q4</td>
<td>0%</td>
<td>0%</td>
<td>0.65%</td>
<td>0.60%</td>
<td>0%</td>
<td>0.08%</td>
</tr>
<tr>
<td>-------------------</td>
<td>--------------------</td>
<td>-----------------</td>
<td>----------</td>
<td>----------</td>
<td>----------------</td>
<td>----------</td>
</tr>
<tr>
<td></td>
<td>Standard Error</td>
<td>1.61%</td>
<td>1.63%</td>
<td>1.44%</td>
<td>1.47%</td>
<td>1.52%</td>
</tr>
<tr>
<td></td>
<td>Normality</td>
<td>0.49</td>
<td>1.16</td>
<td>0.19</td>
<td>2.97</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>Kurtosis</td>
<td>0.36</td>
<td>0.15</td>
<td>0.14</td>
<td>1.93</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
<td>0.13</td>
<td>1.01</td>
<td>0.06</td>
<td>1.04</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>H(30)</td>
<td>1.13</td>
<td>0.79</td>
<td>1.14</td>
<td>0.93</td>
<td>1.03</td>
</tr>
<tr>
<td></td>
<td>r(1)</td>
<td>0.02</td>
<td>-0.06</td>
<td>-0.05</td>
<td>-0.10</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>r(4)</td>
<td>0.13</td>
<td>0.03</td>
<td>-0.04</td>
<td>-0.08</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>r(8)</td>
<td>0.08</td>
<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>DW</td>
<td>1.95</td>
<td>2.12</td>
<td>2.07</td>
<td>2.18</td>
<td>1.87</td>
</tr>
<tr>
<td></td>
<td>Q</td>
<td>Q(8,8)</td>
<td>11.23</td>
<td>5.87</td>
<td>5.52</td>
<td>4.34</td>
</tr>
<tr>
<td></td>
<td>R²</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>R²</td>
<td>0.48</td>
<td>0.47</td>
<td>0.58</td>
<td>0.57</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Note: See Notes for Table 5.1.

The specifications of Models (5) and (6) (with a stochastic trend) are the most simple where only one lagged GDP is needed to capture the adjustment to the long-run path. Models (3) and (4) (with deterministic trend) need the largest number of the lagged variable creating the complex dynamics. Models (1) and (2) also has rather complex lag structure, and air temperature variable appears to be insignificant and is excluded which is contrast to other models. The models with the deterministic seasonal dummies.
(Models (1), (3) and (5)) consistently fail the post sample prediction test, suggesting that the conventional deterministic seasonals do not properly represent the seasonal variation of this demand series. Therefore, it is important to model the seasonality in flexible way with stochastic seasonals in this particular demand series.

The estimated annual growth of the UEDT characterises each model. Although Models (1) and (2) has no growth of the UEDT by assumption, both of Models (3) and (4) estimate the fixed rate at around 0.6% p.a. implying a constant increasing in the UEDT over the sample period. On the other hand, both Models (5) and (6) estimate the non-constant UEDT growth rate; a higher growth during the late 1970s and the late 1980s, but lesser in magnitude at the beginning and the end of the sample period. However, it is interesting that the average growth rates over the sample period estimated by Models (3), (4), (5) and (6) are within the relatively close range (around 0.6% p.a.). This means that, although the overall growth may be well approximated by the deterministic linear trend, the UEDT has some local fluctuations which can only be properly modelled by the stochastic trend. Note the LR test results for Model (6) indicate the constant growth of the UEDT as well as the deterministic seasonals is an improper restriction on the stochastic seasonals. Hence, it is reasonable to choose Model (6) as our preferred model since it is more general in terms of modelling the UEDT and the seasonality encompassing other rival models, and has the simplest lag structure with entirely satisfactory diagnostics and the post-sample prediction test.

The estimated long-run elasticities for income and price are also different between the models which are roughly divided into the three groups: the no trend models (Models
The estimated income elasticities by the no trend models are higher than other models including either the deterministic or stochastic trend. This can be considered as an example of the over-estimation of the income elasticity by the model ignoring the UEDT when it is upward sloping and the GDP is increasing over the sample period, as discussed in Chapter 3.

In contrast, the estimated long-run price elasticities given by the no trend models are almost identical to that of the stochastic trend model. This perhaps does not mean the estimated price elasticities are not biased, but such biases may be obscured by the substantial fluctuation of the price over the sample period. The long-run income elasticities given by the deterministic trend models are rather lower than those of the stochastic trend model. The likely reason for this under-estimation is that the deterministic trend model cannot properly proxy the lower rate of the UEDT growth during the early 1970s and the late 1990s (see Table 5.4), and this may result in a similar outcome in the case when the UEDT is downward sloping and income is rising without proper modelling of the UEDT (see Figure 3.2 case (a)). The reason for the estimated higher price elasticities (in absolute term) by the deterministic trend models may not be very clear since, again, the price fluctuates over time making the theoretical analysis extremely complex. However, from a statistical viewpoint, it is reasonable that the elasticities given by Model (6) are the most acceptable compared to other rival models. The difference in the seasonality modelling (the stochastic or the deterministic seasonal) little affects the estimated elasticities, but, as already discussed, they are necessary to ensure the parameter consistency of the model so that the post-sample
prediction test satisfactorily passes.

**Figure 5.8.** Estimated VEDT (top left), slope of VEDT (top right), estimated seasonal variation (bottom left) and individual seasonal patterns in the UK transportation oil demand.

In our preferred model (Model (6)), the number of lagged variables required is small with just a one quarter lag on income required. This suggests fairly quick adjustment of transportation oil demand along with the demand curve to the price change. Although the estimated hyperparameter of the trend level is non-zero, the estimated hyperparameter of the slope is zero giving an underlying trend of 0.54% p.a. on overall average but the growth rates is not constant as illustrated in the top left and top right charts of Figure 5.8. The stochastic trend in the preferred model is the local level with drift model. This model consists of a random walk component to capture the underlying level that evolves in a particular direction as specified by the fixed slope components.
The UEDT is generally upward sloping as illustrated in the top left chart of Figure 5.8. Therefore, after controlling for the normal income and price effect, the use of transportation oil has been increasing. This illustrates that over the past 25 years (other than the last few years of the estimation period) the sector has become more energy intensive. This increase in energy intensity shown by the upward UEDT reflects a shift in the energy demand curve to the right, ceteris paribus. This is consistent with Schipper et al. (1992, p. 145 - 146).

The hyperparameter of the seasonal components are relatively small compared to that of the level indicating that the stochastic movement in the seasonal component is not as large as the stochastic fluctuation of the trend. However, the changes in the seasonal pattern are still found to be stochastic and are clearly preferred to conventional deterministic seasonal dummies. The pattern is illustrated in the bottom charts of Figure 5.8. This shows that the magnitude of seasonal fluctuations have diminished since the early 1980s, in particular, the first quarter increases and, conversely, the second and quarter demand gradually declines over time. Note, since the model includes the temperature variable, these seasonal movements can be considered as a non-temperature induced seasonal pattern. Again this indicates that seasonality cannot be modelled adequately by conventional deterministic seasonal dummies.
Table 5.8. Recent energy demand studies for the UK transport oil demand

<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated LR elasticities</th>
</tr>
</thead>
</table>
| Dargay (1992b)   | Petrol and diesel oil | Unrestricted ECM irreversible demand model | Annual data 1960 - 88 (29 obs.) | $\eta_y = 1.49$  
|                  |              |                        |                            | $\eta_p = -0.15$ (only for max. price)  
|                  |              |                        |                            | $\eta_p = -0.10$ (for price fall and rise, but insignificant at 10% level)  
|                  |              | Unrestricted ECM conventional reversible demand model | Annual data 1960 - 88 (29 obs.) | $\eta_y = 0.70$ (insignificant at 10% level)  
|                  |              |                        |                            | $\eta_p = -0.40$ (insignificant at 10% level)  
| Dargay (1993)    | Petrol       | Log-linear EG 2-step   | Annual data 1950 - 91 (42 obs.) | $\eta_y = 1.5$  
|                  |              | (structural form model) |                            | $\eta_p = -0.7$ to $-1.4$  
| Hodgson and Miller (1995) | Petrol | DTI energy model | Annual data 1954 - 88 (35 obs.) | $\eta_y = 0.81$  
| Franzén and Sterner (1995) | Petrol | Dynamic log-linear model | Annual data 1960 - 88 (29 obs.) | $\eta_y = 1.6$  
| Fouquet et al. (1997) | Petrol | Log-linear EG 2-step | Annual data 1960 - 94 (35 obs.) | $\eta_y = 1.95$ to $2.05$  
| Ninomiya (1997)  | Petrol       | Log-linear EG 2-step   | Annual data 1955 - 94 (40 obs.) | $\eta_y = 1.0$ to $1.1$  
|                  |              | (structural form model) |                            | $\eta_p = -0.18$  

Note: None of the studies includes any trend. $\eta_y$ = the long-run income elasticity, $\eta_p$ = the long-run price elasticity
The estimated long-run income and price elasticities from the preferred model are 0.80 and -0.13 respectively. Table 5.8 summarises the estimated elasticities of the petrol demand by recent energy demand studies. It can be seen there are substantial differences between the estimates - all of which do not consider the UEDT. The large difference implies there is no consensus for the long-run elasticities and the difficulty of proper modelling of the demand.

An interesting feature of the modelling for this sector is that, since the appliance for transport oil is almost entirely motor vehicle, the number of the stock (registered number of vehicle), capacity utilisation rate (vehicle miles) and energy efficiency (car fuel efficiency) are documented in some countries. Therefore, the demand in this sector is an exception for which the structural from model (see Chapter 2), rather than the usual reduced form model, is applied such as Dargay (1993) and Ninomiya (1997). The critical problem of this approach is that the estimation of the model is quite sensitive to the data accuracy. In reality, data required for the estimation in this approach, particularly vehicle miles and car fuel efficiency, are normally less accurate. In other words, these data are often no more than predicted values. Moreover, fuel efficiency of vehicle in use does not only depend on mechanical (embodied) efficiency of vehicle itself. In fact, it also highly depends on the various other factors which normally difficult to be measured accurately in time series such as the way of driving vehicle (driving habit), load of vehicle in use (number of passengers), maintenance level of vehicle and traffic conditions. The effects of these non-measurable factors are virtually ignored in the structural form model.
As a result, this approach sometimes generates substantially different estimated results depending on the data used. For example, the long-run income and price elasticities found in Dargay (1993) are 1.5 and -0.7 / -1.4 respectively, whereas they are estimated as 1.0 / 1.1 and -0.18 in Ninomiya (1997) although they use relatively similar sample period for the same sector. Although the estimated results of this thesis are fairly close to that of the latter study, the use of the structural form model for this sector seems to be still underdeveloped, given data inaccuracy, poor data availability and cost of data correction which can be non-negligible. Therefore, the majority of the studies are based on the reduced form model as follows.

Dargay (1992b) employs the irreversible demand model and the conventional reversible model with annual data 1960 – 1988 for the road transport oil demand. However, most of the estimated long-run elasticities given by her models are based on insignificant parameters even at the 10% level. Only the long-run income elasticity of 1.5 and the price elasticity of -1.5 for the maximum price changes appear to be significant at the 10% level in the irreversible model. These differ somewhat from the estimated results here. Similar comments also apply to Haas and Schipper (1998) in that their irreversible demand model appears to be not well supported by the data, given the insignificant coefficient estimates. In addition, the result given by the irreversible model is, in my opinion, rather misleading. They appear to imply that oil demand responds to a change in price only if the price increases beyond the historical maximum level: otherwise there is no response what so ever. This result does not, in my view, confirm with conventional economics. That said, however, the irreversible approach still remains an interesting line of research in energy demand modelling.
Hodgson and Miller (1995) found a long-run income elasticity of 0.81 and price elasticity of −0.3 using annual data from 1954–1988 which are relatively close to the estimates here though an inclusion or exclusion of a trend is unknown. On the other hand, using the log-linear model with a cointegration procedure and 1960–1994 annual data, Fouquet et al. (1997) found the considerably different the long-run elasticities of 2.0 for income and zero for price change. The no impact of price change on the demand is induced by their finding that the different data generation processes between the energy demand and the energy price and there is no long-run relationship between them. Using a log-linear dynamic model for 1960–1986 annual data, Franzen and Sterner (1995) found a long-run income elasticity of 1.6 and price elasticity of −0.4 respectively which also diverted from our estimates.

All these studies show the tendency of an over-estimation of the long-run income elasticity when the upward UEDT is not incorporated when income is rising. In contrast, the estimated long-run price elasticity in this thesis is somewhat lower (in absolute terms) than that found by Hodgson and Miller (1995) and Franzen and Sterner (1995), but higher than the assumed zero of Fouquet et al. (1997). Here, there is no consistency with the biases discussed in Chapter 3. This could be due to the cited studies not including the late 1980s and early 1990s, which was characterised by a period of significant lower energy prices. But it could also be due to the uncertainty of the biases when the real energy price has been rising and falling over the estimated period.

12 Fouquet et al. (1997) find that the demand series is I(1) whereas the price series is I(0). Therefore, they conclude that there is no long-run relationship between them, and the long-run price elasticity is zero.
5.3.2. Electricity demand in the UK

5.3.2.1. The data

The data series employed for the estimation of the UK electricity demand are illustrated in Figure 5.9.

Figure 5.9. UK electricity consumption (LTOTEe), Real GDP (LGDP), Real electricity price (LTOTPe) (in log scale) and GB air temperature (TMP)

The demand for electricity increased by nearly 50% during the sample period. Except the stagnation during the early 1980s, its growth was almost steady. The marked seasonal pattern is also clearly observed. The GDP series is the same as used in the previous section. The electricity price initially did not have any seasonal pattern, but it is observed after the early 1980s. In contrast to the petrol case, the electricity price has
continuous declining tendency after 1983.

5.3.2.2. The estimated results

Table 5.9 shows the estimated results by Model (1) to (6) which corresponding to the cells of Table 4.2. Similar to the whole economy energy demand considered as the beginning of this chapter, a substantial impulse shock at 1974q1 was detected by the auxiliary residuals of the irregular component (see Chapter 4) in the demand series. This reflects the impacts of the first oil crisis towards the end of 1973 and, more importantly, the rationing of electricity brought about by the coal miners strike in early 1974. Therefore, an impulse dummy for 1974q1 is included in the models, which effectively captures the shock. As can be seen in Table 6.5, the structural time series model clearly outperforms other rival models. Unless the model has both of the stochastic trend and the stochastic seasonality, it was burdensome to find a statistically sound model specification. In other words, the demand is extremely difficult to be modelled properly by the deterministic modelling of the UEDT and seasonality. The models without the stochastic trend (Models (1) to (4)) always suffer from strong first-order autocorrelation of the residuals. The auto-correlation cannot be removed by adding the higher number of lagged variable up to the forth-order. The large statistics values of the LR tests (a) for Models (2) and (4) indicate the deterministic restrictions on the stochastic seasonals are unacceptable.
Table 5.9. Estimated results for the UK electricity demand 1972q1 - 1995q4

<table>
<thead>
<tr>
<th>Models</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
<th>Model (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Trend and Deterministic</td>
<td>No Trend and Deterministic</td>
<td>Deterministic Trend and</td>
<td>Deterministic Trend and</td>
<td>Stochastic Trend and</td>
<td>Stochastic Trend and</td>
</tr>
<tr>
<td></td>
<td>Seasonals</td>
<td>Seasonals</td>
<td>Deterministic Seasonal</td>
<td>Deterministic Seasonal</td>
<td>Deterministic Seasonals</td>
<td>Deterministic Seasonals</td>
</tr>
<tr>
<td>Estimated</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_t$</td>
<td>0.2231**</td>
<td>0.1760**</td>
<td>0.2308*</td>
<td>0.2174**</td>
<td>0.4152**</td>
<td>0.4329**</td>
</tr>
<tr>
<td>(4.120)</td>
<td>(3.735)</td>
<td>(2.574)</td>
<td>(2.715)</td>
<td>(2.977)</td>
<td>(3.479)</td>
<td></td>
</tr>
<tr>
<td>$\pi_t$</td>
<td>-0.2123**</td>
<td>-0.1674**</td>
<td>-0.4268**</td>
<td>-0.3057**</td>
<td>-0.5154**</td>
<td>-0.2840**</td>
</tr>
<tr>
<td>$\pi_{t-2}$</td>
<td>-0.2890**</td>
<td>0.2963**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4.528)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi_{t-4}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_{t-1}$</td>
<td>0.1947**</td>
<td>0.3900**</td>
<td>0.2295**</td>
<td>0.3439**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2.940)</td>
<td>(5.568)</td>
<td>(3.741)</td>
<td>(5.038)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_{t-2}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_{t-3}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_{t-4}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{\pi}^2 \times 10^{-4}$</td>
<td>5.669</td>
<td>3.362</td>
<td>4.637</td>
<td>3.333</td>
<td>2.141</td>
<td>0.417</td>
</tr>
<tr>
<td>$\sigma_{\gamma}^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.104</td>
<td>0.957</td>
</tr>
<tr>
<td>$\sigma_{\pi}^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\sigma_{\gamma}^2 \times 10^{-4}$</td>
<td>0</td>
<td>0.264</td>
<td>0</td>
<td>0.161</td>
<td>0</td>
<td>0.349</td>
</tr>
<tr>
<td>Nature of Trend</td>
<td>No Trend (Cell ii)</td>
<td>No Trend (Cell ii)</td>
<td>A Linear Trend (Cell v)</td>
<td>A Linear Trend (Cell v)</td>
<td>Local Level with Drift (Cell vi)</td>
<td>Local Level with Drift (Cell vi)</td>
</tr>
<tr>
<td>Corresponding cell of Table 4.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Annual Growth rate of the estimated trend</td>
<td>1972q1 - 1995q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.23%</td>
<td>-0.10%</td>
<td>0.62%</td>
</tr>
</tbody>
</table>
### Diagnostics

<table>
<thead>
<tr>
<th>Equation Residuals</th>
<th>Standard Error</th>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>H(30)</th>
<th>r(1)</th>
<th>r(4)</th>
<th>r(8)</th>
<th>DW</th>
<th>Q</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1972q1 – 1974q4</td>
<td>2.26%</td>
<td>0%</td>
<td>0%</td>
<td>-0.23%</td>
<td>0.57</td>
<td>0.24</td>
<td>0.14</td>
<td>0.20</td>
<td>1.97</td>
<td>18.91*</td>
<td>0.98</td>
</tr>
<tr>
<td>1975q1 – 1979q4</td>
<td>2.04%</td>
<td>0.96</td>
<td>0.91</td>
<td>2.01%</td>
<td>0.67</td>
<td>0.24*</td>
<td>0.06</td>
<td>0.13</td>
<td>1.48</td>
<td>12.27</td>
<td>0.99</td>
</tr>
<tr>
<td>1980q1 – 1984q4</td>
<td>2.01%</td>
<td>0.06</td>
<td>0.01</td>
<td>-0.23%</td>
<td>0.79</td>
<td>0.26*</td>
<td>0.00</td>
<td>0.11</td>
<td>1.44</td>
<td>15.08</td>
<td>0.99</td>
</tr>
<tr>
<td>1985q1 – 1989q4</td>
<td>1.93%</td>
<td>1.44</td>
<td>0.82</td>
<td>0.23%</td>
<td>0.95</td>
<td>0.27**</td>
<td>0.06</td>
<td>0.11</td>
<td>1.43</td>
<td>16.58*</td>
<td>0.99</td>
</tr>
<tr>
<td>1990q1 – 1995q4</td>
<td>1.93%</td>
<td>1.93%</td>
<td>0.08</td>
<td>-0.10%</td>
<td>0.62</td>
<td>0.02</td>
<td>0.00</td>
<td>0.09</td>
<td>1.92</td>
<td>6.13</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5.21</td>
<td></td>
</tr>
</tbody>
</table>

