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Modelling Underlying Energy Demand Trends

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Introduction

This paper analyses the problems of modelling the ***Underlying Energy Demand Trend*** (UEDT) when estimating energy demand models. In particular, it emphasises the need to ensure that a flexible approach is adopted so that the UEDT captures the important influences on energy demand, in addition to the conventional economic variables such as income and price. As Colin Robinson pointed out when writing in a book on energy demand:

> "Most of the other chapters in this volume are concerned with the analysis of the past. That is a fascinating subject, but in practical terms, the main value of historical analysis lies in any guide it gives to what may happen in the future. That guidance is always imperfect and sometimes positively misleading. However, in the absence of direct information about the future, the past is the only indicator we have of possible future events." (Robinson, 1992 p. 215)

Our approach is consistent with his view in that a flexible approach to modelling the UEDT ensures that as much information as possible from the past is employed to fully understand the past and hence enhance future projections. Moreover, it emphasises the importance of correctly specifying the demand function to ensure the most accurate estimate of the price elasticity of energy demand is obtained. This is particularly important at a time when energy and environmental policy is focussed on reducing emissions. If, as found in this study, the price elasticity of energy demand is relatively small then using market mechanisms such as energy taxes, on their own, may not achieve the desired aim – instead non-market restrictions and regulations may also be needed.

This paper therefore demonstrates the importance for energy demand modelling of allowing for UEDTs that are stochastic in form.[1] Inherent underlying trends may be non-linear and reflect not only technical progress, which usually produces greater energy efficiency, but also other factors such as changes in consumer tastes and the economic structure that may be working in the opposite direction to technical progress. To illustrate the models, demand functions are estimated for the UK whole economy (aggregate energy) and the UK transportation sector (oil). In addition, it is shown that unless energy demand models are formulated to allow for stochastic trends and seasonals, estimates of price and income elasticities could be seriously biased.

The next section describes the UEDT in detail, briefly touching upon evolving seasonal patterns, followed by a section explaining the econometric methodology. The penultimate section presents the results for the whole economy and the transportation sector followed by a summary and overall conclusion.

‘Technical Progress’, and the ‘Underlying Energy Demand Trend’

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 desired level

[1] In addition, underlying seasonal influences are also modelled in a stochastic way.

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, we argue that it is not only 'technical progress' that influences energy demand trends; other (exogenous) factors will also influence energy usage, both positively and negatively. We therefore introduce the more general concept of the UEDT, which is illustrated in Table 1 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.

{Table 1 about here}

Autonomous or exogenous 'technical progress' in energy usage can result from a number of factors such as environmental pressures and regulations, and mandated energy efficiency standards. All of these lead to a shift in the energy demand to the left, thus reducing energy consumption at a given level of income and price (Kouris, 1983b).[2]

It is often argued that in addition to the exogenous factors, 'technical progress' or improvement in energy efficiency is induced by sustainable price rises (Walker and Wirl, 1993). Or, as we have argued previously, induced by price 'shocks' above the 'normal bounds' of price changes (Hunt, *et al.*, 2000). Either way, as Jones (1994) emphasises, it is important to distinguish between the normal 'price' effects (as measured by the price elasticity of demand) and the 'endogenous technical progress'

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[2] Kouris (1983b) actually identifies consumer tastes as another exogenous factor that leads to less energy consumed (for a given level of income and prices). We prefer, however to separate this out from 'technical progress' given the ambiguous expected sign, as discussed later.

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. In summary, therefore, the endogenous technical progress referred to in Table 1 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.

We further argue, however, that the induced changes in 'technical progress' can also come about as a result of increases in income or output (Hunt, *et al.*, 2000). [3] In the short-run, this will bring about an increase in 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 'up-graded' more efficient models and hence an irreversible improvement in energy efficiency (and a shift to the left of the (income) energy demand curve).

In addition to the above, we argue that it is important to capture the other exogenous factors identified in Table 1. The first is *consumer tastes*. As mentioned above, change in consumer tastes could, *ceteris paribus*, result in a reduction in the

[3] There is also some debate in the literature as to whether income has a distinct role in energy demand functions (see Kouris, 1983b, Beenstock and Wilcocks, 1983, Welsh, 1989). We take 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, see Hunt, *et al.* (2000) for more discussion.

demand for energy.[4] However, it is equally plausible that it could result in an increase in energy demand and hence work 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 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).[5]

In addition, when estimating aggregate 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.

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[4] For example, if it is a result of a government advertising campaign to encourage energy conservation.
[5] 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, 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.

Given this discussion it is important to consider how the UEDT should be captured. The most common procedure, in energy demand studies is to utilise a simple linear time trend as an approximation (to 'technical progress'), including the recent studies by Barker (1995), and Erdogan and Dahl (1997).

The appropriateness or otherwise of utilising a simple linear time trend is discussed by Beenstock and Wilcocks (1981, 1983) who used time a linear trend as a proxy of technical progress. They openly admit that it is not a satisfactory measure but it is better than just ignoring since in their opinion there is undoubtedly technical progress in energy usage (p. 227). However, Kouris (1983a, 1983b) has argued strongly against using a 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. Moreover, according to Kouris (1983a), 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. Welsch (1989) however, suggests that, Kouris' argument leads to *negative* technical progress if the price of energy falls, which he argues is counterintuitive (p. 286).

There is not, therefore, a general consensus concerning the use of a simple time trend to capture 'technical progress'. Moreover, when considering the wider definition of the UEDT that encompasses 'technical progress' and other factors it would be imprudent, as Kouris argues, to attempt to model it by a simple linear time trend. It is feasible to expect that the UEDT will be non-linear with periods when it could be upward sloping *and/or* periods when it could be downward sloping.[6,7] Thankfully, recent advances in econometric techniques allow for a much more flexible and general approach. The structural time series model developed by Harvey and his associates, see for example, Harvey *et al*. (1986), Harvey (1989), Harvey and Scott (1994) and Harvey (1997), allows for a non-linear stochastic trend that, when used in estimates of energy demand functions, overcomes most, if not all, of the problems discussed above. Moreover, the use of the simple deterministic time trend becomes a limiting case that is present only if statistically accepted by the data.

Before turning to the estimation it is important to consider the possible biases that might exist if the UEDT is not modelled adequately. The failure to model technical progress adequately will result in an over-estimate of the 'true' (absolute) price elasticity of demand. This can be clearly seen in Figure 1a[8]. 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

[6] Note, if the UEDT is *negative* the underlying trend is *downward sloping* whereas if the UEDT is *positive* the underlying trend is *upward sloping*.
[7] This was noted by Hogan and Jorgenson (1991) who found that 'technical progress' is not always energy-saving but could also be energy-using.

further to E_2. The 'true' UEDT effect being 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.

{Figure 1 about here}

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 1 also illustrates the alternative biases that may exist for the price effects. Figure 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.[9] Figure 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.[10] Finally, Figure 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.

