Price it Right: Household Response to a Time-of-Use Electricity Pricing Experiment in Auckland, New Zealand

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ABSTRACT

In 2008, Mercury Energy recruited 400 households in a suburban area of Auckland to participate in a Time-of-Use (TOU) electricity pricing experiment. The experiment lasted one year. Its aim was to gauge consumer interest in and response to electricity prices that vary over the course of the day. This thesis reports the results of analyses of that response in a Constant Elasticity of Substitution (CES) framework. The elasticity of consumer substitution was estimated, on average, to be about -0.051. This implies that a 100% increase in the ratio of peak to off-peak price would result in a 5.1% decrease in the peak to off-peak consumption ratio. The substitution elasticity varied systematically with a variety of house and household characteristics. Of interest, however, is that the response to low off-peak prices was stronger, on average, than the response to higher peak prices. It appears that households took advantage of lower prices off-peak more than they substituted off-peak for peak consumption. A cost benefit analysis nevertheless indicates a potential net benefit from this kind of TOU rate design.

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[1] The Caveman are: Todd, Stephan, Auren, Dan. Robbie is not a Caveman since he did not reside in the cave. Robbie, however, deserves thanks for all his help.

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1 INTRODUCTION

Over the last 30 years electricity consumption in New Zealand has more than doubled. While most of the electricity needed can still be produced for a relatively low cost using cheap, renewable sources of energy some of the peak demand has to be met using less efficient and more costly production techniques.

The problem has been addressed by government initiatives such as the ENERGYWISE campaign that provides information to improve overall energy efficiency. While it has been shown that information is important for electricity conservation, it might not be overall electricity consumption that is the biggest problem. Rather too much consumption during few short periods of peak demand when the cost of generation, transmission and distribution are relatively high.

One reason for relatively high consumption during periods of peak demand is that the price of electricity fails to move in line with marginal production cost. Instead, price typically reflects production costs averaged over the course of the day and week. One reason for this time-invariant pricing is that conventional electricity meters measure cumulative consumption, but not when that consumption occurred. Electricity retailers lack the information they need to adjust prices with cost. A tariff that varies over time improves incentives to conserve during relatively high-cost periods and instead use electricity during the times when demand and production costs are lower.

Electricity retailers have recently begun rolling out so-called “smart” or “advanced” electricity meters. These meters record electricity consumption digitally at relative frequent intervals, thus essentially time-stamping electricity consumption. These meters make possible time-of-use (TOU) prices that vary over relatively short time periods, such as a day. Better aligning prices with costs is attractive to retailers, and some households may prefer TOU pricing should it be offered.

In 2008 – 09, electricity retailer Mercury Energy conducted a TOU pricing experiment in a suburban area in Auckland to investigate residential customer interest in, and response to, time-variant pricing. In this thesis, consumption data is analysed to estimate the extent of load shift from peak to off-peak times during the experiment using a Constant Elasticity of Substitution

(CES) model. Though similar experiments have been conducted elsewhere, New Zealand is unusual in that peak demand for electricity occurs in winter for space heating rather than in summer for cooling. Participant households completed surveys before and after the year-long experiment, which allowed for estimation of the effects of various house and household characteristics on the Elasticity of Substitution (EOS) between peak and off-peak periods.

In that framework we ask the question: to what extent did the households in the experiment respond to the time-variant price and did they shift their consumption from one period to the other? The analysis indicates significant short run substitution elasticities of around -0.0508 on average. This is in line with previous estimates of short-run responses without special "enabling technologies" that enhance control over time of electricity use. The substitution elasticity grows (in absolute value) with the number of hours household members spend away from home, the number of people in the house, and the lower the outside temperature (and, therefore the higher the monthly electricity bill). Substitution elasticity falls with household income, the presence of a householder who is seriously ill, and water heated using a standard electric cylinder (in part because the percentage effect of any shift is reduced by the larger overall consumption).

Of interest is how the average response to variation in prices differs during peak and off-peak times. In particular, the estimated own-price elasticity of demand for peak consumption is smaller than that of off-peak consumption, at least when temperatures are lower during winter. Householders in this sample on average take more advantage of lower prices off-peak than they conserve during peak periods.

Finally, the results from the EOS model are employed in a hypothetical cost-benefit analysis of the time-varying prices. The potential net social benefit, excluding externalities and potential reduction in the need for building new peak infrastructure, was estimated for a group of 293 households as somewhere between $303–1,790, depending on the assumptions made about electricity wholesale prices.

The thesis is organised as follows. Chapter 2 summarizes the theoretical and empirical literature. Chapter 3 describes the New Zealand electricity market to provide context. Chapter 4 describes the experiment, and the data collected. Chapter 5 discusses the empirical methods and models used to obtain the results. Chapter 6 discusses the results and compares the estimation methods

and specifications to alternative methods. Finally, Chapter 7 investigates the social benefits and how they might be distributed across different groups under a TOU pricing regime.

2 LITERATURE REVIEW

When demand varies over the day but price remains fixed at some average level a peak-load problem can arise. The problem is that, if the marginal production cost is increasing with output, then price does not reflect the marginal production cost at all times. The theoretical literature on the problem and the welfare implication of the problem will be outlined in section 2.1 through 2.1.2. In section 2.1.3 the peak-load problem is explained graphically.

Section 2.1 through 2.1.3 suggest a potential solution to the problem is to charge the users different prices during different times. That is, when demand and marginal production cost is high (low) the price paid by the consumer would also be high (low). This idea has been applied in the real world and several rate designs have been proposed and tested. Section 2.2 will introduce and discuss the most common dynamic rate designs that exist and have been tested in the past. The discussion will continue into the potential welfare implications of charging a time-variant rate.

The final part of the chapter will provide a discussion on previous analysis of experiments related to electricity conservation. In the past the effect of improved information and 'enabling technology'—technology that enable and assist with the load shift—has been of interest to researchers. Previous research on information and technology will be discussed in chapter 2.3.1. In chapter 2.3.2 past time-variant pricing experiments and analysis will be discussed. Since information, technology and time-variant rates are often analysed together overlaps between the two sections is to be expected.

Studies that focus on the improved information and enabling technologies, regardless of whether they have a time-variant feature to them or not, tend to be designed experiments and participants have to opt in voluntarily. While the self-selection into the study might be problematic when investigating the response to information and technology, experiments using a time-variant rate often avoid this problem. This is because in a competitive electricity market it is likely that the time-variant rate design would be offered alongside a standard average cost rate instead of being forced on the customers. Research experiments that only focus on time-variant tariffs and do not consider other influential factors have been called 'natural' experiments. In those experiments the electricity utility has either imposed on or sold some customers a time-variant rate design without the intention of conducting an experiment. In those cases the participants have not been

aware of the experiment and limited information on the household characteristics was available to those analysing the data. The issues relating to the experimental design are discussed in more detail in chapter 4 where the Auckland experiment is discussed.

The methodology used to analyse the time-variant pricing experiments differs to some extent. However, the most common way of analysing the data is in a Constant Elasticity of Substitution framework where the objective is to obtain own-price and substitution elasticises. The main focus is usually on the substitution elasticises since they provide a potential measure of the load shift from the peak to the off-peak period.

The Elasticity of Substitution is found by regressing the logged ratio of peak to off-peak consumption on the logged ratio of peak to off-peak prices. The coefficient for the price ratio can then be interpreted as the Elasticity of Substitution. If there is a shift in electricity consumption from the peak to the off-peak period the sign on the coefficient is expected to be negative and the larger the absolute value of the coefficient the greater the load-shift is going to be.

The own-price elasticises are found for each period of the day by regressing the logged price during that period on the logged consumption during the same period. The coefficient on the logged price ratio is the own-price elasticity during that period and if negative the interpretation is that the households responded by using less (more) when the price is high (low). If the absolute value of the own price elasticity is high, then the households are said to be highly responsive to price and if the coefficient is close to zero they are said to be unresponsive to price. These methods are the same as employed in the analysis on the Auckland experiment and will be discussed in greater detail in chapter 5 where the methodology of this thesis is discussed.

2.1 The Peak-Load Problem

The 20th century marked a new chapter in history, bringing electricity and telephones into most homes around the developed world. The new technology brought with it new problems and one of those problems was: how much electricity to produce?

The peak-load problem is a problem that “exists at any price, if the quantities demanded in the two periods at that price are unequal” (Steiner 1957, p. 587). Peak-load pricing is a response to

this. The problem can be seen all over the economy, in resturants, theaters and in fitness centres. In most sectors the agents of the economy solve the problem themselves without any help from regulators. They solve their problem by either accumulating inventory, reducing production, shutting down or varying prices over time, e.g., by offering discounts during off peak times. However, not all producers have the ability to store inventory, or reduce production so their only feasible option is to charge different prices at different times. For that reason, peak-load pricing theory has real and important impications for the welfare of the society.

Ault and Ekelund (1987) detail the development of peak-load pricing theory. They explain how telephone calls and electricity are non-storable services and the demand for the services has unique and identifiable time dimension. Therefore a problem of optimal economic capacity emerges. A non-storable product, like the name suggests, is a good or a service that cannot be produced and stored as inventory to be sold at a later date. A product might be non-storable due to the fact that it is physically impossible to store it, or that it is extremely expensive to store.[2] Therefore a non-storable product has to be consumed at the time of its production. If demand for a product has a unique and identifiable time path then it is possible to identify how demand for a particular product varies over time.[3] When the amount of output maximizes the welfare of agents involved, optimal capacity is reached.

Bye (1929) points out that the principle of joint supply—when one production process results in two or more products being obtained—can apply when producing only one physical output.[4] If the demand for the product can be split into peak and off-peak then the joint supply principle applies. In support of his argument he states that a telephone company "must maintain a plant sufficient to meet the maximum demand for its facilities that may arise during the business hours of the day. A large part of its wires, exchanges and instruments will be idle at other hours." (Bye 1929, p. 45). Applying this to electricity, it is possible to argue that if an electricity plant is fully utilized and all the produce is sold to customers during peak time, but during off-peak time only a part of the electricity is sold and the unsold electricity that does not cost anything extra to produce is a by-product and because it is not sold (or even produced) it is wasted. In the same

[2] Examples of product that are physically impossible to store are services such as massage and a telephone call. Products that are cheap, but bulky, tend to be too expensive to store over long periods.
[3] For example demand for using roads has an identifiable time path. In the mornings and afternoons demand tends to be high and in the night demand tends to be low.
[4] A classic example of joint supply production is cotton as the main product and cotton seed as the by-product.

paper, Bye also showed that the fairest principle to base the price structure on was the time based rate.[5]

Long after Bye's work, Boiteux (1960) published an important paper on stochastic demand and peak-load pricing. In this paper he argued for higher rates being charged when demand exceeded the capacity of the plant. His work sparked some interest in the subject of peak-load pricing.[6] Even though Bye and Boiteux had arrived at the solutions of the peak-load problem before Steiner's (1957) "Peak Loads and Efficient Pricing", Steiner is believed to have done more to "introduce and popularize the theory of joint supply applied to the shifting peak case." (Ault & Ekelund 1987, p. 655). Steiner's solution became a vital part of the literature after its publication in the 1950s. Brown and Johnson (1969) expanded Boiteux's work on Stochastic Demand, by introducing unpredictable random variation into the demand cycle in their model. Their work started a wave of theoretical interest in the effects of stochastic demand on welfare. In the 1970s the theory was extended to account for the cost of rationing. The work on the subject was mostly carried out by Visscher (1973), Crew and Kleindorfer (1976; 1978), Carlton (1977), and Sherman and Visscher (1978).[7]

2.1.1 Welfare and Electricity

Crew, Fernando and Kleindorfer (1995) review the theory behind peak-load pricing and give insight into how and why this is a topic of special interest. The approach used in the paper provides an effective way of analysing and arguing in favour of a peak-load pricing system. Their approach will be the basis of the welfare analysis of Peak-Load Pricing in the electricity market.

In order to find the efficient price in the market Crew at al. (1995) follow Steiner's (1957) work. They define a welfare function and seek to maximize welfare. The welfare function is shown in equation 2.1.

[5] When consumers are charged different rates during different times it can be referred to as time-based rate.
[6] According to Crew et al (1995) the work carried out by Boiteux in 1951 lead to contributions from, primarily French economists and engineers.
[7] The Subject of rationing cost has little implications to the thesis and if the reader would like to know more on the subject he is advised to read the papers suggested in the paragraph before.

Equation 2.1: Total welfare

$$\mathrm{W} = \mathrm{TR} + \mathrm{S} - \mathrm{TC} \tag{2.1}$$

Where W is the total welfare, TR is the total revenue received by the retailer, TC is the total cost of providing the electricity and S is consumer surplus. By definition total revenue (TR) plus consumer surplus (S) is equivalent to the area under the demand curve for some quantity X. Therefore the welfare function for a single product can be expressed, alternatively as:

Equation 2.2: The welfare function

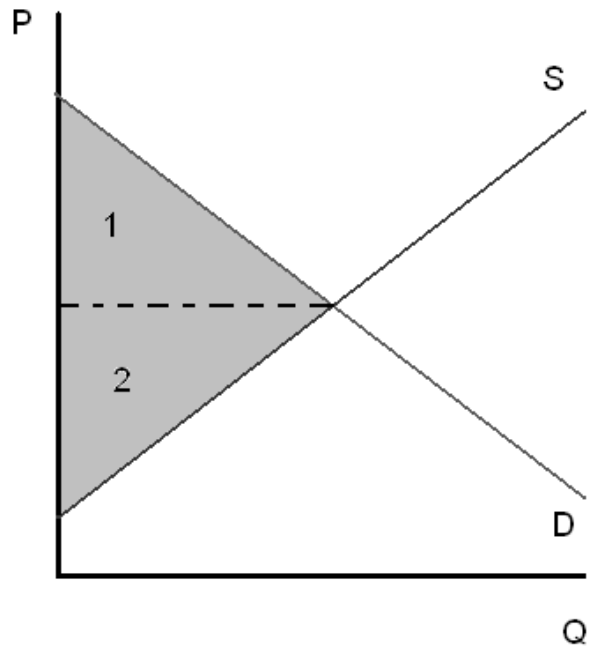
$$W = \int_0^X P(x)dx - C(X) \tag{2.2}$$

The second equation (2.2) represents the net welfare accruing in equation 2.1 at some X amount of electricity produced and sold. P(x) is the inverse demand function for electricity and C(X) is the cost function of producing the electricity. The integral in equation 2.2 represents the 'gross surplus' received by consumers and producers ($[TR + S]$ in equation 2.1) at some X amount of electricity produced. It is possible to split the surplus between the producer and the consumer and at a given quantity X the 'net benefit' received by producers is (TR – TC). The consumer surplus is simply the welfare function less the revenue received by producers.[8]

Figure 2.1 illustrates in the simplest way to split the surplus between producers and consumers. The grey area labelled 1 represents the consumer surplus while the grey area labelled 2 represents the producer surplus. In this basic case, in the welfare function, consumers and producers welfare is valued equally.

[8] In equation 1, W = TR + S – TC, can be rewritten as: S = W - (TR - TC). By plugging in the welafare function in equation 2 we get: S = $\int_0^X P(x)dx - C(X)$ – (TR - TC). Since C(X) is the TC function what we are left with is S = $\int_0^X P(x)dx - TR$

Figure 2.1: Simple illustration of consumer and producer surplus



Maximizing the welfare function in equation 2.2 results in the classic efficiency condition that marginal benefit equals marginal cost at the optimal output level.[9] However, if the cost function, c(X), exhibits decreasing average cost – the case of 'natural monopoly' – then the classic condition P = MC could result in losses for the producer. Without any subsidies, the producer would only be willing to start production if there is a chance to charge a price at least as high as average cost. If average cost is greater than marginal cost, the welfare maximizing amount of electricity is not being produced. This creates a scenario where subsidies to producers or a two-part tariff (fixed and variable charges) could achieve the largest social welfare.

[9] The unconstrained problem is $\max_x \int_0^X P(x)dx - C(X)$, the result of the FOC $\frac{dW}{dX} = 0 \Rightarrow P(X) - C'(X) = 0$ $\Rightarrow P(X) = C'(X)$.

It is important to note that even though it is logical for a single electricity plant to have a decreasing average cost function; it is only true in the short run. In the medium term, when the plant reaches its maximum capacity, the only way to produce more electricity is by building a new power plant. If the most efficient resources and inputs were hired to make the first power plant, the second most efficient resources would be employed in the second plant resulting in a higher long run average cost. In practice the production of electricity is not monopolised and new producers can enter the market. If MC is increasing then under a time-variant tariff a competitive supply is efficient.

2.1.2 Externalities

In Crew et al.(1995) paper, the implications of externalities on welfare are excluded. There are both positive and negative externalities associated with electricity production. Building a hydroelectric power plant creates a lake from the dam which is an example of these externalities. It is possible to argue that the lake provides people with positive externality in the form of a beautiful lake view and a place to enjoy water activities such as water skiing. The negative side could include the loss of recreational land and streams for activities such as white water rafting or fishing. In order to account for that cost we need to determine if the dam will generate this net benefit (or cost) forever or only over a fixed time period. In the case of a fixed time period the net present value of the externality over the period between when the power plant is built and until the project is reversed to its initial state would be represented in equation 2.3. In the case where the power plants benefit/cost is irreversible the cost can be estimated using the perpetuity formula in equation 2.4.

Equation 2.3: Net present value of externalities for definite period

$$NPV = \sum_{t=j}^{n} \frac{E_{j1}+E_{j2}+,\ldots+E_{js}}{[1+r]^{j}} \tag{2.3}$$

In equation 2.3 above the variable E_{i1} represents a positive or negative externality for product 1 at time period j. The r is the discount factor, used to account for people's preference for consuming goods today rather than in the future.

Equation 2.4: Net present value of externalities for perpetuity

$$PV = \frac{\sum_{g=1}^{s} E_g}{r} \tag{2.4}$$

Either equation 2.3 or 2.4 could be added to the welfare function to get a more accurate measure of welfare. In equation 2.5 the present value perpetuity has been added

Equation 2.5: The welfare function including externalities for perpetuity

$$\mathrm{W} = \int_0^X P(x)dx - C(X) + \frac{\sum_{g=1}^{s} E_g}{r} \tag{2.5}$$

In this case, a simple maximization of welfare results in the same condition as before since the externality is not dependent on x. However, it is logical that the externality grows as more power plants are built and through that relationship e is dependent on x. If we assume that power resources are plentiful and inexhaustible, the problem and solution can be seen in problem 2.1.

Problem 2.1: Welfare maximization

$$\max_x \int_0^X P(x)dx - C(X) + \frac{\sum_{i=1}^{s} E_g(X)}{r} \tag{2.1.1}$$

First order condition:

$$\frac{dW}{dX} = 0, P(X) - C'(X) + \frac{\sum_{i=1}^{s} E_g'(X)}{r} = 0 \tag{2.1.2}$$

The solution to the problem is:

$$P(X) = C'(X) - \frac{\sum_{i=1}^{s} E_g'(X)}{r} \tag{2.1.3}$$

This solution (2.1.3) is the same as the original P=MC except that the net marginal cost from the stream of the externality is added. The sign of the term $\frac{\sum_{i=1}^{s} E_i'(X)}{r}$ is of great importance and if there is a net benefit (net cost) from creating a dam, then the sign would be positive (negative) and the price that maximizes welfare would be lower (higher) than in the benchmark solution. In this case, unless transaction costs are low, the market price would be inefficient.

2.1.3 Illustration of the Peak-Load Problem

The issue at hand, however, is demand that varies over time. The standard approach to analyse how to vary price optimally across different time periods when demand varies with time is the supply and demand diagram. The only difference to the standard version (when demand is not time dependent) is that now two demand curves are placed on the diagram. This provides a simple yet effective framework to analyse the effect of average-cost pricing in the retail market for electricity when producers face an upward sloping marginal cost curve. The assumptions needed for the graphical analysis are:

- known demand curves for output in each period;
- the demand curves are a declining function of quantity; and
- the demand curves are independent of each other.

The demand curve in period one (peak period) lies above the demand curve for period two (off-peak period) at all levels of output. In addition I assume linear demand curves in order to make the illustrations more clear. Also for purposes of illustration assume that marginal cost rises with quantity produced (positively sloped) and the marginal cost curve has a positive intercept that is below that of the off-peak demand curve. The graph and assumptions are available below.

Figure 2.2: The peak-load problem illustrated

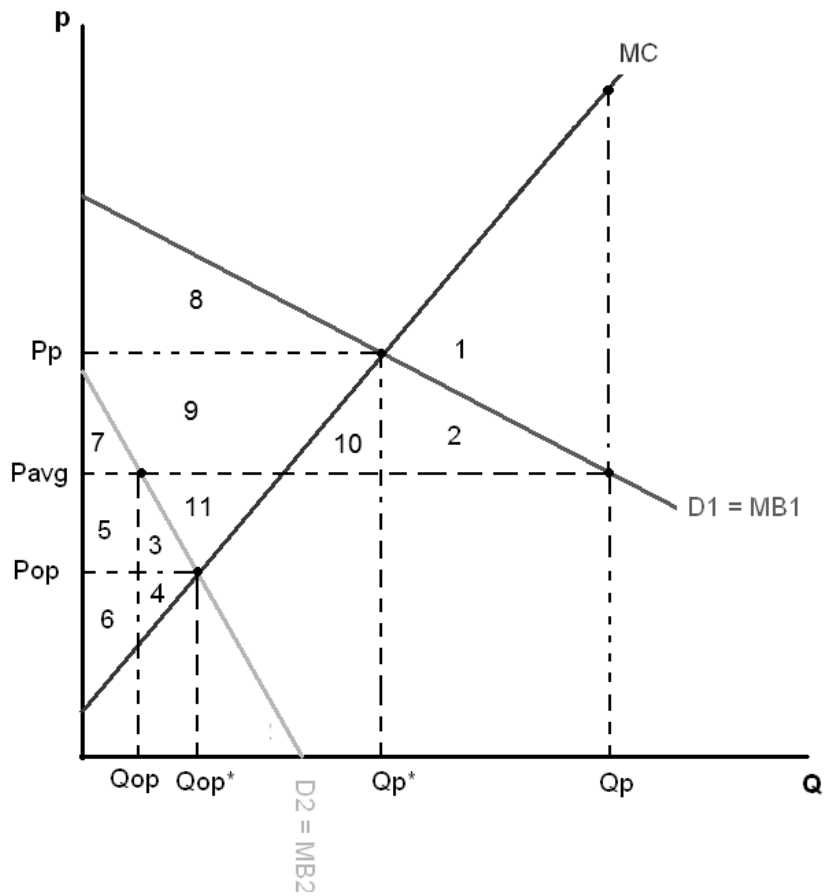


Figure 2.2 looks a bit like the textbook example of third degree price discrimination. In general, third degree price discrimination requires a monopolist to charge a price where marginal revenue (MR) equals marginal cost (MC) in each period. The difference here is that we do not assume that the producer has the ability to set the quantity such that MR = MC. Instead the producer can choose to charge either an average price (P_{avg})—the average of the peak- and off-peak prices—or a peak-load tariff where she charges a higher price (P_p) during peak hours and a lower price (P_{op}) during off-peak hours.