### Auxiliary Residuals

<table>
<thead>
<tr>
<th>Irregular</th>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1972q1 – 1974q4</td>
<td>1.44</td>
<td>0.57</td>
<td>0.87</td>
</tr>
<tr>
<td>1975q1 – 1979q4</td>
<td>1.30</td>
<td>0.15</td>
<td>1.16</td>
</tr>
<tr>
<td>1980q1 – 1984q4</td>
<td>0.49</td>
<td>0.43</td>
<td>0.06</td>
</tr>
<tr>
<td>1985q1 – 1989q4</td>
<td>1.34</td>
<td>0.42</td>
<td>0.93</td>
</tr>
<tr>
<td>1990q1 – 1995q4</td>
<td>0.56</td>
<td>0.54</td>
<td>0.03</td>
</tr>
</tbody>
</table>

### Level

<table>
<thead>
<tr>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1972q1 – 1974q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>1975q1 – 1979q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>1980q1 – 1984q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>1985q1 – 1989q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>1990q1 – 1995q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

### Slope

<table>
<thead>
<tr>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1972q1 – 1974q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>1975q1 – 1979q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>1980q1 – 1984q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>1985q1 – 1989q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>1990q1 – 1995q4</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

### Predictive Tests (1996Q1-1997Q4)

<table>
<thead>
<tr>
<th> </th>
<th> </th>
<th> </th>
<th> </th>
<th> </th>
<th> </th>
<th> </th>
</tr>
</thead>
<tbody>
<tr>
<td>1972q1 – 1974q4</td>
<td>13.34</td>
<td>6.50</td>
<td>12.85</td>
<td>6.53</td>
<td>13.61</td>
<td>6.74</td>
</tr>
<tr>
<td>1975q1 – 1979q4</td>
<td>-2.18</td>
<td>-1.94</td>
<td>-2.40</td>
<td>-1.79</td>
<td>-1.68</td>
<td>-1.40</td>
</tr>
</tbody>
</table>

### LR tests

<table>
<thead>
<tr>
<th>Test</th>
<th>1972q1 – 1974q4</th>
<th>1975q1 – 1979q4</th>
<th>1980q1 – 1984q4</th>
<th>1985q1 – 1989q4</th>
<th>1990q1 – 1995q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test (a)</td>
<td>n/a</td>
<td>23.29**</td>
<td>n/a</td>
<td>10.72**</td>
<td>n/a</td>
</tr>
<tr>
<td>Test (b)</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>31.11**</td>
<td>n/a</td>
</tr>
<tr>
<td>Test (c)</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>124.38**</td>
</tr>
</tbody>
</table>

Note: See Notes for Table 5.1.

It is also noticed that Model (6) is remarkably simpler and the most parsimonious. Model (5) requires the additional lagged term to eliminate the autocorrelation of the residuals. Considering these circumstances, it is reasonable to select Model (6) as the preferred model. Any deterministic restrictions on the stochastic trend and the stochastic trend...
seasonals are decisively refused by the LR tests (a) to (c). The extremely higher LR ratios indicate the restrictions are completely misleading. The significantly large value of the hyperparameter for the seasonal component (0.349) relative to other hyperparameter values suggests that the seasonal pattern of the demand evolves in large magnitude over the sample period. Therefore, the deterministic restriction as in Model (5) immediately results in quite different estimated results. The income and price elasticities become smaller and larger (in absolute term) respectively although the differences are not very substantial.

It is noticed that estimates of both the income and price elasticities given by the deterministic restriction model (Models (1) to (4)) are much larger (in absolute term) compared to Model (6)’s estimates. In terms of the income elasticities, this is an example of biased over-estimation when income is rising and the UEDT is upward sloping without the proper modelling of the UEDT, discussed in Chapter 3. The over-estimations of the price elasticities also can be considered as biased estimates caused by the inappropriate modelling of the UEDT, but it is rather unclear because of the fluctuation of the electricity price over the sample period. In addition, the inappropriate modelling of the stochastic seasonality is very likely to be another source of these biased elasticities.

The growth rates of the trend also show the noticeable variations between the models. Model (5) and (6) estimate the trend as non-linear so that the trend has a remarkable negative growth during the early 1980s with the high growth during the 1970s and the moderate growth during the late 1980s and 1990s. In contrast, the estimated growth
rates by Model (3) and (4) are both negative values, which remain constant over time. Given that the diagnostics of both models are poor, these negative growth rates are the results of incorrect approximation of the UEDT by the deterministic linear time trend.

The preferred model (Model (6)) has no lagged variables, implying that the response of the electricity demand to the changes in income and price along with the normal demand curve is almost instantaneous. The very significant parameter for air temperature \((TEMP)\) means that it is an important factor influencing the demand. However, the impact of the temperature on the demand is adjusted within the short period, since the parameter values of \(TEMP\) are almost stable regardless of the lag structures of the model.

The estimated trend is the Local Level with Drift (cell vi in Table 4.1). The top left chart of Figure 5.10 illustrates this trend. In this model, the stochastic movement of the trend generated by shift in the level along with the fixed slope of 0.9\% p.a. as illustrated in the top right chart of Figure 5.10. In other words, the trend increased but with the stochastic fluctuation in level.

The trend has a marked reduction and stagnation during the early 1980s associated with dramatic increase during other periods. This indicates that, except for the early 1980s, the demand curve shifted to the right, creating more electricity intensive economy, even after controlling for the normal income and price effects. However, conversely, the demand curve shift to the left during the early 1980s implying the economy became electricity saving. Such complex movement of the UEDT is difficult to approximate the
non-linear shape of the trend by a simple deterministic trend. This is one of the reasons why models (1) to (4) always suffer from severe autocorrelation of the residuals.

Figure 5.10. Estimated UEDT (top left), slope of UEDT (top right), estimated seasonal variations (bottom left), estimated individual seasonal pattern (bottom right) in the UK electricity demand (in log scale)

The bottom charts of Figure 5.10 illustrate the stochastic seasonal pattern estimated by Model (6). Reflecting the large value of the hyperparameter for the seasonal component, the seasonal pattern has dramatically changes; the range of the fluctuation is getting narrower over time. Looking closely at the bottom right hand chart, the peak demand in the first quarter declines and conversely the bottom demand in the third quarter increases, implying the electricity demand for heating in winter has been replaced by gas (Harvey, 1989, p.97).
Table 5.10. Recent energy demand studies for the UK electricity demand

<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated long-run income and price elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fouquet et al. (1993)</td>
<td>Disaggregated in several sectors</td>
<td>Log-linear EG 2-step</td>
<td>Annual data 1948 - 81 (34 obs.)</td>
<td>( \eta_y = 0.72 ) (Residential)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>( \eta_p = 1.66 ) (Manufacturing)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>( \eta_p = -1.26 ) (Residential)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>( \eta_p = -1.19 ) (Manufacturing)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>No trend included</td>
</tr>
<tr>
<td>Fouquet (1995)</td>
<td>Residential sector</td>
<td>Log-linear EG 2-step</td>
<td>Quarterly data 1974q1 - 88q1 (41 obs.)</td>
<td>( \eta_y = 0.24 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>( \eta_p = -0.39 )</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>No trend included</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Seasonal dummies included</td>
</tr>
<tr>
<td>Hodgson and Miller (1995)</td>
<td>Disaggregated in several sectors</td>
<td>Log-linear unrestricted ECM</td>
<td>Annual data 1954 - 88 (35 obs.)</td>
<td>( \eta_y = 1.37 ) (Industry and iron)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.7 (Service)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.3 (Residential)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>( \eta_p = -0.3 ) (Industry)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.6 (Service)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.32 (Residential)</td>
</tr>
<tr>
<td>Fouquet et al. (1997)</td>
<td>Other industry only</td>
<td>Log-linear EG 2-step</td>
<td>Annual data 1960 - 1994 (35 obs.)</td>
<td>( \eta_y = 1.34 ) (other industry)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>( \eta_p = -0.53 ) (other industry)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>No trend included</td>
</tr>
</tbody>
</table>

Note: \( \eta_y \) = the long-run income elasticity, \( \eta_p \) = the long-run price elasticity
This changing in the seasonal pattern is also surely difficult to be modelled by the conventional deterministic seasonal dummies. It has been shown that the models without the stochastic seasonals almost always fail the post-sample prediction test. This is the case that stochastic seasonal formulation is absolutely vital.

The estimated long-run elasticities from the preferred model are 0.43 for income and \(-0.28\) for price. The corresponding estimated values by the past studies considering the same sector quite different as seen in Table 5.10. Using annual data 1948 – 1981 with the log-linear model, Fouquet et al. (1993) estimates the long-run income and prices elasticities of \(0.72 \sim 1.66\) and \(-1.2\), both of which are much higher than the estimates here (in absolute term). Using the similar model with different sample period 1960 – 1994, Fouquet et al. (1997) also a higher income elasticity of 1.3 and price elasticity of \(-0.5\). Neither study includes the stochastic trend. The larger estimated elasticities given by these studies exactly parallel to that seen in Table 5.9 when the stochastic trend is ignored.

The estimated long-run elasticities by Hodgson and Miller (1995) are 1.4 for income and \(-0.385\) for price. Although it is not explained whether or not their model includes any form of trend, the larger income elasticity is also estimated. Fouquet (1995) employs the quarterly data 1974q1 – 1988q1 with the log-linear model, giving the long-run income elasticity of 0.24 and the price elasticity of \(-0.39\), which are substantially different from Fouquet et al. (1993 and 1997), but somewhat close to the

---

13 Both studies are based on the annual data. Therefore, the stochastic seasonals are not considered in the comparison.
5.4. Summary and conclusion

In this chapter, the structural time series model has been applied to energy demand in various sectors and fuels of the UK in order to empirically demonstrate how the UEDT and the seasonality can be properly modelled within a log-linear energy demand framework. The restricted models with the various combinations of deterministic trend or/and deterministic seasonals, defined in Table 4.2, were also estimated individually, giving meaningful comparisons between the estimated results from the different models. The first half considered aggregate final energy demand in various sectors which were the whole economy, the residential and the manufacturing sector. The second half examined the demand for two major individual fuels; transportation oil and electricity.

In the application to energy demand series of the whole economy, it appeared that the models without a stochastic trend not only suffered from severe autocorrelation of the residuals at all times, but also consistently fails the post-sample prediction test indicating their poor forecasting properties. In contrast, the models incorporating stochastic trend show excellent estimation performance. This is because the UEDT and the seasonality of the demand were highly stochastic and, therefore, both of stochastic trend and stochastic seasonals are necessary for an appropriate modelling of the demand in this sector. The long-run elasticities were estimated as 0.56 for income and -0.23 for price. An underestimation of the income elasticity by the model ignoring the UEDT,

---

14 The elasticities in Hodgson and Miller (1995) are estimated for the various sectors individually. The
which was theoretically explained in Chapter 3, was actually observed. This suggested that the rather lower estimated income elasticity for this sector appeared in past studies can be a biased result of the underestimation.

For the residential sector, it was found that no trend exists in the model. This may be the result of efficiency improvements of energy appliances being offset by changes in consumer tastes; that is consumers choosing larger and more comfortable energy appliances. However, it was found that stochastic seasonality clearly exists, creating the evolution of the seasonal variation over time. The deterministic seasonal model needed more lagged terms to ensure the residuals to be white noise associated with deterioration of the diagnostic statistics. In addition, the LR test strongly rejected the deterministic seasonal restriction. Therefore, the preferred model has no trend but with stochastic seasonals. The estimated long-run income elasticity was 0.29 and the long-run price elasticity was −0.16. Although the income elasticity was consistent with the results given by past studies, the price elasticity was somewhat lower than other studies.

The structural time series model also outperformed other rival models in the application to the manufacturing sector. The restricted models with a deterministic trend produced implausible elasticity values with wrong signs. In contrast, despite the model with stochastic trend and stochastic seasonals are surprisingly simpler and the most parsimonious, the estimated elasticities values are more conceivable and the residuals are still white noise. The estimated UEDT is non-linear which smoothly changes its direction over time. Similarly, the seasonal pattern also stochastically evolved. Hence, values shown here are overall average values.
for the estimation of this sector, the stochastic modelling of the UEDT and the seasonality is necessary. The long-run income and price elasticities were estimated to be 0.72 and −0.20 respectively. The relatively larger income elasticity in this sector, compared to other sectors, indicates the close link between output and energy in the manufacturing sector.

In the application to the road transport oil demand, the stochastic seasonal played an important role to ensure the parameter consistency of the model which is examined by the post-sample prediction tests. The models with stochastic seasonals passed the test whereas the models with deterministic seasonal consistently fail it. Moreover, the restricted model with deterministic trend required rather complex lag terms to eliminate the autocorrelation, which otherwise appears. In contrast, the most general model with a stochastic trend and stochastic seasonals was the most parsimonious, but associate with entirely satisfactory diagnostics. The UEDT was found to have an upward trend, implying the economy becomes more oil using in the transportation sector even after controlling the normal price and income effects. The seasonality also exhibited strong stochastic variation which cannot be adequately modelled by the deterministic seasonals. The estimated long-run income and price elasticities are 0.80 and −0.13. An overestimation of the income elasticity, when the model excluding the UEDT was employed actually occurred when the model ignored the UEDT, which was also found in the estimated results by the past empirical studies.

For the demand for electricity, the stochastic modelling of the UEDT and the seasonality also appeared to be vital to obtain the statistically sound estimated results.
The models without a stochastic trend are always troubled by severe autocorrelation in the residuals and the need to augment additional lagged terms to minimise it. As a result, such models include a large number of the explanatory variables. On the other hand, the most general model with a stochastic trend and stochastic seasonal does not need such a large number of variables, being the most parsimonious, but the residuals are completely clean. The substantially large values of the LR ratio also suggest the deterministic restrictions are totally unacceptable. The estimated UEDT was highly non-linear which would be impossible to approximate by a deterministic trend. The seasonality also exhibits evolving pattern which became lesser in magnitude over time. The estimated long-run income elasticity was 0.43. An overestimation of the income elasticity, produced by the model ignoring the UEDT, was observed, implying the relatively higher income elasticities estimated by the past studies may be taken with caution.

It is useful to compare the estimated elasticities between the sectors. The road transport oil accounted for 75% of energy consumption in the transportation sector. Therefore, it may be considered as a reasonable approximation of the transportation sector. The long-run income elasticities can be put in scale order as follows: the transportation sector (0.80) > the manufacturing sector (0.72) > the whole economy (0.56) > the residential sector (0.3). The higher income elasticity of the transportation sector is generally known (Kibune, 1994). In terms of the manufacturing sectors, the higher income elasticity indicates, as mentioned, the tight linkage between the energy demand in this sector and the output. The considerably lower income elasticity in the residential sector, which was already pointed out by a number of empirical studies, was
reconfirmed. The value for the whole economy falls into somewhat the middle of these estimated values. The long-run income elasticity of the electricity demand was relatively lower value of 0.43. Since about 60% of electricity is used in the residential sector, this may correspond to the lower income elasticity (0.3) of this sector.

In contrast, the estimated long-run price elasticities appeared to be almost identical of around $-0.2$: $-0.23$ (the whole economy), $-0.22$ (the manufacturing sector), $-0.20$ (the residential). As an exception, the long-run price elasticity of the transportation sector was $-0.13$. This lower price elasticity of the road transportation oil demand implies the difficulty of demand management of this sector through pricing policy, given the demand in this sector has grown the most rapidly over the decades. The slightly larger price elasticity of $-0.28$ was found for the electricity demand suggesting that it is relatively price sensitive compared to others.

Finally, it is meaningful to briefly summarise the impact of the deterministic restrictions on a stochastic trend or/and stochastic seasonals. When the UEDT was found to be stochastic, the deterministic trend model produced over- and under- estimated elasticities for income and price. In addition, autocorrelation of the residuals is more likely to arise. As a result, the deterministic trend model often requires a large number of the lagged terms to eliminate the autocorrelation, but that is often unsuccessful. In particular, when the UEDT contains a stochastic slope component\textsuperscript{15}, the deterministic trend model generates very odd income and price elasticities such as extraordinary large values and wrong signs, as we have seen in the application to the manufacturing sector.

\textsuperscript{15} This means that the UEDT is I(2) (see Chapter 4).
In contrast, when the seasonal pattern was found to be stochastic, which was true for all the sectors, its impact on the estimated elasticity values was relatively small. However, it did considerably affect the statistical property of the residuals and forecasting property of the model. Such adverse impacts were observed, particularly, in the residential sector and in the road transport oil demand.

In conclusion, it has been shown that, in all cases, the stochastic trend model was remarkably robust with entirely satisfactory diagnostics and, in contrast, the restricted deterministic trend/seasonals models very often performed poorly, creating a number of problems with their diagnostics or producing the unacceptable estimated results. The main reason of the inferior performance of the deterministic trend/seasonals model compared to the structural time series model is the existence of the stochastic element in the trend or/and the seasonal components. As the special case, the energy demand in the residential sector, the stochastic element was found only in the seasonal component, not in the trend. However, all other energy demand, both of the trend and seasonals have the stochastic elements in them. It has also seen that the biased estimations when the UEDT is not appropriately modelled, discussed in Chapter 3, were actually often occurred. The charts of the estimated stochastic trend and the stochastic seasonals pattern given by the structural time series model have indicated that they were considerably difficult to be approximated by the conventional deterministic time trend and the deterministic seasonal dummies. Therefore, it was also intuitively understandable that the structural time series model were selected as the preferred model for all the sector and fuels considered in this chapter.

16 In addition, the UK models were also reestimated by the single equation cointegration technique and the results were always inferior to those given by the structural time series model.
CHAPTER 6. APPLICATION OF THE STRUCTURAL TIME SERIES MODEL TO ENERGY DEMAND IN JAPAN

6.1. Introduction

In this chapter, the structural time series model is applied to the estimation of the various energy demands functions in Japan in a similar manner of the application to the UK presented in the previous chapter. Japan is often referred as one of the most energy efficient countries among other OECD countries. Since one of the main drivers of the UEDT is an improvement of energy efficiency, it is of considerable interest to investigate the UEDT in Japan. In addition, it is also of interest to examine the evolution of the seasonal pattern in the energy demand in Japan, because it may be influenced by the economic and industrial structure, social culture, and climate condition. Moreover, it is equally important to examine again how the structural time series model are applicable and useful in application to the energy demand not only in the UK, but also other country such as in Japan. The comparison between the two countries will also be interesting which will be discussed in the final chapter.

The structure of this chapter follows to the previous chapter. The first half considers the application to the aggregated energy demand in the various sectors of Japan; whole economy, manufacturing, and residential-service sectors. The second half presents to the results for the individual fuels; electricity and road transportation oil.

