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Recent Studies of the Demand for Energy in the UK

David Hawdon (editor)
Joyce M Dargay, Roger Fouquet, Andrew Henley,
Keith Miller and John Peirson

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INTRODUCTION

Modelling the demand for energy and recent developments

Understanding the demand for energy is of interest for three main reasons. In the first place, knowledge of demand assists in the assessment of government policy towards energy. The welfare effects of such recent developments as the decision to impose VAT for the first time on energy can only be evaluated with knowledge of relevant demand elasticities. Secondly, prediction of demand is needed for rational choice of levels of investment in energy industries. At a macro level, such investments have been of considerable importance in the overall investment activity of the economy. Finally, the new breed of private energy enterprises in gas and electricity sectors and (shortly) in the coal sector will find it useful to have access to latest research on the determinants of demand. This collection of papers represents an attempt to build on an already extensive base of modelling work in order to satisfy the demand for up to date information in the energy area.

It is however, important to understand that each generation of modelling activity takes place in changing circumstances. The modelling work undertaken in the 1970s and 1980s was conducted in an environment of high energy prices and great concern about potential risks to which the macro economy might be exposed from the pricing and output behaviour of the major oil producers. Today the situation is very different - low international oil prices, much greater choice of energy supplier in all markets and less state involvement in consumer country energy sectors. This affects both the nature of the econometric results attainable and the uses to which they may be put. At a more basic level, the ability to cope with persistent long term trends as well as more recent changes in the energy market is needed in current modelling work. The next section tries to illustrate graphically some of these changes and argues that future emphasis ought to be placed on price and income elasticity estimation in contrast to the complex non economic modelling of the past

The first chart shows in broad detail the development of the four major final demand markets in the UK since 1949/50. The striking features are the overall stability of the domestic (residential) market, the steady decline in industrial demand and the relatively rapid rise of the transport sector. These long term trends were accompanied by rapid changes in appliance ownership, intensity of use and household composition during the 1960s and 70s. Since the mid 1980s however, these movements have tended to stabilise.

CHART 1 **FINAL ENERGY DEMAND UK**
1950 TO 1991

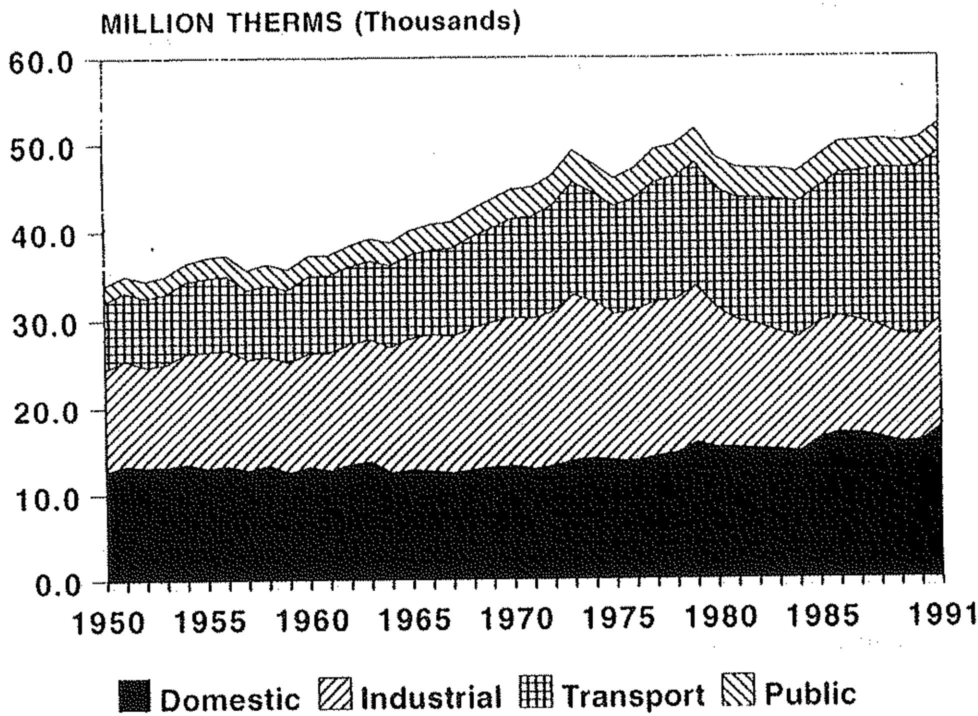
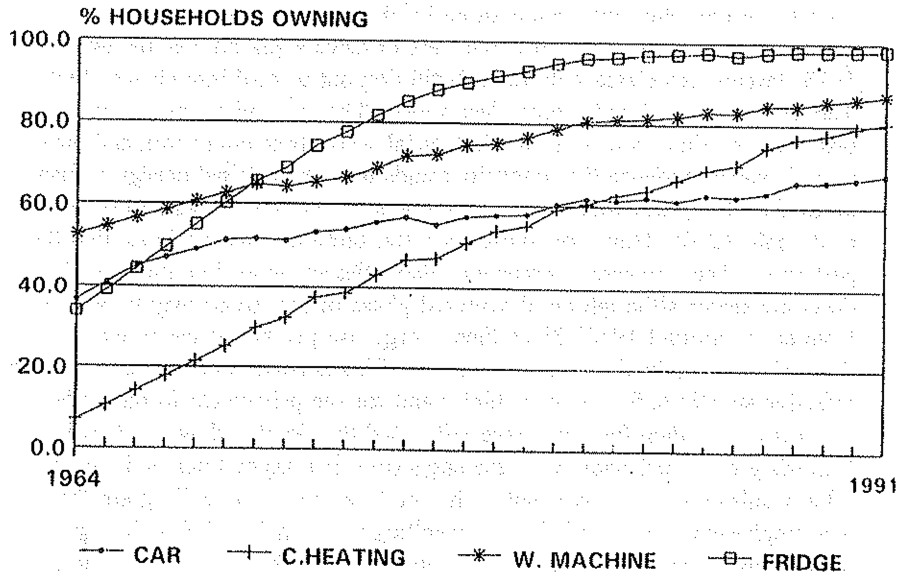


Chart 2 shows that we have now reached a very mature phase of the penetration of heavy energy using durables in the UK. Central heating was associated with the rapid development of gas sales in the 1960s and 1970s. However, now over 80% of households have central heating, and larger proportions have washing machines and refrigerators (including freezers). The significance of these trends for the future is that new appliance sales have ceased to be the driving force of changes in energy demand. Change in future will be much more strongly geared to replacement cycles. Even in the case of the car with a penetration of only 69% of households, little

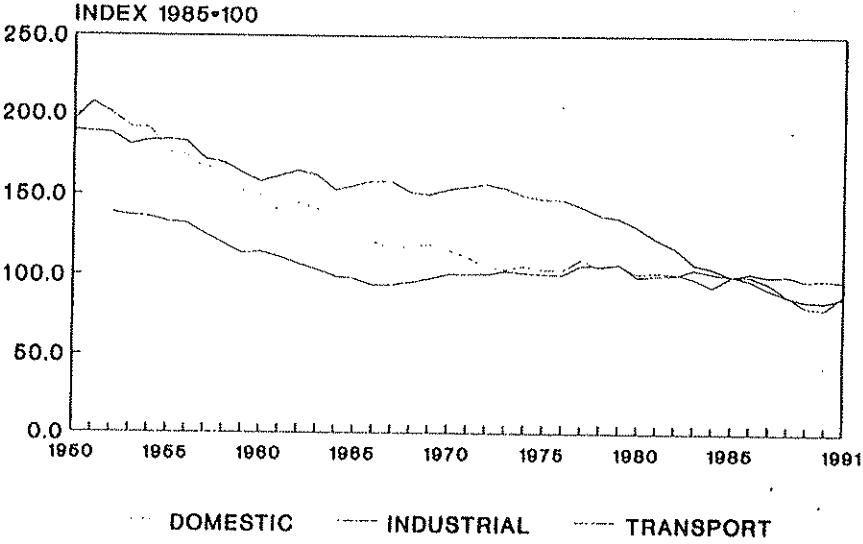
CHART 2 OWNERSHIP OF CONSUMER DURABLES 1964 TO 1991



change has occurred recently except in the proportions of families owning 2 or 3 cars where consumption per vehicle is significantly smaller. In the past there was a strong tendency to regard purchasers of new appliances as innovative, more likely to introduce new technology for the sake of fashion. Currently fashionable durables including audio and video equipment, are of relatively less significance for energy demand. Much early modelling work tried to model the growth in appliance ownership first, and then derived energy demand as a product of the durable stock and energy consumption per durable. In contrast modelling should now treat energy demand more like the demand for any other commodity and focus on the estimation of price and income elasticities making use of developments in the analysis of time series.

Intensities of energy use measured by crude ratios of energy input to activity output, exhibited strong secular downward trends long before the price movements of the early 1970s. This is indicated in Chart 3 for the three major markets - Domestic, Industrial and Transport. In the case of the domestic sector, intensity is measured by the ratio of total domestic final energy demand divided by real PDI. We observe a smooth decline until 1973, largely associated with the substitution out of coal into cleaner fuels. Thereafter, the decline becomes less steep. The same phenomenon is observed in other sectors. In the Industrial sector (excluding iron and steel), there is some evidence that intensity trends in terms of final energy demand divided by the production index, accelerated in the mid 1970s and persisted to the mid 1980s. However, more recently, there is some evidence that the pattern has been reversed. Transport intensities are more like those of the domestic sector although the downward phase of the trend may be seen to have ended around 1966! Since then energy use per kilometre mile of demand has remained remarkably stable. This is partly due to the lack of an effective substitute for motor vehicles and for the private car in particular. In all markets, therefore, we have witnessed the slowing down of trends towards greater efficiency with the suggestion that asymptotes or long run relationships are being reached. The implications for modelling are that less emphasis is now needed on unravelling the complex chains through which these intensities are generated, and more on the general underlying economic relationships.

CHART 3 INTENSITY OF ENERGY USE IN UK 1950 TO 1991



The extension of time of day tariffs and demand management systems is likely to increase the importance of economic factors in the consumer decision making process as consumers are made increasingly aware of alternative ways of reducing expenditure on fuel.

Finally, current interest in carbon and energy taxes both to achieve CO2 emission targets and to raise revenue imply that the principal means by which behaviour is likely to be affected in future will be through prices and taxes. This enhances the importance of reliable econometric estimates based on the more stable relationships which have emerged in recent years in energy markets.

Against this background, Roger Fouquet presents a survey of recent modelling work and provides estimates of energy demand functions for the UK domestic (residential) sector based on his current research at Surrey. Keith Miller of the DTI discusses results from a detailed model of domestic energy demand which has been developed in the government department now responsible for energy policy in the UK. Joyce Dargay of the Institute for Transport Studies in Oxford provides estimates from a new model of private transport demand which suggest that demand is sensitive to both price and income. John Peirson and Andrew Henley of the University of Kent investigate the relationship between temperature and electricity demand in an innovative approach based on an economic analysis of temperature effects.

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RECENT DEVELOPMENTS IN ENERGY DEMAND MODELLING

Roger Fouquet, University of Surrey

1 INTRODUCTION

The first models of energy demand applied basic consumer theory to energy. Theoretical and statistical limitations meant modellers were unable to incorporate even the most basic features of energy demand. Recent developments in modelling techniques and approaches, as well as a greater need and desire to understand, has enabled economists to incorporate some of the basic features of energy demand into their models.

In order to perceive the developments, I will highlight some of the basic features and ways economists have attempted to model them. (For a concise discussion of earlier energy demand models, see Griffin (1993)). The heterogeneous nature of energy demand suggests using a disaggregated approach. Heterogeneity results from the fact that, for every user, the complex relationship between energy use and appliance ownership differs. Through time, even the relationship for individual users changes as a result of technical progress. Progress in appliance efficiency influences consumer reactions to price and income changes. Its influence now leads modellers to question the assumption of constant price elasticity. These interrelated features - heterogeneity, appliance stock, technical progress, and variable price elasticity - must be incorporated into models if economists are to more fully understand and more accurately predict energy demand. Improvements will also emerge from the use of more suitable models, such as the Almost Ideal Demand System and Error Correction Model. A discussion of the features, and the recent econometric modelling techniques used to incorporate them, follows.

2 THE PECULIAR NATURE OF ENERGY DEMAND

Demand for Heat, Power and Light

Econometric models explain economic behaviour determined by the same variables. Many different variables explain total energy consumption. For modelling purposes, therefore, energy consumption must be split into separate sectors: residential, industrial, transport. The split more accurately represents homogeneous groups. Most groups, however, disaggregate further. The transport sector, modelled as one entity, explains little since use of road, rail or air vehicles vary for different reasons. Industrial energy demand disaggregates in a similar fashion. Disaggregating energy consumption into more homogeneous groups characterises certain recent models.

Even within homogeneous groups the importance placed on each determinant varies substantially between consumers. The amount residential consumers demand energy depends on the specifics of many variables: income, socio-economic and demographic characteristics, physical structure of the house, price expectations and appliance ownership and purchase. The reaction to, say, a dramatic rise in electricity prices for a large, wealthy family living in its own centrally-gas-heated home differs considerably to that of an unemployed person based in a rented flat with only an electric heater for warmth. Variables differ for each household. Micklewright (1989) agrees, claiming that "heterogeneity is present on a massive scale when we consider household energy demand." The heterogeneity, also present in other sectors, indicates the need for an even more disaggregated approach.

Important variations within sectors call for a microeconomic approach. Micro studies, such as Peirson and Henley (below) and Poyer and Williams (1993), observe energy demand at the individual level. Studying individual behaviour, however, requires many variables and vast quantities of data. Twenty years ago, such complexity significantly limited empirical micro analysis, both because of number-crunching problems and scant data sources; today, the power of computers and increasing availability of information, such as the Family Expenditure Survey, drive costs down. With costs still well above those of more aggregated studies, benefits of such an undertaking depend on its purpose and the sector investigated.

A disaggregated investigation enables economists to analyze distributional effects of energy policies or improve short run sector forecasts. Baker (1991) admits, however, that such a concern for detail can have its drawbacks and that it may not always be appropriate. On the other hand, he supports a microeconomic approach to energy modelling, arguing that it enables energy economists to see matters from a different angle. From this angle, he stresses, economists can more clearly observe, understand and model one of the fundamental features of energy demand: the relationship between energy use and appliance ownership.

Warmer, Faster, Brighter

Energy-run appliances provide services for users. Whether a reader requiring light or a driver requiring transportation, users demand services from their appliances. The appliances, whether lamps using electricity or cars using petrol, provide the services by consuming energy. In other words, energy demand derives from a two-step procedure: demand for a service, which an appliance provides by using energy.

Energy consumption, therefore, depends on the services required and the rate at which they can be provided. The level required is based on individual taste and is beyond the modeller's grasp. The rate of provision, however, is based on appliances' efficiency and can sometimes be obtained (or at least proxied). For example, modellers cannot predict where a driver wants to travel, but can predict the fuel used to get there, as it depends on the car's efficiency, which is a function of the distance it can travel (all other things being constant) on a gallon of petrol. Thus, economists have started building models of energy demand, in part, based on the rate of appliance efficiency.