It is equally important to recognise that similar biases will occur when estimating the income elasticity of demand. Figure 2 illustrates the possible biases if the UEDT is not modelled adequately. Figure 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 2b shows that if income is rising and the UEDT is positive (upward sloping) then the income elasticity will be over-estimated if

[8] Figure 1a is similar to that in Walker and Wirl (1993, p.188).
[9] If the rise in the UEDT is sufficiently large, but ignored, then the resultant estimated price elasticity could be positive.
[10] If the fall in the UEDT is sufficiently large, but ignored, then the resultant estimated price elasticity could be positive.

the UEDT is ignored. Figure 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 2d shows that if income is falling and the UEDT is positive (upward sloping) then the income elasticity will be under-estimated if the UEDT is ignored.

{Figure 2 about here}

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.[11] 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 by a simple linear time trend.

Methodology

Over recent years energy demand modelling has been dominated by the cointegration technique (As discussed in Hendry and Juselius, 2000 and 2001) with 'technical progress' either ignored or approximated by a deterministic time trend.

The over reliance on the cointegration technique has been questioned (for example, see Maddala and Kim, 1998, p. 487 - 488). In particularly, Harvey (1997) heavily criticises the cointegration methodology as unnecessary and/or a misleading

[11] Harvey *et al.* (1986), when analysing the employment-output relationship also argued 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).

procedure due, to amongst other things, its poor statistical properties.[12] He proposes instead, "to combine the flexibility of a time series model with the interpretations of regression" and argues that this is "exactly what is done in the structural time series approach" (p. 200).

Given the discussion in the previous section, a technique is required that allows the UEDT to be modelled in a general and flexible way, and Harvey's structural time series approach is an ideal tool in these circumstances. The structural time series approach allows for an unobservable trend that is allowed to vary stochastically over time. Thus the UEDT may be highly non-linear and have periods when it is upward sloping, downward sloping or flat. Moreover, the deterministic linear trend (or no trend at all) is a restricted case of the more general model. Thus, the restricted model is preferred only if it is accepted by the data.

Therefore, the structural time series model can be combined with an Autoregressive Distributed Lag (ADL) to estimate energy demand functions. This framework allows for both a stochastic trend and stochastic seasonality when estimating the price and income elasticities of aggregate energy demand:

$$A(L)\, e_t = \mu_t + \gamma_t + B(L)\, y_t + C(L)\, p_t + \theta TEMP_t + \varepsilon_t \qquad (1)$$

where $A(L)$ is the polynomial lag operator $1 - \phi_1 L - \phi_2 L^2 - \phi_3 L^3 - \phi_4 L^4$, $B(L)$ the polynomial lag operator $\pi_0 + \pi_1 L + \pi_2 L^2 + \pi_3 L^3 + \pi_4 L^4$, and, $C(L)$ the polynomial lag operator $\varphi_0 + \varphi_1 L + \varphi_2 L^2 + \varphi_3 L^3 + \varphi_4 L^4$. e_t is the natural logarithm of energy for the

[12] Harvey actually concludes the paper by stating that the "recent emphasis on unit roots, vector autoregressions and co-integration has focussed too much attention on tackling uninteresting problems by flawed methods" (p. 200).

appropriate sector, y_t the natural logarithm of the activity variable of the appropriate sector, p_t the natural logarithm of the real price of energy for the appropriate sector, and $TEMP_t$ the average temperature. *B(L)/A(L)* and *C(L)/A(L)* represent the long-run activity and price elasticities respectively and θ represents the effect of a change in temperature on aggregate energy demand. μ_t, is the stochastic trend, γ_t, is the stochastic seasonal variation and , ε_t is a random white noise disturbance term.[13]

The trend component μ_t is assumed to have the following stochastic process:

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

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

where $\eta_t \sim NID(0, \sigma_\eta^2)$ and $\xi_t \sim NID(0, \sigma_\xi^2)$. Equations (2) and (3) represent the *level* and the *slope* of the trend respectively, and depend upon the variances σ_η^2 and σ_ξ^2, known as the *hyperparameters*. These hyperparameters have an important role in that they govern the shape of the estimated trend model. Table 2 illustrates the various trends that can be estimated from this process. Cell (ix) of Table 2 represents the most general model when $\sigma_\eta^2 \neq 0$ and $\sigma_\xi^2 \neq 0$ so that both the *level* and *slope* of the trend change stochastically over the sample period. The remaining cells of Table 2 represent possible restricted alternatives, depending upon the estimates of the *level* and *slope* of the trend and the hyperparameters, σ_ξ^2 and σ_η^2.[14]

{Table 2 about here}

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[13] I.e $\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$.
[14] Cells (iv) and (vii) are ignored since it is not possible to estimate models of this type.

Cells (i), (ii) and (v) illustrate the conventional regression models (ignoring evolving seasonals) that are special cases of the general stochastic trend models. When both variances are zero, namely $\sigma_\eta^2 = 0$ and $\sigma_\xi^2 = 0$, the model reverts to a conventional deterministic linear trend model, cell (v), as follows:[15]

$$e_t = \alpha + \beta t + \mathbf{Z}'_t\delta + \varepsilon_t \tag{4}$$

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*. If $\sigma_\eta^2 \neq 0$ but $\sigma_\xi^2 = 0$ the trend is the *Local Level Model with Drift* provided the slope is non-zero (slp $\neq 0$), cell (vi) or the *Local Level Model (random walk with drift)* if the there is no slope (slp = 0), cell (iii). If, however, $\sigma_\eta^2 = 0$ but $\sigma_\xi^2 \neq 0$ it is the *Smooth Trend Model*, cell (viii).

The seasonal component γ_t in equation (1) has the following stochastic process:

$$S(L)\gamma_t = \omega_t \tag{5}$$

where $\omega_t \sim NID(0, \sigma_\omega^2)$ and $S(L) = 1 + L + L^2 + L^3$. The conventional case (ignoring the stochastic trend) is again a restricted version of this when the hyperparameter $\sigma_\omega^2 = 0$ with γ_t reducing to the familiar deterministic seasonal dummy variable model. If not, however, seasonal components are moving stochastically over time.

[15] Ignoring the seasonality for simplicity

The equations to be estimated therefore consist of equation (1) with (2) (3) and (5). All the disturbance terms are assumed to be independent and mutually uncorrelated with each other. As seen above, the hyperparameters σ_η^2, σ_ξ^2, σ_ω^2, and σ_ε^2 have an important role to play and govern the basic properties of the model. The hyperparameters, along with the other parameters of the model are estimated by maximum likelihood and from these the optimal estimates of β_T, μ_T and γ_T are estimated by the Kalman filter which represent the latest estimates of the *level* and *slope* of the trend and the seasonal components. The optimal estimates of the trend and seasonal components over the whole sample period are further calculated by the smoothing algorithm of the Kalman filter. For model evaluation, equation residuals are estimated (which are estimates of the equation disturbance term, similar to those from ordinary regression) plus a set of auxiliary residuals. The auxiliary residuals include smoothed estimates of the equation disturbance (known as the irregular residuals), the smoothed estimates of the level disturbances (known as the level residuals) and smoothed estimates of the slope disturbances (known as the slope residuals).[16] The software package STAMP 5.0 (Koopman *et al.*, 1995) is used to estimate the energy demand models.