---

1 Primary energy/GDP ratio in Japan was 96 (o.e.t./1995 million US Dollars) compared to the US (272), the UK (195) and Germany (135) in 1998 (EDMC, 2001).
6.2. Aggregated final energy demand in Japan

6.2.1. Aggregated whole economy final energy demand

6.2.1.1. The data

Figure 6.1. Whole economy final energy demand (LFE), real GDP (LGDP), real aggregated energy price (LEP) (in log scale) and the Heating Degree Days (HDD) in Japan

The quarterly series of the aggregated final energy consumption in Japanese whole economy is unavailable. Instead, the annual data series covering between 1965 and 1999 is used for the estimation, which is illustrated in Figure 6.1. Needless to say, unlike quarterly data series, there is no seasonal variation. The final energy demand in the whole economy, which is available on annual basis only, rapidly increased up to 1974, and then stagnated during the late 1970s and the early 1980s, followed by a moderate growth during the rest of the period.
The GDP series also kinked at 1974 where a rapid economic growth in the 1960s terminated and turned into a moderate growth during the subsequent period with further lower growth towards the end. Similarly, the substantial increase in the real energy price suddenly occurred in 1974 followed by a further rise during the early 1980s and dropping after then. The dramatic fluctuation is highly contrasted to the continuous declining during the 1960s. The HDD is the sum of the differences between 14°C and the average air temperature of the day which is less than 14°C in the major 9 areas in Japan. After the mid-1980s there is a remarkable reduction of the HDD indicating Japan becomes less cold and the global warming is likely to occur. The HDD is available on annual basis only.

6.2.1.2. The estimated results

Table 6.1 presents the estimated results for the whole economy energy demand in Japan. Although the No Trend Model needs more lagged variables than the Stochastic Trend Model in order to eliminate autocorrelation of the residuals, it passes all of the diagnostics satisfactory including the post sample prediction test for 1996 – 1999. The estimated long-run income elasticity is 0.79 which is smaller than the estimates by other models. Conversely, the long-run price elasticity is –0.7 which is substantially higher (in absolute term) than that given by the other models. The trend growth is imposed to be a constant to be zero, assuming there is no UEDT i.e. the movement of the demand is fully explained by the explanatory variables. In order to check further the robustness of the model, the post-sample prediction test was carried again for many longer prediction periods; reserving the last 15 years for the test as explained in Chapter 4.
Table 6.1. Estimated results for the whole economy energy demand in Japan 1965 – 1996

<table>
<thead>
<tr>
<th>Corresponding cell of Table 4.2</th>
<th>I: No Trend Model</th>
<th>II: Deterministic Trend Model</th>
<th>III: Stochastic Trend Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimated Coefficients</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_t$</td>
<td>0.7632**</td>
<td>0.8467**</td>
<td>0.6738**</td>
</tr>
<tr>
<td></td>
<td>(5.186)</td>
<td>(6.176)</td>
<td>(4.942)</td>
</tr>
<tr>
<td>$\gamma_{t-1}$</td>
<td>-0.6474**</td>
<td>-0.4105*</td>
<td>-0.1655**</td>
</tr>
<tr>
<td></td>
<td>(4.431)</td>
<td>(2.441)</td>
<td></td>
</tr>
<tr>
<td>$P_t$</td>
<td>-0.1892**</td>
<td>-0.1311**</td>
<td>-0.1655**</td>
</tr>
<tr>
<td></td>
<td>(6.695)</td>
<td>(9.886)</td>
<td>(6.758)</td>
</tr>
<tr>
<td>$P_{t-1}$</td>
<td>0.0873**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.964)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\epsilon_{t-1}$</td>
<td>0.8548**</td>
<td>0.669**</td>
<td>0.3209**</td>
</tr>
<tr>
<td></td>
<td>(23.512)</td>
<td>(13.440)</td>
<td>(4.202)</td>
</tr>
<tr>
<td>$HDD_t$</td>
<td>0.0001**</td>
<td>0.0001**</td>
<td>0.0001**</td>
</tr>
<tr>
<td></td>
<td>(5.132)</td>
<td>(5.461)</td>
<td>(4.817)</td>
</tr>
<tr>
<td>Long-Run Estimates</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income (Y)</td>
<td>0.7974</td>
<td>1.3181</td>
<td>0.9921</td>
</tr>
<tr>
<td>Price (P)</td>
<td>-0.7023</td>
<td>-0.3962</td>
<td>-0.2437</td>
</tr>
<tr>
<td>Estimated Hyperparameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2 \times 10^{-4}$</td>
<td>2.212</td>
<td>1.880</td>
<td>1.107</td>
</tr>
<tr>
<td>$\sigma_n^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\sigma_e^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0.286</td>
</tr>
<tr>
<td>Nature of Trend</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corresponding cell of Table 4.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nature of Trend</td>
<td>No Trend</td>
<td>Linear Trend Model</td>
<td>Smooth Trend model</td>
</tr>
<tr>
<td>Average Annual Growth rate of the estimated trend</td>
<td>Cell ii</td>
<td>Cell v</td>
<td>Cell viii</td>
</tr>
<tr>
<td>1965 – 1996</td>
<td>0%</td>
<td>-0.82%</td>
<td>-0.56%</td>
</tr>
<tr>
<td>1965 – 1969</td>
<td>0%</td>
<td>-0.82%</td>
<td>1.08%</td>
</tr>
<tr>
<td>1970 – 1974</td>
<td>0%</td>
<td>-0.82%</td>
<td>0.10%</td>
</tr>
<tr>
<td>1975 – 1979</td>
<td>0%</td>
<td>-0.82%</td>
<td>-1.22%</td>
</tr>
<tr>
<td>1980 – 1984</td>
<td>0%</td>
<td>-0.82%</td>
<td>-1.73%</td>
</tr>
<tr>
<td>1985 – 1989</td>
<td>0%</td>
<td>-0.82%</td>
<td>-1.16%</td>
</tr>
<tr>
<td>1990 – 1996</td>
<td>0%</td>
<td>-0.82%</td>
<td>-0.43%</td>
</tr>
<tr>
<td>Diagnostics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equation Residuals</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Error</td>
<td>1.31%</td>
<td>1.29%</td>
<td>1.59%</td>
</tr>
<tr>
<td>Normality</td>
<td>1.25</td>
<td>0.96</td>
<td>2.64</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.98</td>
<td>0.78</td>
<td>0.42</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.27</td>
<td>3.17</td>
<td>2.22</td>
</tr>
<tr>
<td>H(10)</td>
<td>1.66</td>
<td>0.86</td>
<td>1.93</td>
</tr>
<tr>
<td>r(1)</td>
<td>0.02</td>
<td>0.04</td>
<td>0.11</td>
</tr>
<tr>
<td>r(2)</td>
<td>-0.15</td>
<td>-0.21</td>
<td>-0.26</td>
</tr>
<tr>
<td>r(3)</td>
<td>-0.02</td>
<td>0.14</td>
<td>-0.09</td>
</tr>
<tr>
<td>r(4)</td>
<td>-0.22</td>
<td>-0.42*</td>
<td>-0.11</td>
</tr>
</tbody>
</table>
The top left chart of Figure 6.2 shows the actual observations and the predicted values given by the No Trend Model with the prediction intervals which are set at two root mean square errors (RMSEs). The consistent overestimation of the values which lie outside the prediction intervals, reflecting to the cumulative sum of the standardised prediction errors (the Cusum) shown in the same chart. The Cusum goes completely outside the two boundary lines which are based on a significance level of 10%. The predicted values for the same period by the Deterministic Trend Model shown in the bottom chart of Figure 6.2 also indicates that they are systematically overestimated.
These results indicate prediction powers of these models in the longer term are not robust enough. These results will be compared to those given by the Stochastic Trend Model shown in the top right chart of Figure 6.2 shortly.

The Deterministic Trend Model also needs one more additional lagged variable compared to Stochastic Trend model to minimise the autocorrelation of the residuals. However, autocorrelation still
remain at the forth order and others which cannot be removed by adding further lagged variables. In addition, the model cannot completely fail the post-sample prediction test for 1997 – 1999. This is because the negative deterministic linear trend of −0.84% p.a. leads to an under-estimation of the energy demand during the post sample period. These poor statistics imply that this model is clearly inferior to others and likely to be mis-specified. The estimated long-run elasticities are 1.32 for income and −0.40 for price. The former is considerably larger than other estimates and is an over-estimation caused by an incorrectly imposed linear time trend.

The Stochastic Trend Model has much smaller number of the explanatory variables than others, but the diagnostics does not show any sing of misspecification. Thus, the Stochastic Trend Model is the most parsimonious model among others. To compare this model to the No Trend model, both of which have satisfactory diagnostics shown in Table 6.1, the longer term post-sample prediction test for 1985 – 1999 is also applied. The top right chart of Figure 6.2 presents the predicted values and the actual values. Except for 1992 and 1994, the model predicts well the actual observations within two RMSEs. As a result, the Cusum comfortably remains within the boundary lines over the post-sample period, suggesting the Stochastic Trend Model performs clearly better than the No Trend Model and the Deterministic Trend Model in terms of the longer term prediction. Hence, it is reasonable to say that the Stochastic Trend Model is more robust model.

In addition, the LR test for the deterministic restriction on the stochastic trend indicates the restriction is invalid. The stochastic trend is what known as the Smooth Trend, in
which the slope hyperparameter is estimated as non-zero value (0.286) and the trend changes its direction smoothly. Hence, the UEDT in the whole economy energy demand in Japan is non-linear. The UEDT is pictured in the top chart of Figure 6.3 with its slope in the bottom chart. The increasing UEDT gradually changed into the declining trend at the mid-1970s that continued over the rest of the period but getting at moderate rates. The slope of the UEDT, which is an equivalent of its first derivatives, shown in the bottom chart of Figure 6.3 describes this evolution more precisely. The downward slope of the UEDT is the most steep at the early 1980s, and since then, the trend slope was approaching zero i.e. the trend becomes even flatter towards the end the sample period. This implies that substantial improvement of energy efficiency occurred during the early 1980s, but it does not continue after then. After 1985, the rate of the improvement clearly diminishes.

Figure 6.3. The estimated UEDT and its slope (by Stochastic Trend Model)
The average growth rate of the estimated trend in Table 6.1 also shows this evolution of the UEDT over the sample period. Although the overall average growth rate is −0.56% p.a., the rate for 1975 – 1989 is particularly large negative value of −1.16% to −1.73% p.a.. The effect of the UEDT may have been cancelled out by an increasing real GDP for the same period as seen in the top right hand chart of Figure 6.1. In other words, without the UEDT, the actual energy demand would have increased by more than 1.0% p.a.. This rate reduced to −0.43% p.a. during the 1990s and to −0.35% p.a. at the very end of the sample period.

The pattern of the UEDT may provide the reason why Boone, et al. (1995) estimate a large negative rate of −4.06% p.a. for a linear time trend. That is partly due to their data sample period covering between 1978 and 1990 where the particularly higher rates of the UEDT relative to other period are found. Therefore, a generalisation of this higher rate could result in too optimistic future scenario so that significant reduction of energy demand would be achieved by autonomous technical progress. This corresponds to the fact that the Deterministic Trend Model fails the post-sample prediction test due to an under-estimation since it assumes that the UEDT is constantly downward by the fixed rate of −0.8% p.a. which is, again, too much for the 1960s and too little for the 1980s. Figure 6.3 visually indicates that the approximation of the non-linear UEDT by the deterministic linear time trend is clearly inappropriate.

The estimated long-run income and price elasticities by the Stochastic Trend Model are unitary (0.99) and −0.24, which can be compared to that of the recent energy studies
reported in Table 6.2.

Using the log-linear model including a deterministic time trend with annual data 1970 – 1984, Welsh (1989) estimates the long-run income elasticity as 1.23 which is also very close to 1.31 provided by the Deterministic Trend Model in this thesis. This value can be considered as an overestimation of the income elasticity relative to the unitary income elasticity given by the Stochastic Trend Model. This is because, when the direction of the UEDT changed from upwards to downwards at the mid 1970s, an imposing of the downwards linear time trend in the model can lead to an overestimation bias as described in Chart (b) of Figure 3.2.

Employing the similar log-linear model with annual data 1957 – 1983 which is longer than Welsh (1989) but excluding a deterministic time trend, Koshal et al. (1989) estimate the long-run income elasticity of 0.76 and the price elasticity of −0.42. With the similar model without any trend using annual data 1965 – 1998, IEEJ (2001, p.305) estimates the similar long-run income elasticity of 0.73, but the long-run price elasticity is much lower value of -0.02. In comparison between these estimated income elasticity (around 0.7) and the unitary income elasticity by the Stochastic Trend Model in this thesis, the former value can be considered as an underestimation of the income elasticity given by the model ignoring the UEDT when the UEDT is downwards and income rise, as discussed in Chapter 3. Nevertheless, the bias is not huge, because the UEDT is not steadily downwards, but it is upwards up to the mid 1970s, perhaps, cancelling out the bias effects. However, it should be noted that all of the income and price elasticities reported by Koshal et al. (1989) and IEEJ (2001) are based on insignificant parameters
at 5% level (Koshal et al., 1989) or sometimes even at 20% (IEEJ, 2001) level. Therefore, the estimated values should be taken with cautions.

As discussed in Chapter 3, Smith et al. (1995) and Boone et al. (1995) arguably have some fundamental problems with their model and the data used. However, given the estimated income elasticity is found to be unitary in this thesis, the restriction of a unitary income elasticity adopted in these studies may be acceptable. In fact, the long-run price elasticity from Boone et al. (1995) of -0.13 is relatively close to the estimate here of -0.24, although -0.016 given by Smith et al. (1995) is much lower (in absolute term). It should be recalled that both studies solely concentrate on the fossil fuel demand, rather than aggregated energy as a whole.

Finally, using the cross-country data in a single year of 1980, Brenton (1997) estimates the long-run income elasticity of a unitary, which is consistent to that of this thesis, whereas the long-run price elasticity of -0.96 is completely different. This can be caused by use of the cross-country data within the linear expenditure model (Stone, 1954), which is somewhat fundamentally different from the estimation framework in this thesis.

To sum up, it is reasonable to conclude that the long-run income elasticity of the energy demand in this sector is around unitary, which is in the middle of the range (0.8 and 1.2) covering almost all of the past studies' estimates outlined here. On the other hand, there are variety of estimates for the price elasticity ranging from -0.13 (Smith et al, 1995) to -0.88 (Brenton, 1997). These differences may appear to be a result of the approach
taken to modelling the UEDT. Only this thesis and Smith et al. (1995) treat the UEDT as stochastic trend, whereas other studies employ a deterministic linear time trend or it is ignored completely. Given the discussion in Chapter 3, these higher estimated values are likely to be the result of overestimation. This is likely to a case that the inadequate model cannot separate out between a shift of a demand curve, which is represented by movement of the UEDT, and a normal symmetric demand response along with a demand curve, producing estimated elasticities.
<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated LR elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Welsch (1989)</td>
<td>Aggregated energy</td>
<td>Dynamic log-linear model</td>
<td>Annual data 1970 - 84 (15 obs.)</td>
<td>$\eta_y = 1.229$, $\eta_p = 0.859$</td>
</tr>
<tr>
<td>Koshal et al. (1990)</td>
<td>Aggregated energy</td>
<td>Dynamic log-linear model</td>
<td>Annual data 1957 - 1983 (27 obs.)</td>
<td>$\eta_y = 0.76$, $\eta_p = -0.42$ Time trend included, but not reported</td>
</tr>
<tr>
<td>Smith et al. (1995)</td>
<td>Aggregated fossil fuel</td>
<td>Log-linear - Kalman filter</td>
<td>Quarterly data (interpolated from annual data 1978 - 90, but detail not reported)</td>
<td>$\eta_y = 1.0$ (imposed), $\eta_p = -0.016$, $t = \text{stochastic trend}$</td>
</tr>
<tr>
<td>Boone et al. (1995)</td>
<td>Aggregated fossil fuel</td>
<td>Log-linear - VECM</td>
<td>Quarterly data (interpolated from annual data 1978 - 90, but detail not reported)</td>
<td>$\eta_y = 1.0$ (imposed), $\eta_p = -0.133$, $t = -0.0406$</td>
</tr>
<tr>
<td>Brenton (1997)</td>
<td>Aggregated energy</td>
<td>Cross-country LES model</td>
<td>60 cross-country data 1980 (60 obs.)</td>
<td>$\eta_y = 1.003$, $\eta_p = -0.957$</td>
</tr>
<tr>
<td>IEEJ (2000)</td>
<td>Aggregated energy</td>
<td>Dynamic log-linear model</td>
<td>Annual data 1965 - 98 (23 obs.)</td>
<td>$\eta_y = 0.73$, $\eta_p = -0.02$ (insignificant at 20%)</td>
</tr>
</tbody>
</table>

Note: $\eta_y$ = the long-run income elasticity, $\eta_p$ = the long-run price elasticity
6.2.2. Aggregated final energy demand in the residential-service sector in Japan

6.2.2.1. The data

The annual data series used for the estimation is illustrated in Figure 6.4.

Figure 6.4. Residential-service sector final energy demand (LFE), real GDP (LGDP), real aggregated energy price (LEP) (in log scale), and the Heating Degree Days (HDD) in Japan

The energy demand series includes not only the residential sector, but also the service sector. Therefore, the series is called as the 'residential-service sector'. It is customary in Japan to consider the residential and the service sectors as a unit sector against the manufacturing and the transport sectors. Although the consistency between Japan and the UK may be affected in some extent, we treat these two sectors as the
'residential-service sector' mainly due to the data availability. Energy consumption in this sector continuously increased without any substantial breaks over the sample period although the growth rate reduced after the mid 1970s. It is noticed that, even during the early 1980s at which the energy demands in other sectors stagnated and decreased, the demand in the residential-service sector still increased towards the end of the sample period. The past trend of the demand looks parallel to the real GDP which also continued to increase over the period. The price and the HDD are the same as used in the previous sections².

6.2.2.2. The estimated results

The estimated results are outlined in Table 6.3. The one year lagged variables of the price and the energy demand are included in the all models implying the demand needs some adjustment process towards its long-run path. In fact, the specifications of the models are all similar except the modelling of the trend. There are no sign of misspecification for all models. However, the estimated long-run elasticities are very different. Therefore, in order to choose the preferred model, the longer-term (1985 – 1999) post-sample prediction test is applied to the models. The predicted demand series brings dramatic differences between the model performances as can be seen Figure 6.5. The predicted values given by the No Trend Model systematically overestimates the predicted values though some of them still lie within the prediction interval. As a result, the Cusum completely diverts from the boundary lines, suggesting the prediction performance of the model in the longer term is rather unsatisfactory.