So, derived demand now features prominently in energy models. Without using micro data, however, it is difficult to work directly with an appliance variable, since each machine uses energy at different rates depending on appliance depreciation, embodied technical progress and level of services required. The vintage capital approach tackles the problem by assuming there will be a continual replacement of appliance stock, which embodies state-of-the-art technical progress. Every firm - and, to a lesser extent, households - will, therefore, have some new, efficient appliance and some old, less efficient ones. The rate of energy-use is approximated from the expected age and efficiency of appliance stock. (For more on the vintage capital approach, see, for example, Ingham, Maw and Ulph (1992)).

Alternatively, modellers, such as Manning (1988) may avoid directly using appliance stock variables; instead, they often use a variable which influences the cost function. Through time, the cost of providing a service becomes cheaper, since increasing the efficiency of an appliance equates to reducing the quantity of energy required. Modellers simply introduce a variable that reduces the cost of energy as efficiency grows.

But, how does efficiency grow? In the past, modellers have included efficiency or technical progress as a time-trended deterministic variable. Its growth, or annual rate of cost reduction, is constant. Technical progress, however, depends on research and development (R&D). R&D is a function of investment, patent life and luck. Being highly volatile and unpredictable determinants, technical progress appears to be more appropriately modelled as a stochastic variable. Harvey and Marshall (1991) include such a stochastic variable, generated as a random walk with drift in their energy model. But, this assumes technical progress to be only neutral. That is, it affects all cost functions equally, though, in reality, it does not. Through time, technical progress favours certain fuels or appliances. Thus, as efficiency rises in certain appliances more rapidly than others the cost of running them declines faster as well. Like Harvey and Marshall's, certain recent models show that an efficiency variable should be included and, as it varies through time, it should be factor-augmenting.

Including such a variable aids in the understanding of energy consumption. Its omission causes the price variable to be biased upwards, because an increase in appliance efficiency effectively reduces the cost of providing a service relative to its price (Manning 1988). Furthermore, fuel price and total expenditure fluctuations alter energy consumption indirectly, by affecting investment in appliance stock, as well as directly. The inclusion or exclusion of an appliance stock (or efficiency) variable, generally, determines whether price elasticities estimated are short or long-run.

In the short run, when consuming energy-generated services, individuals depend on a fixed set of appliances. Because an appliance costs dearly to acquire, but considerably less to run, it often provides the required service for many years, even when alternative equipment could provide the service more efficiently or using a cheaper fuel. As Waverman (1992) reminds, the services are provided by "long-lived durable equipment" (p.7). As such equipment may not be replaced until it stops working, full adjustments to fuel price or total expenditure fluctuations occur only in the long-run. Thus, 'sticky' (or slow adjusting) markets for energy-using appliances further characterises the demand for energy.

Modellers deal with the problem of durable goods in three ways. Since consumer adjustments are slow, and past events influence present decisions, it becomes necessary to include lagged explanatory variables, such as past investment in appliance stock or fuel price fluctuations. An alternative method uses the error correction method to estimate both short and long-run elasticities and observe the speed of adjustment towards the long run (see section 3). Or, as suggested above, models may incorporate an efficiency variable, which enables them to differentiate between the short and long run. Recent energy demand modelling developments emphasise the relevance of analyzing both immediate and gradual adjustments to circumstantial changes. However, more discussion is required on the very nature of consumer adjustments.

How will they React?

> "The estimation of elasticities , as well as applied econometrics in general, critically depends on the available data, the model specification and the structure of the economy at each point in time. As all of these factors change continuously, any elasticity estimates will incur corresponding changes. Thus, the notion of the 'true' elasticity is more an illusion than a reality. If such a thing as a 'true' elasticity exists, it is certainly a moving target and not a value that remains unaltered through time." (Kouris 1981 p.69)

For quite some time, modellers have been arguing against the assumption of constant elasticities. In energy demand modelling, much recent debate has focused on time-variable price elasticities and ways of dealing with it.

It has been argued that similar price increases and decreases do not lead to equivalent demand adjustments (Dargay 1992). Modellers propose that demand adjustments are subject to a ratchet-effect. It results from a structural change in the nature of demand. The structure of demand changes for at least two reasons: consumers invest in more energy efficient appliances when fuel prices rise but hardly choose to invest in inefficient appliances as they drop, presumably reducing demand; and, as fuel prices rise the demand for energyintensive goods declines, demand for energy drops as well. Thus, the sign of a price change appears to influence demand adjustments.

Demand adjustments vary not only with sign of price changes but also their size and duration, and past fluctuations. Dramatic changes shock consumers into reaction. They react by immediately altering appliance usage and later by investing in more efficient appliances. Small, gradual changes may cause little reaction: a minimal decline in usage and investment in efficient appliances occurs only when replacing 'dead' old ones.

The duration of a price change also affects consumers' reactions. Temporary price changes require future flexibility, since, when the price reverts to its original level, consumers will have to readjust. Thus, consumers will tend to immediately reduce usage rather than gradually alter appliances. Long-term changes lead to more structural inflexible adjustments, such as acquiring more efficient equipment.

Past fluctuations in fuel prices determine consumers ability to adjust. Consumers in the late 1960's had a potential to reduce energy usage and increase appliance efficiency not available to consumers in the 1990's. The potential for reductions in energy demand becomes smaller every time prices rise dramatically.

Perhaps, this somewhat explains contradictions raised by the Khazzoom-Brookes Postulate, which proposes ".. that increases in energy efficiency can lead to increased, not decreased, energy consumption.." (Saunders 1992 p. 143). Nevertheless, the postulate highlights the energy economists' uncertainty about behaviour resulting from fuel price changes. According to Saunders, the postulate occurs as a result of fuel becoming cheaper relative to other inputs and efficiency improvements leading to economic growth, which in turn drags up energy demand.

Price rises induce investment in more energy efficient technology, but because two opposing forces work simultaneously to influence the change in demand resulting from increased efficiency (i.e. a declining energy-use per service provided and the Kazzoom-Brookes postulate), the effect of price changes on energy demand remains ambiguous. Irrespective of the change in energy demand following price fluctuations though, Gately (1992) "conclude[s] that the assumption of perfectly price reversible oil demand must be abandoned." The same can be said for all energy sources.

Time-varying price elasticities suggests econometric estimates are inaccurate. Estimates produced give a value for the whole period of analysis. If reactions to price changes vary through time, then a value for the whole period averages out the time-series. An average value, clearly, limits the accuracy of explanations and forecasts, by ignoring specific and abnormal time-periods.

Splitting the period of analysis into smaller homogeneous sub-periods improves the accuracy of estimates. Estimates are, thus, closer to the 'true' value as they have been modelled for sub-periods during which the determinants of price elasticity were (more or less) constant. Unfortunately, reducing the number of data points in a sub-period causes the accuracy of statistical inferences to decline. Alternatively, modellers can allow price elasticities to change in unusual periods, as Dargay has done for the period between 1979-81. Energy demand modelling now needs to spend more effort tackling the problem of variable price elasticity.

Many uncertainties remain about energy demand. However, recent investigations into the nature of the demand enable economists to understand its fundamental characteristics. By modelling specific characteristics, economists produce more accurate explanations and forecasts of energy demand. This production has also been enhanced by improvements in econometric methods.

3 NEWER, BETTER ECONOMETRIC MODELS

Almost Ideal Demand System

Econometrics took a step forward when Deaton and Muellbauer (1980) introduced the Almost Ideal Demand System (A.I.D.S.). Prior to then, demand models could satisfy some but not all assumptions of consumer theory. The new system enabled econometricians to use a model which did not violate any assumptions of consumer theory.

The model, instead of trying to approximate the direct or indirect utility function, approximates the consumer's cost function. The cost function defines the minimum necessary expenditure to provide a specific level of utility at given prices. In other words, it indirectly takes account of consumer preferences, such as the level of services required from a particular appliance.

Estimates of energy used in appliances proceeds in two steps. The modeller, first, finds the share of energy in consumers' total expenditure and, then, each of the fuels in energy expenditure. Both Manning (1988) and Baker (1991) use A.I.D.S. to estimate energy demand. A.I.D.S. models, unfortunately, do not directly produce elasticities of demand, thus, complicating estimates somewhat. The results, though, are similar to older energy studies using less appropriate models.

Thus, A.I.D.S. provides a new framework to estimate energy demand, which completely meets requirements laid down by consumer theory. Deaton and Muellbauer's framework specifies a particular functional form and ensures that time-series data fits it. An alternative method specifies no functional form and, after estimation, tests to see whether the data fits assumptions of consumer theory; such an approach is used for the Error Correction Model.

Correcting Trends Data, with new Predictive Power

Modellers observe energy demand through two different lenses: the long run and the short run. The long run picture displays a smooth series rising through time, moving around a trend. Long-run time series, unless growing at the same rate, would tend to diverge. Related time series, however, including energy demand and its determinants, such as price and income, can be seen - even expected - to follow similar paths and, therefore, not diverge. There are certain underlying forces that, economic theory prescribes, will keep these time series from drifting apart; the series tend to an equilibrium - a path they follow. The long-run demand for energy follows such a rising path.

Observing the short run (i.e. differenced time-series) tends to produce a picture of a volatile series, moving around a constant. The variables are seen out-of-equilibrium, either moving away from the 'attractor', after a shock, or returning towards it. The short-run demand for energy appears to wander but without rising.

The rising prominence of the error correction model as an econometric method for analyzing energy demand is based on the argument that long-run time-series data are non-stationary (i.e are not moving around a constant but a trend) and, therefore, the standard statistical tests used in econometrics cannot be trusted to give accurate values. The solution to such a problem is to cointegrate the long-run time series data (i.e. find the 'equilibrating' force). Then, the error term of this cointegrated series is introduced, as a stationary series, into an equation which estimates the relationship between the differenced values of explanatory and dependent variables (i.e. the short run). This method should produce short and long-run elasticities of energy demand while using only stationary data.

Since Granger and Weiss (1985) proved that error correction models generate cointegrated series, economists, such as Hunt and Manning (1989) and Bentzen and Engsted (1993), can be confident of estimating coefficients using stationary time series; assuming the long-run series are non-stationary (i.e. I(1) - integrated of order one). This is, indeed, what they found, using the Dickey-Fuller test (see Engle and Granger 1987, for more): non-stationary, I(1), energy demand, price and income time-series and stationary residuals, suggesting the three series are cointegrated. Their results, when compared with previous studies which did not take account of the time-series properties of the variables, appear to be in the same range of values.

The error correction model may be the most suited econometric method for forecasting energy demand. Granger (1993) discussing the properties of cointegrated series and their long-run tendencies towards an 'attractor', states that ".. forecasts from a cointegrated system 'hang together' in ways that other forecasts may not and do correspond to a certain type of equilibrium" (p.313).

Following previous studies using error correction models, (Hunt and Manning; Bentzen and Engsted (1993)), Surrey Energy Economics Centre has produced estimates for price and income elasticities of energy demand (see Table 1). The results are intended to feed into a forthcoming forecasting exercise (three to five years ahead) for United Kingdom energy demand for each sector (e.g. residential, industrial, transport, agriculture, ..).

Such forecasts must be seen as additional information relating to the future path of energy demand. No one model yet produces reliable predictions, even

Table 1: ELASTICITY ESTIMATES FOR ENERGY DEMAND IN UK DOMESTIC SECTOR (1950-1991) - USING ERROR CORRECTION MODEL

Fuel	Equations: Long-Run (Cointegrated) Short-Run	Own Price Elasticity (t-Ratio)	Income Elasticity	R-Squared	Durl Wats Stati
Energy	$LogENt = \alpha_1 + \alpha_2.LogPENt + \alpha_3.LogYt$	-0.37 (-6.85)	0.47 (11.83)	0.837	0.97
Energy	$LogDENt = \beta_1 + \beta_3.LogDPENt + \beta_5.LogTEMPt + \beta_6.[LogENt\text{-}1 - \alpha_1 - \alpha_2.LogPENt\text{-}1 - \alpha_3.LogYt\text{-}1]$	-0.39 (-4.43)	*	0.723	1.34
Coal	$LogCt = \alpha_1 + \alpha_2.LogPCt + \alpha_3.LogYt$	-2.01 (-4.11)	-2.02 (-25.74)	0.957	0.62
Coal	$LogDCt = \beta_1 + \beta_2.LogDCt\text{-}1 + \beta_3.LogDPCt + \beta_5.LogTEMPt + \beta_6.[LogCt\text{-}1 - \alpha_1 - \alpha_2.LogPCt\text{-}1 - \alpha_3.LogYt\text{-}1]$	-1.06 (-4.18)	*	0.486	1.82
Gas	$LogGt = \alpha_1 + \alpha_2.LogPGt + \alpha_3.LogYt$	-1.08 (-5.74)	0.67 (2.32)	0.935	0.09
Gas	$LogDGt = \beta_1 + \beta_2.LogDGt\text{-}1 + \beta_3.LogDPGt + \beta_5.LogTEMPt + \beta_6.[LogGt\text{-}1 - \alpha_1 - \alpha_2.LogPGt\text{-}1 - \alpha_3.LogYt\text{-}1]$	-0.13 (-0.91)	*	0.683	1.32
Electricity	$LogEt = \alpha_1 + \alpha_2.LogPEt + \alpha_3.LogYt$	-1.26 (-21.84)	0.72 (14.88)	0.989	0.65
Electricity	$LogDEt = \beta_1 + \beta_3.LogDPEt + \beta_4.LogDYt + \beta_5.LogTEMPt + \beta_6.[LogEt\text{-}1 - a_1 - \alpha_2.LogPEt\text{-}1 - \alpha_3.LogYt\text{-}1]$	-0.95 (-8.29)	0.07 (0.32)	0.717	1.33
Oil	$LogOt = \alpha_1 + \alpha_2.LogPOt + \alpha_3.LogYt$	-0.90 (-11.23)	-0.19 (-1.23)	0.897	0.32
Oil	$LogDOt = \beta_1 + \beta_3.LogDPOt + \beta_4.LogDYt + \beta_5.LogTEMPt + \beta_6.[LogOt\text{-}1 - \alpha_1 - \alpha_2.LogPOt\text{-}1 - \alpha_3.LogYt\text{-}1]$	-0.50 (-5.16)	0.02 (0.03)	0.499	1.47

ENt, Ct, Gt, Et, Ot: Energy, Coal, Gas, Electricity, Oil Consumption (in Millions of Thermal Units).
PENt: Price of Energy Relative to the Retail Price Index.
PCt, PGt, PEt, POt: Price of Coal, Gas, Electricity, Oil.
DENt, DCt, DGt, DEt, DOt: Change in Energy, Coal, Gas, Electricity, Oil Consumption.
Yt: Real Personal Disposable Income.
TEMPt: Average Annual Temperature.
*: Does not Increase Explanatory Power, so the variable is not included in the equation.
Using the Dickey-Fuller test (see, for example, Engle and Granger (1987) on description and critical values), none of the time-series, except TEMPt, rejected the null hypothesis of non-stationarity.

if it is more suited for the task than earlier ones, and, therefore, its forecasts should be compared with others before being used. Though, forecasts provide a necessary task for planners and policy makers they are vulnerable to the modeller's subjective assumptions and beliefs (Robinson 1992).

