Modelling household electricity consumption

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Abstract

A simulation model of household consumption of electricity is constructed taking account of intra-day climate and electricity price changes. The model is extended to endogenise household decisions concerning the stock and characteristics of appliances based on electricity prices and public policy (price subsidies and energy efficiency standards). Illustrative applications of the model are presented, estimating the effects of various tariff plans, regulatory and policy options, and climate scenarios on household electricity consumption and appliance purchase decisions.

The model utilises a novel theoretical technique to estimate a matrix of relative intra-day price elasticities for individual households and energy functions (including heating, cooling and lighting). Substantial variation is evident in the intra-day elasticities of demand for electricity between both households and energy functions.

A number of conclusions are drawn, however given the limited and non-representative nature of the data on which the model is calibrated, these can be treated as illustrative only. The model predicts that the introduction of intra-day pricing of electricity for the residential sector will yield efficiency benefits, reducing consumption during peak periods as the retail price better reflects the cost of supplying electricity. The distributional impact of the introduction of a time of use (TOU) tariff is not uniform across sample households, highlighting potential political difficulties in implementing pricing reform. The regulatory imposition of a price ceiling limits the extent to which energy efficiency benefits can be realised under a TOU tariff. The potential for policy options such as the introduction of minimum appliance energy efficiency standards, a carbon cap and trade scheme, and subsidies for the purchase of energy efficient appliances to reduce medium and long run electricity consumption is illustrated. Increases in temperature predicted for coastal Australia arising from climate change would increase aggregate household electricity consumption if further analysis based on representative data supported the climate response and intra-day price elasticity estimates of this study.
Declaration

This is to certify that:

- the thesis comprises only my original work towards the Ph.D except where indicated;
- due acknowledgement has been made in the text to all other materials used; and
- the thesis is less than 100,000 words in length exclusive of tables, maps, bibliographies and appendices.

Phillip de la Rue
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Chapter 1

Introduction

Electricity has several unique characteristics that differentiate it from most goods and services. It is difficult to store and is thus most efficiently delivered and consumed at the time it is generated. Substantial variation in demand over the course of each day results in the wholesale cost of electricity varying throughout the day, based on the source of the electricity generated. In addition, a physical maximum exists for supply, based on generation and network capacity. These characteristics, combined with the fact that electricity is a fundamental input to a vast array of processes carried out across all sectors of an economy, have ensured electricity consumption has long been a topic of interest in economic literature and has led economists (and others) to use a wide range of models to analyse and estimate it.

Two issues are central when examining the economics of household consumption of electricity. The first concerns peak load, while the second relates to the environmental impact of generating electricity. The total (household and industry) demand for electricity is not uniform throughout the day, week and year. The implication of this is that electricity generators and the electricity network do not operate at full capacity except during periods when demand for electricity is highest. These periods are known as periods of peak load.

For an electricity system to operate without cuts to power supply (blackouts), the capacity of electricity generators and networks must be sufficient to produce and carry electricity during periods of peak load. However, the return on generation and network assets used only during periods of peak load is limited since these assets are only used for a small amount of time. For generation assets used to supply peak load electricity, this substantially increases the wholesale price of electricity required to make peak load generation assets viable. For network assets, this increases supply costs for users of the network.

When the price of electricity to households is set at a uniform rate, the cost of electricity (made up of generation and network costs) is allocated equally across all electricity supplied
to households. A uniform electricity price does not allow households to take account of the actual cost of their electricity consumption at any given time. This is a growing concern, as household demand for electricity at peak periods has been increasing over time more quickly than total demand (Coates 2007, Brown and Koomey 2003). In an end-use study of electricity consumption by New South Wales households, Bartels and Fiebig (2000) found retailing electricity to households is less profitable than might be expected due to the substantial proportion of electricity consumed by households during peak periods. This trend requires continuing investment in generation and network assets at a rate that exceeds revenue growth (which, under a uniform electricity price, grows at the same rate as total demand). Investment at a rate exceeding revenue growth is only sustainable if the price of electricity is also increased.

There is also a distributional aspect to the variability of electricity demand. Under a uniform tariff the price of electricity during peak times is less than the cost of the electricity supplied, while at other times the price exceeds the cost. Households that consume disproportionate amounts of electricity during periods of peak load (generally through the use of air conditioners and other high capacity household appliances in the afternoon and evening) are effectively subsidised by households that consume a lower proportion of their electricity during peak periods.

The second issue central to household consumption of electricity is environmental. More than ninety per cent of the electricity supplied in Australia is generated by the combustion of fossil fuels (National Electricity Market Management Company 2008). This process creates greenhouse gasses, which are responsible for climate change. The household sector accounts for more than one quarter of all consumption of electricity in Australia (Dickson and Warr 2000, National Electricity Market Management Company 2008).

A number of technical and policy options have been proposed to address the peak load issue and environmental concerns associated with electricity consumption. The focus of this study is on measures affecting electricity demand rather than production. ’Smart’ meters - meters that among other things can record the time at which electricity is consumed (rather than just the aggregate over a period) - offer the promise of increased efficiency in household consumption, using tariff options such as time of use pricing to provide information to households concerning the cost of generating and providing electricity to them throughout the day. This has the potential to reduce peak demand, which would lessen the requirement for additional costly generation and network capacity. Direct load control for appliances such as air conditioners (remotely turning these appliances off for short intervals during periods of peak load) is also an option being trialled (Essential Services Commission of South Australia 2008).

Methods to limit electricity consumption (in order to reduce greenhouse gas emissions) that have been proposed include taxing the consumption of fossil fuels or capping emissions (both of which would increase the price of electricity generated using fossil fuels) and
subsidising or mandating more energy efficient appliances and dwellings.

In order to assess the appropriateness of these instruments in addressing peak load and environmental concerns, analysis is required of the quantitative effect on household consumption of electricity. In addition, the distributional impacts may also be relevant, as they are unlikely to be uniform across households. Technological and policy changes that have unforeseen or substantially regressive distributional effects may be politically more difficult to implement.

1.0.1 Contribution of the study

The purpose of this study is to investigate the effect of time of use pricing for electricity on household electricity consumption in order to estimate the responsiveness of households over a range of uses within the household. Reliable measures of residential intra-day price elasticities of demand are required for a future assessment of various policy responses to environmental, peak load, and regulatory issues. The economic modelling presented is consistent with microeconomic theory, informed by a household production function approach that considers electricity as an input to various different energy functions (heating, cooling, lighting et cetera).

This study makes a number of methodological and empirical contributions to the literature on intra-day household electricity consumption. While empirical studies have been carried out using Australian data to estimate price elasticities of demand for electricity for the household sector (a recent example is Narayan and Smyth 2005), these are based on annual data on aggregate electricity consumption. Using a novel technique introduced by Hirschberg (2000) intra-day own- and cross-price elasticities of demand for electricity are estimated in this study. This technique allows price elasticities to be estimated based on consumption data collected over a period in which no price variation occurred, alleviating the need for the costly rate experiments generally used to estimate intra-day elasticities of demand.

Following household production theory, which suggests that household electricity consumption should be modelled separately based on the type of output generated, elasticities are separately estimated for the different energy functions served by household appliance types. This is the first study in which intra-day elasticities of demand are estimated directly by energy function. The simulation model constructed using the own- and cross-price elasticities estimated is able to forecast electricity consumption by appliance type based on a schedule of intra-day electricity prices (a time of use tariff).

The empirical work presented in this thesis is timely and important for a number of reasons. The introduction of new metering technology combined with increasing concern with the environmental effects of electricity consumption and production have resulted in a variety
of tariff and policy proposals targeting electricity consumption. In order to assess the potential of these proposals to achieve their aims, analysis of the likely quantitative and distributional impacts of these proposals is required. The simulation model constructed in this study is used to empirically estimate the effects of time of use pricing on household electricity consumption and the related impact of various policy proposals intended to address environmental, peak load and regulatory concerns.

A further notable aspect of this study is the nature of the data used to construct the simulation model. This analysis is based on two Australian datasets containing high frequency observations of household electricity consumption by appliance. One of these datasets has not previously been analysed in an economic study; neither have been used to estimate price elasticities of demand. The benefits of using microdata of this nature include the ability to distinguish between appliance types, households and intra-day periods. An example of this is the estimation of the effect of temperature on electricity consumption for cooling and heating. Many studies estimate a single relationship between temperature and consumption, for example using the absolute value of the difference between temperature and 18.3°C (65°F) as an explanatory variable. The microdata used in this study allows the estimation of a comfortable temperature range for each household, taking account of differences in the way households consume electricity for cooling and heating.

A drawback to the two Australian databases utilised in this study is their relative narrowness and non-representative nature. The Mawson Lakes data were obtained from six households in South Australia, while the other data used in this study are from 41 Sydney households. However the simulation model constructed in this study is designed and intended to be utilised with more appropriate, representative microdata as it becomes available. Similarly, the modelling of household appliance updates and replacement relies on data on appliance price and energy efficiency data, which requires updating on a regular basis to appropriately reflect the appliances (and their characteristics) available to households through time.

The analysis adds to the literature in empirical microeconomics. Using a novel approach to estimate intra-day price elasticities for electricity within households, effort has been made to ensure the simulation model is consistent with microeconomic theory. The model is constructed to accommodate extensions allowing distributional analysis of the impact of various policy, economic and environmental changes. Uniquely, it allows for analysis based on intra-day price changes, with the potential to provide guidance on intra-day price variation for industry participants and regulatory and environmental policy. However such analysis would require the estimation of climate and intra-day price elasticities of demand based on representative data. It is hoped that such data are available in future as technology continues to reduce the cost of metering electricity consumption.
1.0.2 Outline of the study

The remainder of this study is organised as follows. Chapter 2 details the construction of a short run simulation model of household electricity consumption in which household responses to climate and intra-day price are estimated. Chapter 3 extends the time frame of the model by endogenising the appliance purchasing and replacement decisions of households with respect to appliance energy efficiency, appliance price and electricity tariff. In chapter 4 the simulation model constructed in the previous chapters is used to illustrate the potential effects of various industry, policy and climate scenarios. Chapter 5 concludes the study, summarising the findings, discussing the limitations of the study and suggesting directions for future research.
Chapter 2

Short run intra-day household electricity consumption

2.1 Chapter overview

In this chapter a short run simulation model of household electricity consumption is constructed. The primary purpose of the model is to predict how households will respond to various changes in the factors that influence their consumption of electricity over the course of a day. The main outputs of the model are estimates of household electricity consumption at the micro level. Households are individually modelled, with estimates made for 24 intra-day periods (of one hour duration) taking into account diurnal climatic factors (temperature, natural light) and allowing for intra-day price variation in the form of time of use (TOU) electricity tariffs. Within this framework the functions of different household appliances (such as heating, cooling and lighting) are separately modelled.

A review of the literature is provided in section 2.2. Household production theory, the theoretical foundation of the model, is described along with a discussion of the contrasting methods of modelling electricity consumption and related empirical findings. High frequency disaggregated data are required to model the intra-day consumption behaviour of individual households. Studies using such data are contrasted with those based on low frequency aggregate data (typically annual data on aggregate electricity consumption in a city or country). Findings concerning the significance of variables commonly included in models of household consumption of electricity are discussed.

The data on which the simulation model is based are described in section 2.3. High frequency intra-day electricity consumption data by household and appliance type sampled from two Australian cities (Adelaide and Sydney) are combined with climate data to create the datasets used in this chapter. An overview of the data is presented in which differences in electricity consumption between appliance types are illustrated along with
the time varying nature of household consumption.

An overview of the model structure is provided in section 2.4. The modelling time frame is discussed and data dimensions, including categories of electricity consuming activities (energy functions) are introduced. Deviations from the theoretical foundation on which the model is based are noted and the nomenclature introduced in this chapter is presented.

Relationships between household consumption of electricity and climate are estimated in section 2.5. The impact of temperature and natural light on intra-day consumption of electricity by individual household and appliance function (including cooling, heating and lighting) are estimated and out of sample forecast evaluations are carried out. Day of week dummy variables are included to account for weekly patterns in household consumption. As would be expected, the effect of climate on electricity consumption varies substantially across the different appliance types. The out of sample forecasts of the model are generally better predictors of household consumption than consumption lagged by either one or seven days.

Household response to variations in the intra-day electricity price are estimated in section 2.6. A novel technique developed by Hirschberg (2000) is used to estimate relative own- and cross-price elasticities of intra-day demand for electricity for individual households and appliance functions. Estimates of own- and cross-price elasticity are obtained by scaling the estimated relative elasticities so the mean price elasticity estimates for each appliance function are consistent with the findings of the literature concerning short run own-price elasticities for electricity. The intra-day own- and cross-price elasticities estimated are used to simulate the effect of intra-day variation in the price of electricity. In addition to the relationships estimated in section 2.5 these comprise the short run simulation model.

Section 2.7 presents an application of the simulation model. Profit maximising intra-day electricity tariffs are estimated based on household electricity consumption forecasts generated using the simulation model. A simple positive quadratic relationship between the wholesale price of electricity and aggregate electricity consumption is assumed along with a price constraint based on household expenditure on electricity. The profit maximising tariffs estimated using the simulation model differ substantially from a single uniform price generally included in household electricity tariffs, having higher intra-day prices during peak periods in the afternoon and evening and lower prices during the morning.

The chapter is concluded in section 2.8 followed by appendices 2.A to 2.E.
2.2 Literature review

The purpose of this literature review is to provide an understanding of the theoretical foundation and modelling approach adopted in this study. This is achieved by selective reference to the literature relied upon in the development of the simulation model presented in this chapter. The first component of the literature is the microeconomic theory used as a foundation for the model. This has informed the modelling approach adopted and assisted in defining the data characteristics required to address the research question. The second component comprises the array of studies examining electricity consumption. Knowledge gained from this literature range from methods concerning the application of theoretical concepts to specific estimation techniques. The findings of this literature are also used to support specific empirical assumptions relied upon in this study.

This literature review comprises three parts. The first introduces household production theory, a body of theory that enhances the standard microeconomic utility maximisation framework by distinguishing between final consumption and consumption as an input to household activities. This framework is well suited to describe electricity consumption as electricity is not consumed directly by individuals, rather it is used to power appliances which generate output such as heat and light. In the second part of this literature review an overview of different approaches used to model electricity consumption is presented. Models differ in a number of areas: purpose; the degree of consistency with microeconomic theory; and the level of detail in the data on which each model is based. The third part of the literature review summarises the findings of studies on electricity consumption.

2.2.1 Theoretical foundation

In this subsection, the theoretical foundation that informs the modelling approach is presented. This comprises microeconomic utility maximising behaviour extended to account for consumption as an input to productive activities, known as household production theory. Household production theory can be viewed as a body of literature that adds theoretical depth and realism to the standard utility maximising framework. The basic model (in which consumption of goods and services yields utility) is made richer with the addition of an intermediate step between consumption and utility. Goods and services can be inputs (as well as factors to be consumed directly) to activities that produce collections of characteristics that yield utility. Household production theory allows classification of goods and services as complements or substitutes in terms of their input to activities, and the resultant characteristics available from those activities. This is because the (utility yielding) characteristics obtainable through activities can be overlapping and/or can require similar goods and services as inputs. Household production theory also emphasises time as an important input to activities.
The development of household production theory is generally attributed to Becker (1965), Lancaster (1966) and Muth (1966). Becker (1965) emphasises time as an input to household production, attempting to replace leisure with time spent on consumption activities (the latter including activities contributing to household production that is then consumed by a household). Observed reductions in working hours in the century to 1960 are explained in terms of increased productivity at work (consistent with the findings of other researchers) and a reduced relative price of consumption activities (which require time as an input).

Lancaster (1966) presents consumer theory not in terms of consumption of goods and services that yield utility, but as the selection of goods and services to be used (as inputs) in 'activities' that produce collections of 'characteristics' that yield utility. The characteristics obtainable through activities can be overlapping and/or can require similar goods and services as inputs. This approach allows classification of goods and services as complements or substitutes in terms of their input to activities, and the resultant characteristics available from those activities, rather than stemming solely from consumer preferences.

Muth (1966) provides a highly technical paper outlining implications of household production theory in determining demand for goods that are inputs to household production. Useful results for microeconometric modelling (in terms of grouping types of goods) and elasticity estimation are presented. Muth (p707) also introduces luxury (or ostentation) as a type of characteristic that can yield utility in order to explain different income elasticities of demand across inputs that are otherwise similar (providing the example of different cuts of meat used as ingredients).

The theoretical framework developed by Becker, Lancaster and Muth is used as a foundation to the model developed in this study. The importance of household production theory lies in the structure it imposes on analyses of consumption behaviour. The basic microeconomic utility maximising framework is not well equipped to describe the productive activities of an individual or household that require the consumption of multiple inputs (including time). No distinction is made between the characteristics of output generated by different productive activities. These aspects of microeconomic theory are especially important when modelling electricity consumption, as electricity is an input rather than a final consumption good. In order to obtain utility from electricity an appliance is required to transform the electricity into a useful output. In this study, household demand for electricity is modelled as demand for an input to various activities that generate different utility yielding characteristics (including space cooling, heating and light). This is discussed in more detail in section 2.4 along with aspects of the model that can be considered departures from household production theory.

In order to demonstrate how household production theory can be applied to the modelling of electricity demand, an outline of the work of Flaig (1990) is presented. Flaig includes electricity as an intermediate good (an input) to household production and in-
tegrates this within an inter-temporal optimisation framework. A theoretical model of electricity demand is presented in which households maximise utility by the consumption of utility yielding characteristics. Some characteristics are only available externally (on the market) while others can be purchased on market or produced within households using intermediate goods (including electricity). An example of the latter is a meal, which can be produced at home or purchased in a restaurant. Flaig specifies intermediate goods including: household work (labour); the stock of durables that consume energy (capital); and energy. The study is based on aggregate annual data for households in Germany over the period 1964 to 1983. Increases in the price of market goods (such as the service provided by laundries, restaurants and theatres) are found to induce increased household production, while higher income and lower prices for energy consuming durables result in substitution of energy for labour. The price of energy is not a significant determinant of demand for durables and electricity.

There are similarities and differences in the way household production theory informs the work of Flaig (1990) and the study presented in this chapter. In both studies electricity is modelled as an input to household production, recognising there is a wide variety in the characteristics of output generated by different electricity consuming household activities. However where Flaig uses aggregate annual data, this study is based on high frequency (intra-day) data on the electricity consumption of a relatively small sample of households. Flaig includes the stock of durables as a variable, while in this chapter the appliance stock is considered fixed. Finally the price of substitute final goods and energy, included by Flaig, are not used in this study due to the relatively short period over which intra-day data is available.

2.2.2 Modelling approaches

There exists a wide variety of modelling approaches in the literature concerning electricity consumption. Models differ in their purpose; degree of consistency with microeconomic theory; and the data on which they are based. The approaches adopted and their theoretical basis are discussed in this subsection, distinguished by the level of aggregation of the data utilised.

Studies based on aggregate data

A substantial part of the modelling work carried out on household electricity consumption uses highly aggregated data. One strand of this focuses on forecasting by fitting statistical models that can replicate the observed dynamics of market price or aggregate electricity demand. Such models can be used to generate series of future electricity prices or demand and associated probability distributions, which are useful in studies of future generation
and network investment requirements. (In this study, the term electricity consumption is used rather than electricity demand, which is generally understood to be a function of price. However in the literature the terms are sometimes used interchangeably. In this literature review, the terminology adopted in an article is used when discussing that article.)

Identifying relatively stable seasonal, weekly and daily cycles forms the basis of this approach to modelling. Separate cycles and their distributional characteristics are estimated. Explanatory variables such as temperature are also included in some models based on this approach. Examples of recent studies of this kind include those of Benth et al. (2007), Magnano and Boland (2007), Li and Flynn (2006) and Cottet and Smith (2003). However, as Magnano and Boland (2007) recognise, models built by fitting statistical distributions to historical data are by their nature static and cannot account for economic or demographic changes affecting the variable being forecast. This limits their usefulness for the purpose of simulation modelling.

Analyses of this type are only weakly supported by microeconomic theory. A focus on cyclical patterns over variables relevant to consumer decisions concerning electricity consumption and the use of highly aggregated data does not follow from household production theory. No account is taken of the role of electricity as an input to a variety of household activities and the different output characteristics produced. For this reason, this modelling approach is not suited to this study, given the purpose of the model constructed in this chapter is to estimate the effects of climate and the intra-day price of electricity. However the identification of intra-day regularities, common to analyses of this type, is a component of this study. As outlined in section 2.5 the impact of climatic variables is modelled separately at different times of the day. This implicitly recognises that household electricity consumption can vary throughout the day in a predictable manner based on variables that are not observed/included in the available data (such as household preferences regarding meal times). The use of dummy variables for the day of week is a second instance where cyclical patterns are identified in the absence of suitable explanatory variables.

In comparison with studies that seek to identify cyclical and distributional characteristics of electricity markets, some studies based on aggregate data estimate electricity consumption using explanatory variables such as price and income. Such studies often report results as elasticities of demand. Recent examples of such studies include Lijesen (2007), Yamaguchi (2007), Zachariadis and Pashourtidou (2007), Narayan and Smyth (2005), Kamerschen and Porter (2004) and Flaig (1990).

Studies of these type are broadly consistent with household production theory. They often include a discussion of the implications of theory for modelling electricity consumption (see the earlier outline of Flaig 1990) and include variables likely to be relevant to the consumption decisions of household members. In these aspects, this study is similar, attempting to identify explanatory variables consistent with the application of household
production theory. However the model developed in this chapter is intended to explain electricity consumption over a shorter time frame than the studies noted in the previous paragraph. Analyses based on aggregate data do not directly address intra-day behaviour of individual households. An example of this is the use of temperature as an explanatory variable in these models. Temperature can vary over the course of a day and household production theory suggests that it is likely to be relevant to intra-day electricity consumption for heating and cooling appliances. However in models based on aggregated data temperature is often included as a count or sum of heating and cooling 'degree days', an aggregate measure of the temperature over a period of time (for an example see Zachariadis and Pashourtidou 2007, p186). Intra-day temperature characteristics are lost in these aggregate measures of temperature.

One aspect of these studies included in the model constructed in this chapter relates concerns the impact of intra-day price variation on electricity consumption. The price elasticity estimates reported in these studies are considered and utilised in the estimation of intra-day price elasticities of demand for electricity. This is discussed in detail in section 2.6.

Studies utilising microdata

While the majority of research modelling electricity consumption is based on aggregated data, studies have been carried out using microdata. These use detailed data on the consumption of individual households, in some cases distinguishing between the different appliances used by time of day. This is the method adopted in the development of the simulation model in this study. Examples of studies utilising microdata include Boonekamp (2007), Ehlen et al. (2007), Reiss and White (2005), Bartels and Fiebig (2000), Hirschberg (2000) and Matsukawa et al. (2000). These studies demonstrate the potential of microdata in explaining and predicting how households consume electricity.

A primary benefit of using microdata that identify the appliances used in the consumption of electricity is that the characteristics output by an activity can be broadly identified, permitting a closer match between theory and modelling approach. Electricity consumed in order to adjust the temperature of a dwelling can be distinguished from electricity used to provide light. Microdata of this type can be used to estimate the impact of explanatory variables on the different electricity consuming activities of households (as in Bartels and Fiebig 2000) and simulate the effect of changes in appliance stock and energy efficiency by appliance type (as in Boonekamp 2007). (The latter is the subject of chapter 3.) In this study, electricity consumption is categorised by the output type of each appliance, following the definitions proposed by Boonekamp (2007) (discussed in detail in section 2.4).

The use of high frequency microdata also facilitates the application of novel theoretical techniques to emerging areas of interest. Technical improvements to the capability of
household electricity meters now allow electricity retailers to set tariffs in which the price of electricity is a function of the time of day. The adoption of TOU tariffs by households has the potential to increase market efficiency (as retail prices better reflect the cost of generating electricity at different times of day). However estimating the likely impact of such tariffs on household intra-day electricity consumption in the absence of high frequency data relies heavily on assumptions concerning household response to intra-day price variation. In presenting a novel technique able to be used to generate relative intra-day price elasticities of demand, Hirschberg (2000) demonstrates the importance of intra-day consumption substitution to the design of TOU tariffs. The effects of TOU tariffs on intra-day electricity consumption is one of two applications used by Hirschberg to introduce a theoretically based method of generating matrices of estimated intra-day own- and cross-price elasticity of demand. This study uses the technique introduced by Hirschberg to estimate matrices of intra-day price elasticities of demand by household and appliance type. This is discussed in detail in section 2.6.

Once estimated, intra-day price elasticities of demand can be used to simulate the effects of various TOU tariff schedules on household electricity consumption. This permits analysis of the potential of these tariffs to improve market efficiency by reducing electricity consumption during periods of peak load. This issue is considered Ehlen et al. (2007), Bartels and Fiebig (2000) and Matsukawa et al. (2000), however these studies do not utilise detailed estimates of intra-day own- and cross-price elasticity in their analyses.

Ehlen et al. (2007) develop an agent based model which simulates the actions of electricity distributors and households in the offering and acceptance of electricity tariffs and the consumption of electricity by households. Rather than utilising matrices of intra-day price elasticity, intra-day household electricity consumption is divided into three categories: optional; movable; and immovable. The choice of electricity tariff by households is then modelled, with households selecting either a uniform or real time price electricity tariff based on the distribution of their electricity use between the categories, choosing the cheapest tariff based on their consumption. Household appliances are allocated to each of the categories and historical household hourly use profiles are used to simulate consumption (including load shifting when a TOU tariff is selected). Ehlen et al. then simulate the profit maximising tariffs offered by electricity retailers depending on recent market conditions (based among other things on the cost of electricity in the wholesale market during the different periods of recent days). While it is not specified how income and economic and demographic variables are included in the simulation, it is stated that household income does affect the level of load shifting.

Bartels and Fiebig (2000) present findings based on microdata obtained from over 250 New South Wales households whose appliances were directly metered for a period of time during 1993 and 1994. The data collected allow for econometric analysis of the consumption of electricity by appliance and time of day and comprise one of the two datasets used
in this study. The empirical results of Bartels and Fiebig provide a detailed and accurate picture of residential electricity consumption by end use. Prices were almost the same for all households across the sample, thus price is not included as an explanatory variable. A generalised seemingly unrelated regression (SUR) model allowing for heteroskedasticity by household, appliance and time of day across a month in winter (August) is estimated. The cost of servicing an average New South Wales household given wholesale electricity prices based on intra-day electricity consumption is also estimated. Bartels and Fiebig conclude that electricity consumed by the average New South Wales household includes an above average proportion of electricity generated during periods of peak load.

Matsukawa et al. (2000) utilise data generated from a three month TOU electricity pricing trial in Japan in 1996. The trial offered 400 participating Japanese households financial incentives to reduce their peak load electricity consumption. The price responsiveness of households is estimated directly, alleviating the need for assumptions concerning intra-day substitution (in contrast to the study of Ehlen et al. 2007). A constant elasticity of substitution (CES) utility function is specified in order to assess utility gained from peak and off-peak electricity consumption, along with non-electricity consumption. This is used to estimate a probit model to predict whether households will reduce peak electricity consumption in response to financial incentives. Matsukawa et al. estimate modest reductions in peak load electricity consumption resulting from the incentive payment offered in the pricing trial.

The model application presented in section 2.7 is in the spirit of Ehlen et al. (2007), Bartels and Fiebig (2000) and Matsukawa et al. (2000). TOU tariffs that maximise the profit of an electricity retailer are estimated using the matrices of intra-day price elasticity generated using the technique of Hirschberg (2000). A similar application (extended to incorporate improvements in appliance energy efficiency) is presented in chapter 3 and profit maximising TOU tariffs are estimated in the simulation scenarios presented in chapter 4.

2.2.3 Empirical findings

The findings of studies in this area are often presented in terms of the explanatory variables used to model electricity consumption. In this part, empirical findings reported in the literature are presented and discussed. The relationship between climatic variables (temperature and natural light) and electricity consumption is considered first, followed by price (both of electricity and other commodities) and demographic variables, concluding with a discussion of the modelling of cyclical and seasonal patterns of consumption.
Climate

The majority of studies account for the effect of temperature on household consumption of electricity. Appliances such as air conditioners and space heaters are used to regulate dwelling temperature, while the electricity consumption of a number of other types of household appliances and systems (most obviously fridges and freezers) may be affected by the ambient temperature. The effect of temperature is tested using a wide variety of methods and functional forms, possibly reflecting the subjective nature of the effect of temperature on comfort.

Magnano and Boland (2007) present a model able to generate sequences of aggregate intra-day electricity demand. Daily, weekly and yearly seasonality are estimated and the impact of daily mean temperature is included in polynomial form. Stochastic volatility is modelled using an autoregressive moving average (ARMA) process. The output of the model is used to build probability distributions of demand for forecasting purposes. The model uses data from South Australia over the period July 2002 to June 2005 (inclusive). The effect of temperature is modelled by classifying their data by daily half hourly period, then further subsetting into five groups based on the average daily temperature (less than 20°C, between 20°C and 22°C, between 22°C and 24°C, between 24°C and 26°C, and greater than 26°C). Magnano and Boland use polynomial functions (quadratic and cubic) to model the effect of temperature on household consumption of electricity, finding that for days where the mean daily temperature exceeds 22°C, the current ambient temperature is positively correlated with consumption for most periods of the day at temperatures above 25°C.

Cottet and Smith (2003) estimate a multi-equation vector autoregression for aggregate intra-day electricity consumption in New South Wales for a three year period from 1998 to 2000. Along with seasonal, trend and autocorrelation components, a bivariate function of temperature and humidity is used to explain household electricity consumption. Consumption is found to be substantially affected by temperature during periods of peak electricity load. The product of humidity and temperature is found to explain increased electricity consumption in the afternoon. Cottet and Smith go on to use the absolute value of temperature less 18.3°C (65°F) as an explanatory variable in a short term forecasting model. (Humidity is not used as it is considered to be less readily available as a meteorological variable.)

Using data collected in a 2003-04 critical peak pricing (CPP) pilot in the US, Herter et al. (2005) examine the average reduction in household electricity consumption during peak pricing events, disaggregated by temperature. Participants in the 2003-04 California Statewide Pricing Pilot on a CPP tariff were further classified as: without control technology (656); or with programmable communicating (advanced) thermostats (122). Herter et al. find that the response to peak pricing events occurring at times where temperatures
are high (-13 per cent) or low (-9 per cent) is more substantial than when the temperature is mild (-4 per cent). In a further comparison limited to high-use residential customers on the CPP tariff, households without control technology were found to respond more to peak pricing events than those with advanced thermostats between temperatures of 75°F (23.9°C) to 84.9°F (29.4°C). At temperatures above 90°F (32.2°C), high-use residential customers with advanced thermostats were found to respond more to peak pricing events than those without control technology. In simulating the effect of emergencies in the Californian electricity system, Herter et al. find that the CPP tariff tested in the California Statewide Pricing Pilot could reduce peak consumption by between one and two per cent without control technology, while use of advanced thermostats by high-use customers could reduce consumption by an additional one percentage point of peak system load.

In contrast to the studies of Magnano and Boland (2007), Cottet and Smith (2003) and Herter et al. (2005), which are based on intra-day data for electricity consumers, Zachariadis and Pashourtidou (2007) analyse electricity consumption in Cyprus using aggregate annual data for the period 1960 to 2004. A vector error correction model is estimated using explanatory variables including: GDP; the real retail price of electricity; and the annual sum of heating and cooling degree days. Heating and cooling degree days (defined respectively as days during which the maximum temperature is less than 18°C or exceeds 22°C) are significantly positively correlated with both household and commercial annual electricity consumption in Cyprus.

Temperature is not universally found to be significantly correlated with electricity consumption. Kamerschen and Porter (2004) use aggregate annual US data for the period 1973 to 1998 to estimate electricity demand and supply functions for the household and industry sectors. Estimates obtained by simultaneous equation models are compared to those of flow-adjustment models that take account of the estimated effect of the price of electricity on the appliance stock. Kamerschen and Porter utilise aggregate heating and cooling degree days (estimated using a midpoint of 18.3°C) as an explanatory variable for aggregate household and commercial electricity consumption. Cold weather (heating degree days) has a significant effect on household consumption, while hot weather is found to have no significant effect on household consumption. Temperature is not found to be a significant explanatory variable for electricity consumption of the commercial sector.

While Narayan and Smyth (2005) find that the sum of heating and cooling degree days is a significant explanatory variable they note that some studies using aggregate Australian data have found no significant correlation between temperature and electricity consumption. Narayan and Smyth estimate long run and short run price and income elasticities of electricity based on data for the period 1969 to 2000. An error correction model with an autoregressive distributive lag framework is estimated using explanatory variables including: real per capita income; the real retail price of electricity; the real retail price of natural gas (a possible substitute for electricity for households); and the sum of heating
and cooling degree days. Narayan and Smyth suggest that findings that cast doubt on the significance of temperature in models of electricity consumption may be the result of the use of quarterly dummy variables. These dummy variables may capture a degree of the effect of temperature variation between quarters (p472).

The study by Benth et al. (2007) based on the Nordpool (Nordic Electricity Exchange) market does not include temperature as an explanatory variable. Benth et al. model the Nordpool wholesale electricity price (rather than consumption) over a three year period beginning in April 1997. A mean-reverting model with stochastic volatility dynamics is estimated, with three separate random jump processes - common, rare and seasonal. Benth et al. conclude that in addition to describing the stylised facts of electricity markets (such as mean reversion and price spikes) the model can also describe additional features such as seasonality. It may be that the effect of temperature on the wholesale price of electricity is captured to some extent by the seasonal factors used by Benth et al. (in line with the suggestion of Narayan and Smyth 2005). However it is possible that in Norway the ambient temperature is usually below the range desired by Norwegian households, resulting in relatively constant electricity consumption for heating and little or no consumption for cooling. In this case, it would not be surprising to find little correlation between the ambient temperature and electricity consumption.

Lijesen (2007) estimates the real-time relationship between aggregate peak electricity consumption and the wholesale price of electricity using hourly price and energy consumption data for the Netherlands. The maximum daily temperature (including as a product with a dummy for noon to 4pm) is included as an explanatory variable in order to account for the effect of air conditioning and is found to be significantly positively correlated with electricity consumption. The use of the maximum daily temperature as an explanatory variable implicitly assumes that there is no point of inversion in the relationship between electricity consumption and temperature - electricity is assumed to be used for cooling but not heating. This is in contrast to most other studies reported, which test extremes of both high and low temperatures in explaining electricity consumption. Lijesen includes a variety of dummy variables in the model specification including dummies for the month of the year. As suggested by Narayan and Smyth (2005) such dummy variables may capture part of the effect temperature has on electricity consumption. An alternative possibility that would explain the inclusion of temperature in this form is if a substantial majority of domestic heating appliances in the Netherlands are fuelled by gas rather than electricity.

Given the variety of functional forms in which temperature is included in models of electricity consumption it is worthwhile considering the theoretical argument for its inclusion as an explanatory variable. Household production theory suggests that cooling and heating appliances are used to regulate the internal dwelling temperature, either to achieve a specific temperature or stay within a comfortable range. As noted above, various polynomial and two sided linear functions (based on aggregate heating and cooling degree days)
are used to describe this relationship between temperature and household consumption of electricity.

The functional form of the relationship between temperature and electricity consumption is an important issue to be addressed in a (simulation) model of household electricity consumption. Assumptions (either explicitly or implicit) regarding both the comfortable temperature range for households and the symmetry and functional form of the relationship outside the comfortable range are required. In using degree days as an explanatory variable, researchers implicitly assume a symmetric (absolute value) linear relationship between temperature and electricity consumption, with the comfortable temperature range assumed to be a point estimate (often 18.3°C or 65°F). For example Cottet and Smith (2003) use the absolute value of temperature less 18.3°C, stating that this is the point of inversion for parametric models widely used in the electricity industry.

In studies examining the functional form of the relationship, Engle et al. (1986) present a semiparametric model using smoothing splines and find it superior to the (linear absolute value) approach of using heating and cooling degree days (with different slopes for heating and cooling degree days) in estimating residential electricity consumption. Al-Zayer and Al-Ibrahim (1996) compare linear and quadratic functional forms, explaining electricity consumption in the Eastern province of Saudi Arabia in terms of degree days for the period 1986 to 1990. Al-Zayer and Al-Ibrahim find both quadratic and linear functional forms satisfactorily capture the relationship between temperature and electricity consumption. However the implications of these findings for a study such as this are not unambiguous. In both the research of Engle et al. (1986) and Al-Zayer and Al-Ibrahim (1996), the explanatory variable degree days (an aggregate) is used rather than intra-day data capturing ambient temperature and concurrent electricity consumption. In addition, there are no negative degree days in the dataset for the Saudi province used by Al-Zayer and Al-Ibrahim.

In this study a flexible functional form is used to estimate the impact of temperature on electricity consumption for space cooling and space heating. An exponential parameter is estimated on the difference between the external temperature and the relevant threshold (upper or lower) of the estimated comfortable temperature range of each household. This is described in detail in section 2.5.

In addition to temperature, the level of natural light is sometimes considered in studies of household lighting demand. Stokes et al. (2004) presents a model of domestic lighting demand based on intra-day data measured half-hourly for 100 households in the United Kingdom in the period from March 1996 to April 1997. The mean level of natural light during each half-hourly period during the year is found to be a significant variable in explaining electricity consumption used for the purpose of domestic lighting. A potential criticism of the use of the mean level of natural light is that the effect of weather (clouds and storms) on the actual level of natural light available is not accounted for. However the
actual level of natural light received by households depends not just on weather conditions but also on the characteristics of each household dwelling. The design of houses (for example the location and size of windows) will affect the natural light available and reduce the potential benefit of precise meteorological measurement of light over mean light levels for individual households.

Lijesen (2007) includes a proxy for the hours of daylight (measured as the quadratic difference from the longest day measured in days) as an explanatory variable. Electricity consumption is negatively related to the mean level of natural light proxied in this way. The significance of daylight as an explanatory variable is increased when included as a cross-product with a dummy variable indicating whether or not the sun sets prior to 6pm on a given day, possibly capturing the effect of natural light on household food preparation and meal times.

Along with temperature, the inclusion of the level of natural light as an explanatory variable in this study is described in detail in section 2.5.

Price

The effect of price on electricity consumption is generally estimated in the literature as a point estimate own-price elasticity of demand. Distinctions are sometimes drawn between long run, short run and time of use or real time (instantaneous) elasticities. A wide variation in estimated price elasticities is reported, varying from near unity to highly inelastic estimates.

Lijesen (2007) presents a survey of recent studies which estimate short run, long run and time of use price elasticities of demand for electricity. Most short and long run price elasticity estimates are between -0.1 and -0.8, with the short run estimates generally of a lower magnitude than those for the long run. Studies based on panel data are found to generally report higher (absolute) price elasticity estimates than those based on aggregate time series data. Lijesen suggests this may be the result of time varying exogenous factors that affect (increase) both consumption and price, partly offsetting the negative effect of price on consumption.

In the time of use studies summarised by Lijesen, own-price elasticity estimates for off-peak periods are generally of lower magnitude than those for peak periods. Estimates of own-price elasticities in these studies vary from zero to -0.2, apart from one study in which they are found to be elastic. However Lijesen suggests that the results of this study (Filippini 1995) are influenced by misspecification. Cross-price elasticities of demand estimated in time of use studies vary from those 'not significantly different from zero' to estimates larger in magnitude than own-price elasticities for adjacent intra-day periods. These imply substantial substitution of electricity consumption will occur between adjacent intra-day
periods following a change in intra-day prices.

Lijesen goes on to list reasons why estimates of price elasticity reported in different studies may vary. In addition to differences in data frequency (categorised by Lijesen as the period in which price changes are observed - short run, long run and time of use or real time) estimates are based on data for different sectors and of varying quality. Results can be based on electricity consumption of an entire market, an industry or a sector (such as the household sector). In addition, data are often not available on the electricity consumption and prices paid by all consumers. Lijesen observes that in the case of the Netherlands the majority of electricity consumed is traded directly between consumers and suppliers rather than through the wholesale market. The details of these contracts are not generally disclosed, severely and systematically limiting the information available on which estimation and inference can be drawn.

Another potential concern with point estimates of price elasticities is that the effect of some factors that may influence the price sensitivity of consumers are not considered. This issue is highlighted in the study of Yamaguchi (2007) in which the price elasticity of energy demand in Japan is estimated taking into account structural breaks. For the ten year period beginning in 1993 (characterised by low economic growth in Japan) aggregate energy demand is found to be more price elastic (-0.43 compared to -0.149) than in the previous eight years (in which economic growth was high). While this may be the result of time varying exogenous factors increasing both consumption and prices more in the earlier period as proposed by Lijesen (2007), it suggests that consideration needs to be given to the characteristics of the underlying data when using point estimates of elasticity presented in the literature.

Addressing a similar question to that of Hirschberg (1991), Reiss and White (2005) suggest a method of estimating point price elasticities for households that face non-linear tariffs (including tariffs characterised by intra-day price variation). Utilising data on annual Californian household appliance ownership from a representative sample of the US Residential Energy Consumption Survey linked with annual electricity consumption and tariff information, Reiss and White present a model of endogenous sorting along non-linear price schedules (tariffs) with heterogeneous price sensitivity based on appliance ownership. To address weather and tariff variability, a projection of monthly household electricity consumption is constructed based on annual household consumption and observed tariff and weather (heating and cooling degree days) data. Dummy variables for appliance ownership are included and electricity consumption by specific appliances are treated as latent outcomes. Substantial variation in household price elasticity of demand is found, with a small proportion of the population responsible for the majority of any response to price variation. Around nine per cent of households are estimated to be price elastic (with price elasticities of demand greater than one), while 44 per cent are price insensitive. The median non-zero household price elasticity of demand is estimated to be around -0.5 (mode
around -0.3). Reiss and White suggest that households can effectively be categorised as either: users of space heating and cooling that exhibit some price elasticity; or households that do not use space heating and cooling appliances and are price insensitive.

Faruqui and Sergici (2009) survey recent experimental results on household response to dynamic pricing of electricity, finding that households do respond to higher prices. Examining studies covering both TOU and critical peak pricing (CPP) tariffs, Faruqui and Sergici find that TOU rates can induce a reduction in peak demand by between three and six per cent, while CPP tariffs can further reduce peak demand by between 13 and 20 per cent. Reduced peak period electricity consumption can disproportionately cut the cost of supplying electricity. Faruqui et al. (2007) note that a five per cent fall in peak consumption in the United States would save around $3 billion annually, largely from reduced capital outlays on generation and distribution. Additional savings by consumers arising from reduced wholesale electricity prices are also described, however these may represent transfers from electricity generators or retailers, rather than economy-wide efficiency increases.

Enabling technology can further increase the sensitivity of residential consumers to dynamic pricing of electricity. Faruqui and Sergici (2009) conclude that thermostatic controls on space cooling appliances can assist CPP tariffs reduce peak consumption by around 27 per cent and up to 44 per cent in the case of ‘gateway’ systems (where multiple appliances are automatically adjusted based on the price of electricity).