² As mentioned in Chapter 4, the price used here is the aggregated energy price for whole economy since
Table 6.3. Estimated results for the residential-service sector energy demand in Japan 1965 – 1996

<table>
<thead>
<tr>
<th>Corresponding cell of Table 4.2</th>
<th>I: No Trend Model</th>
<th>II: Deterministic Trend Model</th>
<th>III: Stochastic Trend Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Estimated Coefficients</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>y</em></td>
<td>0.1964**</td>
<td>0.3847**</td>
<td>0.4376**</td>
</tr>
<tr>
<td></td>
<td>(3.014)</td>
<td>(4.003)</td>
<td>(3.770)</td>
</tr>
<tr>
<td><em>p</em></td>
<td>-0.1672**</td>
<td>-0.1624*</td>
<td>-0.1599**</td>
</tr>
<tr>
<td></td>
<td>(4.412)</td>
<td>(4.690)</td>
<td>(4.246)</td>
</tr>
<tr>
<td><em>p</em>₋¹</td>
<td>0.0947*</td>
<td>-0.0938**</td>
<td>-0.0968*</td>
</tr>
<tr>
<td></td>
<td>(2.518)</td>
<td>(2.733)</td>
<td>(2.515)</td>
</tr>
<tr>
<td><em>e</em>₋¹</td>
<td>0.7951**</td>
<td>0.7310**</td>
<td>0.6102**</td>
</tr>
<tr>
<td></td>
<td>(14.562)</td>
<td>(13.037)</td>
<td>(6.513)</td>
</tr>
<tr>
<td><strong>HDD</strong>₁</td>
<td>0.0001**</td>
<td>0.0001**</td>
<td>0.0001**</td>
</tr>
<tr>
<td></td>
<td>(3.190)</td>
<td>(3.356)</td>
<td>(3.502)</td>
</tr>
<tr>
<td><strong>Long-Run Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income (Y)</td>
<td>0.9588</td>
<td>1.4300</td>
<td>1.1227</td>
</tr>
<tr>
<td>Price (P)</td>
<td>-0.3537</td>
<td>-0.2549</td>
<td>-0.1619</td>
</tr>
<tr>
<td><strong>Estimated Hyperparameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2 \times 10^{-4}$</td>
<td>4.337</td>
<td>3.612</td>
<td>2.402</td>
</tr>
<tr>
<td>$\sigma^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>1.469</td>
</tr>
<tr>
<td>$\sigma^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Nature of Trend</strong></td>
<td>No Trend Model</td>
<td>Linear Trend Model</td>
<td>Local Level model</td>
</tr>
<tr>
<td>Corresponding cell of Table 4.1</td>
<td>Cell ii</td>
<td>Cell v</td>
<td>Cell iii</td>
</tr>
<tr>
<td><strong>Average Annual Growth rate of</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>the estimated trend</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1965 – 1996</td>
<td>0%</td>
<td>-0.52%</td>
<td>-0.10%</td>
</tr>
<tr>
<td>1965 – 1969</td>
<td>0%</td>
<td>-0.52%</td>
<td>0.28%</td>
</tr>
<tr>
<td>1970 – 1974</td>
<td>0%</td>
<td>-0.52%</td>
<td>0.50%</td>
</tr>
<tr>
<td>1975 – 1979</td>
<td>0%</td>
<td>-0.52%</td>
<td>-0.54%</td>
</tr>
<tr>
<td>1980 – 1984</td>
<td>0%</td>
<td>-0.52%</td>
<td>-0.56%</td>
</tr>
<tr>
<td>1985 – 1989</td>
<td>0%</td>
<td>-0.52%</td>
<td>-0.05%</td>
</tr>
<tr>
<td>1990 – 1996</td>
<td>0%</td>
<td>-0.52%</td>
<td>-0.20%</td>
</tr>
<tr>
<td><strong>Diagnostics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Equation Residuals</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Error</td>
<td>1.88%</td>
<td>1.70%</td>
<td>2.05%</td>
</tr>
<tr>
<td>Normality</td>
<td>0.05</td>
<td>0.40</td>
<td>0.19</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.02</td>
<td>0.09</td>
<td>0.00</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.02</td>
<td>0.31</td>
<td>0.19</td>
</tr>
<tr>
<td>H(10)</td>
<td>1.03</td>
<td>0.92</td>
<td>0.99</td>
</tr>
<tr>
<td>r(1)</td>
<td>-0.06</td>
<td>-0.16</td>
<td>-0.15</td>
</tr>
<tr>
<td>r(2)</td>
<td>-0.06</td>
<td>-0.15</td>
<td>-0.05</td>
</tr>
<tr>
<td>r(3)</td>
<td>-0.01</td>
<td>-0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>r(4)</td>
<td>-0.03</td>
<td>-0.02</td>
<td>0.06</td>
</tr>
<tr>
<td>DW</td>
<td>2.01</td>
<td>2.28</td>
<td>2.21</td>
</tr>
</tbody>
</table>

the price for this particular sector is unavailable in Japan. This is one of the limitations of this thesis.
The performance of the Deterministic Trend Model is also very poor. The predicted values continuously underestimate most of which are outside of the prediction intervals associated with the Cusum which also goes far above the boundary lines. In contrast to these two models, the predicted values by the Stochastic Trend Model track the actual observations very well over the post-sample period. Only two predictions (for 1986 and 1993) are marginally outside the prediction interval. Accordingly, the Cusum never crosses the boundary lines, suggesting the longer term prediction by the Stochastic Trend Model is clearly superior to the rival models. Hence, the Stochastic Trend Model is chosen as the preferred model.

---

Note: See Notes for Table 6.1

\[ \chi^2 (t) = 0.76, \ Cusum t = -0.65, \ LR tests = n/a \]
Figure 6.5. The post-sample 1985 – 1999 prediction by No Trend Model (Top left chart), Deterministic Trend Model (top right chart) and Stochastic Trend Model (bottom chart)

The stochastic trend is best formulated by the Local Level Model which does not contain the slope component i.e. the stochastic movement is generated by shifts in the level component creating so-called a random walk process. Despite this, the UEDT has systematic pattern as seen in Figure 6.6.

The evolution of the UEDT is quite similar to that found in the whole economy energy demand shown in Figure 6.3; an increasing trend turns into a downward trend at the mid-1970s and moderate declining after the late 1980. However, the range of the fluctuation of the UEDT is considerably different compared to the other sectors considered in this chapter.
The range of the UEDT between the top and the bottom is a 7% difference for the residential-service sector, whereas it is 23% for the whole economy and 75% for the manufacturing sector (see the next section), indicating that the range of fluctuation of the UEDT in the residential-service sector is smaller than other sectors. The average annual growth rate of the UEDT in the residential-service sector is also much smaller at -0.1% for the full sample period (as seen in Table 6.3) compared to -2.34% for the manufacturing sector and -0.56% for the whole economy.

All of these results suggest that the UEDT in this sector is relatively flat. The relatively flat UEDT in the residential-service sector is parallel to the result of the residential sector in the UK presented in Chapter 5 where the UEDT is found to be perfectly horizontal. This implies that energy efficiency improvement of appliances, which is certainly observed in many cases, are largely cancelled out by an increasing the number of appliances led by changes in tastes of consumers, namely willing to have more luxury quality of life (Schipper et al., 1992, p.175). This is different from the case of the manufacturing in which the large extent of downward slope of the UEDT is estimated as seen in the next section. Finally, The LR test (d) indicates that the No Trend Model is
unacceptable at the 10% of significance.

The estimated long-run income elasticities by the three models are within a relatively narrow range between unitary and 1.4, and the preferred model gives 1.12 which falls around the middle of them. The underestimation of the income elasticity by the No Trend Model (around unitary) is the case described in Chapter 3 when both of the UEDT and income increase. Nevertheless, since the UEDT does not move to a large extent, the underestimation bias is not as large as other sectors considered in Chapters 5 and 6.

Similarly, the overestimation of the income elasticity by the Deterministic Trend Model may arise due to the restriction of the negative trend for the period up to the mid 1970s where the UEDT may be upward sloping rather than downward as seen in Figure 6.6. This is still in line with the discussion for the overestimation bias of income elasticity in Chapter 3 in the case when the UEDT is upward and income increases\(^4\). However, in the residential-service sector, the biases of the estimated income elasticities are not very substantial compared to other sectors cases.

The overestimation of the long-run price elasticities also seems to arise when the UEDT is ignored. The No Trend Model gives \(-0.35\) compared to \(-0.16\) for the Stochastic Trend Model. This larger price elasticity (in absolute term) may be the overestimation bias when price increases and the UEDT is downward sloping, again, as described in Chapter 3, Section 5. However, the price not only increased but also decreased after the

\(^4\) Chart (b) of Figure 3.2 graphically explains this.
mid-1980s and, according to the discussion in Chapter 3, Section 5, the underestimation can also occur at the same condition\(^5\). The likely reason why the overestimation occurs under these circumstances is that the downward sloping of the UEDT is much flatter when the price declined (after the mid 1980s) than when the price increased (during the late 1970s and the early 1980s). As a result, the overestimation bias associated with the price rise can be greater than the underestimation bias associated with price decrease, leading to the overestimation of the price elasticity in total. The overestimation of the long-run price elasticity given by the Deterministic Trend Model can also be explained by Chart (d) of Figure 3.1. Since the Deterministic Trend Model, which only has a fixed negative trend throughout the sample period, does not consider the upward sloping of the UEDT during the late 1960s and the early 1970s, the model is likely to produce the overestimated price elasticity, as actually occurred.

Not many energy demand literature have considered this sector in Japan, which is shown in Table 6.4. Haas and Schipper (1998) estimate the demand using annual data 1970 – 1993 and the log-linear model including irreversible price response terms (see, Dargay (1992b), p.167). The long-run income elasticity is estimated as 1.23, which is very close to the result of this thesis. On the other hand, the long-run price elasticity is estimated as –0.26 which is slightly higher than the estimated value here. However, this price elasticity is only valid when the price exceeds the previous highest level, otherwise the demand has no response to price change at all. They also estimated the same demand using the reversible model producing the long-run income elasticity of 0.38 and the price elasticity of –0.13 which is fairly close to the estimate of –0.16 in this

\(^5\) See Chart (c) of Figure 3.1 in this case.
thesis. It is interesting that the long-run income elasticity becomes much higher when the irreversible price response is incorporated in the model, since the long-run income elasticity also tends to be underestimated when the UEDT is ignored (see Figure 3.2. Chart (a)) in the modelling framework adopted in this thesis.

Using the similar log-linear model under the irreversible price response assumption, Haas et al. (1998) also estimate oil and natural gas demand. Although their results may not be directly comparable to the estimates here, an underestimation of long-run income elasticities is also observed. However, it is worth remembering that the estimated parameters in Haas et al. (1998) and Haas and Schipper (1998) often appear to be insignificant at even 10% level. It is also true for Dargay (1992) who employs the similar irreversible price response model as already mentioned in the previous chapter. Therefore, in spite of its attractive features, the irreversible price response model appears to be underdeveloped.
Table 6.4. Recent energy demand studies for the residential-service sector in Japan

<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated LR elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haas and Schipper (1998)</td>
<td>Aggregated energy</td>
<td>Dynamic log-linear model (Energy intensity included)</td>
<td>Annual data 1970 - 93 (24 obs.)</td>
<td>$\eta_t = 0.38$,$\eta_p = -0.13$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dynamic log-linear model</td>
<td>Annual data 1970 - 93 (24 obs.)</td>
<td>$\eta_t = 1.23$</td>
</tr>
<tr>
<td>Haas et al. (1998)</td>
<td>Oil and natural gas only</td>
<td>Dynamic log-linear model</td>
<td>Annual data 1970 - 93 (24 obs.)</td>
<td>$\eta_t$ (oil) = 0.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dynamic log-linear model</td>
<td>Annual data 1970 - 93 (24 obs.)</td>
<td>$\eta_t$ (oil) = 1.03</td>
</tr>
</tbody>
</table>

Note: $\eta_t$ = the long-run income elasticity, $\eta_p$ = the long-run price elasticity
6.2.3. Aggregated final energy demand in the manufacturing sector in Japan

6.2.3.1. The data

The final energy consumption in the manufacturing sector in Japan is only available on annual basis. Therefore, an annual model is used for the estimation with the various data series illustrated in Figure 6.7.

Figure 6.7. Manufacturing sector final energy demand (LFE), real GDP (LGDP), real aggregated energy price (LEP) (in log scale), the Heating Degree Days (HDD) and the Cooling Degree Days weighted by the diffusion of air conditioner (CDDAC) in Japan

The manufacturing sector is the largest energy consuming sector in Japan, though its share declined from 67% in 1970 to 49% in 1999. A very rapid growth in the energy
demand in this sector was recorded up to the mid 1970s, which was suddenly turned into a continuous stagnation and reduction towards the mid 1980s. After this period it gradually increased with the much lower growth rate compared to the period before the mid 1970s. As a result, the energy demand in this sector increased by about only 10% since 1976. The real GDP and the real energy price series is the same as used in the previous section. The HDD is also the same as used in the previous section. The Cooling Degree Days (CDD) is the annually sum of the differences between 22°C and the average air temperature of the days which are more than 24°C in the major 9 areas in Japan. This CDD weighted by the diffusion of air conditioner gives the CDDAC (see Chapter 4 for the detail). Since the CDDAC better fits the data in this sector, it is used instead of the original CDD.

6.2.3.2. The estimated result

Table 6.5 summarises the estimated results by the three different models; the No Trend Model, the Deterministic Trend Model and the Stochastic Trend Model. The CDDAC is estimated to be insignificant in the No Trend Model and one more additional lagged variable of GDP is needed to minimise the problem of autocorrelation of the residuals. However, it still remains at the second and the sixth orders, which could not be removed by further addition of the lagged variables.

---

6 The price used here is the aggregated energy price for whole economy since the price for this particular sector is unavailable in Japan. This is one of the limitations of this thesis.

7 Although the CDD was initially used for the estimation, it always found to be insignificant. However, the CDDAC appeared to be significant in many cases.
Table 6.5. Estimated results for the manufacturing sector energy demand in Japan 1965 – 1996

<table>
<thead>
<tr>
<th>Corresponding cell of Table 4.2</th>
<th>I: No Trend Model</th>
<th>II: Deterministic Trend Model</th>
<th>III: Stochastic Trend Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Estimated Coefficients</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>0.7187**</td>
<td>0.7871**</td>
<td>0.8220**</td>
</tr>
<tr>
<td></td>
<td>(5.910)</td>
<td>(7.593)</td>
<td>(5.140)</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>-0.5853**</td>
<td>-0.2816*</td>
<td>-0.1903**</td>
</tr>
<tr>
<td></td>
<td>(5.082)</td>
<td>(2.048)</td>
<td>(6.213)</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>0.1318**</td>
<td>-0.1577**</td>
<td>-0.1903**</td>
</tr>
<tr>
<td></td>
<td>(6.970)</td>
<td>(7.870)</td>
<td>(6.213)</td>
</tr>
<tr>
<td>$\epsilon_{t-1}$</td>
<td>0.8200**</td>
<td>0.6628**</td>
<td>0.4041**</td>
</tr>
<tr>
<td></td>
<td>(28.800)</td>
<td>(11.379)</td>
<td>(4.879)</td>
</tr>
<tr>
<td>$HDD_t$</td>
<td>0.0002**</td>
<td>0.0002**</td>
<td>0.0002**</td>
</tr>
<tr>
<td></td>
<td>(4.692)</td>
<td>(5.787)</td>
<td>(4.879)</td>
</tr>
<tr>
<td>$CDDAC_t$</td>
<td>0.0001*</td>
<td>0.0001*</td>
<td>0.0001*</td>
</tr>
<tr>
<td></td>
<td>(2.308)</td>
<td>(2.563)</td>
<td></td>
</tr>
<tr>
<td><strong>Long-Run Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income ($Y$)</td>
<td>0.7407</td>
<td>1.499</td>
<td>1.3796</td>
</tr>
<tr>
<td>Price ($P$)</td>
<td>-0.7321</td>
<td>-0.4673</td>
<td>-0.3193</td>
</tr>
<tr>
<td><strong>Estimated Hyperparameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_e^2 \times 10^{-4}$</td>
<td>4.482</td>
<td>3.149</td>
<td>2.334</td>
</tr>
<tr>
<td>$\sigma_{\pi}^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\sigma_{\epsilon}^2 \times 10^{-4}$</td>
<td>0</td>
<td>0</td>
<td>0.206</td>
</tr>
<tr>
<td><strong>Nature of Trend</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corresponding cell of Table 4.1</td>
<td>No Trend Cell ii</td>
<td>Linear Trend Model Cell v</td>
<td>Smooth Trend model Cell viii</td>
</tr>
<tr>
<td><strong>Average Annual Growth rate of</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>the estimated trend</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1965 – 1996</td>
<td>0%</td>
<td>-1.60%</td>
<td>-2.34%</td>
</tr>
<tr>
<td>1965 – 1969</td>
<td>0%</td>
<td>-1.60%</td>
<td>-1.48%</td>
</tr>
<tr>
<td>1970 – 1974</td>
<td>0%</td>
<td>-1.60%</td>
<td>-2.04%</td>
</tr>
<tr>
<td>1975 – 1979</td>
<td>0%</td>
<td>-1.60%</td>
<td>-2.82%</td>
</tr>
<tr>
<td>1980 – 1984</td>
<td>0%</td>
<td>-1.60%</td>
<td>-3.24%</td>
</tr>
<tr>
<td>1985 – 1989</td>
<td>0%</td>
<td>-1.60%</td>
<td>-2.68%</td>
</tr>
<tr>
<td>1990 – 1996</td>
<td>0%</td>
<td>-1.60%</td>
<td>-1.86%</td>
</tr>
<tr>
<td><strong>Diagnostics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Equation Residuals</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Error</td>
<td>1.91%</td>
<td>1.56%</td>
<td>1.99%</td>
</tr>
<tr>
<td>Normality</td>
<td>0.86</td>
<td>5.18</td>
<td>2.21</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.14</td>
<td>2.18</td>
<td>0.19</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.72</td>
<td>3.00</td>
<td>2.02</td>
</tr>
<tr>
<td>$H(10)$</td>
<td>2.26</td>
<td>0.43</td>
<td>0.88</td>
</tr>
<tr>
<td>$r(1)$</td>
<td>-0.07</td>
<td>-0.02</td>
<td>-0.01</td>
</tr>
<tr>
<td>$r(2)$</td>
<td>-0.36*</td>
<td>-0.09</td>
<td>-0.04</td>
</tr>
<tr>
<td>$r(3)$</td>
<td>0.05</td>
<td>-0.17</td>
<td>-0.08</td>
</tr>
<tr>
<td>$r(4)$</td>
<td>-0.22</td>
<td>-0.32</td>
<td>-0.06</td>
</tr>
<tr>
<td>DW</td>
<td>1.97</td>
<td>1.95</td>
<td>1.98</td>
</tr>
<tr>
<td>$Q$</td>
<td>$Q_{(6,6)} = 11.65$</td>
<td>$Q_{(6,6)} = 7.96$</td>
<td>$Q_{(6,6)} = 1.82$</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
</tr>
</tbody>
</table>
The higher Box-Ljung statistics (11.65) also indicates the residuals are correlated. These test results suggest that the model is mis-specified. The estimated long-run elasticities are 0.74 for income and -0.73 for price which are substantially lower and higher (in absolute term) respectively compared to the estimates by the other models.

Even though the No Trend Model passes the prediction test for the last three observations 1997 – 1999, the longer term prediction test for 1985 – 1999 is carried out for this model to examine its prediction power in the long-run. As already mentioned above, the energy demand in this sector changed from the stagnation to increase at the mid-1980. Therefore, it is of interest whether or not the model can predict this transition and evolution.