In particular, the assumptions made about the future of the explanatory variables, such as fuel prices and income must be analysed thoroughly. To produce forecasts of any practical use, the future path of energy demand's determinants must be 'known' with a high degree of certainty. Energy demand systems may not be a necessary condition to produce accurate forecasts, but the use of determinants based on a genuine understanding of their course or path certainly is.

For a genuine understanding of determinants modellers are starting to ask whether the relationship between variables is non-linear. The growing interest in non-linear analysis, predominantly in other sciences, begins to influence economics (see, for example Baumol and Benhabib (1989)) and even energy analysis (see Peirson and Henley, below). Certainly, it makes intuitive sense that not all relationships, especially ones among economic variables, are linear. This approach to modelling must be encouraged, though complicated systems tend to detract from the real world. Only through continuous trial and error, and regular discussion and debate can economists decide whether non-linear, Almost Ideal Demand Systems or Error Correction models provide the necessary tools for analysis of energy demand.

Improvements in mathematical models, including their predictive powers, inevitably leads us to forget their limits. Many qualitative variables cannot be incorporated in the models, others may be but only with inaccurate data. Qualitative data can, however, be taken into account by influencing post-regression analysis. Inaccurate data slowly becomes a thing of the past as statistics become more accessible and reliable.

Regarding whether the future will provide us with new features, more models, and a change in the basic structure and features of energy demand, the answer is unlikely to be no. No doubt, we will see more discussion of price effects reversibility for explanatory purposes, more micro analysis for policy purposes, and more research into technical progress' role and non-linear dynamics for predictive purposes. This is a feature of the continuing search for improving forecast methods.

4 CONCLUSION

Since the beginning of the 1970's, energy demand modelling has matured into an important field of study. It has borrowed tools from theoretical and applied econometrics for its development, and returned the favour by testing them on a highly publicised sector of the economy. The matters I raised suggest that the complexities of energy demand are being tackled with a certain amount of success. The difficulty ahead lies in integrating these issues into mainstream modelling. This can be done by ensuring that modellers are consistently updated about the ever-expanding web of developments in energy demand modelling and using them to further improve their understandings, estimates and predictions.

I briefly discussed the recent attempts to improve energy demand modelling. I overviewed the peculiarities of energy demand: its heterogeneity; the fact that appliances not energy provide the users with services; and, that technical progress and improvements in appliance efficiency greatly influence users' reactions to price change. Two models were discussed, which provide energy economists with new tools to understand and estimate energy consumption, the Almost Ideal Demand System and the Error Correction Model. In particular, I examined the growing interest in the Error Correction Model, displaying Surrey Energy Economics Centre's results for the United Kingdom's domestic sector as an example of the approach, and the pitfalls relating to energy demand forecasts.

It is clear that energy demand modelling thrived on the oil crises and concerns about high fuel prices. Economists of the 1970's and 1980's developed a generation of models suited to tackle these problems. These models have now matured. Their offspring prepare to explain new problems. The concerns of the 1990's revolve mainly around Third-world development and the symptoms of post-industrial economies, such as environmental and urban degradation. If energy economists intend to use their models to explain, perhaps even resolve, the problems of today and tomorrow, their tools must be aimed at the correct beasts.

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THE DTI ENERGY MODEL

Keith Miller, Department of Trade and Industry[1]

From the late 1970's onwards economists at the Department of Energy developed and used various computer models of energy supply and demand. Following the merger of the Department of Trade and Industry (DTI) and the Department of Energy (DEn) in 1992, responsibility for energy modelling was subsumed within the enlarged DTI.

The increasing significance in recent years of environmental issues associated with energy consumption has reinforced the need for a UK energy model available for use by policy makers. The current DTI energy model has developed out of these revised requirements for a systematic approach to long-term energy futures.

In recent years the DTI energy model has been used in several policy areas, some examples of its use are listed below:

- Environmental policy issues, e.g. projections of CO_2 and SO_2 emissions
- Energy policy issues, e.g. impact of VAT on domestic fuels, and various aspects of the Coal Review

The most recent work describing the projections from the DTI energy model is **Energy Paper Number 59, Energy Related Carbon Emissions in Possible Future Scenarios for the United Kingdom, HMSO.** Details about the energy model used to produce EP59 can be found in a recent paper by Hodgson & Miller (see bibliography). The emphasis in the title of EP59 on scenarios is particularly important as the DTI energy model is <u>not</u> used to produce forecasts

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1 **The author of this paper is an economic adviser in the Economics and Statistics Division of the DTI. He is responsible for the development and upkeep of the Department's energy demand models. Further details of the DTI energy model are available from Keith Miller, Room 4:3:10, Economics and Statistics Divison, DTI, 1 Palace Street, Victoria, London, SWIE 5HE, Tel: 071 238 3338, Fax: 071 238 3121**

of energy demand but is instead used to produce different scenarios of energy demand. Furthermore the emphasis of the model is medium to long term rather than short term. This emphasis on longer term modelling allows a wide range of different input scenarios, e.g. economic activity and fuel prices, to be entered into the model without the need for excessive attention to be paid to short term variations in these model inputs. Short term variations in these inputs are easily swamped by variations in the longer term assumptions once one starts to project into the next decade.

Apart from using in house resources to develop the energy model a number of .outside bodies also provide advice including the following energy consultants:

- Science Policy Research Unit (Industrial & Service Sector Boiler model);
- Building Research Establishment (domestic end use and stock data);
- Energy Technology Support Unit (Industrial and Service Sector data & advice).

Currently the energy model has six sub-sector demand models, they are:

1 Service Sector
2 Iron & Steel Sector
3 Other Industry Sector
4 Agricultural Sector
5 Domestic Sector
6 Transport Sector

The equations used in these sub-sector demand models are typically of the unrestricted error correction mechanism type and are estimated on annual data between 1950 and 1991. The exact period depends on the availability of sub-sectoral stock data etc. Each of the econometric demand equations is specified in terms of useful therms rather than delivered therms as it is the demand for *energy services* that is important not the demand for delivered energy. Increasingly the models are making use of bottom-up analysis as experience with simple econometric relationships between energy demand, income/output and prices suggests they are not always appropriate tools to answer questions regarding the likely effects of long term policy intervention in energy markets. Recently the Department's modelling resources have been devoted to improving the Domestic and Transport sub-sector demand models; further details are given below. In developing these models a conscious attempt has been made to allow for backward integration. It is hoped that this approach will facilitate further improvements if additional detailed data/information becomes available in future.

In adopting a more bottom-up approach to energy modelling there is an implicit recognition that the key relationship to be modelled is between the stock of energy-using capital equipment and energy demand itself. Examples of the stock of energy-using capital equipment include the number of central heating units, petrol cars, diesel cars and the number of industrial/service sector boilers. One major advantage of this approach is that it allows saturation levels to be directly inserted into the energy demand equations via the stock variable. Thus for instance domestic sector energy demand is constrained by the fact that the percentage of households with central heating cannot rise above 100%. An econometric demand equation for the domestic sector that used real personal disposable income as its main driver could not hope to impose a similar saturation level on energy demand. Since the DTI energy model can be used to produce projections over a 30-40 year time horizon, this attention to detail is important.

This increased emphasis on bottom-up modelling is important both for long term consistency and because it allows the model to answer specific questions raised by policy makers increasingly concerned with reducing global warming and acid rain emissions by encouraging the more efficient use of energy. The emphasis in the sub-sector demand models is therefore increasingly weighted towards structural models rather than reduced form models. In order to see how this approach is implemented the domestic and transport sub-sector models are outlined below. It is hoped to develop this approach further in the Service and Other Industry sectors during the last quarter of 1993.

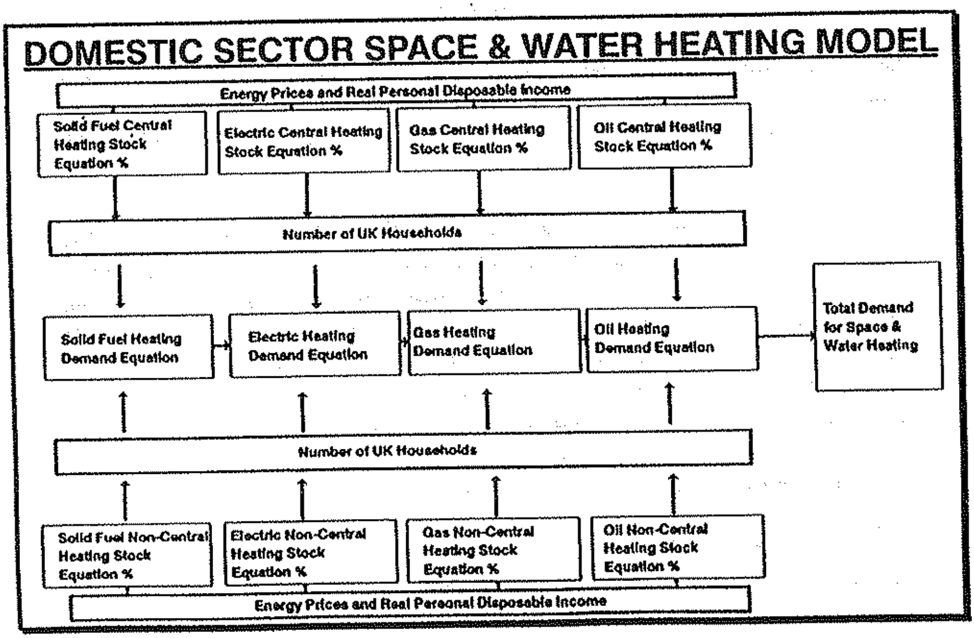
Domestic Sector Model

The recently developed domestic sector model disaggregates energy demand into three end uses:

1 Space & Water Heating
2 Cooking
3 Appliances.

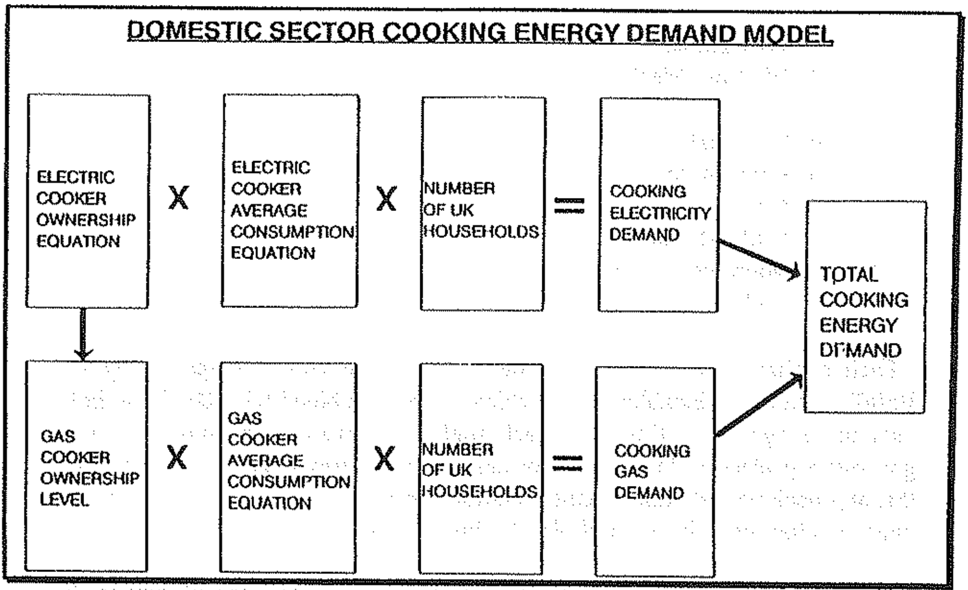
Each of these end uses is discussed below.

The domestic sector's space & water heating model begins by modelling the stock of central heating units by fuel type. Once the total number of households with central heating has been determined the stock of households with non-central heating units is modelled, again by fuel type. These stock equations are based on logit type equations and use energy prices and real personal disposable income to determine their values. The sum of the outputs from the stock equations is constrained in order to ensure that they equal the total number of UK households. Once the number of central heating and non-central heating units by fuel has been estimated these variables are used as inputs in the individual heating (econometric) demand equations. The structure of the space & water heating model can be seen from the following schematic.

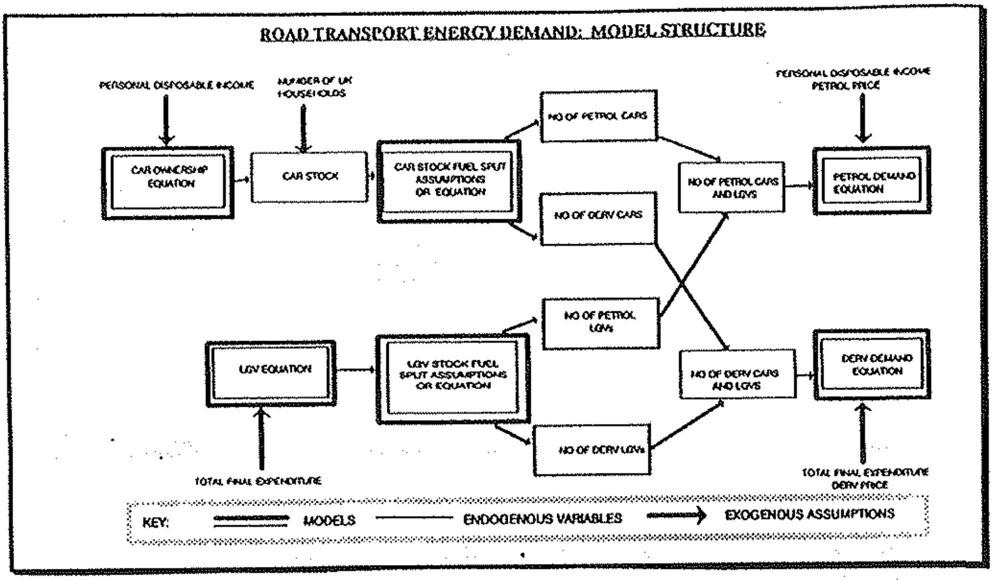


Cooking

Domestic energy demand for cooking is dominated by gas and electricity. This allows just one simple share equation to determine the stock of both electric and gas cookers. Once the stock of electric and gas cookers has been determined two average consumption equations are used to estimate the total amount of energy used for cooking. The structure of the cooking model is shown below:



growth could continue indefinitely. In order to reflect this UK household ownership of cars is assumed to saturate at a level similar to the current level of US household car ownership. In practice even this saturation level may be too high as the size of the US relative to the UK makes the ownership of a car in the US a much greater necessity than is the case in the UK. With these points in mind the DTI road transport model is shown overleaf. Note that LGV's in the schematic refers to light goods vehicles.