The work of Faruqui and Sergici (2009) is expanded by Newsham and Bowker (2010), who identify further experimental studies, focusing on those carried out in North America post-1997 that address summer peak load. Similar to the review of Faruqui and Sergici (2009), Newsham and Bowker conclude that TOU tariffs can reduce peak consumption by around five percent and CPP tariffs by at least 30 per cent. However Newsham and Bowker suggest that the relatively small reduction in peak consumption induced by the introduction of a TOU tariff can be significant, pointing to a study by Rosenzweig et al. (2003) in which a reduction of two to five per cent in peak consumption is estimated to reduce the spot price of electricity by potentially more than 50 per cent during peak periods.

Estimates of price elasticity of demand for Australian residential consumers are reported by Narayan and Smyth (2005). Long and short run price elasticities of -0.54 and -0.26 respectively are estimated. These are consistent with earlier findings for Australia (both as a whole and in studies on specific regions) (Narayan and Smyth 2005, p471).

The findings summarised by Lijesen (2007) concerning short run and time of use intra-day price elasticities along with the short run estimates of Narayan and Smyth (2005) for Australia are used in this study to estimate intra-day price elasticities of demand using the relative elasticities of demand generated using the technique of Hirschberg (2000). This
is discussed in detail in section 2.6.

The price of commodities other than electricity may affect household consumption of electricity. Household production theory suggests that the price of appliances (complements) and energy in forms other than electricity (substitutes) are likely to affect electricity consumption. Studies that take account of the function of electricity as an input to household production generally include a price index for a substitute form of energy (gas or oil, depending on the market being studied and subject to data availability). Examples include Narayan and Smyth (2005), Kamerschen and Porter (2004) and Matsukawa et al. (2000). The price of substitute forms of energy are found not to be significant as explanatory variables in these studies.

Households cannot easily substitute between forms of energy in the short run, as this generally requires the replacement of household appliances. Bartels and Fiebig (2000) state that 'in the short run, appliance stocks are fixed and existing evidence suggests that the bias from ignoring possible exogeneity may be small'. It is also possible that some household appliance types are not able to be fuelled by energy sources other than electricity - entertainment appliances such as televisions for example. Alternative forms of energy (such as reticulated gas) may also not be available to all households if a distribution network does not comprehensively cover the area from which a sample is taken. In addition to the price of alternative forms of energy, availability may also be an important factor. As noted by Narayan and Smyth (2005), the specification of empirical models in studies of electricity demand generally falls short of the ideal based on household production theory due to data constraints (p468). A lack of suitable data is generally the reason variables concerning substitute forms of electricity are often not included in studies of electricity demand.

This study does not include the price of an alternative energy source or a measure of appliance prices in the short run model presented in this chapter. The effect of appliance prices are incorporated in the simulation model in chapter 3. The price of an alternative form of energy is not estimated in this study due to lack of data. The study is also limited to the consumption of electricity by households. A substantial body of work on the non-household electricity consumption exists, including on the effects of intra-day price variation (see Aigner and Hirschberg (1985) on the response to TOU pricing of commercial and industrial consumers).

**Demographic variables**

Households are heterogeneous both in characteristics and preferences and these can influence household electricity consumption. Bartels and Fiebig (2000) include a number of demographic variables in their study (as products with appliance type) including: the number of bedrooms; type of dwelling (apartment or house); household income; and the
number of people comprising the household. All coefficients estimated for these variables are positive and the majority are significant.

In a study of household electricity use, Ironmonger et al. (1995) remind us that ‘appliances do not use energy; people and households do’ (p302). The study combines Australian data sources including the Australian Bureau of Statistics catalogues: 1988-89 Household Expenditure Survey; and 1985-86 National Energy Survey: Annual Consumption of Reticulated Energy by Households. Ironmonger et al. estimate economies of scale in reticulated energy use for households of different types and sizes. Smaller households are found to consume more electricity per member than larger households. Examining the size, age and income demographics of households leads Ironmonger et al. to conclude that older households, which tend to have lower than average income and members, benefit the least from efficiencies of scale in electricity consumption and pay the most per member for electricity.

Herter (2007) examines the impact of a CPP tariff on households with different electricity usage and levels of income. Based on data from the California Statewide Pricing Pilot of 2003-04, Herter finds that high-use customers reduce electricity consumption by more than low-use customers, but that low-use customers experience a larger percentage reduction in expenditure following the introduction of a revenue neutral CPP tariff. A major impediment to the introduction of such a tariff (possibly shared by TOU tariffs) is that low-income customers that use substantial electricity are expected to experience electricity bill increases of 10 per cent or more. Around eight per cent of customers in the sample were classified as low-income, high-use consumers. Herter suggests that these residential customers may benefit from efforts to increase energy efficiency as part of the introduction of a CPP tariff.

Drawing on the results of five US studies, Faruqui et al. (2010) conclude that many low income customers would benefit from the introduction of dynamic pricing of electricity. Such customers are generally less responsive to intra-day price changes. However the intra-day profile of electricity consumption for such customers is such that the majority would experience a reduction in expenditure on electricity, even in the absence of any price response from a revenue neutral CPP tariff.

The characteristics of household appliances and the household dwelling can also affect household electricity consumption. The energy efficiency of an appliance measures how much energy is required to produce a desired output. Likewise the characteristics of a dwelling can influence the energy required to achieve a certain result. For example, an energy efficient air conditioner installed in a well insulated, small house will require less energy to keep the temperature within a desired range than a less energy efficient air conditioner in a poorly insulated, large house. Appliance and dwelling characteristics are the central consideration of Boonekamp (2007) in a study of the likely effectiveness of subsidies for energy efficient appliances/systems and more stringent standards for appliances.
on electricity consumption.

Demographic variables are not considered in this study. This is due to the relatively small number of households in each sample and a lack of data. The impact of household decisions concerning appliance upgrades and replacements is examined in chapter 3.

**Cyclical consumption patterns**

Findings of significant autocorrelation in household electricity consumption are common in studies based on both aggregate and micro-level data. Benth et al. (2007) report the size and frequency of stochastic volatility in the Nordpool wholesale electricity price are seasonally dependent. Li and Flynn (2006) find significant daily and weekday-weekend patterns in wholesale electricity prices in fourteen electricity markets, although the significance of the autocorrelation differs markedly between these markets. Magnano and Boland (2007) find significant daily, weekly and yearly seasonality in aggregate intra-day electricity consumption in South Australia, while the findings of Cottet and Smith (2003) for New South Wales aggregate intra-day electricity consumption are similar, with significant seasonal factors and intra-day autocorrelation.

As noted earlier, this study models the impact of climatic variables by hourly intra-day period and uses day of week dummy variables to identify weekly cycles in household electricity consumption (outlined in section 2.5).

**2.2.4 Concluding remarks**

The review of literature in this chapter has presented the theoretical and empirical literature relied upon in the construction of the model presented in this chapter. Concepts used to guide the modelling approach have been highlighted and the methods and findings utilised presented and discussed.
2.3 Data

In this section the data used to model household consumption are described. Two sets of Australian data comprised of high frequency intra-day observations of household electricity consumption are used in this chapter to estimate the simulation model. One contains data from Mawson Lakes (a suburb of Adelaide, the capital city of South Australia) while the other is compiled using data from Sydney (the capital city of New South Wales). These are combined with data on climatic variables and retail and wholesale electricity prices. An overview of the data is presented in which differences in electricity consumption between energy functions are illustrated along with the time varying nature of household consumption.

In comparison with the ready availability of highly aggregated data, datasets containing intra-day observations of electricity consumption by energy function are scarce. As noted by Bartels and Fiebig (2000, p52), metering individual appliances has traditionally been a costly and time consuming process. Due to data contraints, studies in this area generally either do not disaggregate electricity consumption by energy function or treat consumption by specific appliances as latent outcomes. This lack of data is a drawback, as it limits the certainty with which conclusions can be drawn. In an analysis of a Californian CPP pilot, Herter et al. (2005) conclude that household response to peak pricing events is greatest on hot days and that this reduction appears to arise largely as a result of conservation rather than load shifting. Data on specific appliance use would allow insight into what appliances (presumably space cooling appliances) are used less intensively during peak pricing events and whether there are any substitution between appliance types during these periods.

The processes involved in sourcing the high frequency consumption data used in this study were not trivial, requiring the agreement of multiple stakeholders in two countries. The Mawson Lakes dataset required a significant amount of effort to order and be assured of data quality (outlined in appendix 2.D). A condition of use was the completion of an ordered, quality assured database in a format easily usable in future studies. This was delivered to the University of South Australia in December 2008.

The Sydney (RES) dataset was originally obtained by Pacific Power and Sydney Electricity, which are now part of the firm Energy Australia. Unfortunately Energy Australia does not retain a copy of this dataset. A copy was located (following an extensive search which included previous academic users of these data) in the possession of a New Zealand firm, BRANZ. This firm had been given a copy of the dataset to carry out work for the Australian Government Department of the Environment, Water, Heritage and the Arts. Negotiations with both Energy Australia (the owner of the data) and the Department of the Environment, Water, Heritage and the Arts (whose agreement was requested by BRANZ) were successfully completed in March 2009 and June 2008 respectively.
It is hoped that as the number of smart meters installed and used to meter household consumption for households increases, the cost of collecting data of this type will fall, facilitating the availability of high frequency data for research purposes.

2.3.1 Data sources

Mawson Lakes

The University of South Australia (in conjunction with ETSA Utilities and Envestra Ltd.) conducted a study that involved the monitoring of the electricity consumption of six households in the Adelaide suburb of Mawson Lakes for a period of two years. As outlined in Saman and Mudge (2003), monitoring equipment was installed by the respective utilities to record electrical consumption of all power circuits from April 2002 and March 2004 (inclusive). Power readings were recorded every fifteen minutes over this period. The energy function of each circuit was also recorded, allowing electricity consumption to be linked to specific appliance types. The time recorded in the monitoring is standard time (unadjusted for daylight savings). This data is merged with climate data for Mawson Lakes of one hourly frequency obtained from the Australian Bureau of Meteorology.

Sydney (RES)

NSW electricity distributors Pacific Power and Sydney Electricity (now Energy Australia) carried out a Residential Energy Study (RES) based on a sample of 248 residential customers. These data are used in the study of Bartels and Fiebig (2000), discussed in the literature review (section 2.2). Each household’s electricity consumption was monitored from mid 1993 to late 1994 (the exact period monitored varied by household). Within each household, a sample of appliances were monitored (to a maximum of eight appliances) and the electricity consumption of these appliances was recorded every half hour over the sample period. The time recorded in the monitoring is standard time (unadjusted for daylight savings). Demographic data were collected in survey form in the original RES study, however unfortunately no demographic data are contained in the copy of the RES dataset obtained for use in this study.

Much of the data in the RES dataset obtained are missing. For that reason, a sample of households included in the RES study are used in this study. Households with substantially intact data over a period of fourteen months beginning 1 June 1993 are included in the sample. The sample period is chosen in order to maximise the number of households able to be included in the sample given the period monitored and the data quality. Data from 41 households are included in the Sydney sample.

Data for 16 per cent of households in the RES dataset are completely missing. For another
15 per cent of households, data are more than 99 per cent missing. The distribution of the remaining households with missing data (excluding those in the Sydney sample) in the dataset across the 14 month period used in this study is shown in figure 2.1. While the majority of households have less than half of their associated data missing, the distribution is disappointingly wide. The substantial seasonal differences in household consumption illustrated later in this section (see figure 2.7 for mean aggregate consumption and figures 2.8 to 2.17 for mean consumption by energy function) suggest the utilisation of data for households that have substantial parts missing may be problematic.

![Distribution of households by proportion of missing data](image)

(a) Sydney (RES)

Figure 2.1: Distribution of households by proportion of missing data

The Sydney sample is merged with hourly temperature data for the Sydney central business district obtained from the Australian Bureau of Meteorology. Solar radiation recorded by date and time of day at the Wagga Wagga weather station are also included in the Sydney sample. This weather station is the station nearest to Sydney that recorded solar radiation during the period that the RES dataset was collected. The location of each household in the Sydney sample is not known. The use of temperature for the Sydney central business district and solar radiation for Wagga Wagga for all households in the Sydney sample introduces measurement error for these climatic variables.

**Historical retail and wholesale electricity prices and consumption**

A list of the retail electricity tariffs charged by the Australian Gas Light Company (AGL) in South Australia during the period July 2002 to December 2005 (referred to as Australian Gas Light Company 2005) is used to inform assumptions concerning the electricity price paid by households in the Mawson Lakes sample. These households are assumed to have faced the uniform (intra-day) price tariffs for household general supply (tariff 126)

Half hourly wholesale electricity price and demand data for South Australia for 2002 to 2004 are sourced from the National Electricity Market Management Company internet website (now the Australian Energy Market Operator). These datasets are referred to in this study as National Electricity Market Management Company (2003).

### 2.3.2 Data overview

In this subsection important characteristics of the data used in the study are highlighted. The intra-day profiles of mean temperature and natural light are presented, along with distributions of electricity consumption and the wholesale price in the South Australian regional market for the period the Mawson Lakes sample was collected. Distributions of intra-day electricity consumption from each sample are presented, showing the degree of variation in consumption in each intra-day period. Variations in seasonal intra-day household electricity consumption are illustrated, revealing substantial discrepancies both between seasons and samples. The intra-day profiles of electricity consumption by energy function are compared in order to emphasise the variation in electricity consumption on different household activities that require electricity over the course of a day. These differences are important in chapter 3 in which the effects of improvements in the energy efficiency of different appliance types are simulated.

A period of peak electricity consumption in the Mawson Lakes sample is also shown. Intra-day consumption during four days, three of which are characterised by extremely high temperatures, are included to demonstrate the contribution of air conditioning (space cooling) to peak electricity consumption.

The figures presented in this subsection are based on the first year of data in each sample. This is done to ensure the effects of seasonal factors are included and to enable comparisons between the two samples. The majority of figures included in this subsection comprise two adjacent subfigures, the first of which is based on data from the Mawson Lakes sample, and the second based on the Sydney sample. Figures are included in this form throughout this study when results from the two samples are separately presented.

### Mean climatic variables

A comparison of mean intra-day temperature and natural light (figures 2.2 and 2.3) reveals the Mawson Lakes climate was warmer during summer than that of Sydney in their respective sample periods. Mawson Lakes also received substantially more natural light than Sydney (based on the solar radiation measurements for Wagga Wagga) in all seasons. Seasonal variation is observed in both temperature and natural light across the samples.
The temperature is warmer in summer and colder in winter across all intra-day periods. The level of natural light is greater in summer than winter and the period of daylight varies by three and four hours between these seasons.

![Figure 2.2: Mean seasonal intra-day temperature (°C)](image)

(a) Mawson Lakes  
(b) Sydney

![Figure 2.3: Mean seasonal intra-day natural light (Wh/m²)](image)

(a) Mawson Lakes  
(b) Sydney

**Distribution of electricity consumption and wholesale price (South Australia)**

The distribution of electricity purchased in the South Australia region of the Australian national electricity market in 2003 is presented in figure 2.4. The distribution of the wholesale price of electricity in the South Australian region in 2003 is shown in figure 2.5 (both for prices less than $0.30/kWh and for all prices). No data are presented for the Sydney sample as the RES preceded the introduction of the Australian national electricity market.

In these figures, observations between the 25th and 75th percentiles of each intra-day period are contained in the associated boxes while the lower and upper bars contain observations between the 5th and 25th percentile and 75th and 95th percentile (respectively). The lower and upper whiskers (extending beyond the bars) in the figures contain observa-
tions between the 1st and 5th percentiles and the 95th and 99th percentiles. Minimum and maximum values for each intra-day period are marked with a dot. The distribution of mean household electricity presented in figure 2.6 also follows this structure.

Electricity consumption in South Australia is lowest and least variable in the hours between 2am and 7am (figure 2.4). Electricity consumption generally increases and becomes more variable from 7am to 7pm. The maximum observed levels of consumption occurred in the late afternoon. This profile is reflected to a degree in the distribution of wholesale prices, which are also lowest and least variable between 2am and 7am (figure 2.5). Wholesale prices above $0.10/kWh are observed between noon and midnight, with the majority of these in the mid-afternoon and early evening. The wholesale price was often higher in the hour between 6pm and 7pm, with 25 per cent of the observations greater than $0.06/kWh and five per cent greater than $0.20/kWh (exceeding the retail price of electricity in all tariffs listed in Australian Gas Light Company (2005) for that period). The extreme prices observed between 6pm and 7pm are clear in subfigure 2.5(b) which shows that the wholesale price of electricity reached $2.90/kWh in the hour between 6pm and 7pm.

![Figure 2.4: Distribution of mean South Australian intra-day electricity consumption (kWh): 2003](image)

(a) South Australia

Figure 2.4: Distribution of mean South Australian intra-day electricity consumption (kWh): 2003
Figure 2.5: Distribution of mean South Australian intra-day electricity wholesale price ($/kWh): 2003

**Distribution of mean household electricity consumption**

The distributions of mean household consumption for each sample are presented in figure 2.6. In both the Mawson Lakes and Sydney samples, the majority of observations of mean household consumption are clustered between 0.5 to 2kWh. The profiles of the observations between the 25th and 75th percentiles are similar in both datasets, displaying a diurnal pattern with a minor morning peak and a major evening peak. There is more variation in observations at the upper end in Mawson Lakes, with both the 95th and 99th percentile substantially higher in Mawson Lakes than in Sydney, however this is to be expected since there are more households in the Sydney sample.
Figure 2.6: Distribution of mean intra-day household consumption (kWh)

Mean seasonal consumption

Mean intra-day electricity consumption (across all households in the respective samples) is displayed in figure 2.7 by season. Summer and winter consumption are separately plotted along with the combined mean for spring and autumn. The intra-day profiles of mean consumption differ both across seasons and samples. In the Mawson Lakes sample, mean consumption during summer steadily rises from 6am to peak at around 6pm reflecting the profile of consumption on space cooling (see subfigure 2.8(a)). Winter consumption has two separate peaks: a minor peak around and 8am; and a major peak at around 9pm. The winter profile reflects the space heating consumption profile (figure 2.9(a)). In the Mawson Lakes sample, consumption is generally higher in summer than winter, while mean consumption during both these seasons exceeds mean consumption in spring and autumn.

The Sydney sample has a different seasonal profile than that of Mawson Lakes. While the winter peaks are broadly in line with those of the Mawson Lakes sample, mean consumption is lower in summer than in winter. This could be explained by increases in the size and stock of air conditioners in Australia in the decade from 1993 to 2003 (Energy Efficient Strategies 2006, p9). It is also possible that this is the result of climatic differences in the areas in which the samples were recorded.
Mean seasonal consumption by energy function

Figures 2.8 to 2.17 illustrate mean seasonal household electricity consumption by energy function in the Mawson Lakes and Sydney samples.

Figure 2.8 shows mean seasonal household electricity consumption for space cooling. The summer profiles of both samples are similar: low or no consumption before the late morning, when consumption steadily increases and peaks around 6pm before falling steadily for the rest of the day. This is likely to reflect the temperature profile of an average summer day.

The summer peak in the Mawson Lakes sample is around twice as high as that for the Sydney sample. As noted earlier, this may be due to the effects of climatic differences and increased stock of air conditioners in the more recent sample.

Figure 2.9 shows mean electricity consumption on space heating. The winter profiles of both samples are broadly consistent with a minor morning and major late evening peak.
However the Mawson Lakes observations fall to a lower level following the morning peak. This may be due to greater use of automatic thermostatic control of heating resulting in regular heating from 6am to 9am and 7pm to 11pm in the more recent sample. As with space cooling in summer, the winter space heating peak in the Mawson Lakes sample is around twice as high as that for the Sydney sample.

Figure 2.9: Mean seasonal intra-day household consumption: space heating (kWh)

Figure 2.10 illustrates mean electricity consumption for water heating. As would be expected, consumption is highest in winter followed by spring and autumn and lowest in summer. This is likely to reflect the average seasonal temperature, since in winter water is generally heated from a lower initial temperature. The observations for Mawson Lakes should be viewed with caution as they are based on only one household. All but one household in the Mawson Lakes sample used gas fuelled hot water systems.

The consumption profiles of both samples are similar in the morning, with substantial electricity consumption by off-peak hot water systems. In the Sydney sample water is heated over the course of the entire day, with a second peak in the middle of the day and a minor peak around 8pm.

Figure 2.10: Mean seasonal intra-day household consumption: water heating (kWh)
Figure 2.11 shows mean electricity consumption on food storage. The profiles of all seasons in both datasets are similar, with a diurnal pattern with a minimum at around 7am and a maximum at around 8pm. This is likely to reflect the intra-day dwelling temperature, a supposition supported by seasonal differences. Electricity consumption appears to be positively related to temperature, with the highest electricity consumption during summer, followed by spring and autumn and lowest in winter.

It is not known whether the higher mean consumption in the Sydney sample is the result of the use of appliances with higher capacities or lower energy efficiency (or both). The smoother profile of mean consumption in the Sydney sample is a result of the larger number of households in that sample.

![Figure 2.11: Mean seasonal intra-day household consumption: food storage (kWh)](image)

Figure 2.11: Mean seasonal intra-day household consumption: food storage (kWh)

Figure 2.12 illustrates mean electricity consumption on food preparation. In contrast to the previous energy functions, food preparation does not show clear seasonal differences. The profiles are similar across all seasons and between the two samples. There is a minor peak around the middle of the day and a substantial peak between 5pm and 8pm in both datasets. These peaks appear likely to correspond to the preparation of the lunch and dinner meals by households.

![Figure 2.12: Mean seasonal intra-day household consumption: food preparation (kWh)](image)

Figure 2.12: Mean seasonal intra-day household consumption: food preparation (kWh)
Figure 2.13 details mean electricity consumption on clothes cleaning. No appliances were categorised as belonging to this energy function in the Mawson Lakes sample. In the Sydney sample, more electricity was consumed in the colder months, with the winter profile exceeding the spring and autumn profile. Consumption during summer was lowest, possibly reflecting the use of line drying rather than an electric clothes dryer during the warmer months. The major peak for all seasons is in the morning between 9am and noon, with a secondary peak during winter around 5pm. The secondary winter peak may reflect the use of clothes dryers in the afternoons in the colder months.

![Figure 2.13: Mean seasonal intra-day household consumption: clothes cleaning (kWh)](image)

Figure 2.13: Mean seasonal intra-day household consumption: clothes cleaning (kWh)

Figure 2.14 plots mean electricity consumption on lighting. The seasonal profiles are similar in both datasets, with a minor peak around 8am and a major peak around 8pm, corresponding with periods with little or no natural light. Consumption on lighting falls from around 9pm towards zero in the early morning, when the majority of household occupants are asleep. Lights are switched off later in the mornings and switched on earlier in the evenings during winter, reflecting the reduced period of natural light in the colder months.

![Figure 2.14: Mean seasonal intra-day household consumption: lighting (kWh)](image)

Figure 2.14: Mean seasonal intra-day household consumption: lighting (kWh)
Figure 2.15 shows mean electricity consumption on entertainment. No appliances were categorised as belonging to this energy function in the Mawson Lakes sample. This energy function comprises televisions in the Sydney sample, however it would be expected to include a variety of entertainment appliances (such as stereos, video recorders and games consoles) in a more current dataset as the array and capacity of household audio visual equipment has grown substantially in recent years.

Electricity consumption is nearly zero during the early hours of the morning, increasing in three steps: at 8am; at 1pm; and at 5pm. Consumption is highest between 6pm and 11pm in all seasons.

Figure 2.15: Mean seasonal intra-day household consumption: entertainment (kWh)

Figure 2.16 plots mean electricity consumption on appliances that are not categorised as belonging to one of the functions described above. Only one appliance was categorised as ‘other functions’ in the Mawson Lakes sample (a spa bath) associated with minimal electricity consumption. In the Sydney sample it appears that some of the appliances categorised as serving ‘other functions’ are temperature sensitive, as more electricity is consumed in winter than in summer on this energy function.

Figure 2.16: Mean seasonal intra-day household consumption: other functions (kWh)
Figure 2.17 shows mean electricity consumption on appliances that were not individually metered. Interestingly the profiles of mean consumption are similar in some respects in the two samples, with peaks in the morning and evening. This suggests that some unmetered appliances are heaters (perhaps bathroom heaters or lamps) as these peaks broadly correspond to those for space heating. However there is no clear seasonal trend, as would be expected if many of these appliances were heaters.

Peak period electricity consumption

Figure 2.18 details mean household electricity consumption over four days in the Mawson Lakes sample in which electricity consumption peaked. Temperatures were above average from 23 to 25 January 2003 in Adelaide, reaching 44.7°C at 1pm on 25 January 2003. In contrast, the maximum temperature reached on 26 January 2003 was 27.3°C. During the three days of extreme heat (23 to 25 January 2003) electricity consumption was substantially higher than during the more temperate fourth day (26 January 2003). The wholesale price of electricity in the South Australian region of the national electricity market exceeded $0.30/kWh in the afternoon of 25 January 2003.
Figure 2.19 separately plots mean electricity consumption on space cooling and mean aggregate consumption for all other energy functions during 24 January 2003 in the Mawson Lakes sample. As can be seen, the average electricity consumption for space cooling on this day is substantially above that of the aggregate of all other energy functions after 10am. Electricity consumption on space cooling falls to the level of the other energy functions (in aggregate) around midnight. This highlights the potential impact of household electricity consumption for space cooling on peak electricity load.

(a) Mawson Lakes

Figure 2.19: Mean intra-day household consumption for space cooling (kWh): 24 January 2003
2.4 Model structure

This section provides an overview of the structure of the simulation model. Aspects of the model that do not follow directly from household production theory are noted and the nomenclature used in this study is presented.

2.4.1 Overview

The model developed in this chapter is designed to simulate short run household consumption of electricity using a household production theory approach. The model is estimated in two stages, described in detail in sections 2.5 and 2.6. In the first stage relationships between household electricity consumption and climatic variables are estimated. This involves regressing household electricity consumption on short run variables including temperature and the level of natural light. In the second stage the intra-day price sensitivity of households is estimated. The residuals from a log-linear form of the regression estimated in the first stage are used to construct matrices of household intra-day price elasticities of demand for electricity. These are used to simulate the effect of intra-day price changes on household electricity consumption.

Time frame

The time frame considered in this chapter is the short term. Short term variables used to estimate electricity consumption include climate variables (temperature and natural light) and the price of electricity. Variables concerning the characteristics of the stock of household electrical appliances are considered medium or long term variables. The effects of household decisions concerning appliance upgrades and replacements are addressed in chapter 3.

Data dimensions

The electricity consumption data used in this study are disaggregated by intra-day period, household and appliance. An intra-day period with a length of one hour is used. This period is chosen as climate data matching the electricity consumption data of the Mawson Lakes and Sydney samples are available as hourly observations. The electricity consumption data, metered at a higher frequency, are aggregated within each hourly intra-day period. An alternative choice of a shorter intra-day period (for example a period of thirty minutes) would reduce the level of aggregation required for the electricity consumption data. However this would require the climate data to be interpolated (or
otherwise estimated) across the shorter period, which would introduce measurement error to the regressions estimated using climatic explanatory variables.

In this chapter aggregate electricity consumption is modelled as the sum of the electricity consumption of the households comprising the samples used in this study (Mawson Lakes and Sydney). In chapter 4 an analysis of the correlation between state-wide aggregate electricity consumption and the sum of electricity consumption of the sample households is carried out. This is intended to address the unrealistic assumption that the sample households represent electricity consumers in the wider market (see section 4.3).

Electricity consumption data are disaggregated by household appliance. In this study appliances are categorised by (energy) function as discussed below.

**Energy functions**

The theoretical foundation informing the development of the model is household production theory. As outlined in the literature review (section 2.2) household production theory describes individuals that maximise utility by engaging in activities, producing collections of characteristics that yield utility. Activities include direct consumption of goods and services (such as eating an apple) and those that require consumption of goods and services as inputs (for example reading a book - requiring time, a lamp and electricity to provide lighting, a couch on which to sit and a book to read).

Electricity is one of a number of inputs to a variety of different (productive) household activities. These activities are referred to in this study as energy functions. The energy functions defined in this study are listed in table 2.1 along with a description of the output characteristic of each (that yields utility) and examples of appliances that serve each energy function. The definitions of the energy functions follow Boonekamp (2007) with the addition of space cooling (which is probably not as relevant to households in the Netherlands compared to those in Australia) and disaggregating entertainment from the catch-all category ‘other functions’.
Energy function (activity) | Output (characteristics) | Appliances
---|---|---
Space cooling (SC) | Cooler temperature | Fans, air conditioners
Space heating (SH) | Warmer temperature | Resistance heaters, air conditioners
Water heating (WH) | Hot water | Hot water systems
Food storage (FS) | Availability of fresh food | Refrigerators, freezers
Food preparation (FP) | Nutrition, flavour | Ovens, dishwashers, microwaves
Clothes cleaning (CC) | Clean clothes | Clothes washers, dryers
Lighting (LI) | Light | Lights, lamps
Entertainment (EN) | Entertainment | Televisions, sound systems
Other functions (OF) | Other | Other appliances
Not recorded (NR) | Unknown | Unmetered appliances, residual consumption

Table 2.1: Energy functions

While energy functions (can) use electricity as an input, the activities and output of each are different. The time and intensity with which households engage in each activity are systematically different as noted in subsection 2.3.2 reflecting the diversity in output of each energy function. The factors household members consider when engaging in different energy function activities are also likely to vary. Intuition would suggest the factors a household member considers before using an air conditioner to cool a room are likely to be different to those considered before switching on a light. Household production theory suggests that a model designed for the purpose of simulating household electricity consumption is best approached by separately modelling the household activities that require electricity (energy functions).

In this study household electricity consumption is separately modelled for each energy function. The electricity consumption data for the sample households are disaggregated by appliance. These appliances are categorised by energy function within each household and the associated electricity consumption aggregated. For example, all electricity consumed by a household on lighting is aggregated to obtain a data series for total electricity consumption for lighting for that household. Modelling electricity consumption by household and energy function is intended to allow the impact of changes to the energy efficiency characteristics of specific appliance types over time to be estimated (modelled in chapter 3). This is also designed to permit distributional analysis of the effect of tariff, policy and climate changes (simulated in chapter 4).

2.4.2 Consistency with theoretical foundation

The structure and content of the available data impose constraints on model specification. The extent to which the model developed in this study can precisely follow household production theory is limited to the extent to which data required by the theory are available. Four implications of limited data availability for the model are discussed in this
subsection.

The output of energy functions are likely to often be inputs to other activities. One implication of household production theory is that consumption is best modelled by examining how individuals gain utility by engaging in activities. Different activities can require different inputs and utility and yield differing collections of output characteristics that provide utility. This study is based on data on household electricity consumption. The appliances fuelled by electricity are recorded, however the final outputs generated are not. For example, hot water can be an input to a number of different household activities: dishwashing; clothes washing; showering; and general household cleaning. Data on the final activity and output generated using electricity as an input are not recorded. In this study, energy functions are modelled as final activities due to this lack of data.

The second limitation imposed by the data concerns output characteristics. The data do not include the level of output generated by each energy function engaged in, only the input electricity consumed. This presents a difficulty as the core of household production theory is the link between an activity and the utility providing collection of output characteristics generated by that activity. Taking the example of space cooling, the output characteristic of the energy function is a cooler environment. However the actual output is a function of the characteristics of the appliance used and the space to be cooled as well as the electricity consumed. In this chapter the output of each energy function is assumed to be equal (or proportional) to the electricity consumed. (In chapter 3 changes to appliance energy efficiency characteristics are accounted for, however the implicit assumption that electricity consumption - adjusted for changes in appliance energy efficiency - is a proxy for output is unchanged.)

Thirdly, the level of utility able to be enjoyed from energy functions is dependant on the presence of household members. A space heater that heats an empty house does not yield utility (at least until the house is occupied again). As data on the number of people that are within each dwelling at any time are not available, this aspect of household production theory cannot be included in the model. This is unfortunate, as a number of energy functions have public good characteristics. The output characteristics produced by space cooling, space heating and lighting can yield utility for all members in the area being cooled, heated or lit largely without affecting the utility of other household members also enjoying the output of these energy functions.

Finally the characteristics of the data limit the extent to which certain aspects of household production theory can be included in the model specification. For example, the lack of income data for the households in each sample precludes analysis using the 'luxury' characteristic discussed by Muth (1966). Similarly, price information concerning substitute final goods, services and forms of energy are not included as explanatory variables in the model due to the relatively short period over which data are available.
2.4.3 Nomenclature

The nomenclature used for the major variables used in this chapter is presented in this subsection. These can be categorised as time, economic, or climatic variables. Common identifiers are also presented.

Time

Various measures of time are required to be used due to the use of intra-day data. Three discrete measures are used in the model: time; intra-day period; and day.

\[ t \] discrete time measured in intra-day periods
\[ h \] discrete intra-day period - component of \( t \) (1 to 24)
\[ d \] discrete day - component of \( t \) (1 to 365 in a one year sample period)

Economic

\[ p_t \] price of electricity during period \( t \) (\$/kWh)
\[ w_t \] wholesale price of electricity during period \( t \) (\$/kWh)
\[ E_{i,j,t} \] electricity consumption of household \( i \) for energy function \( j \) during period \( t \) (kWh)
\[ X_{i,j,t} \] expenditure of household \( i \) on electricity for energy function \( j \) during period \( t \) (\$
\[ \varepsilon_{p_t,i,j,t,h} \] relative price elasticity of demand for electricity by household \( i \) for energy function \( j \) during period \( t \) with respect to price in period \( h \)
\[ \varepsilon_{p,i,j,t,h} \] (absolute) price elasticity of demand for electricity by household \( i \) for energy function \( j \) during period \( t \) with respect to price in period \( h \)

Climatic

\[ T_t \] temperature during period \( t \) (°C)
\[ R_t \] solar radiation (natural light) during period \( t \) (Wh/m\(^2\) horizontal plane)

Common identifiers

\( i \) household identifier
\( j \) energy function
2.5 Household response to climate

In this section household electricity consumption is estimated using climatic explanatory variables. The purpose of this is to identify the impact temperature and natural light have on household electricity consumption assuming no change in the price of electricity. The parameters estimated constitute the first of two components that together comprise the short run simulation model. The second component, estimating the impact of intra-day price variation on electricity consumption, is estimated in section 2.6.

The assumptions relied on to estimate the response to climate are listed in this section. The functional forms used to estimate electricity consumed on each energy function are discussed focusing particularly on space cooling and space heating. The regression parameters estimated are presented and interpreted. Results of within sample and out of sample forecasts using the estimated parameters are provided. The section concludes with a discussion of the implications of the analysis.

2.5.1 Modelling assumptions

The assumptions relied on in this section are listed and discussed in this subsection. These are required in the absence of suitable data and for non-data related reasons.

Assumptions required due to limited data

Temperature and natural light are used as explanatory variables in the regressions carried out in this section. As noted in section 2.3 these data are sourced from the Australian Bureau of Meteorology. It is assumed that the observations of temperature and natural light represent those relevant to household members when engaging in electricity consuming household activities. This assumption is required as the data from the Australian Bureau of Meteorology is the only data available for the areas in which the sample households are located. However there are a number of reasons why this assumption may not hold. Firstly, temperature and light levels relevant to household members are likely to be those within household dwellings, rather than ambient external temperature and natural light. While dwelling temperature and light levels may be a function of external temperature and natural light (among other factors) they are unlikely to be equivalent across the entire sample. Secondly, dwelling temperature and light levels are likely to differ depending on location and dwelling characteristics. A degree of measurement error is likely to exist in the climatic explanatory variables.

Measurement error is expected to be more severe in the Sydney sample. The households in the Mawson Lakes sample are located very near one another. Their close proximity
reduces the likelihood of substantial variation in ambient external temperature and light levels. The Sydney sample includes households in locations ranging across the entire city rather than from a single suburb. The Australian Bureau of Meteorology climate data will only approximate ambient external temperature and light levels for households in this sample.

A second assumption required due to limited data availability concerns the price of electricity. It is assumed that the price of electricity for households was constant during the sample periods of each dataset. Electricity price data are not recorded in either of the Mawson Lakes or Sydney samples. While this assumption is likely to be a simplification, the price of electricity for households is unlikely to have changed substantially over the course of a year at least for households in the Mawson Lakes sample. The marginal cost of electricity under the AGL general supply tariff (tariff 126) in South Australia increased by 0.7 per cent in July 2004 and by 1.4 per cent in July 2005 (Australian Gas Light Company 2005). This assumption is required in order to exclude price as an explanatory variable in the regressions carried out in this section.

Non-data related assumptions

The functional forms of the regressions estimated in this section are the same for all households within and across each sample. This assumption is adopted in order to reduce complexity in the simulation model and to allow comparability of parameters between households and samples. A lack of demographic data also limits the ability to introduce specific functional forms for different household types or sizes (or other distinguishing demographic factors).

2.5.2 Regression structure

Separate regressions of electricity consumption on temperature and natural light are carried out by household and energy function using non-linear ordinary least squares (OLS). A sample period of one calendar year is used for both datasets beginning 1 April 2002 for the Mawson Lakes sample and 1 June 1993 for the Sydney sample. A period of a year is chosen as this sample period includes all seasons equally to avoid bias in parameters estimated for climatic variables.

As is common in models estimating electricity consumption based on intra-day data, separate regressions are carried out for each intra-day period (see the literature review for an overview of models utilising this approach). The different intra-day periods effectively act as dummy variables for differences in household consumption patterns across the course of the day. For example, the temperatures recorded at 9am and 9pm on a certain day may
be the same, but the activities of household members are likely to be different at these times.

Each regression equation also includes a dummy variable $D_d$ for the day of the week. The day of the week dummy is included to identify regular weekly patterns in electricity consumption by household; for example a regular television viewing pattern or differences in household activities on weekdays and weekends.

**Space heating and space cooling**

Temperature is included directly in the regressions for most energy functions. However in the cases of space heating and space cooling, temperature is not directly included, rather an estimate of the difference between the external ambient temperature and an estimate of temperature at which a household feels comfortable is used as an explanatory variable. This approach is informed by household production theory. Households use space cooling and space heating to keep a dwelling within a comfortable temperature range. Unless the desired range of a household is centred at $0^\circ$C, household production theory suggests that the direct inclusion of temperature as an explanatory variable in the space cooling and space heating equations will result in misspecification.

In order to quantify the difference between a household’s desired temperature and the external temperature, the comfortable temperature range for a household needs to be estimated. The minimum and maximum of the comfortable temperature range for each household ($T_{\text{IMin},i}$ and $T_{\text{IMax},i}$ for household $i$) are estimated by identifying the temperatures at which a household spends less than five per cent of electricity consumption on heating or cooling using data for the first twelve months of each sample. The minimum comfortable temperature of a household is calculated as the temperature above which less than five per cent of total electricity for space heating is consumed. Similarly, the maximum comfortable temperature is calculated as the temperature below which less than five per cent of total electricity for space cooling is consumed. Tables 2.2 and 2.3 contain the estimated comfortable temperature ranges for each household with monitored heating and/or cooling appliances in the Mawson Lakes and Sydney samples respectively.

<table>
<thead>
<tr>
<th>Household ($i$)</th>
<th>$T_{\text{IMin},i}$</th>
<th>$T_{\text{IMax},i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16.0</td>
<td>18.2</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>22.0</td>
</tr>
<tr>
<td>3</td>
<td>16.8</td>
<td>19.8</td>
</tr>
<tr>
<td>4</td>
<td>16.4</td>
<td>19.7</td>
</tr>
<tr>
<td>5</td>
<td>14.7</td>
<td>21.6</td>
</tr>
<tr>
<td>6</td>
<td>15.2</td>
<td>19.0</td>
</tr>
</tbody>
</table>

Table 2.2: Estimated comfortable temperature range ($^\circ$C) by household (Mawson Lakes)
Comfortable temperature range

<table>
<thead>
<tr>
<th>Household (i)</th>
<th>$T_{\text{Min},i}$</th>
<th>$T_{\text{Max},i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20.0</td>
<td>20.0</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>21.0</td>
</tr>
<tr>
<td>3</td>
<td>19.0</td>
<td>24.0</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>24.0</td>
</tr>
<tr>
<td>5</td>
<td>14.0</td>
<td>14.0</td>
</tr>
<tr>
<td>6</td>
<td>16.0</td>
<td>16.0</td>
</tr>
<tr>
<td>7</td>
<td>19.0</td>
<td>22.0</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>23.0</td>
</tr>
<tr>
<td>11</td>
<td>17.0</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>17.0</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>15.0</td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>20.0</td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>18.0</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>15.0</td>
<td></td>
</tr>
<tr>
<td>41</td>
<td>22.0</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.3: Estimated comfortable temperature range ($^\circ\text{C}$) by household (Sydney)

For three households in the Sydney sample, this approach results in estimates of minimum comfortable temperature greater than maximum comfortable temperature. This may be due to potential measurement error in the Sydney temperature observations or misallocation of reverse cycle air conditioner electricity consumption between space heating and space cooling. For these three households, the minimum comfortable temperature is set equal to the maximum comfortable temperature estimated for each household.

The amount by which ambient external temperature exceeds the maximum of the comfortable range of a household is included as an explanatory variable in the regression equation for space cooling as $T_{\text{elMax},i,t}$ (equation 2.1). If the ambient external temperature is lower than the minimum of the comfortable range for a household, this difference is included as an explanatory variable in the regression equation for space cooling as $T_{\text{elMin},i,t}$ (equation 2.2).

$$T_{\text{elMax},i,t} = \begin{cases} 0 & \text{if } T_t \leq T_{\text{Min},i} \\ T_t - T_{\text{Max},i} & \text{if } T_t > T_{\text{Min},i} \end{cases} \quad (2.1)$$

$$T_{\text{elMin},i,t} = \begin{cases} 0 & \text{if } T_h \geq T_{\text{Min},i} \\ T_{\text{Min},i} - T_t & \text{if } T_t < T_{\text{Min},i} \end{cases} \quad (2.2)$$
Functional form of regression equations

An exponential functional form with additive errors is used to relate the explanatory variables with household electricity consumption. This allows for a highly flexible regression with linear, exponential or inverse relationships estimated depending on the estimated values of the exponent parameters of the explanatory variables. The regression equations for each energy function are contained in table 2.4 for household $i$ during period $t$ (intra-day period $h$, day $d$).