To analyse the welfare effects from each price schedule we start of by investigating what happens when an average price (P_{avg}) is imposed on this hypothetical economy. When price is set at P_{avg}, the quantities demanded during peak and off-peak hours are determined at the points where the horizontal dotted line intersects the peak and off peak demand curves (D_1 and D_2), respectively. In a standard analysis, the producer would produce where $P_{\mathbf{avg}}$ intersects the MC curve; too much during off-peak and too little during peak hours. However, for the purpose of this analysis it can be assumed that the producer is willing to produce to meet demand. As a result of this type of tariff the quantities produced would be Q_{op} and Q_p during off-peak and peak hours, respectively.

If a peak-load tariff is imposed on the economy, then the socially optimal price to charge during off-peak hours is where the demand curve, D2, intersects the marginal cost curve and the socially optimal price during peak hours is where the marginal cost curve intersects the peak demand curve, D1. In this scenario the optimal prices to charge are P_{op} and P_p during off-peak- and on-peak hours respectively. As a result the output produced would be Q_{op}^* and Q_p^* during off-peak and peak hours, respectively.

The graph clearly demonstrates the inefficiencies associated with the average tariff. Note that the dynamic tariff creates no inefficiencies in the market. Price is set equal to marginal cost, therefore generating the socially optimal amounts of electricity Q_{op}* and Q_p*. In the case where an average tariff is imposed on the economy, actual production and consumption during off-peak is less than optimal. As a result a wealth transfer takes place where area 5, which used to be a consumer surplus—the difference in perceived value and price paid for the good by consumers—is now transferred to the producers in the form of a profit increase or producer surplus. As for the

triangles that are marked 3 and 4 they are now lost social benefit, sometimes referred to as dead weight loss. Under a dynamic tariff the area would have been captured as social benefit.

For the peak case, charging an average price, P_{avg}, results in electricity consumed and produced at level Q_p. Under a dynamic tariff the socially optimal amount would have been produced at the level of Q_p* and would have been sold for a higher price P_p. This is less than the amount produced under a dynamic tariff, again creating wealth transfer and dead weight loss. Under a dynamic tariff the benefit received by consumers would have been area 8 and the producer would have received areas 3, 4, 5, 6, 7, 9, and 11. Under the average tariff the producer surplus in areas 7 and 9 is transferred to the consumers. Areas 10 and 2 represent another increase in the benefit received by consumers. However, area 1 now represents the dead weight loss. There is a net loss in overall welfare during peak time when fixed tariff is enforced.

2.2 Dynamic Electricity Pricing Systems and Their Benefits

A time-variable tariff system could take a variety of forms in theory and practice. However, the most common and perhaps realistic systems in application are summarized by Faruqui, Harris and Hledik (2010). The systems described in their paper are:

> *Real Time Pricing (RTP)* is as far away from the conventional average-cost pricing as it can be. While average-cost pricing is simply a flat tariff based on the expected average spot wholesale price, the RTP follows the dynamics of the spot market more than any other plan described here. As a result, it provides the most efficient price signals. RTP prices change over the course of the day and the lifetime of the contract. One example of this plan is an hourly price change where prices adjust according to predicted spot prices each hour of the day. Despite the advantages of this system in the sense that the retail prices most closely reflect the retailer's marginal cost it remains hard to implement on the household level.[10]

[10] The savings from RTP system might be insignificant for households compared to the monitoring costs and the trouble of shifting the consumption. The system may be more realistic for firms and especially the types of firms that can adjust their production over the day and could take advantage of lower prices during certain hours.

Critical Peak Pricing (CCP) provides customers with a discount during most days of the year, but very high prices during few selected peak hours of the year. For example a household facing CCP prices would have a lower than the normal average price for most of the year but during a few hours 20 days a year the price might be as much as 500% higher. While CCP is less efficient than the RTP, for the customers it is simpler to understand and react to and treats especially costly periods of extreme demand.

Time-of-Use (TOU) is probably the simplest of the three systems to understand and apply. The system works in such way that during the hours of the day where the load is on average high (low) the price of the electricity is high (low). Since the system is not based on actual wholesale prices it is not actually considered to be dynamic. This is the system that is being tested in this thesis.

The TOU system, despite its deficiencies has one advantage over the RTP and CCP and that is the simplicity of it. It is easy for users to adjust and take advantage of the system, while the other systems are more attractive from the pure price signalling perspective they might be too troublesome for many households to consider. In some cases utilities have merged two or more types of rate design in order to investigate the efficiency of the design.[11] International experience and research can provide a good indicator for the benefits that it could bring to New Zealand.

2.2.1 The Potential Social Benefit

The potential benefit of a time-variant tariff is not always clear. This section will discuss the potential social benefit that could be gained from introducing a time-variant choice for households. The overall benefit can roughly be split into:

- The reduced need to invest in expensive infrastructure to service only peak demand.
- The potential savings made by consumers.
- The operational benefit received by producers
- The environmental benefit from reduced peak production.

[11] For example in the Baltimore Gas and Electricity (BGE) experiments, that will be discussed in section 3.2.2, BGE combined CPP and a TOU rate.

This section will discuss each of the potential benefits separately and conclude with a discussion on the overall benefit.

Infrastructure savings

Faruqui et al. (2010) report that in the EU 27, excluding Latvia, Lithuania, Malta and Sweden, the marginal 5-8% of installed electricity generation capacity is in use only about 1% of the time. In other words, the peak 5-8% of total generation capacity is in use less than 88 hours a year. Decreased demand during these hours potentially generates relatively large savings. One way to decrease demand is by introducing some form of dynamic rate design. The benefit from a successful rate design that would reduce the need for peak period electricity would reduce:

(1) The need to install new peak generation capacity.
(2) Cost from not having to produce the more expensive peak electricity.
(3) The need to add to transmission and distribution capacity.

Plenty of information on both the cost of installing peak capacity and the cost of producing peak time electricity exist, making the first two benefits straight forward to quantify. It is more challenging to measure the benefits of reduction in transmission and distribution capacity. Faruqui et al. (2010) estimate that by installing smart meters, with the ability to record individual household and firm electricity consumption in real time, and introducing a dynamic rate design, present value savings from not having to build new power plants could be somewhere between 14-67 billion Euros. The adoption rate—the proportion of customers who adopt the new dynamic rate—is what creates the gap of 53 billion Euros and would determine if the installation of smart meters is an investment with a positive return or not.

Faruqui, Hledik, Newell, and Pfeifenberger (2007) argue that "Even without counting other benefits, such as the lowering of wholesale prices in supply-constrained markets, improved reliability, or enhanced customer service, the benefits of demand response are large enough to warrant serious attention by utilities and regulatory commissions throughout the U.S" (p. 74). In the same paper they quantify the savings in generation, transmission and distribution costs at 3

billion USD a year as well as the reduced need for installing and running some 625 power plants in the United States that would be run infrequently only to support the peak demand.

Operational savings

Another important contributor to social welfare is the operational savings made from installing the smart meters needed to monitor a dynamic tariff. The operational benefits consist of the following:

(1) Efficiency in meter services such as meter readings and billing.
(2) Faster response to outage.
(3) Avoidance of electricity theft.
(4) General improvements in customer services.

Since smart meters have the ability to transfer usage information straight to the provider, the cost of sending a person to read the meter in each billing period is eliminated. It would also ensure that correct readings would be provided, making billing more accurate and eliminating the cost of inaccurate readings and estimates. Outages would be more quickly and easily detected, and therefore reduce the time and loss in revenue from the outages. The new meters also make it possible for the provider to connect and disconnect the service with less delay, therefore reducing electricity theft. Finally, the new meters would provide a tool to improve firm-customer relationships that could arguably create value for the firm. (Faruqui et al, 2010).

Consumers' savings

It is important to investigate the consumer benefits realized from a dynamic tariff. The consumer benefit would consist of the increased choice and savings in the electricity bill.

The consumer benefit can be measured in terms of electricity bill savings. One way of doing this is by looking at how much the consumer would have paid under an average rate and compare that to what they actually paid under a time variant rate. Total reduction in electricity expenditure

for a single household and the entire sample or population could be calculated using equations 2.6 and 2.7 respectively.

Equation 2.6: Savings from switching to a TOU rate (one household)

$$Savings_i = \sum_{j=1}^{m} p_{AVG,i} q_{TOT,it} - \sum_{j=1}^{m} [p_{PK,i} q_{PK,it} + p_{OP,i} q_{OP,it}] \quad (2.6)$$

Equation 2.7: Savings from switching to a TOU rate (many households)

$$Savings_{agr} = \sum_{i=1}^{n} \sum_{j=1}^{m} (p_{AVG,i} q_{TOT,it} - p_{PK,i} q_{PK,it} - p_{OP,i} q_{OP,it}) \quad (2.7)$$

The formulas above assume a two period tariff as in the case of the Auckland experiment. $p_{AVG,i}$ is the time-invariant (average-cost) price as most commonly observed in today's market. This price can vary between households because customers can choose among time-invariant rates depending on their geographical location and how much they pay in a daily fixed rate.[12]

Each household's price is represented by the letter i. $q_{TOT,i,j}$ is individual household i's electricity consumption on day t. $p_{PK,i}$ is the individual household's price during a peak period while $q_{PK,i,j}$ is the individual households electricity consumption during peak hours. $p_{OP,i}$ and $q_{OP,i,j}$ are the individual household's off-peak price and quantity consumed, respectively. m denotes the number of days in a month. Equation 2.6 represents the individual household's change in the electricity bill under TOU pricing. If the result is positive, then the household saves on their electricity bill and if the result is negative the household's electricity bill becomes dearer. Equation 2.7 has the same interpretation but summarizes the savings for the entire sample or population which is denoted as n.

Faruqui and George (2002) estimate the net benefits from three different rate designs. Instead of looking at the problem for individual households they aggregate the net benefit (in 2002 present value terms). The analysis reveals significant gains for residential users. In order to quantify the gains, they assume that each rate design would be mandatory for the utility's customers and apply previously observed own price and substitution elasticities to estimate the change in the

[12] A daily fixed rate is a rate that is independent on the daily usage and can customers choose to pay a higher (lower) daily-fixed rate and lower (higher) rate per Kwh.

bill due to price responsiveness of the customers. The largest theoretical savings are observed through the CPP design followed by the Extreme day pricing (EDP) and TOU designs.[13] The TOU rate did a good job for the utility that was located in a geographical location with very cold winters and humid summers, hence high air conditioning saturation. The utility located in an area with cool summers and mild winters, much like the south island in New Zealand, also did well, saving the 1 million customers on average $51 million over the year.

Individual household savings could increase if customers can opt in to TOU pricing. If there were only two choices, TOU and average rate, then the customers who knew they could reduce their bill by going on a TOU plan would select to do so, while the customers who knew it would increase their bill would stick with a fixed rate and may not see any change in their bill (depending on the effect of opt-in TOU pricing on peak demand and cost). A similar principle applies if many different tariff designs were to be offered to customers. If all customers select the rate that would be cheapest for them the net benefit would indeed be bigger than any combination of one variable and average rate design.

Faruqui (2010) analyses the individual gains and reaffirms the benefits that could potentially be delivered to consumers by allowing them to select a rate design that would fit their time of use needs for electricity better. Customers who already rely less on peak period electricity are instantly better off under TOU pricing. In that category could be households who have relatively flat demand over the peak and off-peak periods and households, such as pensioners and people who work nights, whose demand for electricity is negatively correlated with the peaks.

If a time-varying rate design were made compulsory there would certainly be “winners” and “losers”. By profiling customers as: Peaky, Average and Flat the idea of winners and losers is easy to grasp.

[13] Extreme day pricing (EDP) is a variation of CPP. The EDP is like the CPP in the sense that for most days of the year a relatively low price is charged for electricity but for few days an extremely high price is charged for the entire day.

- “Peaky” customers have relatively high peak demand and relatively low off-peak demand compared to the “Average” customers
- “Flat” customers have relatively low peak demand and relatively high off-peak demand compared to the “Average” consumer

If a dynamic pricing system were compulsory, the “peaky” customers would end up with larger electricity bills than before while the “flat” customers would see a reduction in the bill. However, some “peaky” consumers might have sufficient flexibility in time of use to benefit in net by adjusting their electricity consumption. Therefore, using consumption profiles may underestimate the number of “winners” from the compulsory rate design when excluding customer response to the new price.

Given the freedom to develop pricing plans, retailers in a competitive market, as in New Zealand, seem likely to offer a variety of pricing plans. Households whose consumption fits poorly with TOU pricing could simply select to be on a conventional average-cost (time-invariant) pricing plan.

Fairness has been used by some opposed to the idea of changing the norm (Faruqui, 2010). The usual argument is that when a time-variant rate is introduced those with a more peaky than average profile end up subsidising those with a flatter than average profile. This argument, as pointed out by Faruqui (2010), depends on the assumption that the flat tariff system is fair. Furthermore, those opposed to such TOU pricing often argue that the low income households often fall into the “peaky” category. This argument has limited merit and in one utility analysed in the paper it is shown that 92% of low-income households would benefit from a new rate design. Another common argument from critics is that a TOU plan would force low income households to reduce their already low electricity usage and force them to turn off gadgets that are fundamental to human health, such as heaters during cold days. This argument has more merit, but instead of being an argument against TOU pricing it is rather attacking the problem of poverty and inequality in society that require a different set of solutions.

Dupont, De Jonghe, Kessels, and Belmans (2011) used previously observed price elasticities to estimate the short term benefit from a dynamic tariff in the Flemish region of Belgium. The Belgian case is interesting in respect to this thesis as Belgium is in many ways like New Zealand.

Both countries are high income, have similar levels of education and most importantly have a similar climate. The method used to quantify consumer's total bill reduction (TBR) is computed using equation 2.8

Equation 2.8:Total bill reduction

$$\sum_t [q_t * PR * PD_t] = TBR \tag{2.8}$$

Where q_t is the total consumption during a typical day t. PR is the percent peak consumption reduction as a fraction of total consumption and PD_t is the price difference between peak and off peak prices on a typical day t.[14]

In a scenario analysis Dupont et al. (2011) conclude that for the baseline case (the average Flemish consumer case) the demand response resulting from a dynamic rate design could result in a 2.32% bill reduction. In the case for highly responsive users the savings could be as much as 4.66% and the least responsive households would save only around 0.47% of their initial bill. The problem, regarding the findings, is that they are not based on actually observed behaviour by the Flemish residents but on their current usage and assumed elasticities. This is a problem that has been overcome by researchers in other locations by applying the elasticities observed in a particular experiment or place where a dynamic tariff is already in place. This also provides a framework to analyse the bill reduction in the Auckland experiment where actual consumer responses can be observed and applied.

Environmental benefit

Referring back to the theoretical section of the thesis, it is worth pointing out that reduction in negative externalities, such as less pollution, might not be fully included in the price of the electricity. If so, the savings remain understated by any calculation that has been quoted

[14] $PD_i = Ppeak_i - Poffpeak_i$. As the reader can see, this is an alternative to equation 8 and should give the same bill reduction result.

before.[15] On the other hand, some have argued that dynamic electricity pricing is, on balance, not green. This discussion is beyond the scope of this thesis.[16]

The overall benefit

The operational gap is used to describe the difference in operational benefit and the cost of installing the meters. As the previous discussion showed, it is not enough just to compare the operational benefit to the installation cost of the meters. This difference could be enough to deter firms from going ahead with the investment. However, once savings in buying electricity during peak periods in the spot market is taken into account the gap could potentially shrink further. Furthermore, when taking into account consumer savings an argument can be made for encouraging firms to invest in and install advanced technologies. Also the operational gap has been shrinking in recent years and Pacific Gas and Electric in California has seen this gap decrease by 50% from 2005 and 2008. When consumer benefit alone is taken into account the gap is closed and a net benefit realized (Haney, Jamasb, & Pollitt, 2009).

It looks as if there is little doubt about the existence of the benefits from such a system, and almost the savings for the electricity provider is enough to cover the cost of installation of the smart meters. The actual social benefit, derived through a dynamic or semi-dynamic pricing system, depends entirely on the willingness and level of price response by the customers adopting the technology.[17] The response to such pricing systems in past experiments will be discussed in next section.

2.3 Previous Experiments and Analysis

The peak-load problem in electricity has been recognised for decades, as has pricing as a treatment for that problem. Of interest is the extent to which households would respond to time-varying prices. Over the last 40 years a significant number of experiments have been conducted

[15] For more on the subject see Conchado & Linares (2012)
[16] For more on the subject see: Spees K, Lave LB (2007) or Holland SP, Mansur ET (2007).
[17] Both the number of firms and households willing to adopt the dynamic price plan, and their elasticity of substitution will determine the magnitude of the savings. For more on overcoming barriers to adoption see Faruqui, Harris, & Hledik (2010).

to determine the effects of both better information and better pricing on electricity consumption. Before getting into the discussion of previous experiments it seems useful to outline the problems, currently and in the past, that face consumers when it comes to the decision of how much electricity to consume and what potential issues might arise when conducting such experiments.

The situation currently faced by most households

Most households lack access to technology that enables them to monitor how much and when they use electricity. Most households have one conventional meter—usually installed in an inconvenient location such as a garage or outside the house—and rarely go through the effort to read it and keep track of usage. These meters require a bit of training to read and provide only accumulated usage in kilowatt hours since the installation of the meter. So, even if households go through the effort of monitoring the meter, they would still have to keep a log of how much they use and convert the kilowatt hours into monetary values to extract any useful information. For these reasons people tend to have almost no information on how much electricity they are using at any point in time.

This primitive metering system is only a part of the information problem faced by households. Since most household appliances lack systems for metering electricity consumption, consumers have no way of knowing how much they cost to run. People tend not to know how much it costs to, for example, take a shower, toast a slice of bread or dry a load of clothes. Households, off course, have some idea of the relative costs of running different appliances, e.g., that it is more expensive to use the dryer than it is to toast a slice bread, but often the information is not specific to them but rather a crude generalization obtained from an external source. The result of limited information on running costs is most likely overuse of some appliances and underuse of others.

Finally, most households pay the same price per kilowatt hour throughout the day. While the cost of supplying electricity varies over the course of the day, consumers have no incentive to schedule their consumption accordingly. If electricity costs the same regardless of the time of day, then people will use the most expensive appliances at whatever time suits them best. Furthermore, a time-invariant price forces people who would have been willing to shift their

consumption and save on their bill to simply accept the set tariff and use electricity whenever is most convenient.

As a result of both very limited information and time-invariant prices, consumers use either too little or too much electricity, on average, and lack the information and incentive to adjust their time of usage to maximize their potential net benefit from electricity consumption. However, ignorance may be bliss and if electricity is a small enough part of household expenditure, then some people might find the hassle of having to think about it not worth the savings. In that case we would expect to see little response to time-varying prices and better information about the energy-costs of specific behaviours.

Issues in experimental design and analysis

The question of interest is how people respond to prices that vary over the course of the day. Conducting that kind of experiment requires a change in metering. One option is to install an additional conventional meter. The household then has one that runs during peak times and another that operates off-peak. More recently, so-called 'smart meters' are being rolled out that have a clock: they record electricity usage at frequent intervals, such as every half hour. This allows the retailer to vary charges with time of use. It also allows them to supply the householder with more information about when they consumed electricity. The installation of these simple 'smart' meters motivated the experiment described in this thesis.

Of course, there are even smarter systems. Some meters can transmit readings wirelessly to a computer or monitor inside a customer's home. Devices can also be installed that measure electricity flowing through each circuit. Metering devices could even be installed on each appliance. And various technologies could be used to report electricity consumption to consumers, or even to control the timing of appliances.

What does this have to do with the design of experiments with time-varying prices? Participants in the experiment usually receive more information about their usage in addition to experiencing time-varying prices. In the Auckland experiment, for example, the monthly bill included a chart of daily peak and off-peak consumption. Though not a lot of information, it is much more than

they had before the experiment. It should be noted the households know that they are participating in an experiment, which may itself invoke a response.

When the participants are aware that they are part of an experiment there is a chance that some of the response could simply be caused by the fact that people are being watched and, sometimes unknowingly, change their behaviour. Also, some of the response could be attributed to the household's increased awareness of their usage. That is to say, because people know they are in the program, they are constantly reminded of how they are using electricity. This can be avoided when analysing "natural" experiments, where the customers simply select to be on a time-variant rate and are not aware that the usage data is going to be analysed and are not constantly reminded of the fact that they are participating in an experiment related to their electricity consumption.

Not surprisingly, previous research has focused on the various aspects of these effects. We discuss the experimental findings on how better information, time-varying prices and household characteristics influence the consumption decision.

2.3.1 Information Feedback and Other Influential Factors

In the past there has been some interest in which house and household characteristics contribute to electricity demand. While the characteristics of households and houses can guide the way to some extent when it comes to policy making, the effect that added information has on household decision making has been of much interest to researchers in the past. That is no surprise since improving information is relatively cheap and if it is effective it could, at least in theory, influence all socioeconomic groups of consumers.

Several experiments have been conducted and analysed to discover the effect of added information on electricity consumption. One such experiment was the Sothern California Edison SCE experiment that began in May 1979. Sexton, Johnson and Konakayama (1987) analysed the data from the experiment using Analysis of Covariance (ANCOVA) framework. The aim was to determine if the Continuous-Display-Electricity-Use-Monitor (CDEUM) assisted in the conservation decision, whether it complemented the TOU program in load shifting, and whether

the effectiveness of the CDEUM was influenced by the TOU program.[18] They report that, on average, households with the information unit decreased their electricity consumption by 5.5 per cent more than the homes without the monitor. Households with CDEUM installed and on a TOU pricing plan other than the plan with the highest price difference did not shift their consumption more on average than those on the same plan with no CDEUM. However, the group with the highest Peak/Off-peak ratio did respond by shifting their consumption to the cheaper period. The conclusion they come to is that the improved monitoring was more effective as the price difference increased. Since they do not prove a causal relationship between having CDEUM and usage it is just as likely that the monitor actually complements the inter-temporal-electricity-substitution decision.