It can be seen from this diagram that this transport model is much more of a structural model than many of the simple reduced form econometric transport models that often appear in the academic press[1]. The advantage of this more structural approach is that it enables many questions to be answered which a simple econometric approach simply could not hope to answer.

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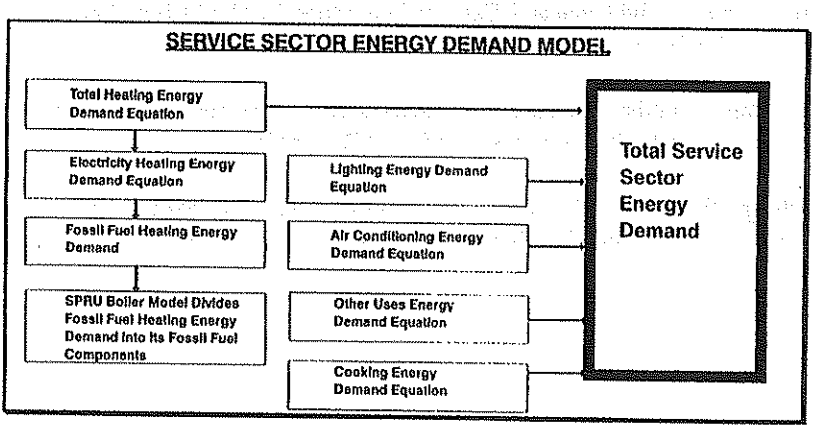
1 See for instance "The Irreversible Effects of High Oil Prices: Empirical Evidence for the Demand for Motor Fuels in France, Germany and the UK" by J. M. Dargay in "Energy Demand: Evidence and Expectations" edited by David Hawdon, Surrey University Seminars, Surrey University Press, 1992.

Future Modelling

As mentioned earlier on in this paper future development of the DTI energy model will during the remainder of 1993 be concentrated on the Service and Other Industry sectors. Although the structure of the new Other Industry demand model has still to be finalised the structure of the new Service sector model is known and this is shown below:



Although a small component of Service sector energy demand, the energy consumption associated with Service sector cooking must reflect the decline in average Domestic sector cooker consumption if these two models are to be consistent. Often energy consultants develop sub-sector models separately and this can lead to problems if these cross-sector restrictions (such as that between domestic and service sector cooking energy demand) are not included in the estimation process.

Summary

This paper has described some of the modelling recently undertaken by the DTI. It has been noted that the emphasis in the modelling is changing from one based on econometric relationships directly linking energy demand to variables such as price or income to one increasingly based on bottom-up/structural modelling. Further progress in this area will depend on the availability of good disaggregated energy demand data.

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THE DEMAND FOR FUELS FOR PRIVATE TRANSPORT IN THE UK

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I INTRODUCTION

Fuel demand for road transport is comprised of petrol and diesel used in private cars, public transport vehicles (taxis and buses), and goods vehicles. The demand relationships for these user groups are not necessarily the same. One might expect fuel demand for private cars to be more income elastic and more price elastic than fuel demand for both public and goods transport. If such differences do exist, elasticities estimated on the basis of aggregate fuel demand would be representative of no particular user group, but instead be some sort of weighted average of the elasticities of the different demand categories. A further problem arises if aggregate demand is estimated for a period during which the shares for the various users have changed. The aggregate elasticities would then also reflect the changes in the relative shares of the user groups in total demand. These elasticities would tend to rise or decline over time and bear little relation to the elasticities for the individual consumer groups. Since aggregation tends to produce "average" elasticities, which are not truly applicable for any consumer category, the use of such elasticities to analyse the effects of price or income changes on individual demand categories or of specific policies would be misleading.

It is thus advantageous to be able to disaggregate the separate user groups. However, this is not so easily done on the basis of most statistical sources, which generally report consumption of petrol and diesel separately, but only for road transport as a whole. Although petrol consumption largely relates to private cars and diesel to commercial and public transport vehicles, this is not entirely the case. Most importantly, the situation has changed significantly over the past decades as first commercial vehicles and then, to a lesser degree, private cars have switched from petrol to diesel engines. At the same time private cars have increased their share of total fuel use for road transport from 60 to nearly 70 per cent. Unfortunately the available data do not allow a complete breakdown of the two fuels for each consumer group for a long enough period of time to permit econometric estimation. Because of this most empirical analyses consider aggregate road transport and either the demand for petrol and diesel separately, or combined. In this paper, an indirect method is employed by which the demand for private transport is analysed and elasticities pertaining to fuel use in private cars are derived. Due to insufficient data, the study is yet incomplete and only some preliminary results are presented here.

2 METHODOLOGY

The demand for transport fuels is most commonly estimated using some sort of reduced form model, in which equilibrium fuel use is specified as a function of fuel prices, P_F some measure of income, Y, and perhaps some other relevant variables, Z, which may be the prices of complementary goods, such as vehicles, or substitutes, such as public transport.

$$F_C = \Theta\ (P_F\ , Y,\ Z_i) \qquad (1)$$

If the model is to be estimated from time series data, some sort of dynamic structure should also be included to allow for lags in the adjustment process. The primary advantage of reduced form models is that they require data on relatively few variables, which are generally easily accessible. Although these models provide useful information about demand and allow the estimation of price and income elasticities, they provide no explanation about the mechanism through which demand responds to changes in the explanatory variables. This will be a disadvantage if we want to use such models to predict demand in the future, as they give no basis for evaluating the plausibility of our predictions in terms of actual behaviour. For this reason, and for a number of others more to do with transport than energy *per se*, it is useful to analyse fuel demand on a more detailed level on the basis of behavioural models.

Similar approaches have been used in a number of transport demand studies including those by Sweeney (1978) and Griffin (1979). The basic idea is that fuel consumption for private transport can be broken down into two components: the demand for travel by private car, eg in km, and fuel use per km. The first of these is largely determined by socioeconomic factors while the second largely by technological factors, which can be economically induced. Aggregate travel demand by private car can be further broken down into the total number of cars (car ownership) and an average utilisation rate (km/vehicle). Fuel consumption for private cars can thus be written as the product of three elements:

$$F_C = [F_C/Km] x [Km/Car] x Cars. \tag{2}$$

The first, fuel consumption per km, is the specific energy use or the inverse of fuel efficiency. The second, Km/Car, is a measure of car use and the last is car ownership. Each of these can be represented by individual demand functions so that the effects of prices and other explanatory variables can be examined for each component.

$$F_C/Km = h\ (Y, P_P, Z_E) \tag{3}$$
$$Km/Car = g\ (Y, P_P, Z_U) \tag{4}$$
$$Cars = f\ (Y, P_C, P_P, Z_C) \tag{5}$$

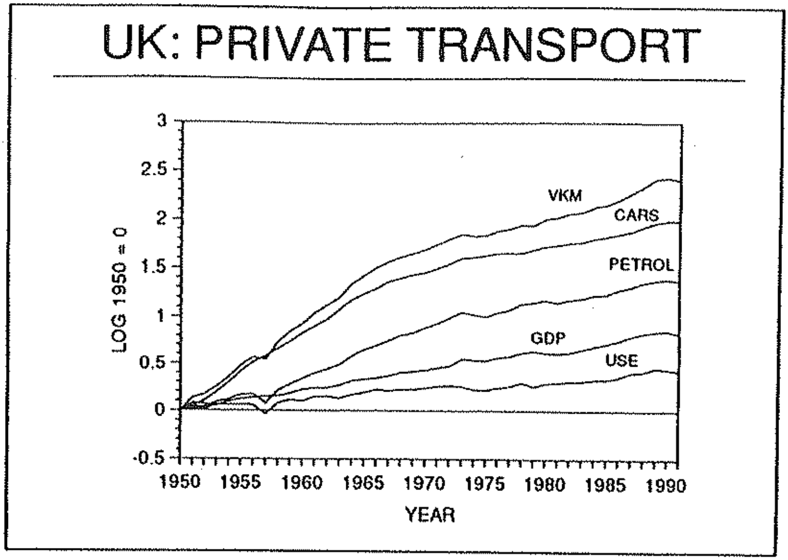
Where Y is income, P_C is the purchase price cf. cars, P_P is the petrol price. Z is a vector of other relevant variables, some of which will be common to two or all equations (eg public transport prices or other car running costs may be in (4) and (5). As written above the individual demand components represent equilibrium relationships, so that some sort of dynamic lag structure must be appended in each case to describe the intertemporal adjustment process. By doing so, we will be able to obtain estimates of both short- and long-run elasticities as well as of the speed of adjustment over time.

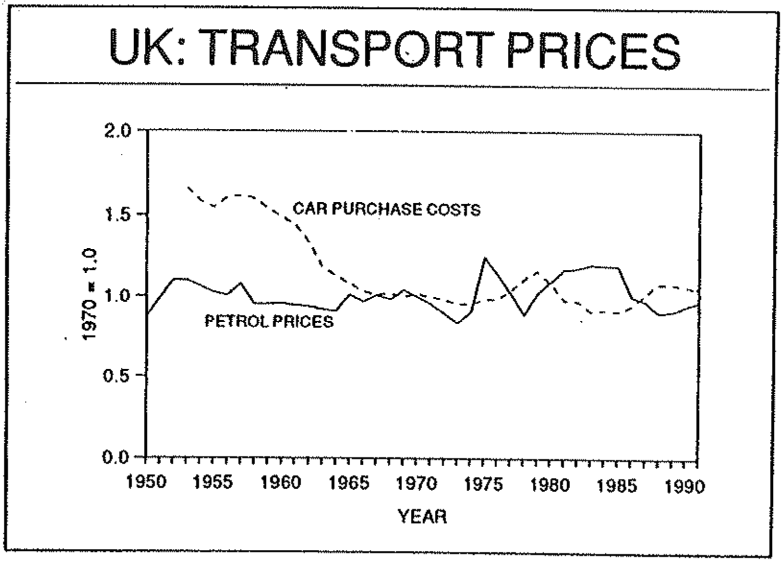
We would expect car ownership to be positively related to income, both as non-car households purchase cars and as car-owning households obtain second ones. The effects of income on car use, however, will be twofold: a positive influence through the greater use of existing cars, but a negative impact through the purchase of second cars. The first effect should occur relatively quickly, while the latter would be more prominent over time. Finally, we would expect fuel use per km to increase with rising income as larger cars with more powerful engines are chosen. Conversely, increases in gasoline prices should lead to a decline in all three variables. The immediate effects will be a decline in car use and perhaps even fuel use per car use as driving habits become more economical. In the longer term, the effects will mainly be on the vehicle stock, both in terms of declining car ownership and fuel use per car as smaller and more fuel efficient cars are chosen, and a more fuel efficient technology is developed.

Given the identity in equation (2), both short- and long-run price and income elasticities for fuel demand can be obtained by adding the elasticities estimated for the individual components in
equation (3) - (5). In this way we not only have an indication of fuel elasticities for private cars, but also some idea of the mechanism of the response to price and income changes. This disaggregate approach will also provide a better basis on which to investigate possible irreversible or asymmetric price response. Particularly, we can examine whether irreversibility is solely explained by fuel efficiency improvements or whether there is also a behavioural component.

3 HISTORICAL DEVELOPMENT

Before presenting the results of the empirical analysis it is useful to have a look at the development of the relevant variables. These are shown in the two figures on the following page. In the top diagram, all variables are shown in index form with the log of 1950's value set equal zero. Annual vehicle kms for cars (VKM), car ownership (CARS) petrol consumption (PETROL) and GDP are all given on a per capita basis, while car use (USE) is calculated as Km per car. All data have been taken from various issues of HMSO Transport Statistics Great Britain. Unfortunately these data are not totally consistent with each other. VKM is annual vehicle km driven by cars and taxis whereas CARS are private passenger cars only. USE, which is calculated as VKM/CARS is thus a slight overestimation of kms driven by private cars. PETROL is petrol consumption for all road transport and thus includes use by petrol-powered cars, taxis, goods vehicles and motorcycles. As mentioned in the introduction, the share of petrol consumption used by private cars has changed significantly over the past four decades. Both the rapid increase in the use of private cars and the conversion of commercial vehicles to diesel powered engines resulted in an increasing importance of the role of private cars on the petrol market, from a share of less than 75 per cent in the fifties to over 90 per cent today. In addition to this, an increasing use of diesel-powered engines for private cars in the 1980s led to significant substitution away from petrol. By 1991 diesel accounted for about 7 per cent of fuel use in cars, increasing from virtually zero in the seventies. Because of both of these developments, our measure of petrol consumption grossly underestimates the growth of petrol - and more importantly fuel - demand for private cars. This should be kept in mind in the following discussion.


UK: PRIVATE TRANSPORT
LOG 1950 = 0
3
2.5
2
1.5
1
0.5
0
-0.5
VKM
CARS
PETROL
GDP
USE
1950 1955 1960 1965 1970 1975 1980 1985 1990
YEAR


UK: TRANSPORT PRICES
1970 = 1.0
2.0
1.5
1.0
0.5
0.0
CAR PURCHASE COSTS
PETROL PRICES
1950 1955 1960 1965 1970 1975 1980 1985 1990
YEAR

A number of important trends are apparent in the diagrams. First, we see from the top graph that over the period as a whole car ownership, km. driven and fuel consumption increased more rapidly than income, while use per car rose less quickly. Secondly, the growth rates of all the variables have been retarded since the mid 70s. From 1960 to 1973, per capita GDP rose by 4 per cent per year, while vehicle kms rose by 15 per cent, car ownership by 13 per cent, petrol consumption by 8 per cent and use per car by 2 per cent. The discrepancy in growth rates between kms driven and petrol consumption reflects the development pointed out earlier, ie the increasing share of petrol consumption used by private cars. Since 1973 the variation in growth rates of the individual variables has narrowed considerably. Car ownership and fuel consumption increased proportionally with GDP, at 2 per cent per annum, while km travelled increased by 3 per cent and use per car by 1 per cent.

The development of real petrol prices and car purchase prices is shown in the lower figure. Both prices are in index form, with 1970 set equal to 1. We see that although petrol prices have been very volatile over the past forty years, there is no apparent trend either upwards or downwards over the period as a whole. Despite the substantial price increases of the seventies, real prices only just surpassed those of the mid-fifties. With the price collapse of 1986, real prices are today lower than they have been at most times previously. Car purchase prices have behaved in a rather different fashion, displaying a significant downward trend during the fifties and early sixties. As we will see later, this decline in car prices is partially responsible for the rapid growth in car ownership, use and fuel consumption during the fifties and sixties.

Given the apparent trends in most of the variables under consideration, it is important to examine their stochastic properties. Specifically, we need to determine two things. Firstly, the order of integration of the individual series must be determined to see which are stationary and which are not. Secondly, we must examine whether or not sets of nonstationary variables move together over time to determine whether or not a long-run relationship can exist.