---

*This is significant at the 10% level.*
Figure 6.8. The post-sample 1985 – 1999 predictions by No Trend Model (top left), Deterministic Trend model (bottom) and Stochastic Trend Model (top right)

The top left hand side chart of Figure 6.8 shows the predicted values by the No Trend Model with the prediction intervals of two root mean square error errors and the actual observations for 1985 – 1999. The predicted energy demand is constantly overestimated, suggesting the model fails to predict the increase in the demand after the mid-1980 towards the end of the sample period. As a result, the corresponding Cusum, shown in just underneath, goes far below the 10% boundary lines. Therefore, the longer term a prediction ability of the No Trend Model is very poor. Given these results, the No Trend Model is not preferred
model since the parameter consistency of this model over the longer term can be questionable.

The Deterministic Trend Model has the largest number of variables to ensure the residuals are white noise. However, the model completely fails the prediction test for 1997 – 1999 since the model produces the underestimated prediction for the period. This underestimation of the demand for the last three observations is mainly caused by the negative deterministic trend of \(-1.60\%\) p.a. with relatively constant GDP and energy price for this period as seen in Figure 6.7. Hence, it is not surprising that the model also poorly performs the longer term predictions 1985 – 1999 as seen in the bottom chart of Figure 6.8. Moreover, the normality and the skewness statistics of the residuals distribution are nearly approaching to the 5% critical region. These statistics suggest that the model is likely to be mis-specified. Thus, the estimated long-run elasticities, 1.50 for income and \(-0.47\) for price are also likely to be biased.

In comparison to the diagnostics and the test statistics, the Stochastic Trend Model outperforms to the others. The residuals are white noise and the post sample prediction test passes satisfactorily. The LR test indicates the deterministic restriction on the stochastic trend is marginally acceptable at 5% level of significance, but it fails at 10% level, and, as we have seen already, the deterministic trend model has very poor forecasting property. Therefore, the Stochastic Trend Model should be preferred. To further examine the longer term prediction power of this model, the post sample prediction test for 1985 – 1999 is also applied. The top right hand chart of Figure 6.8 shows the model predicts well the actual values within the prediction intervals over the
prediction period with an exception of 1994. The corresponding Cusum is very satisfactorily within the boundary lines.

Figure 6.9. The estimated UEDT and its slope in the manufacturing sector

The estimated stochastic trend is the form of the Smooth Trend, which is cell viii of Table 4.1. The trend is characterised by smoothing changes in its direction overtime, generated by the positive value of the slope hyperparameter. This trend is illustrated in the top chart of Figure 7.6. The bottom chart is the slope of the trend, namely the annual growth rate of the trend.

The downward trend gradually becomes steeper towards the early 1980s and after the period it is getting flatter. In 1980, the rate is nearly -3.4% p.a., whereas at the beginning and the end of the sample period the rates are similar, at about -1.5%. Thus, although the trend is steadily downward sloping throughout the sample period, its growth rate changes over time creating the non-linear shape of the UEDT. This brings about an important implication that, as discussed in the previous section, a reduction in the energy demand in the near future including the current period led by the UEDT, which can be mainly energy efficiency improvement, would be not as much as achieved
during the 1980s. Therefore, it is not wise to generalise the higher negative growth rate observed during the 1980s. The failure of the post sample prediction test by the Deterministic Trend Model also indicates this problem.

The estimated long-run elasticities are 1.38 for income and -0.32 for price. The income elasticity of 1.38 is substantially higher than 0.73 which is estimated by the No Trend Model. This lower estimated long-run income elasticity by the No Trend Model is another example of the biased under-estimated elasticity given by the model ignoring the UEDT when income increases and the UEDT is downward sloping (see Figure 3.2. chart (a)). In contrast, the Deterministic Trend Model produces the relatively similar long-run income elasticity of 1.5. This is because the shape of the UEDT, though it is non-linear, is relatively simple and an approximation of the deterministic trend may result in the relatively small biased of the elasticity.

The long-run price elasticity of -0.73 given by the No Trend Model also differs from the estimates by the Stochastic Trend Model (-0.32). Again, this difference can be regarded as a biased overestimate (in absolute term). However, since the movement of the price is not unidirectional as with GDP and, therefore, it is not immediately obvious what the theoretical explanation is for this. The possible reason is that because the slope of the UEDT is steeper when the price increased during the late 1970s and the early 1980s (see Figure 6.9) shifting the demand curve to the left quite rapidly, whereas when the price declined during the late 1980s onwards, the slope of the UEDT becomes flatter (again, see Figure 6.9) shifting the demand curve to the left at lesser proportions. Thus, the over-estimation and the under-estimation caused by an ignorance of the UEDT when
price increase and decrease are not necessary to be symmetric, leading to the over-estimation of the price elasticity, as actually occurred here.

There are very few energy demand studies available for a comparison to the estimated elasticities in the manufacturing sector in Japan. Some of the available studies are summarised in Table 6.6. Using the log-linear model with annual data 1960 – 1989, Atkinson and Manning (1995) estimated the long-run income elasticity of 0.3 and the price elasticity of 0.19. Both are lower (in absolute term) than the estimates by this study, particularly, the difference of the income elasticities is huge. Presumably, as the authors themselves admit, the model does not perform very well. For example, the DW statistics for this model is 0.51; a substantial first-order autocorrelation is likely to occur. Therefore, the estimated elasticities may be biased and require careful considerations.

Although no elasticity value is estimated, Unander et al. (1999) analyse the structural change in the energy demand in the manufacturing sector in Japan through the decomposition analysis. They find that the changes in the energy demand led by the structural change and the energy efficiency improvement, which can be regarded as an equivalent of the UEDT, are estimated to be −5.0% p.a. for 1973 – 1986, −2.8% p.a. for 1986 – 1990, and 0.3% for 1990 – 1994. The corresponding estimated growth rates of the UEDT in this thesis are −3.3% p.a. for 1975 – 1984 (on average), −2.68% p.a. for 1986 – 1990, and −1.86% p.a. for 1990 – 1994. The difference between the two estimates is likely to come from the fact that Unander et al. (1999) do not consider the price effect on the energy demand. Therefore, they seem to be over-estimated for 1973 – 1986 (in absolute term) and 1990 – 1994. Similar comments can be given for Greening
et al. (1997 and 1998) who also apply the decomposition method to the aggregated energy intensity (1998) and the carbon intensity (1997).
<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated LR elasticities</th>
</tr>
</thead>
</table>
|                     |              |                                                            |                         | $\eta_p = -0.19$  
|                     |              |                                                            |                         | Trend included, but not reported |
| Greening et al. (1997) | Aggregated energy intensity | Decomposition analysis (Non econometric) | Annual data 1970 - 92 (23 obs.) | No elasticity value estimated |
| Greening et al. (1998) | Aggregated carbon intensity | Decomposition analysis (Non econometric) | Annual data 1971 - 91 (21 obs.) | No elasticity value estimated |
| Unandar et al. (1999) | Aggregated energy | Decomposition analysis (Non econometric) | Annual data 1971 - 95 (25 obs.) | No elasticity value estimated |

Note: $\eta_r$ = the long-run income elasticity, $\eta_p$ = the long-run price elasticity
6.3. Individual fuel energy demand in Japan

Following Chapter 5.3., the demands for the two fuels, transport oil and electricity are estimated in this chapter. The available quarterly data for the estimate of the road transport oil demand is 1971q4 – 1997q4 and for electricity is 1971q4 – 1997q1. Therefore, for these fuels, the issue of seasonality in addition to the UEDT is explored. It also means that the estimated results can be directly compared to those of the UK.

6.3.1. Transportation oil demand in Japan

6.3.1.1. The data

The data series used for the estimation is displayed in Figure 6.10. The transportation oil demand, here, is defined as the sum of the petrol and diesel consumptions used for transport use. This occupied 86% of the total energy consumption in the transportation sector in 1998, which is absolutely predominate majority in the sector. As can be seen in Figure 6.10, the demand series continued to increase and the actual consumption expanded nearly three times over the sample period, although its growth rate was lowered during the early 1980s. This path seems to be quite similar to the final energy demand in the residential-service sector. The systematic seasonal pattern is clearly observed in the series. The real GDP series also shows steadily increase over the sample period together with a marked seasonal pattern.
The real price of the transportation oil dramatically fluctuated reflecting the oil shocks during the 1970s and the 1980s, but it was relatively modest during the 1990s except in 1990 when the Gulf War occurred.

Air temperature could affect the oil transportation demand in Japan due to heavy use of air conditioners equipped in cars in the summer giving impact on fuel mileage. However, it is also anticipated that any movement of air temperature under a certain degree little affects the demand because use of car heater is normally irrelevant to fuel mileage. Therefore, the higher air temperature deviations \((HotDev)^9\) are used for the

---

9 See Chapter 4 for the detail.
estimation, instead of the original air temperature series.

6.3.1.2. The estimated results

Table 6.7 summarises the estimated results given by the various type of models. The model specifications are based on the categorisation outlined in Table 4.2. Overall, it is found that an appropriate modelling of the transport oil demand in Japan is considerably difficult unless the model incorporates the stochastic trend and the stochastic seasonals. The reason for the necessity of the stochastic modelling is that the demand includes a distinct shape of a non-linear UEDT and a pronounced stochastic seasonal evolution, about which will be further discussed in later.

Model (6) (Stochastic Trend and Stochastic Seasonals model) has a substantially small number of the variables compared to other rivals models. Despite this, there is no sign of misspecification. Thus, model (6) is the most parsimonious model. The models including any non-stochastic component need a large number of the lagged variables in order to eliminate the autocorrelations of the residuals. The estimated coefficients of HotDev are relatively stable at around 0.01 for all models and they are little affected by the different lagged structures.
Table 6.7. Estimated results for the transportation oil demand in Japan 1972q1 – 1995q4

<table>
<thead>
<tr>
<th>Models</th>
<th>No Trend and Deterministic Seasonals</th>
<th>No Trend and Stochastic Seasonals</th>
<th>Deterministic Trend and Deterministic Seasonal</th>
<th>Deterministic Trend and Stochastic Seasonals</th>
<th>Stochastic Trend and Deterministic Seasonals</th>
<th>Stochastic Trend and Stochastic Seasonals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell number of Table 4.2</td>
<td>Model (1)</td>
<td>Model (2)</td>
<td>Model (3)</td>
<td>Model (4)</td>
<td>Model (5)</td>
<td>Model (6)</td>
</tr>
<tr>
<td>Estimated Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_t$</td>
<td>0.6164**</td>
<td>0.4156**</td>
<td>0.6493**</td>
<td>0.5020**</td>
<td>0.5936**</td>
<td>1.0526**</td>
</tr>
<tr>
<td></td>
<td>(5.794)</td>
<td>(4.988)</td>
<td>(6.000)</td>
<td>(5.102)</td>
<td>(3.644)</td>
<td>(6.934)</td>
</tr>
<tr>
<td>$\gamma_t$-2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.6010**</td>
<td>(3.409)</td>
</tr>
<tr>
<td>$\gamma_t$-4</td>
<td>-0.5959**</td>
<td>-0.3811**</td>
<td>-0.5329**</td>
<td>-0.4333**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.723)</td>
<td>(3.840)</td>
<td>(3.997)</td>
<td>(3.682)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta_t$</td>
<td>-0.0882**</td>
<td>-0.0663**</td>
<td>-0.1002**</td>
<td>-0.0798**</td>
<td>-0.0953**</td>
<td>-0.0766**</td>
</tr>
<tr>
<td></td>
<td>(4.711)</td>
<td>(4.181)</td>
<td>(4.909)</td>
<td>(2.211)</td>
<td>(3.813)</td>
<td>(3.707)</td>
</tr>
<tr>
<td>$p_t$</td>
<td>0.0370*</td>
<td>0.0344**</td>
<td>0.0472**</td>
<td>0.0406*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.117)</td>
<td>(2.331)</td>
<td>(2.513)</td>
<td>(2.471)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_t$-2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.2795**</td>
<td>(3.191)</td>
</tr>
<tr>
<td>$p_t$-3</td>
<td>0.0370*</td>
<td>0.0344**</td>
<td>0.0472**</td>
<td>0.0406*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.117)</td>
<td>(2.331)</td>
<td>(2.513)</td>
<td>(2.471)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_t$-1</td>
<td>-0.1975**</td>
<td>0.4486**</td>
<td>0.2047**</td>
<td>0.3704**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.700)</td>
<td>(5.930)</td>
<td>(2.808)</td>
<td>(4.368)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_t$-2</td>
<td>0.2573**</td>
<td>0.5102**</td>
<td>0.2623**</td>
<td>0.4365**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.246)</td>
<td>(6.443)</td>
<td>(3.326)</td>
<td>(4.769)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_t$-3</td>
<td>0.5165**</td>
<td>0.5315**</td>
<td>0.1773</td>
<td>0.1991**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.125)</td>
<td>(6.293)</td>
<td>(1.803)</td>
<td>(2.277)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta_t$-2</td>
<td>-0.1311*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.061)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HotDev</td>
<td>0.0135**</td>
<td>0.0111**</td>
<td>0.0137**</td>
<td>0.0113**</td>
<td>0.0134**</td>
<td>0.0108**</td>
</tr>
<tr>
<td></td>
<td>(3.341)</td>
<td>(3.164)</td>
<td>(3.404)</td>
<td>(3.182)</td>
<td>(3.797)</td>
<td>(3.812)</td>
</tr>
</tbody>
</table>

Long-Run Estimates

| Income (Y) | 0.6818 | 0.8374 | 76.5789 | 4.3301 | 1.2991 | 1.0526 |
| Price (P) | -1.7860 | -0.7737 | -34.8375 | -2.4688 | -0.1036 | -0.0766 |

Estimated Hyperparameters

\[
\begin{align*}
\sigma^2_x &\times 10^{-4} & 3.197 & 2.152 & 3.158 & 2.259 & 2.162 & 1.032 \\
\sigma^2_y &\times 10^{-4} & 0 & 0 & 0 & 0 & 0.166 & 0.228 \\
\sigma^2_t &\times 10^{-4} & 0 & 0 & 0 & 0 & 0.016 & 0.013
\end{align*}
\]

Chapter 6 293
<table>
<thead>
<tr>
<th>σ² x 10^-4</th>
<th>0</th>
<th>0.148</th>
<th>0</th>
<th>0.102</th>
<th>0</th>
<th>0.135</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nature of Trend Corresponding cell of Table 4.1</td>
<td>No Trend Cell ii</td>
<td>No Trend Cell ii (Cell v)</td>
<td>A Linear Trend Model (Cell v)</td>
<td>A Linear Trend Model (Cell v)</td>
<td>Local Trend Model (Cell ix)</td>
<td>Local Trend Model (Cell ix)</td>
</tr>
<tr>
<td><strong>Average Annual Growth rate of the estimated trend</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1972q1 - 1995q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.47%</td>
<td>-0.22%</td>
<td>0.29%</td>
<td>0.50%</td>
</tr>
<tr>
<td>1972q1 - 1974q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.47%</td>
<td>-0.22%</td>
<td>2.01%</td>
<td>2.49%</td>
</tr>
<tr>
<td>1975q1 - 1979q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.47%</td>
<td>-0.22%</td>
<td>0.83%</td>
<td>0.87%</td>
</tr>
<tr>
<td>1980q1 - 1984q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.47%</td>
<td>-0.22%</td>
<td>-1.80%</td>
<td>-1.53%</td>
</tr>
<tr>
<td>1985q1 - 1989q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.47%</td>
<td>-0.22%</td>
<td>-0.57%</td>
<td>-0.18%</td>
</tr>
<tr>
<td>1990q1 - 1995q4</td>
<td>0%</td>
<td>0%</td>
<td>-0.47%</td>
<td>-0.22%</td>
<td>1.51%</td>
<td>1.56%</td>
</tr>
</tbody>
</table>

**Diagnostics**

**Equation Residuals**
- Standard Error: 1.67% 1.61% 2.05% 1.59% 1.78% 1.64%
- Normality: 1.55 0.12 1.66 0.81 0.65 0.40
- Kurtosis: 0.10 0.04 0.60 0.81 0.05 0.38
- Skewness: 1.45 0.08 0.55 0.00 0.60 0.02
- H(30): 0.54 0.48 0.55 0.54 0.43 0.50
- r(1): 0.06 0.05 0.06 0.09 -0.08 0.00
- r(4): -0.06 -0.09 -0.09 -0.08 -0.03 -0.06
- r(8): -0.03 -0.02 -0.06 -0.06 0.02 -0.02
- DW: 1.86 1.88 1.85 1.83 2.13 1.98
- Q (198) = Q (197) = Q (196) = Q (195) = Q (194) = Q (193) =
  - 6.27 2.67 5.97 3.77 3.07 3.97
- R²: 0.99 0.99 0.99 0.99 0.99 0.99
- R₄²: 0.65 0.68 0.66 0.68 0.61 0.66

**Auxiliary Residuals Irregular**
- Normality: 1.63 0.12 1.57 0.87 2.67 1.52
- Kurtosis: 0.12 0.04 0.07 0.21 2.27 1.16
- Skewness: 1.51 0.08 1.50 0.21 0.40 0.36

**Level**
- Normality: n/a n/a n/a n/a 0.80 1.44
- Kurtosis: n/a n/a n/a n/a 0.25 0.97
- Skewness: n/a n/a n/a n/a 0.55 0.47

**Slope**
- Normality: n/a n/a n/a n/a 1.33 1.35
- Kurtosis: n/a n/a n/a n/a 0.65 0.28
- Skewness: n/a n/a n/a n/a 0.69 1.07

**Predictive Tests (1996Q1-1997Q4)**
- χ²: 5.04 2.61 3.91 2.41 4.85 4.87
- Cusum t: -1.00 -0.51 0.28 -0.07 -1.17 -0.91

**LR tests**
- Test (a): n/a 44.00** n/a 13.30** n/a 42.33**
- Test (b): n/a n/a n/a n/a 36.99** 162.73**
- Test (c): n/a n/a n/a n/a n/a 163.98**

**Notes:**
- *-statistics from STAMP 5.0 are given in parenthesis.
- **Indicates significant at the 1% level and * indicates significance at the 5% level.
Normality is the Bowman-Shenton statistic, approximately distributed as $\chi^2_{(0)}$.

Skewness statistic is approximately distributed as $\chi^2_{(0)}$.

H(30) is the test for heteroscedasticity, approximately distributed as $F_{(30, 30)}$.

$\tau(1)$, $\tau(4)$ and $\tau(8)$ are the serial correlation coefficients at the 1st, 4th and 8th lags respectively, approximately distributed as $N(0, 1/7)$.

DW is the Durbin Watson test for first-order autocorrelation;

$Q_{(a, a)}$ is the Box-Ljung Q-statistics based on the first $a^a$ residuals autocorrelation and distributed as $X^2_{(a^2)}$.

$R^2$ is the coefficient of determination;

$R^2$ is the coefficient of determination based on the differences around the seasonal mean (see Harvey, 1989, p.268);

$X^2_{(a)}$ is the post-sample predictive failure test;

The Cusum $t$ is the test of parameter consistency, approximately distributed as the $t$-distribution;

The restrictions imposed for the LR test are explained in the text.