Brandon and Lewis (1999) conduct and analyse an experiment with 120 households in Bath, UK to investigate the effect of information feedback on electricity consumption. In the experiment the participants were spilt into 7 groups, each receiving different amounts of information. The first group simply received a letter comparing the last billing period to the weather-corrected billing period from the last year. Group 2 received the same as group 1 plus quantity data in kWh and the monetary value of the usage. Group 3 received the same information as previous groups plus limited information on the environmental effects of electricity consumption. Group 4, received the same information as previous groups as well as detailed literature on environmental effects. Group 5 received identical information to the other four groups and on top of that a pamphlet with tips on how to save electricity. Group 6 got computer software to monitor and compare in great detail current and past consumption. Group 7 was a control group and did not receive any information feedback.

The approach taken in the paper to analyse and determine the effects of improved information is a multiple OLS regression with kWh as the dependent variable. To begin, historic electricity demand is analysed. Before the experiment started, the following variables had an effect on daily consumption: income, age of respondents, and the number of people in the household. Tenure (i.e. rent or own) was also a contributing factor in explaining the variance in electricity demand. People living in a local authority (public housing) house used the least electricity followed by

[18] CDEUM is a monitor, which continuously updates the current usage of electricity. It is a unit, very similar to the smart meter and makes it easy for customers to monitor their electricity consumption in real time.

those renting, mortgage and owner occupants, respectively. Using control variables that indicate wealth such as income and tenure can be rationalized using neoclassical consumer theory, as budget constraints restrict poorer agents to consume less of everything and electricity is only one of a few goods in the model.[19] In the second stage of their analysis they check what factors contributed to conservation during the experiment.

The variables that were historically significant determinants of consumption did not have an effect on the change in demand during the experiment. The authors seem a little surprised over the finding, however, there is a logical explanation. Since the wealth, age and household size of the occupants might only have changed marginally over the two periods, again, theory would suggest that they had already adjusted their consumption before the trial and the information would only induce them to make changes on things that they did not know before, and this applies to all groups, wealthy or not. The information feedback only had an effect for the group with the most advanced form of information feedback (computer), those in the group that received a leaflet did not respond, on average.

Faruqui, Sergici and Sharif (2010) review a dozen experiments that involve an In-home-Display (IHD). IHD is a real time electricity monitor very much like the CDEUM. On its own, the IHD can help people monitor and adjust their usage. When such a display is available to customers on a time-variant rate it can improve their ability to shift consumption by adding to their information pool. IHD has been installed and implemented by a few commercial electricity retailers around the world and in some cases electricity is sold in prepaid form.[20]

Over 20% of Northern Ireland Electricity customers currently have an IHD and pay for their electricity in advance. Some of the customers on such terms have received some training in how to conserve electricity and, on average, customers who received training and had IHD reduced their consumption by 11%. The customers who did not receive training reduced their consumption by 4%. The difference in response suggests that a real-time display in association with education results in a greater ability to conserve electricity. When looking across all the experiments in the paper it is clear that IHD on its own helps with conserving electricity. In fact,

[19] For more discussion on neoclassical consumer theory and budget constraints see any intermediate economics text book, for example Varian (2003)

[20] The prepaid electricity scheme is equivalent to the prepaid mobile plan, where customers pay first and then use the commodity.

on average, households who actively use their IHD reduced their electricity consumption by 7%. What is even more interesting is that customers who actively use their IHD and are on a prepaid plan could reduce their consumption by 14%. Finally, while the IHD helped with conservation, the authors argue that the IHD could complement a time-variant tariff and that a mix could potentially be more effective than either on its own. Despite the logic of real-time monitoring assisting with shifting consumption from one time period to the other, too few experiments exist where a time-variant tariff and an IHD have been combined to confirm the hypothesis.

While providing the customers with good information is crucial in any time-variant tariff system, it is not necessarily crucial for the time-of-use decision made by households. However, it could inform them of the increased savings they could potentially make during the day. The effect from improving information seems to be effective. The effect from basic forms of information such as pamphlets with electricity savings tips are unclear, while the most advanced, detailed information seems to have a definite effect. Improved usage or cost information seems to be a logical add-on if the goal is to decrease peak usage. Peak load pricing as a welfare generating and peak load reliving mechanism is less effective without detailed information on prices to consumers.

2.3.2 Time-Variant-Pricing Experiments

Caves and Christensen (1980) presented an econometric methodology for the purpose of estimating elasticities for household electricity usage by time-of-use. The method suggested is based on neoclassical consumer theory. Due to the fact that very little information usually exists about household expenditure on goods other than electricity services, they argue that it is desirable to analyse the time of usage response in stages. In the first stage they obtain the partial price and substitution elasticities using the time of usage data only. In the second stage, if existent, survey data can be employed to convert the partial elasticities into total price and substitutions elasticities. The method has since been applied and developed further. In estimating the Constant Elasticity of Substitution (CES) model they find that the partial Elasticity of Substitution (EOS) for a 1977 experiment in Wisconsin falls in the range of -0.09 and -0.17. The EOS is important to compute since it provides a measure of the shift of consumption from the high demand peak period to the relatively low demand off-peak period. Therefore EOS of -0.09

suggests that for a one dollar change in the ratio of peak to off-peak price the ratio of peak to off-peak consumption drops by 0.09.

Based on that approach Faruqui and Sergici (2010) summarize and compare 15 dynamic pricing experiments. On average, every pricing plan; TOU, PTR[21], CPP and RTP did have an effect and the groups, regardless of price plan, with some form of enabling technologies reduced their usage more than the households without the enabling technologies.[22]The CPP plan was the most effective policy in order to reduce critical peak demand, on average, reducing peak consumption by 17%, and when enabling technology was added the reduction was on average 36%. The TOU program, on average, reduced peak consumption by 4% making it the least effective of all the plans without enabling technologies. However, when enabling technologies were added as a complement to the TOU peak consumption fell by 26% on average.

The response to the time-variant rate varied also across experiments that had similar tariff design. That is, in some experiments that had the same tariff design some experiments revealed higher response rates than others.[23] Elasticities estimates of the experiments find that own price elasticities vary from -0.02 to -0.10 and substitution elasticities vary from as little as -0.07 and up to -0.40. The factors that tended to be most influential in determining elasticities were enabling technologies and if air conditioning was a part of the household's appliance stock. As the authors point out, there is a problem with the cross-experimental comparison. First, the heterogeneity of the experimental design makes them hard to compare directly. The different demographics and geographical locations of the participants in each experiment also make them difficult to compare. They suggest pooling the most homogeneous studies from their survey and investigating the effects based on that sample.

Pooling together homogenous experiments has been done previously by Caves, Christensen and Herriges (1984). In the 1984 paper "Consistency of residential customer response in time-of-use electricity pricing experiments" they aggregate five experiments with similar experimental

[21] A PTR is a modified version of the CPP rate. Instead of increasing the price during peak hours the PTR offers significant rebate for the customers who reduce their consumption during the peak periods.
[22] Enabling technologies are any technologies that help with the load shift such as automated technology that turns of electricity intensive appliances when a defined peak period starts.
[23] Two experiments that both were testing the response of a TOU plan found different response rates. This is not surprising since no two experiments are the same and variables such as geographical location and attitudes, amongst other things, tend to affect the responsiveness.

design. The question they hoped to answer was: is the customer response consistent across the different experiments? By controlling for other influential factors such as income, climate and appliance ownership they conclude that the response is consistent over the experiments and that the elasticity of substitution in the summer months of July and August varies from -0.07 to -0.21 depending on the stock of major appliances in the household's portfolio. Another interesting finding is that customers with a large appliance stock tend to be more influenced by their climate and that the response to climate by people with relatively large appliance stock tends to be larger.

Newsham and Bowker (2010) review 22 recent pricing pilots, many of which had been employed in the search for the effects of dynamic pricing by previous researchers. An important observation put forward is the need to be careful when comparing different studies due to methodological differences. According to their findings the CPP design is superior to the other rate designs in relieving the peak load. CPP on its own can be expected, without great inconvenience to the customers, to reduce peak demand by at least 30%. The effectiveness of the TOU rate design had the ability to reduce peak demand by 5%, on average, in the long run.

The French electricity utility, Electricité de France (EDF) has been innovative and experimented with peak load pricing. At the end of the 1980s they conducted an experiment that was later analysed by Auben et al. (1995). The experiment tested a rate design that would best fit the CPP profile. What the paper adds to the literature is of course an analysis of new experiment where the participants, as in most CPP pilots, greatly reduce electricity usage during peak days, supporting the ability of the rate design to improve peak load conservation. The other interesting finding in the paper is that participants are slow to readjust their electricity consumption after the peak days are over, leading to electricity conservation for a short while after the expensive days pass. The consumers also have a tendency to increase their electricity consumption just before the peak days. That is in fact reasonable since they receive a notice before the price rises on the peak day and perhaps make the most of the current, cheaper, time period just before the price rise and execute tasks that would have cost them much more on the more expensive day. Hence, substitute from the dearer peak period to the cheaper off-peak period.

A few years ago the Baltimore Gas and Electric Company (BGE) carried out an experiment in the mid-Atlantic region of the US. Over 1,350 participants opted into the Smart Energy Pricing (SEP) pilot. Three different rate designs were offered to the customers; two rate designs were of

the Peak-Time Rebate (PTR) nature, one with high a rebate and the other with a smaller rebate. The other design offered was a Dynamic Peak Pricing (DPP) rate design. Under the DPP design the subscribers of that rate would face peak prices between 2 pm and 7 pm on all non-holiday weekdays and off-peak prices for other hours of the day. However, 12 days of the year were critical peak days where prices would be significantly higher, therefore making the design a combination of TOU and CPP design. 350 customers were not aware of the experiment and used as a control group. Previous studies had confirmed the existence of load shift by customers, and therefore the existence of the effect of a dynamic rate design was not the main point of interest, rather the magnitude in this particular location.

Faruqui and Sergici (2011) analyse BGE's Smart Energy Pricing pilot in order to determine the substitution effects from the variable rate designs. The substitution elasticities support the claim that customers shift load in the face of dynamic tariffs. They find an average EOS of -0.1 and that suggests that, on average each 1% increase in the price ratio resulted in a 0.1% decrease in the peak to off-peak consumption ratio. Since the price ratio is simply, $\frac{p_{peak}}{p_{offpeak}}$, a one percentage increase in the ratio must reduce the consumption ratio, $\frac{q_{peak}}{q_{offpeak}}$, by 0.1%. Hence, either the usage during the peak (off peak) hours must decrease (increase) or some combination of the two in such way that the consumption ratio decreases by 0.1%.

Information and enabling technologies were provided to some participants to investigate the impact of the two on the substitution decision. The information was in the form of a lamp that showed certain colours when prices were low or high. The technology provided was a gadget that was added to air conditioners and turned them off during peak hours. Both information and the technology reinforced the rate designs and increased the absolute value of the substitution elasticity to -0.18, a major improvement. The technology was fairly simple, cheap and did not require much added effort by the customers, however, the loss of air-conditioning during warm days could have caused disutility for some participants.

In the North American city of Chicago, the Centre for neighbourhood technology (CNT), a non-government organization initiated a dynamic pricing experiment to investigate peak-time conservation. The utility Commonwealth Edison partnered with CNT. They recruited 693 households, including a control group. The participants were assigned a RTP rate where prices

varied on an hourly basis. The price paid by the participants was the expected hourly spot price plus a distribution charge less compensation for participating in the program. The formula used to calculate the rate is summarized in equation 2.9

Equation 2.9: Time-variant rate in the Edison-CNT experiment

$$p_{ht} = p_{ht}^{DA} + D - PI \tag{2.9}$$

- p_{hd} = price per kilowatt hour (Kwh) at hour h and day t.
- p_{hd}^{DA} = day ahead hourly wholesale price per Kwh.
- D = fixed distribution charge.
- PI = participation incentive.

In order to estimate the welfare gain from the experiment Allcott (2011) derives demand functions from an indirect utility function of a Gorman form. One problem with using the Gorman form is that the wealth (or income) effect on demand turns is zero. The author argues that, due to the relatively small share of income that is allocated to electricity, this might not be a troublesome assumption. However, in some markets electricity is a significant proportion of the household's income. For example in the sample from the Auckland experiment, on average, the expenditure share of electricity is 2.2% of income. This is small when considering the average, however, the share is obviously higher for some low earners and can be a significant cost factor for households in the lower income brackets.[24]

Alcott finds that participants respond to the program by conserving electricity. However, they fail to show substitution from expensive to cheaper hours of the day. Instead, participants consume less during expensive hours and do not increase their off-peak consumption by any significant amount. Alcott cleverly argues that despite the failure to show increase in consumption in the off-peak hours households might have made "some investment that conserves energy during all hours by some constant amount, which if combined with a second change that shifts some consumption from afternoon to night time hours [cheaper periods] would make it appear as though no change had occurred at night" (Allcott 2011, p. 833).

[24] The income share of electricity is calculated as the expenditure on electricity divided by the household income. Therefore, a household with average electricity needs and earns half the average income is going to have electricity income share twice the size of the average household.

The author estimates the consumer benefit from the experiment. Having a defined utility function this was a straight forward task and on average the consumer benefit was estimated at US$10 per year. However, the actual savings compared to a fixed rate reveals a US$13 savings per household or a 2.7 per cent reduction in the power bill.

What is not accounted for when computing the consumer benefit is the net change in externality associated with reduced need for peak production. While this experiment on its own is probably too little to reduce peak production by any significant amount, if the rate design would have been implemented on a large scale there would have been some positive externality associated with the reduced need for producing electricity to meet the peak demand. Not accounting for the change in pollution might actually undervalue the consumer benefit. Finally, the producer benefit is left out, and if demand was shifted from the peak period it must have saved the electricity retailer by reducing his need to purchase expensive electricity in the spot market as he would have needed to do without the program. For those reasons and more, the total welfare could, potentially, be greater.

There is plenty of evidence in support of most dynamic pricing systems in the North America and Europe. However, not much work has been done in this area in New Zealand and it is not possible to conclude from the foreign analysis the magnitude and the existence of the benefit in New Zealand. The main reason being that New Zealand, and in this case Auckland, has almost no need for air-conditioning, and to some extent different climate, demographics and culture than the countries where most of the research so far has been focused on.

3 THE NEW ZEALAND CONTEXT

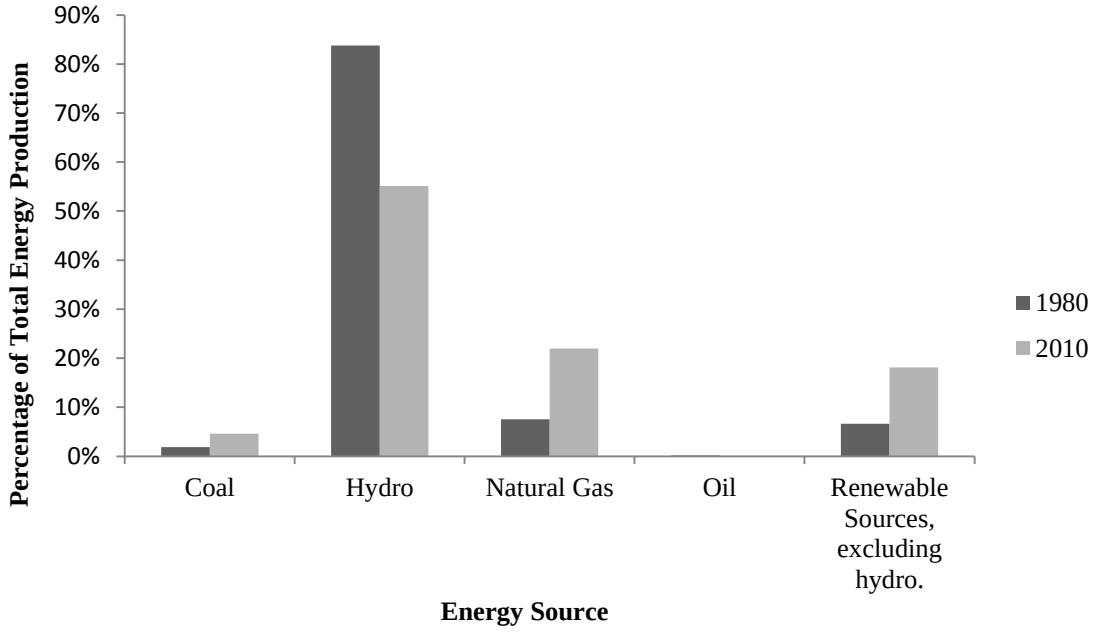
This section is for readers with little or no knowledge of the New Zealand Electricity market. The features that characterize electricity consumption in New Zealand will be explained with emphasis on the household sector in Auckland. Characteristics of Auckland's electricity consumption related to heating and cooling will then be explained. The last part of this section will give insight into the New Zealand electricity market today

3.1 Electricity in New Zealand

Reefton became the country's first town to have its own public electricity supply in 1888. In 1889 Wellington followed and for the rest of the 19th and most of the 20th centuries the New Zealand Government supplied and managed all electricity services. In 1978, generation, transmission, policy advice and regulation were the responsibility of the Ministry of Energy's Electricity Division while the Electricity Supply Authority was responsible for Local Distribution and Supply. In the 1980s major reviews and reforms were made and eventually the system was liberalized. Today there are several electricity retailers competing in the market. Some of these are only in the business of retailing electricity and others are parts of companies that generate and retail, and are sometimes referred to as 'gentailers'. The national transmission grid is operated by the state owned enterprise TransPower.

In 1980 more than 90% of all electricity produced in New Zealand came from renewable sources. For the next 20 years that share shrunk and in 2010 renewable energy as a share of total energy production in New Zealand was down to 73%, still a large proportion relative to most developed countries. For example, the US and UK produced only around 10% and 7%, respectively, of their electricity from renewable sources in 2010. Over the 30 years between 1980 and 2010 electricity consumption in New Zealand almost doubled; natural gas along with new hydro and geothermal generators have been developed to meet the growing demand.

Figure 3.1: Energy sources for electricity in New Zealand 1980 and 2010



Source: World Bank (n.d.).

3.2 What Makes New Zealand Different?

New Zealand is a developed, high-income country and households use appliances similar to those in other countries in that category. What differentiates New Zealand from many other countries where peak-load pricing experiments have already taken place and been analysed is its climate: summers are temperate and winters are mild and average temperatures vary from the north to the south. For example the annual average temperature in Auckland for the period 1971–2000 was 15.1°C while in the south Dunedin's annual average temperature was only 11.0°C.[25] What this means is that very few days of the year require electricity for cooling homes in Auckland or the rest of the country. If we use ATL's[26] (the UK's Association of Teachers and Lecturers) indoor temperature recommendation of 18 degrees, then every month of the year except the first three would require heating on some days in Auckland. May through September

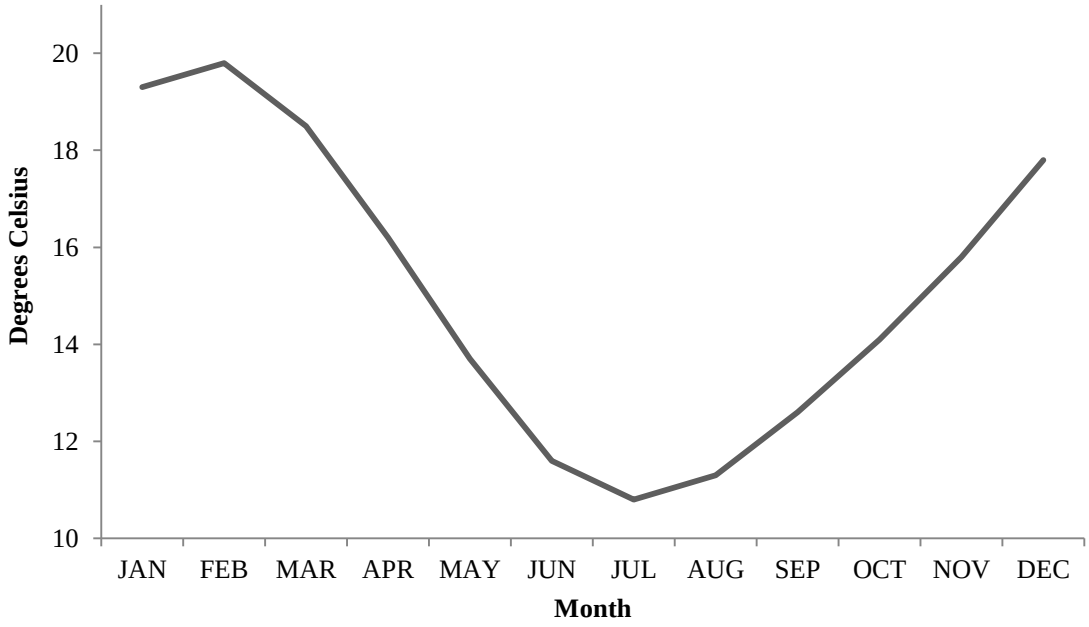
[25] In July, the coldest month of the year the average temperature for Auckland over the period 1971-2000 was 10.8°C. The Average for the warmest month February was 19.8°C. for more information on the New Zealand climate see: http://www.niwa.co.nz.

[26]See: http://www.atl.org.uk/health-and-safety/work-environment/temperature.asp

are the coldest months of the year where the daily minimum temperatures can drop well below 10 degrees while the daily maximum temperatures around and above 15 degrees are common.

The result of the variable winter temperatures in Auckland is a difficult-to-predict change in electricity demand for heating homes and offices. Another interesting problem when it comes to heating homes in Auckland, and New Zealand in general is the variability in temperatures even over a single day. It is not uncommon for temperatures to drop fast making the timing of the heating even more unpredictable. Not all heating is achieved through electricity and some homes use gas, log burners and other technologies to heat their home. However, a large proportion of homeowners depend to a significant extent on electricity to heat their dwellings.

Figure 3.2: Average temperatures in Auckland, 1971 – 2000



Source: National Institute of Water and Atmospheric Research (n.d.).

Finally, temperatures and electricity demand can vary considerably across years. For example the winter of 2009 was colder than in 2008 and, as figure 3.3 shows, electricity demand, in gigawatt hours (GWh), at Otahuhu was much higher in 2008 than in 2009. While weather is not the only factor contributing to the difference in demand between the years, it is a significant factor.