The tests for stationarity of the individual variables are shown in Table 1. Both augmented Dickey Fuller and Durbin Watson statistics are given. The first two columns report the tests for the null hypothesis that the variable Is I(1), while the second two test for 1(2). For all variables, both tests are in agreement: car ownership, vehicle kms, car use, petrol consumption, car purchase costs and

Table 1: Tests for The Order of Integration of Data Series (X). Dickey Fuller, Augmented Dickey Fuller and Cointegrating Regression Durbin Watson Tests

	H_o:X is I(1)		H_o:X is I(2)	
	DF/ADF	CRDW	DF/ADF	CRDW
Car Ownership	-2.18 (c,t,1)	0.01	-3.69*** (c,0)	1.04***
GDP	-2.85 (c,t,1)	0.01	-4.37*** (c.0)	1.44***
Vehicle Km	-2.72 (c,t,1)	0.01	-4.79*** (c.0)	1.26***
Car Use	-2.99 (c,t,1)	0.08	-7.86*** (c.0)	1.74***
Petrol	-2.31 (c,t,1)	0.01	-5.42*** (c,0)	1.71***
Petrol Price	-4.65*** (c,1)	074***	-5.66*** (c,0)	1.64***
Car Price	-1.75 (c,1)	0.05	-3.07** (0)	0.88***

Note: The form of the ADF/DF equation is shown in parenthesis under the test statistics: c and t indicate a constant and trend are included, and the number gives the number of lagged differences included. The * indicate significance levels: * 10 %, ** 5 % and *** 1 %.

GDP are all integrated of the first order I(1), whereas petrol prices are stationary or I(0). Apart from this, all non-price variables also contain a deterministic trend. This is as one would expect from the graphs of these variables.

An implication of this non-stationarity is that a long-run relationship can only exist between any set of these variables if their paths do not diverge over time. In order to test for a long-run relationship Dickey Fuller (or ADF) and Durbin-Watson tests for cointegration were carried out.

The results are shown in Table 2, for both linear and logarithmic forms of the variables. Two tests are carried out in each case: first for cointegration between the transport variables and GDP only, and then also including car purchase costs (CPC). Given the stationarity of petrol prices, this variable cannot be included in the cointegrating relationship. Although the exact critical values for the DW tests are unavailable, it seems that there is some conflict between the DF and DW test results. Given the general preferability of the DF tests, the strongest evidence appears to be in favour of the logarithmic model. Both car ownership and vehicles kms appear to be cointegrated with GDP and car

Table 2 Tests for Cointegration

	Linear Model				Logarithmic Model			
	GDP		GDP & CPC		GDP		GDP & CPC	
	DF	DW	DF	DW	DF	DW	DF	DW
CARS	-1.87	0.19	-2.80	0.73	-2.08	0.09	-4.12**	0.28
VKM	-2.45	0.61	-2.56	0.80	-2.02	0.14	-3.99**	0.45
USE	-3.46*	1.00	-3.64*	1.08	-3.71**	1.09	-3.76*	1.11
PET-ROL	-1.91	0.23	-2.51	0.52	-1.74	0.22	-3.34	0.83

Note: The * indicate significance level for the DF/ADF tests: * 10 %, ** 5 %. Critical values for the DW tests for the specific cases estimated here are not available.

purchase costs, while car use is cointegrated with GDP only (car purchase costs are extraneous). The evidence for petrol consumption is less clear, but cointegration is suspect. The necessity of including car purchase costs in the cointegrating equations for CARS and VKM indicates that the long-term development of both car ownership and vehicle kms has been driven not only by income growth but also by the decline in car purchase costs, particularly during the fifties and early sixties.

4 EMPIRICAL RESULTS

Given that we accept the evidence of cointegration suggested above, non-stationarity is no longer a problem, so we can proceed to estimate the dymamic relationship. The following error correction model is estimated for each variable X = CARS, USE, VKM and PETROL:

$$\Delta X_t = \alpha + \beta_G GDP_{t-1} + \beta_C CPC_{t-1} + \beta_P P_{t-1} + \beta_X X_{t-1} + g_G \Delta GDP_t + g_C \Delta CPC_t + g_P \Delta PP_t \quad (6)$$

Dummy variables are also included to account for petrol rationing during the Suez crisis in 1956 and 1957 and the Gulf crisis in 1974. Initially, lagged differences of GDP, CPC, PP and the X variables were included but these were found to be non-significant. The results of the final specification are presented in Table 3. The estimated coefficients are all of the expected sign, although some of them are not statistically different from zero. In particular, the long-run impact of car purchase costs is very poorly determined in both the CARS and VKM equations. Since this variable proved necessary for cointegration, it was kept despite its low significance. The poor performance of the variable may have to do with measurement problems, since the prices of both new and used cars must be included.

In general the R^2 values indicate that the models explain the data reasonably well, and the DW and LM tests suggest no problems with autcorrelated errors. The RESET-test for functional misspecification is insignificant for both car ownership and car use models, but does suggest functional misspecification for vehicle kms and petrol consumption. Parameter stability over the observation period was examined by recursive estimation and various Chow tests. The only significant departures from constancy were indicated for the post-1986 period for petrol consumption. One explanation of this "structural break" in petrol

Table 3	**Estimated Coefficients for the Error Correction Model 1954-1991**			
	CARS	USE	VKM	PETROL
constant	0.12 (10.1)	0.03 (3.04)	0.19 (5.72)	0.91 (5.16)
GDP	0.11 (2.35)	0.28 (5.07)	0.27 (1.67)	0.22 (2.13)
CPC	-0.04 (0.98)	-	-0.11 (1.00)	-0.14 (2.91)
PP	-0.07 (1.79)	-0.06 (1.68)	-0.11 (1.59)	-0.10 (2.80)
X_{t-1}	-0.11 (3.40)	-0.59 (5.47)	-0.18 (2.13)	-0.22 (2.98)
ΔGDP	-0.46 (3.41)	-0.02 (0.12)	0.05 (0.16)	0.11 (0.56)
ΔCPC	-0.20 (3.30)	-	-0.13 (0.86)	-0.01 (0.93)
ΔPP	-0.03 (0.41)	-0.14 (3.19)	-0.17 (2.45)	-0.18 (3.91)
D56	-	-	-0.04. (1.36)	-0.06 (2.820
D57	-	-0.11 (5.58)	-0.13 (4.19)	-0.15 (7.57)
D74	-	-0.06 (2.72)	-0.08 (2.29)	-0.07 (3.20)
R^2	0.84	0.74	0.66	0.81
DW	2.25	1.66	1.49	1.59
LM Serial Correlation	1.14 (1,23)	1.31 (1,28)	0.71 (1,28)	0.47 (1,28)
RESET Functional Form	0.99 (1,29)	1.21 (1,29)	3.42 (3,27)*	3.71 (3,27)*
Chow Forecast 1986-91	1.26 (6,24)	1.23 (6,24)	1.65 (6,24)	2.52 (6,24)*

Note: t-statistics for estimated coefficients shown in parentheses. F-tests for LM, RESET and Chow tests with degrees of freedom shown in parentheses. The test statistics denoted with * are significant at the 5 per cent level.

demand for the period following the oil price collapse is the irreversible response to the oil price shocks of the seventies, particularly in the form of improved vehicle fuel efficiency (Dargay, 1991).

Judging from the estimated coefficients and diagnostics, the models for car ownership and use perform "better" than those for vehicle kms and petrol consumption. Although VKM is identically equal to CARS plus USE, since these are all in logarithmic form, the assumptions underlying the model for VKM are quite different dynamically than those underlying the individual models for CARS and USE. In the former, consumers are assumed to adjust vehicle kms whereas in the latter, car ownership and use are adjusted separately, with different time structures.

The estimated elasticities are displayed in Tables 4 and 5. For car ownership, we find a short-run income elasticity of about 0.5 and long-run income elasticity of very near unity. Adjustment to income changes is quite quick, with half of the total effect (mean lag) occurring within two years. Both car purchase prices and petrol prices also have a considerable effect on car ownership, although adjustment to changes in these two price variables is very different. Car prices seem to affect demand immediately, with more than half of the long-term effect occurring within the first year following a price change. Petrol prices, on the other hand, appear to have little or no immediate impact on car ownership, but a relatively large effect over time. The adjustment is quite slow, however, with a mean lag of seven years compared to less than one year for purchase costs. After six years following a price increase the elasticity with respect to petrol prices surpasses that with respect to car purchase prices. However, as mentioned earlier, this latter elasticity is rather poorly determined.

Car use also responds to changes in income and petrol prices, although the effects are considerably smaller than those for car ownership, and the adjustment far more rapid. The long-run income and price elasticities of car use appear to be around 0.4 and -0.1 respectively. The dynamics of the response of car use to petrol prices and to income changes are somewhat different: the total effect of petrol price changes appears to occur within one year, whereas the response to income changes occurs only more slowly over time, but still with a mean lag of two years.

Table 4 Estimated Elasticities						
	Car Ownership		Car Use		Ownership + Use	
	Short Run	Long Run	Short Run	Long Run	Short Run	Long Run
Income	0.46	1.05	0	0.41	0.46	1.46
Petrol Price	-0.03	-0.63	-0.14	-0.11	-0.17	-0.74
Car Price	-0.20	-0.36	-	-	-0.20	-0.36

As stated above the elasticities for vehicle kms can be obtained by adding together the car ownership and car use elasticities. These are presented in the final two columns of the table. For both price and income variables, we find that the short-run elasticities are significantly smaller than the long-run elasticities. The effects of income on traffic or vehicle kms is chiefly through its effects on car ownership. Of the total long-run effect, 70 per cent is due to changes in car ownership. Changes in petrol and car prices also have their greatest effect on car ownership, although in the short-run the primary impact of petrol prices changes is on car use.

The elasticities resulting from the vehicle km and petrol equations are shown in Table 5. Although those for vehicle kms are rather similar to those obtained from the ownership and use models, there are some notable differences. Particularly, the short-run income elasticity is considerably smaller and the long-run purchase price elasticity is larger than those derived from the individual models. It would appear that the aggregate model underestimates the short-run income elasticity. Little could be said about the long-term impact of car purchase costs, however, since the coefficients are poorly determined in both cases.

Finally the elasticities estimated on the basis of petrol consumption are reported in the next two columns. These appear to be of a reasonable magnitude and not vastly different from those reported in other studies. However, we recall that the estimated equations showed signs of instability and

Table 5 Estimated Elasticities						
	Vehicle Km		Petrol Estimated		fuel/km	Petrol
	Short Run	Long Run	Short Run	Long Run		Long Run
Income	0.05	1.47	0.10	1.00	+	about 1.5
Petrol Price	-0.17	-0.63	-0.17	-0.45	-	about -1.4
Car Price	-0.13	-0.62	0.00	-0.66	-	about -0.4

incorrect functional specification, so the elasticities estimates are also questionable.

Given the identity in equation (1), the elasticities for fuel use in private cars will be the sum of the elasticities for car ownership, use and fuel/km. Although we do not as yet have sufficient data to estimate the last of these, we would expect the income and price elasticities to be of normal signs, as shown in the next column. Fuel/km should increase with increasing income as larger and more powerful cars are chosen, but we would expect the effects to be rather small. The fuel price should have a negative impact, in the short ran as households choose smaller, more fuel-efficient cars and in the longer term by inducing a technological development towards greater fuel efficiency. We would expect this effect to be relatively small in the short run, but probably equally as great as the car ownership and use elasticities in the long run. The final variable, car purchase costs should also have a negative impact, since cars are complementary goods. The effect, however, is most likely insubstantial even in the long run.

Using the "guesstimates" the long-run elasticities for fuel consumption in private cars should be in the region of those shown in the final column of the table. At first glance, the estimated elasticities do not at all appear consistent with these results. The income and petrol price elasticities are much lower and car purchase price elasticity larger. However, we recall that the measure of petrol consumption employed relates to all road vehicles rather than the private cars (or cars and taxis) on which the rest of the analysis is based. Given the earlier discussion concerning the petrol variable's underestimation of the growth rate of fuel consumption in private cars, we might expect an underestimation of the income elasticity as well as a biased price elasticity. The lower price and income elasticities for total petrol demand are also consistent with the proposition that the demand for goods transport is less elastic than the demand for private car transport.

4 CONCLUSIONS

In the preceding sections, we have seen how the determinants of the demand for fuel use in private cars could be derived on the basis of a structural model describing car ownership use and specific fuel consumption. As data on fuel efficiency are not yet available, only some preliminary results for car ownership and use models are reported. On the basis of the estimated price and income elasticities for these components of fuel consumption, likely values of the elasticities for fuel demand are derived. Although the study is still incomplete, the results obtained thus far are rather encouraging.

The main conclusions could be summarised as follows:

- Fuel demand is highly sensitive to both price and income.
- Fuel prices affect demand through the effects on car ownership and car use. Impact is greatest on car ownership, but this occurs slowly over time. Effects on car use are predominantly short run and small.
- Car prices affect fuel demand through their effects on car ownership.
- Income affects both car ownership and use per car.

Based on the estimates for car ownership and car use, and assumptions concerning the effects of income and prices on fuel use per km, the following elasticities for fuel demand for private cars can be derived:

Income around 1.5
Fuel Price -0.7 to -1.4
Car Price around -0.4

Although these results should be treated with caution, there is reasonable evidence that fuel consumption for private cars and total car use are both price and income elastic. This has clear policy implications. On the one hand, fuel consumption as well as car use increases more rapidly than income, so that all else being equal we can expect increasing levels of traffic and fuel use and pollution. On the other hand, however, total car use and fuel consumption are relatively sensitive to fuel prices, so that petrol prices can provide an effective instrument for reducing both traffic levels and fuel demand. This will be extremely relevant for the possibility of attaining environmental or traffic-reduction goals.

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ELECTRICITY LOAD AND TEMPERATURE: Issues in Dynamic Specification

John Peirson and Andrew Henley[1]

1 INTRODUCTION

The subject of this paper is the econometric modelling of the relationship between electricity load and air temperature. Temperature, and more generally natural conditions, are the most important causes of changes in electricity load in the short term. The effect of changes in natural conditions on electricity load can be significant.[2] In order to manage the generation and supply of electricity, it is important to understand and be able to predict the effects of natural variables on load. When generation and distribution of electricity are undertaken by separate commercial companies, as in the British Electricity Supply Industry, it is particularly important for these companies to be able to predict the effects of the climate on load. The development of methods for appropriate normalisation of actual load to given weather conditions is of importance to academic and commercial energy economists engaged in the energy demand modelling.

This paper considers four topics that are of importance to understanding the relationship between electricity load and air temperature. Firstly, the use of commonly adopted general-to-specific time-series modelling methodologies on highly autoregressive load data of a high periodicity (typically monthly or daily observations) may yield complex and unwieldy dynamic specifications (section

[1] **Acknowledgements**

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[2] For example, during the winter, a fall in temperature of one degree Celsius would result in an increase of 3 % in average load during the half-hour 17.00-17.30 for British unrestricted domestic consumers in the year 1990/91, see Peirson and Henley (1992).