<table>
<thead>
<tr>
<th>Energy function</th>
<th>Regression equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space cooling (SC)</td>
<td>$E_{i,1,t} = \alpha_{1,1,i} T_{i,t}^{\gamma_{1,1,i}} R_{i,t}^{\theta_{1,1,i}} \delta_{i,1,h}^{D_{i,d}} + u_{i,1,t}$</td>
</tr>
<tr>
<td>Space heating (SH)</td>
<td>$E_{i,2,t} = \alpha_{1,2,i} T_{i,t}^{\gamma_{1,2,i}} R_{i,h}^{\theta_{1,2,h}} \delta_{i,2,h} + u_{i,2,t}$</td>
</tr>
<tr>
<td>Water heating (WH)</td>
<td>$E_{i,3,t} = \alpha_{1,3,i} T_{i,t}^{\gamma_{1,3,i}} R_{i,t}^{\theta_{1,3,i}} \delta_{i,3,h}^{D_{i,d}} + u_{i,3,t}$</td>
</tr>
<tr>
<td>Food storage (FS)</td>
<td>$E_{i,4,t} = \alpha_{1,4,i} T_{i,t}^{\gamma_{1,4,i}} R_{i,t}^{\theta_{1,4,t}} \delta_{i,4,h} + u_{i,4,t}$</td>
</tr>
<tr>
<td>Food preparation (FP)</td>
<td>$E_{i,5,t} = \alpha_{1,5,i} T_{i,t}^{\gamma_{1,5,t}} R_{i,t}^{\theta_{1,5,t}} \delta_{i,5,h}^{D_{i,d}} + u_{i,5,t}$</td>
</tr>
<tr>
<td>Clothes cleaning (CC)</td>
<td>$E_{i,6,t} = \alpha_{1,6,i} T_{i,t}^{\gamma_{1,6,t}} R_{i,t}^{\theta_{1,6,t}} \delta_{i,6,h} + u_{i,6,t}$</td>
</tr>
<tr>
<td>Lighting (LI)</td>
<td>$E_{i,7,t} = \alpha_{1,7,i} T_{i,t}^{\gamma_{1,7,t}} R_{i,t}^{\theta_{1,7,t}} \delta_{i,7,h}^{D_{i,d}} + u_{i,7,t}$</td>
</tr>
<tr>
<td>Entertainment (EN)</td>
<td>$E_{i,8,t} = \alpha_{1,8,i} T_{i,t}^{\gamma_{1,8,t}} R_{i,t}^{\theta_{1,8,t}} \delta_{i,8,h} + u_{i,8,t}$</td>
</tr>
<tr>
<td>Other (OF)</td>
<td>$E_{i,9,t} = \alpha_{1,9,i} T_{i,t}^{\gamma_{1,9,t}} R_{i,t}^{\theta_{1,9,t}} \delta_{i,9,h} + u_{i,9,t}$</td>
</tr>
<tr>
<td>Not recorded (NR)</td>
<td>$E_{i,0,t} = \alpha_{1,0,i} T_{i,t}^{\gamma_{1,0,t}} R_{i,t}^{\theta_{1,0,t}} \delta_{i,0,h} + u_{i,0,t}$</td>
</tr>
</tbody>
</table>

Table 2.4: Regression equations for climatic explanatory variables

The regression equations for all energy functions include a multiplicative constant $\alpha$ and a dummy variable $D_d$ for the day of the week (with Monday as the control) on parameter $\delta$. Temperature $T$ is included in the regressions for all energy functions either directly or transformed (as discussed above for space cooling and space heating). The level of natural light $R$ is included in the regressions for all energy functions. The merits of assuming an additive over multiplicative error term are discussed in appendix 2.C.

While the functional form of the regression equations varies across the different energy functions, for a given energy function the functional form is constant across all households in each sample. This is a simplification intended to allow comparison of the regression parameters estimated by household.

Constraints on parameter range

The parameters estimated in the regression ($\alpha, \gamma, \zeta, \delta, \eta,$ and $\theta$) are constrained to lie between -10 and 10. (Where an explanatory variable has no explanatory power, the associated parameter will have an expected value of zero, except for the day of week parameter $\delta$, which will have an expected value of one.) This constraint is imposed because the non-linear estimation of the parameters returns unrealistic outliers (in the order of $10^{400}$) in a few cases, which skew forecasts and summary statistics.
2.5.3 Preliminary tests

Prior to estimating climate parameters, a number of tests are carried out. These are to gauge the appropriateness of utilising non-linear least squares. The results of tests of unit root (stationarity), heteroskedasticity and serial correlation are reported in this subsection.

Unit root

Electricity consumption is physically limited at the household level to the aggregate electricity capacity of household appliances. At the system level, the load limit of the distribution network and maximum generation capacity will act as a ceiling for electricity consumption. For this reason, electricity consumption in both the Mawson Lakes and Sydney samples could be expected to be stationary.

Augmented Dickey-Fuller unit root tests are carried out on the intra-day electricity consumption data. The null hypothesis of a unit root is tested against the alternative of a single (stationary) mean for lags numbering one to three (the most recent three hours) and 24 (the same period of the previous day). The tests are carried out for aggregate sample consumption, across individual households and by specific energy functions. (Dickey and Fuller (1979) used Monte Carlo techniques to estimate the distribution of the least squares estimator for a simple unit root.)

Tables 2.5 and 2.6 present the mean p-values of the test for the Mawson Lakes sample, while tables 2.7 and 2.8 contain the corresponding results for the Sydney sample. At the five per cent level, the null hypothesis of a unit root is rejected for all tests on both aggregate and disaggregated (by household and electricity function) data for both samples (negating the need to report the rejection proportion for test statistics in the tables).

For data collected over a longer time period, unit root tests incorporating a trend over time may be required, as the electrical capacity of the stock of household appliances may change over time. However the test against an alternative of a stationary mean is appropriate for relatively short time periods and has the benefit of being less likely to reject the null hypothesis of a unit root.
### Table 2.5: Augmented Dickey-Fuller unit root test: mean p-values (Mawson Lakes)

<table>
<thead>
<tr>
<th>Lag</th>
<th>Aggregate consumption</th>
<th>Individual households</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>2</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>24</td>
<td>0.002</td>
<td>0.002</td>
</tr>
</tbody>
</table>

### Table 2.6: Augmented Dickey-Fuller unit root test by energy function: mean p-values (Mawson Lakes)

<table>
<thead>
<tr>
<th>Lag</th>
<th>SC</th>
<th>SH</th>
<th>WH</th>
<th>FS</th>
<th>FP</th>
<th>LI</th>
<th>OF</th>
<th>NR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>2</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>24</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

### Table 2.7: Augmented Dickey-Fuller unit root test: mean p-values (Sydney)

<table>
<thead>
<tr>
<th>Lag</th>
<th>Aggregate consumption</th>
<th>Individual households</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>2</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>24</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

### Table 2.8: Augmented Dickey-Fuller unit root test by energy function: mean p-values (Sydney)

<table>
<thead>
<tr>
<th>Lag</th>
<th>SC</th>
<th>SH</th>
<th>WH</th>
<th>FS</th>
<th>FP</th>
<th>CC</th>
<th>LI</th>
<th>EN</th>
<th>OF</th>
<th>NR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>2</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>24</td>
<td>&lt;0.001</td>
<td>0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
Heteroskedasticity

Estimation using least squares is inefficient (although still unbiased and consistent) in the presence of heteroskedasticity. The estimated covariance matrix will be inappropriate, resulting in inaccurate standard errors. White’s general test is used to test for heteroskedasticity across all households and intra-day time periods in regressions carried out using ordinary least squares (White 1980), with a null hypothesis of homoskedasticity.

The proportion of tests (across households and intra-day periods for which the null hypothesis is rejected is contained in tables 2.9 and 2.10 respectively for the Mawson Lakes and Sydney samples. A hypothesis of homoskedasticity is rejected at the five per cent level across all energy functions in a substantial proportion of cases, ranging from 0.20 for space heating to 0.83 for water heating for Mawson Lakes.

The regressions carried out in this study estimate White’s heteroskedastic robust covariance matrix, scaled by \((n/n-k)\) for \(k\) regressors as suggested by Davidson and MacKinnon (1993). The adjustment is used as, taken individually, the data for each energy function comprise relatively small samples.

<table>
<thead>
<tr>
<th>Energy function</th>
<th>SC</th>
<th>SH</th>
<th>WH</th>
<th>FS</th>
<th>FP</th>
<th>LI</th>
<th>OF</th>
<th>NR</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.31</td>
<td>0.20</td>
<td>0.83</td>
<td>0.26</td>
<td>0.66</td>
<td>0.47</td>
<td>0.63</td>
<td>0.37</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.9: White’s general heteroskedasticity test: null rejection proportion by energy function (Mawson Lakes)

<table>
<thead>
<tr>
<th>Energy function</th>
<th>SC</th>
<th>SH</th>
<th>WH</th>
<th>FS</th>
<th>FP</th>
<th>CC</th>
<th>LI</th>
<th>EN</th>
<th>OF</th>
<th>NR</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.29</td>
<td>0.39</td>
<td>0.61</td>
<td>0.52</td>
<td>0.45</td>
<td>0.57</td>
<td>0.40</td>
<td>0.47</td>
<td>0.36</td>
<td>0.45</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.10: White’s general heteroskedasticity test: null rejection proportion by energy function (Sydney)

Serial correlation

As in the case of heteroskedasticity, serial correlation renders least squares estimation inefficient. As there are no lagged values of the dependant variable (electricity consumption) included in the regression equations (see table 2.4), least squares will remain unbiased and consistent, although with potentially undesirable small sample properties. The Breusch-Godfrey Lagrange multiplier test (see Breusch 1978 and Godfrey 1978) has a null hypothesis of no autocorrelation (or ‘white noise’) against alternative hypotheses of residuals of moving average or autoregressive form. The test is carried out across all households and energy functions.
Tables 2.11 and 2.12 report the proportion of cases in which the null hypothesis of an absence of serial correlation is rejected, presented by energy function for seven lags. While the proportion of rejections generally exceeds five per cent for each sample, it is not by a substantial amount. This appears surprising, as household electricity consumption could be expected to exhibit correlation based at a minimum on continuity of dwelling occupation across periods.

No modification is used to adjust for serial correlation in this study. If the level of serial correlation presented a problem, a different modelling approach would be warranted.

<table>
<thead>
<tr>
<th>Energy function</th>
<th>SC</th>
<th>SH</th>
<th>WH</th>
<th>FS</th>
<th>FP</th>
<th>LI</th>
<th>OF</th>
<th>NR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.07</td>
<td>0.08</td>
<td>0.08</td>
<td>0.02</td>
<td>0.05</td>
<td>0.06</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>2</td>
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<td>0.06</td>
<td>0.09</td>
<td>0.05</td>
</tr>
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<td>0.08</td>
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<td>0.07</td>
<td>0.09</td>
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</tr>
<tr>
<td>4</td>
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<td>0.06</td>
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<td>0.06</td>
<td>0.09</td>
<td>0.05</td>
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<td>0.08</td>
<td>0.02</td>
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<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>7</td>
<td>0.06</td>
<td>0.07</td>
<td>0.08</td>
<td>0.02</td>
<td>0.05</td>
<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 2.11: Breusch-Godfrey LM serial correlation test: null rejection proportion by energy function (Mawson Lakes)

<table>
<thead>
<tr>
<th>Energy function</th>
<th>SC</th>
<th>SH</th>
<th>WH</th>
<th>FS</th>
<th>FP</th>
<th>CC</th>
<th>LI</th>
<th>EN</th>
<th>OF</th>
<th>NR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>0.07</td>
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<td>0.06</td>
<td>0.07</td>
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</tr>
<tr>
<td>2</td>
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<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>3</td>
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<td>0.08</td>
<td>0.06</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>0.08</td>
<td>0.08</td>
<td>0.06</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>5</td>
<td>0.07</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>6</td>
<td>0.07</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>7</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.09</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 2.12: Breusch-Godfrey LM serial correlation test: null rejection proportion by energy function (Sydney)

2.5.4 Regression results

Tables 2.13 and 2.14 present the mean parameters by energy function estimated for the Mawson Lakes and Sydney samples respectively. The mean parameters are calculated averaging across all households and intra-day periods. The proportion of t-values significant at the five per cent level (across households and intra-day periods) is included in brackets beneath each mean parameter estimate. This proportion rather than the mean t-value for each parameter is reported because the latter underestimates the significance of
variables with both positive and negative parameters estimated across different households and intra-day periods.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Energy function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>1.05 (0.53) 5.14 (0.60) 1.88 (0.29) 0.06 (1.00) 8.41 (0.45) 3.85 (0.61) 6.80 (0.61) 0.39 (0.90)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>-0.31 (0.33) 0.36 (0.85) -0.30 (0.36) -0.02 (0.55) -0.40 (0.29) 0.19 (0.71)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>1.29 (0.63)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.99 (0.56)</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>0.18 (0.44) -0.23 (0.44) 0.04 (0.33) 0.03 (0.49) 0.52 (0.45) -0.43 (0.67) 0.25 (0.53) 0.05 (0.58)</td>
</tr>
<tr>
<td>$\delta$ (tue)</td>
<td>0.58 (0.33) 0.64 (0.23) 1.15 (0.04) 1.00 (0.04) 0.83 (0.09) 1.01 (0.09) 1.01 (0.04) 0.99 (0.10)</td>
</tr>
<tr>
<td>$\delta$ (wed)</td>
<td>0.78 (0.28) 0.91 (0.21) 1.08 (0.08) 1.00 (0.02) 1.06 (0.13) 0.96 (0.15) 0.94 (0.04) 1.00 (0.06)</td>
</tr>
<tr>
<td>$\delta$ (thu)</td>
<td>0.86 (0.26) 0.78 (0.23) 0.99 (0.04) 1.00 (0.04) 0.83 (0.09) 1.17 (0.09) 1.18 (0.08) 0.96 (0.08)</td>
</tr>
<tr>
<td>$\delta$ (fri)</td>
<td>0.81 (0.32) 0.90 (0.23) 0.97 (0.04) 0.99 (0.06) 1.02 (0.15) 1.06 (0.11) 0.86 (0.04) 0.99 (0.11)</td>
</tr>
<tr>
<td>$\delta$ (sat)</td>
<td>0.98 (0.35) 1.40 (0.26) 0.03 (0.08) 1.03 (0.11) 1.03 (0.13) 1.42 (0.21) 1.64 (0.13) 0.96 (0.15)</td>
</tr>
<tr>
<td>$\delta$ (sun)</td>
<td>1.07 (0.35) 1.37 (0.24) 1.03 (0.08) 1.05 (0.08) 1.19 (0.15) 1.32 (0.17) 1.02 (0.08) 1.05 (0.16)</td>
</tr>
</tbody>
</table>

Table 2.13: Mean estimated climate variable parameters (Mawson Lakes)
The estimated parameters for temperature for all other energy functions are generally smaller in 56 per cent of periods. However, in the Sydney sample, the mean impact of low temperature below each household’s comfortable temperature range is an unexpected result, which may reflect measurement error in the temperature data. High temperatures in the Sydney sample are estimated to be near zero (\(\delta = 0\)). As \(\gamma\) is greater than one, these households are expected to consume electricity for space cooling at an increasing rate as temperature exceeds each household’s comfortable range. In contrast, the mean intra-day household response to high temperatures in the Sydney sample is estimated to be near zero (\(\gamma = 0.02\)). This is an unexpected result, which may reflect measurement error in the temperature data matched to the Sydney sample (as discussed in section 2.3).

The estimated impact of temperature on space heating is similar to that of space cooling for each sample. Electricity consumption on space heating is almost linearly related to temperature below each household’s comfortable temperature range (\(\eta = 0.99\)), significant in 56 per cent of periods. However, in the Sydney sample, the mean impact of low temperature is smaller (\(\eta = 0.13\)).

The estimated parameters for temperature for all other energy functions (\(\theta\)) are the expected sign. The mean parameters estimated for food storage are positive in both the Mawson Lakes and Sydney samples, most likely because more energy is required to keep food fresh in warmer ambient temperatures. The mean parameters estimated for water

<table>
<thead>
<tr>
<th>Parameter</th>
<th>SC</th>
<th>SH</th>
<th>WH</th>
<th>FS</th>
<th>FP</th>
<th>CC</th>
<th>LI</th>
<th>EN</th>
<th>OF</th>
<th>NR</th>
</tr>
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<tr>
<td>(\alpha)</td>
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<td>0.12</td>
<td>2.87</td>
<td>2.57</td>
<td>2.30</td>
<td>1.08</td>
<td>8.78</td>
<td>4.26</td>
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<tr>
<td></td>
<td>(0.17)</td>
<td>(0.29)</td>
<td>(0.36)</td>
<td>(0.97)</td>
<td>(0.25)</td>
<td>(0.17)</td>
<td>(0.48)</td>
<td>(0.58)</td>
<td>(0.48)</td>
<td>(0.40)</td>
</tr>
<tr>
<td>(\theta)</td>
<td>-0.34</td>
<td>0.49</td>
<td>-0.29</td>
<td>-0.30</td>
<td>-0.36</td>
<td>-0.31</td>
<td>1.05</td>
<td>-0.21</td>
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</tr>
<tr>
<td>(\gamma)</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
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<tr>
<td>(\eta)</td>
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</tr>
<tr>
<td>(\zeta)</td>
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<td>0.04</td>
<td>0.06</td>
<td>0.18</td>
<td>0.06</td>
<td>0.36</td>
<td>0.22</td>
<td>-0.18</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>(\delta)</td>
<td>0.62</td>
<td>0.75</td>
<td>0.96</td>
<td>1.01</td>
<td>1.03</td>
<td>0.89</td>
<td>0.99</td>
<td>0.99</td>
<td>0.97</td>
<td>1.10</td>
</tr>
<tr>
<td>(\delta)</td>
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<td>0.74</td>
<td>1.02</td>
<td>1.00</td>
<td>0.96</td>
<td>1.02</td>
<td>1.00</td>
<td>0.92</td>
<td>1.09</td>
<td>1.13</td>
</tr>
<tr>
<td>(\delta)</td>
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<td>0.72</td>
<td>0.97</td>
<td>1.02</td>
<td>0.94</td>
<td>1.01</td>
<td>0.99</td>
<td>0.85</td>
<td>0.98</td>
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</tr>
<tr>
<td>(\delta)</td>
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<td>0.84</td>
<td>0.99</td>
<td>1.03</td>
<td>1.02</td>
<td>1.06</td>
<td>1.08</td>
<td>1.13</td>
<td>1.01</td>
<td>1.07</td>
</tr>
<tr>
<td>(\delta)</td>
<td>0.69</td>
<td>0.84</td>
<td>1.58</td>
<td>1.01</td>
<td>1.22</td>
<td>1.25</td>
<td>1.39</td>
<td>1.06</td>
<td>1.06</td>
<td>1.03</td>
</tr>
<tr>
<td>(\delta)</td>
<td>0.57</td>
<td>0.77</td>
<td>1.43</td>
<td>1.01</td>
<td>1.23</td>
<td>1.11</td>
<td>1.33</td>
<td>1.18</td>
<td>1.12</td>
<td>1.17</td>
</tr>
</tbody>
</table>

Table 2.14: Mean estimated climate variable parameters (Sydney)
heating, food preparation and other functions are negative in both samples. The sign of the parameter for electricity consumption for water heating is expected, since less energy is required to heat water to a given temperature on warm days. In contrast to space cooling, space heating and water heating, electricity consumption for other energy functions is not directly linked with temperature through a physical heating/cooling relationship. The relationships estimated may be the result of changing household behaviour based on the climate and season (for example households may prepare less energy intensive meals in warm weather - more salads and fewer roast dinners).

Temperature is found to have little effect on lighting (−0.02 and 0.06 in Mawson Lakes and Sydney samples respectively). The mean parameters estimated for appliances allocated to the 'not recorded’ category are of different signs in the different samples (0.19 for Mawson Lakes and −0.21 for Sydney) which is not surprising given it is not known what appliances are contained in this category.

Natural light

The mean estimated parameters (ζ) on natural light are generally of the expected sign. Natural light is a substitute for electric lighting and in both samples a negative relationship is found (−0.43 for Mawson Lakes and −0.36 for Sydney). Sunlight can heat as well as provide light for dwellings, potentially increasing the internal temperature relative to the outside air. Consistent with this observation, the mean estimated parameters are positive for space cooling (0.18 for Mawson Lakes and 0.05 for Sydney) and negative for space heating (−0.23 for Mawson Lakes and −0.06 for Sydney). The level of natural light is generally positively correlated with electricity consumption on other energy functions with the exception of 'other functions’ in the Sydney sample.

Day of week

The day of the week (with Monday as control) is included as an explanatory variable in the regressions for all energy functions. Increased weekend electricity consumption is expected for some energy functions while others have little or no systematic day of week effect. Electricity consumption on food preparation and lighting are substantially higher on the weekend in both samples. More electricity is consumed for space heating in the Mawson Lakes sample on the weekend, while in the Sydney sample weekend consumption on water heating is higher than during the week.
Intra-day variation

The regression parameters vary by intra-day periods and household, a point that may be overlooked when considering the mean estimates of the parameters contained in tables 2.13 and 2.14. This is highlighted in figure 2.20, which contains mean, maximum and minimum values of $\eta_h$ (calculated across households in the Mawson Lakes sample) by intra-day period $h$. $\eta_{i,h}$ is the parameter relating the electricity consumption of household $i$ on space heating with external temperatures lower than the minimum comfortable temperature for household $i$.

The mean estimate of $\eta_h$ is positive across all intra-day periods, indicating that household consumption of electricity for space heating is positively correlated with temperatures below the minimum comfortable temperatures estimated for the sample households. The estimated parameter is highest in the early morning, falling in the hours between 8am and noon, then rising again after 4pm. This is likely to reflect the operation of thermostatic heaters that are set to operate in the early hours of the morning and in the evening. The minimum $\eta_h$ estimated by intra-day period fluctuates around zero for much of the day, indicating little or no correlation with temperatures below the household minimum ideal temperature. The maximum estimate of $\eta_h$ is substantially higher in the early morning hours, most likely the result of a large thermostatically controlled heating system set to operate during that period in one of the households in the Mawson Lakes sample.

![Figure 2.20: Estimated $\eta$ parameter by intra-day period (Mawson Lakes)](image)

Structural break test on the price of electricity

To test the assumption that the price of electricity is constant over the period of the sample (see page 46) a structural break (Chow) test is carried out on electricity consumption at July 2003. Changes to the AGL general supply tariff were made annually at the start of each financial year (July) during this period and this may be expected to result in different levels of consumption before and after a price change.

The null hypothesis of no structural break at July 2003 is rejected at the 1 per cent level,
suggesting a price change at this time may have affected consumption behaviour. Average household electricity consumption was 8.0 per cent higher in the sample from July 2003 onward. It is possible that households became aware that the price increase at July 2003 was less than the rate of inflation and that the real price had actually fallen. However the annual increase in the consumer price index for the city of Adelaide over the two year period from July 2003 to June 2005 was relatively low at 3.1 per cent (Australian Bureau of Statistics 2011), limiting the magnitude of any fall in the real price of electricity.

Disaggregating electricity consumption by energy function reveals substantial variations (figure 2.21). Consumption on space cooling and space heating increased substantially (by 25.0 per cent and 9.2 per cent respectively) while consumption decreased for hot water (9.4 per cent) and lighting (8.7 per cent). The degree of heterogeneity in outcomes between energy functions suggests caution should be exercised in attributing the differences observed pre- and post-July 2003 to a price change at this time.

![Figure 2.21: Change in mean sample consumption post-July 2003 by energy function (Mawson Lakes)](image)

2.5.5 Model evaluation

In this subsection the predictive ability of the simulation model is evaluated. The evaluation metrics used to assess the forecasts made by the model are described in appendix 2.E.

Andersen et al. (1999) and Hansen (2005) argue that there is no single best measure of the predictive ability of a model. For this reason a broad approach to model and forecast evaluation is adopted. Forecasts of household electricity consumption are made both within and out of sample periods and the accuracy of these forecasts are assessed. Five metrics are used to assess and compare the predictive ability of the simulation model (presented in detail in appendix 2.E). These are:

- Mean squared error (MSE);
- Mean absolute error (MAE);
- Coefficient of determination ($R^2$);
- Theil inequality coefficient (Theil); and
- Diebold-Mariano equal predictive ability test with mean squared and mean absolute error loss functions.

The sample periods used are those noted earlier in this section, each of one year duration. The Mawson Lakes out of sample period is of one year duration beginning 1 April 2003, while the Sydney out of sample period is of two months beginning 1 June 1994. The out of sample period for the Sydney sample is small and contains only two winter months, with the result that the forecast evaluation for the Sydney sample is likely to over represent electricity consumption for space heating and lighting and little or no consumption on space cooling.

Three forecasts are compared in this subsection. The first forecast is that of the simulation model based on the parameters estimated in this section. The second and third forecasts are prior consumption outcomes (by energy function, household and intra-day period) lagged one day and one week. Actual climate data are used in the forecast evaluation by the simulation model. This limits the potential of the model to forecast electricity consumption in advance (as the lagged forecasts are known one day and one week in advance), which is a potential drawback if the simulation model were to be used for applications such as critical peak pricing rather than the setting of TOU tariffs.

**Sample period evaluation**

The forecasts of the simulation model of household electricity consumption in the sample period are superior to those obtained using household electricity consumption lagged one and seven days. The forecasts of the simulation model (F01 in table 2.15) result in the lowest mean squared error, highest coefficient of determination ($R^2$) and lowest Theil inequality coefficient over the sample period. The lagged values of household electricity consumption are inferior estimators of household electricity consumption than forecasts based on the simulation model across all evaluation metrics (MAE, MSE, $R^2$ and Theil) for Mawson Lakes. The results for the Sydney sample are similar, with the simulation model forecasts having lower MSE, higher $R^2$ and lower Theil inequality coefficients in the sample period. The MAE of all three forecasts is the same (at 0.17) for the Sydney sample.

It is interesting that of the forecasts based on lagged electricity consumption, consumption lagged one day is a better forecast than consumption lagged one week in the Mawson Lakes sample, while the opposite is true for the Sydney sample. It appears that the patterns of
household electricity usage change more week to week than day to day in the more recent Mawson Lakes sample.

<table>
<thead>
<tr>
<th>Mawson Lakes</th>
<th>Sydney</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>MSE</td>
</tr>
<tr>
<td>F01: sim mod</td>
<td>0.09</td>
</tr>
<tr>
<td>F02: 1 day lag</td>
<td>0.11</td>
</tr>
<tr>
<td>F03: 7 day lag</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Table 2.15: Forecast evaluation statistics (in sample)

Tables 2.16 and 2.17 contain Diebold-Mariano test statistics for each forecast calculated using the other forecasts as bases over the sample period. The forecast used as the base is listed in the column heading. Diebold-Mariano test statistics calculated based on MSE and MAE loss functions are contained in tables 2.16 and 2.17 respectively. A negative DM test statistic indicates the forecast being evaluated has a lower mean loss function (either MSE or MAE) than the base forecast it is measured against.

In the sample period, the null hypothesis of equal predictive ability is not rejected for any forecast in either sample. While the forecasts based on the simulation model have smaller mean loss functions for both MSE and MAE than forecasts using lagged consumption as an estimator, in no test is the difference significant at the ten per cent level.

<table>
<thead>
<tr>
<th>Base</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mawson Lakes</td>
</tr>
<tr>
<td>F02: 1 day lag</td>
</tr>
<tr>
<td>F01: sim mod</td>
</tr>
<tr>
<td>F02: 1 day lag</td>
</tr>
<tr>
<td>F03: 7 day lag</td>
</tr>
</tbody>
</table>

Table 2.16: Diebold-Mariano with MSE loss function (in sample)

<table>
<thead>
<tr>
<th>Base</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mawson Lakes</td>
</tr>
<tr>
<td>F02: 1 day lag</td>
</tr>
<tr>
<td>F01: sim mod</td>
</tr>
<tr>
<td>F02: 1 day lag</td>
</tr>
<tr>
<td>F03: 7 day lag</td>
</tr>
</tbody>
</table>

Table 2.17: Diebold-Mariano with MAE loss function (in sample)
Out of sample period evaluation

The simulation model forecast (F01 in table 2.18) is superior to forecasts using household electricity consumption lagged one and seven days in the Mawson Lakes out of sample period. It has the highest coefficient of determination (R\(^2\)) and the lowest Theil inequality coefficient. However a comparison of the within and out of sample evaluation metrics for the simulation model forecasts reveals a reduction in forecasting performance. A similar comparison of the evaluation metrics for the forecasts based on lagged consumption shows that the performance of these forecasts is largely unchanged (or slightly improved) in the out of sample period. These results may stem from changes in the electricity consumption patterns or decisions of households between the within and out of sample periods. Forecasts based on consumption lagged one and seven days will incorporate changes in electricity consumption of these types in the out of sample period, while the forecasts of the simulation model will not. However forecasts based on lagged values are only available as far ahead as the lag chosen, while forecasts using the simulation model are able to be generated for any time horizon based on estimates of the climatic explanatory variables.

The seven day lagged forecast (F03 in table 2.18) slightly outperforms the forecasts based on the simulation model on three forecast evaluation metrics (all except MSE) in the Sydney sample. This may be an anomalous result due to the small out of sample period for this sample. However the superiority of the in sample period forecasting performance of the simulation model over the forecasts using lagged consumption is not as great for the Sydney sample as for the Mawson Lakes sample. This may be due to the existence of measurement error in the climatic explanatory variables for the Sydney sample previously noted in section 2.3. Neither the small out of sample period or measurement error in the explanatory variables temperature and natural light will negatively affect the performance of the forecasts based on lagged electricity consumption.

<table>
<thead>
<tr>
<th>Mawson Lakes</th>
<th>Sydney</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>MSE</td>
</tr>
<tr>
<td>F01: sim mod</td>
<td>0.10</td>
</tr>
<tr>
<td>F02: 1 day lag</td>
<td>0.11</td>
</tr>
<tr>
<td>F03: 7 day lag</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Table 2.18: Forecast evaluation statistics (out of sample)

Tables 2.19 and 2.20 contain the Diebold-Mariano test statistics for each forecast for the out of sample period. Similar to the results for the in the sample period, the null hypothesis of equal predictive ability for each forecast included is not rejected for any forecast in either sample. Reflecting the results reported in table 2.18 the forecasts based on the simulation model have smaller mean loss functions for both MSE and MAE than
forecasts using lagged consumption in Mawson Lakes. The simulation model forecasts for the Sydney sample result in smaller or equal mean loss functions for MSE than forecasts based on lagged consumption but larger MAE loss functions.

<table>
<thead>
<tr>
<th></th>
<th>Base Mawson Lakes</th>
<th>Sydney</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F02: 1 day lag</td>
<td>F03: 7 day lag</td>
</tr>
<tr>
<td>F01: sim mod</td>
<td>-0.02</td>
<td>-0.03</td>
</tr>
<tr>
<td>F02: 1 day lag</td>
<td>-0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td>F03: 7 day lag</td>
<td>-0.01</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 2.19: Diebold-Mariano with MSE loss function (out of sample)

<table>
<thead>
<tr>
<th></th>
<th>Base Mawson Lakes</th>
<th>Sydney</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F02: 1 day lag</td>
<td>F03: 7 day lag</td>
</tr>
<tr>
<td>F01: sim mod</td>
<td>-0.06</td>
<td>-0.12</td>
</tr>
<tr>
<td>F02: 1 day lag</td>
<td>-0.12</td>
<td>0.02</td>
</tr>
<tr>
<td>F03: 7 day lag</td>
<td>-0.06</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Table 2.20: Diebold-Mariano with MAE loss function (out of sample)

2.5.6 Interpretation of results

In this section the first component of a simulation model of household electricity consumption is constructed, estimating consumption using climatic explanatory variables. Temperature and natural light are found to affect household electricity consumption, with the sign and magnitude of effect varying substantially by energy function and in some cases between samples. In particular, electricity consumption for space cooling and space heating are more strongly correlated with temperature in the Mawson Lakes sample than the Sydney sample (however this difference may be due to measurement error in the climate data for Sydney). However the mean effects of the climatic variables are generally the expected sign for electricity consumption for each energy function.

The simulation model forecasts of household electricity consumption are equal or superior to forecasts based on lagged consumption for the Mawson Lakes sample based on forecast evaluation statistics calculated for in and out of sample periods. However a null hypothesis of equal predictive ability is not rejected comparing the simulation model forecasts with those based on lagged consumption. The in sample simulation model forecasts based on the Sydney sample are equal or superior to forecasts using lagged consumption. However household electricity consumption with a lag of seven days provides better forecasts than those of the simulation model based on some forecast evaluation statistics in the out of
sample period. As with the Mawson Lakes sample, a null hypothesis of equal predictive ability is not rejected for the simulation model forecasts and those based on lagged consumption.

The relatively poor out of sample forecasting performance of the simulation model based on the Sydney sample may be the result of the small out of sample period and measurement error in the climatic explanatory variables.
2.6 Household response to intra-day price

In this section the second component of the simulation model is constructed. In the previous section relationships between household electricity consumption (by energy function) are estimated using climatic explanatory variables. These can be used to forecast electricity consumption in the absence of price change. The purpose of this section is to estimate the effects of intra-day changes in the price of electricity on household electricity consumption. This constitutes the second of the two components that make up the short run simulation model.

The assumptions underlying the model are discussed in this section. The methodology used to generate matrices of intra-day price elasticities of demand for electricity is presented along with the price elasticities estimated for each energy function. The mean intra-day own-price elasticity profile of the energy functions are compared and the section concludes with a discussion of the implications of the analysis.

2.6.1 Modelling assumptions

Assumptions required due to limited data

As in the previous section it is assumed that the price of electricity for households was constant during the sample periods of each sample. This assumption is required in order to utilise the technique developed by Hirschberg (2000) to estimate relative price elasticities of demand for electricity (described in detail in the following subsection).

To estimate intra-day price elasticities of demand for electricity using the technique developed by Hirschberg (2000) requires a method of transforming the relative intra-day price elasticities of demand to (absolute) elasticities. The method adopted in this study uses mean price elasticities of demand for electricity by energy function in the calculation of intra-day price elasticities. These must be assumed in the absence of electricity consumption data containing price variation with which to directly estimate elasticities. The mean price elasticities of demand for electricity by energy function ($\bar{\varepsilon}_{p,j}$ for energy function $j$) used in this study are contained in table 2.22. A discussion of the basis for assuming these mean price elasticities precedes table 2.22.

2.6.2 Estimation methodology

The effects of intra-day variation in the price of electricity are simulated using price elasticities of demand for electricity estimated for each household and energy function. Matrices consisting of own- and cross-price elasticities of demand for electricity by intra-day period
are estimated for each household and energy function in the Mawson Lakes and Sydney samples. These are based on relative price elasticities of demand and values for mean price elasticity of demand for electricity by energy function consistent with those in the literature.

Estimating relative price elasticities of demand

A novel technique developed by Hirschberg (2000) is used to estimate relative own- and cross-price elasticities for each intra-day period. This technique provides a theoretically based method using the estimated second moments of demand to generate a matrix of relative own- and cross-price elasticity estimates by time period for data in which there is no apparent price variation.

The technique requires the removal of the effects of any systematic factors that affect electricity consumption. The regressions carried out in section 2.5 are re-run in log form to remove the effects of temperature, natural light and day of week regularities from household electricity consumption (by household and energy function). The log form of the equations (contained in Table 2.21) are used to obtain positive residuals when they are transformed from log to levels, a requirement for the estimation of price elasticities using this technique.

<table>
<thead>
<tr>
<th>Energy function</th>
<th>Regression equation (log form)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space cooling (SC)</td>
<td>$\ln E_{t,1,h} = \lambda_{t,1,h} + \rho_{t,1,h} \ln T_{1,1,1,t} + \rho_{t,1,h} \ln R_t + D_d \ln \xi_{t,1,h} + \epsilon_{t,1,h}$</td>
</tr>
<tr>
<td>Space heating (SH)</td>
<td>$\ln E_{t,2,h} = \lambda_{t,2,h} + \tau_{t,2,h} \ln T_{1,1,2,t} + \tau_{t,2,h} \ln R_t + D_d \ln \xi_{t,2,h} + \epsilon_{t,2,t}$</td>
</tr>
<tr>
<td>Water heating (WH)</td>
<td>$\ln E_{t,3,h} = \lambda_{t,3,h} + \xi_{t,3,h} \ln T_3 + \rho_{t,3,h} \ln R_t + D_d \ln \xi_{t,3,h} + \epsilon_{t,3,t}$</td>
</tr>
<tr>
<td>Food storage (FS)</td>
<td>$\ln E_{t,4,h} = \lambda_{t,4,h} + \xi_{t,4,h} \ln T_4 + \rho_{t,4,h} \ln R_t + D_d \ln \xi_{t,4,h} + \epsilon_{t,4,t}$</td>
</tr>
<tr>
<td>Food preparation (FP)</td>
<td>$\ln E_{t,5,h} = \lambda_{t,5,h} + \xi_{t,5,h} \ln T_5 + \rho_{t,5,h} \ln R_t + D_d \ln \xi_{t,5,h} + \epsilon_{t,5,t}$</td>
</tr>
<tr>
<td>Clothes cleaning (CC)</td>
<td>$\ln E_{t,6,h} = \lambda_{t,6,h} + \xi_{t,6,h} \ln T_6 + \rho_{t,6,h} \ln R_t + D_d \ln \xi_{t,6,h} + \epsilon_{t,6,t}$</td>
</tr>
<tr>
<td>Lighting (LI)</td>
<td>$\ln E_{t,7,h} = \lambda_{t,7,h} + \xi_{t,7,h} \ln T_7 + \rho_{t,7,h} \ln R_t + D_d \ln \xi_{t,7,h} + \epsilon_{t,7,t}$</td>
</tr>
<tr>
<td>Entertainment (EN)</td>
<td>$\ln E_{t,8,h} = \lambda_{t,8,h} + \xi_{t,8,h} \ln T_8 + \rho_{t,8,h} \ln R_t + D_d \ln \xi_{t,8,h} + \epsilon_{t,8,t}$</td>
</tr>
<tr>
<td>Other (OF)</td>
<td>$\ln E_{t,9,h} = \lambda_{t,9,h} + \xi_{t,9,h} \ln T_9 + \rho_{t,9,h} \ln R_t + D_d \ln \xi_{t,9,h} + \epsilon_{t,9,t}$</td>
</tr>
<tr>
<td>Not recorded (NR)</td>
<td>$\ln E_{t,0,h} = \lambda_{t,0,h} + \xi_{t,0,h} \ln T_0 + \rho_{t,0,h} \ln R_t + D_d \ln \xi_{t,0,h} + \epsilon_{t,0,t}$</td>
</tr>
</tbody>
</table>

Table 2.21: Regression equations for systematic factors (log form)

Using the residuals of household electricity consumption from these regressions, matrices of relative price elasticities of demand for electricity are generated using the technique developed by Hirschberg (2000) (discussed in appendix 2.A). Matrices are generated by household and energy function of dimensions 24 by 24 (as an intra-day period of one hour is used in this study). The own-price elasticities of demand for electricity by a household for an energy function during each intra-day period are contained on the main diagonal of each matrix. The off-diagonal elements of each matrix are comprised of the cross-price elasticities of demand during intra-day period $h$ (where $H = 24$) with respect to the price
of electricity during intra-day period $k$. The form of the matrices is shown in equation 2.3. The estimated relative price elasticity of demand for electricity of household $i$ for energy function $j$ during intra-day period $h$ with respect to price in intra-day period $k$ is denoted $\varepsilon_{\text{rel},i,j,h,k}$ in equation 2.3. The matrix (denoted with an underscore) containing the relative intra-day price elasticity estimates for household $i$ for energy function $j$ is denoted $\varepsilon_{\text{rel},i;j}$. 

\[
\varepsilon_{\text{rel},i;j} = \begin{bmatrix}
\varepsilon_{\text{rel},i,j,1,1} & \varepsilon_{\text{rel},i,j,1,2} & \cdots & \varepsilon_{\text{rel},i,j,1,H} \\
\varepsilon_{\text{rel},i,j,2,1} & \varepsilon_{\text{rel},i,j,2,2} & \cdots & \varepsilon_{\text{rel},i,j,2,H} \\
\vdots & \vdots & \ddots & \vdots \\
\varepsilon_{\text{rel},i,j,H,1} & \varepsilon_{\text{rel},i,j,H,2} & \cdots & \varepsilon_{\text{rel},i,j,H,H}
\end{bmatrix}
\] (2.3)

### Estimating price elasticities of demand

In order to identify a level of consumption (rather than just the relative intra-day effect) estimates of intra-day (absolute) price elasticities of demand for electricity are required. To obtain these from the relative intra-day price elasticities estimated using the technique of Hirschberg (2000) requires a method by which the relative elasticities can be 'anchored' to an (absolute) elasticity value. The method adopted involves the multiplication of each relative price elasticity matrix by a scalar calculated to ensure the average intra-day price elasticity of the resulting matrix (weighted by mean intra-day electricity consumption) equals a specific (assumed) mean price elasticity of demand. The assumed mean price elasticities of demand ($\bar{\varepsilon}_{p,j}$) vary by energy function $j$ and are contained in table 2.22.

The assumed mean price elasticities of demand used in this study are constant. While empirical findings of price elasticities of demand for electricity are often presented as point estimates in the literature (see section 2.2) this is not an assumption well supported by household production theory. Changes in factors such as climate, household income and the price of electricity relative to other goods and services may be expected to affect the responsiveness of a household to changes in the price of electricity. In the extreme, the price elasticity of demand for a household or an entire market for any good cannot be inelastic across the entire range of prices for that good given a finite budget constraint.
Table 2.22: Assumed mean price elasticities of demand for electricity

<table>
<thead>
<tr>
<th>Energy function</th>
<th>$\hat{\xi}_{p,j}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space cooling (SC)</td>
<td>-0.3</td>
</tr>
<tr>
<td>Space heating (SH)</td>
<td>-0.3</td>
</tr>
<tr>
<td>Water heating (WH)</td>
<td>-0.1</td>
</tr>
<tr>
<td>Food storage (FS)</td>
<td>-0.01</td>
</tr>
<tr>
<td>Food preparation (FP)</td>
<td>-0.1</td>
</tr>
<tr>
<td>Clothes cleaning (CC)</td>
<td>-0.3</td>
</tr>
<tr>
<td>Lighting (LI)</td>
<td>-0.2</td>
</tr>
<tr>
<td>Entertainment (EN)</td>
<td>-0.2</td>
</tr>
<tr>
<td>Other functions (OF)</td>
<td>-0.2</td>
</tr>
<tr>
<td>Not recorded (NR)</td>
<td>-0.2</td>
</tr>
</tbody>
</table>

A value of $-0.2$ is assumed for the mean price elasticity of demand for electricity for energy functions: lighting; entertainment; and other. An elasticity of demand for electricity of this magnitude is consistent with findings for both short run and intra-day elasticity estimates in the economic literature (see the literature reviewed in section 2.2). Space cooling, space heating and clothes cleaning are assumed to be more price elastic; a value of $-0.3$ is assumed for the mean price elasticities of demand for these energy functions. This reflects the judgement that it is relatively easier for households to adjust their consumption of electricity on space cooling, heating and clothes cleaning than consumption on other energy functions. Substitutes exist for each of these energy functions that do not involve electricity consumption. Household members can adjust their attire to suit the ambient temperature (for example, wearing more clothes in cold weather). Households can also reduce the electricity used in clothes cleaning by ensuring clothes are only washed when clothes washers are full and by using washing lines to dry clothes rather than electric clothes dryers.

In contrast, electricity consumption for water heating and food preparation are assumed to be less elastic with respect to price, with a value of $-0.1$ assumed as the mean price elasticity of demand for electricity for these energy functions. The capacity for households to adjust their consumption of electricity to heat water and prepare food is limited; reduced showers and substituting to restaurant meals and food that requires less heating may result in some response to increased electricity prices. Food storage is assumed to be almost perfectly inelastic. Electricity consumed by households for the purpose of food storage is largely used to power refrigerators and freezers. Households do not have any realistic way to adjust the short run power consumption of these devices other than shutting them down, which is an unlikely response to changed intra-day electricity prices (at least for households with only one refrigerator or freezer). A mean price elasticity for food storage of $-0.01$ is assumed.