In practice therefore, the general model, equation (1), is estimated initially, and a suitable restricted model selected by testing down from the over-parameterised model of equation (1) which satisfies parameter restrictions without violating a battery of diagnostic tests. In addition, following Harvey and Koopman (1992), normality, kurtosis and skewness statistics for the auxiliary residuals are examined in order to

[16] In practice the level and slope residuals are only estimated if the level and slope components are present in the model, i.e. η_t and/or ξ_t are non-zero.

identify outliers and structural breaks and, if necessary, appropriate dummies incorporated in the models.

A number of checks are undertaken to ensure the acceptability and robustness of the stochastic formulations. Firstly, the stochastic elements are either restricted to their deterministic form and/or omitted. This generates six ‘general specifications’ being initially estimated as follows:

Specification I:	Stochastic trend and stochastic seasonals (as discussed above)
Specification II:	Stochastic trend and deterministic seasonals
Specification III:	Deterministic trend and stochastic seasonals
Specification IV:	Deterministic trend and deterministic seasonals
Specification V:	No trend and stochastic seasonals
Specification VI:	No trend and deterministic seasonals

Each specification is estimated using the general to specific approach as outlined above for specification I. The results therefore indicate the appropriateness of the stochastic specifications. Moreover, they illustrate the impact on the estimated price and income elasticities of any mis-specification by assuming a deterministic trend or no trend at all.

Secondly, (where appropriate) the preferred models for each specification are re-estimated and tested, via Likelihood Ratio (LR) tests, for the following restrictions:

(a) deterministic seasonal dummies;

(b) a deterministic time trend;

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

This acts as a further check of the stochastic specifications to ensure they are always accepted by the data.

Results

To illustrate the approach, quarterly unadjusted data for 1971q1 – 1997q4 are used to estimate an aggregate energy demand function for the UK whole economy and an oil demand function for the UK transportation sector. Data for the period 1972q1 – 1995q4 are used to estimate the models; the first four observations are lost due to the four period lag in the general model and eight observations (for 1996 and 1997) are retained for post sample prediction tests.

Whole Economy aggregate energy demand

The results for specifications I – VI for the whole economy are given in Table 3 (details of the definitions and sources of the data are given in the appendix). Note, each specification has been found individually by following the general to specific procedure outlined in the previous section; therefore, Table 3 gives the preferred models for each specification.

{Table 3 about here}

For all specifications, GDP (y) the real energy price (*p*), and air temperature (*TEMP*) are significant drivers of whole economy aggregate energy demand. In addition, the auxiliary residuals for the irregular component indicated that there is a significant impulse shock in energy demand in the first quarter of 1974 - reflecting the first oil crisis and the effect of the UK miners strike. To capture this outlier, an impulse dummy variable for 1974q1 is included in all specifications, which is always significant. No other signs of outliers or structural breaks were found.

The diagnostic statistics presented in Table 3 show that specifications (I) and (II) are clearly preferred since the residuals are white noise without any signs of mis-specification; furthermore, these specifications predict well, clearly passing the post-sample prediction tests. On the other hand, specifications (III – VI), that include one or more deterministic components, not only suffer from severe auto-correlation, but also consistently fail the prediction tests, even at the 1% level of significance. These signs of mis-specification cannot be removed from specifications (III - VI) regardless of the number of additional lagged variables[17]. In addition, the LR tests (where applicable) indicate that the stochastic form of the trend is always preferred by the data when there are restricted to be deterministic. Overall, therefore, these results suggest that the stochastic formulation of the UEDT is necessary for the appropriate modelling of UK whole economy aggregate energy demand.

The stochastic seasonal component appears to play a relatively small role, however, other than specification III, the LR tests (where applicable) indicate that the stochastic seasonals are preferred by the data. In particular, the LR test (a) for specification (I) indicates that the deterministic restriction on the stochastic seasonal is invalid. Overall, this clearly suggests that that the specification that includes both the stochastic trend and the stochastic seasonals (I) is preferred by the data.

The estimated elasticities for the different specifications in Table 3 are quite different. The long-run income elasticities estimated by the models without any trend (specifications V and VI) are zero. The estimated long run income elasticities from

Specifications (I) to (VI) are much higher; at around 0.6. This is a clear example of the biased estimated elasticities discussed earlier, which may be brought about by ignoring the UEDT when it should be included.[18] Given the shape of the estimated UEDT for specification (I) (see Figure 3 below) it is not surprising that there is no great divergence between the estimated long-run income elasticities for specifications (I) to (IV); the UEDT, in this case, can be reasonably approximated by a deterministic trend. In a similar fashion, the estimated long-run price elasticity does not vary considerably between specifications (I) to (IV). However, the estimates for specifications (V) and (VI), without a trend at all, are larger (in absolute terms). This is another example of biased estimates caused by inappropriate modelling of the UEDT.[19]

It is useful to discuss the shape of the UEDT for the preferred specification (I) in some detail. It is the Local Level with Drift trend (cell (vi) of Table 2). It includes a stochastic trend level with a fixed slope. The estimated UEDT has a clear 'downward' shape over the period driven entirely by the stochastic movement of the level as illustrated in the top right hand chart of Figure 3. This implies that the UEDT in the energy demand declined almost continuously, even after controlling for the income and price effects. However, looking more closely the top left hand chart of Figure 3, 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. The different estimated average annual growth rates of the UEDT over various sub-periods are

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[17] Therefore, the results shown in Table 3 are estimated by the models after deleting the insignificant variables at 5% level. Again, the deletion has no discernible affect on the diagnostics - which are consistently poor.

[18] I.e. the exclusion of the UEDT may lead to an under-estimation of the long-run income elasticity when the UEDT is generally downward sloping.

[19] In contrast, the differences between modelling seasonality appear to have little effect on the estimated income and price elasticities. This is to be expected, since the estimated hyperparameters for the seasonals are much smaller (0.009) than those of the trend (0.341) as seen in Table 3.

summarised in Table 3, and this emphasises the non-linearity of the UEDT. In summary, therefore, the UEDT generally declines, but *not* at a fixed rate as the conventional deterministic model assumes.

{Figure 3 about here}

Evolution of the stochastic seasonal component is illustrated in the bottom half of Figure 3. Although its stochastic movement is relatively moderate in contrast to the estimated UEDT, it is observed that the demand in the 1st and the 2nd quarters gradually increased and decreased respectively over time, suggesting conventional seasonal dummies are too restrictive. Not surprisingly, the LR test (a) rejects the restriction of deterministic dummies in favour of the stochastic formulation as seen in Table 3.