2). The use of autoregressive error representations are found to provide a good explanation of present load even in the absence of any dynamics in the causal relation between load and temperature. Secondly, it is shown that ignoring dynamic specification has an important impact on the estimated effects of temperature on load. The use of static models to predict the effect on load of a marginal change in temperature may be overstated due to serial correlation bias (section 3). Thirdly, the use of imposed declining lag structures on daily temperature data (the effective temperature concept) as a means of modelling dynamics is shown to be unduly restrictive. The assumptions underlying the concept of effective temperature and its empirical validity are investigated. In particular, it is found that the structure of the dynamic relationship between load and temperature may vary over the day (section 4). It is found that for time periods before noon the particular declining lag structure of noon effective temperature cannot be accepted statistically. Finally, the paper shows that there are theoretical reasons for believing that heating load is a non-linear function of temperature. Furthermore, empirical evidence is shown to suggest that these non-linearities exist and are of importance.

2 SERIAL CORRELATION AND DYNAMIC SPECIFICATION

Serial correlation

Particularly in the industrial literature, dynamic specification is often ignored in the modelling of short term energy demand, e.g. see the reviews by Williams (1985) and Granger (1987). In econometric studies of load, as distinct from time series and state space studies (see the previously mentioned reviews), it is common to ignore dynamic specification, e.g. see the discussion in Ramanathan, Granger and Engle (1985), DRI (1981) and QUERI (1981). Sensible applied econometric practice suggests that time series models of energy demand should be subject to the now conventional array of diagnostic tests.[1] The effect of serial correlation on the estimated effects of air temperature on load should be investigated as the presence of serial correlation will yield inefficient estimates of the regression coefficients. Furthermore, the failure to reject the presence of significant serial correlation in time series models may

[1] Hendry (1992) gives an a good account of the importance of diagnostic testing in the practice of applied econometrics.

indicate the possibility of dynamic misspecification (Hendry and Mizon 1978). If the underlying model structure is dynamic then OLS estimation of a static representation, which is autocorrelated, is very likely to produce biased coefficient estimates. Importantly, prediction of the effects of temperature change on load using an autocorrelated regression may be unreliable. This is because prediction can be improved if information about the previous period's residual is introduced into the calculation.

Dynamic specification: the appropriateness of an autoregressive structure

A commonly used method to introduce dynamics into an econometric regression is to incorporate a number of lags on the dependent variable. This procedure has been followed in econometric, Box-Jenkins, State Space and other approaches to explaining electricity consumption and load, see Granger (1987) and Bunn and Farmer (1985a). In the case of econometric models, there are two possible problems with this procedure. Firstly, in the presence of other explanatory variables, a common dynamic structure is imposed on all the independent explanatory variables, including temperature and other natural variables. Secondly, it may appear that the lagged dependent variables, rather than the other explanatory variables, are explaining load.

The problem of a common lag structure for explanatory variables is rarely explicitly stated. This problem is obviously reduced when there are few variables, With regard to this problem, the validity of the specification of lagged dependent variables depends on judgement about the relative merit of parsimony and the cost of any induced errors, both of which are difficult to assess. However, it should be remembered that there are physical reasons for believing that past temperature affects the heating load (see below), but less reason to believe that other natural variables such as illumination and rainfall have a similar lagged effect on electricity load.

The second problem concerning the specification of lagged dependent variables is that they may serve to model the data rather than represent actual dynamic behaviour. This possibility is analyzed here in terms of a simple model. The only variables are load for a particular half-hour d on day t, $Q_{d\,t}$, and air temperature, θ_t. Assume the true static relation between these variables is a linear relationship with a serially correlated error term, $e_{d\,t}$,

$$Q_{d\,t} = \alpha_d \, \theta_t + e_{d\,t} \qquad (1)$$

$$e_{d\,t} = \rho_d \, e_{d\,t-1} + \epsilon_{d\,t}$$

where ϵ_t is white noise. Assume that the relation between temperature on successive days is given by

$$\theta_t = \theta_{t-1} + v_t \qquad (2)$$

where v_t is an undefined random term. If load is specified as a function of the lagged dependent variable and temperature, the following rearrangement is helpful, where u_t is a further error term assumed to be independently normally distributed

$$\begin{aligned} Q_{d\,t} &= \lambda_d \, Q_{d\,t-1} + \pi_d \, \theta_t + u_{d\,t} \\ &= \lambda_d \, [\alpha_d \, \theta_{d\,t} + e_{d\,t} - \alpha_d \, v_t + e_{d\,t-1} - e_{d\,t}] \\ &\quad + \pi_d \, \theta_t + u_{d\,t} \\ &= \lambda_d \, [Q_{d\,t} - \alpha_d \, v_t + e_{d\,t-1} - e_{d\,t}] \\ &\quad + \pi_d \, \theta_t + u_{d\,t} \end{aligned} \qquad (3)$$

Equation (3) shows that if the error term e is strongly serially correlated (so $e_t - e_{t-1}$ is small) and the random temperature component v is small relative to θ, then a regression of the form of (3) is likely to give a quantitatively important and statistically significant estimate of λ. This estimate is obtained in spite of the absence of any dynamics in the causal relation given in equation (1). The problem is complicated further by the presence of higher order serial correlation in e and higher orders to the random temperature component.

Evidence for an autoregressive structure

The evidence for the assumptions underlying this analysis is strong. Column 1 of Table 1 provides estimates of equation (1) using, for illustrative purposes, daily observations on domestic electricity consumption for the half-hour 12.30

to 13.00 hours for the winter period 1st November 1990 to 28th March 1991.[1] The data used is from the Electricity Association Load Research programme, see Peirson and Henley (1992) for details about the Load Research programme and the calculation of the variables. This continuing survey measures the consumption in each half hour of the year for stratified random samples of

Table 1: Estimates of equations (1) and (2)

	Equation 1	Equation 2
Dependent variable	Q_t	θ_t
constant	0.835	6.042
	(10.188)*	(3.272)*
θ_t	-0.007	
	(-3.670)*	
θ_{t-1}		0.861
		(20.442)*
R-squared	0.084	0.741
Durbin-Watson	1.396	2.318
Regression standard error	0.141	3.187
Mean of dep. variable	0.537	43.4088
1st order autocorrelation χ^2 (1)	13.222*	5.110*
7th order autocorrelation χ^2 (7)	93.974*	9.784

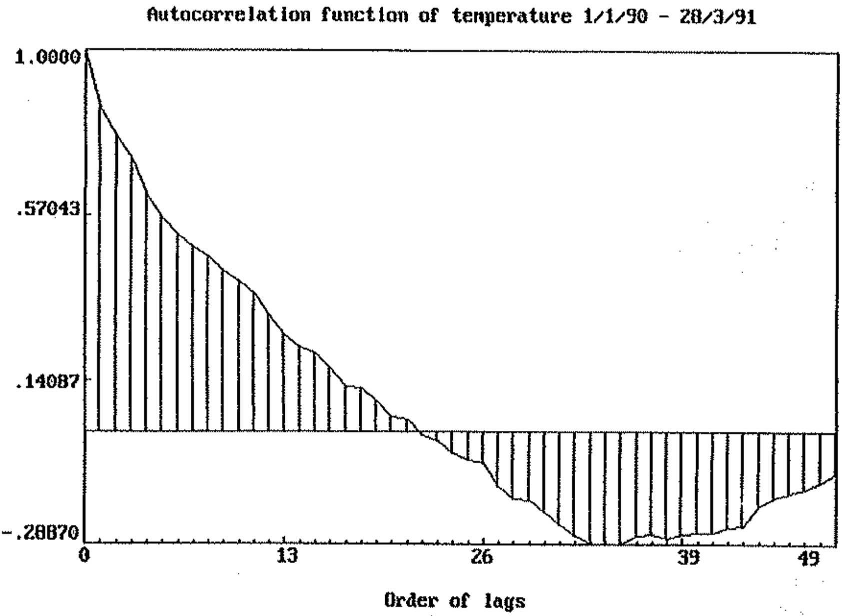
Note: Sample: Residential consumers on unrestricted tariff, 1/1/90 to 28/3/91, n = 148; t-statistics in brackets; * indicates significance at 5%.

consumers. The 1991/2 consumption data for unrestricted domestic consumers was averaged, using the appropriate population weights, to give the dependent

1 The sample period ends on 28th March as that date corresponds to the switch from Greenwich Mean Time to British Summer Time.

variable Q in equation (1). θ is measured as actual noon temperature in Fahrenheit averaged over 13 weather stations across the UK. The results of Lagrange multiplier test statistics for autocorrelation indicate significant 1st and 7th order autocorrelation. Column 2 of Table 1 reports estimates of equation (2) for the same time period. It shows that the current and previous day's temperatures are very highly correlated. This is confirmed by Figure 1 which graphs a straightforward autocorrelation function for noon temperature. The first order autocorrelation coefficient is 0.853 with a standard error of 0.082. Column 2 of Table 1 also shows that standard error of the residuals from the regression is only 7.3 percent of the mean daily temperature for the period in question, confirming that v_t is small relative to θ_t.

Figure 1: Autocorrelation function for average noon temperature in Great Britain



However, in terms of allowing for the effect of temperature, a specification of the form of equation (3) may still be appropriate. The size of the λ

parameter will be balanced by a smaller parameter for π. Thus, using the right hand side of equation (3) to calculate the artificial equilibrium effect of temperature on load may give an adequate measure of the actual effect. The suggestion that an autoregressive structure may not be part of a dynamic causal process but may just be explaining the data in terms of itself can be applied to dynamic econometric methodology more generally, as long as the two assumptions hold approximately.

3 ASSESSING THE EXTENT OF SERIAL CORRELATION BIAS IN STATIC LOAD MODELS

Time series modelling in the presence of serial correlation

Modelling strategy in the presence of serial correlation can follow various lines. If OLS bias can be ruled out *a priori* then increased estimation efficiency can be obtained by using a form of generalised least squares (Newey and West 1987). If dynamic misspecification is suspected and there is the additional presence of heteroscedasticity or functional form misspecification then a full scale investigation of model dynamics through estimation of an autoregressive distributed lag (ADL) model is warranted. Evidence of significant higher order autocorrelation would, in the present context where load data is typically of a daily frequency, make full scale dynamic modelling highly complex. General (high-order ADL specifications) to simple modelling strategies may lead to complex and unwieldy dynamic specifications, which are inefficient to implement for frequent and repetitive exercises in normalising electricity load for weather conditions.

A traditional solution to autocorrelation is to be found in the use of autoregressive least squares, where a simple (possibly static) specification is preserved but omitted dynamics are captured through an autoregressive representation of the error structure, e.g. see QUERI (1981) and Engle, Mustafa and Rice (1992). Developments in direct forms of maximum likelihood estimation and improvements in computing technology now allow easier use of higher order autoregressive (AR) estimation. AR estimation with an autoregressive error structure of order i is observationally equivalent to a full scale ADL(i, i) model if a series of "common factor" restrictions between the ADL coefficients are accepted by the data. Thus, in Hendry and Mizon's

(1978) terminology, AR estimation can form a "convenient simplification". In the present context, where daily data is under investigation, the results in column 1 of Table 1 suggest that an initial general ADL(i, i) specification would require i to be at least seven. Without considerable simplification such a model would be heavily over-parameterised. On the other hand, an adequate but parsimonious representation of the data generating process may be difficult to obtain.

The difficulties associated with parsimonious modelling of and prediction from the dynamic structure of daily observation data provides a justification for direct consideration of higher order AR estimation. To assess the bias induced by serial correlation in static models of the relation between electricity demand and air temperature, AR estimation of models of electricity load data is undertaken. For prediction and normalisation purposes, models obtained in this way may be used in exactly the same way as static ones, since the dynamic behaviour of the data is captured through the error process, without the inclusion of lagged dependent or explanatory variables.

Evidence of serial correlation bias

Table 2 reports a comparison of results of a typical load normalisation equation in which electricity load is regressed on temperature, sunset and dummy variables for days of the week and public holidays. The estimating equation takes the following form

$$
\begin{aligned}
Q_{d\,t} \quad = \quad & a_{d\,0} + a_{d\,1}\,\theta_t + a_{d\,2}S_t + \Sigma_{k=1,2,4,5,6,7}\, b_{d\,k}\, D_k \\
& + b_{d\,8}\,XMAS_t + b_{d\,9}\,BOXD_t \\
& + b_{d\,10}\,NEWY_t + e_{d\,t} \qquad (4)
\end{aligned}
$$

S is sunset time measured as number of minutes after 6 p.m. at which sunset occurs in Birmingham on day t. D_k are day dummy variables with Tuesday omitted as base day. XMAS, BOXD and NEWY are public holiday dummy variables for Christmas Day, Boxing Day and New Year's Day respectively. Table 2 reports results for two half-hour periods, 12.30 to 13.00 hours and

Table 2: ***Illustration of Serial Correlation Bias***

	12.30-13.00		17.00-17.30	
	OLS	AR(7)	OLS	AR(7)
constant	0.768	0.563	1.064	1.003
	(21.534)*	(9.737)*	(33.419)*	(20.179)*
O_t	-0.0075	-0.0028	-0.0066	-0.0051
	(-10.264)*	(-2.528)*	(-10.057)*	(-4.861)*
S_t	-0.0004	-0.0003	-0.0016	-0.0015
	(-0.534)	(-1.067)	(-21.808)*	(-8.939)*
Sunday	0.368	0.359	-0.020	-0.020
	(21.775)*	(26.247)*	(-1.289)	(-1.177)
Monday	0.065	0.054	-0.011	-0.009
	(3.833)	(4.179)	(-0.743)	(-0.575)
Wednesday	0.017	0.009	-0.002	0.001
	(1.018)	(0.711)	(-0.150)	(0.003)
Thursday	0.008	0.024	-0.025	-0.021
	(0.482)	(0.177)	(-1.661)+	(-1.262)
Friday	0.008	-0.002	-0.213	-0.017
	(0.458)	(-0.152)	(-1.409)	(-0.905)
Saturday	0.131	0.121	-0.020	-0.012
	(7.732)*	(8.354)*	(-1.352)	(-0.624)
ρ_1		0.449		0.201
		(4.933)*		(2.210)*
ρ_2		0.093		0.197
		(0.914)		(2.149)*
ρ_3		0.020		0.040
		(0.200)		(0.424)
ρ_4		0.139		-0.110
		(1.367)		(-1.174)
ρ_5		0.092		0.047
		(0.932)		(0.511)
ρ_6		-0.078		0.103
		(-0.790)		(1.139)
ρ_7		0.131		0.191
		(1.454)		(2.098)*
R-squared	0.879	0.923	0.847	0.875
Regression std. error	0.0534	0.0441	0.0476	0.0453
F(k,n-k-1)	89.536*	80.923*	68.493*	47.258*
Durbin-Watson	1.116	2.025	1.529	1.979
1st order autoco. χ^2 (1)	30.290*		7.776*	
7th order autoco. χ^2 (7)	36.462*		18.939*	

Note: Sample: Residential consumers on unrestricted tariff, 1/1/90 to 28/3/91, n = 148; Regressions include dummy variables for Christmas Day, Boxing Day and New Years Day, coefficients not reported; t-statistics in brackets; * indicates significance at 5%, + at 10%.