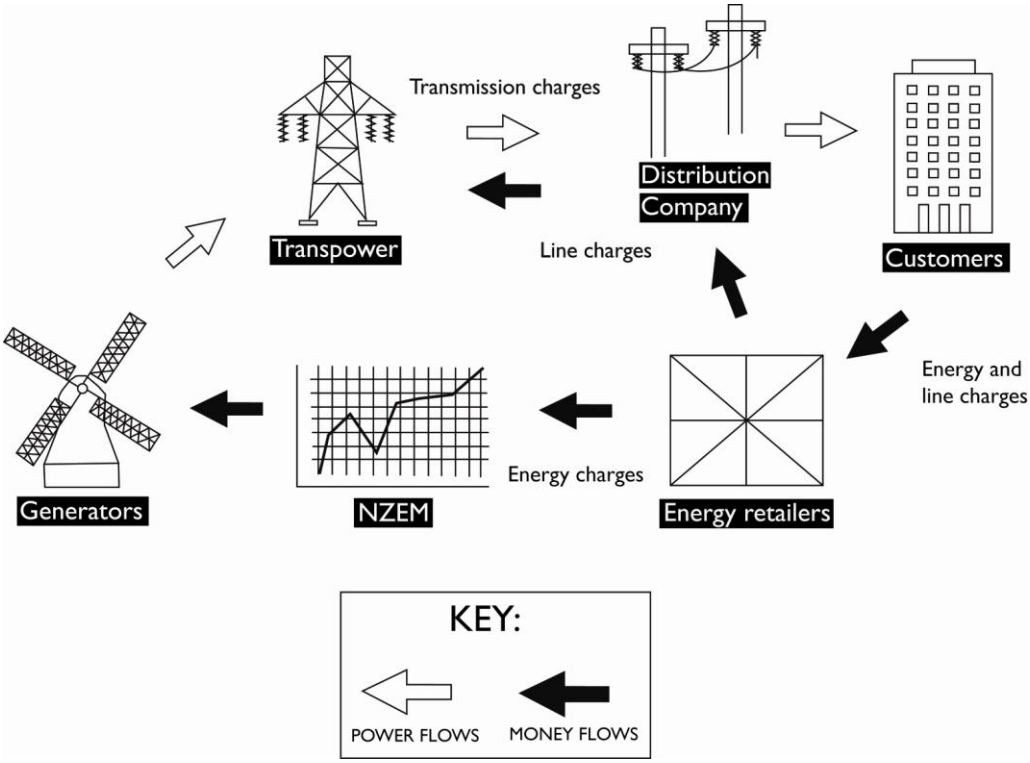
Figure 3.3: Two weeks moving average electricity demand by grid exit point, Otahuhu

Source: Electricity Authority (n.d.).

3.3 The New Zealand Electricity Market Structure

The mechanics of the New Zealand electricity market are fairly simple and standard. Generators produce energy, mostly from hydro or other renewable sources. The electricity is then transferred using the national grid, operated by the nationally owned Transpower company. At the receiving end is the local distributer who delivers the electricity from the grid exit point to firms and households in their city or town. In order for the distributer to have electricity to deliver to customers, the energy retailer needs to buy electricity from the wholesale market. Generators supply the market. Retailers pay for electricity and the services provided by the distribution company who pays Transpower for using the national grid. Finally, the customers pay the retailer which makes up the retailer's revenues. Figure 3.4 gives an example of how the process described works.

Figure 3.4: The flow of electricity and payments in New Zealand



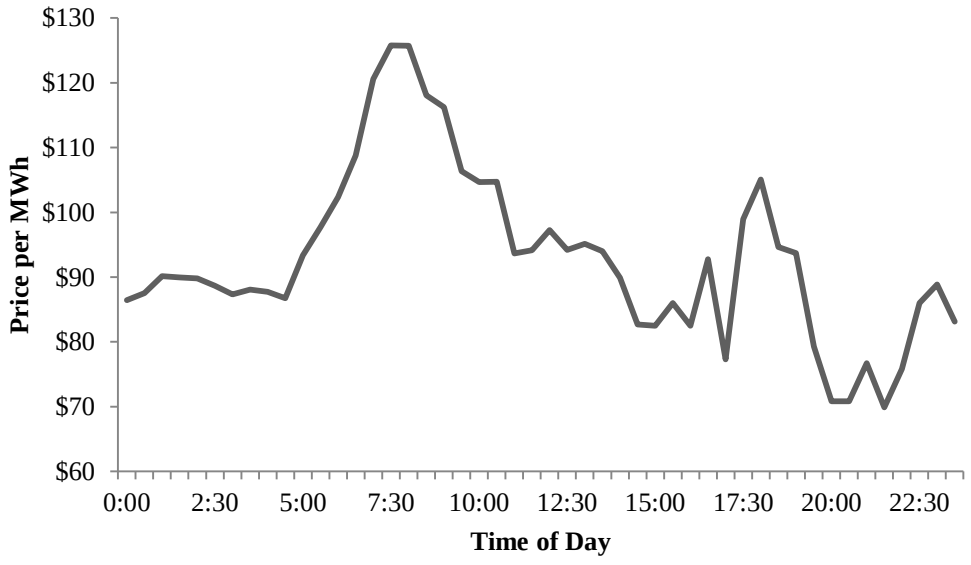
Currently there are restrictions to vertical ownership within the New Zealand electricity market. The laws are designed to protect consumers. Firms can either generate and retail electricity or distribute it. If a firm is a distributer it is not allowed either to generate nor retail electricity. This is done to make sure that competition is present in the retail market and to make sure no retailer has a monopoly over certain segments of the market. There are several retailers in the Auckland area, some of the retailers are also generators, producing for them self and selling electricity to other retailers through the wholesale market.

The price paid for electricity in each trading period by retailers is determined by supply and demand in the wholesale market, better known in the literature as the spot market. Each trading period covers half an hour, every day, all year. In the spot market generators offer to generate an amount of electricity at a certain price. Each generator is allowed to make up to 5 offers in each trading period. These offers, effectively, make up the basis of the market supply. The system operator, Transpower, forecasts demand for the next half hour. The marginal offer determines

the wholesale price. The price information is then pooled by Transpower and run through the Scheduling, Pricing and Dispatch Model to deliver accurate prices to market participants.

In all, the retailers cost of delivering electricity to their customers is made up of the cost of using the distributer's network—the network pays Transpower for using the national grid to get the electricity from the generator to the distributers—and the spot-electricity price established in the wholesale market. Since both supply and demand are volatile, the retailers marginal cost can vary by significant amounts over the course of every day. Half hourly data from the 20th of July 2012 has been plotted in figure 3.5. The spot price varies from $125.78 to $69.88 per MWh (or from roughly 7¢ to 12.5¢ per kilowatt hour) at 7:30 and 21:30 respectively. One probable explanation of the high price in the morning is that many households turn on heating in the morning and businesses are starting their day.[27] There is also a smaller up-tick in prices around the time that households arrive home from work and turn on appliances. At night prices are usually low since most households and businesses are simply asleep.

Figure 3.5: Half hourly spot price for Otahuhu.



Source: WITS (n.d.).

[27] Since most households wake up at the same time and cook, take showers at the same time there is inevitably going to be a jump in demand during the mornings.

On the receiving end of the power line is the user who is either a firm or a household. The price they pay for electricity on daily and hourly basis is quite different to the one that the retailer pays. Some larger firms do pay the spot price plus some mark-up and therefore pay a dynamic rate over the day just like the retailers. There are some customers who are currently on a TOU or CPP plan where they pay more (less) during some predefined peak (off-peak) period. However, most customers, and certainly most households, pay a flat rate. A flat rate is a rate that does not vary over the day, or the month and is therefore time-invariant.

As a result of the different marginal cost structure for the retailer and the customer, New Zealand could suffer from a peak-load problem. The reason being, the marginal cost for the retailer varies over the day while the price paid for the service from the customers is flat. This could potentially cause over-consumption during peak hours and under-consumption during off-peak hours in New Zealand.

4 DATA

This chapter describes the data employed in the project. The first part of this section will detail how the data came to exist and the second part will discuss the potential problems with the data. The methodology will be detailed in chapter 5.

4.1 The Experiment

As of August 2007 Metrix, the metering arm of Mercury Energy, had installed advanced meters in about 4,000 homes in the area of Pakuranga in Auckland. The advanced meters differed from the traditional meters in the way the retailer was able to monitor individual household consumption. While the traditional meters had to be read at their physical location by a retail company staff member, the advanced meters sent half-hourly readings to the company through wireless technology.

Early in 2008, Mercury Energy invited 1,400 of those households to participate in a TOU pricing experiment. After 400 households had been recruited, the search for new participants ceased. These 400 households opted into the study; Mercury did not require any household to participate. This is important because TOU pricing will most likely be added as an option to existing pricing plans. Any household who opted in to the experiment could opt out any time, and some did. No additional households were recruited or allowed to opt in after commencement of the experiment. The experiment started officially on 1 August 2008 and ended 31 July 2009. The households that volunteered to take part were surveyed in June 2008 before the experiment began and again in August 2009 after it had ended.

Two Surveys—one conducted before the experiment (pre-survey) and another after (post survey)—were carried out by professional staff employed by a market research company. The surveys' goal was to collect data on characteristics of the house (the dwelling of the participants) including energy using appliances, household energy behaviours, demographics and householder attitudes toward energy and the environment. For the purpose of this research selected variables from the survey will be used in the analysis. Not all of the recruited households responded to the post survey.

Each of the 400 households was assigned randomly by Mercury Energy staff into one of four groups:

(1) Information only (info): a group that received a statement every month explaining their daily energy consumption but faced the same price all day.

(2) Low price difference (low): a group that had a relatively low difference in peak and off-peak prices (4¢).

(3) Medium price difference (medium): a group that had a larger price difference than the second group (10¢) but smaller than the fourth group.

(4) High price difference (High): a group that had a relatively high price difference (20¢).

Mercury Energy also provided price and consumption information for 55 customers in the same neighbourhood to serve as a control group. The households in the control group were unaware of the experiment and therefore did not participate in any surveys; the house and household characteristics of the control group are unknown.

Any household that was listed as a commercial/industrial property or as a Life Style Block was excluded from the analysis. Of the 400 initial participants, 334 remained in the study throughout the duration of the experiment and 302 participants answered the post survey. The data set I received had already been reduced by a further 10 due to problems with the data. This left data from 292 households with which to determine the effect of the different pricing schemes on consumption. The final distribution of the participants into the four experimental groups and each group's price schedule is set out in table 4.1.

Table 4.1: Peak and off-peak price difference by groups

Group	Number of Households	Price Difference per kWh
Control	52	$ 0.00
Info	74	$ 0.00
Low (4¢)	64	$ 0.04
Medium (10¢)	77	$ 0.10
High (20¢)	77	$ 0.20
Total	344	

The peak/off-peak price differential in each group was the same but it is worth noting that not every household in a given group paid exactly the same price. This is due to the structure of the conventional pricing plans offered by the electricity provider. Households pay a fixed daily tariff varying around a dollar and also a price per kilowatt hour. The customers can choose whether they want to pay a higher daily fixed tariff and a lower variable tariff, or vice-versa, or an average of the two. Table 4.2 shows all the variable prices in the groups.

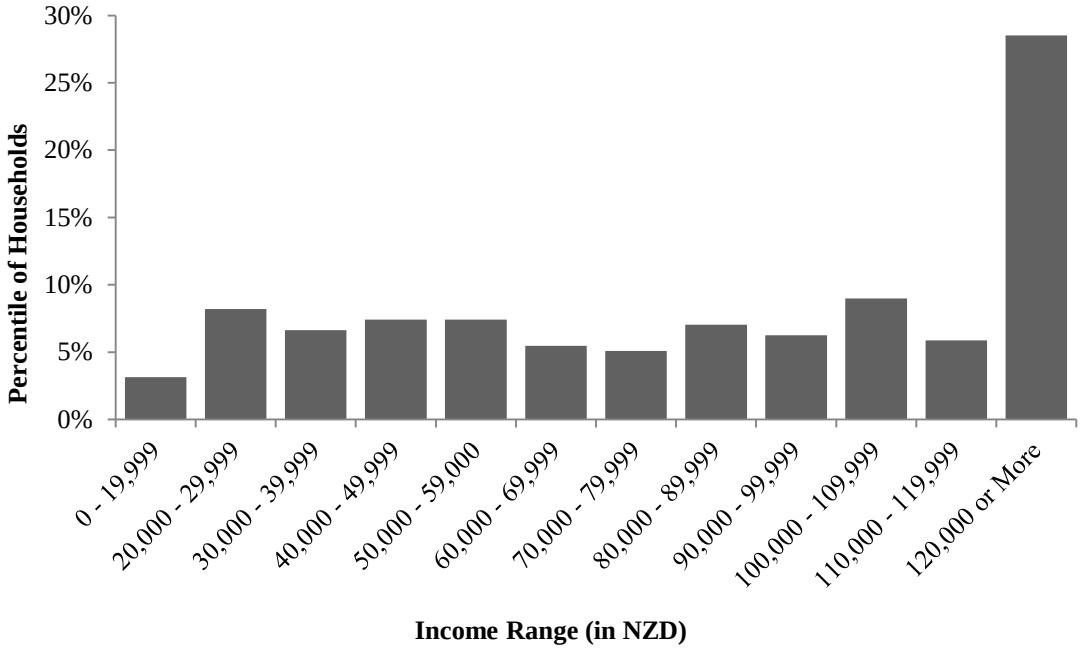
Table 4.2: Prices per kWh within and between the groups

Group	Number of Households	Peak Price(c)	Off-Peak Price(c)
Info Only	4	17.31	17.31
	27	17.78	17.78
	5	19.31	19.31
	30	20.77	20.77
	8	22.30	22.30
Low	1	20.23	16.23
	56	20.29	16.29
	7	20.47	16.47
Med	2	24.00	14.00
	12	24.06	14.06
	2	24.24	14.24
	36	24.52	14.52
	25	25.03	15.03
High	1	30.27	10.27
	8	30.33	10.33
	1	30.51	10.51
	43	30.79	10.79
	24	31.3	11.3

4.1.1 Demographics and Dwellings

The sample of households in the experiment is not highly representative of the New Zealand population. However, the sample is arguably representative of the 'meat of the market' in the sense that the households are located in the largest city, have relatively high incomes and live in relatively new and well insulated houses. The median household income in the sample lies in the range $80,000 – 90,000 per annum (before tax) well above the national median of around $66,000 in 2008 when the survey was conducted. Another interesting income statistic in this sample is the whopping 28.5% of the households in the sample that have a combined income of more than $120,000 per year. Figure 4.1 shows the income distribution of the sample.

Figure 4.1: Income distribution of sample households

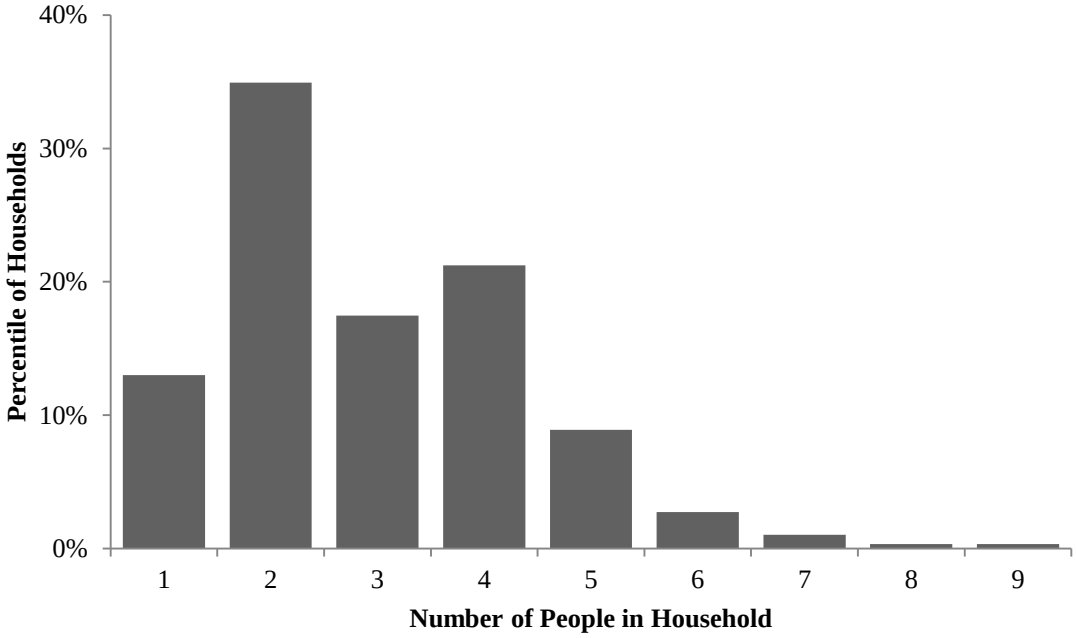


Source: Statistics New Zealand (2006).

On average the households in the sample are made up of around 3 people. Over 86% of the households had 4 or less people, and 47% were made up of two people or less. By far the largest single household combination was two people. The average age of the first and second household member in the sample was 50-54 years, well above the national average at the time. And the third member average age was between 10-14 years.

As expected for working people, on average, the first three household members spent between seven and eight hours away from home each day. If households had more than three members, the extra household member would usually be younger and spend more time at home.

Figure 4.2: Household sizes before the experiment started

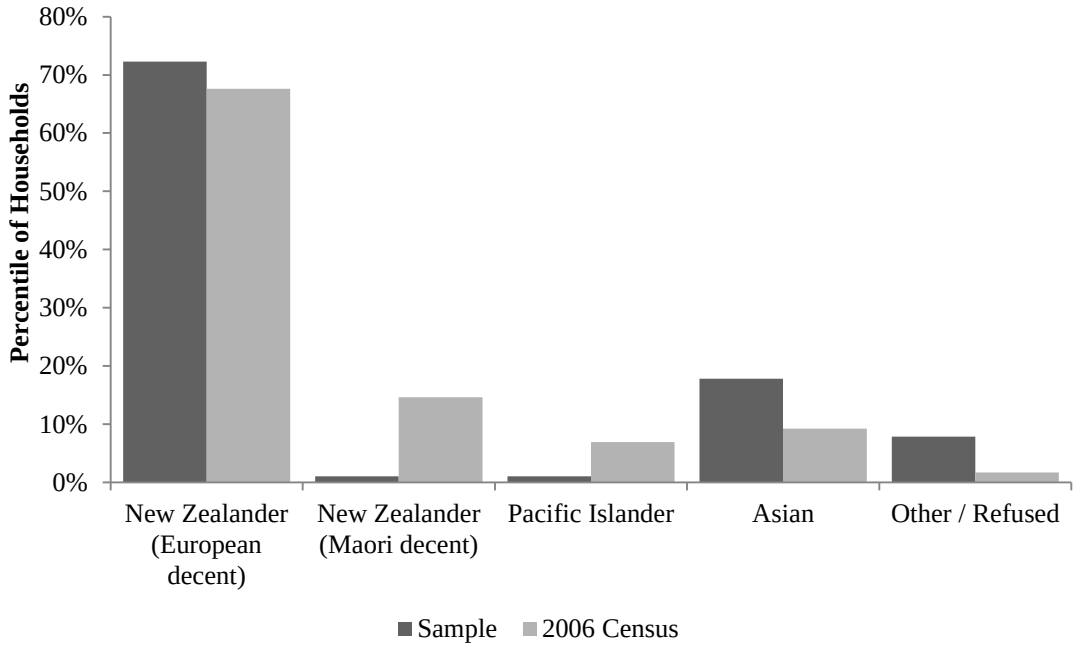


Source: Statistics New Zealand (2006).

The sample was heavily populated with New Zealand people of European descent, and Pacific and Maori people are underrepresented in the sample, making up only around 2%. The Asian population is also overrepresented in the sample compared with Statistics New Zealand's Census (2006).

More than 78% of households in the sample had at least one household member fully- or self-employed. No household in the sample had all members of the household unemployed, and only 10 out of 859 people in the survey were temporarily unemployed. 32% had at least one person in the household retired, higher than the average.

Figure 4.3: Sample population compared with Statistics NZ 2006 census

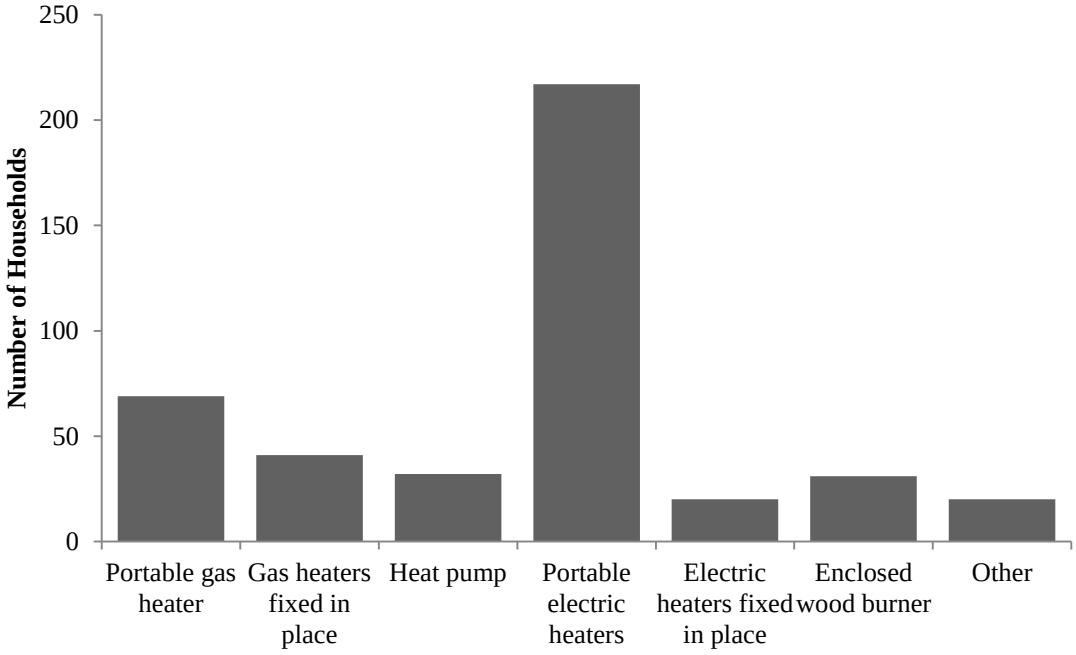


Source: Statistics New Zealand (2006).