Table 4 summarises some previous estimates of long-run energy demand elasticities for the UK whole economy. It can be seen that the estimates from our preferred specification, of 0.56 and –0.23 for the income and price elasticity respectively, fall in the middle of those given in Table 4. Of all the studies given in Table 4 only Welsch (1989) includes a time trend as a proxy for the UEDT, the other studies all ignoring it completely. The inclusion of a deterministic time trend is considered as an important issue by Welsch. Although the estimated long-run income and price elasticities are 0.71 and –0.21 which are somewhat different from the estimates here[20], 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 (in absolute terms) are generated. Welsch argues that the lower price elasticity implies that energy efficiency improvement is mostly induced by

[20] These differences may be caused by the significantly different estimation period used in the studies. Haas *et al*. (1998) show the estimation using the data covering only before the plummeting in oil prices,

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 – as illustrated above.

{Table 4 about here}

Transport oil demand

Table 5 reports the estimated results for all six specifications for UK transportation oil demand. Unlike for the whole economy, there are no auto-correlation problems, with all specifications passing the diagnostic tests presented. However, specifications (II), (IV) and (VI), with deterministic seasonals, all fail the post-sample prediction tests; thus indicating that stochastic seasonals are necessary for the oil transportation.[21]

The results for the Specifications (I) and (II) (with a stochastic trend) are the most parsimonious with a lag of only one quarter on *y* required to capture the adjustment to the long-run. Specifications (III) and (VI) (with a deterministic trend) need the largest number of the lagged variables with complex dynamics. Specifications (V) and (VI) also has a rather complex lag structure with the temperature variable insignificant and hence excluded – in contrast to the other specifications

{Table 5 about here}

In determining the preferred specification for transportation oil demand, those with deterministic seasonal dummies, (II), (IV) and (VI), are rejected given their poor forecasting performance. The choice is therefore between specification (I) with a

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).

stochastic trend, specification (III) with a deterministic trend and specification (VI) with no trend (all with stochastic seasonals). There is little to choose between these specifications in terms of the diagnostics. However, specification (I) with the stochastic trend is preferred given it is the most parsimonious of the models and more importantly the LR tests (a) and (c) clearly reject the restriction of a deterministic trend.

The shape of the estimated UEDT for specification (I) is given in the top left hand chart of Figure 4. This shows that the UEDT is generally upward sloping; therefore, after controlling for the normal income and price effect, the use of transportation energy 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). However, the different estimated average annual growth rates of the UEDT over various sub-periods summarised in Table 4, emphasise again the non-linearity of the UEDT. In the oil transportation case, therefore, although the UEDT is generally increasing, it is *not* at a fixed as the conventional deterministic model would assume.

{Figure 4 about here}

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, as already stated, are clearly preferred to conventional deterministic seasonal dummies. The pattern is illustrated in

[21] This is despite the LR test (a) for specification (III) suggesting that the restriction of deterministic

the bottom charts of Figure 4. 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.

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 (specifications V and VI), the deterministic trend models (specifications III and IV) and stochastic trend models (specifications I and II). The estimated income elasticities by the no trend models are higher than other models including either the deterministic or stochastic trend. This is another example of the over-estimation of the income elasticity by a model that ignores the UEDT when it is upward sloping and GDP is increasing over the sample period. In contrast, the estimated long-run price elasticities given by the no trend models are almost identical to that of the stochastic trend models.

{Table 6 about here}

The estimated long-run income and price elasticities from the preferred model are 0.80 and -0.13 respectively. Table 6 summarises the estimated elasticities of UK petrol demand from previous studies – none of which consider the UEDT. It can be seen there are substantial differences between the estimates with most given a much higher income elasticity to that found here – Dargay's (1992) conventional model being the exception. These higher estimates being consistent with the biases outlined earlier: that is the income elasticity is over estimated if the 'true' upward sloping UEDT is

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seasonals is acceptable by the data.

omitted during a period when income is increasing. Other than Fouquet *et al.* (1997), where the long-run price elasticity is constrained to zero, all estimated long-run price elasticities give in Table 6 are greater (in absolute terms) than the –0.13 estimated here. Given the volatility in the real energy price variable, it is not possible to ‘predict’ any bias. But given our statistical results it suggest that these previous results are over estimates (in absolute terms).

Summary and Conclusion

This paper has highlighted the important concept of the Underlying Energy Demand Trend (UEDT), which encompasses technical progress, consumer tastes, and changing economic structure. It has also shown that it is important to include the UEDT in the general form when estimating energy demand elasticities and that the appropriate econometric technique employed is flexible enough to allow the UEDT to take a non-linear form – as dictated by the data.

The structural time series model has therefore been used to estimate the UEDT (and evolving seasonals) for the UK whole economy and transportation sector. A non-linear downward sloping UEDT is found for whole economy aggregate energy demand, whereas a non-linear upward sloping UEDT is found for transportation oil demand. Moreover, it is clearly demonstrated that the stochastic form of the UEDT and the seasonals are preferred to the deterministic alternatives.

An important policy implication is the low estimated price elasticity of demand for the transportation sector coupled with an upward sloping UEDT. This illustrates that any improvement in the technical energy efficiency in the energy appliances (cars, lorries, etc.) has been more than cancelled out by a) an increase in more energy using luxury/comfortable appliances and/or b) greater utilisation of the appliances. Given this, and the relative price insensitivity, energy policy should focus more on changes in peoples life style, via advertising campaigns, stricter regulations, etc. in order to reduce oil demand and hence emissions – rather than an over reliance on market mechanisms such as energy taxes.

Data Appendix

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

Energy Consumption

The energy consumption data for the whole economy refers to UK Final Consumption of aggregate energy in million tonnes of oil equivalent (mtoe), E(we). For the transportation sector the energy consumption data refers to UK Final Consumption of 'petroleum' in million tonnes of oil equivalent (mtoe), E(o). These were taken from various issues of the *UK Energy Trends* up to June 1999. Data before 1992 have been converted to mtoe from millions of therms. *e(we)* and *e(o)*represents the natural logarithm of E(we) and E(o) respectively.

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 both the whole economy and the transportation sector, (Y) 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. *y* represents the natural logarithm of Y.

Energy Prices

The real price index for the whole economy, P(we), is a weighted average of the real price indexes form the manufacturing sector, the transportation sector, P(o), and the residential sector. 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 1999). The nominal aggregate price series for the industrial 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 1999). The nominal price series for transportation oil is the Oil and Petrol index from the GB Domestic Fuel Price Index (taken from various issues of the *UK Energy Trends* up to June 1999). For all three sub-sectors the nominal indexes were deflated by the GDP(E) deflator and re-based to 1990=100 to give the real energy price indexes for the three sub sectors. *p(we)* and p*(o)*represents the natural logarithm of P(we) and P(o) respectively.

Temperature

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

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Table 1. Underlying Energy Demand Trend (UEDT)

Underlying Energy Demand Trend (UEDT)			
(Pure) **Technical energy efficiency**		**Consumers tastes**	**Economic Structure**
Endogenous	Exogenous	Exogenous	Exogenous

Table 2: Classification of Possible Stochastic Trend Models[22]

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

[22] The seasonal component is omitted at this stage for simplicity.