17.00 to 17.30 hours, estimated by table OLS and by AR(7) estimation.[1] In the more general AR(7) case, the error term is assumed to be determined by the following process

$$e_{d\,t} = \rho_{d\,1}\, e_{d\,t-1} + \rho_{d\,2}\, e_{d\,t-2} + \rho_{d\,3}\, e_{d\,t-3} + \rho_{d\,4}\, e_{d\,t-4} + \rho_{d\,5}\, e_{d\,t-5} + \rho_{d\,6}\, e_{d\,t-6} + \rho_{d\,7}\, e_{d\,t-7} \tag{5}$$

The results show that the coefficient on temperature is reduced (in absolute magnitude) by a quantitatively significant amount once the autocorrelation structure is taken into account. For the period 12.30-13.30, the coefficient falls from 0.0075 to 0.0028 and, for the period 17.00-17.30, it falls from 0.0066 to 0.0051. Thus, in these cases estimation of a static specification by OLS is likely to lead to an upward bias in the estimate of the effect of marginal change in temperature on consumption.

The extent of the potential bias was investigated by estimating equations such as those in Table 2 for all 48 half hours using unrestricted domestic consumers' demand in the winter period. The absolute values of the marginal temperature effects for the OLS and AR(7) models are plotted in Figure 2. The OLS coefficients are typically twice as large as those obtained using AR(7) estimation. The differences are greatest in the morning and early-afternoon, and least in the early evening. In only one half-hour period (16.00 to 16.30 hours) does AR(7) estimation give a temperature coefficient below the corresponding figure 2 OLS coefficient. Therefore this evidence suggests that static

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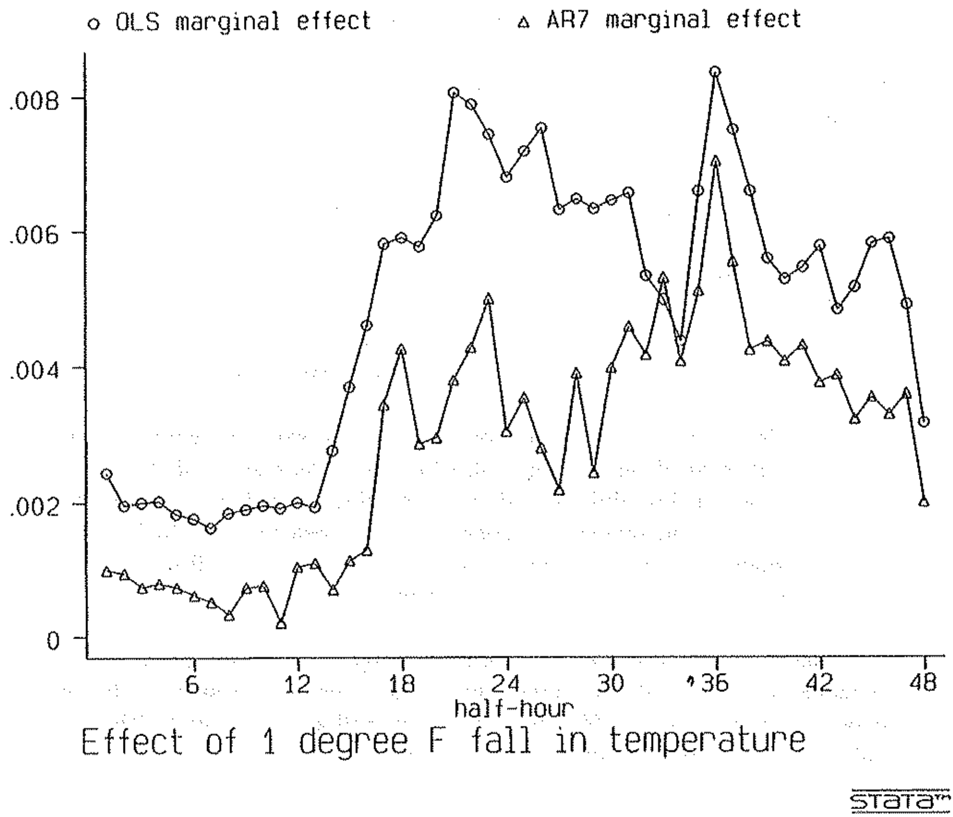
[1] Estimation is performed by the Gauss-Newton iterative method for models with serially correlated errors using MICROFIT 3 (Pesaran and Pesaran 1991). The method is one of "successive substitution" with each iteration involving two steps in which firstly the autocorrelation coefficients, ρ, and secondly the coefficient vector are held fixed. It is therefore not an exact maximum-likelihood method. Exact maximum-likelihood estimation for orders of serial correlation above two is extremely complicated and time-consuming, with the problem increasing exponentially in complexity as the order increases. However a comparison with exact maximum-likelihood estimates with a moving average error structure, yielded very similar coefficient estimates to those obtained by AR(7) and reported here.

Figure 2: Comparison of marginal effect on temperature estimated by OLS and AR(7)



specifications may seriously overpredict the effect of changes in temperature on demand.[1]

4 TEMPERATURE DYNAMICS

The potential importance of temperature dynamics

We now go on to assess the importance of dynamics in the causal relationship between temperature and load. Past air temperature may affect current load in three ways:

(1) The thermal capacities of buildings act as barriers between outside and internal temperatures. Thus, changes in outside temperatures do not instantaneously establish new equilibrium thermal gradients in buildings.

(2) Consumers may only adjust with a lag to changes in air temperatures.

(3) Consumer behaviour may be habitual. For example, consumers may only close down electric central heating systems at certain times of the year, paying little attention to perceived transitory movements in outside temperature. So consumers may respond to cold "snaps" in summer months by short term use of gas or electric fires rather than switching on central heating systems.

In considering the effect of past values of temperature on electricity load and consumption, it should be noted that it is generally considered that past temperature only has an effect for a few days and at most a week. Thus, it is only relevant to consider such effects for relatively short periods.

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1 Though there are considerable differences in the estimated marginal effects of the two models, differences in the other estimated coefficients of the models, particularly the intercept term, compensate. Thus, close to the mean temperature, both models predict nearly the same load. Further from the mean, the two models begin to give more radically different predictions of load.

A number of past econometric studies have modelled the effects of lagged temperature responses through the imposition of restrictive lag structures on a temperature variable. In the QUERI study (1981) of hourly load for different American regions, the two lagged temperature variables employed were a moving average of hourly temperatures over the last 24 hours and a moving average of midnight temperatures over the last five days. The latter variable was found to be statistically insignificant. In a related study, Ramanathan *et al.* (1985) found a moving average of past air temperatures to be a statistically significant variable in explaining hourly domestic consumption. These studies use variables which impose specific lag structures on the effects of past temperatures on demand.

The effective temperature concept

An important method that specifies the effects of past temperatures on load is the effective temperature construct. This approach was developed by Davies (1958) and has been followed by the Electricity Council/Electricity Association (see Boggis, 1973, Skinner, 1984 and Electricity Association 1990) and British Gas (see Lyness, 1984), and was followed by the Central Electricity Generating Board (see Baker, 1985 and CEGB 1986). The effective temperature approach attempts to allow for the thermal capacity of buildings by considering the relationship between the internal and outside temperature of an unheated building.

Effective temperature analysis considers the dynamic relation between internal and outside temperatures, respectively T and θ, for an *unheated* building through the following equation

$$dT/dt = \beta(\theta - T) \tag{6}$$

This simple continuous time equation states that the rate of decrease in the internal temperature is proportional to the difference between the internal and outside temperatures. As an approximation this is physically correct, see Kreith (1972) or Gebhart (1971). Davies (1958) shows that, in discrete time, the effective internal temperature (ET) can be approximated by a distributed lag formulation of the following form

$$ET_t = \beta(\theta_t + \gamma\,\theta_{t-1} + \gamma^2\,\theta_{t-2} + \ldots\ldots) \tag{7}$$

Thus, Davies (1958) and subsequent researchers have suggested that the effective temperature given by equation (7) should be used to model the effect of past and present outside temperatures.

However, space heating increases the internal temperature of a building. The usefulness of equation (6) is that it forms the physical basis of the demand for space heating. In equilibrium, the demand for space heating is equal to the heat loss through the building structure. When the outside temperature changes, thermal disequilibrium occurs as the thermal gradients in the building change. The desired equilibrium temperature may change. The time taken for thermal equilibrium to be restored depends on the extent of the change in the outside temperature, the internal temperature, the thermal properties of the building and the capacity and use of space heating to establish new equilibrium thermal gradients. These relationships are not modelled by the differential equation (6) and its solution (7). These equations represent a quite different occurrence, namely the cooling of an unheated building.

Equilibrium and dynamic effects of temperature on load may alternatively be modelled by the linear specification

$$\begin{aligned} Q_t &= \delta_0 (T_t - \theta_t) + \delta_1 (T_{t-1} - \theta_{t-1}) \\ &\quad + \delta_2 (T_{t-2} - \theta_{t-2}) + \ldots \end{aligned} \tag{8}$$

The first term of equation (8) is a linear approximation to the equilibrium state and the remaining terms are linear approximations to dynamic effects. There is no reason to expect to observe the simple relationship between the parameters of this equation as imposed by the construction of an effective temperature measure. Given that θ is generally unmeasured, an empirical implementation of equation (8) would include present and past outside temperature variables and allow free estimation of their lag structure.[1] A similar, but more complicated specification was used by Schneider, Takenawa and Schiffman (1985).

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1 Allowance for non-linearity in the temperature effects may be desirable. This would complicate the specification. A parsimonious specification could be to allow the present temperature variable to enter the specification in a non-linear manner.

Noon effective temperature variable - empirical evidence

The noon effective temperature variable construct assumes that the effect of past temperature can be represented by a fixed lag structure, as given in equation (7), on actual midday temperature. The fixed lag structure used by the Electricity Association (1990), following Davies (1958), is

$$ET_t = 0.57\,\theta_t + 0.28\,\theta_{t-1} + 0.15\,\theta_{t-2} \tag{9}$$

where t denotes daily observations. Apart from the Electricity Association (1990), there appears to have been little subsequent assessment of whether this is an appropriate lag formulation.

An evaluation of noon effective temperature can be made by freely estimating equation (4) augmented with 1st and 2nd order lags on actual noon temperature. Table 3 presents AR(7) regression results of such an exercise for five representative half-hours. The same sample data as earlier is used. An inspection of the coefficients on θ_t, θ_{t-1} and θ_{t-2} reveals that a declining weight lag structure is not always observed. For example for 02.30 to 03.00 hours and for 12.30 to 13.00 hours the coefficient on θ_{t-1} is larger (in absolute magnitude) as that on θ_t, and for 08.00 to 08.30 hours the coefficient on θ_{t-2} is larger than that on both θ_t and θ_{t-1}. An anomaly is apparent in the 02.00 to 02.30 half hour when consumption is "backward-looking", as indicated by the larger and more significant response arising from the previous day's noon temperature level than from the current day's noon temperature. A similar effect occurs for the 1230 to 1300 half hour. Thus, consumers are not as forward looking as is implicit in implementations which use noon effective temperature. This effect could be explained by lagged temperature being more important in explaining thermal gradients than is predicted by the noon effective temperature construct, the present noon temperature not yet having occurred and the lagged temperature being used by consumers to predict the current day's temperature. It is only by the late afternoon and evening half-hours that the lag structure on temperature appears to conform to the declining structure implied by the noon effective temperature construct. Thus, the structure of the dynamic relationship between load and current and past actual temperature varies considerably over the day and need not conform to any fixed distributed lag structure.

Table 3: ***Illustration of Temperature Dynamics***

	02.30 to 03.00	08.00 to 08.30	12.30 to 13.00	17.00 to 17.30	21.30 to 22.00
constant	0.214	0.831	0.665	1.051	0.916
	(11.097)*	(16.945)*	(9.501)	(18.014)*	(26.373)*
θ_t	-0.00051	-0.0025	-0.0019	-0.0035	-0.0023
	(-1.813)+	(-2.510)*	(-1.547)	(-2.787)*	(-3.022)*
θ_{t-1}	-0.00072	-0.00065	-0.0021	-0.0025	-0.0017
	(-2.531)*	(-0.694)	(-1.688)+	(-1.784)+	(-2.041)*
θ_{t-2}	0.00014	-0.0027	-0.0012	-0.00022	-0.0012
	(0.487)	(-2.799)*	(-1.045)	(-0.184)	(-1.537)
S_t	-0.000005	-0.00019	-0.00028	-0.0016	-0.00023
	(-0.086)	(-1.551)	(-1.115)	(-10.052)*	(-1.436)
R-squared	0.792	0.852	0.926	0.879	0.758
Regression std. error	0.0103	0.0347	0.0436	0.0449	0.0270
F(20,120)	22.790*	34.406*	74.901*	43.544*	18.809*
Durbin-Watson	2.009	1.966	2.022	1.982	2.021
Wald χ^2 (2)	7.156*	26.602*	2.206	0.310	1.866

Notes: Sample: Residential consumers on unrestricted tariff, 1/1/90 to 28/3/91, n = 148; AR(7) Estimation, $\rho_{d\,t-i}$ coefficients not reported; regressions include dummy variables for day-of-the-week, Christmas Day, Boxing Day and New Years Day, coefficients not reported; t-statistics in brackets; * indicates significance at 5%, + at 10%.

This evidence suggests that merely measuring temperature at one time during the day is inefficient. For loads at times before midday, it would appear sensible either to define and use temperature variables for times closer to the load observations or to allow free estimation of lagged temperature responses or both. The Wald tests reported beneath each regression in Table 3 are tests of the imposition of the net effective temperature restriction against a free lag structure, as reported. They confirm the suggestion that the noon effective temperature construct may be particularly inappropriate before midday. For the first two half-hours reported in the table the Wald tests reject statistically the imposition of the fixed lag structure implied by noon effective temperature.

5 NON-LINEARITY IN THE RELATION BETWEEN LOAD AND TEMPERATURE

In applied time-series econometric analysis, it has been common to assume that a relationship between demand and independent variables can be approximated by a linear specification, see for example Judge *et al.* (1985). Thus, the effect of air temperature on load has usually been specified in a linear form. However, consideration ought to be given to whether a linear specification is adequate on *a priori* grounds, to the empirical evidence on non-linearities and to the specification of non-linear relationships.

To maintain a system at a given temperature depends on the difference between the desired temperature and the outside air temperature. This relation is typically assumed to be linear. e.g. see Dubin (1985) and Parti and Parti (1980). Engle *et al.* (1986) appeal to the theory of thermodynamics in disputing this assumption.

The non-linearity of the response of electricity load and consumption to temperature variables has been discussed and investigated in the literature, see, for example, QUERI (1981) and DRI (1981), Train *et al* (1983), Baker (1985), Ramanathan *et al.* (1985), Engle *et al.* (1986), Ander and Hayslip (1985), Gregory and Wordley (1985), Brown (1987), Hagan and Behr (1987), Reddy (1990), Central Electricity Generating Board (1986), Electricity Association (1991), Peirson and Henley (1992) and Engle *et al.* (1992). With only the exception of the Central Electricity Generating Board study, all the cited studies found evidence that electricity load responded to temperature in a non-linear manner. The CEGB study found linearity for the winter period, but this finding is not inconsistent with possible non-linearities over the wider temperature rang observed over a full year.