The dwellings of the participants in the sample were fairly new and large; on average the houses were built in the 1990s with floor area of 190 square meters. 96% of the dwellings in the sample were single units not connected to another property. Only 5% of the sample rented their dwelling while the number of people who owned their property with or without a mortgage was almost the same.[28] Many participants used a combination of different technologies to heat their homes. The most common heater was a portable electronic heater, with over 217 of the 292 households using that either as a primary heater or as a complement to another heater. Gas heaters, either portable or fixed in place, were also being utilized in many of the households. Around 10% of the sample had and actively used a wood burner to heat their homes; fewer than 11% of the homes had and used heat pumps to heat their homes.

[28] 137 people owned their property debt free while 139 people owned their property with a mortgage.

Figure 4.4: Heater types in dwellings



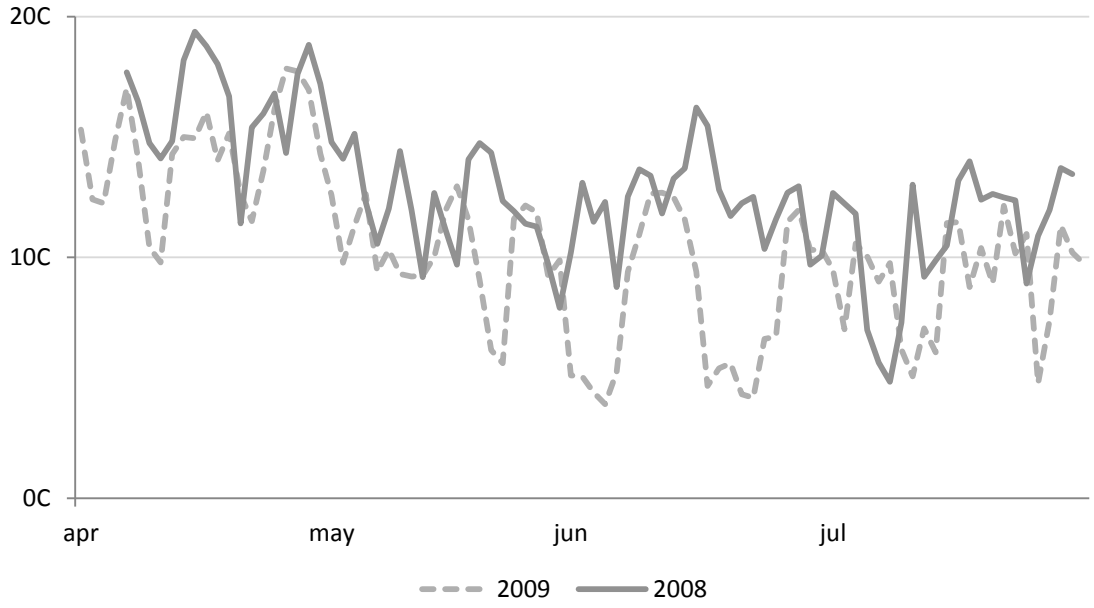
To summarize, on average, the households in the sample tended to be relatively wealthy middle aged New Zealand European couples, who heat their relatively new and decent-sized home with portable electronic heaters and have one teenager in the house.

4.2 Quantity and Temperature Data

The TOU pricing schedule is very simple. The peak period ran from 7 am to 7 pm on non-public-holiday weekdays for one year from 1 August 2008 to 31 July 2009. All other times were off-peak. Mercury staff supplied daily peak and off-peak consumption and price data from the year before and the year of the experiment. Temperature data was obtained from the nearest weather station through the National Institute of Water and Atmospheric Research (NIWA) data base. The mean temperature over the day has been computed by averaging the daily maximum and minimum readings.

Figure 4.5 shows that temperatures during the experiment (in 2009) were on average lower than 2008. Since this might pose a problem when analysing the experiment daily mean temperature will be controlled for in every model used to analyse the experiment.

Figure 4.5: Mean temperatures at the nearest weather station in 2008 and 2009



4.2.1 Overview and Problems

In the empirical literature on electricity peak-load and marginal cost pricing experiments, there is very little emphasis on the practical problems that may and do arise over the course of these experiments. This section summarizes the original data and discusses the issues the data raise.

We expect seasonality in the response to time-varying prices. Electricity consumption rises as temperature falls with the approach of winter. Data are analysed from early autumn into mid-winter (April through July) in 2008, the year before the experiment and 2009, the year of the experiment. It would seem more natural to extend this time period through winter, i.e., through September. However, the experiment began 1 August 2008 and ceased 31 July 2009. So we lack data from a continuous winter-time interval, and the response at the beginning of the experiment may differ from that at the end. It seems preferable to look at data from the end of the experimental period as households will have had time to make adjustments in response to prices.

While it might seem unorthodox to report regression results in section describing the data, the results motivate discussion of data issues. The regression specification reflects a standard differences-in-differences approach using Ordinary Least Squares (OLS). The dependent variable is non-holiday weekday peak or off-peak consumption in April through July. The

explanatory variables are dummy variables for each of the four experimental groups (the reference category is the control group), a dummy for the year 2009 (the reference category is 2008), year-group interactions and mean daily temperature. The equation that was estimated is shown in equation 4.1 and the results are shown in in table 4.3.

Equation 4.10: Average year-on-year differences in electricity usage by groups

$$q_z = \delta_0 + \gamma_0 MEANTEMP + \alpha_1 INFO + \alpha_2 LOW + \alpha_3 MED + \alpha_4 HIGH + \beta_0 D2009 + \beta_1 D2009xINFO + \beta_2 D2009xLOW + \beta_3 D2009xMED + \beta_4 D2009xHIGH + e_z \quad (4.1)$$

Where the variables have the following definitions:

- z = Peak, Off-Peak
- q_z is the average daily, weekday, non-public or school holiday quantity of electricity consumed during either peak or off-peak period
- δ_0 is the intercept and can be interpreted as the average daily electricity consumption by the control group at 0°C.
- $MEANTEMP$ is the control variable for average temperature measured at the nearest weather station. γ_0 shows the average change in daily consumption with each one degree increase in mean temperature.
- INFO, LOW, MED, HIGH denote the different groups that the participants were assigned into, they take on the value 1 if the household is a part of the group and 0 if it is not. $\alpha_1 - \alpha_4$ show the difference in average use for each group from control.
- D2009 is a dummy variable that takes on the value 1 for the year of the experiment, 2009. If the year is 2008 it takes on the value 0. β_0 represents the average change in consumption from year to year in the control group.
- D2009xINFO..., D2009xHIGH are interaction dummy variables that take on the values 1 and zero. β_1 through β_4 represent the average daily difference from control in year-on-year change in consumption.

The first regression has daily peak kWh electricity usage (Peak Usage) as the dependent variable while the second regression's dependent variable is daily off-peak kWh electricity usage (off-peak). The independent variables are listed in the first column while the second and third columns show estimated coefficients with standard errors in parenthesis.

Table 4.3: Average year-on-year differences in electricity usage by groups

Dependent Variable:	Peak Usage	Off-Peak Usage
Average daily temperature	-0.4358** (0.0091)	-0.4997** (0.0089)
INFO	0.3978** (0.1429)	0.0002 (0.1396)
LOW	4.5209** (0.1436)	3.2679** (0.1404)
MED	-2.8749** (0.1418)	-2.1935** (0.1386)
HIGH	-3.3588** (0.1415)	-3.5423** (0.1383)
D2009	-0.3621* (0.1562)	-0.0427 (0.1523)
D2009 x INFO	-0.7637** (0.1997)	-0.8479** (0.1947)
D2009 x LOW	-0.3974* (0.2007)	-0.1848 (0.1957)
D2009 x MED	-0.3801 (0.1982)	-0.4177* (0.1932)
D2009 x HIGH	-0.5604** (0.1977)	-0.4635* (0.1927)
CONSTANT	18.6170** (0.1608)	18.5726** (0.1571)
Observations	63,257	63,257
R-Squared	0.1643	0.1444
Number of households	369	369

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

The results from the Peak usage regression show the coefficient on the constant is significant at the 1% level and suggests, at zero degrees Celsius, a daily average electricity consumption of 18.62 kWh by the control group. The coefficient on temperature indicates that consumption falls by about half a kWh with each degree increase in mean temperature.

The coefficient on each of the group dummies is significant at the 1% level for all groups indicating that average consumption differed across groups prior to the experiment. Before the experiment began the households assigned into the Low group had the highest daily usage while the people assigned into the High group had the lowest daily usage.

The coefficient on the 2009 dummy indicates lower daily consumption by the control group in 2009 relative to 2008. This corresponds to the generally milder temperatures in the winter of 2009.

The coefficients on interaction terms tell us how much energy each group conserved on average in 2009 relative to the control. All the groups in the experiment used less electricity in 2009 relative to control. This indicates conservation, on average, as a result either of the additional information households received during the experiment or of simply participating in the experiment. The monthly bill received by households in the experimental groups included a chart that showed daily peak and off-peak consumption over the month. As the experiment had been in effect for at least eight months when the data were collected, it seems plausible that the conservation may be driven largely by the more detailed consumption information in the monthly bills.

On average, we would expect larger reductions in consumption by the groups facing the highest prices. The results seem to tell a somewhat different story. The group assigned the lowest peak price (INFO) surprisingly saves the most during the peak hours. More in line with expectation is that the highest peak prices appear to induce more conservation than lower peak prices. On the other hand, the lowest off-peak prices also seem to induce more conservation than higher peak prices. The results are a mixed bag.

These odd results suggest that there might be a problem with the data and inspire a further investigation into the quality of the data. Potential problems, will therefore be addressed in steps. The potential problems are:

- participants dropped out of the experiment,
- outliers and influential observations,
- unexplained change in usage from year to year, and
- estimated usage data not observed from actual readings

Participants dropped out of the experiment

Of the original 400 households in the experiment 317 (this excludes controls) were in the data set supplied by Mercury Energy. Of those 317 complete survey data were available for only 292 households. Those participants who dropped out did not for the most part appear unrepresentative. However, one group that had more dropouts than the other groups was those that were assigned to the low price difference group. The details can be observed in table 4.4.

Only households that were definitely living in the house before, during and when the experiment finished were included in the final analysis. Because a survey had been carried out soon after the experiment finished there was a way of confirming if the same tenants where staying in the same house for the entire period. Anybody that could not be confirmed as a tenant for both years was therefore excluded from the analysis. This restriction left 292 households to be analysed.

Table 4.4: Number of households that dropped out of the experiment

Group	No. of participants in 2008	Number of dropouts	No. Of participants in 2009
Info	78	4	74
Low	76	12	64
Med	81	4	77
High	82	5	77

Outliers and influential observations

Observations that influence the OLS estimates significantly are referred to as outliers. The outliers can have a large effect on the OLS estimates. A simple rule was developed to rid our data of outliers. Any day where the quantity consumed exceeded 3 standard deviations from the mean was excluded.

As well as daily usage outliers some individual household usage profiles appear suspect. An example of a strange household profile, this one in the control group, is shown in the scatter graph in figure 4.6. The graph is plotted with electricity consumption on the vertical axis and time on the horizontal axis. The graph shows no variation at all in 2008. Figure 4.7 provides a comparison scatter plot of a more typical consumption profile.

Figure 4.6 shows that for the "strange" control household electricity consumption does not vary at all in 2008. If we then compare this with figure 4.7 in 2008 we can see that the typical household consumption, while increasing into the colder months, varies between days and is certainly not constant for the entire time period as for the household in figure 4.6. Most of the households that posed this problem were in the control group. Since all households that did not take part in the post survey had already been excluded and most of the problematic households did not complete the post survey, an additional rule for dealing with them was not required.

Figure 4.7 for the "typical" household exposes another problem. That is the problem of no change in consumption over few days and is highlighted with a circle on the graph. In some cases people might be away from home, for example on a holiday, but in many cases these patterns occurred due to lost meter readings.

Figure 4.6: Peak and off-peak usage for a "strange" houshold in 2008

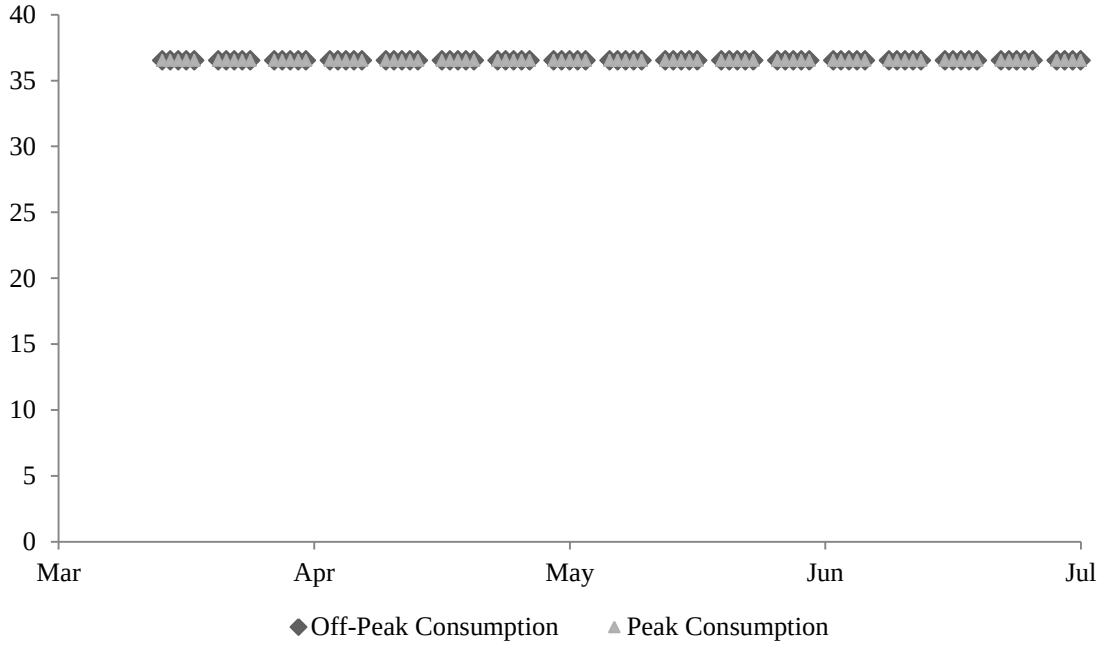
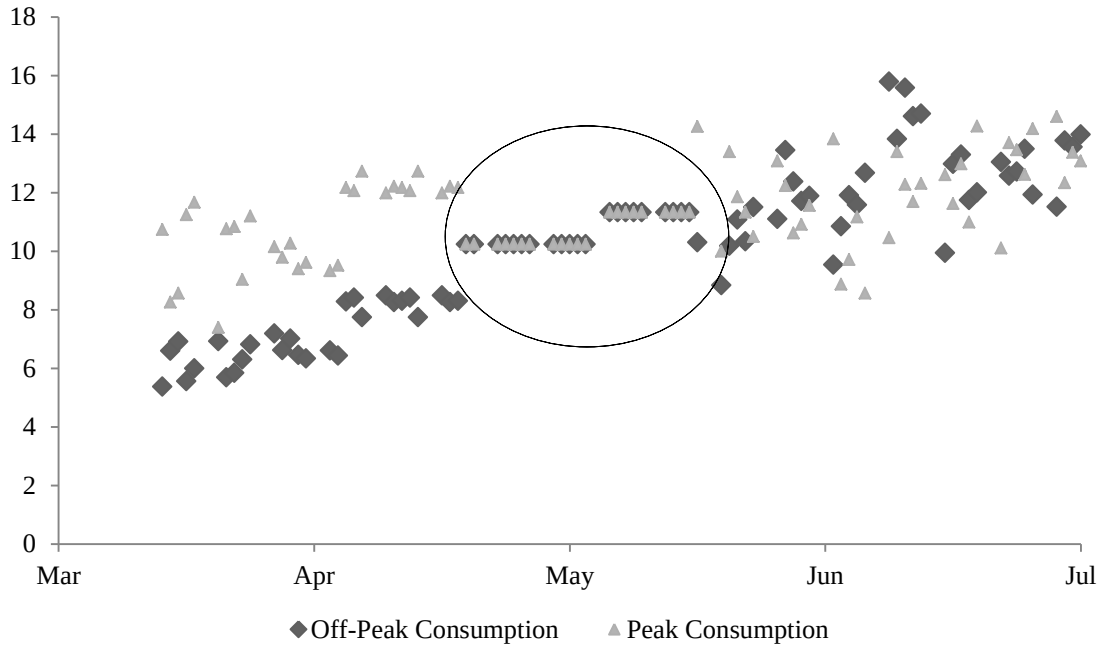


Figure 4.7: Peak and off-peak usage for a "typical" household in 2008



Estimated usage data

Some of the daily usage data was marked, by the electricity company, as estimates. The estimates were a result of problems with obtaining the half hourly reading. For example in some cases the wireless signal carrying the meter reading got interrupted either by a technical fault or by a physical barrier that stood in the way of the unit sending and receiving the data.[29] These estimates probably do not cause large problem on average since they usually extend only over a few hours of the day and the estimates were probably within reasonable range of the actual usage anyway. However, as the data points within the circle in figure 4.7 shows, in few cases they did persist for a long period of time. Estimated readings were therefore all excluded from the analysis.

Unexplained change in usage from year to year

This problem was discovered in the data when we had a look at the average change between the years for individual households. Some homes displayed more than 100% change in daily average electricity usage from 2008 to 2009. Sometimes large changes had an explanation in the post survey, for example a household had gone on a holiday for two months in 2009. However, when there was no explanation in the post survey it was impossible to determine what caused such dramatic change in consumption between the years. The problem of those unexplainable differences was not addressed directly and the majority of these large differences disappeared after the previously stated issues had been resolved.

Figure 4.8 shows the percentage change in average year-on-year consumption for all the households in the experiment including the control group before any of the data restrictions were applied. The horizontal axis measures the average percentage change in consumption from 2008 (before the experiment started) to 2009 (during the experiment). The bars to the far right show that some households increased consumption by more than 100% in 2009. Though there might be reasonable explanations for the change it is likely that the tenants of the houses with the

[29] For example a large van could be parked outside the room that had the meter in it and that could interrupt the wireless transmission from the meter to the antenna receiving the signal.

extreme change did not live in the house for a long period in 2008 or that they moved out of the house permanently.

Figure 4.9 is exactly the same graph as the one before except that the restrictions mentioned earlier (and summarized at the end of chapter 4.3) have been imposed on the data. In that graph the average year-on-year change does not exceed 50%. While 50% is a large change in consumption, the range is much more reasonable than before the restrictions were imposed. The previous data restrictions seem sufficient to eliminate the extreme users as well.

Figure 4.8: Total % Change in consumption from 2008 to 2009 before data restrictions.

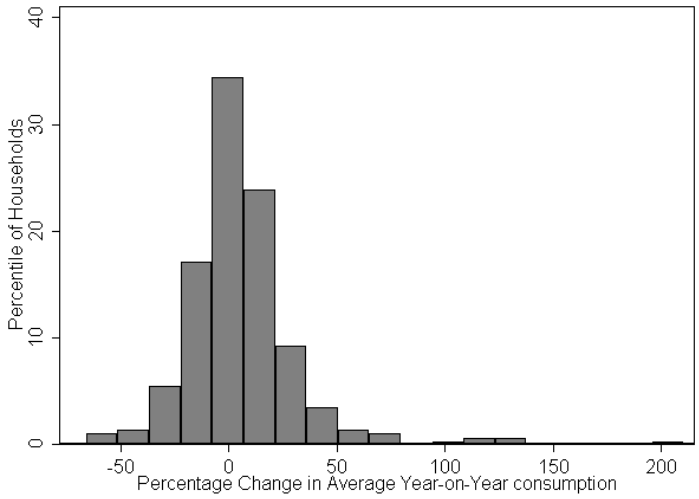
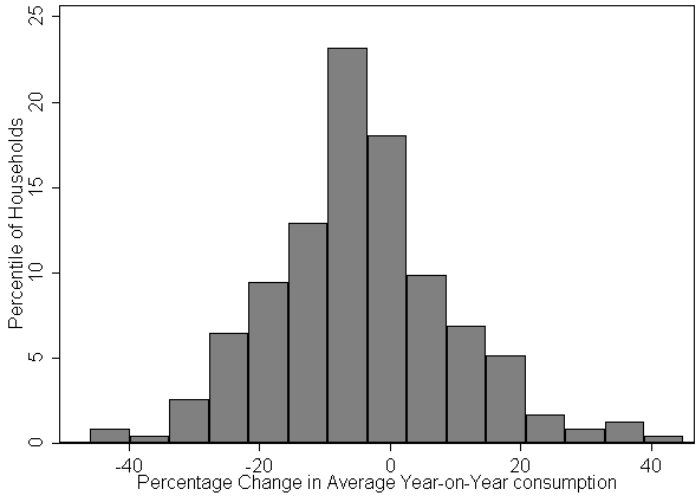


Figure 4.9: Total % Change in consumption from 2008 to 2009 after data restrictions.



4.3 Final Data Set

The data set used for analysis consists of 292 of the 400 households that began the experiment. Most either withdrew before completing the experiment or did not take part in the post-experiment survey. Of those who completed both surveys some refused to answer certain question reducing the sample for some of the analysis. We expect a seasonal response as there is limited need for cooling in summer and greater need for heating in winter, which leads to more extreme peak demand in winter over summer. Therefore, data from April through July was used to estimate the response. Over weekends and public holidays prices did not vary over the day. The customers only paid the off-peak tariff during these days and therefore they are excluded from the analysis. School holidays were also discarded because it is difficult to know whether people are at home or away on a holiday during those periods.

The original data were collected on a half hourly basis. The half hourly data were then aggregated into two groups for each day; peak and off-peak. All the data was searched for errors and any pattern that was detected that was likely to have been due to a missed reading was eliminated from the analysis as the information was deemed unreliable. Once all the data had been cleaned one more rule had to be applied and is listed below as R6. All restrictions left 256 households in the sample to be analysed.

Data restrictions and manipulations summary:

(R1) Only data from April through to July in 2008 (before the experiment) and 2009 (during the experiment) were included.

(R2) Only households that completed the post survey were included.

(R3) No weekends or school holidays.

(R4) If a whole day was an estimate instead of an actual reading it was discarded.

(R5) Days where the quantity consumed exceeded 3 standard deviations from the mean were excluded.