Table 3 Estimated results for the UK whole economy energy demand 1972q1 – 1995q4

	SPECIFICATIONS					
	(I) Stochastic Trend and Stochastic Seasonals	(II) Stochastic Trend and Deterministic Seasonals	(III) Deterministic Trend and Stochastic Seasonals	(IV) Deterministic Trend and Deterministic Seasonals	(V) No Trend and Stochastic Seasonals	(VI) No Trend and Deterministic Seasonals
Estimated Coefficients						
y_t	0.6847** (5.934)	0.8096** (7.316)	0.4705** (4.941)	0.5234** (5.437)		
y_{t-3}	-0.2256* (2.095)	-0.2992** (2.822)	-0.3366* (2.480)	-0.4032** (3.367)		
$\Delta_3 y_t$					0.2955** (3.306)	0.4066** (4.446)
y_{t-4}			0.2340 (1.909)	0.2960** (2.658)		
p_{t-3}	-0.1897** (3.880)	-0.2050** (3.979)	-0.1963** (7.549)	-0.2031** (7.456)	-0.2359** (10.196)	-0.2673** (10.877)
e_{t-1}	0.1848** (3.330)	0.1124* (2.202)	0.3269** (5.661)	0.2731** (4.829)	0.4137** (6.966)	0.3111** (5.173)
$TEMP_t$	-0.0239** (12.117)	-0.0242** (12.005)	-0.0231** (10.179)	-0.0235** (10.131)	-0.0221** (9.221)	-0.0229** (8.955)
Irr1974q1	-0.0764** (4.470)	-0.0761** (4.226)	-0.1001** (4.894)	-0.0990** (4.703)	-0.0974** (4.624)	-0.0987** (4.326)
Long-Run Estimates						
Income (Y)	0.5632	0.5750	0.5465	0.5725	0	0
Price (P)	-0.2327	-0.2309	-0.2917	-0.2794	-0.4024	-0.3879
Estimated Hyperparameters						
$\sigma_\varepsilon^2 \times 10^{-4}$	1.489	1.969	3.214	3.606	3.442	4.411
$\sigma_\eta^2 \times 10^{-4}$	0.341	0.401	0	0	0	0
$\sigma_\xi^2 \times 10^{-4}$	0	0	0	0	0	0
$\sigma_\omega^2 \times 10^{-4}$	0.094	0	0.055	0	0.136	0
Nature of Trend Corresponding cell of Table 1	Local Level with Drift (Cell vi)	Local Level with Drift (Cell vi)	A Linear Trend (Cell v)	A Linear Trend (Cell v)	No Trend (Cell ii)	No Trend (Cell ii)
Average Annual Growth rate of the estimated UEDT						
1972q1 – 1995q4	-0.76%	-0.85%	-0.73%	-0.82%	0%	0%
1972q1 – 1974q4	-0.44%	-0.44%	-0.73%	-0.82%	0%	0%
1975q1 – 1979q4	-0.64%	-0.67%	-0.73%	-0.82%	0%	0%
1980q1 – 1984q4	-1.26%	-1.44%	-0.73%	-0.82%	0%	0%
1985q1 – 1989q4	-0.95%	-1.07%	-0.73%	-0.82%	0%	0%
1990q1 – 1995q4	-0.42%	-0.48%	-0.73%	-0.82%	0%	0%
Diagnostics						
Equation						

Residuals						
Standard Error	1.68%	1.65%	1.82%	1.78%	1.99%	2.00%
Normality	0.35	0.82	2.39	1.60	0.19	0.03
Kurtosis	0.35	0.41	0.00	0.06	0.00	0.00
Skewness	0.00	0.41	2.39	1.54	0.19	0.02
H(30)/H(31)	0.91	0.99	0.97	1.28	0.75	0.54
r(1)	-0.07	-0.03	0.24**	0.27**	0.24*	0.28**
r(4)	0.04	0.12	0.29**	0.33**	0.28**	0.40**
r(8)	0.02	0.04	0.14	0.17	0.11	0.21*
DW	2.12	2.03	1.47	1.42	1.48	1.37
$Q_{(x,n)}$	$Q_{(8,6)}$ = 6.21	$Q_{(8,7)}$ = 4.62	$Q_{(8,7)}$ = 34.34**	$Q_{(8,8)}$ = 40.62**	$Q_{(8,7)}$ = 35.36**	$Q_{(8,8)}$ = 51.62**
R^2	0.99	0.99	0.99	0.99	0.98	0.98
R_d^2	0.84	0.84	0.81	0.82	0.77	0.77
Auxiliary Residuals						
Irregular						
Normality	0.67	2.83	0.57	0.37	0.23	0.04
Kurtosis	0.30	0.02	0.37	0.26	0.11	0.02
Skewness	0.38	2.81	0.20	0.10	0.11	0.03
Level						
Normality	0.75	0.11	n/a	n/a	n/a	n/a
Kurtosis	0.00	0.00	n/a	n/a	n/a	n/a
Skewness	0.74	0.11	n/a	n/a	n/a	n/a
Slope						
Normality	n/a	n/a	n/a	n/a	n/a	n/a
Kurtosis	n/a	n/a	n/a	n/a	n/a	n/a
Skewness	n/a	n/a	n/a	n/a	n/a	n/a
Predictive Tests (1996Q1-1997Q4)						
$\chi^2_{(8)}$	9.62	14.06	23.55**	25.66**	24.15**	25.64**
Cusum *t*	1.34	1.20	4.34**	4.30**	4.40**	4.34**
LR tests						
Test (a)	4.25*	n/a	2.23	n/a	7.50**	n/a
Test (b)	28.27**	29.67**	n/a	n/a	n/a	n/a
Test (c)	33.92**	n/a	n/a	n/a	n/a	n/a

Note:

- $\Delta_3 y_t$ 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 $\chi^2_{(2)}$;
- Skewness statistic is approximately distributed as $\chi^2_{(1)}$;
- 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 1st, 4th and 8th lags respectively, approximately distributed as N(0,1/*T*);
- DW is the Durbin Watson test for first-order autocorrelation;
- $Q_{(x,n)}$ is the Box-Ljung Q-statistics based on the first x^{th} residuals autocorrelation and distributed as $\chi^2_{(n)}$;
- 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.268);
- $\chi^2_{(8)}$ 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.