The estimated long-run elasticities are different depending on the models. In particular, the models including the deterministic trend (Models (3) and (4)) produce very peculiar estimates: their estimated income elasticities are 4.33 and 76.58, and the price elasticities are $-2.47$ and $-34.84$, none of which conforms to the norms of conventional economics. These results are generated by the extremely slow adjustment process of the demand towards the long-run path based on the estimated lagged dependent variables, which are, again, required to ensure no autocorrelation of the residuals. The slow adjustment process is consistently estimated by the models excluding the stochastic trend which itself is questionable. For the estimation of the petrol demand in Japan, Franzén and Sterner (1995, p.112) also estimate the extraordinary slow adjustment process producing similar odd income elasticity. However, since they are unable to address this problem, the lagged dependent variable is arbitrary imposed to be 0.8, with which a reasonable value of the long-run income elasticity of 0.8 is eventually presented\(^{10}\). The source of this problem is likely to be inappropriate modelling of the stochastic UEDT, since Models (5) and (6) estimate much reasonable adjustment process as can be seen in Table 6.7. Moreover, any deterministic restrictions on the

---

\(^{10}\) Franzén and Sterner (1995) say that "Another country with which problems were encountered was Japan, where an unrestricted estimate of 0.93 for $\lambda$ and (insignificant) negative income elasticities was obtained. Since such as value for the lagged endogenous variable implies an unreasonably slow adjustment (adjustment would be only 75 per cent complete twenty years after a change in gasoline
stochastic trend and seasonals of Model (6) are very strongly rejected by the LR test (a) to (c). Hence, the estimated long-run elasticities of 1.1 for income and −0.08 given by Model (6) seem to be the most sound estimates.

It is interesting to compare estimated elasticities from Models (1) and (2), which are somehow within anticipated range, with those the preferred versions. The income elasticity becomes almost half (0.68) and lowered value (0.83) and, conversely, the price elasticity jumps up to very large value of −1.8 and −0.77 (in absolute term). The underestimation of income elasticity and the overestimation of the price elasticities clearly occur in systematic way here. It is also noticed that the deterministic restriction on the stochastic seasonals also results in the biased elasticities, in particular for income (1.3), as seen the result by Model (5). In contrast, price elasticity (−0.1) is not substantially biased.

The estimated trend by Model (6) is the most general model known as the Local Trend Model (cell (ix) of Table 4.1) which consists of a stochastic level and a stochastic slope. Hence, all of the hyperparameters of Model (6) are positive values. The top left chart of Figure 6.11 illustrates the estimated UEDT, which is highly non-linear. Therefore, it is not surprising that the deterministic trend models (Models (3) and (4)) generate the substantially biased elasticities given the linear trend does not act as a good proxy for the UEDT.

__________________________

price!) this parameter was arbitrarily set to 0.8” (p.112).
Since the underlying trend contains both a stochastic level and a stochastic slope, there is no clear continuous direction for the UEDT as seen in Figure 6.11. This means that the UEDT does not move in one direction. Instead, as indicated in the top left-hand chart of Figure 6.11, the UEDT moves in a non-linear fashion, increasing rapidly during the 1970s followed by a substantial decline during the early 1980s before beginning to increase again in the late 1980s. Since the late 1980s the UEDT grew strongly, paralleling the 1970s. The growth rates of the UEDT in Table 6.7 also describe the movement of the UEDT. Although the overall average growth rate is 0.5% p.a., they are drastically different for the each sub-period, which is highly contrasted to the fixed constant rate of −0.22% p.a. and −0.47% estimated by Models (3) and (4) (the
Deterministic Trend Model). According to Model (6), at the end of the estimation period, the UEDT was growing by 1.71% p.a..

The movement of the UEDT between 1979 and 1987 was a period when, ceteris paribus, there was a decline in the use of transportation oil leading to less energy intensity. This is in contrast to the increase in usage and the rise in energy intensive periods of the rest of the estimation period. Hence, during the period between 1979 and 1987, holding income and price constant, the oil transportation demand curve in Japan was shifting to the left whereas at other times it was shifting to the right. This illustrates that the total UEDT consists of the pure 'technical progress' effects and changes in 'tastes'.

Note the relatively higher hyperparameter in the seasonal component of 0.135 compared to the level hyperparameter (0.228) indicates that changes in the seasonal movement over the sample period exhibit a very strong stochastic pattern that is clearly difficult to model by conventional deterministic seasonal dummies. The estimated stochastic seasonal pattern is shown in the bottom two charts of Figure 6.11. The seasonal fluctuation diminished until about 1980 but increased since then. In particular, the demand in the third quarter has grown over the sample period in contrast to the second quarter which dropped from the most consumed period during the 1970s to the second the 1980s onwards. The demands in the first quarter and the fourth quarter have also decreased since 1980. An increase in relative importance of the third quarter against others could be explained by i) a diffusion of air conditioner for summer season equipped in cars and ii) a relative increase in private cars that are used for leisure activities in the summer season.
The recent energy studies, though there are not many available, for this sector are outlined in Table 6.8. Yokoyama, et al. (2000) estimate petrol and diesel oil demands separately in Japan using the log-linear model with quarterly data 1985 – 1998. The UEDT is not considered in their model and the deterministic seasonal dummies are employed to address the seasonal fluctuation. The estimated elasticities are 0.85 for income and –0.20 for price. The former is not far from the estimate here, but the latter is much higher than the estimated value in this thesis. However, the reported DW statistics is 1.303 for the model which is clearly significant at 5% level, indicating the model is mis-specified. Given the questionable model specification, their estimated values are not further considered seriously. Again, in addition to Franzen and Sterner (1995), it would be another example to emerge the difficulty of an appropriate modelling of the petrol demand in Japan without incorporating the stochastic trend and the stochastic seasonals in the model. Finally, the estimated long-run elasticities given by Franzen and Sterner (1995) are 0.8 for income and –0.3 to –0.8 for price. Knowing the arbitrary restriction is made on the adjustment process, the estimated price elasticity still seems to be too large, although the income elasticity does not completely differ from the preferred estimate in this thesis.

11 The 5% critical value of the lower boundary of the DW statistics is 1.374 for n=55 and k=5.
<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated LR elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Franzén and Sterner (1995)</td>
<td>Petrol</td>
<td>Dynamic log-linear model</td>
<td>Annual data 1960 - 88 (29 obs.)</td>
<td>( \eta_y = 0.77 )  ( \eta_p = -0.76 ) (Arbitrary restriction on the lagged dependent variable)</td>
</tr>
<tr>
<td>Yokoyama (2000)</td>
<td>Petrol and Diesel</td>
<td>Dynamic log-linear model</td>
<td>Quarterly data 1985q1 - 98q1 (53 obs.)</td>
<td>( \eta_y = 0.85 ) (Petrol)  ( \eta_p = -0.20 ) (Petrol)  ( \eta_y = 1.75 ) (Diesel)  ( \eta_p = -0.04 ) (Diesel)  DW = 1.30  DW = 0.91</td>
</tr>
</tbody>
</table>

Note: \( \eta_y \) = the long-run income elasticity, \( \eta_p \) = the long-run price elasticity
6.3.2. Electricity demand in Japan

6.3.2.1. The data

The data series for the estimation of the electricity demand is illustrated in Figure 6.12.

Figure 6.12. Electricity demand (LEL), Real GDP (LGDP), Real electricity price (LPEL)(in log scale), Cooler air temperature deviations (CoolDev) and Higher air temperature deviations (HotDev) in Japan

The electricity demand series increased almost steadily over the sample period with some stagnation at the mid-1970s and the early 1980s. The former included an impact of the electricity rationing which took place in January 1974. The Seasonality of the electricity rationing, which was based on the Electricity Industry Law #27, included a 15%
series is not only a single one-year cycle pattern with a perk in winter, which is often observed in energy demand series such as the UK electricity as seen in Figure 5.9, but also has another one-year cycle pattern with a peak in summer. Therefore, the seasonal variation of this series appears to be rather unusual. The real GDP series is the same used in the previous section. The real electricity price looks also unique. Reflecting the first oil crisis, the price suddenly jumped by 57% in June 1974 followed by 23% rise in June 1976. After the further 52% increase came about in February 1980 corresponding the second oil crisis, the price gradually declined towards the end of the sample period but associated with the systematic seasonal pattern which has its peak at every third quarter. Hence, the series can be differentiated between without seasonality and with seasonality at 1980.

To capture the impact of the air temperature on the electricity demand, the higher air temperature deviation (HotDev) and the cooler air temperature deviation (CoolDev) are included in the models. The HotDev is the same as used for the transportation oil demand in the previous section. The reason for the use of these deviations in place of the original air temperature series was explained in Chapter 4. There are obvious tendencies that a decrease in the CoolDev and an increase in the HotDev towards the late 1990s which is, as mentioned several times already, an indication of the global warming in this area.

reduction in the electricity consumption by all of the higher voltage (more than 500kW) users, prohibition of neon lamps and electricity advertising pillars. It was eventually lifted in June 1974.
6.3.2.2. The estimated results

Table 6.9. Estimated results for the electricity demand in Japan 1972q1 – 1995q4

<table>
<thead>
<tr>
<th>Cell number of Table 4.2</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
<th>Model (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Models</td>
<td>No Trend</td>
<td>No Trend</td>
<td>Deterministic Trend</td>
<td>Deterministic Trend</td>
<td>Stochastic Trend</td>
<td>Stochastic Trend</td>
</tr>
<tr>
<td></td>
<td>and</td>
<td>and</td>
<td>and</td>
<td>and</td>
<td>and</td>
<td>and</td>
</tr>
<tr>
<td></td>
<td>Deterministic</td>
<td>Stochastic</td>
<td>Seasonal</td>
<td>Seasonal</td>
<td>Seasonal</td>
<td>Seasonal</td>
</tr>
<tr>
<td></td>
<td>Seasonals</td>
<td>Seasonals</td>
<td>Seasonals</td>
<td>Seasonals</td>
<td>Seasonals</td>
<td>Seasonals</td>
</tr>
<tr>
<td><em>Estimated Coefficients</em></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$y_t$</td>
<td>0.7816**</td>
<td>0.7141**</td>
<td>0.7378**</td>
<td>0.6569**</td>
<td>0.8580**</td>
<td>0.7400**</td>
</tr>
<tr>
<td>$y_{t-1}$</td>
<td>-0.5841**</td>
<td>-0.4799**</td>
<td>-0.5732**</td>
<td>-0.3736**</td>
<td>-0.3688**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.624)</td>
<td>(3.448)</td>
<td>(4.620)</td>
<td>(2.981)</td>
<td>(3.248)</td>
<td></td>
</tr>
<tr>
<td>$y_{t-3}$</td>
<td>0.2132**</td>
<td>0.1609**</td>
<td>0.1740**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.208)</td>
<td>(1.757)</td>
<td>(1.800)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_{t-1}$</td>
<td>-0.0542**</td>
<td>-0.0539**</td>
<td>-0.0570**</td>
<td>-0.0556**</td>
<td>0.0611**</td>
<td>-0.0635**</td>
</tr>
<tr>
<td></td>
<td>(5.659)</td>
<td>(6.485)</td>
<td>(6.000)</td>
<td>(6.969)</td>
<td>(3.771)</td>
<td>(3.995)</td>
</tr>
<tr>
<td>$p_{t-3}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.0406**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(2.681)</td>
</tr>
<tr>
<td>$e_{t-1}$</td>
<td>0.3305**</td>
<td>0.3767**</td>
<td>0.3036**</td>
<td>0.3491**</td>
<td>0.2244**</td>
<td>0.1775**</td>
</tr>
<tr>
<td>$e_{t-2}$</td>
<td>0.2414**</td>
<td>0.2108**</td>
<td>0.2270**</td>
<td>0.2159**</td>
<td>0.1944**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.117)</td>
<td>(3.881)</td>
<td>(4.483)</td>
<td>(3.377)</td>
<td>(3.877)</td>
<td></td>
</tr>
<tr>
<td>$HotDev_{1}$</td>
<td>0.0322**</td>
<td>0.0335**</td>
<td>0.0317**</td>
<td>0.0325**</td>
<td>0.0300**</td>
<td>0.0306**</td>
</tr>
<tr>
<td>$CoolDev_{1}$</td>
<td>0.0097**</td>
<td>0.0107**</td>
<td>0.0095**</td>
<td>0.0106**</td>
<td>-0.0098**</td>
<td>0.0087**</td>
</tr>
<tr>
<td>$Lvl 1975q4 -$</td>
<td>0.0411**</td>
<td>0.0407**</td>
<td>0.0438**</td>
<td>0.0418**</td>
<td>0.0364**</td>
<td>0.0366**</td>
</tr>
<tr>
<td></td>
<td>(5.884)</td>
<td>(6.741)</td>
<td>(6.278)</td>
<td>(7.344)</td>
<td>(3.961)</td>
<td>(3.867)</td>
</tr>
</tbody>
</table>

| Long-Run Estimates       |           |           |           |           |           |           |
| Income (Y)               | 0.9593    | 0.9579    | 0.7212    | 0.6512    | 0.8422    | 0.8997    |
| Price (P)                | -0.1267   | -0.1307   | -0.1214   | -0.1278   | -0.1051   | -0.1265   |

| Estimated Hyperparameters|           |           |           |           |           |           |
| $\sigma_{\epsilon}^2 \times 10^{-4}$ | 1.511 | 1.080 | 1.455 | 0.983 | 1.119 | 0.293 |
| $\sigma_{\eta}^2 \times 10^{-4}$ | 0 | 0 | 0 | 0 | 0.123 | 0.330 |
| $\sigma_{\epsilon_1}^2 \times 10^{-4}$ | 0 | 0 | 0 | 0 | 0 | 0 |
| $\sigma_{\epsilon_2}^2 \times 10^{-4}$ | 0 | 0.046 | 0 | 0.052 | 0 | 0.065 |

| Nature of Trend          | No Trend | No Trend | A Linear Trend | A Linear Trend | Local Level with Drift | Local Level with Drift |
| Corresponding cell of Table 4.1 | (Cell ii) | (Cell ii) | (Cell v) | (Cell v) | (Cell vi) | (Cell vi) |

| Average Annual Growth rate of the estimated |           |           |           |           |           |           |

Chapter 6 303
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
<td>0%</td>
<td>0.42%</td>
<td>0.50%</td>
<td>0.62%</td>
<td>0.79%</td>
</tr>
<tr>
<td></td>
<td>0%</td>
<td>0%</td>
<td>0.42%</td>
<td>0.50%</td>
<td>1.01%</td>
<td>1.80%</td>
</tr>
<tr>
<td></td>
<td>0%</td>
<td>0%</td>
<td>0.42%</td>
<td>0.50%</td>
<td>1.28%</td>
<td>1.66%</td>
</tr>
<tr>
<td></td>
<td>0%</td>
<td>0%</td>
<td>0.42%</td>
<td>0.50%</td>
<td>0.23%</td>
<td>0.37%</td>
</tr>
<tr>
<td></td>
<td>0%</td>
<td>0%</td>
<td>0.42%</td>
<td>0.50%</td>
<td>0.12%</td>
<td>-0.32%</td>
</tr>
<tr>
<td></td>
<td>0%</td>
<td>0%</td>
<td>0.42%</td>
<td>0.50%</td>
<td>0.63%</td>
<td>1.13%</td>
</tr>
</tbody>
</table>

**Diagnostics**

<table>
<thead>
<tr>
<th>Equation</th>
<th>Residuals</th>
<th>Standard Error</th>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>H(30)</th>
<th>r(1)</th>
<th>r(4)</th>
<th>r(8)</th>
<th>DW</th>
<th>Q</th>
<th>Q(8.8)</th>
<th>Q(8.7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1.14%</td>
<td>7.01*</td>
<td>6.95**</td>
<td>0.06</td>
<td>0.49</td>
<td>0.18</td>
<td>0.28**</td>
<td>0.15</td>
<td>1.62</td>
<td>16.18*</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.09%</td>
<td>0.15</td>
<td>0.04</td>
<td>0.11</td>
<td>0.49</td>
<td>0.27**</td>
<td>0.09</td>
<td>0.02</td>
<td>1.44</td>
<td>10.60</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.12%</td>
<td>11.63</td>
<td>6.25</td>
<td>5.38</td>
<td>0.35</td>
<td>0.17</td>
<td>0.31</td>
<td>0.18</td>
<td>1.64</td>
<td>17.58</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.06%</td>
<td>1.76</td>
<td>1.38</td>
<td>0.38</td>
<td>0.31</td>
<td>0.25*</td>
<td>0.14</td>
<td>0.10</td>
<td>1.48</td>
<td>13.73</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.16%</td>
<td>3.29</td>
<td>0.87</td>
<td>2.43</td>
<td>0.31</td>
<td>-0.09</td>
<td>0.33**</td>
<td>0.26**</td>
<td>1.88</td>
<td>25.78**</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.84</td>
<td>0.25</td>
<td>1.59</td>
<td></td>
<td></td>
<td>0.07</td>
<td></td>
<td>2.05</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Auxiliary Residuals**

<table>
<thead>
<tr>
<th>Irregular</th>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>Q</th>
<th>R²</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>12.15**</td>
<td>12.14**</td>
<td>0.01</td>
<td>16.18*</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>3.81</td>
<td>3.78</td>
<td>0.03</td>
<td>10.60</td>
<td>0.99</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>15.54**</td>
<td>15.45**</td>
<td>0.01</td>
<td>17.58</td>
<td>0.99</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>3.02</td>
<td>2.72</td>
<td>0.31</td>
<td>13.73</td>
<td>0.99</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>4.14</td>
<td>3.40**</td>
<td>0.24</td>
<td>25.78**</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>0.35</td>
<td>0.22</td>
<td>0.13</td>
<td>4.49</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Level**

<table>
<thead>
<tr>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>Q</th>
<th>R²</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>1.32</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>3.62</td>
<td>0.99</td>
<td>0.85</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>1.32</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>3.62</td>
<td>0.99</td>
<td>0.85</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>1.32</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>3.62</td>
<td>0.99</td>
<td>0.85</td>
</tr>
</tbody>
</table>

**Slope**

<table>
<thead>
<tr>
<th>Normality</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>Q</th>
<th>R²</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>0.91</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>1.65</td>
<td>0.99</td>
<td>0.85</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>0.91</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>1.65</td>
<td>0.99</td>
<td>0.85</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>0.91</td>
<td>0.99</td>
<td>0.83</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>1.65</td>
<td>0.99</td>
<td>0.85</td>
</tr>
</tbody>
</table>

**Predictive Tests**

<table>
<thead>
<tr>
<th>(1996q1-1997q1)</th>
<th>Q(8.8)</th>
<th>Q(8.7)</th>
<th>Q(8.6)</th>
<th>Q(8.6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9.53</td>
<td>9.23</td>
<td>4.95</td>
<td>1.42</td>
</tr>
<tr>
<td></td>
<td>2.86</td>
<td>1.61</td>
<td>0.93</td>
<td>-0.37</td>
</tr>
</tbody>
</table>

Note: See Notes for Table 6.7.

Table 6.9 reports the summary of the estimated results for the electricity demand in Japan. The HotDev and the CoolDev always appear to be very significant which means that the temperature, as well as income and price, is a principal determinant of the
electricity demand. \textit{Lvl} 1975q4 is the level dummy variable to represent shifting in
the level 1975q4 onwards, which will be explained later.