To obtain matrices containing (absolute) price elasticities of demand, the matrices of
Relative price elasticities are adjusted by a scalar scaling factor. This is done to ensure the mean price elasticity of demand (calculated across all intra-day periods) equal those assumed in table 2.22 for each energy function. The calculation of the scaling factor \( s_{X,i,j} \) is shown in equation 2.5. It is effectively the mean of the effect of all intra-day price variation by intra-day period (weighted by mean intra-day electricity consumption \( \bar{E}_{i,j,h} \) for household \( i \) for energy function \( j \) in period \( h \)).

\[
\bar{p}_{i,j} = \frac{1}{2} \frac{p_{i,j,1}}{p_{i,j,2}} \cdots \frac{p_{i,j,1}}{p_{i,j,H}} = s_{X,i,j} \tilde{p}_{rel,i,j} \tag{2.4}
\]

\[
s_{X,i,j} = \bar{p}_{p,j} \left( \sum_{m=1}^{24} \left( \bar{E}_{i,j,h=m} \sum_{g=1}^{24} \left( \varepsilon_{p,i,j,h=m,k=g} \right) \right) \right)^{-1} \tag{2.5}
\]

Calculating price elasticities for electricity by adjusting relative price elasticities so that the mean price elasticity is equal to a given value (contained in table 2.22) results in different price elasticities of demand for different households. The overall sensitivity of a household to changes in the intra-day price of electricity will depend on the amount of electricity the household uses on each energy function. To illustrate this point, consider two households: the first consumes electricity solely for the purpose of watching television (entertainment); while the second consumes electricity solely to heat their dwelling. The mean intra-day price elasticity of demand for electricity will be \(-0.2\) for the first household and \(-0.3\) for the second. In reality, households are likely to consume electricity on a variety of activities (energy functions) and the discrepancy highlighted in the above example is likely to overstate the difference in price elasticities of demand between households.

**Estimating the effect of intra-day price variation**

The effect of intra-day electricity price variation on household consumption of electricity is modelled using the matrices of price elasticity of demand estimated for each household and energy function. The effect on aggregate consumption is the sum of the effects on households by energy function. The approach used is the conventional method to incorporate price changes in demand models using price elasticities. The difference is that the matrices of price elasticities are constructed with time as the main dimension (intra-day consumption by intra-day price) rather than for different goods and services.

The effect of electricity price variation on electricity consumption for household \( i \) on energy function \( j \) is estimated in equation 2.6. Both own-price and cross-price elasticities are
used to estimate the effect on consumption of changes in the price of electricity over the course of a day. The effect on consumption is estimated as the product of the ratios of new and old prices in each intra-day period raised to the price elasticity estimate for the period. Electricity consumption following intra-day price variation \((E_{new,i,j,t})\) is estimated as the product of electricity consumption expected prior to the price variation \((E_{old,i,j,t})\) and the estimated price effect on consumption.

\[
\hat{E}_{new,i,j,t} = E_{old,i,j,t} \prod_{g=1}^{24} \left( \frac{p_{new,h=g}}{p_{old,h=g}} \right)^{\hat{\varepsilon}_{p,i,j,h,k=g}}
\]  

(2.6)

### 2.6.3 Estimation results

In this subsection figures containing the estimated own- and cross-price elasticities for each energy function and across energy functions are presented. The figures contain mean elasticity estimates averaged across households. The purpose of this subsection is to highlight differences in elasticity profiles between energy functions and between the samples (Mawson Lakes and Sydney). The estimated effects of intra-day variation in the price of electricity are determined by the price elasticities estimated for each energy function. Differences in price elasticities estimated for different energy functions are crucial to the analysis presented in chapter 3 where the effects of appliance upgrades and replacements are simulated.

The mean price elasticities of demand estimated across all energy functions are presented in figure 2.22 and for each energy function in figures 2.23 to 2.32. Own-price elasticities of demand are shown across the main diagonal while cross-price elasticities are represented in the areas off the main diagonal. These areas indicate the estimated price elasticity of demand during period one with respect to the price of electricity during period two.
All energy functions

The mean intra-day own- and cross-price elasticities of demand estimated for the two datasets mask significant variation by energy function. The Mawson Lakes sample has some variation in own-price elasticity across the course of the day, increasing around 8am, while relatively less elastic in the early morning and afternoon. There is very little variation discernable in the Sydney sample.

![Figure 2.22: Mean intra-day price elasticity: all energy functions](image)

(a) Mawson Lakes  
(b) Sydney

Space cooling

There are substantial discrepancies between the estimated price elasticities for space cooling in the two datasets (figure 2.23). Electricity consumption for space cooling in the Mawson Lakes sample is increasingly elastic later in the day, with own-price elasticities increasing across the main diagonal of the matrix. This is consistent with patterns of consumption, with the majority of electricity used for space cooling consumed between 1pm and 11pm. Estimated cross-price elasticities for electricity for space cooling in the Mawson Lakes sample are negative. This is not the case for other energy functions, where estimates of cross-price elasticities around zero are the norm. The elasticity profile estimated for the Sydney sample has almost completely inelastic cross- and own-price elasticities prior to midday and substantially elastic cross- and own-price elasticity estimates for the afternoon.

The discrepancy in estimated price elasticities between the samples may be due to measurement error affecting temperature in the Sydney sample. As noted earlier, the temperature observations used in the analysis of the Mawson Lakes households were measured in close proximity to the actual households. However the temperature observations for Sydney are for the central business district rather than the different suburbs in which each household is located.
Space heating

There are differences in the estimated intra-day price elasticities between the Mawson Lakes and Sydney datasets. There are two periods where the magnitude of the estimated own-price elasticities of demand are elevated in the Mawson Lakes sample - between 5am and 8am, and from 5pm to 10pm. These periods coincide with the periods of highest consumption of electricity for space heating, with the afternoon period showing relatively higher and more persistent elasticity. The estimates for Sydney also reveal two periods of relatively high magnitude own-price elasticities. However these are not the same periods as for Mawson Lakes, rather they are found between 3am and 7am, and from 9pm to midnight. The heightened morning period for Sydney is also greater than that for the evening period, perhaps reflecting the higher proportion of electricity consumed in the morning in Sydney (with a peak around two-thirds the evening peak) relative to Mawson Lakes (where the morning peak is less than half the evening peak).

Similar to space cooling, the discrepancy between estimated price elasticities for space heating may be due to measurement error affecting temperature in the Sydney sample.
Water heating

The intra-day price elasticity estimates for Mawson Lakes are estimated for one household, as all other households in the Mawson Lakes sample use gas for the purpose of water heating. The Mawson Lakes household with an electric water system uses electricity between midnight and 2am.

Subfigure 2.25 shows the highest magnitude price elasticities estimated are early in the morning in the Sydney sample between the hours of 2am and 6am.

Food storage

In contrast to the intra-day price elasticities estimated for the preceding energy functions, the price elasticity matrices for food storage for both Mawson Lakes and Sydney are
remarkably consistent. Intra-day own-price elasticities show little variation across the day, while all the cross-price elasticities estimated are around zero.

Food preparation

As with food storage, there are strong similarities to the profiles of intra-day price elasticities for Mawson Lakes and Sydney. Own-price elasticities increase in the morning (from around 6am), plateau during the day (with a small fall between 1pm and 3pm), peak between 3pm and 8pm before falling prior to midnight. For both datasets the estimated cross-price elasticities are around zero.

Clothes cleaning

There are no metered appliances that serve the energy function clothes cleaning in the Mawson Lakes sample. The Sydney sample reflects an intra-day price elasticity profile
similar to that of electricity consumption on this energy function, with the highest magnitude own-price elasticity estimates corresponding to the consumption peaks at 10am to noon and 4pm to 6pm. The cross-price elasticities estimated are close to zero.

![Diagram](image)

(a) Sydney

Figure 2.28: Mean intra-day price elasticity: clothes cleaning

Lighting

The estimated intra-day price elasticities for lighting are similar for both Mawson Lakes and Sydney. The estimated own-price elasticities across the day are consistent, with a small increase during the morning from 5am to 9am. It is interesting to note that in neither the Mawson Lakes or Sydney sample does the own-price elasticity peak during the consumption peak of the day (between 6pm and 10pm).

![Diagram](image)

(a) Mawson Lakes

(b) Sydney

Figure 2.29: Mean intra-day price elasticity: lighting
Entertainment

There are no metered appliances that serve the energy function entertainment in the Mawson Lakes sample. As noted earlier, this category comprises only televisions in the Sydney sample. While entertainment electricity consumption is minimal prior to 5pm, the estimates of intra-day price elasticity for Sydney show two periods of high elasticity - between 10am and 4pm and from 7pm to midnight.

![Figure 2.30: Mean intra-day price elasticity: entertainment](image)

Other functions

There are discrepancies between the profiles of estimated intra-day price elasticities for the Mawson Lakes and Sydney samples. It is likely that these result from different types of appliances allocated to the 'other functions' category in each sample. The Mawson Lakes sample has only one appliance serving 'other functions' while in the Sydney sample, seven appliances are included in this category.

![Figure 2.31: Mean intra-day price elasticity: other functions](image)
Not recorded

There are relatively few differences in the estimated profiles of intra-day price elasticities in the Mawson Lakes and Sydney samples for appliances with energy functions not recorded in the datasets. There are few variations in intra-day own-price elasticities of demand while the cross-price elasticities of demand are close to zero in both samples.

![Figure 2.32: Mean intra-day price elasticity: not recorded](image)

(a) Mawson Lakes  
(b) Sydney

Comparative intra-day elasticity estimates

As shown in figures 2.23 to 2.32 there are substantial differences in intra-day price elasticities between energy functions. Figure 2.33 plots the mean price elasticity of demand for each energy function with respect to price variation in the ten prior and subsequent intra-day periods. Price elasticity estimates are averaged across households and intra-day periods in each sample. Negative values on the horizontal axis indicate the impact of a price change in a prior period, while positive values indicate the impact of a price change in an upcoming period.

In both the Mawson Lakes and Sydney samples, cross-price elasticity estimates for space cooling are persistently negative. Space heating has a similar profile in the Mawson Lakes sample and, to a lesser extent, in the Sydney sample. Most other energy functions have low mean cross-price elasticities, with estimates close to zero. The substantial mean negative cross-price elasticity for space cooling and space heating are highlighted in figure 2.34 which isolates the estimates for space cooling, space heating and plots these against the mean of all other energy functions. The effect of the estimated negative cross-price elasticities for space cooling and space heating is that the effect of a price change (increase) will affect (reduce) consumption in prior and subsequent intra-day periods. One intuitively appealing explanation for this price elasticity profile for space cooling and space heating is that household members use appliances serving these energy functions for a number of
hours, encompassing multiple intra-day periods. A household may be less likely to turn a cooling or heating appliance on in one period if the price of electricity will rise in a subsequent period, knowing that the appliance will continue to operate during the later period.

![Figure 2.33: Mean price elasticity by energy function with respect to price during the ten prior and subsequent intra-day periods](image)

![Figure 2.34: Mean price elasticity by selected energy function with respect to price during the ten prior and subsequent intra-day periods](image)

### 2.6.4 Interpretation of results

In this section the second component of a simulation model of household electricity consumption is constructed, estimating the impact of intra-day price variation on electricity consumption. A novel method of calculating relative price elasticities of demand proposed by Hirschberg (2000) is used in conjunction with assumed mean price elasticity values (consistent with findings in the literature) by energy function to estimate elasticity matrices. These comprise estimates of own- and cross-price elasticities of demand for electricity across intra-day periods. Elasticity matrices are estimated separately for each household and energy function.
Substantial differences in the profiles of estimated intra-day price elasticities of demand are found between samples and energy functions. In combination with differences in intra-day household consumption of electricity by energy function (noted in section 2.3) response to intra-day price variation will not be uniform across samples and energy functions. An example of the variety of elasticity estimates is that of the cross-price elasticities estimated for space cooling and space heating. The estimates for these energy functions are negative while those of other energy functions are close to zero.

The implication of this is that an anticipated price change (increase) in one intra-day period is expected to affect (reduce) estimated electricity consumption on space cooling and space heating in prior and subsequent intra-day periods.

The estimated intra-day price elasticities of demand are generally consistent with short-run price elasticities of demand reviewed in section 2.2. While intra-day estimates by energy function are rare in the literature, the findings of this study are generally consistent with those for space heating (air conditioning), with increasing price-elasticity found for periods in which the temperatures are generally high (in the afternoon). The non-zero cross-price elasticities estimated for space cooling and space heating are also consistent with a degree of consumption substitution seen in TOU and CPP studies between high and low price periods (for example Herter et al. 2005).
2.7 Model application

2.7.1 Constrained profit maximising intra-day tariff

Using the absolute price elasticity estimates obtained in this chapter, optimal (profit maximising) intra-day prices are estimated subject to a price constraint. Under a uniform intra-day tariff (where the price of electricity is constant throughout the day) electricity retailers make higher profits per unit of electricity in periods of low consumption, as the price of electricity in the wholesale market is typically low during these periods. Conversely, electricity retailers make losses during peak periods of electricity consumption when the wholesale price of electricity exceeds the retail price.

In this section, the simulation model is used to estimate the effects of the introduction of a TOU electricity tariff for households. Specifically the model is used to estimate intra-day prices that maximise an electricity retailer's profit subject to a price constraint. The price constraint chosen for this application is that aggregate expenditure by households on electricity must not rise given existing patterns of household electricity consumption following the introduction of the new tariff. In other words, if households do not change the timing or quantity of electricity consumption, their expenditure on electricity must be no higher in aggregate than under the previous (uniform) electricity tariff. All households are served by a single (monopolist) retailer that must offer one tariff to all households. The electricity retailer purchases electricity in the wholesale market and supplies the electricity to households in the retail market. The wholesale price of electricity is assumed to be a function of aggregate electricity consumption. In this application, the sample households are assumed to comprise the entire market for electricity. The profit of the electricity retailer is equal to the revenue gained from selling electricity to households less the cost of purchasing that electricity in the wholesale market. Optimal intra-day prices are estimated for each sample (Mawson Lakes and Sydney).

An estimate of the relationship between aggregate electricity demand and the wholesale price of electricity is required in this application. Using National Electricity Market Management Company (NEMMCO) price data of half hourly frequency for the twelve month period April 2002 to March 2003 for South Australia (National Electricity Market Management Company 2003), regressions are carried out to estimate this relationship using a single quadratic term. Equation 2.7 describes the relationship estimated between wholesale period price $w_t$ ($/kWh$) and total electricity consumption $E_t$ (kWh) in each half hourly period. The estimated coefficient is significant at the one per cent level, with a $t$-value of 306.69 (exceeding the relevant standard normal critical value of 2.58). As no intercept term is included in the regression, an uncentred coefficient of determination is calculated. The uncentred coefficient of determination is generally higher than the standard coefficient of determination ($R^2$) (Verbeek 2004, p21). This appears to be the
case in this regression, with an uncentred coefficient of determination value of 0.91 (far
larger than the standard $R^2$ values calculated for comparable regressions in section 4.3).

\[ \hat{w}_t = 1.24 \times 10^{-14} E_t^2 \] \hspace{1cm} (2.7)

For the purposes of this application, the relationship between aggregate electricity demand
of the six Mawson Lakes households and the wholesale price of electricity is assumed to
be of quadratic functional form with the coefficient chosen to ensure the wholesale price
exceeds the retail price around five per cent of the time. The relationship specified is shown
in equation 2.8. This cost relationship would result in an electricity retailer supplying
the Mawson Lakes households making a profit of around $1,500 over the estimates period
when charging a standard uniform electricity tariff of $0.16269 per kWh. This price
was the household general supply tariff (tariff 126) in South Australia applying from 1

The corresponding relationship for the households in the Sydney sample is given by equa-
tion 2.9. A quadratic functional form is again assumed and the same uniform electricity
tariff of $0.16269 per kWh is used to estimate the coefficient, on the basis that the whole-
sale price exceeds the retail price for around five per cent of intra-day periods. This
cost relationship would result in an electricity retailer serving the Sydney sample to lose
around $1,500 charging a uniform tariff of $0.16269 per kWh.

\[ \hat{w}_t = 1.47 \times 10^{-3} E_t^2 \] \hspace{1cm} (2.8)
\[ \hat{w}_t = 4.50 \times 10^{-5} E_t^2 \] \hspace{1cm} (2.9)

The relationships estimated are based on basic assumptions concerning the functional
form and market structure. They are utilised only to demonstrate this application of the
simulation model. A more detailed examination of the relationship between electricity
demand and wholesale prices, in which the impact of sectors other than the household
sector are considered, is carried out in section 4.3.

Figure 2.35 contains the profit maximising intra-day tariffs estimated for households in the
Mawson Lakes and Sydney samples. The initial (uniform) electricity price of $0.16269 per
kWh is contrasted with the optimised intra-day electricity tariff where the price is permit-
ted to vary in each intra-day period (optimised profile tariff). Figure 2.36 compares the ini-
tial price with the optimised tariff comprising five intra-day price periods (off-peak, shoul-
der, peak, shoulder and off-peak) (optimised period tariff). The intra-day price periods
chosen are those used in Energy Australia’s PowerSmart Home tariffs: 10pm to 7am (off-
peak); 7am to 2pm and 8pm to 10pm (shoulder); and 2pm to 8pm (peak) (Energy Australia
The profit of an electricity retailer charging the initial (uniform intra-day) tariff is $1,519 over the estimates period of one year for all households in the Mawson Lakes sample. This profit rises to $1,673 under the optimised profile tariff, while the profit under the optimised period tariff is $1,620. An electricity retailer serving the households in the Sydney sample is estimated to lose $1,538 charging the initial uniform tariff, $932 with the optimised profile tariff and $1,508 with the optimised period tariff.

![Figure 2.35: Profit maximising intra-day electricity prices: optimised profile tariff ($/kWh)](image)

![Figure 2.36: Profit maximising intra-day electricity prices: optimised period tariff ($/kWh)](image)

The optimised intra-day tariffs comprise higher prices during times of high demand balanced by lower prices during periods of low demand resulting from the price constraint applied. The increased profitability of the optimised tariffs is due primarily to the better matching of retail and wholesale prices of electricity. The price of electricity in the wholesale market is less likely to exceed the retail price under the optimised intra-day tariffs. The optimised tariffs result in a reduction in household electricity consumption for electricity during peak periods and an increase during off-peak periods. A retail tariff allowing intra-day variation in the price of electricity provides a more accurate signal to
households of the cost of providing them electricity during different periods of the day. This results in increased market efficiency, as households can more effectively consider the costs and benefits of marginal consumption of electricity on the various household energy functions.

There is little variation in the optimised period tariff estimated for the Sydney sample. It is clear that the off-peak, shoulder and peak periods used in this application do not match the periods of low, medium and high optimal prices estimated for the Sydney sample in subfigure 2.35(b). The off-peak, shoulder and peak periods used in the optimised period tariff all include intra-day periods in which the prices in the optimised profile tariff are both above and below the initial uniform price. This is not the case for the Mawson Lakes sample, where the periods generally correspond to the low, medium and high optimal prices estimated in subfigure 2.35(a).

It is interesting to note that the range between minimum and maximum optimal intra-day prices in the optimised period tariffs is less than the range of Energy Australia’s PowerSmart Home tariff. As at July 2009, the PowerSmart tariff (including GST) comprises:

- $0.0841 per kWh (off-peak rate);
- $0.1408 per kWh (shoulder rate); and
- $0.3564 per kWh (peak rate).

A similar TOU tariff plan available is Integral Energy’s General Supply Time of Use tariff. The range between high and low intra-day prices for this tariff is lower than for Energy Australia’s PowerSmart tariff, but still larger than the estimated optimised tariffs. The Integral Energy time of use intra-day prices (including GST) are:

- $0.10274 per kWh (off-peak rate: 10pm to 7am);
- $0.22528 per kWh (shoulder rate: 7am to 1pm and 8pm to 10pm); and
- $0.26169 per kWh (peak rate: 1pm to 8pm).

Increases in the price level may account for some of the difference in the range between minimum and maximum TOU prices between the market rates on offer in July 2009 and the optimal rates estimated for Mawson Lakes in 2002-03. The uniform intra-day price charged by Integral Energy in July 2009 is $0.1815 per kWh (including GST) under Integral’s General Tariff - higher than the $0.16269 per kWh assumed for Mawson Lakes in 2002-03. A more likely reason for the disparity is that the household sector is responsible for a disproportionate and growing percentage of electricity demand at peak periods. This is not reflected in the basic demand-price relationship assumed in this extension. The
relationship between electricity demand and wholesale prices is examined in more detail in section 4.3. Since demand at peak periods is largely being driven by the household sector, the range between minimum and maximum prices for optimal electricity tariffs would be expected to vary more for households than for the market as a whole.
2.8 Chapter conclusion

In this chapter a simulation model of short run household consumption of electricity is constructed based on intra-day climate and electricity price. Temperature and natural light are found to affect household electricity consumption, the effect of each varying by appliance type (energy function). Space cooling and space heating are correlated with temperatures outside a comfortable range, while a negative relationship between electric lighting and the level of natural light is found. The effect of climatic variables on electricity consumption differs between the Mawson Lakes and Sydney samples. In particular, the relationships between electricity consumption on space cooling and heating and temperature are found to be stronger in the Mawson Lakes sample than the Sydney sample (however this may be due to measurement error in the Sydney climatic variables).

Intra-day own-price and cross-price elasticities of demand for electricity by household and energy function are estimated using a novel technique proposed by Hirschberg (2000). The price elasticities of demand estimated are used to simulate the impact of intra-day electricity price variation on household electricity consumption. The profiles of own- and cross-price elasticities vary by energy function with implications for the setting of TOU tariffs for electricity. In particular, the profiles of intra-day elasticity of demand for electricity for space heating and cooling suggest that a price change (increase) in one intra-day period affect (reduce) consumption in prior and subsequent periods. This is generally not the case for the other energy functions, where the effect of a price change is largely confined to the period in which the change is made.

An application of the model highlighting the use of the estimated intra-day price elasticities of demand is presented in which profit maximising TOU tariffs for electricity are estimated. It is shown that an electricity retailer can benefit by introducing a TOU tariff that does not result in increased aggregate electricity expenditure or reduced consumption by households. Rather, the benefit arises from improved market efficiency, as households shift a proportion of their electricity consumption from peak to shoulder and off-peak intra-day periods.

The model constructed in this chapter assumes that the household stock of appliances does not change. In chapter 3 the characteristics of household appliances are endogenised based on their price, effective life and energy efficiency characteristics.
2.A Overview of Hirschberg technique

In this appendix an overview of the technique proposed by Hirschberg (2000) is provided. This technique is used in this study to estimate relative intra-day price elasticities of demand (as described in section 2.6). (Note, the nomenclature of this appendix follows that of Hirschberg (2000) rather than that presented in section 2.4.)

The Hirschberg technique is a theoretically-based method using the estimated second moments of demand to estimate relative own- and cross-price elasticities of demand in the absence of price variation. The technique relies on the theory of demand - that demand is a function of preferences, income and prices. Where preferences and income are unchanging, variation in demand can be attributed to changes in (perceived) price. This is specified in equation 2.10, where the log of the perceived price \( p_t \) at time \( t \) is a function of the observed price \( p_{0t} \) and a stochastic component \( \varepsilon_t \) that is independent with an expected value of zero and a variance of \( \sigma^2 \).

\[
p_t = p_{0t} + \varepsilon_t \quad \text{(2.10)}
\]

\[
E[\varepsilon_t] = E[\varepsilon_t \varepsilon_s] = 0 \quad \text{(when } t \neq s \text{)} \quad \text{(2.11)}
\]

\[
E[\varepsilon_t^2] = \sigma^2 \quad \text{(2.12)}
\]

A logarithmic demand relationship can be specified for each intra-day period (shown in equation 2.13). \( X \) is an \( n \) by \( m \) matrix, where \( n \) is the number of days in the sample and \( m \) is the number of intra-day periods specified. \( P \) is an \( n \) by \( m \) matrix of the log of the perceived price, while \( E \) is an \( m \) by \( m \) (symmetric) matrix of intra-day price elasticities.

\[
X = PE^T \quad \text{(2.13)}
\]

A constraint is provided by the elasticity version of the Slutsky equation. This is used to define the relationship between intra-day demand elasticities, weighted by share of expenditure. This is shown in equation 2.14 where \( e_{ji} \) is the intra-day price elasticity of at intra-day period \( j \) with respect to price at intra-day period \( i \), \( m_j \) is the income elasticity for the commodity at intra-day period \( j \) and \( w_j \) is the expenditure share at intra-day period \( j \).

\[
e_{ji}w_j + m_jw_iw_j = e_{ij}w_i + m_iw_iw_j \quad \text{(2.14)}
\]

This constraint is then substituted in to the demand relationship, giving equation 2.15 where \( H \) is a symmetric matrix with elements \( e_{ji}w_j \) and \( \bar{w} \) is a matrix with expenditure
shares on the diagonal. Note: the intra-day income elasticities (for the same good at different times of day) are assumed to be equal, which simplifies the constraint.

\[ X = PE^T = PH \text{diag}(\bar{w})^{-1} \]  
\[ E^T = H \text{diag}(\bar{w})^{-1} \]  

Estimates of relative intra-day own- and cross-price elasticities (as contained in matrix \( E \)) can be generated by estimating \( H^T H \) utilising a matrix decomposition method. Hirschberg (2000) employs the eigenvalue decomposition which is shown in equations 2.17 and 2.18.

\[ H^T H = \text{diag}(\bar{w}) \text{cov}(X) \text{diag}(\bar{w}) = L\Lambda L^T \]  
\[ \hat{\sigma} H = L - \Lambda^{1/2} L^T \]  
\[ \hat{\sigma} E = \hat{\sigma} H \text{diag}(\bar{w}) \]

In the two examples provided by Hirschberg (2000), the bootstrap technique suggested by Efron (1982) is used to estimate \( \hat{\sigma} H \).
2.B Structural break test on RES dataset

Structural break tests are carried out in this appendix, in order to assess whether the data selected and used from the RES dataset in this study are significantly different from data not selected.

As noted in section 2.3, much of the data in the RES dataset obtained for use in this study are missing. Data for 41 households are used in this study. The distribution of remaining households by the level of missing data (excluding those with more than 99 per cent data missing) is shown in figure 2.37 (a reproduction of figure 2.1). In this appendix, data on an additional 68 households are added to those for the 41 households selected for use in this study. These additional households are selected on the basis that less than 20 per cent of data relating to household consumption are missing for each.

![Figure 2.37: Distribution of households by proportion of missing data](image)

To test whether the data for the additional households are substantially different from those of the 41 used in this study, structural break (Chow) tests are carried out on the parameters estimated for each household in section 2.5. These parameters are estimates of the responsiveness of household electricity consumption (by energy function) to temperature and the level of natural light, along with a multiplicative constant and day-of-week effects as show in table 2.23 below (a copy of table 2.4).
Energy function  | Regression equation
---|---
Space cooling (SC)  | $E_{i,1,t} = \alpha_{i,1.1}^{T_{i,\text{M},a}} + R_{i,1.1}^{\delta_{i,1.1}} + u_{i,1,t}$
Space heating (SH)  | $E_{i,2,t} = \alpha_{i,2.2}^{T_{i,\text{M},a}} + R_{i,2.2}^{\delta_{i,2.2}} + u_{i,2,t}$
Water heating (WH)  | $E_{i,3,t} = \alpha_{i,3.3}^{T_{i,\text{M},a}} + R_{i,3.3}^{\delta_{i,3.3}} + u_{i,3,t}$
Food storage (FS)  | $E_{i,4,t} = \alpha_{i,4.4}^{T_{i,\text{M},a}} + R_{i,4.4}^{\delta_{i,4.4}} + u_{i,4,t}$
Food preparation (FP)  | $E_{i,5,t} = \alpha_{i,5.5}^{T_{i,\text{M},a}} + R_{i,5.5}^{\delta_{i,5.5}} + u_{i,5,t}$
Clothes cleaning (CC)  | $E_{i,6,t} = \alpha_{i,6.6}^{T_{i,\text{M},a}} + R_{i,6.6}^{\delta_{i,6.6}} + u_{i,6,t}$
Lighting (LI)  | $E_{i,7,t} = \alpha_{i,7.7}^{T_{i,\text{M},a}} + R_{i,7.7}^{\delta_{i,7.7}} + u_{i,7,t}$
Entertainment (EN)  | $E_{i,8,t} = \alpha_{i,8.8}^{T_{i,\text{M},a}} + R_{i,8.8}^{\delta_{i,8.8}} + u_{i,8,t}$
Other (OF)  | $E_{i,9,t} = \alpha_{i,9.9}^{T_{i,\text{M},a}} + R_{i,9.9}^{\delta_{i,9.9}} + u_{i,9,t}$
Not recorded (NR)  | $E_{i,0,t} = \alpha_{i,0.0}^{T_{i,\text{M},a}} + R_{i,0.0}^{\delta_{i,0.0}} + u_{i,0,t}$

Table 2.23: Regression equations for climatic explanatory variables

The parameters estimated for each household (by energy function) are partitioned, separating those for the 41 households selected for use in this study and the additional 68 households. The null hypothesis of the Chow test is that there is no structural break - that each parameter being estimated does not differ between the partitioned datasets.

The proportion of parameters for which the null hypothesis is rejected are reported in table 2.24 by energy function. For most energy functions the null hypothesis of no structural break is rejected for less than ten per cent of parameters. The exceptions are clothes cleaning, lighting and energy consumption by appliances that were not individually metered (the 'not recorded' category). This may reflect the effect of missing data for specific parts of the sample period (of one year) for these energy functions that exhibit a substantial degree of seasonality.

<table>
<thead>
<tr>
<th>Energy function</th>
<th>Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space cooling (SC)</td>
<td>0.076</td>
</tr>
<tr>
<td>Space heating (SH)</td>
<td>0.032</td>
</tr>
<tr>
<td>Water heating (WH)</td>
<td>0.051</td>
</tr>
<tr>
<td>Food storage (FS)</td>
<td>0.034</td>
</tr>
<tr>
<td>Food preparation (FP)</td>
<td>0.070</td>
</tr>
<tr>
<td>Clothes cleaning (CC)</td>
<td>0.167</td>
</tr>
<tr>
<td>Lighting (LI)</td>
<td>0.126</td>
</tr>
<tr>
<td>Entertainment (EN)</td>
<td>0.019</td>
</tr>
<tr>
<td>Other (OF)</td>
<td>0.046</td>
</tr>
<tr>
<td>Not recorded (NR)</td>
<td>0.245</td>
</tr>
</tbody>
</table>

Table 2.24: Structural break (Chow) test: null rejection proportion by energy function
2.C Log-linear estimation of climate regressions

The preliminary modelling approach used to estimate household response to climate included a log-linear form of the regression equations (as shown in table 2.21). The resulting parameters were transformed to levels form prior to inclusion in the simulation model. This has the advantage of requiring only a single (log-linear) regression form to estimate both household response to climate and the residuals required to estimate matrices of own- and cross-price elasticities of demand. However to use the results of a regression of this form to estimate household electricity consumption requires the transformation from logarithms to levels and yields parameters that are biased estimators of the expected value of the relevant (levels) parameters. The resulting transformed and adjusted estimates of household electricity consumption are inferior to those gained by directly estimating consumption as described in section 2.5.

This appendix outlines the process required to transform and adjust a log-linear form regression in order to estimate household electricity consumption (rather than the natural log of consumption) and shows that this generally results in inferior forecasts of consumption than those generated by the simulation model.

Transformation from logarithms to levels

The log-linear regression estimates the log of electricity consumption for each household as shown in table 2.21. Transforming the regression by taking the exponent of the estimated log electricity consumption yields estimates of median household electricity consumption rather than mean consumption (Miller 1984). This is because the error term estimated for the regressions in log form is not additive with mean of zero in the level, rather it is a multiplicative term $e^{u_t}$ where $u_t \sim (0, \sigma^2)$. The expected value of the levels error term is dependant on its distribution. If the error is assumed to be lognormal the expected value of the multiplicative error will be $e^{1/2\sigma^2}$ (Miller 1984).

One method of obtaining unbiased estimates of household electricity consumption would be to follow Miller by assuming a lognormal error distribution and adjusting the estimate by the expected value of the error ($e^{1/2\sigma^2}$). However examination of the moments of the residuals from the regressions carried out in section 2.5 (table 2.25) does not provide support for the assumption of a lognormal error distribution for either sample. Table 2.26 contains the results of normality tests (Kolmogorov-Smirnov, Cramer-von Mises and Anderson-Darling) carried out on these residuals. The null hypothesis of normality is rejected at the one per cent level in each of these tests for both samples.
Moments

<table>
<thead>
<tr>
<th></th>
<th>Mawson Lakes</th>
<th>Sydney</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>287105</td>
<td>1927993</td>
</tr>
<tr>
<td>Mean</td>
<td>−0.0048183</td>
<td>−0.0046193</td>
</tr>
<tr>
<td>Variance</td>
<td>0.09208875</td>
<td>0.25032074</td>
</tr>
<tr>
<td>Skewness</td>
<td>−6.4338135</td>
<td>−4.2531565</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>135.547682</td>
<td>66.479171</td>
</tr>
</tbody>
</table>

Table 2.25: Descriptive statistics: regression residuals

Tests of normality

<table>
<thead>
<tr>
<th>Test</th>
<th>Mawson Lakes</th>
<th>Sydney</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic</td>
<td>p-value</td>
</tr>
<tr>
<td>Kolmogorov-Smirnov</td>
<td>0.326712</td>
<td>&lt; 0.0100</td>
</tr>
<tr>
<td>Cramer-von Mises</td>
<td>11705.3</td>
<td>&lt; 0.0050</td>
</tr>
<tr>
<td>Anderson-Darling</td>
<td>56694.16</td>
<td>&lt; 0.0050</td>
</tr>
</tbody>
</table>

Table 2.26: Normality tests: regression residuals

Rather than assume a lognormal error distribution, a direct estimate of bias is made by comparing the estimates of household electricity consumption (by energy function) with actual household consumption during the sample period. This is the nonparametric ‘smearing’ estimate proposed by Duan (1983) which is superior to a parametric correction (such as that suggested by Miller) when the implied distributional assumptions of the latter are not supported. The smearing corrections - the expected value of the ratio of estimated (\( \hat{E}_{j,t} \)) to actual (\( E_{j,t} \)) household electricity consumption by energy function \( j \) - are calculated as shown in equation 2.20.

\[
\text{smearing correction: } s_{\text{smear},j} = T^{-1} \sum_{t=1}^{T} \left( \frac{E_{j,t}}{\hat{E}_{j,t}} \right)
\]  

(2.20)

Corrected estimates are obtained by dividing the initial estimates of household electricity consumption by the estimated smearing correction as shown in equation 2.23. (Note: equations 2.21 and 2.22 are based on the functional form used for space cooling.) This only corrects the estimates of consumption - leaving the parameters estimated from the original log-linear regression unchanged. These parameters are not unbiased estimators of the expected values of the associated parameters.
\[
\ln \hat{E}_{i,1,t} = \hat{\lambda}_{i,1,h} + \hat{\nu}_{i,1,h} \ln T_{elMax,i,t} + \hat{\rho}_{i,1,h} \ln R_t + D_d \ln \hat{\xi}_{i,1,h} + E \left[ \epsilon_{i,1,t} \right] \quad (2.21)
\]
\[
\hat{E}_{i,1,t} = e^{\hat{\lambda}_{i,1,h} T_{elMax,i,t}^{\hat{\nu}_{i,1,h}}} R_t^{\hat{\rho}_{i,1,h} D_d \hat{\xi}_{i,1,h}} e^{E \left[ \epsilon_{i,1,t} \right]} \text{ (biased estimate)} \quad (2.22)
\]
\[
\hat{E}_{\text{unbiased},i,1,t} = s_{\text{smear},1} \hat{E}_{i,1,t} \text{ (unbiased estimate)} \quad (2.23)
\]

**Forecast evaluation**

The forecast evaluation metrics presented in appendix 2.E are used to contrast the forecasting performance of the model based on a direct regression of household electricity consumption (used in the simulation model presented in this chapter) and the model based on the transformed and adjusted log-linear regression described in this appendix. The results are presented in table 2.27 where the first forecast is that of the simulation model and the second is that of the transformed and adjusted log-linear model for the Mawson Lakes sample. The forecasts of the simulation model are generally superior to those of the transformed and adjusted log-linear model, as evaluated by the four metrics (MAE, MSE, R² and Theil). The forecasts of the direct regression model are better for the Mawson Lakes sample, however they are mixed in the Sydney sample, with only the coefficient of determination favouring the directly estimated model.

<table>
<thead>
<tr>
<th></th>
<th>Mawson Lakes</th>
<th>Sydney</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE</td>
<td>MSE</td>
</tr>
<tr>
<td>F01: sim mod</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>F02: log-l mod</td>
<td>0.12</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Table 2.27: Forecast evaluation statistics (in sample): directly estimated and log-linear models
2.D Data validation and processing

Mawson Lakes

The dataset was made available for this study in the form of multiple Microsoft Excel workbooks. The data for each household were provided in two Excel workbooks (one for each year surveyed) comprising multiple sheets for electricity consumption. As part of this study these data are consolidated in a Microsoft Access database and transferred to SAS 9.2.

Data are missing for each household in the sample. Missing records range from a single observation to periods of multiple days. An average of ten days worth of observations per household is missing over the two year measurement period. The majority of missing data are for the period from 14:00 2 December 2003 to 01:15 8 December 2003. No electricity consumption readings are recorded for any household during this period.

Along with checks for missing data, the date and time have been verified for each record to ensure that no multiple records exist. A number of identical records were found and deleted.

Sydney (RES)

The dataset was made available in the form of multiple dBase files. The data for each household were provided in a dBase file comprising electricity consumption by monitored appliance. As part of this study these files are consolidated in a Microsoft Access database and transferred to SAS 9.2.

Data are missing for the majority of households in the RES survey. A sample of households were selected for analysis in this study: households with the majority of data intact over a period of fourteen months from 1 June 1993 were included in the sample. The sample period is chosen in order to maximise the number of households in the sample. Data on appliances that were not monitored in the RES survey are not included in the dataset made available for this study.

Along with checks for missing data, the date and time have been verified for each record to ensure that no multiple records exist. A number of identical records were found and deleted.

Data processing

A number of data processing steps are carried out to enable analysis. To synchronise the climate and electricity consumption datasets within each sample, inter-hourly values
for variables in the electricity consumption datasets are aggregated to obtain aggregate electricity consumption during each hourly period. Appliances are categorised as serving an energy function. Reverse cycle air conditioners are a special case, as these appliances can be used for both space cooling and space heating. As the energy function a reverse cycle air conditioner served (space cooling or space heating) in any one intra-day period is not recorded, electricity consumption by these appliances is categorised according to the date of electricity consumption. It is assumed that reverse cycle air conditioners provide space cooling from November to April and space heating from May to October.

Electricity consumed by appliances on powerpoints is allocated to the energy function 'not recorded'. Also categorised as 'not recorded' is any positive discrepancy between the aggregate of monitored electricity consumption and total electricity consumption (typically zero or close to zero). Appliances that do not fit in any of the energy function categories are allocated to the energy function 'other functions'. An example of an appliance included in this category is a spa bath.
2. Evaluation metrics

The metrics used in this study to assess and compare the predictive ability of the simulation model are described in this appendix. The metrics are specified in this appendix for forecasts over period $t = 1$ to $T$ unless otherwise stated. $E_t$ represents electricity consumption during period $t$, while $\hat{E}_t$ is forecast electricity consumption during period $t$. The evaluation metrics described are:

- Mean squared error;
- Mean absolute error;
- Coefficient of determination ($R^2$);
- Theil inequality coefficient; and
- Diebold-Mariano equal predictive ability test with mean squared and mean absolute error loss functions.

**Mean squared error**

Mean squared error (MSE) is a commonly used measure of the average squared error of a forecast. It is not a scale invariant measure, therefore it is used to compare different models that forecast the same series. It is not valid to compare forecasts of different series using this metric.

\[
\text{Mean squared error of forecast } f: \quad \text{MSE}_f = T^{-1} \sum_{t=1}^{T} (\hat{E}_t - E_t)^2
\]

**Mean absolute error**

Mean absolute error (MAE) is a measure of average error similar to MSE. Like MSE it is not scale invariant. MAE is less sensitive to the presence of outlier errors than MSE.

\[
\text{Mean absolute error of forecast } f: \quad \text{MAE}_f = T^{-1} \sum_{t=1}^{T} |\hat{E}_t - E_t|
\]

**Coefficient of determination ($R^2$)**

The $R^2$ metric measures the fit between forecast and outcomes. This metric will lie between zero and one, with one indicating a perfect fit between forecasts and outcomes.
\[ R^2 \text{ of forecast } f \quad : \quad R_f^2 = \frac{\sum_{t=1}^{T} (\hat{E}_t - \bar{E}_k)^2}{\sum_{t=1}^{T} (E_t - \bar{E}_k)^2} \]

where \( \bar{E}_k = T^{-1} \sum_{t=1}^{T} E_t \)

Where a model does not contain an intercept term, the coefficient of determination is not an appropriate measure. In these cases the uncentred coefficient of determination can be calculated.

\[
\text{Uncentred coefficient of determination of forecast } f = \frac{\sum_{t=1}^{T} (\hat{E}_t)^2}{\sum_{t=1}^{T} (E_t)^2}
\]

**Theil inequality coefficient**

The Theil inequality coefficient (Theil) is a scale invariant measure of how well a forecast fits actual outcomes. It always lies between zero and one, with zero indicating a perfect fit between forecast and outcomes.

\[
\text{Theil inequality coefficient } f: \text{Theil}_f = \frac{\left( \sum_{t=1}^{T} (E_t - \hat{E}_t)^2 \right)^{1/2}}{\left( \sum_{t=1}^{T} \hat{E}_t^2 \right)^{1/2} + \left( \sum_{t=1}^{T} E_t^2 \right)^{1/2}}
\]

**Diebold-Mariano equal predictive ability test**

The Diebold-Mariano equal predictive ability test (DM) is an explicit test of the null hypothesis that there is no difference in the accuracy of two forecasts. Forecast accuracy is assessed with reference to a loss function, generating a statistic that provides a measure of the average relative performance of the two forecasts in terms of the chosen loss function. The DM test statistic is asymptotically normally distributed, thus the null of equal predictive ability for both forecasts is rejected if the DM test statistic is significant at a given level against the relevant critical value for the normal distribution.

A loss function needs to be selected as the base for comparisons of forecast accuracy. Standard loss functions include MSE and MAE; these are the loss functions used in this study.
MSE loss function for forecast $f$ at $t$: 
$$L(f_t)_{\text{MSE}} = (\bar{E}_t - E_t)^2$$

MAE loss function for forecast $f$ at $t$: 
$$L(f_t)_{\text{MAE}} = |\bar{E}_t - E_t|$$

The DM test is based on a loss differential series, of which the mean is taken. This is divided by the square root of the variance of the loss differential series to obtain the Diebold-Mariano test statistic.