Table 4. Previous energy demand studies for UK whole economy aggregated energy demand

Study (years)	*Technique / model used*	*Data used*	*Estimated long-run income and price elasticities*
Westoby and Pearce (1984)	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)	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 details given
Hunt and Manning (1989)	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)	Johansen - VECM	Annual data 1967 - 94 (28 obs.)	$\eta_y = 0.23$ $\eta_p = -0.29$ No trend included

Note: η_y = the long-run income elasticity, η_p = the long-run price elasticity

Source: Hunt and Lynk (1992), Atkinson and Manning (1995), Fouquet (1996) and Clements and Madlener (1999) with some additions and modifications

Table 5. Estimated results for the UK transportation oil demand 1972q1 – 1995q4

	SPECIFICATIONS (I) Stochastic Trend and Stochastic Seasonals	(II) Stochastic Trend and Deterministic Seasonals	(III) Deterministic Trend and Stochastic Seasonals	(IV) Deterministic Trend and Deterministic Seasonals	(V) No Trend and Stochastic Seasonals	(VI) No Trend and Deterministic Seasonals
Estimated Coefficients						
y_t	0.5634** (5.387)	0.5912** (6.031)	0.4381** (5.006)	0.4757** (5.393)	0.4128* (5.937)	0.4657** (6.702)
y_{t-1}	0.2327* (2.266)	0.2746** (2.834)				
y_{t-2}			-0.2389* (2.511)	-0.2605** (2.716)		
p_t	-0.1285** (4.323)	0.1269** (4.120)				
p_{t-2}			-0.1042** (4.369)	-0.1120** (4.595)	-0.0429* (2.596)	-0.0487** (2.746)
Δp_t			-0.1896** (5.576)	-0.1930** (5.575)	-0.1702** (4.717)	0.1713** (4.618)
e_{t-1}			0.5728** (7.947)	0.5391** (7.615)	0.6515** (11.401)	0.6065** (10.636)
$TEMP_t$	0.0045** (2.901)	0.0047** (2.818)	0.0041* (2.266)	0.0044* (2.369)		
Long-Run Estimates						
Income (Y)	0.7961	0.8658	0.4662	0.4667	1.1843	1.1835
Price (P)	-0.1285	-0.1269	-0.2438	-0.2430	-0.1230	-0.1237
Estimated Hyperparameters						
$\sigma_\varepsilon^2 \times 10^{-4}$	0.736	1.106	2.083	2.315	2.393	2.828
$\sigma_\eta^2 \times 10^{-4}$	0.798	0.799	0	0	0	0
$\sigma_\xi^2 \times 10^{-4}$	0	0	0	0	0	0
$\sigma_\omega^2 \times 10^{-4}$	0.039	0	0.030	0	0.006	0
Nature of Trend Corresponding cell of Table 4.1	Local Level with Drift (Cell vi)	Local Level with Drift (Cell vi)	A Linear Trend (Cell v)	A Linear Trend (Cell v)	No Trend (Cell ii)	No Trend (Cell ii)
Average Annual Growth rate of the estimated UEDT						
1972q1 – 1995q4	0.54%	0.41%	0.60%	0.65%	0%	0%
1972q1 – 1974q4	-0.06%	-0.28%	0.60%	0.65%	0%	0%
1975q1 – 1979q4	1.03%	0.92%	0.60%	0.65%	0%	0%
1980q1 – 1984q4	0.63%	0.57%	0.60%	0.65%	0%	0%
1985q1 – 1989q4	0.85%	0.61%	0.60%	0.65%	0%	0%
1990q1 – 1995q4	0.08%	0.00%	0.60%	0.65%	0%	0%
Diagnostics						
Equation Residuals						
Standard Error	1.51%	1.52%	1.47%	1.44%	1.63%	1.61%
Normality	0.31	0.43	2.97	0.19	1.16	0.49

Kurtosis	0.00	0.26	1.93	0.14	0.15	0.36
Skewness	0.31	0.18	1.04	0.06	1.01	0.13
H(30)/H(31)	0.75	1.03	0.93	1.14	0.79	1.13
r(1)	0.02	0.05	-0.10	-0.05	-0.06	0.02
r(4)	-0.05	0.07	-0.08	-0.04	0.03	0.13
r(8)	-0.02	0.04	0.04	0.04	0.05	0.08
DW	1.95	1.87	2.18	2.07	2.12	1.95
$Q_{(x,n)}$	$Q_{(8,6)}$ = 0.60	$Q_{(8,7)}$ = 5.50	$Q_{(8,7)}$ = 4.34	$Q_{(8,8)}$ = 5.52	$Q_{(8,7)}$ = 5.87	$Q_{(8,8)}$ = 11.23
R^2	0.99	0.99	0.99	0.99	0.99	0.99
R_s^2	0.54	0.54	0.57	0.58	0.47	0.48
Auxiliary Residuals						
Irregular						
Normality	2.81	0.73	0.27	0.01	0.70	0.58
Kurtosis	2.70	0.59	0.00	0.01	0.67	0.55
Skewness	0.11	0.14	0.27	0.00	0.03	0.03
Level						
Normality	1.22	0.57	n/a	n/a	n/a	n/a
Kurtosis	0.89	0.43	n/a	n/a	n/a	n/a
Skewness	0.34	0.14	n/a	n/a	n/a	n/a
Slope						
Normality	n/a	n/a	n/a	n/a	n/a	n/a
Kurtosis	n/a	n/a	n/a	n/a	n/a	n/a
Skewness	n/a	n/a	n/a	n/a	n/a	n/a
Predictive Tests (1996Q1-1997Q4)						
$\chi^2_{(8)}$	11.98	20.27**	11.97	17.01*	12.88	17.97*
Cusum *t*	-0.45	-0.47	-1.37	-1.37	-2.30	-2.38
LR tests						
Test (a)	7.45**	n/a	2.08	n/a	4.53*	n/a
Test (b)	48.50**	41.53**	n/a	n/a	n/a	n/a
Test (c)	48.97**	n/a	n/a	n/a	n/a	n/a

Note: See Notes for Table 3

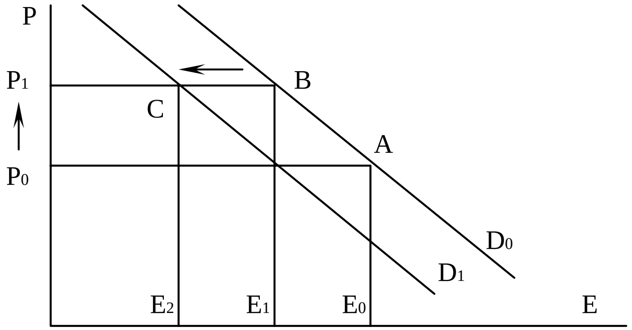
Table 6. Previous energy demand studies for the UK transport oil demand

Study (years)	*Technique / model used*	*Data used*	*Estimated LR elasticities*
Dargay (1992)	Unrestricted ECM irreversible demand model	Annual data 1960 - 88 (29 obs.)	η_y = 1.49 η_p = -0.15 (only for max. price) η_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.)	η_y = 0.70 (insignificant at 10% level) η_p = -0.40 (insignificant at 10% level)
Dargay (1993)	Log-linear EG 2-step (structural form model)	Annual data 1950 - 91 (42 obs.)	η_y = 1.5 η_p = -0.7 to -1.4
Hodgson and Miller (1995)	DTI energy model	Annual data 1954 - 88 (35 obs.)	η_y = 0.81 η_p = -0.3
Franzén and Sterner (1995)	Dynamic log-linear model	Annual data 1960 - 88 (29 obs.)	η_y = 1.6 η_p = -0.4
Fouquet *et al.* (1997)	Log-linear EG 2-step	Annual data 1960 - 94 (35 obs.)	η_y = 1.95 to 2.05 η_p = 0
Ninomiya (1997)	Log-linear EG 2-step (structural form model)	Annual data 1955 - 94 (40 obs.)	η_y = 1.0 to 1.1 η_p = -0.18