(R6) If a household had less than 30 observations either during peak or off-peak period the household was excluded from the analysis.

5 METHODOLOGY

This chapter details the methodology employed to estimate the response to different prices in the Auckland experiment. Section 5.1 discusses the household characteristics that best explain the cross sectional variation in daily consumption before the experiment commenced. Section 5.2 and 5.3 explain the econometric model used to obtain the substitution and own-price elasticity.

5.1 Factors Affecting Daily Household Consumption

In 2008 the sample households were unaware they would take part in an experiment in the future and all faced time-invariant prices. To get an idea of the factors that influence the electricity usage decision by households, I regress daily total kWh consumption on a range of household characteristics taken from the pre-experiment survey. The variables were selected based on previous research and experimentation. The results are shown in table 5.1.

At the 1% level of significance, all the listed variables contribute to daily electricity consumption, except whether the occupier owns the property on a mortgage. The results will be discussed in two parts. First the effect of the physical characteristics of the house and heating appliances will be discussed, followed by the effects of household characteristics. The results, however, need to be interpreted carefully since the variables might be influenced by unobserved factors or suffer from multi-collinearity.

Table 5.1: The partial effect of the houshold caracteristics and dwellings on total usage

Dependent variable: Daily usage (kWh)

Floor area (10sqm intervals)	0.0675**	Years living in the house	0.2666**
	(0.0025)		(0.0155)
Age of house (10 year intervals)	-0.0383**	Own the house with mortgage	0.3110
	(0.0072)		(0.1967)
Total number of rooms	-0.7916**	Renting the house	2.2502**
	(0.0627)		(0.3823)
Total number of rooms heated	0.3675**	Household income (10k interval)	0.0843**
	(0.0326)		(0.0027)
Central gas heating	-5.5014**	Ill household member	8.0095**
	(1.0989)		(0.4301)
Central electric heating	5.0797**	Household size	2.6382**
	(0.5445)		(0.0690)
Heat pump in house and used	2.2441**	Hours spent away from home	-0.2474**
	(0.2720)		(0.0254)
Electric water heating	11.5146**	Years living in the house	0.2666**
	(0.2001)		(0.0155)
		Mean temperature	-0.6821**
			(0.0331)
Observations	16332		
R-Squared	0.3764		
Number of households	256		

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

Dwellings and appliances

The left-hand columns show how daily total electricity consumption, in kWh, is influenced by things that characterize the dwellings of the participants. All of the dwelling characteristics are highly significant.

There is a positive relationship between the total floor area and consumption. This is to be expected since larger houses are usually associated with more need for heating and electronic activity in general. The age of the house is negatively correlated with consumption and is logical

since older houses tend not to be as well insulated and not as efficient in retaining heat as newer houses. Essentially the price of warmth is higher in older houses, so households respond by economising on heat: heating fewer rooms to lower temperatures. These results suggest the net effect of economising is less use of electricity. The sizes of the coefficients appear moderate and plausible.

Total number of rooms in the house would, at first, have been expected to be positively associated with daily consumption; instead it takes on a negative sign. However, more rooms for a given amount of floor area provides more control over what areas are heated in the house. As a result, a large house with few rooms would require more power to keep the communal areas warm. Total number of rooms heated, not surprisingly, takes on a positive sign simply telling the story that the more space a household heats, the more energy is needed.

Gas central heating and electric central heating are dummy variables that take on either the value 1 or 0 if the household utilizes either gas or electric central heating. There is obviously large electricity conservation associated with having gas central heating. The large increase in electricity usage with electric central heating is sensible but surprisingly big. Since most people in the sample use some form of electric heating, there should not be a huge difference in usage by people with central electric or just normal electric heating. Households with an installed heat pump (an air conditioner-like heating device) tend to consume more electricity. Like better insulation, heat pumps decrease the price of warmth and encourage households to consume more warmth. This warmth is, of course, produced more efficiently. The net effect appears to be increased electricity use among those households who choose to install a heat pump (and who probably have a relatively high value of warmth).

The effect of heating water using electricity was found using a dummy variable that takes on the value 1 if the household has electric water heating and 0 if not. The large effect of the electric water heater is unsurprising and the size of the coefficient is roughly around the average daily electricity needs for the appliance.

Householder characteristics

The right-hand columns show how daily total electricity consumption, in kWh, is influenced by householder characteristics.

We might expect the relationship between duration of occupation (years living in the house) and daily consumption to be negatively correlated. We would expect households who intend to remain in the house for a long time to make improvements that economize on electricity, which might reduce electricity consumption. Again, however, those households that make those improvements likely have a relatively strong demand for the service produced with electricity. The net effect appears to be increased electricity use (though we have to be cautious with these interpretations in the context of cross-sectional analysis).

It makes no difference if the households owns with or without a mortgage, however, households who rent the house tend to use 2.25 kWh more daily than those who own their property. A reasonable explanation for this is the anticipated long run cost savings benefit from investing in cheaper technology by the households who own and tend to stay for long in the house and the value added to their asset by improving the heating efficiency of the houses. However, only a small number of households rented their property and therefore the results may not be representative.

Household income is recorded in ranges starting at $0–20,000 and from then on in $10,000 intervals to a maximum of $120,000 or more a year. There is a positive relationship between usage and income, as expected; people tend to consume more of all normal goods as their income rises. However, this might not be linear since there is probably a limit to how much electricity the households can, and want to, consume.

If a household member was ill, on average, the daily consumption was more than 8 kWh higher. This can be explained by the fact that the ill individual, often, has to spend a significant proportion of the day at home and sometimes there are medical devices that have to run over the entire day.

Household size is the number of people in the household and, as expected, there is a positive relationship between daily consumption and household size. More people need more electricity.

Hours spent away from home is on average how many hours the householders are away from home on a weekday. Those householders who spend more time away from home consume less electricity, on average.

Finally we control for the average outside temperature. Daily consumption is negatively correlated with the mean temperature as expected since more electricity is needed to heat the homes during cold days.

It is important to emphasise that multi-collinearity is a potential issue in the regression and some of the coefficients might show smaller or larger effect because everything else in the model is being held constant. The regression results are not intended to conclude what factors have an effect on the households rather to investigate what factors might be important to take into account when estimating the experiment's effect and the ability of the participants to adjust and shift their consumption.

5.2 Demand Model

To estimate the econometric demand model for the households in the Auckland experiment we follow the approach demonstrated in Faruqui and Sergici (2011). The model suggested is a Constant-Elasticity-of-Substitution (CES) specification. One alternative to the CES model is a Cobb-Douglas (CD) model. The CD model is inferior when trying to determine the magnitude of the substitution between the two periods since CD imposes the restriction that the elasticity of substitution to be equal to one. Alternatively a flexible functional form model could be adopted. Such models include the Almost Ideal Demand System, Trans-log, Generalized Leontief and Generalized McFadden. The problem with the flexible functional form models in this particular context is that they might not globally satisfy the concavity condition imposed by utility maximization and they are significantly harder to interpret (Faruqui & Sergici, 2011).

For simplicity the households can be assumed to have a fixed income share devoted to electricity consumption. Theoretically the fixed income share assumption is not a harmful one since the elasticity of substitution between any commodity i and j is constant in the CES model. For estimating the daily demand equation the assumption of fixed income share allocated to electricity is not too unrealistic since there is limited flexibility within the households to

substitute their consumption of electricity with another good in the short run. This is especially true for households that have kids and also in the winter time, when darkness makes up a higher proportion of the day, restricting people's ability to spend their time outdoors. The maximization problem faced by the customer is described in Problem 5.1.

Problem 5.1: Constant Elasticity of Substittuion model

$$\max_{q_p, q_{op}} U(q_p, q_{op}) = (\gamma_p q_p^{-\rho} + \gamma_{op} q_{op}^{-\rho})^{-\left(\frac{1}{\rho}\right)} \tag{5.1.1}$$

$$Subject\ to: p_p q_p + p_{op} q_{op} \leq I_e \tag{5.1.2}$$

Where q_p and p_p is the daily peak quantity and price respectively. q_{op} and q_p is the daily off-peak quantity and price respectively. I_e is the income share devoted to electricity. $\gamma_p > 0$, $\gamma_{op} > 0$ are constants and $\rho \leq 1$ is a preference parameter to be estimated.

The demand functions derived from the problem are:

$$q_p = \frac{\gamma_p^{\sigma} p_p^{1-\sigma}}{\gamma_{op}^{\sigma} p_{op}^{1-\sigma}} * \frac{I_e}{p_p} \tag{5.1.3}$$

$$q_{op} = \frac{\gamma_{op}^{\sigma} p_{op}^{1-\sigma}}{\gamma_p^{\sigma} p_p^{1-\sigma}} * \frac{I_e}{p_{op}} \tag{5.1.4}$$

$$\text{Where: } \sigma = \frac{1}{1+\rho} \tag{5.1.5}$$

The elasticity of substitution between peak and off-peak consumption is defined by the following formula:

$$\sigma_{p,op} = -\frac{\partial \ln\left(\frac{q_p(.)}{q_{op}(.)}\right)}{\partial \ln\left(\frac{p_p}{p_{op}}\right)} = \sigma = \frac{1}{1+\rho} \tag{5.1.6}$$

Traditionally, the substitution elasticity is found by estimating the demand functions and deriving the substitution elasticity from the own price elasticities. While the peak and off-peak prices are different from each other, each price stays the same over the entire investigation period. This results in perfectly collinear prices. Thus it is impossible to estimate the demand equation with both prices included.

The solution to this problem is to estimate the model in steps and individually estimate substitution and own-price elasticities. First, the substitution elasticities are estimated directly, then the peak and off-peak demand equations. This is done to determine whether the elasticities represent shifting behaviour or, if the households simply increase their consumption during the off-peak periods without decreasing their peak consumption or, conversely, if they only decrease their peak consumption but do not actually increase their off-peak consumption. Finally the method deviates from the CES model to estimate the conservation effect of better consumption information and/or participation in the experiment. Understanding how and if the load actually changes is of utmost importance since most policy makers would like to see a decrease in peak load. However, if the results show no substitution there is still an argument for offering variable prices based on the improved welfare received by consumers and increased sales by retailers during off peak hours.

5.3 Econometric Estimation

One way of estimating the elasticities is to follow the procedure demonstrated by Faruqui and Sergici (2011). Their method is a household Fixed-Effects (FE) approach that controls for the effects of any unobserved variables that do not vary over time. This method is preferred when limited information on household characteristics exists. One problem with using FE is because most of each household's control variables are constant over time it excludes estimation of the effects of the rich data collected from the pre-survey. Since it is of interest to analyse how different household characteristics affect the substitution decision FE is not the most suitable method of obtaining the substitution elasticities for this particular data.

Another way of estimating the model is using the random-effects estimator, however, a Hausman test rejects the random-effects specification. Therefore I turn to an effectively cross-sectional analysis using house and household controls, including interaction terms, to estimate the substitution elasticities in the later part of the experiment. To check the robustness of the substation elasticity estimates group fixed-effects[30] and individual household fixed-effects[31] equations using data from before and during the experiment will be estimated.

[30] Where individual groups fixed-effects are controlled for.

The model can be broken into two stages: (1) substitution elasticity stage and (2) own price elasticity stage. As the names suggest stage (1) seeks to determine the magnitude of any shift in load from the peak to the off-peak period. Stage (2) seeks to determine how the participant's usage varied with price both peak and off-peak. The procedure used to determine the price effects on peak time conservation due to the pricing scheme is to first estimate the model in its simplest form. Next the control variables are added. Finally the full model is estimated with both control variables and interaction terms in order to investigate the dependence of the price elasticities on the household characteristics and temperature. Both stages have the same procedures and control variables.

Stage 1: Substitution equations

The purpose of the substitution equation is to estimate the extent to which households substituted electricity from one period to the other. The magnitude of the effect is determined by the ability and willingness of the household to shift load from more expensive peak times to less expensive off-peak. The first step in estimating the substitution elasticity is to estimate:

Equation 5.1: Simple substitution equation

$$\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_t = \alpha_1 + \alpha_2 \ln\left(\frac{p_{peak}}{poffpeak}\right)_t + e_t \tag{5.1}$$

Where:

- $\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_t$: is the logarithm of the peak-quantity demanded over the off-peak-quantity demanded in day t.
- α_1: is the intercept and represents the average logged consumption ratio. It has no effect on the elasticity of substitution (EOS).[32]

[31] Where individual household fixed-effects are controlled for.

[32] Since: $dln\left(\frac{q_{peak}}{q_{offpeak}}\right)_t \Big/ d\ln\left(\frac{p_{peak}}{poffpeak}\right)_t = \alpha_2$, only the coefficient on the logged price ratio contributes to the EOS.

- α_2: is the coefficient of interest and represents the substitution elasticity, i.e., the average ability of the households to shift the load from one period to the other.
- $\ln\left(\frac{p_{peak}}{poffpeak}\right)_t$: is the logarithm of the peak-price over the off-peak price assigned to the households. This ratio is fixed for each household for the entire period.
- e_t: is a normally distributed error term.

The interpretation of the equation is: a one percentage point increase (decrease) in the price ratio results in an α_2 percentage point increase (decrease) in the quantity ratio. Therefore, a larger estimated α_2 indicates greater ability/willingness of the households to substitute between the two periods. However, it is important to mention that this interpretation should be applied with caution for at least two reasons.

First, the assumption of fixed income proportion allocated to electricity might not hold. If the share allocated to electricity is adjustable then the consumers might reduce their consumption of other goods and increase the share allocated to electricity in order to take advantage of the lower off-peak prices, hence the quantity ratio decreases due to the cheaper off-peak prices while the quantity during peak time does not change, or changes relatively little. In this case, rather than substituting between the two periods households are increasing their off-peak consumption and not changing their peak consumption. This possibility will be investigated in the next chapter.

Second, there are many variables that potentially contribute to householder's quantity ratio. For example, people who are at home more of the day, have an illness or are dependent on electric water heating might be relatively more dependent on peak usage then others.

The next step in the model is to estimate the substitution elasticity while controlling for the factors that potentially influence the household's quantity ratio. By doing so we can further isolate the effect of the new pricing scheme. The equation to be estimated is:

Equation 5.2: Substitution equation including control variables

$$\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_t = \alpha_1 + \alpha_2 \ln\left(\frac{Ppeak}{Poffpeak}\right)_t + \alpha_3 MEANTEMP_t + \alpha_4 INCOME + \alpha_6 HRSAWAY + \alpha_7 HHSIZE + \alpha_8 HEATPUMP + \alpha_9 ELECTRICWATER + \alpha_{10} ILLNESS + e_t \quad (5.2)$$

Where:

- $\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_t$, α_1, α_2, $\ln\left(\frac{Ppeak}{Poffpeak}\right)_t$ $and\ e_t$: have the same interpretation as before.
- MEANTEMP is the outside daily mean temperature at the nearest weather station,
- INCOME is the household's self-reported pre-tax income,
- HRSAWAY is the number of hours the household members spent on average away from home,
- HHSIZE is the number of people in the household,
- HEATPUMP is a dummy variable that takes on the value 1 if a household has a heat-pump heating device installed and the value 0 otherwise,
- ELECTRICWATER is a dummy variable that takes on the value 1 if a household has depends on electric water heating and the value 0 otherwise,
- ILLNESS is a dummy variable that takes on the value 1 if a household has a permanently ill household member and the value 0 otherwise.

The second equation of the model is a better way of investigating the effect of the different prices assigned to different households. The interpretation remains the same as before but with the added value of controlling for other potentially influential factors. All of the control variables are expected to have some influence on the ability or willingness to shift the consumption from one period to the other.

All the variables included in the model have historically been influential on daily total usage in the sample. This was investigated in section 4.4.1. While some variables can make a great contribution to daily demand they may have little or no effect on the substitution between peak and off-peak periods. For example, the daily demand might be different for people who rent and people who own their property but the two groups might have the same ability, on average, to substitute their consumption from one period to another in the short run.

Mean temperature could go either way: if people are home more during the peak period and dislike cold houses, then we would expect the sign to be positive. Conversely, if people spend equal or less time at home during peak period than we would expect the sign on the coefficient to be zero or negative, respectively. Finally, if colder days on average, require more electricity than warmer days the households have more electricity on each day to shift between the periods. That is, they could indeed select to heat more during the cheaper hours and less during the more expensive hours. Therefore, the sign will determine the interpretation of the variable for the households in the experiment.

Household pre-tax income would be expected to be negatively associated with substitution.[33] Since the savings from shifting would be relatively smaller in the richer than in the poorer household's budget. Therefore it would seem logical that wealthy households would be more reluctant to shift.

Hours spent away from home are expected to be positively associated with the household's willingness to shift the consumption. Because the peak period is during the day, and the hours people spent away from home tend to be during the day, we would expect the people who are away from home more to be less dependent on peak electricity, and may be more able to adjust their time a way in response to the peak-load pricing. For example, a worker may choose to come home a bit later to avoid high peak prices.

Household size and its relationship with the substitution ability in relative terms are hard to predict. One way in which household size could affect the shifting decision is through collective action. If all household members actively take part in reducing peak consumption and take advantage of the off-peak cheaper prices we could expect household size to assist with the substitution decision. However, two people do not necessarily use two times the electricity of one person to begin with so it might be that there is smaller usage to adjust in a larger household. The interpretation of the variable will therefore depend on the coefficient sign and its significance.

[33] When EOS is estimated it is expected to have a negative sign. Therefore, any variable that is expected to reduce the households' willingness to shift consumption is going to have a positive sign.

The ownership status of a heat-pump is important to include. Because heat-pumps are more energy efficient than conventional electronic heaters and can be set on a timer to turn on and off we would expect people with more efficient technology to be able to take better advantage of a TOU rates.

Homes with electric water heating installed are expected to restrict the households' ability to substitute since the water heater has to run during the day to keep the water warm. Therefore, homes that depend on electricity to heat water are more dependent on peak time electricity than the households' who use alternative sources to heat their water.

Illness is also important to control for and investigate since households with an ill member at home are probably going to be more restricted in shifting their consumption. First, if the member is at home during the day, it is harder for the household to reduce daytime consumption and second many people who are ill at home depend on electronic medical machinery that cannot be turned off.

Therefore all the variables are expected not only to affect the substitution decision but also the daily demand elasticities. These variables will be used in all elasticity estimations of the model.

The final step of the substitution elasticity estimation is to evaluate the elasticities using the full model. The full model includes all the control variables and adds interaction terms for the price ratio and the control variables. This enables us to estimate the substitution elasticities for households with different characteristics. The final equation to be estimate in the first stage of the model is:

Equation 5.3: Complete substitution equation

$$\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_t = \alpha_1 + \alpha_2 \ln\left(\frac{Ppeak}{Poffpeak}\right)_t + \alpha_3 MEANTEMP_t + \alpha_4 INCOME$$
$$+ \alpha_5 HRSAWAY + \alpha_6 HHSIZE + \alpha_7 HEATPUMP + \alpha_8 ELECTRICWATER$$
$$+ \alpha_9 ILLNESS + \alpha_{10} \ln\left(\frac{Ppeak}{Poffpeak}\right)_t xMEANTEMP_t$$
$$+ \alpha_{11} \ln\left(\frac{Ppeak}{Poffpeak}\right)_t xINCOME + \alpha_{12} \ln\left(\frac{Ppeak}{Poffpeak}\right)_t xHRSAWAY \quad (5.3)$$
$$+ \alpha_{13} \ln\left(\frac{Ppeak}{Poffpeak}\right)_t xHHSIZE + \alpha_{14} \ln\left(\frac{Ppeak}{Poffpeak}\right)_t xHEATPUMP$$
$$+ \alpha_{15} \ln\left(\frac{Ppeak}{Poffpeak}\right)_t xELECTRICWATER + \alpha_{16} \ln\left(\frac{Ppeak}{Poffpeak}\right)_t xILLNESS$$
$$+ e_t$$

The interaction terms allow for more precise estimation of the substitution elasticities for a given set of household characteristics. This feature allows us to test which house and household characteristics enable substitution. The complete regression output for the first stage of the model is available in the results chapter in section 6.1.

Stage 2: Own price equation

The purpose of the own-price or sometimes referred to simply as a demand equation is to capture the extent of households' response to price. As with the substitution elasticity estimation the own-price elasticities will be estimated in three steps. However, the own price elasticities will be estimated separately for the peak and off-peak periods. Equation 5.4 shows how the own-price elasticities will be estimated in the simplest form.

Equation 5.4: Simple own price equation

$$\ln(q_{zt}) = \alpha_{1z} + \alpha_{2z}\ln(p_{zt}) + e_{zt} \tag{5.4}$$

Where:

- z = peak, off-peak
- $\ln(q_{zt})$: is the logarithm of the quantity used during the ith period.
- α_{1z} : is the intercept for the zth period and has no interpretation.
- α_{2z} :is the coefficient of interest in the zth period. It represents the own-price elasticity or in other words how the households responded differences in prices during the experiment.
- $\ln(p_z)$: is the logarithm of the price in period z.
- e_{zt} : is a normally distributed error term.

The equation has similar properties as the one discussed in the substitution section. The α_{2z} coefficient, the coefficient of interest, has a simple interpretation: for a one percentage point increase (decrease) in the price during period z, the quantity used increased (decreased) by α_{2z} percentage points. As before, caution is required when interpreting the coefficient at this stage.

The next step involves estimating the elasticities while including control variables as shown in equation 5.5.

Equation 5.5: Own price equation with control variables

$$\begin{aligned}\ln(q_{zt}) = {} & \alpha_{1i} + \alpha_{2z}\ln(p_{zt}) + \alpha_{3z}MEANTEMP_t + \alpha_{4z}INCOME + \alpha_{5z}HRSAWAY \\ & + \alpha_{6z}HHSIZE + \alpha_{7z}HEATPUMP + \alpha_{8z}ELECTRICWATER \\ & + \alpha_{9z}ILLNESS + e_{zt}\end{aligned} \tag{5.5}$$

Finally, an equation that interacts the controls with log price is estimated. The interaction terms help determine to what extent the ability of the households to respond to prices depends on various characteristics. The last equation of the model is:

Equation 5.6: Complete own price equation

$$\begin{aligned}\ln(q_{zt}) = {} & \alpha_{1z} + \alpha_{2z}\ln(p_{zt}) + \alpha_{3z}MEANTEMP_t + \alpha_{4z}INCOME + \alpha_{5z}HRSAWAY \\ & + \alpha_{6z}HHSIZE + \alpha_{7z}HEATPUMP + \alpha_{8z}ELECTRICWATER + \alpha_{9z}ILLNESS \\ & + \alpha_{10z}\ln(p_z)xMEANTEMP + \alpha_{11z}\ln(p_z)xINCOME + \alpha_{12z}\ln(p_z)xHRSAWAY \\ & + \alpha_{13z}\ln(p_z)xHHSIZE + \alpha_{14z}\ln(p_z)xHEATPUMP \\ & + \alpha_{15z}\ln(p_z)xELECTRICWATER + \alpha_{16z}\ln(p_z)xILLNESS + e_{zt}\end{aligned} \tag{5.6}$$

6 RESULTS AND DISCUSSION

This chapter reports and discusses the results from estimating the equations described in the previous chapter. In section 6.1 through 6.1.1 substitution elasticities are estimated and regression diagnostics carried out. In section 6.2 through 6.2.1 own-price elasticities for both the peak and off-peak period are estimated. In section 6.3 we ask the question whether or not the households shifted their consumption from the peak to the off-peak period.