Loss differential series for forecasts $f$ and $g$ at $t$: 
$$d_{t,f,g} = L(f_t) - L(g_t)$$

Mean of loss differential series for forecasts $f$ and $g$: 
$$\bar{d}_{j,f,g} = T^{-1} \sum_{t=1}^{T} d_{t,f,g}$$

Diebold-Mariano test statistic for forecasts $f$ and $g$: 
$$DM_{j,f,g} = \frac{\bar{d}_{j,f,g}}{\left[V(\bar{d}_{j,f,g})\right]^{1/2}}$$
where: $V(\bar{d}_{j,f,g})$ is the asymptotic variance of $\bar{d}_{j,f,g}$

The null hypothesis of equal predictive ability is tested against the alternative.

$$H_0 : E[d_{t,f,g}] = 0$$
$$H_1 : E[d_{t,f,g}] \neq 0$$

Diebold and Mariano 1995 show that $DM \sim A_N(0, 1)$ under the null hypothesis. If $|DM_{j,f,g}| > \text{critical value}(N, \text{level})$ then the null of equal predictive accuracy is rejected. If $DM_{j,f,g} > 0$ and significant, then the model generating forecast $f$ is found to have inferior predictive ability than the model generating forecast $g$ (and vice versa if $DM_{j,f,g} < 0$ and significant).

The standard normal values for the one per cent level, five per cent level and ten per cent levels are 2.58, 1.96 and 1.65 respectively.
Chapter 3

Household appliance upgrade and replacement decisions

3.1 Chapter overview

In this chapter the simulation model of household electricity consumption developed in chapter 2 is extended to endogenise the appliance upgrade and replacement decisions of households. The purpose of this chapter is to introduce a framework that permits examination of how households weigh up appliance purchase (capital) costs, electricity tariffs and appliance energy efficiency in making appliance purchasing decisions. The simulation model can then be used to investigate the impact of household appliance purchases on the electricity consumption of households in the medium and long run, taking account of the impact of changes in appliance energy efficiency. Changes in electricity consumption resulting from appliance upgrades and replacements also have implications for the profitability of electricity retailers and the setting of optimal (profit maximising) TOU tariffs.

Section 3.2 contains a review of the literature. Methods of accounting for changes in the stock and characteristics of household appliances when modelling household electricity consumption are presented and discussed. Particular focus is given to models that address changes in appliance energy efficiency and household decision making concerning the purchase of new appliances.

Section 3.3 describes the appliance dataset included in the simulation model in this extension. This dataset enables net present value analyses of household purchases of appliances, used to simulate household appliance upgrade and replacement decisions.

The structure of the model presented in this extension is described in section 3.4. An overview of the extension is provided along with a discussion of its consistency with the
theoretical foundation (household production theory) used in the simulation model. The nomenclature introduced in this chapter is also presented.

The approach used to simulate appliance upgrade decisions of households is presented in section 3.5. The short run estimates of household electricity consumption of the simulation model developed in chapter 2 are extended to include medium run estimates based on appliance upgrades by households. The net present value analysis used to estimate the cost to households of purchasing and operating appliances is discussed and estimation results are presented and interpreted. The simulation model suggests that appliances serving the space cooling and heating, water heating and lighting energy functions are those households will upgrade to more energy efficient models.

Section 3.6 contains the details of the method by which appliance replacement decisions are simulated. These differ from appliance upgrades in that the appliances considered for replacement have reached the end of their effective lives. The short run estimates of household electricity consumption of the simulation model developed in the previous chapter are extended to include long run estimates based on appliance replacement decisions of households. With the exception of lighting, households are expected to choose appliances with a range of different levels of energy efficiency (high, median, low) when replacing existing appliances (almost all households are financially better off choosing the most energy efficient light globes when replacing existing globes).

Three factors concerning household behaviour and characteristics that are central to the modelling of household appliance upgrade and replacement decisions are discussed in section 3.7: the intra-day pattern of household consumption; the time horizon; and the existing stock of appliances.

Three applications of the simulation model incorporating the extension presented in this chapter are contained in section 3.8. Changes in the price of electricity and appliances (respectively) required to ensure the most efficient appliance serving each energy function are estimated in the first two extensions. In the third extension the effect of household appliance upgrades (to the most energy efficient appliances for various energy functions) on profit maximising intra-day prices is examined.

The chapter is concluded in section 3.9 followed by appendix 3.A.
3.2 Literature review

This review presents an overview of the development of the literature concerning the consideration of the stock and characteristics of appliances in modelling electricity consumption. Attention is drawn to research addressing appliance energy efficiency and household appliance upgrade and replacement decisions.

Early papers concerning household production theory note the importance of the productivity of household appliances. Estimates of the quality of appliances (and many other goods and services) are introduced to the literature as part of the development of hedonic indices. Later work emphasises demand for electricity as a derived demand for the output of appliances and systems (energy functions) based on optimising behaviour. Such studies typically examine the aggregate effects of changing appliance stock levels and characteristics on determinants of demand including price and income elasticities. Finally, there are studies that directly model household decision making concerning the stock and characteristics of appliances.

This literature review comprises three parts. The first discusses the introduction and use of the stock of appliances in studies modelling electricity consumption. The second part of the review concerns the role of appliance energy efficiency in models of household electricity consumption, while the third presents studies that directly model or simulate household appliance purchase decisions.

3.2.1 The stock of appliances

Electricity is not a final good. As noted in chapter 2, electricity is an input to processes that produce outputs (energy functions). Household production theory extends the basic model of utility maximisation, explaining utility in terms of characteristics (outputs) arising from productive activities. Electricity, along with the services provided by household appliances, is an input to the (productive) activities of households.

Without appliances a household cannot engage in activities that require electricity as an input. Energy functions such as space heating and lighting would have to be served in other ways (for example by burning wood and lighting candles) if at all. The stock and capacity of household appliances are limiting factors on the level of energy functions able to be served using electricity.

Much of the research concerning the estimation of residential electricity consumption does not take account of changes in the stock and characteristics of household appliances and systems. Models explaining consumption in the short run often explicitly or implicitly assume an unchanging stock of appliances. However models that address or are calibrated
over a substantial time period that do not include measures of appliance stock and energy efficiency characteristics run the risk of omitted variable bias.

The majority of the studies described in the literature review of the previous chapter (section 2.2) do not take account of the stock of appliances. Some studies are based on data covering relatively short periods of time, over which it may be argued that the relevant stocks of appliances do not vary substantially. These studies include Benth et al. (2007) (based on data over a three year period), Magnano and Boland (2007) (three year period) and Cottet and Smith (2003) (three year period). However examples of research based on data of longer periods include Li and Flynn (2006) (three to six year period depending on the market), Yamaguchi (2007) (aggregate quarterly data from 1986 to 2004), Zachariadis and Pashourtidou (2007) (aggregate annual data from 1960 to 2004) and Narayan and Smyth (2005) (aggregate annual data from 1969 to 2000). These analyses rely on data over periods that are likely to encompass substantial changes in the relevant appliance stocks. The most likely reason such data are not included is that they are not available. Zachariadis and Pashourtidou state that for their data on electricity consumption in Cyprus there are no matching information concerning the appliance stock, energy efficiency, utilisation, or replacement rates.

There is a body of literature concerning the framework for deriving electricity demand in terms of household production theory and optimising household behaviour. Examples include Dubin and McFadden (1984), Clarke (1983), Willett and Naghshpour (1987) and Flaig (1990). In these studies, long and short run demand for electricity by households are derived based on assumptions concerning household utility consistent with household production theory. The steady state ‘desired’ stock of household appliances is estimated as a function of prices and optimal household expenditure, demonstrating that only the price (rather than the stock) of appliances is required to estimate steady state (long run) demand. However the appliance stock is found to be important in explaining short run demand when prices (of electricity, appliances and other goods) change.

An important assumption noted by Flaig (and implicitly or explicitly relied upon in many models of this type) is that adjustment costs in the demand functions derived for durables (capital) and energy are insignificant. While this may be appropriate for demand for energy, changing the stock of household appliances is likely to involve substantial costs. Replacing appliances prior to the end of their useful lives and the installation of some appliances (for example heating and cooling systems) is costly, since continuing to use an existing appliance with a scrap value of zero has no (capital) opportunity cost.

Studies of this type are based on a foundation of microeconomics, modelling the optimising decisions of individual households concerning their stock and utilisation of appliances. However researchers have adopted different approaches. In the absence of reliable data on the aggregate stock, early work incorporated partial (flow) adjustments to proxy the appliance stock. An example of this approach is Houthakker and Taylor (1970), while a
short review of the literature in which this approach is utilised is provided by Kamerschen and Porter (2004). As outlined in chapter 2, Kamerschen and Porter compare different ways in which the aggregate stock of appliances are included in models estimating aggregate consumption of electricity. A simultaneous equation approach (including both demand and supply) is found to yield more realistic estimates of price elasticity of demand than estimates based on a partial (flow) adjustment approach that do not take account of supply considerations that can influence price.

Some researchers use appliance penetration rates (average number of appliances per household) rather than estimates of the aggregate appliance stock to model electricity demand. Penetration rates are often disaggregated by appliance type when used for this purpose. Chern and Bouis (1988) investigate structural changes in residential electricity demand using annual aggregate data from 48 contiguous states of the United States over a period from 1955 to 1978. Parameters are estimated for 24 overlapping ten year periods using starting years from 1955 to 1969. Chern and Bouis report a substantial fall in the absolute value of the price elasticity of demand for electricity over this period. This is attributed to large increases in household penetration rates of appliances that use large quantities of electricity over this period (particularly air conditioners, space heaters and clothes dryers). Chern and Bouis argue that prior to 1970 consumers could adjust to price changes by more slowly or more rapidly accumulating appliances. However growth in the appliance penetration rate slowed substantially after 1970, reducing the scope of households to respond by adjusting their stocks of appliances. Increases in the durability (effective life) of appliances over the period further reduced the incentive for households to adjust their appliance stock in response to changes in the price of electricity.

Goldschmidt (1988) uses penetration rates to estimate electricity consumption. Penetration rates disaggregated by appliance type and categorised by household size (in terms of the number of residents) are used to estimate residential electricity consumption in Western Australia. Combined with survey data from 1980 and 1983 on Australian household appliance use, Goldschmidt also reports marginal annual energy estimates by appliance type and 'semi-elasticities', estimating the percentage increase in energy usage resulting from a one percentage point increase in the market penetration of appliance types.

### 3.2.2 Appliance energy efficiency

Along with the appliance stock, appliance energy efficiency directly affects the amount of electricity consumed by households. Appliance energy efficiency has improved over time, characterised by both incremental gains and substantial one-off improvements as new technology is incorporated in household appliances. However improvements in energy efficiency are not consistent across appliances serving different energy functions. There is likely to be little difference in the energy efficiency of an electric kettle made ten years
ago and one currently available for purchase; both are almost certain to be based on the same underlying (resistance heating) technology. In contrast, a current reverse cycle air conditioner is likely to be far more efficient than a model made ten years ago. Incremental improvements combined with the introduction of inverter systems (that allow air conditioners to operate more efficiently at medium and low loads) over the past ten years have substantially increased the energy efficiency of air conditioners. de Almeida and Fonseca (2006, p10) reports that the mean energy efficiency of reverse cycle air conditioners available in Japan increased by over 60 per cent in the decade to 2005.

Studies based on aggregate measures of appliance energy efficiency generally address the question: what impact has improved energy efficiency on aggregate consumption? Haas and Schipper (1998) compare price and income elasticity estimates for residential energy demand for the period from 1970 to 1993 with sub periods: 1970 to 1982/1985 and 1982/1985 to 1993. The first sub period is characterised by increasing real energy prices while prices were constant or falling during the second. An index of energy efficiency (as the inverse of a measure of energy demand per unit of service) is constructed to determine whether improvements in efficiency are useful in modelling residential energy demand. Haas and Schipper find price elasticities are different for rising and falling prices. For periods when prices are falling, price elasticities are close to zero. Energy efficiency is an important explanatory variable when modelling residential energy demand. Finally estimates of income elasticity are found to be higher once indicators of technological efficiency are included in the model. Haas and Schipper conclude that ‘irreversible’ energy efficiency improvements are a significant factor in explaining the moderate growth in energy demand following the substantial falls in the price of oil during 1985.

Along with Haas and Schipper, Allan et al. (2007) find cause for optimism in the potential for improvements in energy efficiency to moderate energy demand. In an assessment of the price effect of increased energy efficiency in the United Kingdom industrial sector Allan et al. estimate a price elasticity associated with an increase in efficiency of between -0.30 and -0.55. This is based on the results of a computable general equilibrium model of the UK economy simulating the effect of a 5 per cent improvement in the efficiency of energy use in all production sectors. No sector is found to increase energy consumption following the introduction of more efficient technology. The estimates are sensitive to a number of assumptions, in particular the elasticities of substitution in production.

In contrast to the positive findings of Haas and Schipper and Allan et al., the results of Brännlund et al. (2007) raise doubts as to the benefits of improved energy efficiency in slowing energy consumption. Brännlund et al. estimate a model of non-durable consumer demand based on aggregate quarterly data for Sweden for the period from 1980:1 to 1997:4. The model consists of equations for the non-durable components of consumer demand based on estimated income and expenditure elasticities. These are paired with estimates of the direct and indirect share of emissions associated with each component. The model
is then used to simulate the effects of a 20 per cent increase in the energy efficiency of transport and heating (both jointly and separately). Brannlund et al. find that taking into account both the substitution and income effects arising from the simulated increases in energy efficiency result in substantially increased emissions of carbon dioxide, sulphur dioxide and nitrous oxides. The (additional) tax on carbon consumption in Sweden required to neutralise the additional carbon dioxide emissions is estimated to be 135 per cent.

### 3.2.3 Modelling household appliance purchase decisions

The purpose of this chapter is to develop a method by which the appliance purchase decisions of individual households can be modelled. The studies discussed in this part of the literature review are examples of the differing methods by which this decision has been modelled for household appliances serving a single energy function (space cooling in the cases of Krumm 1983, Lillard and Aigner 1984 and Sailor and Pavlova 2003; space heating in the case of Nesbakken 2001) and household appliances in general (Boonekamp 2007).

There are two general approaches to modelling household appliance purchase decisions. Purchases (or appliance penetration) can be estimated directly based on a variety of factors, as carried out by Lillard and Aigner (1984), Sailor and Pavlova (2003) and Nesbakken (2001). Alternatively, a net present value framework can be explicitly specified, involving the estimation and evaluation of the costs and benefits to households of different appliances to model purchase decisions, as in the studies of Krumm (1983) and Boonekamp (2007). The former approach has the advantage of being general in approach, while the latter is a more tractable method which also permits simulation based on changing appliance and electricity prices and appliance characteristics.

Krumm (1983) models the household choice of air conditioner based on the comparative net benefits of room unit and central systems. Air conditioning has a public good component for households as the output (a cooler dwelling) is able to be enjoyed by all members of a household in the area served by an air conditioner. Room units and central air conditioning systems differ in the level of public good provided, as well as in their associated capital and operating costs. Krumm specifies and estimates a discrete choice model of the household decision of which class of air conditioner to purchase. The public good nature of central systems is found to be greater than that of room units (singly or in combination). Household demand and system cost are highly heterogeneous and household and dwelling characteristics are found to substantially affect household choices.

Lillard and Aigner (1984) focus on the impacts of TOU pricing of electricity and temperature on household purchases of air conditioners. The data used were collected from a two year experiment beginning in March 1979 run by the Southern California Edison
Company to investigate the impact of TOU pricing of electricity. Households are assumed to maximise a constant elasticity of substitution household utility function. A discrete choice model is constructed that predicts the type of air conditioner (none, room unit or central system) likely to be installed based on household characteristics and the local climate. Differing public good aspects of the different types of air conditioner are not explicitly accounted for. Estimates are made for two groups of households: those that faced a peak electricity price between 10am to 8pm during the pricing experiment; and those that faced a peak price between noon and 10pm. There is little difference in the parameters estimated for these groups. Lillard and Aigner also present electricity peak-uniform price ratios calculated to ensure aggregate welfare neutrality within household groups based on the specification of household utility adopted.

Sailor and Pavlova (2003) model the relationship between air conditioner penetration and cooling degree days in 39 cities of the United States and use this to simulate the effect of climate change. Penetration of air conditioners in cities with low to medium levels of current air conditioner ownership is predicted to substantially increase in response to a warmer climate. For these cities increases in the stock of air conditioners is estimated to be two to three times more important in explaining increases in electricity consumption than additional use of existing air conditioners in response to a warmer climate. This is concerning since air conditioners contribute disproportionately to electricity demand during peak periods.

Nesbakken (2001) estimates energy demand for space heating using a discrete-continuous choice model. Household choice of space heating appliance is estimated (the discrete choice component of the model) along with energy consumption using the chosen appliance (the continuous choice component). The study is based on Norwegian survey data on the utilisation of heating equipment of 551 households in 1990. Similar to the approach of Lillard and Aigner (1984), households are assumed to maximise a constant elasticity of substitution utility function. The purchase decision of households of space heating appliances fuelled by a variety of energy sources (electricity, oil, wood and combinations of these) is modelled based on climate, dwelling and household characteristics. Nesbakken finds that both appliance price and energy efficiency have a significant impact on the choice of heating system and that household characteristics are also important explanatory variables. Larger households are more likely to choose wood heaters (possibly due to the associated physical work required to use these heaters), while households living in cooperatives or rented accommodation are more likely to choose electric only.

As noted in chapter 2, Boonekamp (2007) investigates the sensitivity of households in the Netherlands to the price of electricity and gas in the period 1990 to 2000. Of particular relevance for this chapter is the cost-benefit ratio used to explain household take up of appliances of differing price and energy efficiency combinations. Boonekamp estimates a cost-benefit ratio for each appliance based on the price (less any government subsidy
available) allocated across the effective life of the appliance and any associated saving (accounting for the price of electricity, including relevant taxes) relative to a base ‘reference’ appliance. The estimated cost-benefit ratio for an appliance is the same for all households. However to account for the fact that the saving (and perhaps the available subsidy) will vary between households based on their particular intra-day pattern of usage and aggregate utilisation Boonekamp uses a logistic function (discussed in more detail in section 3.4) to approximate the take up of each particular appliance by households in aggregate. The long run elasticity estimates of Boonekamp reported in chapter 2 take account of households upgrading to more energy efficient appliances as predicted using the estimated appliance cost-benefit ratio. The energy efficient options available to households in the Netherlands and the associated cost-benefit ratio estimates have informed the appliance dataset used in this extension (presented in section 3.3).

Simulating household appliance purchase decisions using cost-benefit analysis (similar to the approach of Boonekamp) relies on households being informed of the energy efficiency of different appliances and that energy efficiency is a dominant factor in appliance selection. As noted by Deutsch (2010), the empirically observed difference in decision making between expected and actual appliance choice (based on energy efficiency) is known as the ‘energy paradox’ or ‘energy efficiency gap’. Deutsch reviews the literature on this aspect of household behaviour, outlining the issues of imperfect information and high consumer discount rates for optimal decision making. In an experiment measuring the effects of additional appliance efficiency information to online (internet) purchasers of clothes washers, Deutsch reports a change in consumer behaviour. However the resulting mean reductions in electricity and water use (-0.8 per cent and -0.7 per cent) are relatively small. In a study of appliance stocks by German households, Mills and Schleich (2010) find that both knowledge of appliance energy efficiency and likelihood of purchasing more energy efficient ‘class-A’ appliances are generally positively correlated with household income, households that rent or have recently purchased a house, household size and regional energy prices. The correlation between household income and stock appliance energy efficiency is evidence against a cost-benefit approach, as the potential savings associated with operating more energy efficient appliances will not vary with income. This finding may reflect a financing issue, where low income households find it difficult to purchase an expensive, energy efficient appliance. Correlations between household size and regional energy prices with appliance energy efficiency appears to provide some support for efficiency as a factor in appliance purchase decisions.

In addition to presenting a simulation model, Boonekamp also discusses issues relevant to the choice of implicit discount factor that underlies household decisions involving future costs and benefits, noting that empirical work supports the assumption of high households implicit discount rates (Hartman and Doane 1986, Sanstad et al. 1995).
3.2.4 Concluding remarks

The review of literature in this chapter has presented an overview of the approaches used in the literature to incorporate appliance stock and energy efficiency data in models of household appliance purchase decisions. The literature used to inform and support the extension to the simulation model presented in this chapter (estimating the appliance upgrade and replacement decisions of households) has been highlighted and the context of this work in terms of the relevant body of literature has been provided.
3.3 Data

The data used to simulate household electricity consumption are the same as those used in the previous chapter, sourced from the Mawson Lakes and Sydney samples. A dataset of household appliances is added to these in order to carry out net present value analyses on household purchases of appliances. In this section the source and structure of the appliance dataset are described.

3.3.1 Data sources

Australian Commonwealth, State and Territory government agencies publish information on household appliance energy efficiency, minimum energy performance standards and energy star ratings on the website www.energyrating.gov.au. All air conditioners, refrigerators, freezers, dishwashers, clothes washers and clothes dryers manufactured in or imported into Australia are required to carry an energy star rating issued by the Equipment Energy Efficiency (E3) Committee. The E3 Committee consists of officials from Commonwealth, State and Territory government agencies and representatives from New Zealand, and is responsible for managing the Australian end-use energy efficiency program.

All appliances with energy star ratings are listed on the website, with their brand, model, description, energy star rating, awards won and ten year energy operating cost in Australian dollars (based on a uniform intra-day electricity price of $0.17 per kWh). Depending on the appliance type, the following energy efficiency information is also provided for appliance types:

- air conditioners: energy input and output (kWh) for cooling and heating;
- refrigerators and freezers: annual energy consumption (kWh/annum);
- dishwashers: annual energy consumption (kWh/365 uses);
- clothes washers: annual energy consumption (kWh/365 uses) for both cold and warm washes; and
- clothes dryers: annual energy consumption (kWh/52 uses).

Using the data available on the www.energyrating.gov.au website, an appliance dataset is compiled containing the absolute and relative energy efficiency of household appliances by energy function. For each energy function, four different appliance models are selected, representing:

1. the most energy efficient appliance available (referred to as the appliance of high energy efficiency);
2. an appliance of median energy efficiency;

3. an appliance of low energy efficiency; and

4. an appliance representative of existing household stock (assumed to be less energy efficient that appliances currently available for purchase).

The recommended retail price (RRP) of these appliances is included along with estimated installation costs for air conditioners and hot water systems. While discounts may be available on appliances included in the dataset, the RRP is used as a reliable estimate of price that is not subject to the pricing policies and terms and conditions of specific retailers. Installation costs for air conditioners are estimated at $800 based on the estimates reported by Bintec Coorporation (2009) and Whirlpool Coorporation (2009). The details of the selected hot water systems and light globes were obtained from the manufacturer’s websites. Estimated installation costs for hot water systems were obtained from quotes by VIP Plumbing Victoria, a Victorian company that supplies and installs hot water systems. This was $400 for each system included in the dataset.

An effective life for each appliance of ten years is used in this study (with the exception of light globes). Ten years is the most common warranty period offered by manufacturers on the appliances included in the dataset.

3.3.2 Data overview

A subset of the appliance dataset is contained in table 3.1. Appliance models one to three (appliances with high, median and low levels of energy efficiency) are included in table 3.1 while the estimated existing appliance stock (model four) is omitted. The inclusion of the existing appliance stock would convey no additional information as these appliances have purchase costs of zero (as it is assumed they are already installed and owned by households). Relative energy efficiency is measured using the energy efficiency of the existing appliance stock as the denominator (the relative efficiency of all existing appliance stock is set equal to one).

The purchase cost (including installation costs for reverse cycle air conditioners and hot water systems) of the appliances included in the dataset within energy function is positively correlated with the relative efficiency of each appliance. The purchase cost of appliances included in every energy function is ordinally ranked by the relative efficiency of each appliance.
The details of each model in the appliance dataset are contained in table 3.2. Care is taken to ensure that the appliances included in each category of energy function are broadly comparable in terms of their output. All air conditioners are wall mounted reverse cycle units of similar cooling output. Recognising that reverse cycle air conditioners are used for both space cooling and space heating, the same models are included in both energy functions. The hot water systems included in the dataset are of similar volume, as are the fridges included in the food storage energy function and the dishwashers contained in the food preparation energy function. Both a clothes washer and a clothes dryer are included in each model category of the clothes cleaning energy function.

For the clothes cleaning energy function, the energy efficiency of each combination of washer and dryer is obtained by inverting the sum of the annual electricity consumption per volumetric capacity estimated for each appliance (contained on the website www.energyrating.gov.au) as shown in equation 3.1. This results in a comparable estimate of energy efficiency for each combination, as the annual electricity consumption estimates are based on a single set of assumptions - that clothes washers are used seven times each week and clothes dryers are used once each week. The energy efficiency of the combined clothes cleaning energy function for households that do not use these appliances in this seven-to-one ratio will differ from the estimate contained in the appliance dataset. However this variation will be small, as there is little difference in the energy efficiency of

<table>
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<th>Energy function</th>
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<th>Purchase cost</th>
<th>Relative efficiency</th>
<th>Energy star</th>
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</tr>
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<td></td>
<td>2</td>
<td>$1,319</td>
<td>1.319</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$999</td>
<td>1.196</td>
<td>4</td>
</tr>
<tr>
<td>Food preparation (FP)</td>
<td>1</td>
<td>$1,799</td>
<td>2.489</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$1,049</td>
<td>1.993</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$849</td>
<td>1.200</td>
<td>2</td>
</tr>
<tr>
<td>Clothes cleaning (CC)</td>
<td>1</td>
<td>$5,898</td>
<td>3.646</td>
<td>5.5</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$2,198</td>
<td>2.267</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$1,288</td>
<td>1.238</td>
<td>1.5</td>
</tr>
<tr>
<td>Lighting (LI)</td>
<td>1</td>
<td>$300</td>
<td>8.333</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$150</td>
<td>2</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$30</td>
<td>1</td>
<td>NA</td>
</tr>
</tbody>
</table>

Table 3.1: Purchase cost and efficiency of appliances
the two appliances included in each combination.

\[
\hat{\xi}_{q,x} = \left( \frac{\hat{E}_q}{V_q} + \frac{\hat{E}_x}{V_x} \right)^{-1}
\]  \hspace{1cm} (3.1)

where:
- \(\hat{\xi}_{q,x}\) is the estimated energy efficiency of the washer \(q\) and dryer \(x\) combination
- \(\hat{E}_q\) is the estimated annual electricity consumption of appliance \(q\)
- \(V_q\) is the volume (L) of appliance \(q\)

In contrast to the other energy functions included in the appliance dataset, the globes included in the appliance dataset for the lighting energy function have different estimated effective lives depending on the model (high, median and low energy efficiency models). While the estimated effective life of (highly efficient) compact fluorescent globes is ten years, consistent with that of the appliances in the other energy functions, halogen MR16 globes (of median energy efficiency) have effective lives of five years, while incandescent globes (of low efficiency) have an effective life of only one year. These estimates are obtained from the website www.energysmart.com.au (Department of Energy Utilities and Sustainability, New South Wales 2009). The differing estimates of effective life of the light globes is accounted for in the model by including replacement purchases of the globes over a ten year period in the present value estimates.

All models included in the appliance dataset were available for purchase as at August 2009.
<table>
<thead>
<tr>
<th>Energy function</th>
<th>Model</th>
<th>Model description</th>
<th>Model number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space cooling (SC)</td>
<td>1 Fujitsu inverter 3.5kW AC</td>
<td>ASTB12LDC</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 Panasonic 3.6kW AC</td>
<td>CS/CU-W12EKR</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 Acson 3.5kW AC</td>
<td>A5WM15GR</td>
<td></td>
</tr>
<tr>
<td>Space heating (SH)</td>
<td>1 Fujitsu inverter 3.5kW AC</td>
<td>ASTB12LDC</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 Panasonic 3.6kW AC</td>
<td>CS/CU-W12EKR</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 Acson 3.5kW AC</td>
<td>A5WM15GR</td>
<td></td>
</tr>
<tr>
<td>Water heating (WH)</td>
<td>1 Quantum 270L heat pump</td>
<td>270-11AC3-134</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 Rinnai 250L conventional</td>
<td>HFE250S36</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 generic 250L conventional</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td>Food storage (FS)</td>
<td>1 Electrolux 431L fridge freezer</td>
<td>EBM4300SC</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 Westinghouse 420L fridge freezer</td>
<td>WTM4200WB</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 Samsung 395L fridge freezer</td>
<td>SR394NW</td>
<td></td>
</tr>
<tr>
<td>Food preparation (FP)</td>
<td>1 Bosch 14 place dishwasher</td>
<td>SMU65M15AU</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 LG 14 place dishwasher</td>
<td>LD1415T1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 Whirlpool 12 place dishwasher</td>
<td>ADP6000WH</td>
<td></td>
</tr>
<tr>
<td>Clothes cleaning (CC)</td>
<td>1a Kleenmaid 6.5L front load washer</td>
<td>KFL1600</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1b Miele 6kg heat pump dryer</td>
<td>T8027WP</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2a Simpson 7L front load washer</td>
<td>SWF1076</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2b Fisher and Paykel 8kg dryer</td>
<td>DEIX1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3a Simpson 6L top load washer</td>
<td>36S550M</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3b Whirlpool 6kg dryer</td>
<td>AWD60A</td>
<td></td>
</tr>
<tr>
<td>Lighting (LI)</td>
<td>1 30 12W compact fluorescent globes</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 30 50W halogen MR16 globes</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3 30 100W incandescent globes</td>
<td>NA</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2: Appliance model descriptions and numbers
3.4 Model structure

This section provides an overview of the structure of the extension to the simulation model contained in this chapter. The consistency of the approach adopted in the study with the theoretical foundation (household production theory) is discussed and a comparison is made with an alternative approach suggested in the literature. The nomenclature for this chapter is also presented.

3.4.1 Overview

The extension to the model presented in this chapter is designed to simulate how and when households update their electrical appliances. Consistent with the simulation model, estimates are made for individual households to allow distributional analysis of the effects of tariff structure and appliance price and energy efficiency. Net present value analysis is used to estimate the cost to each household of purchasing new appliances (categorised by energy function). For each energy function, appliances of various prices and levels of energy efficiency are considered.

Time frame

Two time frames are considered in this chapter: the medium and long run. These are defined as the time frames in which households consider upgrading their appliances (the medium run) and must replace their appliances (the long run). An appliance upgrade refers to the purchase of a new appliance by a household in place of an existing appliance that has not yet reached the end of its effective life. In the simulation model, a household will do this if the cost of operating the existing appliance exceeds the cost of purchasing and operating a new appliance. A household replaces an appliance when an appliance is purchased to replace an existing appliance that has reached the end of its effective life.

As noted in the previous section, the effective life of new appliances is defined to be ten years in the appliance dataset (with the exception of light globes). An effective life is required for net present value analysis to account for appliance operating costs incurred over time. However this does not imply that ten years is the period in which the long run is reached. Households replace appliances as they fail; for some appliances this will be before they are ten years old while other appliances will continue operating for more than ten years. In the medium run, changes to factors including climatic variables, intra-day electricity prices (tariffs), appliance prices and appliance energy efficiency characteristics will affect household appliance upgrades. In the long run changes to these factors are reflected in the entire stock of household appliances as households replace their existing appliances in full knowledge of these factors.
The short run simulation model developed in chapter 2 is extended to include the medium and long run appliance upgrade and replacement decisions of households. The effects changes in appliance energy efficiency characteristics make to medium and long run household electricity consumption are estimated in sections 3.5 and 3.6.

**Energy functions not considered**

Three energy functions are not considered in the extension to the simulation model presented in this chapter. These are the energy functions: entertainment, other; and not recorded. In the simulation model the characteristics of appliances serving these energy functions are assumed to be constant and unchanging.

Appliances categorised as serving the entertainment energy function consist solely of televisions in the samples used in this study. These are not suitable to be included in this extension since televisions, along with other modern entertainment appliances such as video recorders and game consoles, are unlikely to be comparable on purchasing and operating costs alone. The simulation of changes in the medium and long run stock of entertainment appliances is discussed in more detail in appendix 3.A.

The appliances comprising the energy function category ‘other’ vary widely in their purpose and characteristics, making estimating appliance price and relative energy efficiency impossible. The type and characteristics of appliances contained in the energy function ‘not recorded’ are unknown, precluding the inclusion of meaningful appliance price and energy efficiency information in the appliance dataset.

**Combined cooling and heating energy function**

The majority of electrical appliances serving the space cooling and space heating energy functions in this simulation model are reverse cycle air conditioners. As reverse cycle air conditioners serve both of these energy functions, in this chapter space cooling and space heating are treated as one combined energy function in the simulation model. In analysing whether a household will be financially better off upgrading or replacing an existing reverse cycle air conditioner, the effect on expenditure on electricity for both space cooling and space heating is considered.

**3.4.2 Consistency with theoretical foundation**

Household production theory is the theoretical foundation informing the simulation model constructed in chapter 2. Household production theory is an expansion of the microeconomic utility maximisation framework. According to household production theory, the
decision to purchase an appliance involves an assessment of the contribution of the additional appliance to household activities which produce characteristics that yield utility, weighed against the opportunity cost of purchasing the appliance. Relevant factors include the appliance price, appliance characteristics and the associated opportunity cost (the best alternative use of the funds).

Net present value analysis is used in this chapter to estimate the cost of appliances to households in terms of their purchasing and operating costs. These estimates are used to categorise and (ordinarily) rank appliances in order to simulate the appliance upgrade and replacement decisions of households. These appliance cost estimates, associated rankings and the appliance purchasing decisions of households based on these are consistent with those that maximise utility consistent with household production theory where two assumptions hold.

1. The utility gained by purchasing at least one of the appliances being considered is greater than the opportunity cost of the funds required to purchase the appliance.

2. The appliances under consideration materially differ only in their purchasing and operating costs.

If assumption 1 does not hold, a household would be better off not purchasing an appliance irrespective of the estimated NPV of the appliance. This is because the household would gain more utility by spending the funds on the alternative use implicit in the opportunity cost. In this extension to the simulation model, it is assumed that assumption 1 holds where a household is upgrading or replacing an appliance. This is supported by the fact that the existence of an appliance indicates that this assumption was satisfied at one time (when the existing appliance was purchased).

The implication of a violation of assumption 2 is that the net present value estimated for an appliance does not include all relevant factors (costs and benefits). If this is the case, the estimated net present value will not reliably measure the value of an appliance to a household. The degree to which this assumption is satisfied will vary by the energy function an appliance serves. Hot water systems of similar size are likely to be comparable based on their purchasing and operating costs. These systems provide a standardised output: hot water. In contrast, entertainment appliances are unlikely to be comparable on purchasing and operating costs alone. Taking the example of televisions, even controlling for screen size there is substantial variation in factors affecting their contribution to utility: type (cathode ray tube, liquid crystal display, plasma or light emitting diode), inputs (analogue, digital and/or multimedia) and other capabilities (including recording broadcasts and the functionality to simultaneously watch and record multiple broadcasts on different channels). As noted earlier, changes in the characteristics of appliances serving the energy function entertainment (along with those serving ‘other’ and ‘not recorded’
energy functions) are not modelled in this study.

As noted in section 3.3, within each energy function appliance price is ordinally ranked by the relative energy efficiency of each appliance. This lends some credence to assumption 2, since if characteristics other than the financial costs associated with each appliance were highly important to customers, it could be expected that the relative efficiency of an appliance would not be a good predictor of its purchase cost.

Comparison with a similar modelling approach

The net present value analysis presented in this chapter to model household purchasing decisions concerning appliances and systems is similar in concept to the cost-benefit ratio utilised in Boonekamp (2007). The main point of difference is in the approach used by Boonekamp to estimate the distribution of households expected to upgrade to each highly energy efficient appliance introduced to the market. Using energy efficiency trend and survey data, Boonekamp notes that different households face different situations and this will result in a distribution of uptake of more energy efficient appliances. Boonekamp uses a logistic function to forecast purchases of newly introduced energy efficient appliances based on the characteristics (such as pay back period and barriers to uptake) of each appliance and observed outcomes.

The argument for adopting an approach similar to that of Boonekamp is not strong for this simulation model given the availability of disaggregated household data on electricity consumption by energy function. The potential benefit (in terms of reduced expenditure on electricity) to each household in the Mawson Lakes and Sydney samples of upgrading or replacing an appliance with a more energy efficient appliance is able to be estimated directly using the simulation model. While demographic and household information concerning household demographics and energy efficiency of existing appliances is not available for the Mawson Lakes and Sydney samples, the sample data are disaggregated by individual appliance type and related intra-day electricity consumption by household. The use of these data to estimate the appliance upgrade and replacement decisions of individual households rather than use an assumed distribution of appliance uptake is likely to result in a more accurate simulation of household behaviour (notwithstanding the lack of data on the demographics and appliance energy efficiency for the sample households).

3.4.3 Nomenclature

The nomenclature used in this chapter is presented in this subsection.
Appliance characteristics

$\xi_q$  energy efficiency of appliance $q$ (as described in section 3.3 for each energy function - higher is better)

Economic

$C_{\text{pur}, q, t}$  cost of purchasing appliance $q$ during period $t$ ($\$$)

$C_{\text{op}, i, q, t}$  cost to household $i$ of operating appliance $q$ during period $t$ ($\$$)

$PV_{i, q, t}$  present value of the costs to household $i$ associated with purchasing and operating appliance $q$ from period $t$

$NPV_{i, q, t}$  net present value to household $i$ of upgrading an existing appliance to appliance $q$ from period $t$

Common identifiers

$q$  appliance identifier
3.5 Simulating appliance upgrades

In this section the approach used to simulate appliance upgrade decisions of households is presented. Appliance upgrades involving changes to appliance energy efficiency levels can affect household electricity consumption. The short run estimates of household electricity consumption of the simulation model developed in chapter 2 are extended to include medium run estimates based on appliance upgrades by households.

The assumptions used to simulate household appliance upgrade decisions are noted in this section. The net present value analysis used to estimate the cost to households of purchasing and operating appliances is discussed and the results estimated for the households in the Mawson Lakes and Sydney samples are presented and interpreted.

3.5.1 Modelling assumptions

The simulation of appliance upgrade decisions by households relies on four assumptions, all of which concern appliance characteristics.

The first assumption is that the appliances included in the appliance dataset broadly represent the appliances considered by households when deciding whether or not to upgrade an existing appliance. As noted in section 3.3 the appliance dataset includes four appliance models for each energy function, representing: the most energy efficient appliance; appliances of median energy efficiency; appliances of low energy efficiency; and existing installed appliances. The price and relative energy efficiency of these appliances is central to the modelling of household appliance upgrade and replacement decisions. While the characteristics of appliances available for purchase are able to be verified, the energy efficiency of appliances installed in the sample households used in this study are not known, necessitating this assumption.

It is also assumed that the value in the secondary market of a existing appliance removed to make way for a new upgrade appliance is zero. These appliances have not reached the end of their effective lives, however this assumption avoids the need to estimate the value of existing household appliances.

The third assumption adopted in this section is that the effective life of existing appliances is the same as that of new appliances available for purchase. This assumption simplifies the estimation of the net present value of costs associated with the purchase and operation of existing appliances.

The second and third assumptions relied upon in this section favour the retention of existing appliances over appliance upgrades by households. The only reason households will upgrade an existing appliance with zero value in the secondary market that has an
effective life that matches a new appliance is if the new appliance is substantially more energy efficient.

3.5.2 Estimation methodology

Net present value analysis is used in this chapter to evaluate the cost of purchasing and operating appliances of different prices and levels of energy efficiency. This analysis underlies the simulation of appliance upgrade decisions by households as well as the simulation of appliance replacement (presented in section 3.6). The factors affecting the cost of purchasing and operating an appliance for a household considered in this study are: appliance price; appliance energy efficiency; intra-day price of electricity (TOU tariff structure); intra-day pattern and intensity of household use of an appliance; and how a household values current and future consumption. In this study, the upgrade and replacement decisions of households are simulated. For a household to decide to purchase an appliance as an upgrade or replacement, an existing appliance must exist.

An appliance is more energy efficient than another if it produces the same level of output (such as heat or light) using less energy. A more energy efficient appliance will cost less to operate as it will require less electricity to be input to produce a given level of output. If two appliances serving the same energy function have the same purchase price, the net present value of the cost of purchasing and operating the appliance with the higher energy efficiency will be less than that of the appliance with the lower energy efficiency.

Under a TOU tariff the intra-day pattern of use by a household of an appliance can affect the cost of operating the appliance. For an appliance used by a household mainly in the off-peak period of a TOU tariff, there is less scope to reduce expenditure on electricity by purchasing a more energy efficient appliance, as the cost of the electricity consumed is low. Conversely, the potential benefit of purchasing a more energy efficient appliance used predominantly during the peak period of a TOU tariff is increased. Similarly, the benefit from purchasing a more energy efficient appliance for a household is greater if that appliance is used in place of an appliance that is responsible for a large part of a household’s electricity consumption.

Net present value analysis is used to compare a series of benefit and cost flows over time. An appliance with a high purchase cost and high energy efficiency will cost more to purchase but less to operate than an appliance with a lower price and of lower energy efficiency. The value to a household of reduced (future) expenditure on electricity must be weighed against the higher (present) purchase cost. Households that more highly discount future consumption relative to present consumption will less highly value a more energy efficient appliance.
Estimation parameters

To estimate the net present value to a household of upgrading from an existing appliance to a new appliance, parameters for the discount factor relevant to household decisions concerning inter-temporal consumption and the intra-day price of electricity are required. The discount factor used for all households in this study is seven per cent per annum. This strikes a balance between a measure of the cost of borrowing as measured by variable home loan interest rates (less than seven per cent in Australia in November 2009) and the high implicit discount rates for households reported in the literature. The higher the discount factor used, the lower the present value of the benefit realised from reduced (future) operating costs resulting from more energy efficient appliances. A higher discount factor reduces the net present value of energy efficient appliances relative to less efficient appliances.

Two net present value estimates are made for each appliance in this chapter: the first based on a uniform intra-day tariff of $0.16269 per kWh; and the second under a TOU tariff. The TOU tariff used is the optimised (profit maximising) period tariff estimated in section 2.7 of the previous chapter. The TOU rates for this tariff are:

- $0.10114 per kWh (off peak rate: 10pm to 7am);
- $0.15925 per kWh (shoulder rate: 7am to 2pm and 8pm to 10pm); and
- $0.22265 per kWh (peak rate: 2pm to 8pm).