Theoretical considerations

In Peirson and Henley (1992a), a theoretical model is developed to examine the relation between electricity load, Q, and air temperature, θ, and the chosen level of thermal comfort, T.

$$Q = f(T - \theta) \tag{10}$$

The function f is a technical relation that gives the energy necessary to support a chosen temperature difference ($T - \theta$). The economic aspect of this function enters through the choice of T.

An increase in θ increases real income and, as f" is positive, reduces the price of thermal comfort. This ensures that $0 < dT/d\theta < 1$. It can be shown that the effect of an increase in air temperature on heating load is negative.

$$\frac{dQ}{d\theta} = f'\left(\frac{dT}{d\theta} - 1\right) \tag{11}$$

The shape of the function f can be investigated through by considering the second derivative of (9)

$$\frac{d^2Q}{d\theta^2} = f''\left(\frac{dT}{d\theta} - 1\right)^2 + f'\frac{d^2T}{d\theta^2} \tag{12}$$

and considering two effects:

(1) Convection, conduction and radiation heat losses ensure that f' and f'' are positive, see Gebhart (1971).

(2) A satiation effect is likely to exist and eventually give a negative $d^2T/d\theta^2$.

The first term of the right hand side of equation (12) is positive. This suggests that f is a convex function of θ. The second term contains the term $d^2T/d\theta^2$, the sign of which is determined by the income and price effects stated above. If thermal comfort is a luxury service, a lowering of price and an increase in income would give a positive $d^2T/d\theta^2$, but a satiation effect for thermal comfort may give a negative value. Thus, satiation suggests that f is a concave function of θ. The sum of these effects is likely to give a non-linear heating energy load function. The non-linear function may contain convex and concave elements.

A formal microeconomic analysis of this model is given in Peirson and Henley (1992a).

Other more practical causes of non-linearities are fixed thermostat settings, the limited power of heating systems, air-conditioning and use of freezers/fridges.

Empirical evidence

It is important to consider the existence and extent of non-linearities in the load function. This is achieved though considering the literature and reporting on work carried out for the Electricity Association. There are two major approaches to modelling non-linear relationships between load and air temperature. The first approach is to specify an alternative functional form to the standard linear specification, e.g. a quadratic or log-linear specification. This approach has the advantage of simplicity and was used in Baker (1985), Ramanathan *et al.* (1985), Train *et al.* (1983), Engle *et al.* (1987), Gregory and Wordley (1985), Brown (1987), Central Electricity Generating Board (1986), Electricity Association (1991) and Peirson *et al.* (1991).

The second approach is to use semi- or non-parametric regression to describe the non-linear relationship between load and air temperature without a prior restriction on the functional form of the relationship.[1] This approach is the preferred when describing and testing for non-linear functions, but it is less convenient to use in forecasting. Non-parametric estimation is complicated to implement, but it essentially consists of approximating the true function by a continuously varying parametric form, see Hardle (1991). There are only two past studies – Engle *et al.* (1986) and Peirson and Henley (1992a) – that have considered semi- or non-parametric estimation of the response of electricity load to air temperature. Both studies found non-linear responses to be statistically significant and quantitatively important.

Peirson and Henley (1992a) allowed the response to vary linearly within each of a number of temperature intervals, through the use of a piece-wise linear

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1 The practice adopted, for example, by Electricity Association (1991) of dividing the year into several seasonal sub-periods and fitting a linear temperature-load relationship can be seen as a semi-parametric approach in that the annual relationship is being captured by a piece-wise linear relationship.

spline function. The model was estimated on panel household data from a Time-of-Use electricity pricing experiment and assumed a fixed household effect. The large number of households and observations justified not using the smoothing techniques of more complicated non-parametric estimation techniques. A non-linear response function was found for most estimation periods and most types of consumers; the non-linearity being greatest for night-time consumption and households with off-peak electric storage heating. The last result emphasises the importance of allowing for differences in the non-linear responses of different types of consumers and making air temperature responses conditional on the ownership of heating equipment.

In Peirson and Henley (1992a), the data used to estimate these non-linear response functions were daily observations on a sample of domestic consumers over two month periods. Thus, the results showed that statistically and quantitatively significant non-linear responses can be detected over relatively limited temperature ranges.

The more statistically sophisticated non-parametric study by Engle *et al.* (1986) used "a cubic smoothing spline" function that was fitted to the data on the basis of the goodness of fit and smoothness of the function. The dependent variable used by Engle *et al.* was average monthly sales per residential consumer. The differences in Engle *et al.*'s procedure from that of Peirson and Henley (1992a) was necessitated by the considerably fewer number of observations and the greater number of regressors. Though it was not possible to test simply for non-linearity, the reported and graphical evidence strongly suggests that the non-parametric estimates are statistically superior to those obtained under the assumption of linearity.

The practical importance of the non-linearity in the relationship between load and outside air temperature should be considered. Engle *et al.* (1986) give convincing graphical evidence of the importance of the differences in the estimated non-parametric response of Utility monthly consumption to temperature and the estimated linear specification of heating and cooling degree days. Peirson and Henley (1992a) estimated that the use of a linear specification of domestic night-time consumption in forecasting the effect of a fall in temperature from 8 to 6 degrees Celsius overpredicts the magnitude of the change by 23%. The DRI (1981) and QUERI (1981) studies estimated statistically significant non-linear effects which are of a moderate size.

The data from the Electricity Association Load Research Programme was used to investigate the existence of non-linearities in the relationship between load and temperature. This relationship may vary considerably between the same half hour of different days of the week, between different half hours and between different types of consumer. The variability of this relationship will arise because of variations between consumers in electricity use (for heating, lighting or other temperature-independent purposes) and because of variations in habitual patterns of behaviour across the day and across the week. For the different types of consumers, half hours and days of the week, smoothed cubic spline functions were fitted to the data on average load and air temperature. Full details of the estimation and data are given in Peirson and Henley (1992a).

The cubic spline function is fitted between data for load on day d and actual noon temperature on day d. This follows the common practice of only using the temperature at one time of the day and not using the temperature variables for different times of the day. Any functional relationship can be approximated using a polynomial function of a sufficiently high order. Thus, this approach allows a graphical presentation of the relationship between the two variables, which allows the data to dictate the form of the relationship. It allows one to investigate the extent to which the relationship changes over the range of the data. Although this form of non-parametric data investigation is rather technical in implementation, it produces very easily comprehended results, which can provide a very useful basis for exploratory data analysis. It also has the important advantage that the fitted relationship is one that places little weight on outlier observations. The principal drawback is that it is not possible to control for the effects of variation in other factors.

By illustration, Figures 3 and 4 present the cubic spline relationship for unrestricted domestic consumers in the year 1990/91 for the periods 02.00-02.30 and 17.00-17.30. The panels show scatter plots for 52 observations (53 in the case of Sunday). Load is plotted in the vertical direction and actual temperature in degrees Celsius in the horizontal. The panels show that for the average domestic unrestricted consumer the relationship between load and temperature exhibits clear non-linearities for most days and times of the day.

Figure 3: Smoothed cubic spline function for temperature and load: 02.00 to 02.30 hours

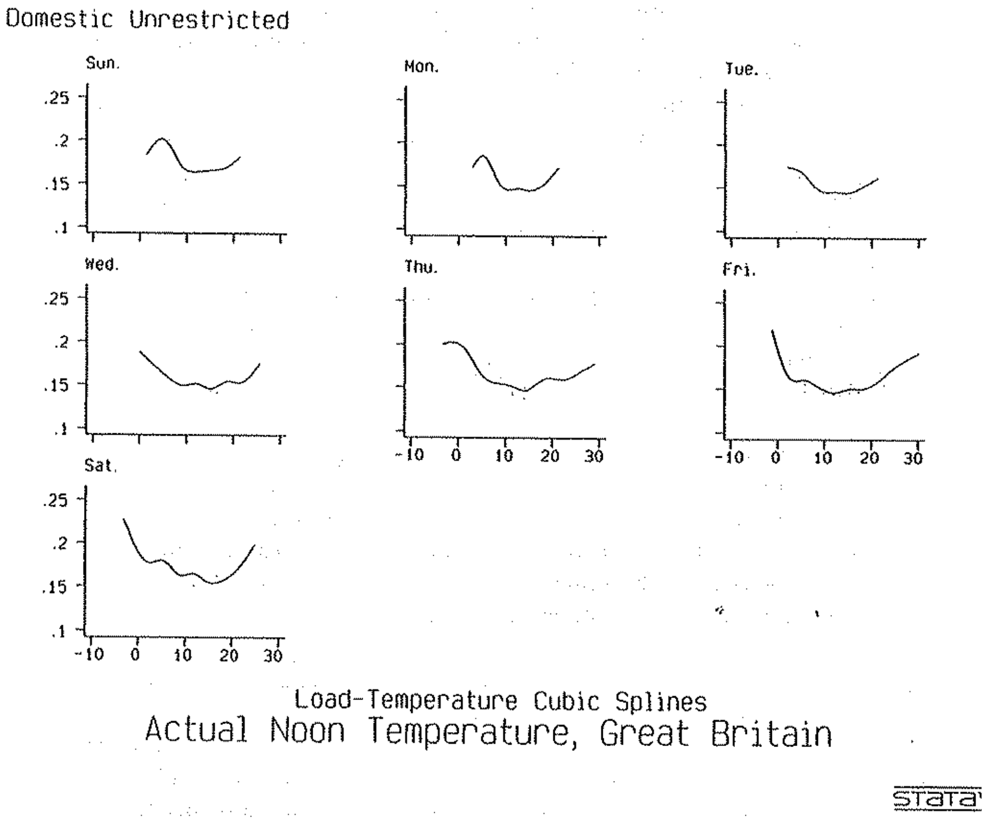
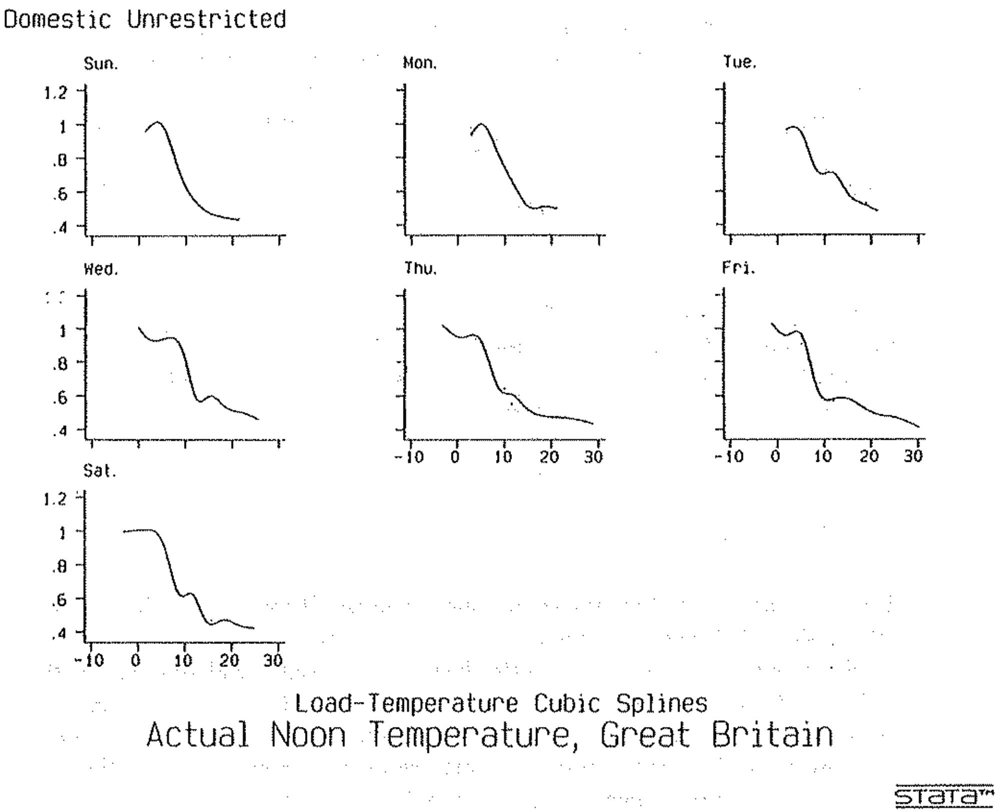


Figure 4: Smoothed cubic spline function for temperature and load: 17.00 to 17.30 hours



For the later half hour, a general pattern is for the effect on load of a additional degree rise in temperature to be smaller at higher temperatures. The cubic spline indicates a possible threshold effect at about 10 degrees Celsius. The panels also show that there are significant differences between the seven days of the week. For the early night-time half hour, there is a clear U-shaped relationship. This is commonly observed in the United States. In the British context, this may be due to the relative importance at night of the consumption of refrigerators and freezers. In the daytime, this consumption is relatively less important and the U-shape disappears. The panels also suggest the possible existence of convex and concave non-linearities in the relationship between load and temperature. More pronounced non-linearities are likely to be observed, as here, over a full year. It may be argued that linearity could represent an adequate specification over shorter periods of time, however this assumption was only supported by some of the sub-period data investigated in Peirson and Henley (1992).

These results are very similar for those for other types of domestic consumers and half hours. The response of commercial load to temperature is less marked, though there is still evidence of non-linearities. There is little evidence of any systematic relation between industrial load and temperature. These results are presented and discussed in Peirson and Henley (1992).

6 CONCLUSION

This study shows the importance of appropriate specification in modelling the relationship between electricity load and temperature. Simple static specifications of load appear to suffer badly from serial correlation, and with daily data the extent of this autocorrelation may extend beyond the first order. Serial correlation appears to bias upwards the estimates of the marginal response of load to temperature, and may result in serious overprediction of load when temperature departs significantly from average.

Even if there is no dynamic causal relationship between past natural variables and load, it is possible that the autoregressive specifications will provide good statistical explanations of load which can be easily used for normalisation purposes. This outcome requires the true static relationship to involve a strongly serially correlated error term and a high correlation between past and lagged temperature. Both of these are confirmed by empirical analysis of daily data.

The paper has also investigated the assumptions underlying the effective temperature construct. It is shown that allowing the coefficients of lagged temperature variables to vary freely can give quite different lag structures than that imposed by the noon effective temperature construct. Noon effective temperature may be particularly inappropriate when modelling before midday electricity load. Overall, the results in the paper suggest that the impact of temperature on electricity load cannot be accurately predicted by simply specifying lagged temperature variables which are estimated either freely or with an imposed restriction, whilst ignoring the highly autoregressive nature of observed data on both electricity load and temperature.

Finally, the paper shows that there are theoretical reasons for believing that heating load is a non-linear function of temperature and that empirical evidence suggests that these non-linearities do exist and are of importance. There are likely to be of greatest importance over a full year when summer cooling load causes an upward relationship between load and temperature and leads to a slight U-shaped profile for the full year. There is also evidence of a less pronounced curvature in the negative relationship between load and temperature at other times of the year.

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