6.1 Elasticity of Substitution

The results from the first stage of the model, equations 5.1 through 5.3, were obtained using OLS. Data from only the year of the experiment, 2009, were analysed because all groups faced time-invariant prices in 2008. Weekends, public and school holidays, households that could not be confirmed as tenants in both years and influential observations were excluded. The restrictions have already been summarized in section 4.3.

The aim is to estimate the average elasticity of consumer substitution (EOS) in this group of households, and the extent to which the EOS varies with house and household characteristics. Since EOS is defined as: $EOS = \frac{\partial \ln(qpeak/qoffpeak)}{\partial \ln(ppeak/poffpeak)}$, the coefficient on the logged price ratio and the coefficients where the logged price ratio is interacted with other variables are of more interest than other control variables. In equations 5.1 and 5.2 only the price ratio contributes to the EOS. In equation 5.3 the coefficients on the interaction terms contribute to EOS. The output from stage 1 is shown in table 6.1 below.

Table 6.1: Substitution equations (equations 5.1 through 5.3)

Substitution model equation number:	Equation .5.1	Equation. 5.2	Equation. 5.3
Dependent variable: ln(Peak-Usage/Off-Peak-Usage)			
ln(Peak-Price/Off-Peak-Price)	-0.0334** (0.0104)	-0.0929** (0.0107)	-0.2264** (0.0514)
Average daily temperature		0.0061** (0.0013)	0.0023 (0.0019)
Income (10K intervals)		-0.0129** (0.0014)	-0.0172** (0.0022)
Hours away from home		-0.0335** (0.0013)	-0.0216** (0.0020)
Household size		-0.0008 (0.0034)	0.0151** (0.0051)
Heat-pump		-0.0350** (0.0127)	-0.0551** (0.0203)
Electric-water-heating		0.1677** (0.0095)	0.0209 (0.0157)
Ill household member		0.1732** (0.0212)	0.1157** (0.0330)
ln(Peak-price/Off-Peak-Price) x Average daily temperature			0.0087** (0.0031)
ln(Peak-price/Off-Peak-Price) x Income			0.0082* (0.0036)
ln(Peak-price/Off-Peak-Price) x Hours away from home			-0.0224** (0.0031)
ln(Peak-price/Off-Peak-Price) x Household size			-0.0438** (0.0106)
ln(Peak-price/Off-Peak-Price) x Heat-pump			0.0325 (0.0316)
ln(Peak-price/Off-Peak-Price) x Electric water heating			0.2866** (0.0248)
ln(Peak-price/Off-Peak-Price) x Ill household member			0.1521** (0.0484)
Constant	0.0444** (0.0062)	0.1908** (0.0216)	0.2676** (0.0321)
Observations	14,379	12,389	12,389
R-squared	0.0007	0.126	0.1433
Number of households	233	201	201

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

Model equation 5.1

In equation 5.1, the price ratio explains little of the variation in the quantity ratio, as evidenced by the very small R-squared. However, the price ratio coefficient is significant at the 1% level. The coefficient estimate suggests that a 1% increase in the price ratio results in a 0.03% decrease in the quantity ratio. This value is interpreted economically as the average elasticity of substitution across the sample of households.

Is the magnitude of this statistically significant coefficient economically significant? As an example, if the off-peak price and peak price are initially the same at 20c per Kwh and are changed such that peak and off-peak prices are 25c and 15c, respectively, resulting in a rise in the price ratio from 1 to 1.667 (a 66.7% increase), then the ratio of peak to off-peak consumption shrinks by approximately 2.2%. If half of the change is due to peak-period reduction, then the financial effect on a typical household is very small. However, even a 1% drop in expensive peak consumption could generate considerable social benefit.

Model equation 5.2

Equation 5.2 controls for factors other than price that influence a household's peak relative to off-peak consumption:

- The average outside temperature. When the temperature is high households tend to have higher usage during peak relative to off-peak.
- Hours spent away from home. Most hours spent away from home are during peak hours, reducing the peak-to-off-peak consumption ratio.
- Household income. High income households tended to consume more during peak relative to off-peak.
- If a household had heat pump installed they tended to have higher peak-to-off-peak consumption ratio.
- If people depend on electricity to heat water they also tended to have a higher ratio.

- If one or more person in the household suffers from serious illness they tend to use more off peak electricity than off-peak.
- The number of people living in the house was insignificant.

Including these controls affects the estimate of the substitution elasticity. Holding other included factors constant statistically, each 1% increase in the price ratio results in a 0.093% decrease in the quantity ratio, on average. Using the same example as before, a 66.7% change in the price ratio would result in a -6.2% change in the quantity ratio. Again a small number, however, on a larger scale a daily decrease in the peak usage by as little as ½Kwh makes a big difference in aggregate household savings, the need to build peak infrastructure and the emission of CO2 from thermal generators used primarily during peak times (e.g., gas turbine generators).

Model equation 5.3

Equation 5.3 is the one that should be emphasised in the analysis. The equation has the largest explanatory power and can be utilized to analyse the impact of variation in house and household characteristics on a household's willingness and ability to substitute peak for off-peak consumption. Due to the interaction terms, the partial effect of changes in the price ratio depend on household income, average outside temperature, hours spent away from home, the size of the household, energy used to heat water, health status and heat pump ownership.

If the EOS measure is negative, then a shift from peak to off-peak consumption is happening, whereas if it is positive it is the other way around. Therefore, a positive coefficient on the interaction terms means that the EOS is getting smaller in absolute terms and therefore the factor is negatively correlated with the ability to shift consumption.

A one degree Celsius increase in average temperature increases the size of the EOS by 0.0087. Since an increase represents an absolute reduction in the EOS, this suggests that at higher temperatures households are less willing or able to shift their consumption from one period to the other. This is logical since homes tend to be coldest in the mornings and at nights or during the off-peak hours and warmer during the day or the peak hours. On warmer days there is less need

for heating in the morning and the night, therefore, it is to be expected that the load is flatter over the warmer days.

The absolute value of EOS falls on average by 0.0082 for each $10,000 increase in household income. Higher-income households tend to be less willing to shift from one period to the other. Not surprisingly, on average, households with higher incomes are less sensitive to price.

For each hour the members of the household spend away from home, the EOS increases in magnitude by 0.0224. It is logical that people who spend less time at home, they tend to be more able to consume during off-peak hours since, in general, people are away from the house during peak hours.

The number of people in the household also increases the magnitude of the EOS. Each additional person in the household increases the absolute value of EOS by, on average, 0.0438. This seems a bit surprising. It seems sensible that more people in the house would make it more difficult to shift the load from one time to the other, due to factors such as kids' dependence on heating; instead the relationship seems to be the opposite. An alternative explanation for the extra willingness to shift the consumption could be that with more household members, holding income constant, per capita income is lower. Therefore, it could be an income effect that is contributing to the increased ability to shift from one period to the other.

Whether a household owns a heat-pump or not is insignificant. This suggests that, despite the ability of a heat pump to conserve energy, on average, owning the device does not help with the load shifting. That is not unreasonable since the heat pump is utilized when the house needs heating and has no ability to take electricity from one time period to the other. Heating equipment that has the ability to store electricity during off-peak hours would be more able to affect the ability to shift from one period to the other.

Most of the households in the experiment depend on electric water heating. Electric water heating is one of the most restrictive factors on the households' ability to shift the load. Having electric water heating resulted in a 0.2866 absolute reduction in EOS. This may in part be due to lack of control over when the water heater operates. It is also the case that electric water heating increases total consumption significantly, so any absolute shift in other areas result in a smaller percentage shift.

Illness was another factor restricting the householder's ability to shift the load. On average the ratio increased by 0.1521 if one or more household member was ill for a long time period. The illness coefficient is sensible since people with illness are often unable to leave the house during the day, depend on electronic equipment for medical reasons and often need to maintain a warm temperature in the house.

Scenario analysis helps illustrate how responsive different households are. To calculate the EOS a partial derivative has to be taken of the logarithm of the quantity ratio with respect to the logarithm of the price ratio. The substitution elasticity is therefore calculated using equation 6.1. The values for α_2 through α_{16} are drawn from equation 5.3 in table 6.1.

Equation 6.1: Elasticity of Substitution equation

$$\frac{\partial \ln\left(\frac{qpeak}{qoffpeak}\right)}{\partial \ln\left(\frac{ppeak}{poffpeak}\right)} = EOS = \alpha_2 + \alpha_{10}MEANTEMP + \alpha_{11}INCOME + \alpha_{12}HRSAWAY + \alpha_{13}HHSIZE + \alpha_{14}HEATPUMP + \alpha_{15}ELECTRICWATER + \alpha_{16}ILLNESS \quad (6.1)$$

Table 6.2: Variation in participants' Elacticities of Substitution

State of independent variable:	**Low**	**Average**	**High**
Independent variable		**Electricity of Substitution**	
Average temperature	-0.0793	-0.0508	-0.0222
Income	-0.0804	-0.0508	-0.0211
Hours away from home	0.0297	-0.0508	-0.1312
Household size	0.0097	-0.0508	-0.1112

Table 6.2 shows how EOS varies with circumstances. The middle column, labelled average EOS, shows EOS using the coefficients from Equation 5.3 (On table 6.1) and average values of each of the house and household characteristics. The table assumes that people had electric water heating, no heat pump and no household member suffered from serious illness. The average temperature during the experiment was approximately 10.3 degrees Celsius and the average income of the group was between $80,000–90,000. People on average spent 6 hours away from

home and had 3 people living in the house. A household with these characteristics, if it existed, would have an expected EOS of -0.0508, or for every 1% increase in the price ratio the peak to off-peak consumption ratio decreases by 0.0508%.

When keeping all other variables at the average value and checking how the EOS responds to a one standard deviation change in the average outside temperature it is obvious that at the higher end of the confidence interval the households are less responsive than at the lower band.

When the outside temperature is 3.3 degrees higher (lower), on average, EOS equals -0.0793 (-0.0222). EOS is approximately zero when the average outside temperature reaches 16 degrees.

Assuming all other factors at their average levels, households with income one standard deviation above the average income in the sample were less willing or able to substitute from one period to the other. For those households the EOS was -0.0211 implying only a 1.4% reduction in the ratio of peak to off-peak usage for a 66% increase in the peak to off-peak price ratio.

On average, if the members of the household spent an additional 3.6 hours away from home, then their willingness/ability to take advantage of the lower-priced off-peak electricity was greatly improved. However, 3.6 hours more spent at home eliminated their ability to shift consumption. For those who spent long time periods away from home, on average, a 66% increase in the price ratio resulted in an 8.8% decrease in the quantity ratio.

The household's dependence on electronic water heating had an effect on the EOS. Keeping all other factors of the model at their average level, if a household was not dependent on electric water heating then they had greater ability to respond (at least on a percentage basis). If a household did not depend on electric water heating then the EOS was -0.337.

While the results suggest that households shifted their consumption in response to TOU pricing, it is important to investigate this further. Did people in the experiment actually shift their consumption or did they simply change their consumption in one of the two periods. Because it is a ratio of peak to off-peak consumption and the sign is negative, we know that people facing higher prices are using either less during peak, more during off-peak or some combination of both. While the EOS suggests a shift we need to confirm whether or not the participants did shift their consumption. This will be investigated later in this chapter.

6.1.1 Substitution Regression Diagnostics

It is important to investigate the validity of the previous results and the following actions will be taken to check the robustness of the results:

(1) A model with household fixed effects will be estimated,

(2) the original model will be estimated and extremely high and low users will be excluded,

(3) the original model will be estimated using a mid-quantile estimator and

The fixed effects model

To check the validity of the EOS estimates I follow the approach in Faruqui and Sergici (2011) as closely as possible. They estimate the CES model using household fixed effects. They control for temperature and humidity and the month of the year. They also account for variation across their sample in information technology and if the day was a CPP day, but these are impossible to include here because of the differences in the experimental design.[34]

Our sample includes price and consumption information from before (2008) and during (2009) the experiment, which allows fixed-effects estimation. First the model will be estimated in a simple form where the logged consumption ratio is regressed on the logged price ratio. The FE model controls for all household characteristics that do not vary over time but it does not control for factors that do vary over time. Therefore I will include a variable to control for temperature and the interaction between temperature and the logged price ratio. The equation to be estimated is:

[34] There were no CPP days or any information technology in the Auckland experiment.

Equation 6.2: Simple Elasticity of Substitution FE model

$$\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_{it} = \alpha_0 + \alpha_1 \ln\left(\frac{p_{peak}}{p_{offpeak}}\right)_{it} + \alpha_2 MEANTEMP_t + \alpha_3 \ln\left(\frac{p_{peak}}{p_{offpeak}}\right)_{it} xMEANTEMP_t + v_i + e_{it} \quad (6.2)$$

Where:

- i denotes the household and t denotes the day.
- $\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_{it}$, $\ln\left(\frac{p_{peak}}{p_{offpeak}}\right)_{it}$ $and\ MEANTEMP_t$: have the same interpretations as before
- v_i: is time-invariant fixed effects for the households
- e_{it}: is a randomly distributed error term

The second version of the model to be estimated is just slightly modified. Variables were added to the model to try and control for the year and the interaction of year and the weather. The model is still very simple and can be stated as:

Equation 6.3: Elasticity of Substitution FE model controlling for treatment period

$$\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_{it} = \alpha_0 + \alpha_1 \ln\left(\frac{p_{peak}}{p_{offpeak}}\right)_{it} + \alpha_2 MEANTEMP_t + \alpha_3 \ln\left(\frac{p_{peak}}{p_{offpeak}}\right)_{it} xMEANTEMP_t + D\alpha_4 2009 + \alpha_5 D2009xMEANTEMP + v_i + e_{it} \quad (6.3)$$

Where:

- All previous variables have the same interpretation
- D2009 is a dummy variable that takes on the value 1 if the year is 2009 and 0 if the year is 2008.

Finally the complete model, which most closely resembles Faruqui and Sergici (2011) model, is estimated. In this model, instead of controlling for the year, each month of each year is controlled for individually as well as the interaction between temperature and the month. The model can therefore be stated as:

Equation 6.4: Elasticity of Substitution complete FE model

$$\begin{aligned}\ln\left(\frac{q_{peak}}{q_{offpeak}}\right)_{it} = \alpha_0 + \alpha_1 \ln\left(\frac{p_{peak}}{p_{offpeak}}\right)_{it} + \alpha_2 MEANTEMP_t \\ + \alpha_3 \ln\left(\frac{p_{peak}}{p_{offpeak}}\right)_{it} xMEANTEMP_t + \sum_{k=1}^{3} \beta_k MONTH2008_k \\ + \sum_{k=1}^{3} \gamma_k MONTH2009_k + \sum_{k=1}^{3} \delta_k MONTH2008_k xMEANTEMP_t \\ + \sum_{k=1}^{3} \eta_k MONTH2009_k xMEANTEMP_t + v_i + e_{it}\end{aligned} \tag{6.4}$$

Where:

- MONTH2008 is a dummy for May, June and July in 2008
- MONTH2009 is a dummy for May, June and July in 2009

Table 6.3: EOS, Fixed effects model estimates

Substitution FE model equation number: Dependent variable: ln(Peak-Usage/Off-Peak-Usage)	Equation 6.2	Equation 6.3	Equation 6.4
ln(Price-peak/Price-off-peak)	-0.1261** (0.0216)	-0.1363** (0.0247)	-0.1328** (0.0238)
Average daily temperature	0.0042** (0.0009)	0.0051** (0.0013)	0.0052* (0.0019)
ln(Price-peak/Price-off-peak) x Average daily temperature	0.0065** (0.0018)	0.0061** (0.0021)	0.0069** (0.0019)
Year 2009		0.0201 (0.0227)	
Year 2009 x Average daily temperature		-0.0006 (0.0018)	
May 2008			-0.0112 (0.0546)
June 2008			-0.0441 (0.0506)
July 2008			-0.2458** (0.0753)
May 2009			0.0163 (0.0523)
June 2009			0.0640 (0.0445)
July 2009			0.2824** (0.0770)
Average daily temperature x May 2008			0.0003 (0.0042)
Average daily temperature x June 2008			0.0065 (0.0038)
Average daily temperature x July 2008			0.0229** (0.0060)
Average daily temperature x May 2009			0.0019 (0.0029)
Average daily temperature x June 2009			0.0010 (0.0026)
Average daily temperature x July 2009			-0.0013 (0.0040)
Constant	0.0111 (0.0110)	-0.0036 (0.0176)	-0.0198 (0.0305)
Observations	24,754	24,754	24,754
Number of households	233	233	233

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

All three versions of the model return very similar coefficients on the price ratio, temperature and the interaction with temperature and the price ratio. The coefficients on the price ratio are negative as in the OLS model and somewhat larger in magnitude. The coefficient on the interaction term between temperature and the price ratio is positive as in the OLS model but smaller. The EOS computed using the FE model are not going to be too different from the EOS estimated using the OLS model. For all three models the method of obtaining a value for the EOS is the same and the equation is:

Equation 11: Elasticity of substitution in the FE model

$$EOS = \frac{\partial \ln\left(\frac{qpeak}{qoffpeak}\right)_{ti}}{\partial \ln\left(\frac{ppeak}{poffpeak}\right)_{ti}} = \alpha_1 + \alpha_3 * MEANTEMP_t \tag{6.5}$$

The simple model, that includes only the price ratio, average temperate and the interaction between the two, is probably too simple since it does not take into account the different time periods. However, when using the simple model to compute the EOS, using the average temperate for the two years of 11.5 degrees Celsius, we get that the EOS is -0.0510. The original model, estimated using OLS, predicted that the EOS would equal -0.0508 when averages on the control variables were used. The difference of 0.0002 is very small and therefore the FE results support the results from the original model.

The second version of the model estimated included only a control for the year and its interaction with the average temperature. Both variables turned out to be insignificant and the coefficients on the variables that were included in the previous regression did not change significantly. The EOS using average temperature for the two years equates to -0.0662 or 0.0154 smaller than the original OLS model estimated. This is a small difference and supports the original model.

The results from the last model estimated are listed under equation 6.4 on table 6.3. That model included each month of each year as well as an interaction terms for them and the temperature variable. Most of the control variables for the month of the year are insignificant. Only July, both in 2008 and 2009, turned out to be significant at the 1% level. It is perhaps not surprising since July is usually the coldest month in the data. Of the interaction terms only July, interacted with average daily temperature, was significant at the 1% level. Average daily temperature turned out

to be significant at the 5% level. All other control variables, except the logged price ratio and average temperatures interacted with the logged price ratio, turned out to be insignificant.

The logged price ratio and logged price ratio interacted with average temperature are significant. This is consistent with the substitution model using only 2009 data. The coefficient on the price ratio is, in absolute terms, smaller in the FE regression than in the one estimated in the OLS model. The coefficient on the interaction term, where average daily temperature is interacted with the price ratio, is also smaller than in the OLS regression. When the EOS is computed using the average temperature for the period the EOS is -0.0535 or only 0.0027 smaller than the EOS computed in the original model, when averages for all household characteristics and temperature was used. This small difference once again supports the findings of the original (essentially cross-sectional) model.

Over all it looks as if the FE model supports the original OLS model results, at least when averages are used to compute the value for the EOS.

Influential high and low users

Since some households could be using well above the average and others well below the average it seems important to run the model excluding those observations. Table 6.4 reports results from the specification in the right-hand column of Table 6.1.it is the same model and data as used to obtain the original model (reported in table 6.1) and only data from 2009 was used. The only difference is in the households included in the sample: the first one excludes households that used, on average, more than 50 kWh of electricity each day. The second set of results estimates the same equation excluding households who, on average, used less than 10 kWh per day. Finally the third set of estimates eliminates both high and low users.

Table 6.4: Substitution equations estimated without extreme users

Substitution model equation number: Dependent variable: ln(Peak-Usage/Off-Peak-Usage)	No high Users	No Low users	Only average users
ln(Peak-price/Off-Peak-Price)	-0.2093** (0.0541)	-0.2511** (0.0518)	-0.2347** (0.0545)
Average daily temperature	0.0029 (0.0019)	0.0015 (0.0019)	0.0020 (0.0019)
Income (10K intervals)	-0.0162** (0.0022)	-0.0136** (0.0022)	-0.0130** (0.0023)
Hours away from home	-0.0243** (0.0020)	-0.0199** (0.0020)	-0.0226** (0.0020)
Household size	0.0179** (0.0051)	0.0007 (0.0055)	0.0044 (0.0055)
Heat-Pump	-0.0667** (0.0203)	-0.0760** (0.0206)	-0.0877** (0.0205)
Electric water heating	0.0471** (0.0162)	0.0315* (0.0158)	0.0576** (0.0164)
Ill household member	0.1107** (0.0328)	0.1803** (0.0364)	0.1730** (0.0362)
ln(Peak-price/Off-Peak-Price) x Average daily temperature	0.0070* (0.0032)	0.0098* (0.0032)	0.0080* (0.0032)
ln(Peak-price/Off-Peak-Price) x Income	0.0087* (0.0037)	0.0032 (0.0036)	0.0040 (0.0038)
ln(Peak-price/Off-Peak-Price) x Hours away from home	-0.0162** (0.0033)	-0.0244** (0.0032)	-0.0179** (0.0034)
ln(Peak-price/Off-Peak-Price) x Household size	-0.0520** (0.0108)	-0.0223* (0.0110)	-0.0317** (0.0113)
ln(Peak-price/Off-Peak-Price) x Heat-Pump	0.1193 (0.0331)	0.0630* (0.0316)	0.1524 (0.0331)
ln(Peak-price/Off-Peak-Price) x Electric water heating	0.2433** (0.0264)	0.2713** (0.0249)	0.2271** (0.0264)
ln(Peak-price/Off-Peak-Price) x Ill household member	0.1713** (0.0481)	0.0926 (0.0501)	0.1139* (0.0499)
Constant	0.2392** (0.0326)	0.2874** (0.0327)	0.2610** (0.0333)
Observations	11,720	11,956	11,287
R-Squared	0.1431	0.1413	0.1407
Number of households	190	194	183

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

Excluding the extreme users from the data does not generate significant differences in the results. The coefficients that determine the substitution elasticity all have the same signs as in the original model and in general do not deviate much from the coefficients in the original model. Ownership of a heat pump is volatile, however not many households had a heat pump in the first place and the ownership status was insignificant in the original model. Household ability to substitute from one period to the other seems to be diminished when excluding the low users. What that means is simply that people who use a little more on average tend to be more sensitive at low levels of income but insensitive at high levels of income. The coefficient on the log of the price ratio differs when excluding the low users only. However, when the actual elasticities are computed using the average values as in Table 6.2 the elasticities become almost the same, supporting the validity of the original model.