Present value of appliance costs

The present value to a household of the costs associated with an appliance is calculated as the sum of purchase and operating costs, the latter of which are discounted over the life of the appliance (as shown in equation 3.2). \( PV_{i,q,t} \) is the present value of the cost to household \( i \) of purchasing and operating appliance \( q \) from period \( t \). \( C_{\text{pur},q,t} \) is the purchase cost of appliance \( q \) during period \( t \), while \( C_{\text{op},i,q,s} \) is the operating cost for household \( i \) of appliance \( q \) during period \( s \). The present value estimation for appliance \( q \) includes the operating costs from period \( t \) to \( T_q \) (the period in which appliance \( q \) reaches the end of its effective life). The factor by which household \( i \) discounts future consumption relative to present consumption is \( d_i \) (in per period terms in equation 3.2).

\[
PV_{i,q,t} = C_{\text{pur},q,t} + \sum_{s=t}^{T_q} (C_{\text{op},i,q,s} (1 + d_i)^{t-s}) \tag{3.2}
\]

In the model, the operating costs associated with an appliance in a given calendar year are discounted by a constant amount (as shown in equation 3.3) rather than a value dependant
on the specific time and day the cost is incurred. This is done to simplify the present value calculation. \(y_t\) is the calendar year containing period \(t\). As stated earlier, the discount factor used in the simulation model is defined in per annum terms, as in equation 3.3.

\[
PV_{i,q,t} = C_{\text{pur},q,t} + \sum_{s=t}^{T_q} (C_{\text{op},i,q,s} (1 + d_i)^{y_t-y_s})
\]  

(3.3)

Changes in the intra-day price of electricity faced by households will affect the cost of operating an appliance at different times of day. As noted above, under a TOU tariff expenditure on electricity is higher in peak than in off-peak tariff periods. The operating cost of appliance \(q\) for household \(i\) during period \(t\) is shown in equation 3.4. This is equivalent to the expenditure on electricity incurred by using the appliance. \(E_{i,q,t}\) is the electricity consumption of household \(i\) using appliance \(q\) during period \(t\).

\[
C_{\text{op},i,q,s} = p_t E_{i,q,t}
\]  

(3.4)

In order to estimate whether a household will be unambiguously better off upgrading an appliance, the present value of the cost of operating a new appliance is estimated assuming no change in appliance usage. That is, the present value is estimated based on the usage of the existing appliance. This is not the same as assuming that the electricity (input) consumed by the existing and new appliances are the same. If an existing appliance is replaced with one that uses half as much energy to fulfil its energy function, the present value of the operating costs of the new appliance will be half of that of the existing appliance as the new appliance will consume half as much energy. A household is assumed to require the same output from a new appliance (for either input to household productive activities or to be consumed directly). The operating cost to household \(i\) of appliance \(q\) (replacing appliance \(x\)) in period \(t\) is shown in equation 3.5, where \(E_{i,x,t}\) is electricity consumed by household \(i\) by appliance \(x\) in period \(t\).

\[
C_{\text{op},i,q,s} = p_t E_{i,x,t} \left(\frac{\xi_q}{\xi_x}\right)^{-1}
\]  

(3.5)

The assumption of unchanged appliance usage is adopted to unambiguously determine whether a household is better off upgrading an existing appliance with a more energy efficient appliance. While a household may utilise a new more energy efficient appliance more because the effective marginal cost of doing so has fallen, the net present value analysis of costs involved in purchasing and operating different appliances requires the estimates to be comparable. The effect on household expenditure of differing energy efficiency characteristics of each appliance is directly measured by assuming appliance usage is unchanged. This ensures that the net present value analysis used to simulate household appliance upgrades is conservative. While a household may increase appliance
usage following an upgrade to a more energy efficient appliance, only the benefit arising from reduced expenditure is measured in the net present value analysis. Benefits from changes in consumption patterns induced due to the reduced cost of using the new, more energy efficient appliance are not considered. This is the equivalent of considering only the income effect arising from an expansion in the household budget constraint, resulting from a fall in the price of the energy function served by the more efficient appliance.

**Net present value of appliance upgrades**

To obtain an estimate of the net present value of purchasing and operating a new appliance a cost benchmark is required. The cost benchmark adopted in this study is the continued use of the existing appliance for which an upgrade is being considered. The net present value of upgrading to a new appliance during period $t$ is the present value of the cost of operating the existing appliance $x$ less the present value of the cost of purchasing and operating the new appliance $q$ as shown in equation 3.6. $\text{NPV}_{i,q,t}$ is an estimate of the present value of how much household $i$ will save when upgrading (the existing) appliance $x$ with appliance $q$ during period $t$. It is assumed that the existing appliance is installed and owned by the household, therefore the purchasing cost of the existing appliance ($C_{\text{pur},x,t}$) is zero. The net present value of upgrading to a new appliance can therefore only be positive if the new appliance is more energy efficient that the existing appliance to be upgraded.

$$\text{NPV}_{i,q,t} = \text{PV}_{i,x,t} - \text{PV}_{i,q,t}$$ \hspace{1cm} (3.6)

The household appliance upgrade decision is modelled using the net present values estimated for the new appliances being considered. Where one or more of the new appliances are estimated to have positive net present value, in the simulation model the household purchases the new appliance with the highest estimated NPV in place of the existing appliance. Where all net present value estimates for the new appliances are negative, a household continues to use the existing appliance.

**Integration with short run simulation model**

Households may change their appliance usage after upgrading (or replacing) an existing appliance with a more energy efficient appliance. This is because the marginal cost of using a more energy efficient appliance to produce a given level of output is lower. This is equivalent to a reduction in the price of electricity as shown above in equation 3.5. Where a household upgrades or replaces an existing appliance to a more energy efficient appliance, this is accounted for in the simulation model by adjusting the effective price
of electricity used by the new appliance. The effect on electricity consumption of a fall in the effective price of electricity used to power a more efficient appliance is modelled in the same way as that of any other variation in the price of electricity (as described in section 2.6).

3.5.3 Estimation results

The results of the net present value estimates used to simulate household appliance upgrades are discussed in this subsection. These highlight substantial variation in the estimated benefits from upgrading appliances that serve different energy functions.

Purchase costs (including installation costs) are substantial for new appliances serving most energy functions (the exception being lighting). For the households in the Mawson Lakes and Sydney samples, positive net present values for appliance upgrades are estimated for appliances in three energy functions: space cooling and space heating (combined), water heating and lighting.

Space cooling and space heating

Of the households with reverse cycle air conditioners included in this study, one household in the Mawson Lakes sample is estimated to have a positive net present value for an appliance upgrade to their air conditioner. The estimates indicate that this household would be financially better off (in terms of reducing the present value of the cost associated with space cooling and space heating) replacing their existing air conditioner with either the most efficient model or the model of median energy efficiency included in the appliance dataset. Under both the uniform and TOU tariff used in this chapter, these new air conditioners are estimated to have positive net present values for this household, with the most efficient model having the higher net present value under each tariff. The net present values estimated for both the air conditioners of high and median energy efficiency are greater under the TOU tariff. This is a result of the intra-day profile of use of the air conditioner by the household, as the majority of electricity used by this household for space cooling and space heating is in the peak TOU period.

Water heating

One household in the Mawson Lakes sample has an electric hot water system, while a large majority of the Sydney sample households use electric hot water systems. Positive net present values for appliance upgrades are estimated for almost all of these households in both samples for hot water systems of both high and median energy efficiency. Around half of the households in the Sydney sample also have positive net present values estimated
for the cheapest, least efficient new hot water system in the appliance dataset (which is slightly more energy efficient than the mean existing system included in the dataset). The net present value estimates generally remain positive but fall significantly under the TOU tariff, as hot water systems use the majority of their electricity during the off peak TOU period in the early hours of the morning.

On the basis of these estimates, most households in the samples with electric hot water systems would be better off immediately replacing these with a new, highly energy efficient hot water systems. However caution should be exercised in taking these results at face value. The differences in net present value estimates between the uniform and TOU tariffs demonstrate that household expenditure on hot water is significantly reduced when the electricity consumed is covered by a low, off peak rate. Off peak rates for hot water systems are generally available in Australia. While upgrading an existing electric hot water system with a new, highly efficient system will reduce electricity consumption on water heating, for households paying an off peak water rate, the net present value estimated based on the uniform tariff used in this chapter will overstate the benefit of an upgrade.

**Lighting**

A large majority of households in both the Mawson Lakes and Sydney samples have large positive net present value estimates for upgrading existing incandescent globes to compact fluorescent globes. Most households also have smaller but still positive net present value estimates for upgrading to halogen globes. This suggests that the majority of households in this study would be better off immediately purchasing compact fluorescent globes in place of their existing incandescent globes.

The estimated net present values for a small number of households were negative for all lighting upgrade options. Metered readings for lighting for these households are very low, suggesting: substantial use of lighting that is not metered; or that these households already have energy efficient globes installed. The latter possibility reveals a shortcoming of the data used in this study. There is an implicit assumption of homogenous energy efficiency within energy functions across different households. However without data on the energy efficiency and electrical capacity of existing household appliances and systems there is no obvious alternative approach.
3.6 Simulating appliance replacement

In this section the method by which appliance replacement decisions are simulated is described and estimation results for the households in the samples used in this study are presented. These differ from appliance upgrades in that the appliances being replaced have reached the end of their effective lives. The short run estimates of household electricity consumption of the simulation model developed in the previous chapter are extended to include long run estimates based on appliance replacement decisions of households (along with the medium run appliance upgrades outlined in section 3.5).

3.6.1 Modelling assumptions

The simulation of appliance replacement decisions by households uses the first two of the three assumptions relied on when modelling appliance upgrade decisions. Appliances included in the appliance dataset are assumed to broadly represent the appliances considered by households for appliance upgrade and replacement purposes. The value in the secondary market of appliances replaced by new appliances is assumed to be zero. The second assumption is more likely to describe appliances at the end of their useful lives than for the appliances upgraded prior to the end of their useful lives (modelled in section 3.5).

3.6.2 Estimation methodology

The net present value analysis developed in the previous section to model appliance upgrades is used to simulate the appliance replacement decisions of households. This minimises the estimated cost to households of replacing existing appliances. The present value of appliance costs (including purchasing and operating costs) estimated as in section 3.5 for each appliance and household are compared and households are assumed to purchase the appliance with the lowest present value of appliance costs. The present value to household \(i\) of purchasing and operating appliance \(q\) from period \(t\) is given by equation 3.3 (restated below).

\[
PV_{i,q,t} = C_{\text{pur},q,t} + \sum_{s=t}^{T_q} (C_{\text{op},i,q,s} (1 + d_i)^{y_t - y_s})
\]

Appliances are replaced in the long run when they reach the end of their effective lives. Only new appliances are considered in household appliance replacement decisions, as the existing appliances (being replaced) have reached the end of their effective lives.
3.6.3 Estimation results

The results of the present value analysis comparing the cost of replacing appliances that have reached the end of their effective lives are presented by energy function for both the Mawson Lakes and Sydney households. The present value of purchasing and operating the appliances (of different price and energy efficiency levels) contained in the appliance dataset are displayed in radar figures. (A technical overview of the radar figures used in this chapter is provided in appendix 3.B.)

Estimates for the Mawson Lakes and Sydney samples are presented in adjacent subfigures. The upper two subfigures in each radar figure contain estimates based on the uniform tariff while the lower two subfigures contain estimates based on the TOU tariff. These tariffs are those specified in section 3.5.

The present value of appliance cost are presented by energy function in figures 3.1 to 3.6 for the appliances in the appliance dataset of high, median and low energy efficiency.

Space cooling and space heating

The reverse cycle air conditioner with the lowest present value cost for most households in both Mawson Lakes and Sydney is the cheapest, least efficient model under both the uniform tariff and the TOU tariff. As shown in figure 3.1 one household in the Mawson Lakes sample consumes enough electricity using their reverse cycle air conditioner to justify the higher purchase cost of the most energy efficient model in the appliance dataset. For all other households the present value of appliance cost is lowest for either the median or lowest energy efficient model.

The cost of running an air conditioner under the TOU tariff is higher for most households than under the uniform tariff. This result is not unexpected, as air conditioners are generally used during (and are major contributors to) peak periods of electricity consumption. Under the TOU tariff the most efficient air conditioner is relatively more attractive to households as it requires less electricity to operate.
Figure 3.1: Present value of appliance costs: space cooling and heating
**Water heating**

The replacement hot water system with the lowest present value appliance cost for most households in the samples is the most efficient model as illustrated by figure 3.2. The present value appliance costs for Mawson Lakes are presented in bar charts as there is only one household with an electric hot water system in this sample.

The cost of operating an electric hot water system is less under the TOU tariff than under the uniform tariff, as the majority of electricity consumed by a hot water system is in the early hours of the morning (when the price of electricity is low under the TOU tariff). For the Mawson Lakes household, the hot water system of median energy efficiency has the lowest estimated present value appliance cost of the three systems in the appliance dataset under both tariffs. The effect of the TOU tariff is clearly illustrated for the Mawson Lakes household. Under the TOU tariff the operating costs of the less efficient hot water systems (which consume a large amount of electricity during the off peak tariff period) are substantially reduced compared with costs under the uniform tariff.

![Image](image-url)  
(a) Mawson Lakes (uniform tariff)  
(b) Sydney (uniform tariff)  
(c) Mawson Lakes (TOU tariff)  
(d) Sydney (TOU tariff)

Figure 3.2: Present value of appliance costs: water heating
Food storage

All the four households in the Mawson Lakes sample with metered food storage appliances minimise their net present appliance cost for food storage by replacing their existing appliance at the end of its effective life with the least energy efficient fridge-freezer in the appliance dataset. This is also the case for the majority of households in the Sydney sample. A small number of households in the Sydney sample are estimated to be best served purchasing the fridge-freezer of median efficiency.

There is little difference in operating costs for food storage under the uniform and TOU tariffs. While costs are estimated to be slightly lower under the TOU tariff, refrigerators operate over the course of each day, resulting in minimal differences under the two tariff structures.

Figure 3.3: Present value of appliance costs: food storage
Food preparation

The most efficient dishwasher has the highest present value appliance cost for all households in the Mawson Lakes sample and the majority of the households in the Sydney sample. The least cost replacement dishwasher for most households in both samples is the cheapest, least efficient model. The optimal replacement model for the remainder is the model of median energy efficiency efficiency.

Expenditure is estimated to be slightly increased under the TOU tariff relative to that expenditure based on the uniform tariff.

(a) Mawson Lakes (uniform tariff)  (b) Sydney (uniform tariff)

(c) Mawson Lakes (TOU tariff)  (d) Sydney (TOU tariff)

Figure 3.4: Present value of appliance costs: food preparation
Clothes cleaning

There are no metered clothes cleaning appliances in the Mawson Lakes sample. The present value appliance cost for the households in the Sydney sample is clear cut: the least cost replacement appliance combination for all households is that comprised of the cheapest, least efficient model clothes washer and clothes dryer.

There is little difference made to estimated present value appliance costs by the choice of the uniform or TOU tariff.

![Figure 3.5: Present value of appliance costs: clothes cleaning](image)

(a) Sydney (uniform tariff)

(b) Sydney (TOU tariff)

Figure 3.5: Present value of appliance costs: clothes cleaning
Lighting

As noted in section 3.5 energy efficient compact fluorescent light globes are the optimal choice for household lighting (with high positive net present values against a benchmark of incandescent globes). Almost all of the households in the Mawson Lakes and Sydney samples would also minimise lighting costs by choosing compact fluorescent globes when replacing their existing globes. (In fact, the optimal decision for almost all households is to upgrade from incandescent and halogen globes to compact fluorescent globes irrespective of the condition of the existing lights.)

Expenditure on electricity for lighting is estimated to be slightly higher under the TOU tariff.

As noted earlier, the few households with very low electricity consumption on lighting may have energy efficient light globes installed which will result in misleading estimates of the cost of upgrading and replacing lights.

Figure 3.6: Present value of appliance costs: lighting
3.7 The impact of household behaviour and characteristics

In this section three factors concerning household behaviour and characteristics that are central to the modelling of household appliance upgrade and replacement decisions are discussed. These are: the intra-day pattern of household consumption; the time horizon; and the existing stock of appliances.

Intra-day household consumption

Households consume electricity on various energy functions. The pattern of household consumption differs throughout the day as different appliances (serving different energy functions) are used. Lighting is required at times when household members are awake and there is insufficient natural light, while space cooling is required at times when the internal temperature of the dwelling is higher than desired.

Under a uniform intra-day tariff, the pattern of household electricity consumption does not affect household electricity expenditure. Electricity expenditure during any given period is simply the product of the uniform rate and the sum of electricity consumption during that period. However under a TOU tariff the intra-day pattern of electricity consumption is an important determinant of expenditure. Since the intra-day pattern of household electricity consumption is not uniform for all energy functions, the introduction of a TOU tariff can affect the expense associated with operating different appliance types. The associated cost of upgrading or replacing an existing appliance with a more energy efficient appliance can also be (positively or negatively) affected.

Figure 3.7 illustrates the proportions of electricity consumed during peak and non-peak periods for each energy function. Peak and non-peak periods are defined in terms of aggregate electricity consumption in the samples. Intra-day periods in which aggregate consumption was in the top five per cent of consumption during the relevant twelve month sample period (defined in subsection 2.5.5 for the Mawson Lakes and Sydney samples) are defined as peak periods for figure 3.7. In the Mawson Lakes sample the two energy functions with the highest proportions of consumption during peak periods are space cooling (with around than two-thirds of consumption during peak periods) and space heating (around one-quarter during peak periods). The energy function with the lowest peak period consumption is water heating. In the Sydney sample the two energy functions with the highest peak period consumption are space heating (more than half during peak periods) and lighting (around one-third during peak periods). All peak periods in the Sydney sample occur during the winter months.
Under a TOU tariff that has been designed to maximise the profit of an electricity retailer, the price of electricity is high during intra-day periods correlated with peak electricity demand. Conversely, the price is low at times correlated with periods of low electricity demand. Such a TOU tariff will increase the operating expenditure associated with using appliances like reverse cycle air conditioners and will reduce the cost of operating appliances like hot water systems. Under a TOU tariff, there is likely to be an additional incentive to replace reverse cycle air conditioners with more efficient models and less financial benefit from replacing existing hot water systems. Examining the present value estimates of the energy functions associated with these appliances in section 3.6 reveals this is the case for the households in the Mawson Lakes and Sydney samples.

The introduction of TOU pricing for household electricity can either reduce (act as a substitute) or complement incentives for households to upgrade appliances to more energy efficient models. The effect is dependant on the intra-day pattern of use of particular appliances. There is a increased incentive for households to upgrade appliances predominantly used during peak periods, while the incentive to upgrade appliances generally used outside of peak periods is reduced.

**Time horizon**

The estimates of the cost of purchasing and operating appliances made in this chapter are based on a ten year time horizon. Household decisions concerning appliance upgrades and replacements are modelled using the purchase and operating costs of an appliance over a ten year period. In the case of halogen and incandescent light globes (with effective lives less than ten years) the cost of purchasing replacement globes during the ten year period is included in the estimated present value appliance cost.

If a household’s expectations of the period that they are likely to enjoy the use of an appliance is more or less than the time horizon used in this chapter, the present value of
the operating costs associated with an appliance will be affected. Where an appliance is expected to have an effective life greater than ten years, the net present value estimated for that appliance will be greater if it is more energy efficient than the existing appliance serving the relevant energy function. Conversely, if an appliance is expected to be used for less than ten years, it will have a lower net present value relative to a less efficient existing appliance.

The time horizon of households may differ based on whether they own or rent their dwelling. Households that rent rather than own their dwelling are less likely to make the decisions concerning appliance upgrades and replacements (other than light globes); these are more likely to be made by the owner of the dwelling. An owner of a rental property will not directly benefit from reduced electricity expenditure from more energy efficient appliances and may therefore install appliances of relatively low energy efficiency. This is likely to be the case if (prospective) tenants are considered unlikely to correctly value the benefit of energy efficient appliances.

A similar externality may exist with respect to tenant purchases. If a household that rents a dwelling is uncertain how long they will stay at the dwelling they may discount the value of more energy efficient products. Taking lighting as an example, a tenant unsure of the time period that they will rent a dwelling (or who believes they will move out relatively soon) will not fully value the reduced electricity expenditure resulting in purchasing compact fluorescent globes. Such a purchase generates a positive externality since part of the benefit of purchasing and installing more energy efficient globes will be enjoyed by the household that next occupies the property.

The proportion of rented residential properties has been relatively steady for at least 40 years at around 30 per cent in Australia (Australian Bureau of Statistics 2008, p313). This suggests that issue described above may affect a substantial number of households and perhaps result in appreciably reduced demand for energy efficient appliances.

**Appliance stock**

In the absence of data concerning the existing stock of household appliances the extension to the simulation model presented in this chapter relies on assumptions concerning the energy efficiency characteristics of these appliances. Perhaps the least realistic assumption is that of homogenous appliance energy efficiency across households, which can result in misleading estimates of the present value of purchasing and operating appliances of various energy efficiency levels (noted earlier in section 3.5 with respect to lighting). To illustrate the issue, consider a household that has installed compact fluorescent light globes. The electricity consumption on lighting of that household is likely to be very low relative to households using halogen or incandescent globes. Without data on the type of globes installed, it is assumed that all households are using the most common type of
globe: incandescent. Net present value analysis based on this assumption will under-
estimate the benefit of the more energy efficient globes. The estimates used to model
household decision making concerning upgrades and replacement will rely on the (rela-
tively small) household electricity consumption on lighting and may result in a simulation
of the household replacing their globes with the least efficient type.

The possibility of incorrectly estimating the cost of appliance upgrades and replacements
underlines the need for caution when interpreting the medium and long run predictions
of the simulation model at the level of individual households. A survey of the appliances
used by households is required prior to reaching a definitive conclusion concerning the
benefits to a specific household of upgrading or replacing their appliances.
3.8 Model applications

Three applications of the extension to the simulation model presented in this chapter are contained in this section. Changes in the price of electricity and appliances (respectively) required to ensure the most efficient appliance serving each energy function is the optimal choice for households replacing existing appliances. Also estimated is the effect household appliance upgrades have on optimal (profit maximising) intra-day electricity prices.

3.8.1 Electricity price and appliance choice

The price of electricity is a key parameter in estimating the present value of the costs associated with purchasing appliances with different prices and levels of energy efficiency. Two tariffs underlie the estimates presented and described in sections 3.5 and 3.6: a uniform intra-day price of $0.16269 per kWh; and an associated TOU tariff. If the price of electricity was increased, the most energy efficient appliances serving each energy function would become more attractive to households, as the increase in appliance operating costs stemming from the increase in the price of electricity would be lowest for these appliances.

In this application, the price multiple required for the most energy efficient appliance serving each energy function to have the lowest present value appliance cost is estimated for each household under both the uniform and TOU tariffs. Figure 3.8 shows the distributions of required price multiples for each energy function under the two tariffs. In all subfigures observations between the 25th and 75th percentiles are contained in the box corresponding to each energy function, while the lower and upper bars contain observations between the 1st and 25th percentiles and 75th and 100th percentiles (respectively). The energy function for clothes washing is not included in the subfigures as the price multiple required for the most efficient clothes washer and clothes dryer combination to be the cost minimising choice for any household is in the hundreds. This is due to the very large purchase price of the most energy efficient clothes washer and clothes dryer combination.

Based on the uniform tariff, with no price change (a multiple of one) many households will minimise costs by purchasing the most energy efficient hot water system and compact fluorescent light globes. In fact, a multiple of almost zero is required for any household to be better off purchasing globes of median or low energy efficiency. This explains the apparent absence of observations in either sample for this energy function.

If electricity prices are doubled (corresponding to a multiple of two) some households in the Mawson Lakes sample will be better off purchasing the most efficient reverse cycle air conditioner for space cooling and heating. The most energy efficient fridge-freezers are also estimated to have the lowest present value appliance cost for some households in both the Mawson Lakes and Sydney samples at this price multiple.
Under the TOU tariff, there are differences in the distributions of price multiples, most obviously for reverse cycle air conditioners and hot water systems. In the Mawson Lakes sample a lower increase in the price of electricity is required for the most efficient reverse cycle air conditioner to minimise households costs under the TOU tariff. In comparison the household with an existing electric hot water system would require a larger price rise to warrant purchasing the most efficient hot water system under the TOU tariff.

![Figure 3.8: Distribution of required price multiplier for most efficient model to be chosen (by energy function)](image)

With access to household demographic data, it would be possible to investigate the price multiple changes required by household type and characteristic (for example: based on household income; number of occupants; or households with a pensioner). This could provide the basis for targeted policy to encourage purchases of energy efficient appliances, or to subsidise households made worse off by policy requiring new appliances to be more energy efficient.

### 3.8.2 Subsidies for purchases of energy efficient appliances

In the previous application the change in the price of electricity required for the most energy efficient appliance to have the lowest estimated present value financial cost for
households is estimated. This extension estimates the up-front subsidy needed for the most energy efficient appliance to have the lowest present value appliance cost (and therefore represent the optimal choice when replacing an existing appliance). The subfigures of figure 3.9 plot the distributions of required subsidies for each sample. The box in the figures contains observations between the 25th and 75th percentiles, while the lower and upper bars contain observations between the 1st and 25th percentiles and 75th and 100th percentiles.

Under the uniform tariff, no subsidy is required for most households to replace their existing hot water systems and incandescent light globes with the most efficient hot water system and compact fluorescent globes. In fact, subfigures 3.9(a) and 3.9(b) show that the price of these new, more efficient appliances would have to rise substantially for a household to be better off purchasing less efficient appliances serving these energy functions. A subsidy of $500 for the most efficient appliances would result in around half of the Mawson Lakes households being better off purchasing the most efficient reverse cycle air conditioner and fridge freezer. A subsidy of this level would mean almost three quarters of the Sydney households would be better off purchasing the most efficient fridge-freezer, with some also better off purchasing the most efficient dishwasher. A $750 subsidy would leave all households in both samples financially best served purchasing the most efficient fridge freezer, while a $1,000 subsidy would leave all households also better off purchasing the most efficient reverse cycle air conditioner and dishwasher.

The most obvious change under the TOU tariff is for reverse cycle air conditioners and hot water systems. The required subsidy for reverse cycle air conditioners is marginally lower than that required under a uniform tariff, while the subsidy required for purchases of the most efficient hot water system has substantially increased. In the Mawson Lakes sample, the household with an electric hot water system would require a subsidy of over $1,000 for the most efficient system under the TOU tariff.
As for the previous application, with household demographic data more detail could be provided on purchase subsidies based on household type and characteristic. This could assist in designing lower cost, targeted policies to encourage purchases of energy efficient appliances.

### 3.8.3 Appliance choice, electricity tariffs and retailer profitability

In the previous chapter (section 2.7) the simulation model is used to estimate intra-day electricity prices that maximise the profit of an electricity retailer subject to a price constraint. In this extension the effect of household use of the most energy efficient appliances on profit maximising TOU tariffs is examined. Figures are presented showing the optimal intra-day prices estimated based on the existing appliance stock (as in section 2.7) along with optimal intra-day prices estimated if households upgrade their reverse cycle air conditioners or hot water systems.

Subfigures 3.10(a) and 3.10(b) detail the optimised profile tariffs (for Mawson Lakes and Sydney respectively) where the price is permitted to vary between each intra-day period. Subfigures 3.10(c) and 3.10(d) present optimal TOU tariffs with a constraint of five dif-
different intra-day price periods (taken from off peak, shoulder and peak prices). As in the previous chapter, the price periods chosen are those used in Energy Australia’s PowerSmart Home tariffs: 10pm to 7am (off peak); 7am to 2pm and 8pm to 10pm (shoulder); and 2pm to 8pm (peak). An initial uniform tariff of $0.16269 per kWh is included in all subfigures as a reference. The price constraint imposed is the same as the constraint used in section 2.7 - that total household expenditure must not rise under an assumption that household consumption does not change as a result of the introduction of the new tariff.

Compared to the optimal intra-day tariff based on the existing appliance stock, after upgrading to the most energy efficient reverse cycle air conditioners the optimal tariff is 'flatter' in both samples and under both period constraints shown in figure 3.10. During peak periods the optimal intra-day tariff is lower with the more efficient air conditioner, while during non-peak periods the optimal tariff is higher. This result stems from the reduction in peak period consumption achieved by the use of more efficient reverse cycle air conditioners, which are commonly used during peak periods. The profit of the electricity retailer is substantially higher based on the relationship assumed between household electricity consumption and the wholesale price of electricity in the previous chapter.

In contrast, upgrading to the most efficient hot water system results in a steeper optimal tariff schedule, with higher peak prices and lower off peak prices. This results from the fact that most electricity used by hot water systems is at off peak times. The electricity retailer profit is also reduced. This is the result of reduced off peak consumption of electricity when the most efficient hot water system is installed - increasing the variation between peak and off peak consumption.
This application demonstrates that household decision making concerning the purchase of appliances can have direct consequences for the setting of TOU tariffs and the profitability of electricity retailers. Tariff schedules and retailer profit can depend on whether households upgrade appliances that are used generally during peak or off peak times. The application also suggests that there may be incentives for retailers to subsidise households to upgrade appliances used intensively during peak periods (like reverse cycle air conditioners) for specific households.
3.9 Chapter conclusion

In this chapter the simulation model of short run household electricity consumption presented in chapter 2 is extended to take account of the medium and long term upgrade and replacement decisions of households concerning their stock of appliances. Net present value analysis is used to model a subset of characteristics considered by utility maximising households when deciding whether to upgrade or replace existing appliances. Higher purchasing costs generally associated with more energy efficient appliances are weighed against the present value of operating cost savings over the effective life of an appliance to determine which appliances (of high, median or low energy efficiency levels) minimise cost for individual households.

Applications of the extension are presented, showing the effect of electricity prices and tariffs along with subsidies for energy efficient appliances on the cost minimising appliance purchase decisions of households. Positive and negative impacts on the profit of electricity retailers from household purchases of more energy efficient appliances are demonstrated along with the potential effect of appliance upgrades on profit maximising TOU tariffs.

The following chapter uses the simulation model incorporating the extension presented in this chapter to simulate the effects of various industry, policy and climate scenarios on household electricity consumption in the short, medium and long run.
3.A Entertainment: an energy function requiring a different approach

The extension to the simulation model presented in this chapter uses net present value analysis to model the financial costs associated with purchasing appliances of various prices and energy efficiency characteristics. As noted in section 3.4 net present value analysis can only be used to provide a measure of comparative utility where the appliances being considered for purchase differ materially only in terms of their purchasing costs and operating costs (the costs able to be quantified in financial terms). This assumption does not hold for every appliance and it is unlikely to be suitable for appliances in the energy function category: entertainment.

This energy function consists of televisions in the samples used in this study. However this category also covers video recorders, stereos, games consoles and other audio-visual appliances that are increasingly common in modern households. Appliances such as these generally have a wide variety of characteristics important to households in addition to their price and level of energy efficiency. In addition, the pricing, energy efficiency and technical characteristics of entertainment devices tend to change more frequently than those of appliances serving other energy functions. In the case of televisions, price may not be correlated with energy efficiency. Price is also a function of television size, and the larger the television, the more likely it is to have a LCD or plasma screen - technologies that are more attractive to consumers but less efficient than televisions with conventional cathode ray tubes.

The stock of entertainment devices has grown in recent years. de Almeida and Fonseca (2006) report preliminary results of a monitoring project measuring intra-day household electricity consumption by appliance type in twelve European countries. Entertainment and communications devices are found to be key contributors to household electricity consumption, with a wide range of characteristics (including energy efficiency performance) within each appliance type and energy function. Ownership (or penetration) rates for televisions of over 1.6 per household are estimated, while rates for compact audio devices, computers and printers of above 0.4 are estimated. These are comparable to estimates of owner rates for appliances serving other energy functions (for example dishwashers and clothes dryers) and are projected to increase rapidly over the next decade (de Almeida and Fonseca 2006, p3).

The modelling of changes to the stock of household entertainment appliances requires a different approach to that taken in this chapter. The scope to model the utility maximising purchase decisions of individual households is limited due to the complexity of estimating the comparative value of the many varied characteristics embodied in different appliances. In addition, the opportunity cost relevant for the purchase of an entirely new appliance (discussed in section 3.4) needs to be considered in contrast to purchases in which an
existing appliance is being upgraded or replaced.

One approach that could be pursued is to conduct an aggregate analysis of appliance purchase trends and combine this with distributional assumptions linking household characteristics (such as: income; number of occupants; or pensioner households). Aggregate data on entertainment appliances are available (for example de Almeida and Fonseca 2006, Digital CEnergy 2007). Projections of sales by type could be combined with projected electric capacity (and other relevant technical characteristics) and average household usage to estimate electricity consumption. An example of this general approach is the projections of Western Australian residential electricity consumption by Goldschmidt (1988).
3.B Technical overview of radar figures

This appendix provides an overview of the reading of the radar figures used in this chapter to compare the present value of purchasing and operating different appliances. The results of the replacement of space cooling and heating appliances from section 3.6 are used for this purpose.

In this chapter, the results of present value analysis comparing the cost of replacing appliances that have reached the end of their effective lives are presented by energy function for both the Mawson Lakes and Sydney households. The present value of purchasing and operating the appliances (of different price and energy efficiency levels) contained in the appliance dataset are displayed in radar figures. These radar figures plot the present cost of purchasing appliances that serve a given energy function for households that have an existing appliance serving that energy function.

Households are 'spokes' in these radar figures. For example, the six households comprising the Mawson Lakes dataset are each represented in subfigure 3.11(a) as spokes, offset from each other by 60 degrees around the centre (or hub) of the subfigure.

Lower estimates are contained nearer the centre of each figure while higher estimates are nearer the periphery. Three series are contained in each figure, representing the present value appliance cost for each household of purchasing appliances of high, median and low energy efficiency. The present value of the costs associated with purchasing the most efficient appliance is represented by a solid line, the appliance of median energy efficiency is plotted with a long-dashed line, while the appliance of low energy efficiency is represented with a short-dashed line. For example, in the Sydney dataset (subfigure 3.11(b)) the present value of replacing the existing space cooling and heating appliances used by each household with appliances of the highest energy efficiency exceeds the present value of replacing with either median or low efficiency appliances. This can be seen in the radar subfigure as the solid line encompassing both the long-dashed and short-dashed lines around the entire subfigure.

Estimates for the Mawson Lakes and Sydney samples are presented in adjacent subfigures. The upper two subfigures in each radar figure contain estimates based on the uniform tariff while the lower two subfigures contain estimates based on the TOU tariff. These tariffs are those specified in section 3.5.

To further illustrate the interpretation of radar figures, the description of the present value analysis of the replacement of space cooling and space heating appliances is reproduced in this appendix (follows).

The reverse cycle air conditioner with the lowest present value cost for most households in both Mawson Lakes and Sydney is the cheapest, least efficient model under both the
uniform tariff and the TOU tariff. As shown in figure 3.11 (a reproduction of figure 3.1) one household in the Mawson Lakes sample consumes enough electricity using their reverse cycle air conditioner to justify the higher purchase cost of the most energy efficient model in the appliance dataset. For all other households the present value of appliance cost is lowest for either the median or lowest energy efficient model.

The cost of running an air conditioner under the TOU tariff is higher for most households than under the uniform tariff. This result is not unexpected, as air conditioners are generally used during (and are major contributors to) peak periods of electricity consumption. Under the TOU tariff the most efficient air conditioner is relatively more attractive to households as it requires less electricity to operate.

![Diagram](image)

(a) Mawson Lakes (uniform tariff)  
(b) Sydney (uniform tariff)

(c) Mawson Lakes (TOU tariff)  
(d) Sydney (TOU tariff)

Figure 3.11: Present value of appliance costs: space cooling and heating
Chapter 4

Illustrative simulation of industry, policy and climate scenarios

4.1 Chapter overview

In this chapter the model presented in the two previous chapters is used to simulate the effects of various industry, policy and climate scenarios on household electricity consumption. The purpose of this chapter is to illustrate how intra-day elasticities of demand for electricity of individual households by energy function estimated using the methods adopted in this study have the potential to inform questions of public interest involving the electricity industry and the household sector. The climate and price elasticity parameters estimated in the preceding chapters are used in the scenarios simulated in this chapter, however (as has been noted earlier) these are limited by the narrow and non-representative nature of the households for which data are available in Australia. The simulations carried out and conclusions made are illustrative only.

A literature review is presented in section 4.2 in which an overview of the options being considered to address the problems of peak load and negative environmental impact of electricity production is provided. These include the introduction of TOU tariffs for households and the direct load control of household air conditioners. Policy options concerning price regulation and electricity consumption by households are summarised. These include regulatory options to constrain electricity price increases following the introduction of TOU electricity tariffs for households. A summary of policy instruments designed to limit or reduce electricity consumption (and/or associated greenhouse gas emissions) is provided. Traditional policy instruments include appliance efficiency standards and building standards, while more recent instruments include carbon cap and trade schemes, subsidies for the purchase of relatively efficient appliances, and prohibitions on the supply of relatively inefficient types of appliances.
A more detailed relationship between household consumption and the price of electricity in the wholesale market is estimated in section 4.3 than that used in the extensions to the previous chapters (sections 2.7 and 3.8). This is incorporated in the simulation model with implications for retailer profitability and optimal TOU tariffs.

Section 4.4 provides an overview of the parameters used, output generated and scenarios simulated in this chapter.

The illustrative results of simulations based on industry, policy and climate scenarios are discussed respectively in sections 4.5, 4.6 and 4.7. Results reported for the scenarios include estimated: profit maximising intra-day prices; distributional impacts on electricity consumption (across households and by energy function); effects on intra-day electricity prices in the wholesale market; and electricity retailer profitability. Simulations are generated for three time periods: the short term; medium term; and long term. In the short term the household stock of appliances is assumed to be fixed. In the medium term households upgrade appliances based on the relative net present value of operating their appliances under various electricity tariffs given the energy efficiency of their existing appliances and appliances available for purchase. In the long run households replace appliances as they reach the end of their effective lives with appliances with the lowest present value appliance (purchase and operating) costs. The criteria used by households to decide which appliances to upgrade and replace is described in chapter 3.

Section 4.5 contains the illustrative results of the simulation model following the introduction of TOU pricing by electricity retailers to households. Simulations suggest that the introduction of TOU pricing can affect household appliance upgrade and replacement decisions. These in turn can affect the optimal (profit maximising) TOU tariffs. Households that consume an above average proportion of their electricity during off-peak times (commonly for water heating) are likely to benefit most from the introduction of TOU tariffs. Direct load control of air conditioners is also simulated and found to have the potential to be as (or more) effective in alleviating the problems associated with peak load than the introduction of TOU tariffs.

The illustrative results of policy scenario simulations are reported in section 4.6. A regulatory constraint on electricity tariffs based on household expenditure is found to be more effective than the imposition of a maximum price (or price ceiling) for TOU tariffs. Higher minimum appliance energy standards are shown to have the potential to reduce electricity consumption in the medium term but increase consumption in the long term. Subsidies for relatively efficient appliances are shown to reduce electricity consumption in the medium and long term but are potentially very costly. A carbon cap and trade scheme is shown to affect the optimal price profile of a TOU tariff, reducing the range between peak and off-peak prices.

The effect of various climate change scenarios are reported in section 4.7. The scenarios
are drawn from the ten, forty and seventy year climate projections for Australia of the Intergovernmental Panel on Climate Change (Hennessy et al. 2007). Simulation of these scenarios suggest that the temperature increases projected in these scenarios will result in increased electricity consumption by households.

Illustrative conclusions are drawn in section 4.8 and appendices follow in sections 4.A and 4.B. The limited and non-representative nature of the underlying data prohibit the extension of these conclusions being taken as having any general applicability.
4.2 Literature review

The purpose of this literature review is to briefly discuss the literature concerning the options currently being considered to meet the challenges of peak load and adverse environmental impact from electricity consumption and production. This review is comprised of two parts. Various technical and policy options currently proposed to meet the challenges currently facing market participants and policy makers responsible for the electricity market in Australia are discussed. The first part covers the challenge of peak load, while the second relates to the environmental impacts associated with increased electricity consumption and production.

4.2.1 Industry options to address peak load

Economists have long argued that TOU pricing has a role to play in increasing the efficiency of markets in which peak load consumption is an issue. In the seminal article on the issue, Boiteux (1960) outlines how intra-day pricing of electricity can be used to align the price of electricity faced by consumers with the cost of producing the electricity used. Boiteux constructs a framework in which both capital (fixed) and operating (variable) costs are included in estimating dynamic optimal pricing for electricity. The purpose of pricing in this framework is to reduce the level of variation in electricity consumption. Boiteux (p176) notes that the theoretical framework presented supports the ‘experimental’ two-period, two-season TOU tariff introduced by Electricité de France in 1956 known as the green tariff. (For more details on this early TOU tariff see Boiteux et al. 1964.)

A variation on intra-day pricing is real-time pricing. Under real-time pricing, the price charged at any point in time can vary based on market (supply and demand) conditions. Real-time pricing has the advantage that the price can be set to ensure that it remains at or above marginal cost at all times. Following the California electricity crisis of 2000-01, a group including economists, engineers and electricity industry professionals endorsed the implementation of real-time pricing (Bandt et al. 2003). The desirability of charging consumers the cost of generating and distributing electricity at the time of consumption is highlighted, along with the potential discipline that demand response would bring to strategic behaviour in the wholesale market. A recent paper by Borenstein (2005) illustrates the potential efficiency benefits of real-time pricing over TOU and uniform tariffs.

However there are drawbacks to real-time pricing (recognised as early as Boiteux 1960, pp173-174). It is difficult and costly for consumers to be informed of the price and it is not possible to be certain of price in future periods. In a paper providing guidance on the purpose, design and timing of smart grid pilots (covering electricity pricing and enabling technologies) Faruqui et al. (2009) suggest that real-time pricing (along with variable-rate and variable-period CPP) provide more information that residential customers can use.
Based on the results of a residential real-time pricing tariff pilot initiated in Illinois in 2003 (the Community Energy Cooperative Energy-Smart Pricing Plan), Faruqui et al. report that hour-to-hour price variation did not influence consumption patterns. Customers were found to respond to times that were, on average, high or low price periods. For CPP tariffs, households appeared to respond to notification of high price days rather than hourly price increases.

The introduction of electricity tariffs that include intra-day variation appears to be politically difficult. The Victorian State Government temporarily suspending the introduction of TOU tariffs for households in early 2010 (Batchelor 2010). The call by Bandt et al. (2003) also included an affirmation of key principles: reliance on markets; competitive procurement (unregulated electricity generation); and the clarification of regulatory agency responsibilities. These principles reflect concerns by the authors with electricity industry policy following the California electricity crisis, highlighting the political constraints associated with reforming electricity pricing in the residential sector. This study does not simulate the introduction of real-time pricing for electricity, as this is unlikely to be a politically feasible alternative for residential customers without the imposition of substantial regulatory constraints.

Other methods of addressing the peak load problem have been suggested. Combining priority of service contracts for electricity with capital reductions has been proposed as a way to reduce the costs involving servicing peak load consumption (Wilson 1989, Reitman 1991). Under such a system, electricity is rationed during periods of peak load, with electricity not provided to some consumers. Consumers can pay a premium to purchase a higher priority of service from their electricity retailer. These customers would be less likely to have their electricity supply cut off during periods of peak consumption. Such a system was advocated following the California electricity crisis of 2000-2001 (McAfee 2002, Rassenti et al. 2001). (For a detailed examination of the 2000-2001 California electricity crisis see Cicchetti et al. 2004.)

This study does not simulate priority of service contracts. However the short run effects of a related non-price method of reducing peak period consumption are simulated. Direct load control involves the reduction of electricity consumption of appliances remotely by electricity retailers or distributors. An Australian direct load control trial was carried out in Adelaide, South Australia in 2006 to 2008 as reported by the Essential Services Commission of South Australia (2008). In this trial, direct load control resulted in substantial reductions in peak electricity consumption for little cost, with few participants reporting reduced thermal comfort following the load control of their air conditioners. Newsham and Bowker (2010) present a summary of six US direct load control pilots, comparing estimates of reduced electricity consumption. Newsham and Bowker (2010) conclude that direct load control is effective in reducing peak load through reduction in electricity consumption for air conditioning even without supportive, dynamic price tariffs.
Efforts to increase awareness of the effects of household electricity consumption have been suggested as non-price methods of reducing peak load consumption. These may include appropriate feedback on household consumption and communication of information about the capital costs of increased generation from growing peak load (and the consequent flow on effects to retail electricity prices). Fischer (2008) presents a psychological model illustrating how feedback operates and provides a survey of international evidence of which kinds of feedback are most effective in reducing electricity consumption. Fischer concludes that the most successful feedback is characterised by: frequent communication over a substantial period; appliance-specific information; clarity of presentation; and the use of computerised and interactive tools. Cultural differences in preferences for graphics and presentation and the difficulties consumers have in linking appliance use with electricity consumption presented in a monthly or quarterly bill are recognised. In considering the evidence presented Fischer finds that for action to be taken to reduce electricity consumption, motivation to conserve is required, otherwise both information and feedback are irrelevant to consumers.