Figure 6.13. Electricity demand (LEL), Real GDP (LGDP) and Real
electricity price (LPEL) in Japan 1973q1 – 1979q4

As explained in Chapter 4, one of the additional advantages of the structural time series
model is that the auxiliary residuals, which are estimators of the disturbances associated
with the irregular, level and slope components, can be used to detect possible structural
break and outliers in the series. This is because they may be able to separate out the
relevant information which is often mixed up in the normal equation residuals. As
demonstrated by Harvey and Koopman (1992, p.385), an excess higher value of the
auxiliary level residuals by a correctly specified model can be an indication of a
structural break. Through this procedure, the structural break of a significant increasing

\footnote{In order to illustrate the three series in one chart, LEL and LPEL have been rescaled to be comparable to LGDP.}
in the level at 1975q4 was identified. Hence, to capture this effect, \( Lvl \ 1975q4 \) was included in the model, which is highly significant for all models.

This structural break was created by the sudden increase in the electricity demand at 1975q4 pointed by the arrow in Figure 6.13. The trend level of the electricity clearly shifted up from 1975q4 onwards, whereas the corresponding GDP and the electricity price at the same period just moderately changed. The air temperature also did not show any abnormalities at the period. The likely reason for this sudden increase is that, one year after of the first oil crisis, the economic agents began to perceive the oil crisis was almost ended and massively retuned into the pre-oil crisis consumption behaviour. It is worth remembering that, at the pre-oil crisis period, the electricity demand in the country continuously increased by more than 10% p.a. over 20 years. It was also true that, around 1975, there was general agreement that the crisis was already gone, because the crude oil price in real term even started to drop. Since this sudden jump in the demand is fully explained by an neither an increase in the GDP nor a drop in the price nor changes in the air temperature, and it is reasonable to treat it as a shift up of the level, which indicates the changes in the consumption behaviour without major income and price changes.

Table 6.9 shows that, similar to the transportation oil demand case, it is considerably difficult to identify statistically sound specifications unless the models incorporate both of a stochastic trend and stochastic seasonals. Models (1) to (5), which include at least a deterministic trend or deterministic seasonals, have a large number of the lagged variables in order to minimise the autocorrelation of the residuals.
Figure 6.14. Estimated UEDT (top left), slope of UEDT (top right), estimated seasonal variation (bottom left) and estimated individual seasonal pattern in the electricity demand in Japan.

However, all of them still suffer from the severe autocorrelation, which consistently appear regardless of the number of the lagged variables, implying there are critical problems of the modelling. In contrast, Model (6), including a stochastic trend and stochastic seasonals, has very satisfactory diagnostics in which there is no sign of misspecification. The distribution of the auxiliary residuals is all normal implying there is no anymore structural break and outlier. The LR tests decisively reject all of the deterministic restrictions on the stochastic component in all cases considered here. In addition, Model (6) has the smallest number of variables and is the most parsimonious. Take into account these results, the most credible model can be Model (6) which
includes both of a stochastic trend and stochastic seasonals.

The estimated stochastic trend by Model (6) is known as the Local Level with Drift, which is illustrated in the top left chart of Figure 6.14. As described in Table 4.1, the trend consists of a stochastic level and a fixed slope. Therefore, the trend generally goes a certain direction (an upper trending here) governed by the slope component shown in the top right chart of Figure 6.14, but along with which there are stochastic shifts in the level. Thus, the growth rate of the trend does not remain constant, but changes over time. The rapid growth of nearly 2% p.a. turned into almost zero growth during the 1980s and it even declined at the mid-1980s. However, the trend resumed to increase at the end of the 1980s and continued to do so towards the late 1990s. Hence, the UEDT is found to be highly non-linear shape which surely cannot be approximated by a deterministic linear trend or an constant term (hence, no trend). The tremendous deteriorations of the diagnostics for these models, as seen in Table 6.9, support this argument.

The upwards UEDT indicates that the economy becomes more electricity intensive. Since the UEDT has the positive slope, the overall tendency of the Japanese economy is being electricity intensive. In other words, the higher GDP the economy achieves, the even greater electricity the economy requires. This was precisely what occurred during the 1970s and 1990s. However, the relatively flat trend during the 1980s suggests the economy was electricity neutral at that time i.e. an increase in the GDP did lead to just the same portion of additional electricity demand, but not more. This period is often considered as the distinguish period in which Japan made tremendous efforts for saving energy, particularly electricity consumption, in any sectors as a kind of the national...
movement. It was enhanced by the introduction of the Energy Saving Law in 1979 by which the energy conservation policies were powerfully enforced. Private companies also increased the energy saving investment which occupied 3.2% of all investment in the manufacturing sector in 1982. As a result, a substantial improvement of energy efficiency of electricity appliances for households was achieved. Moreover, most of the aluminium refinery and ferroatloy industries, which requires substantial portion of electricity, were forced to be shut down due to loss of international competitiveness.

However, the stagnation of the UEDT in the electricity demand during 1980s is relatively slight when compared to that of, say, the whole economy aggregated final energy demand shown in Figure 6.3. This reflects the fact that the electricity demand kept to be relatively higher than the whole aggregated energy, since the most of the energy saving technologies at that period focused on the use of the heating energy (IEEJ, 1986, p.218). The continuous increase in the UEDT during the 1990s indicates the energy efficiency improvement in electricity usage seems to be exhausted or not fast enough to cancel out the effect of the increase in the stock of electricity appliances. Consequently, the electricity intensive tendency of the economy, represented by the upwards UEDT, is nearly parallel to the pre-oil shock period.

The estimated seasonal pattern is shown the bottom charts of Figure 6.14, exhibiting stochastic evolution over the sample period. A relative increase in the first quarter and a relative reduction in the second quarter are clearly observed towards the mid-1980s, whereas the third and forth quarters remain stable. The conventional seasonal dummies

\[14 \text{ Between 1973 and 1983, the energy efficiency of refrigerator, air conditioner and colour television}\]
cannot approximate such a changing in the seasonal pattern. Therefore, the deterministic restriction on the stochastic seasonals immediately results in the autocorrelation and the non-normality distribution of the residuals in Model (5) as can be seen in Table 6.9. Although the hyperparameter for the stochastic seasonals are relatively small values compared to, for instance, those for the UK electricity demand, the stochastic seasonals play the important role to model the evolving seasonal variation.

Curiously enough, the estimated long-run income elasticities given by the models fall in the relatively narrower range between 0.8 and 0.95 except the deterministic trend models (Models (3) and (4)). Similarly, the estimated long-run price elasticities also lie within the even narrower range between −0.11 and −0.13 which is highly contrasted to the case of the transport oil demand considered in the previous section. However, except for the preferred Model (6), all of other models suffer badly from the severe autocorrelation of the residual terms. In addition, Model (1) suffers from also non-normality of the residuals. Given these very poor statistics bases, the estimated elasticities are not seriously considered as plausible values. Therefore, according to the results given by Model (6), the stochastic trend and stochastic seasonals model, the long-run income elasticities of the electricity demand in Japan are estimated to be 0.9 for income and −0.13 for price.

As summarised in Table 6.10, there are few studies available to compare to the results in this chapter. Among them, the estimated results can be compared to Tomita (1994) who employs the dynamic log-linear model and the annul data 1971 – 1990 without the were improved by 65%, 40% and 40% respectively in Japan (IEEJ, 1986, p.218).
UEDT considered. His estimate for the long-run income elasticity is 0.91, which is close to the estimated here. On the other hand, the price elasticity is estimated to be -0.07, which is somewhat smaller than the estimate here. A critical problem of the estimation by Tomita (1994) is the way to address the autocorrelation of his estimated model. Although he uses the Cochrane-Orcutt procedure as a common practical process, it is known that autocorrelation often the result of a misspecification of the model rather than 'true' autocorrelation of the residuals. Therefore, when this is the case, the Cochrane-Orcutt procedure is completely irrelevant and should lead to substantial biased estimator (Thomas, 1993, p.108). According to the analysis, it is now clear that the autocorrelation is likely to arise when the non-linear UEDT is neglected which is clearly misspecification of the model. Hence, the estimated results given by Tomita (1994) should be viewed with care.

Perkins (1994) estimates the electricity demand using the fuel share (electricity, oil, coal and gas) translog model with the quarterly data 1960q1 – 1987q4\(^\text{15}\). The estimated own price elasticity of electricity demand is -0.4, which is much higher than the estimate here. The possible reason for the large elasticity value may be that the estimation period used by Perkins (1994) covers the 1960s and the early 1970s when the electricity demand dramatically increased and, conversely, the price electricity continuously dropped throughout the period, which tends to lead to higher price elasticity. It is observed that the estimations used for the 1960s and 1970s tend to produce higher price elasticities compared to the studies using after the late 1970s\(^\text{16}\). The income elasticity is

---
\(^15\) Although the deterministic time trend is included in the model to capture fuel using or saving bias, this framework is out of scope of this thesis.

\(^16\) For example, see Pindyck (1979) who uses annual data 1955 – 1973, or a survey by Bohi (1981). The
imposed to be unitary by the assumption of the model. The treatment of the seasonality is not reported at all. Finally, it should be noticed that the model used by Perkins (1994) also suffers from autocorrelation and heteroscedasticity of the residuals. It is worth recalling that the autocorrelation consistently occurs both in Tomita (1994) and Perkins (1994), as well as the mis-specified models (Models (1) to (5)) in this thesis. This may further emphasise the importance of proper modelling the UEDT and seasonality for estimation of the electricity demand in Japan.

estimated long-run price elasticities reported in the studies are generally much higher than those appeared in the recent energy demand studies.
Table 6.10. Recent energy demand study for the electricity demand in Japan

<table>
<thead>
<tr>
<th>Study (years)</th>
<th>Area covered</th>
<th>Technique / model used</th>
<th>Data used</th>
<th>Estimated LR elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tomita (1994)</td>
<td>Aggregated electricity</td>
<td>Dynamic log-linear</td>
<td>Annual data 1971 - 90 (20 obs.)</td>
<td>$\eta_y = 0.91$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\eta_p = -0.07$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Trend not included</td>
</tr>
</tbody>
</table>

Note: $\eta_y$ = the long-run income elasticity, $\eta_p$ = the long-run price elasticity
6.4. Summary and conclusion

Following the application to the UK in Chapter 5, the structural time series model has also been applied to various energy demand functions in Japan to obtain the long-run income and price elasticities. The aggregated final energy demand in the whole economy, the manufacturing sector, and the residential-service sector, and two individual fuels, the transport oil demand and the electricity demand were examined. The models with deterministic components were also employed to compare the estimation performance and the estimated results. Overall, the results have highlighted the importance role of the stochastic trend and the stochastic seasonals in order to gain the statistically satisfactory estimated result. The necessity of the stochastic modelling was even further emphasised when the quarterly data was used for the estimation.

Due to the data availability, the annual models were estimated for the whole economy final energy demand, the manufacturing sector final energy demand, and the residential-service sector final energy demand using the data for 1965 – 1999 holding 3 observations 1996 – 1999 for the post-sample prediction test. Unlike the cases of the quarterly models, sometimes it was rather unclear how to choose the most preferred model on the grounds of the test statistics. Therefore, the longer-term post-sample (1985 – 1999) prediction test was applied to the models, which brought about dramatic differences between the models indicating the distinct performance of the stochastic trend model. Therefore, for all sectors and fuels analysed the stochastic formulations of the UEDT and seasonals (if applicable) were found to be superior.
The long-run elasticities of the whole economy energy demand were estimated as unitary for income and $-0.24$ for price. The underestimation by the No Trend Model and the overestimation by the Deterministic Trend Model were detected. They are consistent with the theoretical argument in Chapter 3. On the other hand, the price elasticity was always overestimated (in absolute term) when the stochastic trend was excluded. Again, it is still in line with the theory described in Chapter 3. The estimated UEDT was found to be a non-linear shape. It was moderately upward sloping until the mid-1970s and smooth turning into a downward sloping, but it was flatter after the late 1980s and the rate of the negative growth diminished to be $-0.35\%$ p.a. at the end of the sample.

The long-run income elasticity of the final energy demand in the residential-service sector was estimated as $1.1$. Similar to the whole economy demand case, the underestimation of the No Trend Model and the overestimation of the Deterministic Trend Model were found. The long-run price elasticities were also consistently overestimated (in absolute term) by the two models. The preferred Stochastic Trend Model estimated it as $-0.16$. The UEDT is estimated as a stochastic process. It increased up to the mid-1970s and dropped until the mid-1980s followed by nearly stable period during the 1990s, which was generally similar to the UEDT found in the whole economy energy demand, but the rate of the negative growth was found to be much smaller than that of the whole economy and the manufacturing sector. This implies that improvements of energy efficiency in appliances may have been largely cancelled out by changes in consumer's taste such as choosing larger and more comfortable appliances. This finding for the residential-service sector in Japan is consistent to the result of the UK residential sector considered in Chapter 5.
For the manufacturing sector, the long-run income was estimated to be 1.4, which was highly in contrast to the underestimated value given by the No Trend Model. The long-run price elasticity was found to be -0.3. Similar to the case of the whole economy energy demand, the consistent overestimation of the price elasticity also occurred. The estimated UEDT was a steady downward sloping over the period but it was non-linear and smoothly altered the direction, the slope was much steeper during the late 1970s and the early 1980s than the beginning and the end of the sample period.

Since the quarterly data was available for the estimations of the transport oil demand and the electricity demand, quarterly model was employed in the manner of the application to the UK energy. For both the cases, the model fully incorporating a stochastic trend and stochastic seasonals clearly showed an outstanding estimation performance compared to the rival deterministic models. The stochastic trend and stochastic seasonal model were always the most parsimonious associated with the satisfactory diagnostics and test statistics and the plausible estimated elasticities.

The long-run income and price elasticities of the transport oil demand were found to be unitary and -0.08 respectively by the preferred stochastic model. Almost all of other models produced implausible values for the elasticities that were generated by the extremely slow adjustment process implied by the estimated lagged parameters. The UEDT was found to be highly non-linear which fluctuated up and down with the peak at the early 1980s, and the bottom at the late 1980s. This non-linear UEDT certainly cannot be approximated by a deterministic linear trend or a constant term. Therefore, it
was not surprising that the models without the non-linear UEDT consistently failed to give the sound estimated results. It also emerged that the seasonal pattern of the demand stochastically evolved over time. This further emphasised the necessity of the stochastic modelling for both of the UEDT and the seasonality in this demand.

Finally, for electricity demand, the long-run income and price elasticities were estimated as 0.9 and -0.13 respectively. Unlike the transportation oil demand, the estimated elasticities are within a relatively small range irrespective of the trend and the seasonality modelling. However, the diagnostics of the models with deterministic components always considerably poor and, in particular, the severe autocorrelation of the residuals signalled the models were mis-specified. The estimated UEDT was not linear at all, which could not be approximated by a simple deterministic trend. In addition, the seasonal pattern was also found to be stochastically changing. Hence, again, this was the case that the inappropriate modelling of the UEDT and the seasonality led to the statistically unsatisfactory results.

It is meaningful to compare the estimated elasticities between the sectors considered. Since the transport oil demand occupies nearly 90% of the whole transport energy demand, it can be considered as a reasonable proxy of the final energy demand in the whole transport sector. Then, the estimated income elasticities by the various sectors can be put in scale order as follows; the manufacturing sector (1.4) > the residential-service sector (1.1) > the transport sector (unitary). The higher income elasticity suggests that the energy demand in the manufacturing sector is highly sensitive to the change in the economic activities compared to others. Nevertheless, since all of sector have more than,
or equal to, the unitary long-run income elasticity, the energy demand in Japan are generally more sensitive to the changes in the economic factors, compared to the UK energy demand.

Similarly, the long-run price elasticities can be put in the same order (in absolute term) such that: the manufacturing sector (−0.32) > the residential-service sector (−0.6) > the transport sector (−0.08). Again, the sensitivity of the manufacturing sector to the price change is clearly higher than other sectors. This implies that a reduction in energy prices, which is expected as a result of the liberalization of the Japanese energy market, could lead to a non-negligible increase in the energy demand in the manufacturing sector. At the same time, it also implies that the energy demand in this sector could effectively be reduced by an introduction of carbon taxation to meet the CO₂ emissions target given in the Kyoto Protocol. On the other hand, much lower sensitivity of the demand of the transport sector implies the limitation of the demand control through the price changes. Finally, it is noticed that the long-run income and price elasticities of the transport oil demand and the electricity demand are equally higher than others, suggesting there are tight relationship between the growth of the demands and the GDP growth and, again, it can be difficult to control the demand in these sectors by pricing policies.

In conclusion, the estimated results provided the clear evidences that the flexible modelling of the UEDT and the seasonality is essential to obtain the statistically sound estimate. It was particularly vital when one considers the quarterly model. As discussed in Chapter 3, the biased estimators were actually obtained when the UEDT and the seasonality were not proper modelled and this highlighted the importance of the
structural time series model for the application to the energy demand.
CHAPTER 7. SUMMARY AND CONCLUSION

This thesis has investigated the econometric modelling of the UEDT (Underlying Energy Demand Trend) and seasonality inherent in energy demand. This final chapter summarises the analysis and results. Moreover, it concludes by returning to consider the primary research questions (and the sub-questions) introduced in Chapter 1. Therefore, the first section summarises the analysis and answers the main research questions. The next section summarises the estimated results, gives answers to the sub-research questions and compares the results for the UK and Japan. The chapter ends with a brief conclusion and identifies some issues for further research based on the lessons from the research underpinning this thesis.

7.1. Summary of the analysis: Answers to the primary research questions

Chapter 1 highlighted the main research questions for this thesis, which are repeated here:

- What is the conceptual basis for attempting to estimate the underlying energy demand trend (UEDT) when estimating energy demand functions?
- In a log-linear functional framework, what is the optimal methodology for modelling the UEDT inherent in energy demand?
- In a log-linear functional framework with quarterly time series data, what is the optimal methodology for modelling seasonality inherent in energy demand?

Through the review of past energy demand modelling in Chapter 2, it was found that the majority of recent energy demand studies have employed the log-linear model as a modelling framework. Moreover, this has been accompanied by the recent 'rather
excessive' popularity of the unit root and the cointegration technique. Furthermore, as indicated, Professor A. C. Harvey strongly criticises this approach. However, the log-linear model itself was found to be a useful functional form on the grounds of simplicity, easy handling, less costly data requirement, data coherency and, most importantly, its flexibility in terms of dynamic specification which can be directly linked to Professor D. F. Hendry's general to specific approach. The general to specific approach was consistently employed in the empirical chapters as a principal estimation technique.

In Chapter 3 the thesis moved onto the important aspect of energy demand modelling, that of the underlying energy demand trends. Energy demand is essentially a derived demand, dependent upon, not only economic variables such as income and price, and air temperature, but also on the technical efficiency of the energy using appliances and capital stock. Since this has been accepted by energy demand modellers, a number of past energy demand studies has attempted to model 'technical progress'. Unfortunately, technical progress is normally unobservable or difficult to be measured particularly at the aggregated level. Therefore, this effect has been implicitly ignored or, at the best, approximated by a deterministic linear time trend. However, the appropriateness of a deterministic linear time trend as an approximation for technical progress has been questioned by a number of studies, creating a hot debate on how to model such effect within a log-linear energy demand function.

Given this background, the UEDT was introduced that encompasses the 'technical progress' that has been attempted to be estimated in previous empirical studies. The UEDT is made up of changes in technical energy efficiency, consumer tastes and
economic structure.

Technical energy efficiency can be brought about by embodied technical progress and disembodied technical progress both of which can be endogenous and exogenous. It was discussed that exogenous technical progress is more likely to move at a constant rate and, therefore, might be modelled by a deterministic linear time trend. On the other hand, endogenous technical progress does not necessarily develop at a constant fixed rate, implying a deterministic linear time trend can be an inappropriate way to capture this effect. However, whatever the source of the increased energy efficiency and whether the improvements are constant or not, it leads to a shift in the energy demand curve to the left; reducing energy consumption for a given level of income and price.