Note: None of the studies includes any trend. η_y = the long-run income elasticity, η_p = the long-run price elasticity

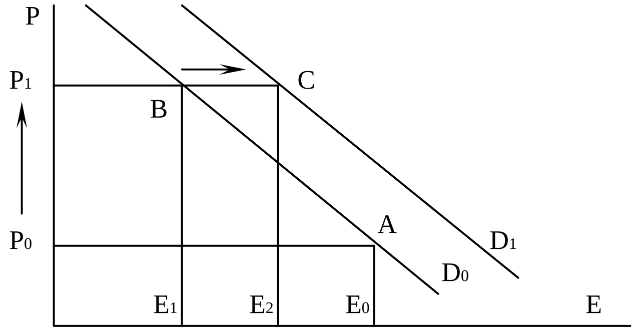
Figure 1: Possible biases in estimated price elasticities of energy demand

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



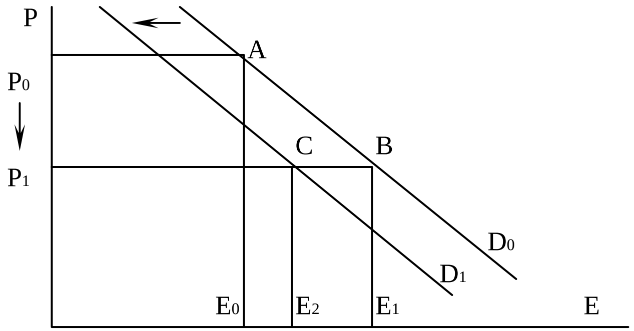
$E_0 – E_1$ = Price effect
$E_1 – E_2$ = UEDT effect
$E_0 – E_2$ = Estimated price effect if UEDT is not modelled
Therefore, price elasticity may be over-estimated if UEDT is not incorporated in the model.

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



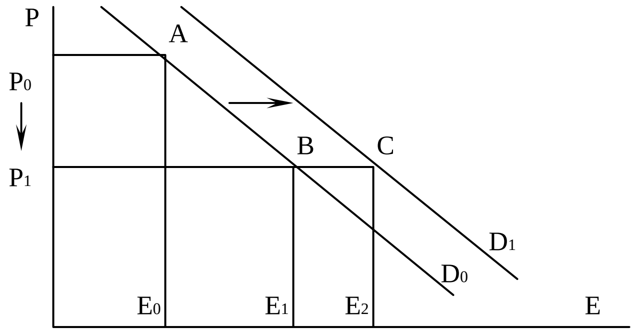
$E_0 – E_1$ = Price effect
$E_1 – E_2$ = UEDT effect
$E_0 – E_2$ = Estimated price effect if UEDT is not modelled
Therefore, price elasticity may be under-estimated if UEDT is not incorporated in the model.

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



$E_1 – E_0$ = Price effect
$E_1 – E_2$ = UEDT effect
$E_0 – E_2$ = Estimated price effect if UEDT is not modelled
Therefore, price elasticity may be under-estimated if UEDT is not incorporated in the model.

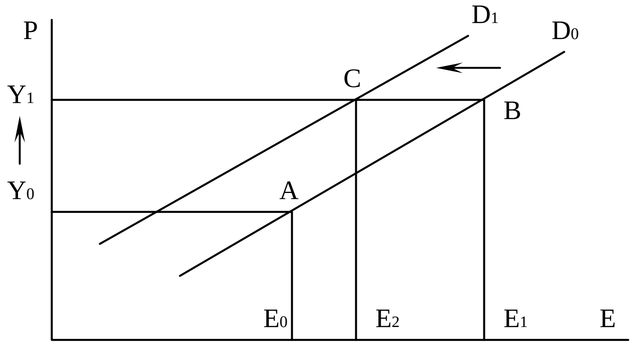
(d) Positive UEDT (upward sloping) and price decline



$E_1 – E_0$ = Price effect
$E_1 – E_2$ = UEDT effect
$E_0 – E_2$ = Estimated price effect if UEDT is not modelled
Therefore, price elasticity may be over-estimated if UEDT is not incorporated in the model.

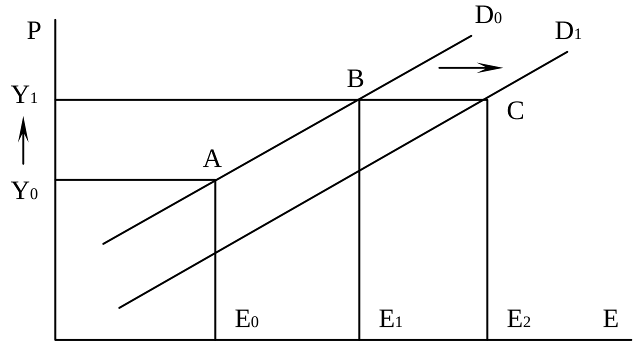
Figure 2: Possible biases in estimated income elasticities of energy demand

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



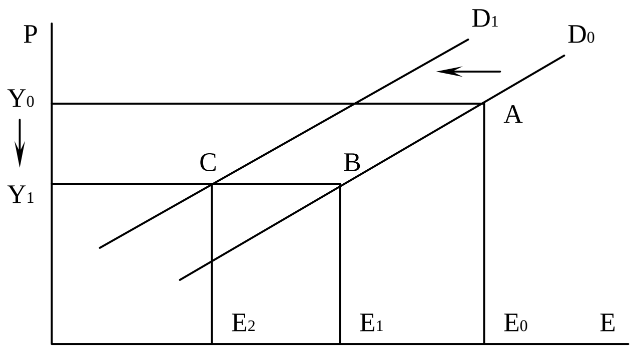
$E_0 – E_1$ = Income effect
$E_1 – E_2$ = UEDT effect
$E_0 – E_2$ = Estimated income effect if UEDT is not modelled
Therefore, income elasticity may be under-estimated if UEDT is not incorporated in the model.

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



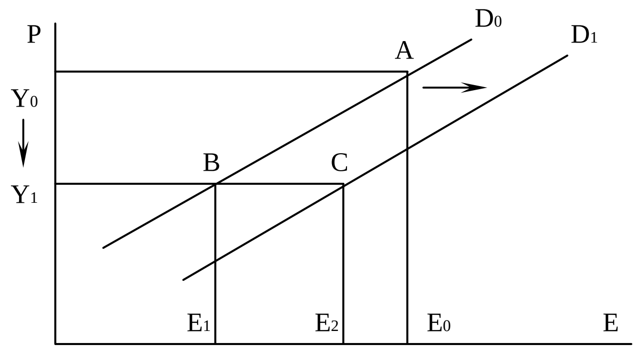
$E_0 – E_1$ = Income effect
$E_1 – E_2$ = UEDT effect
$E_0 – E_2$ = Estimated income effect if UEDT is not modelled
Therefore, income elasticity may be over-estimated if UEDT is not incorporated in the model.