4.2.2 Policy options to reduce environmental impact

The generation of electricity has been linked to a range of environmental concerns. The use of fossil fuels can cause pollution including smog and acid rain. Accidents at generators using nuclear fuel have the potential to cause nuclear fallout and associated contamination. The use of non-renewable fuel sources also raises questions of the sustainability of electricity consumption. Finally, electricity generation using fossil fuels is a major source of greenhouse gas emissions.

This thesis does not examine the potential environmental impacts of electricity generation in detail. (For an overview of these, see Goodstein 2008 and Harris 2006.) Rather it examines the potential for various policy options to address these impacts based on the simulation model developed in the preceding chapters.

The policy options intended to address the environmental impact of electricity consumption and production that are simulated in this chapter operate to either reduce electricity consumption or to internalise associated negative externalities. Increases in appliance energy efficiency standards, and subsidies for highly energy efficient appliances are examples of the former, while a carbon cap and trade scheme is an attempt to price the negative externalities associated with the emission of greenhouse gases. These policy options are currently utilised in or proposed for Australia (as at December 2009).

As noted in chapter 3, the Australian Government sets minimum energy performance standards for appliances manufactured in or imported into Australia. These standards are published on the website www.energyrating.gov.au, along with information concerning the energy efficiency of appliances sold in Australia.
The Australian Government mandated the supply of an additional 9500 GWh of renewable energy by 2010 in order to reduce greenhouse gas emissions and to develop a renewable energy industry. Electricity retailers and large consumers are required to purchase a portion of their energy from renewable sources. To facilitate this, tradable Renewable Energy Certificates (RECs) are generated by certain activities that increase renewable energy production or reduce electricity consumption. RECs can be used by electricity retailers and large consumers to satisfy their obligations to use energy from renewable sources. The purchase of energy efficient appliances can generate RECs. Gerardi et al. (2007) describe the system under which RECs are generated and traded.

In addition to RECs, a number of programs are run by the Australian and State Governments to encourage the purchase of appliances that are highly energy efficient. An example of these is the Renewable Energy Bonus Scheme, under which the Australian Government provides cash rebates of between $600 and $1000 to households that replace existing electric hot water systems with solar or heat pump systems. (Department of Climate Change and Energy Efficiency (2010)). The Victorian Government solar hot water rebate (of between $300 and $1500) is an example of a scheme run by a State Government that can (further) reduce the cost of purchasing a highly energy efficient appliance (Sustainability Victoria (2010)).

The Australian Government has proposed the introduction of a carbon cap and trade scheme to reduce Australian greenhouse gas emissions. The policy, known as the Carbon Pollution Reduction Scheme (CPRS) is designed to reduce carbon emissions by between five and 25 per cent by 2020 relative to emission levels in 2000. Detailed modelling of the policy by the Department of the Treasury (2008) suggests that robust economic growth can be achieved even as emissions fall in the future. The Treasury report, titled ‘Australia’s low pollution future’ was carried out for the Australian Government in order to model the economic effects of policies to reduce greenhouse gas emissions, in particular the proposed CPRS carbon cap and trade scheme. The focus of the report is the medium to long term impacts on the Australian economy. The report draws on an earlier study of the potential impacts of climate change conducted by Garnaut (2008).

Parts of the contribution of this study can be illustrated by considering how the analysis conducted could augment the Treasury report. The modelling underlying the report does not take account of the effects of the introduction of TOU pricing on household electricity consumption. The introduction of the CPRS is expected to substantially increase the price of electricity. This increases the potential for TOU pricing to play an important role in the period of transition between high to low electricity generation technologies, by aligning the cost of generating electricity (including the cost imposed by a carbon cap and trade scheme) and the retail price. This study presents a method by which the response of household electricity consumption to changes in the intra-day price of electricity can be modelled, both for individual households and for households in aggregate.
In addition, the Treasury report relies on general household and income demographics for its distributional analysis. Such an approach does not incorporate the characteristics of individual households and the associated appliance stocks. The disaggregated approach underlying the construction of the simulation model in this study, combined with a larger and more representative dataset, would allow for more detailed analysis. This could include an examination of specific methods that would be most efficient and effective in compensating households (either partially or fully) for the effects of the CPRS.

4.2.3 Concluding remarks

The review of literature in this chapter has provided an overview of the literature concerning the options currently being considered to meet the challenges of peak load and adverse environmental impact from electricity consumption and production. In this chapter, these options are examined using the simulation model developed in this study.
4.3 Household consumption and wholesale electricity prices

The relationship between electricity consumption and the wholesale price of electricity is an important determinant of profitability in the retail electricity market. When electricity consumption is relatively low, electricity is provided by efficient 'baseload' generators. The wholesale price of electricity is generally very low during periods of low consumption. As electricity consumption increases, the capacity of efficient generators to supply the electricity demanded is exceeded and less efficient generators are required to be operated. As these 'peaking' generators are less efficient, a higher wholesale price of electricity is required to ensure that demand for electricity is met during peak periods. An electricity retailer selling electricity under a uniform tariff can make a loss during periods of peak electricity consumption if the wholesale price of electricity exceeds the fixed price specified in their tariff.

In section 2.7 the short run form of the simulation model is used to estimate optimal (profit maximising) intra-day electricity prices. A simple relationship between electricity consumption and the wholesale price of electricity is assumed for the purpose of that application. In this section a more detailed model of the relationship is estimated. This model is used in the scenario simulations presented in this chapter.

4.3.1 Estimating a more detailed relationship

The simple relationship between electricity consumption and the wholesale price of electricity used in section 2.7 (restated in equation 4.1 for the Mawson Lakes sample) has a number of drawbacks for use in simulation modelling. Firstly there is an implicit assumption that electricity purchased in the wholesale market is sold solely to households - no allowance for non-household consumption is made. Secondly household consumption is represented as a scaled aggregation of the sample of households included in the sample used to calibrate the simulation model. This will overestimate the variance of aggregate household consumption, since households included in the sample comprise a very small proportion of the population of households. While the electricity consumption of individual households may be expected to be correlated to a degree (resulting from similar patterns of intra-day consumption and responses to exogenous factors such as temperature) they will not be perfectly correlated.

\[ \hat{w}_t = 1.47 \times 10^{-3} E_t^2 \]  

(4.1)

In order to address the drawbacks inherent in using the simple relationship between household consumption and wholesale electricity prices introduced in section 2.7 a more detailed model is estimated. This involves two steps. The first is estimating the relationship be-
tween aggregate consumption of electricity and the sum of electricity consumed by the households in the sample underlying the simulation model. The second step is estimating the relationship between aggregate consumption of electricity and the wholesale price of electricity with a more flexible functional form than the simple quadratic function estimated for the simple relationship.

Rather than simply scaling up the sum of electricity consumption by the households included in the simulation model, aggregate consumption is estimated by OLS regression. Estimates of aggregate consumption \( (E_t) \) are obtained by regressing hourly aggregate electricity purchased in the South Australian wholesale electricity market on the sum of forecast electricity consumption of the sample households and a constant (as shown in equation 4.2). The parameters estimated are contained in Table 4.1 (with t-values in brackets) along with the coefficient of determination \( (R^2) \) for each regression.

\[
E_t = \gamma_h + \delta_h \sum_{i=1}^{f} \hat{E}_{i,t} + u_h
\]  

<table>
<thead>
<tr>
<th>( h )</th>
<th>( \gamma_h ) (68.21)</th>
<th>( \delta_h ) (6.87)</th>
<th>( R^2_h )</th>
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<td>31304 (9.65)</td>
<td>0.2063</td>
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</tbody>
</table>

Table 4.1: Aggregate South Australian electricity consumption: regression parameters by intra-day period
The parameters estimated for periods after 11am generally are more significant than those estimated prior to 11am - especially the periods between 7am and 10am. This may be due to substantial variation in consumption during these morning periods in the sample households. Over the course of a day, much of the variation in aggregate electricity consumption can be explained in terms of electricity consumption variation of the households in the sample. It is interesting to note that across all intra-day periods the constant term is relatively large and significant. This indicates that a large component of aggregate consumption is not correlated with that of the sample households.

The parameters contained in table 4.1 are used to estimate aggregate electricity consumption from the consumption of households in the sample. These are then used to estimate the wholesale price of electricity. In contrast to the simple quadratic functional form used in section 2.7, constant and linear terms are included in the functional form along with the quadratic term as shown in equation 4.3. The results from the OLS regression of the wholesale price of electricity on estimated aggregate consumption (including the square of aggregate consumption) are shown in table 4.2 along with the coefficient of determination of the regression.

\[ w_t = \nu + \rho E_t^2 + \tau E_t^2 + u_t \]  

(4.3)

<table>
<thead>
<tr>
<th>$\nu$</th>
<th>$\rho$</th>
<th>$\tau$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
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<td>0.01064</td>
<td>-3.1502 x 10^-8</td>
<td>3.0552 x 10^-14</td>
<td>0.0460</td>
</tr>
</tbody>
</table>

Table 4.2: Wholesale electricity price: regression parameters

The estimated parameters include a positive constant, a negative coefficient for aggregate consumption and a positive coefficient on the square of aggregate consumption. The minimum wholesale price estimated by the regression is $0.0106/kWh associated with aggregate consumption of 1.0311GWh. Aggregate consumption exceed this level in the South Australian wholesale market for more than 99 per cent of the observations in the year of interest. Ninety per cent of aggregate consumption is bounded by 1.1229GWh and 1.7741GWh. Over this period, the estimated wholesale price increases from $0.0138/kWh to $0.0509/kWh.

Of the estimated parameters, only the coefficient on the squared term is significant at the five per cent level, with a t-value of 4.08. The coefficient of determination is relatively low at 0.0460. However when observations associated with high wholesale prices are excluded from the sample, the significance of the parameters and the coefficient of determination improve. Table 4.3 contains the results from regressions where observations associated with wholesale prices exceeding certain levels ($1; $0.50; and $0.17 per kWh) are excluded, along with the results from the regression in which all observations are in-
cluded. The relationships estimated in these regressions are displayed in figure 4.1 along with the distribution of wholesale price - aggregate consumption data. One explanation for the improvement in coefficient of determination for regressions in which data for the highest prices are excluded is that some of these observations may be the result of unscheduled power outages by major electricity generating plants. Such outages are (necessarily) not associated with high aggregate consumption, which would result in a reduction in goodness of fit statistics.

<table>
<thead>
<tr>
<th>maximum price</th>
<th>observations</th>
<th>$\nu$</th>
<th>$\rho$</th>
<th>$\tau$</th>
<th>$R^2$</th>
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<tbody>
<tr>
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<td>0.01064</td>
<td>-3.1502×10^{-8}</td>
<td>(-1.32)</td>
<td>3.0552×10^{-14} (4.08)</td>
</tr>
<tr>
<td>$1.00$</td>
<td>8749</td>
<td>0.03305</td>
<td>-5.5559×10^{-8}</td>
<td>(-5.33)</td>
<td>3.5506×10^{-14} (10.84)</td>
</tr>
<tr>
<td>$0.50$</td>
<td>8737</td>
<td>0.03536</td>
<td>-5.5565×10^{-8}</td>
<td>(-8.27)</td>
<td>3.4101×10^{-14} (16.14)</td>
</tr>
<tr>
<td>$0.17$</td>
<td>8683</td>
<td>0.00628</td>
<td>-1.1035×10^{-8}</td>
<td>(-2.65)</td>
<td>1.7222×10^{-14} (13.07)</td>
</tr>
</tbody>
</table>

Table 4.3: Wholesale electricity price: regression parameters (Mawson Lakes)
Figure 4.1: Estimated wholesale price - aggregate consumption relationship ($/kWh)

Notwithstanding the improved coefficient of determination associated with the regressions based on sets excluding observations associated with high wholesale prices, the simulations presented in this chapter are based on a relationship between household consumption and wholesale price using the coefficients shown in table 4.2. This is done to avoid systematically underestimating the wholesale price associated with any given level of household consumption.
4.3.2 Using the more detailed relationship to estimate electricity tariffs

In the previous chapter the simulation model is used to examine the impact of household appliance choices on profit maximising TOU electricity tariffs (subsection 3.8.3). Three scenarios are simulated. Optimal intra-day prices are estimated assuming: an unchanged household appliance stock; a stock of household appliances with all air conditioners upgraded to the most efficient model; and a stock of appliances with all hot water systems upgraded to the most efficient model.

These simulation scenarios are re-run using the more detailed relationship between household electricity consumption and the wholesale price of electricity estimated in this section. In all scenarios, it is assumed that TOU tariffs (if included in a given scenario) are introduced to ten per cent of households. In order to quantify retailer profit, it is assumed that the TOU tariff applies only to the component of aggregate consumption correlated with the household consumption estimated by the simulation model. This is the second term $\left( \delta_h \sum_{i=1}^{l} \hat{E}_{i,t} \right)$ contained in equation 4.2 multiplied by 0.1 to account for the proportion of households to whom a TOU tariff is being introduced. The remaining electricity consumers (both household and non-household) are assumed to pay an unchanging retail tariff of $0.16269 per kWh during all intra-day periods. Thus revenue changes arising from the introduction of a TOU tariff are limited to a component of aggregate consumption, while the impact on the wholesale price of electricity affects all electricity supplied by a retailer.

Figure 4.2 shows the optimised profile tariffs for the Mawson Lakes sample based on both the simple and more detailed consumption-wholesale price relationships estimated. Subfigure 4.2(a) illustrates the optimised tariffs estimated in the previous chapter based on the simple relationship, while subfigure 4.2(b) shows the optimised tariffs based on the more detailed relationship. As in previous chapters, the price periods chosen are those used by Energy Australia’s PowerSmart Home tariffs: 10pm to 7am (off-peak); 7am to 2pm and 8pm to 10pm (shoulder); and 2pm to 8pm (peak). The uniform tariff of $0.16269 per kWh is included in both subfigures as a reference. The price constraint imposed is that previously used: that total household expenditure must not rise under an assumption that household consumption does not change as a result of the introduction of the new TOU tariff.

The optimal TOU tariffs estimated under both the simple and more detailed consumption-wholesale price relationships are ordinarily similar. The estimated optimal tariff after reverse cycle air conditioners are upgraded to the most efficient model is ‘flatter’ than the tariff estimated following the installation of efficient hot water systems in both cases. However there are quantitative differences. All peak period prices are higher using the
more detailed consumption-wholesale price relationship, while off-peak and shoulder period prices are lower.

Retailer profitability increases under both appliance upgrade scenarios using the more detailed relationship, increasing 4.4 per cent upgrading to the most efficient reverse cycle air conditioner and 2.3 per cent with the most efficient hot water system. This is in contrast to the result based on the simple relationship, when retailer profit increased under the scenario with more efficient air conditioner but decreased with more efficient hot water systems. This result stems from the inclusion of electricity consumption that is uncorrelated with the consumption of households estimated in the simulation model. The revenue from this component of consumption is not reduced in the off-peak period following the upgrade to more efficient hot water systems - it is assumed that these consumers face a tariff unrelated to the TOU tariff paid by households. However the cost of providing electricity to these consumers is affected. Reduced consumption of electricity arising from increased household hot water system efficiency results in reduced wholesale price of electricity, increasing the profitability of selling electricity to these consumers.

![Figure 4.2: Comparing period constrained profit maximising optimal prices based on different consumption-wholesale price relationships ($/kWh)](image)
(a) Simple relationship

![Figure 4.2: Comparing period constrained profit maximising optimal prices based on different consumption-wholesale price relationships ($/kWh)](image)
(b) More detailed relationship

Figure 4.2: Comparing period constrained profit maximising optimal prices based on different consumption-wholesale price relationships ($/kWh)
4.4 Description of model simulation and scenarios

In the remainder of this chapter the model developed in the previous chapters is used to simulate various industry, policy and climate change scenarios. An overview of the simulation model is provided in this section along with a description of the various scenarios simulated.

4.4.1 Overview of simulation model

Each scenario examined in this chapter is simulated over three different time periods: the short term; medium term; and long term. In the short term the household appliance stock and associated appliance characteristics are assumed to be fixed (as in chapter 2). Households adjust their consumption behaviour based on the price of electricity and climatic parameters. This is described in figure 4.3, which summarises the short term simulation in the form of a flow chart.

![Flowchart of simulation model and output: short run](image)

Figure 4.3: Flowchart of simulation model and output: short run

In the medium term, households are able to upgrade their appliances (scraping existing appliances prior to the end of their effective lives). The long term is defined as the time when households have completely replaced their initial stock of appliances after these appliances reached the end of their effective lives. Figure 4.4 describes the simulations for the medium and long term in the form of a flow chart.
Electricity tariffs

Profit maximising TOU tariffs are estimated in each simulation scenario for each of the short, medium and long terms. These tariffs will differ to the extent that the appliance stock differs in each period. The TOU tariffs are period constrained, comprising three prices based on the price periods used by Energy Australia’s PowerSmart Home tariffs: 10pm to 7am (off-peak); 7am to 2pm and 8pm to 10pm (shoulder); and 2pm to 8pm (peak). Henceforth, these tariffs are referred to as optimal TOU tariffs.

In addition to optimal TOU tariffs, scenario simulations are also carried out for the short term and long term based on the retention of an initial uniform tariff of $0.16269 per kWh. These are used to compare the short and long term impacts of moving from a uniform tariff to a TOU tariff.

Figure 4.5 in the following section (p170) shows the optimal TOU tariffs estimated in the short, medium and long term simulations of the introduction of TOU pricing to the residential sector. The initial uniform price of $0.16269 per kWh is also shown.

The intra-day price of electricity (marked as 1 in both flow chart figures 4.3 and 4.4) is a variable in all time periods in the simulation model, affecting the intra-day electricity consumption of households and electricity retailer profit. The effect of intra-day price variation on household electricity consumption is presented in section 2.6 (p64).
Household appliance stock and characteristics

The capacity and energy efficiency of household appliances directly affect household electricity consumption. As noted earlier, in short term simulations the stock and characteristics of household appliances are assumed to be fixed. (These are marked 2 and 3 in both flow chart figures 4.3 and 4.4). Figure 4.3 lists both the stock and characteristics of household appliances as parameters in the short term. This is in contrast to figure 4.4 in which these are variables in medium term and long term simulations.

In the medium term, households take account of the effect of changes in the (intra-day) price of electricity and are able to upgrade their appliances. However this involves the scrapping of existing appliances prior to the end of their useful lives. As outlined in chapter 3, households are expected to purchase a new appliance to replace a functional existing appliance if the present value of the savings from reduced electricity consumption outweigh the price of the new appliance.

In the long term all household appliances have been replaced. The opportunity cost of scrapping existing appliances is zero in the long term since over this period all existing appliances are assumed to have reached the end of their effective lives. The characteristics of household appliances in the long term reflect decisions taken in full knowledge of electricity tariffs (either uniform or TOU) and minimise the present value of purchasing and operating these appliances.

The simulation of household appliance upgrades (medium term) and replacements (long term) are discussed in sections 3.5 (p117) and 3.6 (p124) respectively.

Other parameters

The estimated intra-day price elasticities of demand for households and climatic data are parameters in the simulation of intra-day household electricity consumption (in the short, medium and long term) and household decisions concerning appliance upgrades and replacements (medium and long term). The effects of these parameters on household electricity consumption are discussed in sections 2.5 (p45) and 2.6 (p64). These parameters affect appliance upgrade and replacement decisions through their effect on electricity consumption as described in chapter 3.

Electricity consumption and wholesale price

The simulation model estimates aggregate household electricity consumption (marked 9 in flow chart figures 4.3 and 4.4) as the sum of the consumption of individual households
based on their simulated intra-day consumption decisions (marked 6). Aggregate household consumption is then used to estimate electricity consumption in the entire market (marked 10) - as distinct from the sample of households used in the simulation model. This is done using the relationship estimated in the previous section (equation 4.2, p156) between aggregate electricity consumption and the aggregate electricity consumption of sample households.

The wholesale price of electricity (marked 11 in flow chart figures 4.3 and 4.4) is estimated using aggregate electricity consumption based on the relationship estimated in the previous section (equation 4.3, p157).

Electricity retailer price setting and profit

The relationships representing the supply side of the electricity market used in the simulation model are both simple and stylised. A detailed, comprehensive model of electricity generators and retailers, including strategic behaviour and wholesale market institutions is beyond the scope of this study. However such a model could be substituted for the simple relationships representing the supply side in this chapter, given the modular design of the simulation model presented in this thesis. Allcott (2009) is an example of a paper in which a detailed structural model of a wholesale electricity market is constructed and calibrated. Allcott constructs indirect utility and demand functions for electricity by individual households based on a dataset of 693 US households that participated in an eight month pilot of real-time pricing in Chicago in 2003 (103 of these households were allocated to a control group on a uniform tariff). The demand functions estimated do not allow for intra-day substitution, however Allcott considers this is unnecessary as price variation in the pilot is largely the increase or decrease of all intra-day prices in a day by a "fairly constant" proportion. Allcott proceeds to construct a simulation model of the Pennsylvania-Jersey-Maryland electricity market that endogenises both firm entry and imperfectly-competitive price setting behaviour. Wholesale market equilibrium is modelled by estimating firm forward contract positions (using confidential bidding and cost data provided by the market operator), iterating in a learning process towards a counterfactual equilibrium based on the estimated demand response of consumers to firm pricing. Firm entry is modelled following Borenstein (2005) in a two-stage process, where firms with three different technologies first choose capacity, then bid alongside incumbents to supply the wholesale electricity market.

In the simulation carried out in this study, it is assumed that there is one (monopoly) electricity retailer serving the market. This means that the effect of changes in the wholesale price of electricity arising from variations in household electricity tariffs are fully internalised by the sole retailer. For example, if the introduction of a TOU tariff results in a reduction in the mean wholesale price of electricity, the additional profit made
on sales of electricity to customers in the market is completely captured by the (monopoly) retailer. In a more competitive market with multiple electricity retailers, a tariff change by one retailer that affects the wholesale price of electricity would generate an externality that would affect all retailers.

The profit of the electricity retailer serving the market in the simulation model (marked 12 in flow chart figures 4.3 and 4.4) is affected by the (intra-day) price of electricity, aggregate market electricity consumption and the wholesale price of electricity. The retailer sets TOU tariffs to maximise profit. Optimal TOU tariffs can change in the medium term and long term as household appliances are upgraded and replaced.

All simulation scenarios involving the introduction of a TOU tariff are based on the (non-voluntary) transfer of ten per cent of households from a uniform price tariff to a TOU tariff. For the purpose of estimating aggregate market electricity consumption, the TOU tariff is assumed to apply to the component of aggregate consumption correlated with household consumption (the second term of equation 4.2, p156). The remaining consumers (comprising the 90 per cent of households remaining on a uniform price tariff and non-household electricity consumers) are assumed to pay an unchanging uniform price tariff of $0.16269 per kWh. Revenue changes arising from the introduction of a TOU tariff are limited to a component of aggregate consumption (ten per cent of households) while the impact on the wholesale price of electricity affects all electricity supplied by the retailer. Profit estimates presented in this chapter are based on the entire retail market (households on both uniform and TOU tariffs and non-household consumers).

The optimal TOU tariffs estimated in each scenario simulation are not unconstrained. With the exception of the scenario simulating the effect of the regulatory imposition of a maximum price constraint (subsection 4.6.1) all tariffs are estimated using an aggregate household expenditure constraint. This is the constraint used in previous chapters (and the previous section). Under this constraint, a new TOU tariff must not result in an increase in aggregate household expenditure on electricity based on household consumption of electricity (both the level and intra-day pattern) under the initial uniform tariff. In all scenarios the initial tariff is taken to be $0.16269 per kWh.

4.4.2 Simulation scenarios

Various industry, policy and climate change scenarios are simulated in this chapter. These simulations are based on the Mawson Lakes sample. This is because the electricity consumption data for Sydney (collected in 1992-1993) are not able to be matched to aggregate consumption or prices in the wholesale electricity market due as these data are not available.
Industry

The following section details the results of two simulation scenarios. The first is the introduction of TOU tariffs. This is used as a baseline for all other scenarios. The second simulates the introduction of direct load control of space cooling appliances.

Policy options and instruments

Two scenarios are simulated in which a regulatory price ceiling is imposed on the electricity retailer. In the first scenario the price ceiling is imposed in the absence of the aggregate household expenditure constraint, while in the second scenario, the price ceiling and expenditure constraint are jointly imposed.

Three scenarios concerning the effect of policy instruments designed to improve energy efficiency and environmental outcomes are also simulated. The first estimates the impact of an increase in minimum appliance energy efficiency standards. The second examines the effect of the introduction of a carbon cap and trade scheme, while the third simulates the effect of subsidies for purchases of energy efficient appliances. The prohibition of relatively inefficient appliances and an increase in the level of insulation required to be installed in new homes are also discussed.

Climate change scenarios

Three climate change scenarios are simulated: increases in temperature of 1°C, 2°C and 4°C. These values fall within the mean increased temperature ranges for coastal Australia in 2020 (0.1 to 1.0°C), 2050 (0.3 to 2.7°C) and 2080 (0.4 to 5.4°C) projected by the Intergovernmental Panel on Climate Change.
4.5 Simulating electricity industry changes

The electricity industry currently faces a number of challenges. Chief among these is the issue of peak load. The capacity of electricity generators and networks must be sufficient to supply electricity during periods of peak load if blackouts are to be avoided. However, the return on industry assets used only during periods of peak load is limited since these assets are only used for a small amount of time. This increases the average cost of providing electricity per unit delivered. Peaking generators and network infrastructure that are used only infrequently require a high wholesale price of electricity to be economically viable.

When the price of electricity to households is set at a uniform rate, the cost of electricity (comprising the cost of generating and distributing electricity) is allocated equally across all electricity supplied. A uniform electricity price does not allow households to take account of the actual cost of their electricity consumption at any given time.

The issue of peak load is of increasing concern, as household consumption of electricity at peak periods has been growing over time more quickly than total demand (Coates 2007, Brown and Koomey (2003)). In an end-use study of electricity consumption by New South Wales households, Bartels and Fiebig (2000) found retailing electricity to households is less profitable that may be expected due to the large proportion of electricity consumed by households during peak periods. Such a trend requires investment in generation and network assets at a rate that exceeds associated revenue growth, which given a constant uniform tariff is directly proportional to total consumption. Investment at a rate exceeding revenue growth is only sustainable if the price of electricity is also increased.

A number of instruments have been put forward as methods to address the issue of peak load. ‘Smart’ meters - meters that among other things can record the time at which electricity is consumed (rather than just the aggregate over a period) - offer the promise of increased efficiency in household consumption, using tariff options including TOU and dynamic peak pricing to allow households to take account of the actual cost involved in their consumption of electricity at a given time. This has the potential to reduce peak consumption, lessening the requirement for additional costly generation and network capacity in future and reducing consumption of electricity generated from the most costly sources. Direct load control for appliances such as air conditioners (remotely turning these appliances off for short periods of time during peak load) is also an option being trialled to reduce electricity consumption during peak periods of demand (Essential Services Commission of South Australia 2008).

In this section the introduction of TOU pricing and direct load control are simulated. Simulations are generated for three time periods: the short term; medium term; and long term. The household appliance stock is a function of the electricity tariff, climatic parameters and household characteristics in each time period, as described in chapter 3.
In the short term the household stock of appliances is assumed to be fixed. The stock of household appliances in the medium term reflects the upgrade decisions of households following changes in electricity tariffs and appliance energy efficiency. In the long run households have completely replaced their initial stock of appliances following the end of their effective lives. The price constraint imposed is that used in previous chapters; that total household expenditure must not rise under an assumption that household consumption does not change as a result of the introduction of the new tariff. All aggregates are calculated for a period of one year (unless otherwise noted).

**Time of use pricing**

TOU pricing has the potential to increase electricity market efficiency (resulting in higher retail profits) without increasing electricity consumption. This may become an important factor in future, since the other major challenge the electricity industry faces is the increasing level of concern about the environmental impact of greenhouse gas emissions from fossil fuel powered generators.

The simulation results of this scenario are used as baseline results for all scenarios estimated in this chapter that include the introduction of optimal TOU tariffs. This is because this scenario is simulated in the absence of any changes other than the introduction of TOU tariffs.

Figure 4.5 shows the estimated optimal TOU tariffs. The optimal TOU tariff is different in the short, medium and long term. With the existing stock of appliances the optimal tariff is ‘flatter’ than in the medium term and long term (after households have respectively upgraded and replaced appliances). The peak tariff increases after households upgrade appliances and further increases after households replace appliances.

The annual short run profit of the electricity retailer introducing an optimal TOU tariff is estimated to be $1,418m, 0.09 per cent higher than under the initial uniform tariff alone. This figure includes all electricity sold in the market (to households on TOU and uniform tariffs and non-household consumers) over the course of a year. Profit estimated in the simulation model is the aggregate margin between the retail and wholesale prices of electricity. No additional allowance is made for costs (such as distribution and capital costs) other than the cost of purchasing electricity in the wholesale market. Profit is 0.02 per cent (or $290,000) higher in both the medium term and long term following appliance upgrades and replacements by households and subsequent adjustments to optimal TOU tariffs.
Table 4.4 lists upgrades households are expected to make following the introduction of the optimal short term TOU tariff (estimated based on the initial stock of appliances). The majority of households upgrade their lights to model 1 (the most efficient model: compact fluorescent) and one household upgrades their reverse cycle air conditioner to model 1 (the most efficient).

Table 4.5 describes the stock of appliances in the long term, after which all appliances installed initially have been replaced. Replacement decisions are simulated based on the optimal medium term tariff (estimated following the appliance upgrades listed in table 4.4). There is an even spread of space cooling and heating appliances by energy efficiency: two households have the most efficient type (model 1); two households choose a model of median efficiency (model 2); while two households select a model of low efficiency (model 3). The household in the sample with an electric hot water system (household six) replaces it with a model of low efficiency in the long term. Refrigerators are expected to be replaced with models of low efficiency and households replacing dishwashers mainly select models with low efficiency (one household is expected to purchase a model of median efficiency). (Note: not all refrigerators and dishwashers were separately metered in the sample households.) In the long term, all households use compact fluorescent light globes.

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Table 4.4: Upgrades of household appliances
Consumption and expenditure estimates for this simulation scenario are illustrated in figure 4.6. These are presented by energy function and time period simulated. Within each energy function, estimates for the three time horizons simulated (short, medium and long term) are included, along with long term estimates based on the retention of the initial uniform price of electricity.

Household electricity consumption on space cooling (SC), space heating (SH) and lighting (LI) is expected to fall over time. This is largely due to upgrades and replacements by households to more energy efficient air conditioners and light globes. However the introduction of TOU tariffs is not expected to substantially reduce aggregate mean electricity consumption for these energy functions. Consumption for space heating and water heating fall relative to consumption under the initial uniform tariff. Consumption for lighting falls to very similar levels under both tariff scenarios, reflecting expected upgrades to compact fluorescent globes under both the TOU or uniform tariff. In contrast, consumption of electricity for water heating (WH) rises after the introduction of a TOU tariff. This is because electricity is far cheaper (at less than a third of the initial uniform rate) during the off-peak period, when the majority of electricity is used to heat water. If the uniform tariff were retained, electricity consumption for water heating falls, following an upgrade to a more efficient hot water system. Electricity consumption for food storage (FS) and food preparation (FP) is simulated to fall over time as households upgrade appliances, however there is little difference compared to the expected consumption over time under the initial uniform tariff.

In addition to estimates for the three time periods (short, medium and long) and long term estimates assuming a uniform electricity tariff is retained, the figures for consumption also include a calculation of expenditure based on the optimal TOU tariff in the short run assuming no change to household electricity consumption (shaded in grey). This calculation is used to enforce the price constraint - that aggregate household expenditure will not rise assuming no change in consumption behaviour following changes to the electricity tariff.

A comparison of electricity consumption and expenditure reveals the effects of the introduction of TOU pricing. In the long term, electricity consumption for space cooling falls
(and is marginally lower than it would be if the uniform tariff were retained). However expenditure on space cooling is substantially higher under a TOU tariff, as space cooling is often required during periods of peak electricity consumption. In contrast, electricity consumption on water heating is higher under a TOU tariff, while expenditure is far lower. As noted earlier, this is because the majority of electricity consumed by hot water systems is during the off-peak period of a TOU tariff.

The minimal reduction in electricity consumption for space cooling under TOU tariffs is due largely to the profile of absolute price elasticity of demand for electricity for space cooling for households. As noted in section 2.6 the intra-day own-price elasticities estimated for space cooling are relatively low. These are matched with cross-price elasticity estimates of greater magnitude than for any other energy function. This effectively results in a household response to a price increase in a particular period across a longer period of time rather than specific to the period in which the price increase applies to. The optimal TOU tariffs estimated in this scenario result in some reduction in electricity consumption during peak periods for space cooling. However the effect is spread over adjacent intra-day periods. This contrasts to the sharp reduction in consumption, confined to peak periods that would be expected for other energy functions with near zero cross-price elasticities of demand. This casts doubt on the role TOU tariffs may play in reducing consumption during peak periods by reducing consumption on space cooling.

The estimate indicating expenditure under the price constraint (shaded in grey in subfigure 4.6(b)) allows a comparison of the impact of TOU pricing based on initial household electricity consumption by energy function. The optimal TOU tariff effectively increases the cost of space cooling while reducing the cost of running an electric hot water system. There are marginal reductions in the cost of space heating, food storage and correspondingly small increases in the cost of running appliances used for food production and lighting.

Under a uniform tariff the price of electricity during periods of peak consumption can be
less than the cost of the electricity supplied (the wholesale price) while at other times the price far exceeds the cost. Households that consume substantial amounts of electricity during periods of peak load (generally through the use of air conditioners and other high capacity household appliances in the afternoon and evening) are effectively subsidised by households that consume a lower proportion of their electricity during peak periods.

Figure 4.7 illustrates electricity consumption and expenditure estimates disaggregated by the households included in the sample. Most households reduce electricity consumption in response to the introduction of the TOU electricity tariff and all households reduce consumption over time (as households upgrade and replace appliances).

Subfigure 4.7(b) contains expenditure estimates by household assuming household electricity consumption is unchanged following the introduction of TOU pricing (shaded in grey). It is clear that the aggregate expenditure constraint does not guarantee any individual household will not pay more for their electricity consumption under the constrained TOU tariff. Four households are estimated to spend more on electricity following the introduction of the TOU tariff unless they reduce their electricity consumption or change their intra-day pattern of appliance use to consume more electricity during the off-peak period. The aggregate expenditure constraint results in one household (household six, the household with the electric hot water system) paying less for electricity assuming prior usage patterns continue. This household would categorically benefit from the price reduction in the off-peak period. This is because their hot water system consumes a substantial amount of electricity during the off-peak period of the TOU tariff.

In the long run, the household with the electric hot water system is the only household in the sample which would receive a lower electricity bill under an optimal TOU tariff. Comparing household expenditure in the long run, when all households have replaced their appliances based on a TOU electricity tariff (shaded in cross hatch) with their long term expenditure estimated under the original uniform tariff shows that most households in the sample spend slightly more.

![Figure 4.7: Annual consumption and expenditure by household](173)
Figure 4.8 presents mean wholesale electricity prices estimated under the optimal TOU tariffs estimated for the short, medium and long terms and long term estimates made assuming the retention of the initial uniform tariff (shaded in black). In subfigure 4.8(a) the estimates are grouped by price range based on the initial uniform tariff (less than $0.02, $0.02 to $0.03, $0.03 to $0.04 and greater than $0.04 per kWh). Subfigure 4.8(b) shows the estimated mean wholesale prices grouped by time period (3am to 7am, 2pm to 8pm and other periods).

The range of mean prices in the wholesale electricity market is reduced under the TOU tariffs estimated using the simulation model. This effect is most clear when examining wholesale prices that are relatively high. Subfigure 4.8(b) reveals that the reduced wholesale price is achieved mainly in the peak period of the TOU tariff - 2pm to 8pm.

![figure 4.8](image)

(a) Mean wholesale price by range

(b) Mean wholesale price by selected period

Figure 4.8: Mean wholesale electricity price ($/kWh)

**Direct load control**

Direct load control refers to the reduction of electricity consumption of appliances remotely by electricity retailers or distributors. Space cooling appliances are generally those subject to direct load control. A recent large scale trial has been conducted in South Australia. Following a successful small scale pilot in 2005 to 2006, ETSA Utilities trialled a direct load control pilot in Adelaide from 2006 to 2008. The air conditioners of 750 households in the Adelaide metropolitan area were fitted with load control units in December 2006 and further units were installed in 2007. During the trial these air conditioners were switched off for up to 15 minutes at a time during days of high temperature. (The fans of the air conditioners remained running during this period, making it difficult for households to identify when direct load control was being used.) As reported by the Essential Services Commission of South Australia (2008, pp16-23) the trial resulted in significantly reduced electricity consumption, with few participants reporting reduced thermal comfort. Most households stated they were not aware that their air conditioners had been periodically turned off during the trial.
This scenario involves the simulation of direct load control of reverse cycle air conditioners. Intra-day periods in the top 2.5 percentiles of expected electricity consumption are subject to direct load control. During these intra-day periods, electricity consumption on reverse cycle air conditioners is reduced by 20 per cent. This is to simulate the aggregate effect of direct load control over a large number of households, rather than the remote switching off of individual air conditioners during these periods. This method of simulation is required because the number of individual households in the sample is small.

The simulation is carried out for the short term. Since it is reported that households are not generally aware that the level of space cooling is reduced, direct load control is assumed to have no effect on household decisions concerning appliance upgrades and replacements.

Figure 4.9 shows mean wholesale electricity prices estimated under three scenarios: the original uniform tariff; optimal short term TOU tariffs; and direct load control. As electricity consumption under direct load control is the same as under the original uniform tariff except in the top 2.5 percentile of intra-day period consumption, wholesale prices in the direct load control scenario are the same as under the uniform tariff in the lower ranges and intra-day price periods. However direct load control results in lower wholesale prices in the highest range and period shown in subfigures 4.9(a) and 4.9(b) respectively. It is interesting to compare the impact of direct load control with that of the short term TOU tariff. Under the optimal TOU tariff, the mean wholesale price of electricity is higher in off-peak and shoulder price ranges and periods, due to increased consumption from the lower electricity prices at these times. However even in the highest range the mean wholesale price is lower under direct load control. This is because the prices comprising the TOU tariff apply irrespective of actual consumption levels, while direct load control is simulated based on consumption levels. Direct load control as a demand management tool is focused on the variable of interest - consumption - while TOU tariffs take account of consumption indirectly, based on mean consumption in each intra-day period.

Estimated profit for an electricity retailer undertaking direct load control increases by 0.11 per cent.
over the initial uniform tariff. This is comparable to the increase in profit estimated to be achieved in moving to an optimal TOU tariff - an increase of 0.09 per cent.
4.6 Simulating policy options and instruments

The adoption by the electricity industry of technology that allows more flexible pricing of electricity to households creates a number of issues for regulators and public policy makers. One regulatory issue arising directly from the introduction of TOU tariffs by the electricity industry to the household sector is how to constrain the prices included in these tariffs. While uniform tariffs are amenable to regulation by imposing a simple maximum price, TOU tariffs comprise a number of different prices. A maximum price imposed by a regulator limits the degree to which an electricity retailer can offer a TOU tariff with a substantial price range between off-peak and peak periods, with potential implications for both profitability and market efficiency. However if price constraints are removed from household electricity tariffs a substantial increase in prices could be expected. Apart from competition from other electricity retailers, there are no factors other than price regulation acting to keep the price of electricity for households low. Studies estimating price elasticities of demand for electricity (summarised in section 2.2) consistently find households are price inelastic. Higher electricity prices also act to limit or reduce (to a degree) electricity consumption, reducing the wholesale price of electricity.

Along with price regulation there are issues concerning how TOU tariffs will interact with existing and proposed public policy schemes affecting household consumption of electricity. The purpose of public policy schemes can be summed up as encouraging ‘sustainability’ - improving energy efficiency and environmental outcomes - by increasing the efficiency with which households consume electricity and to limit or reduce pollution associated with electricity production and consumption. Traditional policy instruments include appliance energy efficiency and building standards while more recent instruments include carbon cap and trade schemes, subsidies for efficient appliances and prohibitions on the supply of relatively inefficient appliance types.

In this section, scenarios involving regulatory and public policy changes are simulated. Approaches to price regulation are simulated, with the expenditure constraint used previously compared to a maximum permitted price. Three public policy scenarios are simulated: an increase in minimum appliance energy efficiency standards; subsidies for the purchase of efficient appliances; and the introduction of a carbon cap and trade scheme. The distributional impacts of the regulatory and public policy changes simulated in these scenarios is a focus of this section. A discussion of further policy options follow these scenario simulations. These options include the introduction of prohibitions on the supply of relatively inefficient appliance models and increases in the amount of building insulation required for new homes.
4.6.1 Price regulation

Distributional concerns arising from the introduction of TOU tariffs for households may motivate regulators and policy makers to restrict the prices that can be charged for electricity. Concerns have been raised that TOU tariffs could result in households with elderly, unemployed, young or sick members turning off their air conditioners during periods of hot weather (see Australian Broadcasting Corporation 2003, Australian Broadcasting Corporation 2007).

The regulatory imposition of a maximum price constraint is simulated in this subsection. Two scenarios are presented: a maximum price constraint imposed in isolation and one imposed in combination with the constraint based on aggregate household expenditure used previously in this study.

Imposition of a maximum price

An electricity retailer introducing an optimal TOU tariff for households subject to a maximum price imposed by a regulator will set prices in all intra-day periods equal to the maximum price permitted. Figure 4.10 plots the optimal TOU tariffs estimated under a maximum price constraint of $0.19/kWh. For reference the initial uniform price of $0.16269 per kWh is also shown. In all intra-day periods and across all time horizons (short, medium and long term) the optimal tariff for an electricity retailer facing a maximum permitted price is to increase all intra-day prices to that maximum level. This is because the price elasticity of households are assumed to be inelastic (for all energy functions) and wholesale price is an increasing function of aggregate consumption. (As previously noted, this assumption is not realistic, however it is not likely to be cause for concern given the relatively small price increase considered in this scenario.) Increases in the retail price of electricity increase revenue and decrease the variable cost of an electricity retailer. (The mean own-price elasticities by energy function used in the simulation model are contained in table 2.22.)