In contrast, a change in consumer tastes can lead to the energy demand curve either way to the left and the right. In the case of the latter, the effect of an improvement of technical energy efficiency can be largely cancelled out, resulting in an increase in energy demand even if income and price remain unchanged. Since numerical measures of a change in consumer tastes is practically unattainable, the UEDT implicitly takes into account the effect of changes in consumer tastes. A change in economic structure also affects the energy demand, hence it is included in a part of the UEDT. As a result, the UEDT is not necessarily downward sloping, but can also be upward sloping, have no slope at all, and it can be non-linear.

Chapter 3 also highlighted that biased estimates of the estimated income and price elasticities are likely to be obtained when the UEDT is ignored or inadequately modelled.
This could be both an underestimation and an overestimation of the income and price elasticities. This depends upon the direction of the UEDT and the general trends (upwards or downward) of income and price. Therefore, it was further emphasised that modelling of the UEDT must be as flexible as possible given the possibility of potential biases since an improper restriction on the UEDT could result in seriously misleading estimates.

It was clearly demonstrated in Chapter 3 that the preferred modelling of the UEDT within the log-linear functional form is a stochastic trend model, since this is the most general and flexible form of trend. Deterministic linear trends (or no trend at all) are encompassed by a stochastic trend as restricted cases. Therefore, such restrictions are nested and can be tested statistically. Moreover, modelling the UEDT by a stochastic trend is linked to the general to specific procedure in the estimation process.

The analysis in Chapter 3 gives a clear answer to the first main research question of this thesis: "what is the conceptual basis for attempting to estimate the UEDT when estimating energy demand functions?" This may be summarised as: the UEDT is an aggregate concept encompassing technical progress, changes in consumer tastes and economic structure. Therefore, the UEDT can move in any direction and can be non-linear which should be modelled in a flexible form as possible without any prior restrictions.

Seasonality, another important aspect of energy demand modelling, was also considered in Chapter 3. Although deterministic seasonal dummy variables are commonly used to capture seasonal variations, very little attention has been paid to the highly probable
situation of evolving seasonal patterns in energy demand. After examination of various ways of modelling seasonality, stochastic seasonal dummy variables were found to be the most appropriate procedure for an application to energy demand within the log-linear framework. It was particularly stressed that the model that includes stochastic seasonals is the general model thus encompassing deterministic seasonal dummies as a restricted case. Therefore, this procedure is also linked to the general to specific procedure in the estimation process, which is consistent to the UEDT modelling by a stochastic trend mentioned above.

Given the need for modelling the UEDT and seasonality in a general and flexible way, Professor A. C. Harvey's structural time series model as set out in Chapter 4 is the central econometric model to analyse energy demand. This model incorporates both the UEDT as a stochastic trend and seasonality as stochastic seasonal component within the log-linear energy demand function without any prior restrictions whether they are deterministic or stochastic. It was shown that the structural time series model is a very general model, which encompasses a deterministic trend or/and deterministic seasonals as restricted models. Therefore, a deterministic restriction on a trend or/and seasonals can be statistically tested as a part of sequential testing down process in the general to specific approach, and if the restrictions are accepted, the model can easily revert into the restricted deterministic trend or/and seasonals model. Given these circumstances, the structural time series which incorporates a stochastic trend and stochastic seasonals was regarded as the optimal methodology.

In Chapter 5 and 6, the structural time series model was applied to energy demand for
various sectors and fuels in the UK and Japan using unadjusted quarterly data 1972q1 – 1998q4 or annual data 1965 – 1999. The main thrust of these empirical chapters are to examine how the model can best estimate the UEDT and seasonality inherent the energy demand; in comparison to the restricted deterministic trend or/and seasonals models. The general to specific approach was adopted for the principal estimation procedure. The estimated results with the quarterly data showed that the stochastic trend model is clearly preferred on a whole range of criteria, with only one exception. Hence, the UEDT was generally found to be non-linear other than the one exception where it was not found. The results with the annual data also showed that the stochastic trend model is preferable. It was found, with the only one exceptional case, the UEDTs are highly non-linear and can have phases where they are both downward and upward sloping.

Table 7.1 reports the adverse effects for each estimated sector and fuel which occurred when the deterministic restrictions were inadequately imposed on a stochastic trend and stochastic seasonals. It can be seen in the table that the models imposing a deterministic trend and no trend are always inferior to the stochastic trend model mainly due to autocorrelation of the residuals, poor post-sample predictions and being less parsimonious. In some cases (UK manufacturing sector and transportation oil in Japan), the deterministic restriction and no trend restriction resulted in implausible estimated elasticity values, which do not conform to the norms of conventional economics.
Table 7.1. Deterministic restrictions on the stochastic trend/seasonals and problems occurred

<table>
<thead>
<tr>
<th>Restrictions</th>
<th>Deterministic Seasonal</th>
<th>Deterministic Trend</th>
<th>No Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>UK</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregated whole economy</td>
<td>- LR test rejects the</td>
<td>- Severe autocorrelation</td>
<td>- Severe autocorrelation</td>
</tr>
<tr>
<td></td>
<td>restriction</td>
<td>- Failure of the post-</td>
<td>- Failure of the post-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>sample prediction tests</td>
<td>sample prediction tests</td>
</tr>
<tr>
<td>Aggregated residential sector</td>
<td>- Needs more lagged</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td>variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Deterioration of the</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>diagnostics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregated manufacturing sector</td>
<td>- LR test rejects the</td>
<td>- Positive price elasticities are estimated</td>
<td>- Negative income</td>
</tr>
<tr>
<td></td>
<td>restriction</td>
<td>- Needs more lagged</td>
<td>elasticities are estimated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>variables</td>
<td>- Needs more lagged</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>variables</td>
</tr>
<tr>
<td>Road transportation oil</td>
<td>- Failure of the post-</td>
<td>- Needs more lagged</td>
<td>- Needs more lagged</td>
</tr>
<tr>
<td></td>
<td>sample prediction tests</td>
<td>variables</td>
<td>variables</td>
</tr>
<tr>
<td>Electricity</td>
<td>- Failure of the post-</td>
<td>- Severe autocorrelation</td>
<td>- Severe autocorrelation</td>
</tr>
<tr>
<td></td>
<td>sample prediction tests</td>
<td>- Needs more lagged</td>
<td>- Needs more lagged</td>
</tr>
<tr>
<td></td>
<td></td>
<td>variables</td>
<td>variables</td>
</tr>
</tbody>
</table>

| Japan                        |                        |                     |         |
| Aggregated whole economy     | n/a                    | - Failure of the post- | - Poor predictions for the |
|                               |                        |  sample prediction tests|  loger-term post-sample |
|                               |                        | - Autocorrelation     |  period    |
|                               |                        | - Needs more lagged   | - Needs more lagged |
|                               |                        |  variables           |  variables    |
| Aggregated residential-service sector | n/a           | - Failure of the loger-term | - Poor predictions for the |
|                                      |                        |  post-sample prediction tests|  loger-term post-sample |
|                                      |                        |                      |  period    |
|                                      |                        |                      | - LR test rejects the |
|                                      |                        |                      |  restriction at 10% level|
| Aggregated manufacturing sector  | n/a                    | - Failure of the post-  | - Autocorrelation |
|                                      |                        |  sample prediction tests| - Very poor predictions for |
|                                      |                        | - Needs more lagged   |  the loger-term |
|                                      |                        |  variables           |  post-sample period    |
|                                      |                        | - LR test rejects the |                  |
|                                      |                        |  restriction at 10% level|             |
| Road transportation oil         | - Needs more lagged    | - Rather odd elasticity | - Needs more lagged |
|                                      |  variables             |  values estimated    |  variables    |
|                                      | - LR test strongly rejects | - Needs more lagged |                  |
|                                      |  the restriction        |  variables           |  variables    |
|                                      |                        | - LR test strongly rejects |                  |
|                                      |                        |  the restriction      |             |
| Electricity                    | - Severe autocorrelation| - Severe autocorrelation | - Severe autocorrelation |
|                                | - Needs more lagged     | - Needs more lagged   | - Needs more lagged |
|                                |  variables              |  variables           |  variables    |
|                                | - LR test strongly rejects| - LR test strongly rejects |                  |
|                                |  the restriction        |  the restriction      |             |

Similarly, for all the quarterly data sets for both the UK and Japan, stochastic seasonals
are undoubtedly preferred on a whole range of criteria. This is because that, in all cases with no exception, the seasonality inherent in the energy demand clearly exhibited stochastic variations. Table 7.1 also presents the unfavourable outcomes when the deterministic restriction was imposed on the stochastic seasonals. The adverse effects include failure of the post-sample prediction tests, being less parsimonious and sometimes causing autocorrelation.

These empirical analysis presented in Chapter 5 and 6 (as summarised in Table 7.1) clearly expresses the answers to the second and third main research questions: ‘what is the optimal methodology for modelling the UEDT inherent in energy demand time series?’ and ‘what is the optimal methodology for modelling seasonality inherent in energy demand time series?’ This can be encapsulated by the following: the structural time series model, incorporating a stochastic trend and stochastic seasonals and employing the general to specific procedure, is the optimal methodology for modelling both the UEDT and seasonality within the log-linear functional framework.

To emphasise this finding the clear advantages of the structural time series model can be summarised as follows:

- The UEDT and seasonality are easily incorporated in the structural time series model in a very general and flexible way. This is extremely important property since it was found that energy demand is more likely to exhibit a non-linear UEDT and stochastically evolving seasonality, and inappropriate restrictions on the UEDT and seasonality can cause serious misleading results.
• The structural time series model can be employed in a general-to-specific way (as advocated by Professor D. F. Hendry) which ensures a systematic and consistent estimation process.

• Following from the previous point, the preferred model can be a deterministic linear time trend and/or deterministic seasonal model if accepted by the data, since the deterministic restrictions are all encompassed by the stochastic approach within the structural time series model.

7.2. The Estimates: Answers to the sub-research questions

In addition to the primary research questions, Chapter 1 introduced a number of sub-questions to be answered for various sectors and fuels for the UK and Japan:

• What are the shape and direction of the UEDTs?
• What are the patterns of the seasonality?
• What is the best estimate of the long-run income elasticity?
• What is the best estimate of the long-run price elasticity?

The answers to these sub-questions were demonstrated in chapters 5 and 6, and are summarised in Table 7.2. The plot of the UEDT and seasonality in each sector and fuel are presented in the relevant charts in Chapters 5 and 6. In comparing the estimated elasticities for the UK and Japan, a clear difference is found in the long-run income elasticities; energy demand in Japan is much more sensitive to income change than that of the UK, except for the road transportation oil.
Table 7.2. Summary of the estimated elasticities, UEDT and seasonality

<table>
<thead>
<tr>
<th></th>
<th>Estimated Long-run Income elasticity</th>
<th>Estimated Long-run Price elasticity</th>
<th>Estimated UEDT and its average annual growth over the full sample period</th>
<th>Estimated Seasonality</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>UK</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregated whole economy</td>
<td>0.56</td>
<td>-0.23</td>
<td>Local level with drift (I(1)): -0.76%</td>
<td>Stochastic evolving pattern</td>
</tr>
<tr>
<td>Aggregated residential sector</td>
<td>0.30</td>
<td>-0.22</td>
<td>None: 0.00%</td>
<td>Strong stochastic evolving pattern</td>
</tr>
<tr>
<td>Aggregated manufacturing sector</td>
<td>0.72</td>
<td>-0.20</td>
<td>Smooth trend (I(2)): -2.66%</td>
<td>Stochastic evolving pattern</td>
</tr>
<tr>
<td>Road transportation oil</td>
<td>0.80</td>
<td>-0.13</td>
<td>Local level with drift (I(1)): 0.54%</td>
<td>Stochastic evolving pattern</td>
</tr>
<tr>
<td>Electricity</td>
<td>0.43</td>
<td>-0.28</td>
<td>Local level with drift (I(1)): 0.91%</td>
<td>Stochastic evolving pattern</td>
</tr>
<tr>
<td><strong>Japan</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregated whole economy</td>
<td>0.99</td>
<td>-0.24</td>
<td>Smooth trend (I(2)): -0.56%</td>
<td>n/a</td>
</tr>
<tr>
<td>Aggregated residential-service sector</td>
<td>1.12</td>
<td>-0.16</td>
<td>Local level (I(1)): -0.10%</td>
<td>n/a</td>
</tr>
<tr>
<td>Aggregated manufacturing sector</td>
<td>1.38</td>
<td>-0.32</td>
<td>Smooth trend (I(2)): -2.34%</td>
<td>n/a</td>
</tr>
<tr>
<td>Road transportation oil</td>
<td>1.05</td>
<td>-0.08</td>
<td>Local trend (I(2)): 0.50%</td>
<td>Stochastic evolving pattern</td>
</tr>
<tr>
<td>Electricity</td>
<td>0.90</td>
<td>-0.13</td>
<td>Local level with drift (I(1)): 0.79%</td>
<td>Stochastic evolving pattern</td>
</tr>
</tbody>
</table>

It is particularly noticeable that the UK residential sector has the lowest long-run income elasticity, at just 0.3; the lowest of all estimates. In contrast, there is a one-to-one relationship between energy demand and income in Japan in all sectors and fuels analysed, suggesting energy demand in this country is likely to further increase, at least in the near future, as income rises.

On the other hand, the long-run price elasticities of the sectors and fuels in the two countries fall into a relatively similar range from -0.15 to -0.30, although the estimated
values for Japan are somewhat lower (in absolute terms). Energy demand in the manufacturing sector in Japan appears to be the most price sensitive, with an estimated long-run price elasticity of $-0.32$. Hence, pricing policy might be effective to control the demand in this sector. In contrast, the demand for transportation oil for both countries was found to be particularly price insensitive with an estimated long-run price elasticity of $-0.08$ for Japan and $-0.13$ for the UK. As illustrated in Chapter 1, for both countries, energy consumption in the transportation sector is the fastest growing compared to the other sectors. Unfortunately, the price insensitivity of this sector suggests possible difficulties in attempting to control the rising demand in the sector through pricing policy, such as fuel taxation. Non-pricing policy such as efficiency standards of car, increase in public transportation service and car sharing policy might be needed for effective reduction in energy consumption in the transportation sector for both countries.

Except for the UK residential sector, the estimated UEDTs are non-linear for all sectors and fuels in both countries. For the UK, only the manufacturing sector has the UEDT that is the smooth trend that is I(2). On the other hand, the whole economy, the manufacturing sector in Japan and road transportation oil have the UEDTs that are a smooth trend or a local trend that are also I(2). It is worth noting that when a deterministic trend is imposed for the UK manufacturing sector and the Japanese transportation oil demand (both of which have a UEDT that is I(2)) then very strange estimated income and price elasticities are obtained. This implies that when the UEDT is the form of I(2), it is particularly difficult for the deterministic trend model to yield plausible estimated elasticity values.

The shapes of the UEDTs are also relatively similar between the sectors and fuels in the
UK and Japan (see relevant charts in Chapters 5 and 6) with exceptions of the road transportation sectors and the residential sector. There are also similarities in the average annual growth rates of the UEDTs in the all sectors and fuels between the two countries for the whole sample period. For example, the average rates of the UEDT in the aggregated whole economy are $-0.76\%$ p.a. in the UK and $-0.56\%$ p.a. in Japan. Similarly, for the manufacturing sector, the rates are $-2.66\%$ p.a. in the UK and $-2.34\%$ p.a. in Japan, and for the transportation oil, the rates are $0.54\%$ p.a. in the UK and $0.50\%$ p.a. in Japan. Moreover, for the electricity demand, the rates are $0.91\%$ p.a. in the UK and $0.79\%$ in Japan. No UEDT was found in the aggregated residential sector in the UK, which is not that dissimilar to the very small value of $-0.1\%$ p.a. found for the residential-service sector in Japan. These similarities of the UEDTs suggest that the aggregated overall impact of technical progress, changes in consumers tastes and economic structure on energy demand are not substantially different between the two countries.

It is worth noting that, for transportation oil and electricity, a positive UEDT is found for both the UK and Japan. This suggests that the driving forces of energy demand in these sectors are not only an increase in income, but also changes in consumer tastes. This means that an improvement of technical energy efficiency in energy appliance is largely cancelled out by an increase in more energy using luxury and comfortable large appliances. Therefore, these sectors have become more energy intensive given the same income level. Taking into account that the demand for these fuels are generally price insensitive (other than UK electricity demand) the results implies that energy policy should focus more on changes in people’s life style in order to reduce the energy demand for these fuels.
In terms of the seasonality, whenever quarterly data were used, stochastic seasonality was always preferred. In some cases, for example UK electricity demand and the Japanese transportation oil demand, very strong evolving patterns were identified. Although only two fuels cases can be compared between the UK and Japan, since annual data was used for a number of sectors in Japan, there are no similarities in the evolving seasonal patterns between them.

Overall, apart from the seasonality, the difference between the UK and Japan seems to come from mainly the variations of the long-run income elasticities. Other indicators, the price elasticities, the UEDT are relatively similar between the two countries. Therefore, it can be anticipated that, as the Japanese economy is approaching saturation, the long-run income elasticity of the energy demand might become lower as in the UK has.

7.3. Conclusion and future research areas

To summarise, this thesis has shown the importance of allowing for an all-encompassing UEDT when estimating energy demand models and, in addition, allowing for evolving seasonal patterns when using quarterly data. The appropriate estimation technique in these circumstances is the structural time series model since it is general enough and flexible enough to encompass all these effects. If this technique is not used, and the actual UEDT and/or the underlying seasonal pattern are non-linear, then severe biases in the estimated income and price elasticities could be introduced. Therefore, any energy economist that continues to apply more traditional techniques, such as a linear time trend
to capture any 'technical progress', should be aware of the consequences.

That said, the research underpinning this thesis has indicated a couple of issues that should now be explored within the framework adopted here. Firstly, and perhaps most importantly, it would be desirable to explicitly analyse the driving factors of the estimated non-linear UEDTs and evolving seasonal patterns. In the structural time series model, the predicted direction of the UEDT and predicted seasonal variation are the mean values of the trend and slope at the last observation. Although it has been demonstrated that the model predicts the future values far better than the deterministic trend models, the prediction performance could be reinforced if the directions of the UEDT and variations of stochastic seasonality are explained by other variables. Secondly, the structural time series model and non-linear UEDTs could be combined with the irreversible price response model or other asymmetric response models. Thirdly, when quarterly data is available, it could be used for estimation of the aggregate energy demand in Japan. This would enable us to make more precise comparison between the results for the UK and Japan in terms of the estimated elasticities as well as the UEDTs and seasonal patterns.
REFERENCES


References

**DUKES** (Digest of United Kingdom Energy Statistics), *Digest of United Kingdom Energy Statistics*, Department of Trade and Industry, UK (various issues).


Energy Balance Table in Japan, Agency of Natural Resource and Energy, Ministry of International Trade and Industry, Japan (various issues)


Pindyck, R.S. (1979) *The Structure of World Energy Demand*, MIT press, Cambridge, MA.


Williams, R. H. (1990) “Low-cost strategy for coping with CO2 emission limits”, 