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



$E_0 – E_1$ = Income effect
$E_1 – E_2$ = UEDT effect
$E_0 – E_2$ = Estimated income effect if UEDT is not modelled
Therefore, income elasticity may be over-estimated if UEDT is not incorporated in the model.

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



$E_0 – E_1$ = Income effect
$E_1 – E_2$ = UEDT effect
$E_0 – E_2$ = Estimated income effect if UEDT is not modelled
Therefore, income elasticity may be under-estimated if UEDT is not incorporated in the model.

Figure 3: UK Whole Economy Aggregate Energy Demand
Estimated UEDT (top left), slope of UEDT (top right), estimated seasonal variation (bottom left) and individual seasonal variations (bottom right)

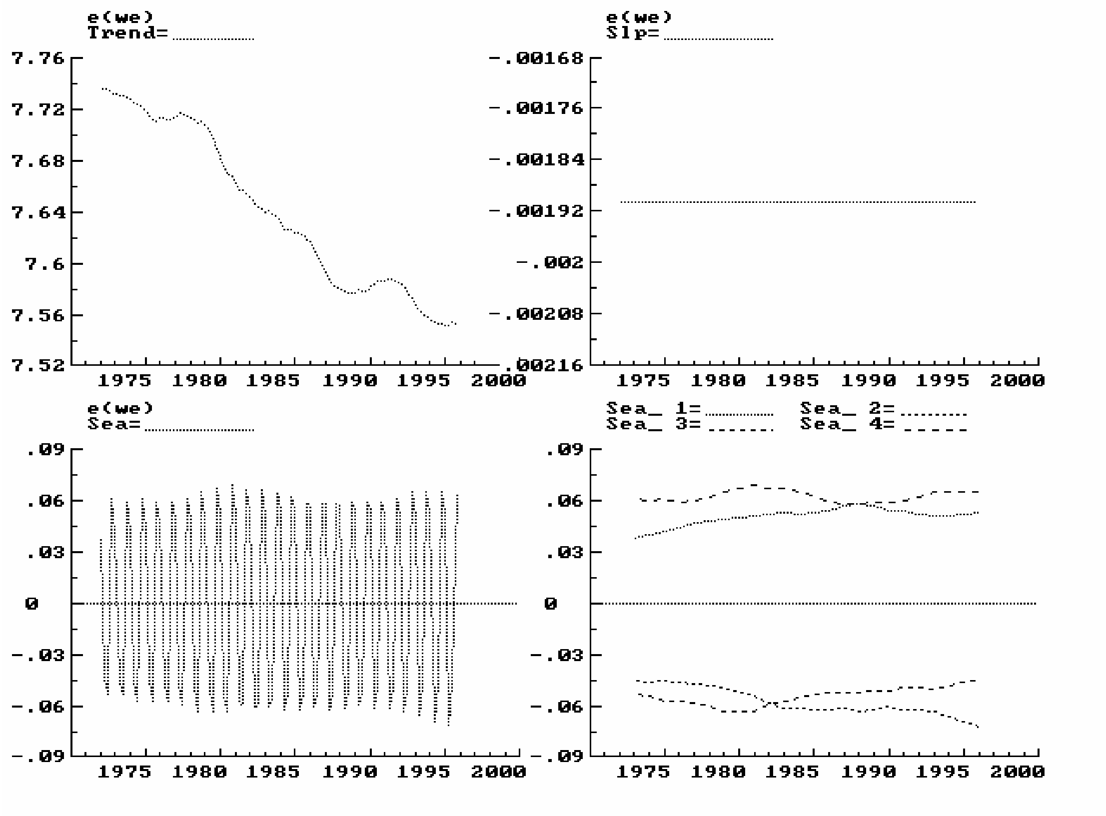
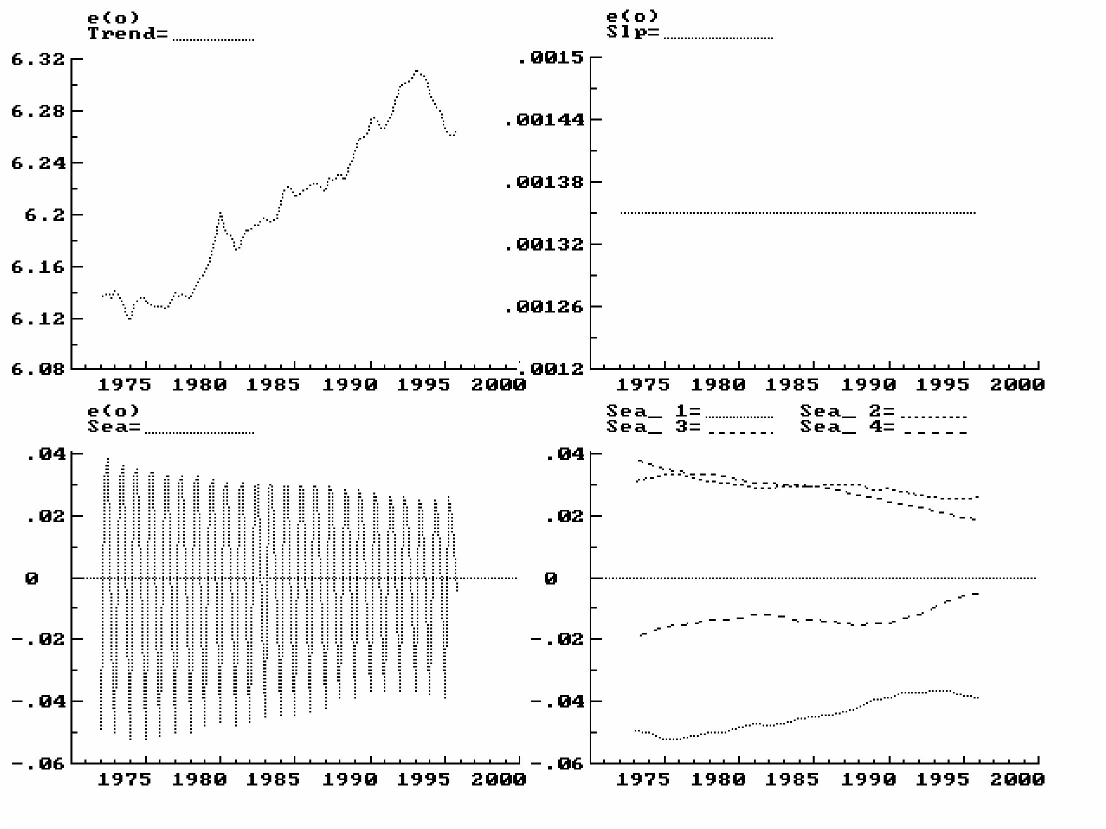


Figure 4: UK Transportation Oil Demand
Estimated UEDT (top left), slope of UEDT (top right), estimated seasonal variation (bottom left) and individual seasonal patterns (bottom right)



Note:

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