As would be expected, short run profit is higher under the optimal tariffs estimated with a maximum price constraint, rising 0.15 per cent (more than $2m). However medium and long run profit are lower than under the baseline scenario (by 0.02 and 0.03 per cent respectively) due to the upgrade of hot water systems to the most efficient type in response to the introduction of the TOU tariff, substantially reducing electricity consumption during the off-peak period. This reduction in electricity consumption combined with the lower (constrained) rate during the peak period is responsible for the reduced medium and long term profitability relative to the baseline scenario.
As noted, the household with an electric hot water system upgrades in the medium term to the most efficient model (table 4.6). This is a result of the relatively high price of electricity in this scenario in the early hours of the morning, when electricity is used by the hot water system.

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Table 4.6: Upgrades of household appliances

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Table 4.7: Long run stock of household appliances

The substantial fall in medium and long term electricity consumption (and corresponding expenditure) for water heating is shown in figure 4.11. Note that given the TOU tariff simulated in this scenario under an assumption of unchanged electricity consumption, expenditure on electricity (shaded in grey) increases across all energy functions (subfigure 4.11(b)) and households (subfigure 4.12(b)). This is because the price of electricity
increases in all intra-day periods in the absence of an aggregate expenditure constraint.

![Graph](image)

(a) Consumption (kWh)  
(b) Expenditure ($)  

Figure 4.11: Annual consumption and expenditure by energy function

The electricity consumption and expenditure of the household with an electric hot water system (household six) falls substantially in the medium and long term following their upgrade to the most efficient hot water system (figure 4.12).

![Graph](image)

(a) Consumption (kWh)  
(b) Expenditure ($)  

Figure 4.12: Annual consumption and expenditure by household

The higher uniform price of electricity induces a small reduction in the wholesale price in all time periods across all price ranges and intra-day periods (figure 4.13).
Figure 4.13: Mean wholesale electricity price ($/kWh)

Imposition of both maximum price and aggregate expenditure constraints

If both maximum price and aggregate expenditure constraints are imposed, an electricity retailer is unable to increase electricity prices in all intra-day periods (as they would under a maximum price constraint in isolation). This would increase aggregate household expenditure given initial household consumption levels, violating the aggregate expenditure constraint.

Figure 4.14 plots the optimal TOU tariffs estimated under both a maximum price constraint of $0.19/kWh and an aggregate expenditure constraint. The optimal peak period price for all time horizons (short, medium and long term) is identical; the maximum permitted price. Profits are lower in all periods relative to the baseline scenario, with levels 0.05, 0.03 and 0.06 per cent lower in the short, medium and long terms respectively. The optimal TOU tariffs estimated in this scenario are less effective in reducing electricity consumption during periods of peak consumption and do not offer off-peak prices low enough for households to operate hot water systems of relatively low efficiency in the long term. Both factors result in reduced profit.

Figure 4.14: Profit maximising tariffs with both maximum price and aggregate expenditure constraints ($/kWh)
Household appliance upgrades in the medium term are the same as for optimal TOU tariffs under only an aggregate expenditure constraint (table 4.4). In the long term, one household (household three) purchases a reverse cycle air conditioner of median rather than high energy efficiency and the household with an electric hot water system upgrades to a system of median efficiency instead of a system with low energy efficiency. The ‘flatter’ TOU tariff reduces the incentive to purchase a highly efficient air conditioner (as the peak price is not as high) and increases the incentive to purchase a more efficient hot water system (as the off-peak price is not as low).

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Table 4.8: Upgrades of household appliances

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Table 4.9: Long run stock of household appliances

The main effect of the regulatory imposition of both a maximum price constraint and an aggregate expenditure constraint is to mitigate both the reduction in consumption of electricity on space cooling and the increased consumption on water heating. Figure 4.15 shows consumption and expenditure estimates over the simulated time periods by energy function. Relative to the optimal tariffs estimated without a maximum price constraint (figure 4.5) there is less incentive for households to reduce electricity consumption during peak periods and increase consumption during off-peak periods.
Figure 4.16 illustrates electricity consumption and expenditure estimates disaggregated by household. As with the optimal TOU tariff estimated subject to only an aggregate expenditure constraint (in section 4.5) most households reduce electricity consumption under the optimal TOU tariff and all households reduce consumption over time. However household consumption in the long term is very similar under the uniform and TOU tariffs, reflecting the reduced range of the TOU tariff. The household with the electric hot water system is the only household to be categorically better off with the TOU tariff, although the benefit for this household is not as great since the optimal off-peak price is not as low in this scenario as for other scenarios.

The effect on the wholesale price of electricity of the TOU tariff estimated with both constraints is less than the effect with only an aggregate expenditure constraint. Wholesale prices in the highest range and during peak period are only slightly lower under the TOU tariff than the uniform tariff in the long term (figure 4.17).
4.6.2 Sustainability

Various public policy instruments designed to improve energy efficiency and environmental outcomes associated with the production and consumption of electricity are simulated in this subsection. One scenario estimating the impact of a current (or traditional) policy instrument is simulated (an increase in minimum appliance energy efficiency standards) along with two more recent instruments (a carbon cap and trade scheme and subsidies for purchases of energy efficient appliances). Two other policy instruments are discussed: the prohibition of relatively inefficient appliance types; and an increase in the level of insulation required to be installed in new homes.

Minimum appliance energy efficiency standards

As discussed in section 4.2, appliances sold in Australia are subject to minimum energy performance standards (MEPS). Appliances with energy efficiency levels below those set out in the standards are not able to be manufactured in or imported to Australia. This scenario models the impact of increasing the required energy efficiency standards of all appliance types from low to median. This is simulated by setting the energy efficiency levels of the cheapest, least efficient appliances (model 3) in the appliance dataset to match the energy efficiency levels of the appliances of median energy efficiency (model 2). Effectively this reduces the cost of purchasing appliances of median energy efficiency. The cost of meeting higher energy efficiency standards is assumed to be borne by appliance manufacturers and importers in this simulation scenario, as appliance prices are assumed not to rise as a result of the increased minimum energy efficiency standards.

Figure 4.18 shows the optimal TOU tariffs estimated in this scenario. Increased minimum energy efficiency standards have little impact on optimal TOU tariffs when compared to the optimal tariffs estimated in the baseline scenario, with only a slightly higher peak...
intra-day price (compare with figure 4.5). Retailer profit in the short and long term is also almost identical to that in the baseline scenario. Medium term profit is 0.02 per cent higher following upgrades to reverse cycle air conditioners.

![Image](image.png)

Figure 4.18: Profit maximising tariffs with increased minimum appliance energy efficiency standards ($/kWh)

The impact of increased minimum appliance energy efficiency standards are mixed when it comes to appliance upgrades and replacements (tables 4.10 and 4.11 respectively). (In this scenario the appliances available to households comprise model 1 - of highest efficiency and purchase price - and model 3 - of median efficiency and lowest price.) In the medium term an additional household (household three) is predicted to upgrade their air conditioner as a result of the higher energy efficiency standard required. However one household that would otherwise upgrade to the most efficient model air conditioner (household six) is now expected to upgrade to the model of median efficiency. In the long term, one household (household three) that would have otherwise purchased the most efficient model air conditioner (model 1) replaces their air conditioner with the model of median efficiency. The energy efficiency of the stock of air conditioners in the long run is reduced as a result of the increased minimum appliance energy efficiency standard. This result stems from the effective reduction in the purchasing price of the air conditioner of median energy efficiency.

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Table 4.10: Upgrades of household appliances
The differences in the upgrade and replacement decisions of households following the changes to minimum energy efficiency standards results in higher consumption and expenditure on space cooling (figure 4.19) relative to the baseline scenario.

There is no discernable difference in the distribution of wholesale electricity prices in this scenario either by price range or intra-day period (figure 4.21).
Carbon cap and trade scheme

The introduction of a carbon cap and trade scheme will increase the wholesale price of electricity (disregarding compensation payments to households and electricity retailers). The cost of baseload electricity, currently generated in Australia almost exclusively by burning coal, is likely to increase more than electricity generated to meet peak consumption. This is because peak period electricity is generated by gas and hydro powered generators, which produce less (or no) greenhouse gas emissions.

To simulate the effect of introducing a carbon cap and trade scheme, the estimated relationship between aggregate electricity consumption and the wholesale price of electricity used in the simulation model is adjusted. Equation 4.4 shows the relationship estimated in section 4.3 and used in the simulation scenarios in this chapter. This equation is adjusted by adding a constant term of $0.05 per kWh and reducing the coefficient on the square of aggregate consumption by 20 per cent, as seen in equations 4.5 and 4.6 (simplified). The addition of the constant term increases wholesale cost for all electricity generated (from baseload through to peaking generation) while the reduced coefficient on the square of aggregate consumption reduces the impost for peak period generation.

Estimated consumption-wholesale price relationship:

\[ \hat{w}_t = 0.01064 - 3.1502 \times 10^{-8} E_t + 3.0552 \times 10^{-14} E_t^2 \]  \quad (4.4)

For carbon cap and trade scenario:

\[ \hat{w}_t = 0.01064 - 3.1502 \times 10^{-8} E_t + 3.0552 \times 10^{-14} E_t^2 \times 0.8 + 0.05 \]  \quad (4.5)

\[ \hat{w}_t = 0.06064 - 3.1502 \times 10^{-8} E_t + 2.4442 \times 10^{-14} E_t^2 \]  \quad (4.6)

The new minimum wholesale price given by the regression is $0.0505/kWh associated
with aggregate consumption of 0.6444GWh. As noted in section 4.3 in the South Australian market, 90 per cent of aggregate consumption during the estimate period is within the range 1.1229GWh to 1.7741GWh. Over this range, the estimated wholesale price under a simulated carbon cap and trade scheme ranges from $0.0561 (up from $0.0138) to $0.0817 (up from $0.0509) per kWh. The estimated aggregate consumption-wholesale price relationship and the relationship used in this scenario are plotted in figure 4.22.

![Figure 4.22: Aggregate electricity consumption - wholesale price relationship ($/kWh)](image)

As with all simulation scenarios, an aggregate household expenditure constraint is imposed. This effectively means electricity retailers are not permitted to pass on any of the increased wholesale electricity price resulting from a carbon cap and trade scheme to their customers. While this is an unrealistic assumption, it allows the cost of imposing a cap and trade scheme to be examined directly as it is entirely reflected in the profit of the electricity retailer in this simulation scenario.

The carbon cap and trade scheme ‘flattens’ the optimal TOU tariffs across all time horizons (figure 4.23) resulting in lower retail peak prices and higher off-peak prices. This is not an unexpected result, since the cap and trade scheme is modelled by increasing the wholesale price of baseload electricity more than that electricity generated during peak periods. Retailer profit is substantially reduced following the introduction of the scheme; down 33 per cent ($470m) in all time horizons.

![Figure 4.23: Profit maximising tariffs under a carbon cap and trade scheme ($/kWh)](image)
As the cost imposition arising from the introduction of a cap and trade scheme is wholly borne by the electricity retailer in this scenario simulation, it is unsurprising that household appliance upgrades and replacements are unaffected (tables 4.12 and 4.13 respectively). Appliance upgrades and replacements are almost identical to those simulated in the absence of a cap and trade scheme, the only change being the replacement of a hot water system with a model of median rather than low energy efficiency (tables 4.4 and 4.5).

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Table 4.12: Upgrades of household appliances

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Table 4.13: Long run stock of household appliances

The 'flatter' TOU tariffs result in a less marked reduction in electricity consumption for space cooling and a fall in electricity consumption for water heating.

![Figure 4.24: Annual consumption and expenditure by energy function](image-url)

(a) Consumption (kWh)  (b) Expenditure ($)
The mean wholesale price of electricity is substantially increased by the carbon cap and trade simulated in this scenario (figure 4.26) following directly from the adjustment made in equation 4.5. Under all tariffs (comprised of uniform or TOU prices) and across all price ranges and intra-day periods, the mean wholesale price of electricity is higher. (A comparison with figure 4.8 illustrates the simulated impact of the carbon cap and trade scheme).

Subsidies for purchases of energy efficient appliances

In this scenario, the impact of subsidising the purchase of energy efficient air conditioners and hot water systems is simulated. A subsidy of $500 is paid to purchasers of the most efficient reverse cycle air conditioner, making it only $110 more expensive than the air conditioner of median energy efficiency. A subsidy of $2,000 is provided to buyers of the most efficient hot water system, making it $700 more expensive than the median efficiency hot water system. As noted in section 4.2 specific Australian policy programs currently provide subsidies comparable in nature and amount to those simulated in this scenario.
The short term simulation results for this scenario are identical to that of the baseline scenario. In the short term the household stock of appliances is fixed and the subsidies included in this scenario have no effect. The medium and long term optimal TOU tariffs estimated scarcely vary from those estimated in the baseline scenario. Profit levels are higher in both the medium and long term (by 0.05 and 0.03 per cent) due to higher upgrades and replacements of air conditioners with the most efficient model.

Figure 4.27: Profit maximising tariffs with subsidies for purchases of energy efficient appliances ($/kWh)

The subsidies simulated in this scenario result in more upgrades and replacements of reverse cycle air conditioners with the most efficient model of air conditioner (see tables 4.14 and 4.15). In the medium term the subsidy is expected to induce one household (household three) that would otherwise continue to use their existing air conditioner to upgrade to the most efficient model. In the long term two households (households four and five) that would otherwise replace their existing air conditioners with one of median energy efficiency to choose the most efficient model. However the subsidy for the most energy efficient hot water system does not result in its purchase. Under the TOU tariffs estimated, the cost of operating an electric hot water system are reduced. The higher purchase cost of the most efficient model, even after including the subsidy, outweighs the reduced operating cost of running the most efficient hot water system.

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Table 4.14: Upgrades of household appliances
The increased use of most efficient model of air conditioner reduce estimated consumption of electricity for on space cooling and space heating in the medium and long term.

Figure 4.28: Annual consumption and expenditure by energy function

Figure 4.29: Annual consumption and expenditure by household

The wholesale price of electricity is expected to be marginally lower in high price ranges (subfigure 4.30(a)) and peak periods (subfigure 4.30(b)).
Prohibitions on the supply of relatively inefficient appliance types

The prohibition of relatively energy inefficient appliances by type is becoming a more commonly used policy instrument by governments attempting to increase appliance energy efficiency. Prohibitions (via import restrictions) on inefficient incandescent general lighting service light bulbs for general lighting purposes came into effect on 1 February 2009 (Australian Customs and Border Protection Service 2009). Proposed prohibitions to apply from 1 January 2010 disallow the installation of (standard resistance) electric hot water systems in new and existing houses where there is access to piped natural gas (Department of the Environment, Water, Heritage and the Arts 2009). In these cases the energy functions can be served using more efficient appliances currently available, such as compact fluorescent globes for lighting and gas, solar or heat pump hot water systems.

It is possible to model these appliance prohibitions using the simulation model. However in all scenarios simulated in this chapter households uniformly replace their existing lights with the most efficient globes in the long run, while the prohibition on new electric hot water systems has effectively already been simulated in section 4.3. Figure 4.2 illustrates the impact on optimal TOU tariffs of requiring the installation of the most efficient electric hot water system (which uses a heat pump). Disaggregated results of the simulation are not provided since only one household in the sample uses an electric hot water system.

Increased building insulation

The level of insulation in a building affects the level of energy required to keep the building at a comfortable temperature range. Less heat is lost from a well insulated building when the outside temperature is low and less external heat is transferred to the dwelling interior when the outside temperature is high. Increased building insulation can be expected to reduce electricity consumption on both space cooling and heating. Public policy
makers could consider increasing the requirements for the level of building insulation in new buildings in an attempt to reduce electricity consumption for space heating and space cooling.

The simulation model does not include a component on the physical characteristics of dwellings. Such a component would require detailed information concerning each specific building to be modelled. If such data were available, software such as AccuRate (Commonwealth Scientific and Industrial Research Organisation (2010)) and the Building Energy Rating System (BERS, Department of the Environment, Water, Heritage and the Arts (2010)), accredited under the Nationwide House Energy Rating Scheme, could be used in the simulation model to estimate the energy efficiency of various dwelling upgrades.

The effect of increased building insulation could be roughly gauged by simulating a scenario where the energy efficiency of space cooling and space heating appliances is increased. This would provide a basic approximation, as less energy would be required to be consumed by space heating and space cooling appliances to keep a well insulated dwelling within a specific temperature range. However there are limitations to such an approximation. Chief among these is the absence of an empirically supported relationship between building insulation levels and electricity consumption on which to base the scenario. In addition, the approach does not take account of any effect increased insulation may have on the energy consumption of appliances other than those used for space cooling and space heating. The electricity consumption of food storage appliances such as fridge-freezers may be less responsive to the external temperature in better insulated dwellings.

Given the limitations identified for a scenario approximating increased building insulation, such a scenario is not simulated in this study.
4.7 Simulating the effects of climate change

In this section, the impact of higher temperature on electricity consumption is simulated. The model developed in this study allows the simulation of higher temperatures along with the introduction of TOU tariffs, which have the potential to mitigate the problems associated with peak load. Climate change has the potential to exacerbate these problems given the degree to which electricity consumption on space cooling contributes to peak load.

Three temperature scenarios are simulated in this section: increases of 1°C, 2°C and 4°C. These values fall within the mean increased temperature ranges for coastal Australia in 2020 (0.1 to 1.0°C), 2050 (0.3 to 2.7°C) and 2080 (0.4 to 5.4°C) projected by the Inter-governmental Panel on Climate Change (Hennessy et al. 2007, p515).

Increase of 1°C

Perhaps surprisingly, there is little impact on estimated optimal TOU tariffs of a simulated temperature increase of 1°C. The prices comprising the TOU tariffs estimated for the short, medium and long term (figure 4.31) are almost identical to those estimated with an unchanged climate (figure 4.5). Profit is lower than in the baseline scenario for all time horizons, reduced by 0.06, 0.01 and 0.02 per cent in the short, medium and long term respectively.

Relative to the medium term appliance upgrades simulated in the absence of climate change (table 4.4) an additional household purchases a highly efficient (model 1) reverse cycle air conditioner (table 4.16). However in the long term one household that would otherwise replace their air conditioner with a median efficiency model purchases a model of low energy efficiency (table 4.17). This household (household five) consumes a relatively large proportion of their total electricity consumption on space heating, with a relatively high upper limit to their estimated ideal comfortable temperature range of 21.6°C (see...
A rise in temperature of 1°C is expected to reduce the amount of electricity this household consumes on space cooling and space heating in total, reducing the benefit of operating the most energy efficient reverse cycle air conditioner.

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Table 4.16: Upgrades of household appliances

An increase of 1°C is expected to result in a substantial increase in consumption for space cooling (19.6 per cent in the short run and 20.4 per cent in the long run) and reduced consumption for space heating (-25.6 per cent in the short run and -23.6 per cent in the long run) relative to the baseline scenario estimates. Aggregate electricity consumption for the households in the sample increases by 1.35 per cent in the short run and 1.61 per cent in the long run. In the medium term consumption does not increase relative to the baseline scenario. This is due to appliance upgrades that increase the energy efficiency of reverse cycle air conditioners in the medium term. This effect is temporary, lasting only as long as it takes households to replace their air conditioners in the baseline scenario. However this effect has the potential to delay increases in household electricity consumption on space cooling due to climate change if the energy efficiency of air conditioners continues to increase over time.
Estimated wholesale electricity prices increase following a temperature increase of 1°C (figure 4.34).
Increase of 2°C

Relative to the increase of 1°C simulated in the previous scenario, a 2°C increase in temperature is expected to result in even higher aggregate electricity consumption, arising from increased consumption for space cooling. However there is little difference in the profile of optimal TOU tariffs. Profit is lower than in the baseline scenario for all time horizons, reduced by 0.15, 0.07 and 0.06 per cent in the short, medium and long term respectively.

![Figure 4.35: Profit maximising tariffs ($/kWh)](image)

Relative to the scenario of a 1°C increase, an additional household (household four) upgrades their air conditioner to the most efficient model under a 2°C temperature increase (table 4.18).

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Table 4.18: Upgrades of household appliances
Aggregate electricity consumption for the sample households increases by 3.22, 1.61 and 2.95 per cent in the short, medium and long term respectively, due to higher consumption for space cooling offset to a degree by reduced consumption for space heating relative to the baseline scenario.
An extreme increase in temperature of 4°C is expected to result in substantially increased aggregate electricity consumption. Despite this, profit is lower than in the baseline scenario. The profit level of an electricity retailer is estimated to be reduced by 0.45, 0.12 and 0.11 per cent in the short, medium and long term. Increased electricity consumption and upgrades and replacement of air conditioners mitigates the lower profit level to some degree in the medium and long terms.

Table 4.20: Upgrades of household appliances
Estimated electricity consumption on space cooling almost doubles in the short term as a result of a temperature increase of 4°C, increasing by 91.3 per cent relative to the baseline scenario. Medium and long term increases in consumption are 67.8 per cent and 88.8 per cent respectively, driven by the increased use of electricity on space cooling. Consumption for space heating falls by 78.5, 80.2 and 78.2 per cent in the short, medium and long terms respectively relative to the baseline scenario of no temperature change. Aggregate electricity consumption for the households in the sample is higher than the levels in the baseline scenario by 9.21, 5.53 and 8.23 per cent in the short, medium and long term respectively.
The expected effect of increased temperature on the wholesale price of electricity are clear in figure 4.42. A 4°C increase in temperature is expected to result in a substantial increase in wholesale price in all ranges. The effect is most extreme in the range of prices greater than $0.04/kWh, with an increase of more than $0.005 (more than ten per cent) when compared with the estimates for a no temperature change scenario (figure 4.8).
4.8 Chapter conclusion

The technical and environmental issues currently facing the electricity industry are substantial. Growth in peak electricity consumption requires large capital investment in network infrastructure that is only utilised a few hours every year. This increases the unit cost of supplying electricity. Environmental concerns with greenhouse gas emissions from electricity generation using fossil fuels are leading to the consideration of a variety of policy and regulatory options to reduce electricity consumption and encourage consumption of electricity generated from processes that do not generate greenhouse gasses.

In this chapter the simulation model developed in chapters 2 and 3 is used to illustrate possible impacts of various industry, policy and climate scenarios. In the illustrative simulations carried out, TOU tariffs and direct load control appear to have potential to alleviate the issues associated with peak load. However the impact of TOU tariffs on individual household electricity consumption and expenditure is likely to depend on the intra-day pattern of their consumption, which varies substantially between households. The estimation of representative intra-day elasticities of demand for electricity by energy function from a sample of appropriate size is required for any reliable conclusions to be reached from simulations of this kind.

A regulatory constraint on electricity tariffs based on household expenditure is more effective in constraining the retail electricity price for household TOU tariffs than the imposition of a maximum price in the illustrative scenario simulation modelling. Policy options including subsidies for purchases of relatively efficient appliances reduce electricity consumption in the medium and long term. However the long term effect of more stringent minimum appliance energy efficiency standards is potentially ambiguous as this can induce some households to purchase appliances that meet the (increased) minimum standard rather than more efficient models. A carbon cap and trade scheme is expected to reduce the difference between the peak and off-peak prices offered under an optimal TOU tariffs. Again, for any of these illustrative conclusions to apply more generally would require the simulations carried out to be based on a wider, more representative dataset.

Finally, potential increases in temperature arising from climate change result in increased net household electricity consumption in the illustrative scenario simulation modelling, with increased electricity consumption on space cooling only partially offset by reduced consumption on space heating. Households in the sample dataset are expected to respond to higher temperatures by purchasing more energy efficient air conditioners. Simulations relying on more representative data are required for any general (rather than illustrative) conclusions to be drawn.
4.A Alternative functional forms for wholesale price - consumption relationship

In section 4.3 the relationship between aggregate electricity consumption and the wholesale price of electricity is estimated using a quadratic function (including constant and linear terms). In this appendix, two alternative functional forms are used to estimate this relationship. The resulting relationships are compared to the quadratic relationship used in this study and the sensitivity of simulation model results to the functional form of this relationship is discussed. Aggregate electricity consumption is measured in GWh in this appendix.

The functional form and coefficients estimated for the relationship between aggregate electricity consumption and the wholesale price of electricity are presented respectively in equation 4.3 and table 4.2 (repeated below in equation 4.7 and table 4.22 with electricity consumption measured in GWh).

\[ w_t = \nu + \rho E_t + \tau E_t^2 + u_t \]  

<table>
<thead>
<tr>
<th>$\nu$</th>
<th>$\rho$</th>
<th>$\tau$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01064 (0.57)</td>
<td>-3.1502×10^{-2} (-1.32)</td>
<td>3.0552×10^{-2} (4.08)</td>
<td>0.0460</td>
</tr>
</tbody>
</table>

Table 4.22: Wholesale electricity price: regression parameters (electricity consumption measured in GWh)

Two alternative functional forms for this relationship are estimated in this section: a non-linear form (displayed in equation 4.8); and a 3rd-degree Laurent series (equation 4.9).

\[ w_t = \varphi + \theta E_t^\psi + u_t \]  \hspace{1cm} (4.8) \hfill
\[ w_t = \sum_{m=-3}^{3} (\chi_m E_t^m) + u_t \]  \hspace{1cm} (4.9)

Estimation using alternative functional forms

The resulting coefficients from OLS regressions using the non-linear and Laurent series functional forms are shown respectively in tables 4.23 and 4.24 (along with the associated equations for reference).

\[ w_t = \varphi + \theta E_t^\psi + u_t \]
\[ w_t = \sum_{m=-3}^{3} (\chi_m E_t^m) + u_t \]

<table>
<thead>
<tr>
<th>( m )</th>
<th>( E_t^m )</th>
<th>( \chi_m )</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>( E_t^3 )</td>
<td>1.038</td>
</tr>
<tr>
<td>2</td>
<td>( E_t^2 )</td>
<td>-10.664</td>
</tr>
<tr>
<td>1</td>
<td>( E_t^1 )</td>
<td>44.443</td>
</tr>
<tr>
<td>0</td>
<td>( E_t^0 = 1 )</td>
<td>-95.702</td>
</tr>
<tr>
<td>-1</td>
<td>( E_t^{-1} )</td>
<td>112.618</td>
</tr>
<tr>
<td>-2</td>
<td>( E_t^{-2} )</td>
<td>-68.820</td>
</tr>
<tr>
<td>-3</td>
<td>( E_t^{-3} )</td>
<td>17.098</td>
</tr>
</tbody>
</table>

Table 4.24: Wholesale electricity price: regression parameters for Laurent series (electricity consumption measured in GWh)

The relationship estimated using the non-linear functional form is very similar to that estimated using the quadratic form (used in the simulation model in this chapter). The constant term \((\varphi)\) is near zero while the power term \((\psi)\) is 2.360 - not dissimilar to the quadratic relationship estimated in the simulation model over the relevant range for aggregate consumption. As noted earlier, ninety per cent of observations of aggregate consumption are contained in the range 1.123GWh to 1.774GWh in the South Australian wholesale electricity market in the year of interest.

The relationship estimated using the Laurent series diverges to a degree from the quadratic form estimated and used in this chapter. While the coefficient on the cubic and linear terms are greater than one (1.038 and 44.443 respectively) the coefficient estimated for the quadratic term is negative \((-10.664)\). There are two ranges of aggregate consumption over which the rate of increase in price falls: 1.116 to 1.312GWh; and 1.832 to 2.362GWh. However the relationship between aggregate consumption and the wholesale price of electricity remains positive over these ranges. The coefficients estimated for aggregate consumption raised to negative powers are marginally less relevant given the range of aggregate consumption.

In figure 4.43 the relationships estimated between aggregate electricity consumption and the wholesale price of electricity are compared for the three functional forms estimated (quadratic, non-linear and Laurent). Subfigure 4.43(a) shows the three relationships esti-
The relationships estimated using the quadratic and non-linear functional forms are almost indistinguishable over the range of aggregate electricity consumption observed. In contrast, the relationship based on the Laurent series differs from that using a quadratic functional form, with lower estimated wholesale prices over the ranges from 1.333 to 1.742GWh and 2.168 to 2.955GWh. (There are no observations where aggregate electricity consumption exceeded 3GWh.)
Figure 4.43: Estimated wholesale price - aggregate consumption relationships ($/kWh)

Effect on simulation model

Simulations incorporating the three functional forms used to estimate the relationship between aggregate electricity consumption and the wholesale price of electricity in this
appendix are carried out to identify the optimal TOU tariff estimated under each. The simulations carried out are equivalent to that described in section 4.5 based on the initial stock of appliances (medium and long run appliance upgrades or replacements are not included).

Figure 4.44 shows the optimal TOU tariffs estimated based on the three different functional forms. The tariffs estimated using the non-linear relationship are very similar to those estimated using the quadratic form used in this chapter. This is not unexpected, since (as noted previously) the relationship between aggregate electricity consumption and the wholesale price of electricity estimated using the quadratic and non-linear function form are similar. However the optimal tariffs estimated using the functional form based on the Laurent series are different from those based on the quadratic, with discernably higher prices for the off-peak and shoulder periods and a lower price for the peak period. This implies that the difference in wholesale prices between these periods (based on aggregate electricity consumption) is estimated to be less using the Laurent series than the quadratic or non-linear estimates.

![Figure 4.44: Profit maximising tariffs - initial appliance stock ($/kWh)](image-url)
4.B Electricity price indices for time of use tariffs

Price indices are important tools for policy makers. Price indices are used to index security payments and certain taxation scales. The stance of Australian monetary policy is determined with reference to the rate of consumer price inflation. Regulatory authorities are also informed by price indices in assessing the level of competition and the distributional characteristics of industries. In this appendix the effect of the introduction of TOU tariffs on the calculation of price indices is discussed.

Calculating price indices for electricity tariffs that do not vary during the course of a day (uniform tariffs) is trivial: it is simply the price in the current period divided by the price during a previous (base) period. Equation 4.10 shows the general formula for calculating a price index for time \( t \) (day \( d \)) using a base time \( x \) periods prior. The intra-day profile of electricity consumption is not relevant to the calculation when uniform tariffs are used as there is no need to weight by intra-day consumption when the price is identical across all intra-day periods (as shown in equations 4.11 and 4.12).

\[
p_{\text{index},t} = \frac{E_{d-x}}{E_d} \sum_{h=1}^{H} \left( \frac{p_h E_h}{p_{h-x} E_{h-x}} \right) 
\]

(4.10)

\[
p_{\text{index},t} = \frac{E_{d-x}}{E_d} \frac{p_h}{p_{h-x}} \sum_{h=1}^{H} \left( \frac{E_h}{E_{h-x}} \right) \text{ for uniform tariffs} 
\]

(4.11)

\[
= \frac{E_{d-x} p_h}{p_{h-x} E_{d-x}} \frac{E_d}{p_h} 
\]

(4.12)

However for TOU tariffs, intra-day consumption is relevant. For the purposes of calculating an index, the price of electricity over the course of a day is calculated as the weighted average of the intra-day price weighted by the proportion of household consumption in each period (as shown in equation 4.10). This construction will result in the calculation of different price indices for any TOU tariff for households or groups of households based on the intra-day profile of the household or group electricity consumption. This is not a drawback, rather it reflects the different average price paid per day based on their differing intra-day pattern of electricity consumption.

The technique used to estimate the intra-day own- and cross-price elasticities of demand used in the calibration of this simulation model could be applied in the calculation of price indices when a TOU tariff is introduced. Given the existence and availability of appropriate data on intra-day consumption, the technique proposed by Hirschberg (2000)
can be used to generate matrices of price elasticities and from these, estimates of intra-day consumption following the introduction of a TOU tariff. Such an approach would allow for the effect of intra-day substitution to be estimated. A simple alternative approach would be to use the intra-day profile of consumption prior to the introduction of a TOU tariff in calculating a price index. However this would effectively only account for the income effect of the introduction of a TOU tariff and would disregard any substitution effect the change may induce.
Chapter 5

Conclusion

5.1 Motivation of the study

The objective pursued in this study has been to investigate the effect of time of use pricing for electricity on household electricity consumption in order to estimate the responsiveness of households over a range of uses within the household. Reliable measures of residential intra-day price elasticities of demand are required for a future assessment of various policy responses to environmental, peak load, and regulatory issues.

The accurate simulation of the effects of TOU pricing and climatic variables on household electricity consumption promises a number of benefits. Chief among these is the quantification of the potential for TOU tariffs to mitigate the problems of peak load and the negative environmental impacts of electricity consumption and production. The estimation of the intra-day prices comprising optimal (profit maximising) TOU tariffs and the simulation of effectiveness and operation of various regulatory constraints on electricity retailers also offer potential benefits to industry participants and policy makers. Assessment of the likely efficacy of policies intended to improve energy efficiency and environmental outcomes (such as minimum appliance energy efficiency standards, a carbon cap and trade scheme and subsidies for the purchase of energy efficient appliances) along with their interaction with TOU pricing is timely given the current Australian policy debates on these issues.
5.2 Main findings

For the households examined in this study, temperature and natural light affect electricity consumption. Electricity consumption on space cooling and heating increases as temperature diverges from comfortable levels, while electric lighting and natural light are found to be substitutes. Substantial variation is evident in the intra-day electricity consumption of households. These are accentuated when comparing households in the two samples used in this study, which are both geographically and inter-temporally different.

The intra-day own-price and cross-price elasticities of demand for electricity estimated using a novel technique proposed by Hirschberg (2000) vary by appliance type (energy function). The impact of a price change in one intra-day period on electricity consumption in that period along with preceding and subsequent periods will be different depending on the types of electrical appliances being used by a household.

The introduction of TOU tariffs or the direct load control of space cooling appliances may reduce the contribution of households to peak load consumption. The effect of TOU tariffs on the electricity consumption (and expenditure) of an individual household depends on the intra-day consumption profile and price elasticity of demand of that household. These vary substantially, even between the relatively limited number of Australian households included in this study.

The distributional impacts of the introduction of TOU tariffs depends on the profile and composition of household electricity consumption. Under the parameters used in the scenarios simulated in this study (including an aggregate expenditure constraint on the TOU tariffs able to be offered) households with substantial off-peak electricity consumption have the potential to gain the most from a TOU tariff. The heterogeneous impacts of TOU tariffs on household expenditure suggest that they may be politically difficult to implement.

The regulatory imposition of a price ceiling limits the extent to which a TOU tariff will achieve substitution of household electricity consumption from peak to off-peak and shoulder periods, reducing its potential contribution to efficiency. Illustrative simulation modelling indicates that policy options including the introduction of minimum appliance energy efficiency standards, a carbon cap and trade scheme and subsidies for the purchase of energy efficient appliances may reduce electricity consumption in the medium and long term.

Potential increases in temperature arising from climate change are expected to result in increased aggregate household electricity consumption. The increased use of space cooling in these scenarios increases the benefit of energy efficient air conditioners to households. In the long term, the illustrative simulation modelling carried out in this study suggests households may purchase more energy efficient air conditioners in the climate change
5.2.1 Implications of findings

While metering equipment that will enable the implementation of TOU tariffs is being installed in households in a number of Australian States, there is a lack of evidence and analysis concerning the impact of TOU tariffs on households. A recent moratorium announced by the Victorian Government on the introduction of TOU pricing structures (Batchelor 2010) is indicative of the uncertainty as to the distributional impacts of such a change in the minds of policy makers. The moratorium followed the release of a report (Johnston 2010) questioning the adequacy of the consumer protection framework to minimise adverse impacts for vulnerable and disadvantaged households.

If the findings of this study (designed to facilitate distributional analysis) were replicated in analysis based on a larger, representative study of households, they would have implications for price regulation and other aspects of policy affecting both households and the electricity industry. Analysis of this type is timely, evidenced by the Victorian moratorium and recent Australian regulatory review of customer protection and safety relating to smart meters (Ministerial Council on Energy, Standing Committee of Officials 2010), in which community concern (and ongoing consideration by the Council) is noted regarding the distributional impacts of "time-related pricing" and direct load control.

Subsidies for electricity consumption paid as a proportion of electricity consumption may not be an efficient method of providing support to households adversely affected by the introduction of TOU tariffs. While most energy concessions in Victoria operate in this manner (Batchelor 2010, p2), of the households comprising the sample used in the simulation model, increases in household expenditure on electricity following the introduction of a TOU tariff are found to be confined to households consuming relatively low amounts of electricity. The expenditure of the household consuming the most electricity in this study fell immediately, while the expenditure of households consuming less electricity did not fall until they purchased more energy efficient appliances. Even in the long term, many of these households would have been better off if a uniform tariff were retained.

A regulatory constraint on TOU tariff pricing that limits the permitted increase in aggregate household expenditure following the introduction of a TOU tariff is found to be more appropriate than the imposition of a price ceiling for the households included in this study. A uniform intra-day price ceiling limits the ability of a TOU tariff to improve efficiency by reducing peak load consumption. This finding presents a challenge, as residential electricity tariffs are generally regulated using price ceilings, which are relatively transparent and simple to enforce.

The various policy options examined in this study are found to increase energy efficiency
and reduce electricity consumption in the illustrative simulation modelling carried out, improving environmental outcomes associated with the generation and consumption of electricity. However there are aspects of these policy options that may warrant further consideration. The long term effect of more stringent minimum appliance energy efficiency standards is potentially ambiguous, as this may induce some households to purchase appliances that meet the (increased) minimum standard rather than more efficient models (depending on how the costs associated with the policy are distributed). The introduction of a carbon cap and trade scheme will have implications for TOU tariffs to the extent that there are differences in the carbon emissions of baseload and peak electricity generators (noting that the vast majority of Australian baseload generators consume coal, while peak electricity is often produced by gas and hydro powered generators). Similarly, the cost of subsidising the purchase of more energy efficient appliance types varies widely based on appliance type. Efficient light globes and water heaters require little or no subsidy, while efficient air conditioners, dishwashers and clothes washers and dryers require substantial subsidies for a large proportion of households to purchase these appliances. Analysis based on a larger, more representative sample is required before any general conclusions can be drawn from the illustrative simulation modelling carried out.

The illustrative result that increased temperature due to climate change may increase aggregate household electricity consumption emphasises the challenge faced in electricity markets similar to that of South Australia. In the absence of innovative industry or policy action to address the peak load issue, growth in electricity generation and distribution capacity must exceed growth in aggregate household electricity consumption. This will serve to heighten concerns regarding the impact of electricity generation on the environment.
5.3 Limitations of the study

The empirical findings of this study are valid for the areas in which the samples were collected: Mawson Lakes, South Australia and Sydney, New South Wales. The findings are based on the climatic conditions, appliance stocks and consumption patterns of households in these areas. While changing climate and appliance characteristics are able to be simulated, households with different consumption patterns and demographics, living in different dwellings are unlikely to be well described by this model without recalibration using appropriate data.

The small sample sizes of the datasets used to calibrate the simulation model further limits the extent to which the findings of the model can be generalised. While the datasets are comprised of many high frequency records (through time) a substantially larger number of households need to be included before the samples are likely to be representative. The age of the Sydney sample also limits the applicability of the simulation results relating to this sample. This is one reason that all scenarios simulated in chapter 4 are based on the Mawson Lakes sample rather than the Sydney sample.

The limitations of the simulation model presented in this study in the main stem from the scarcity of high frequency, appliance specific consumption data that are both broad and representative. In the absence of such data, the empirical findings of the simulation model will not have wide application to questions of pricing and policy. However, even with appropriate data, two specific limitations will remain.

Firstly, it is assumed that households will purchase like for like when upgrading and replacing household appliances. This is not necessarily the case since household requirements and preferences can change and the development of new appliance types may result in the purchase of different appliance configurations. Households may simply cease using a particular appliance. In order to capture these changes in the stock and characteristics of household appliances the simulation model would need to be periodically recalibrated using more recent data. The prediction of long run changes in household preferences and future technological advancement is beyond the scope of the simulation model presented in this study.

Secondly, the characteristics of appliances beyond price and energy efficiency are difficult to quantify. This study excluded entertainment devices, as measures of comparative utility for such appliances based solely on purchasing and operating costs are highly unlikely to be accurate. To a lesser degree, this issue is present for appliances serving any energy function. The approach taken in the simulation model can quantify financial costs, rather than the true opportunity costs to households inherent in appliance purchasing decisions.
5.4 Directions for future research

In this section areas of future empirical and theoretical research are identified.

5.4.1 Empirical research

Few economic studies suffer from the over availability of relevant data. Improved data are required to improve the reliability of estimates of the simulation model and permit the inclusion of a wider variety of variables. Data on household characteristics would allow more detailed distributional modelling of the impact of various policy options and TOU tariff schedules. Similarly, data on the stock of installed household appliances would allow for the relaxation of the assumptions concerning the characteristics of these appliances.

A related issue is the public good aspects of appliances serving particular energy functions. An air conditioner will reduce the temperature for all members of a household, while a radio can be enjoyed by everyone within earshot. This issue is similar to the question of economies of scale in energy use investigated by Ironmonger et al. (1995). Data that include occupancy information (such as the number of people in a dwelling in each intraday period) would allow the examination of whether some energy functions have public good characteristics.

While this study examines household electricity consumption, the approach adopted could be extended to other components of aggregate electricity consumption. The response of small and medium size industrial consumers could be estimated (in the spirit of Aigner and Hirschberg (1985)) and contrasted with those of individual households and the household sector as a whole.

Another empirical question of interest concerns the potential impact of the introduction of TOU tariffs on the environment. The optimal TOU tariffs estimated in this study are the result of profit maximisation by an electricity retailer subject to a regulatory constraint. In the scenarios simulated (with the exception of the carbon cap and trade scenario) no account is taken of the potential effect on the environment of increasing the proportion of electricity generated by baseload electricity generators. Baseload generators are fuelled in Australia by black and brown coal, while peaking generators use gas, wind and solar power.

A number of assumptions underlie the empirical findings of this study. Chief among these is the assumption of constant (fixed) inelastic mean own-price elasticities of demand for electricity (discussed in subsection 2.6.1). While the elasticities adopted are consistent with estimates reported in the economic literature, it is not realistic to expect that the own-price elasticity of demand for electricity (for an individual household or in aggregate) is not a function of both income and the price of electricity. Data on the response of
households to large variations in the real price of electricity and income could be utilised to incorporate these dimensions in the simulation model. Data of this type could also be used to compare and benchmark the method of Hirschberg (2000) used to estimate the relative own- and cross-price elasticities in this study.

5.4.2 Theoretical research

The simulations carried out in this study assume that the market is served by a single (monopolist) electricity retailer. As noted, this allows the costs and benefits of introducing a TOU tariff to be internalised. A theoretical analysis of the effect of multiple electricity retailers may provide insight on the setting of optimal TOU tariffs. Such an analysis could include the effect of permitting electricity retailers to offer different tariffs (TOU or uniform price) to households with different characteristics or demographics. Similarly, the effects of behaviour such as strategic bidding to manipulate the wholesale price of electricity seem promising extensions.

The only costs considered in the simulation of household appliance purchases are those associated with purchasing and operating the appliances. In some cases the cost of inputs other than electricity (such as household labour, water or gas) may be substantial. Where these inputs vary between the different appliances available for purchase within an energy function the associated costs may affect appliance purchasing decisions. The role of these inputs in household appliance purchasing decisions is an area that may benefit from further study.

As reported by Brannlund et al. (2007), increases in the energy efficiency of some appliance types may result in increased net electricity consumption. While the substitution effect induced by improved appliance energy efficiency is central to the simulation of household appliance purchasing decisions, the income effect (as modelled by Brannlund et al.) is not accounted for. An analysis and estimation of the scale of the income effect arising from improvements in appliance energy efficiency could be valuable to modelling household electricity consumption.
Bibliography


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