Median-based estimator

Another way of estimating the model is using a quantile regression. The quantile regression is a median-based regression (rather than mean-based) and is therefore less influenced by unusual observations (i.e., the estimates are less sensitive to outliers). The same model as in equation 5.3 was estimated but using a quantile estimator. As in the original model only data from 2009, the year of the experiment, was used. The results from the quantile regression as well as the results from the original model are shown in table 6.5.

Table 6.5: Substitution equations using mid-quantile and OLS estimators

Estimation method :	Original OLS regression	Quantile Regression
Dependent variable: ln(Peak-Usage/Off-Peak-Usage)		
ln(Peak-price/Off-Peak-Price)	-0.2264**	-0.1314*
	(0.0514)	(0.0636)
Average daily temperature	0.0023	0.0040
	(0.0019)	(0.0023)
Income (10K intervals)	-0.0172**	-0.0197**
	(0.0022)	(0.0027)
Hours away from home	-0.0216**	-0.0214**
	(0.0020)	(0.0024)
Household size	0.0151**	0.0282**
	(0.0051)	(0.0063)
Heat-Pump	-0.0551**	-0.0215
	(0.0203)	(0.0251)
Electric water heating	0.0209	0.0569**
	(0.0157)	(0.0194)
Ill household member	0.1157**	0.0693
	(0.0330)	(0.0408)
ln(Peak-price/Off-Peak-Price) x Average daily temperature	0.0087**	0.0047
	(0.0031)	(0.0039)
ln(Peak-price/Off-Peak-Price) x Income	0.0082*	0.0087*
	(0.0036)	(0.0044)
ln(Peak-price/Off-Peak-Price) x Hours away from home	-0.0224**	-0.0201**
	(0.0031)	(0.0039)
ln(Peak-price/Off-Peak-Price) x Household size	-0.0438**	-0.0382**
	(0.0106)	(0.0131)
ln(Peak-price/Off-Peak-Price) x Heat pump	0.0325	0.0259
	(0.0316)	(0.0391)
ln(Peak-price/Off-Peak-Price) x Electric water heating	0.2866**	0.2160**
	(0.0248)	(0.0307)
ln(Peak-price/Off-Peak-Price) x Ill household member	0.1521**	0.2383**
	(0.0484)	(0.0597)
Constant	0.2676**	0.1883**
	(0.0321)	(0.0397)
Observations	12,389	12,389
R-Squared	0.1433	
Number of households	201	201

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

The coefficient on the price ratio is smaller when using a quantile regression method. The control variables take on similar values when using a quantile regression as they did in the OLS. Heat-pump and illness are insignificant in the quantile regressions, but were significant in the original regression. The variable controlling for whether or not people heated their water using electricity was insignificant in the original regression but significant in the quantile regression.

The interaction terms also take on similar values in both regressions. However, average daily temperature interacted with the price ratio is not significant in the quantile regression. The coefficient on electric water heating interacted with the price ratio is smaller in the quantile regression and if the household had a sick member living at home it became a larger contributor to the EOS. All the signs of the coefficients on all variables are the same regardless of method.

When the average values are used to compute the EOS what is observed is a small deviation from the original value of -0.0508. The value in the quantile regression is -0.0323. The difference is not negligible, but still small and the EOS remains negative and significant both statistically and economically.

Overall the findings don't change much when using the quantile method but it does indicate some influential skew in the distribution of EOS.

All the checks support the findings of the original model of significant negative substitution elasticity. The signs on the coefficients of the model variables are consistent and the results from the original model seem reasonably robust to specification and sample.

6.2 Own-Price Elasticity.

The results from the second stage of the analysis, equations 5.4 through 5.6 were also obtained using OLS. As before results of analysis of data only from 2009 are reported. In this case, common sense and regression diagnostics reveal that the base specification fails to produce reliable estimates of the own-price elasticities. Table 6.6 and 6.7 report the results from the Own price equation for the peak and off-peak period, respectively.

Table 6.6: Peak own-price equations (equations 5.4 through 5.6)

Substitution model equation number:	Equation 5.4	Equation 5.5	Equation 5.6
Dependent variable: ln(Peak-Usage)			
ln(Peak-Price)	-1.3141** (0.0248)	-0.8383** (0.0252)	-1.4793** (0.1225)
Mean-temperature		-0.0314** (0.0013)	-0.1156** (0.0223)
Income (10K intervals)		0.0307** (0.0015)	0.0378 (0.0257)
Hours away from home		-0.0377** (0.0014)	-0.1685** (0.0225)
Household size		0.0959** (0.0037)	0.3982** (0.0681)
Heat-pump		0.0703** (0.0134)	-0.9222** (0.2337)
Electric-water-heating		0.4790** (0.0103)	-0.9812** (0.1906)
Ill household member		0.3903** (0.0224)	0.6700 (0.3426)
ln(Peak-Price) x Mean-temperature			0.0267** (0.0071)
ln(Peak-Price) x Income			-0.0019** (0.0081)
ln(Peak-Price) x Hours away from home			0.0417** (0.0071)
ln(Peak-Price) x Household size			-0.0991** (0.0219)
ln(Peak-Price) x Heat-Pump			0.3162** (0.0732)
ln(Peak-Price) x Electric water heating			0.4566** (0.0594)
ln(Peak-Price) x Ill household member			-0.0837 (0.1076)
Constant	6.5226** (0.0784)	4.6873** (0.0879)	6.7437** (0.3913)
Observations	14,379	12,389	12389
R-Squared	0.1633	0.3919	0.4004
Number of households	233	201	201

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

Table 6.7: Off-peak own-price equations (equations 5.4 through 5.6)

Substitution model equation number: Dependent variable: ln(off-peak-usage)	Equation 5.4	Equation 5.5	Equation 5.6
ln(Peak-Price)	0.4754**	0.1713**	0.1313
	(0.0230)	(0.0206)	(0.0992)
Average daily temperature		-0.0375**	-0.0325
		(0.0014)	(0.0169)
Income (10K intervals)		0.0463**	0.0050
		(0.0015)	(0.0193)
Hours away from home		-0.0012	0.1650**
		(0.0014)	(0.0170)
Household size		0.1163**	-0.0580
		(0.0038)	(0.0625)
Heat-Pump		0.0945**	0.2619
		(0.0141)	(0.1669)
Electric water heating		0.3875**	-0.0521
		(0.0104)	(0.1285)
Ill household member		0.2054**	-1.0447**
		(0.0235)	(0.2656)
ln(Peak-Price) x mean temperature			-0.0019
			(0.0062)
ln(Peak-Price) x Income			0.0156*
			(0.0071)
ln(Peak-Price) x Hours away from home			-0.0614**
			(0.0063)
ln(Peak-Price) x Household size			0.0626**
			(0.0227)
ln(Peak-Price) x Heat-Pump			-0.0607
			(0.0619)
ln(Peak-Price) x Electric water heating			0.1649**
			(0.0475)
ln(Peak-Price) x Ill household member			0.4668**
			(0.0997)
Constant	1.0613**	1.2803**	1.3887**
	(0.0625)	(0.0586)	(0.2686)
Observations	14,393	12,403	12,403
R-Squared	0.0288	0.3028	0.4101
Number of households	233	201	201

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

The own-price-elasticity estimates are hard to justify. The coefficient on the price variable is positive in the off-peak regression (Table 6.7) and the results in table 6.6, from the peak period model, show implausibly large own-price elasticities. When the appropriate numbers have been entered into the equation the own price elasticity during peak hours is around -0.8. That suggests a 0.8% reduction in electricity consumption for every 1% increase in prices during peak hours. If that would be the case, then the participants in the high price difference group should have reduced their peak consumption, on average, by approximately 40% from one year to the other. That did not happen according to the data.

Since the peak and off-peak prices for each household do not change over the experiment, the analysis is effectively cross-sectional. It seems highly likely that the results suffer from omitted variable bias. The households that most influence the extreme peak-price elasticity are those who have relatively high (low) off-peak price and low (high) peak price and have relatively high (low) daily total consumption.

These extreme users that cause problems in the own-price model are not as problematic in the substitution model because their absolute consumption is not relevant when estimating the ratio. It is only the effect on the consumption ratio that is being estimated not the absolute consumption. The problematic results from the own price elasticities are addressed in the next section.

6.2.1 Own-Price Regression Diagnostics

The model estimated in the last section yields implausible results, so an alternative method of obtaining the own price elasticities will be tested here. As in section 6.1.1 where substitution elasticities were obtained using a FE model it is possible to obtain own price elasticities using almost the same model. The only difference is that instead of regressing the quantity ratio on the price ratio, the price in one quantity in one period can be regressed on the price in that period to find the own price elasticity. The three equations to be estimated are:

Equation 6.6: Simple own-price FE model

$$\ln(q_z)_{it} = \alpha_0 + \alpha_1 \ln(p_z)_{it} + \alpha_2 MEANTEMP_t + \alpha_3 \ln(q_z)_{it}\, xMEANTEMP_t + v_i + e_{it} \tag{6.6}$$

Equation 6.7: Own-price FE model controlling for treatment period

$$\ln(q_z)_{it} = \alpha_0 + \alpha_1 \ln(p_z)_{it} + \alpha_2 MEANTEMP_t + \alpha_3 \ln(p_z)_{it}\, xMEANTEMP_t + \alpha_4 D2009 + \alpha_5 D2009 xMEANTEMP + v_i + e_{it} \tag{6.7}$$

Equation 6.8: Complete own-price FE model

$$\begin{aligned}\ln(q_z)_{it} = {} & \alpha_0 + \alpha_1 \ln(p_z)_{it} + \alpha_2 MEANTEMP_t + \alpha_3 \ln(p_z)_{it}\, xMEANTEMP_t \\ & + \sum_{k=1}^{3} \beta_k MONTH2008_k + \sum_{k=1}^{3} \gamma_k MONTH2009_k \\ & + \sum_{k=1}^{3} \delta_k MONTH2008_k xMEANTEMP_t + \sum_{k=1}^{3} \eta_k MONTH2009_k xMEANTEMP_t \\ & + v_i + e_{it}\end{aligned} \tag{6.8}$$

All three equations are identical to the once used to estimate the substitution elasticities in section 6.1.1. All the variables have the same interpretation except q_z and p_z.

- z = peak, off-peak
- q_z is the total daily quantity consumed in period z.
- p_z is the price faced by household i in period z.

The model is estimated with the same data restrictions as listed in section 4.3 and data for both 2008 and 2009 are included. The results for the FE model are reported in table 6.8 and 6.9 for peak and off-peak elasticities, respectively.

Table 6.8: Peak own-price elasticities, fixed effects model estimates

Own price model equation number:	Equation 6.6	Equation 6.7	Equation 6.8
Dependent variable: ln(Peak-usage)			
log(Peak-price)	-0.2600**	-0.1703**	-0.1202**
	(0.0399)	(0.0456)	(0.0430)
Average daily temperature	-0.0567**	-0.0823**	-0.0246*
	(0.0100)	(0.0113)	(0.0101)
log(Peak-price) x Average daily temperature	0.0088**	0.0170**	0.0109**
	(0.0032)	(0.0038)	(0.0033)
Year 2009		-0.0471*	
		(0.0202)	
Year 2009 x Average daily temperature		-0.0013	
		(0.0016)	
May 2008			0.4166**
			(0.0470)
June 2008			0.5401**
			(0.0436)
July 2008			0.0778
			(0.0647)
May 2009			0.5266**
			(0.0328)
June 2009			0.6224**
			(0.0288)
July 2009			0.5086**
			(0.0381)
Average daily temperature x May 2008			-0.0151**
			(0.0036)
Average daily temperature x June 2008			-0.0190**
			(0.0033)
Average daily temperature x July 2008			0.0237**
			(0.0052)
Average daily temperature x May 2009			-0.0250**
			(0.0025)
Average daily temperature x June 2009			-0.0236**
			(0.0022)
Average daily temperature x July 2009			-0.0144**
			(0.0034)
Constant	3.5059**	3.2753**	2.3702**
	(0.1245)	(0.1351)	(0.1358)
Observations	24,754	24,754	24,754
Number of households	233	233	233

Standard errors in parenthesis.

** and * indicate $p < 0.01$ and $p < 0.05$ respectively

To calculate the own price elasticities a partial derivative has to be taken of the logarithm of the quantity with respect to the logarithm of the price. The substitution elasticity is therefore calculated using equation6.9.

Equation 6.9: Own price elasticity in the FE model

$$\frac{\partial \ln(q_z)}{\partial \ln(p_z)} = \alpha_2 + \alpha_3 MEANTEMP_t \tag{6.9}$$

Table 6.8 reports the peak period results from the FE model stated in equation 6.6 through 6.8. The simple model (in column labelled equation 6.6) results show own price elasticity as -0.2600 when temperature is assumed to be at zero degrees Celsius. Each one degree increase in the temperature results in an absolute decrease in the own price elasticity by 0.0088. While this model returns more realistic results then the model in the chapter before, it is probably underspecified and overestimates the own price elasticity.

The model that controls only for the year, temperature and the interaction between the two (equation 6.7) produces an own price elasticity of -0.1703 during peak time when average daily temperature is zero. For every degree increase in daily mean temperature the absolute value of the elasticity decreases by 0.017. Therefore, at around 10 degrees Celsius the own price elasticity is 0.

The column labelled equation 6.8 reports the results from the complete model during peak time. The own price elasticity before taking into account temperature (that is assuming 0 degrees Celsius temperature) are -0.1202. For every one degree increase in the average daily temperature the absolute value of the own price elasticity falls by 0.0109. Therefore, according to this version of the model, the own price elasticity is zero when the mean temperature reaches 11 degrees.

Table 6.9: Off-peak own-price elasticities, fixed effects model estimates

Substitution model equation number: Dependent variable: ln(Off-Peak-Usage)	Equation 6.6	Equation 6.7	Equation 6.8
log(Off-Peak-Price)	-0.0124 (0.0328)	-0.0554 (0.0366)	-0.1047** (0.0341)
Average daily temperature	-0.0401** (0.0076)	-0.0228* (0.0092)	-0.0021 (0.0079)
log(Off-Peak-Price) x Average daily temperature	0.0018 (0.0027)	-0.0050 (0.0031)	0.0013 (0.0027)
Year 2009		-0.0562** (0.0187)	
Year 2009 x Average daily temperature		-0.0008 (0.0015)	
May 2008			0.4197** (0.0441)
June 2008			0.5757** (0.0409)
July 2008			0.3155** (0.0610)
May 2009			0.1025* (0.0422)
June 2009			0.0228 (0.0359)
July 2009			0.1571* (0.0623)
Average daily temperature x May 2008			-0.0151** (0.0034)
Average daily temperature x June 2008			-0.0251** (0.0031)
Average daily temperature x July 2008			0.0013 (0.0049)
Average daily temperature x May 2009			-0.0269** (0.0024)
Average daily temperature x June 2009			-0.0239** (0.0021)
Average daily temperature x July 2009			-0.0131** (0.0032)
Constant	2.7602** (0.0907)	2.9410** (0.1087)	2.3702** (0.1358)
Observations	24,754	24,754	24,754
Number of Households	233	233	233

Standard errors in parenthesis.
** and * indicate $p < 0.01$ and $p < 0.05$ respectively

Table 6.9 reports the results from the equations stated in equation 6.6 through 6.8 for the off-peak period. The results from the simple model in equation 6.6 for the off-peak period are in column labelled equation 6.6. In that estimation, neither the logged off-peak price nor the interaction between the price and daily average temperature are significant. The column labelled Equation 6.7 reports the results from the model stated in equation 6.7 for the off-peak period. That model also controls for the year and the interaction between the year and average temperature. Only the year and the average outside temperature are significant (at the 1% and 5% level, respectively). Therefore both of those models fail to report any own price elasticity during off-peak hours.

The column in table 6.9 labelled 6.8 reports the results from the complete model listed in equation 6.8 for the Off-peak period. In that version of the model the coefficient for the logged prices is significant at the 1% level. The own price elasticity reported is -0.1047. The coefficient on the interaction term of the logged off-peak price and the average daily outside temperature is statistically insignificant.

What the results from the complete model in equation 6.8 for both peak and off-peak own price elasticities suggests is that the customers did to some extent react to peak prices, but only when temperatures are relatively low. Since the average daily temperature did not frequently go below 8 degrees the response to peak prices appears to be small. However, during off-peak the temperature appears to have no effect on the participants response to the price during off-peak period and the own price elasticity is reasonably high regardless of the outside temperature. What these results suggest is that householders on average took advantage of the lower off-peak prices and increased consumption during off-peak but did not respond much to the higher peak prices. This finding will be investigated further in next section.

Whereas the own price elasticity estimates reported in the previous section were implausible, the FE estimates appear sensible and in line with existing estimates.

6.3 Did the Households Shift Their Consumption?

The EOS is an important variable to compute for any welfare analysis of peak-load pricing since it provides a value to predict to what extent users shift their electricity consumption from one period to the other. If there is a fixed proportion of the household income spent on electricity then there is no need to check if an actual shift took place since the income share must always sum up to the total peak and off-peak cost. Since this might not be the case in reality it is important to investigate if the households actually shifted their consumption.

There are two possible ways where the EOS could take on a negative value but not actually be a measurement of load shift. One possibility, suggested by the estimates of own price elasticity, is that households took advantage of the lower off-peak prices by increasing consumption off-peak. If this is the case the EOS would take on the expected negative sign but would not reflect load shift as peak usage does not change. In that case no savings in peak infrastructure would occur and the EOS would overstate the overall welfare change from a TOU rate design.

The other possibility is that the households could be discouraged by the high peak prices and use less during peak periods but not increase their usage during off-peak hours. In that case the EOS would also take on the expected negative sign. If that were to happen the social benefit yielded from the TOU program would again be overstated.

A classic differences-in-differences analysis will be carried out to further test whether participants changed their consumption in 2009 relative to 2008. Specifically, it was tested whether there are differences across experimental groups in the differences between 2008 and 2009 consumption. Two models for each time period were estimated: One simple model that does not take into account household characteristics and another where the same household characteristics as before are controlled for. When estimating the model the same restrictions as in the original model are imposed. The time period is the winter months in 2008 and 2009. The method used to obtain the coefficients is OLS. The models to be estimated are:

Equation 6.10: Simple differences-in-differences model

$$\ln(q_z) = \alpha_{z0} + \alpha_{z1}LOW + \alpha_{z2}MED + \alpha_{z3}HIGH + \beta_{0z}D2009 + \beta_{1z}D2009LOW + \beta_{2z}D2009MED + \beta_{3z}D2009HIGH + e_{iz} \quad (6.10)$$

Equation 6.11: Differences-in-differences model with control variables.

$$\ln(q_z) = \alpha_{0z} + \alpha_{1z}LOW + \alpha_{2z}MED + \alpha_{3z}HIGH + \beta_{0z}D2009 + \beta_{1z}D2009LOW + \beta_{2z}D2009MED + \beta_{3z}D2009HIGH + \sum_{m=1}^{7} \gamma_{mz}CONTROL_m + e_{iz} \quad (6.11)$$

Where:

- z = peak and off-peak
- α_{i0}: is the intercepts and is the average logged quantity for the info-only group.
- LOW, MED, HIGH are dummy variables that denote the group. if the price difference was 4c, 10c and 20c took on the value 1 for LOW, MED and HIGH, respectively. Otherwise they take on the value zero.
- $CONTROL_m$: denotes the control variables from 1 through 7 which are listed in the results. They have all been introduced before.

Table 6.10: Peak and off-peak year-on-year changes in consumption

Equation number:	6.10.peak	6.11.peak	6.10.off-peak	6.11.off-peak
	Dependent variable: ln(peak usage)		Dependent variable: ln(off-peak usage)	
LOW (4c price difference)	0.3220**	0.1926**	0.2749**	0.1415**
	(0.0152)	(0.0143)	(0.0153)	(0.0146)
MED (10c price difference)	-0.2874**	-0.1264**	-0.2139**	-0.1127**
	(0.0150)	(0.0141)	(0.0151)	(0.0144)
HIGH (20c price difference)	-0.3884**	-0.2716**	-0.4591**	-0.2962**
	(0.0151)	(0.0141)	(0.0151)	(0.0144)
D2009	0.0433**	-0.0428**	0.0052*	-0.0847**
	(0.0137)	(0.0129)	(0.0137)	(0.0131)
D2009 X LOW	-0.0536**	-0.0288	0.0430*	0.0454*
	(0.0201)	(0.0186)	(0.0201)	(0.0190)
D2009 X MED	-0.0556**	-0.0488**	0.0438*	0.0472*
	(0.0198)	(0.0183)	(0.0199)	(0.0187)
D2009 X HIGH	0.0241	0.0151	0.1285**	0.1308**
	(0.0197)	(0.0184)	(0.0198)	(0.0188)
Average daily temperature		-0.0320**		-0.0371**
		(0.0011)		(0.0011)
Income		0.0274**		0.0437**
		(0.0011)		(0.0011)
Hours away from home		-0.0354**		-0.0035**
		(0.0010)		(0.0011)
Household size		0.1003**		0.0881**
		(0.0027)		(0.0028)
Heat-Pump		0.0905**		0.0899**
		(0.0100)		(0.0103)
Electric water heating		0.4512**		0.3033**
		(0.0079)		(0.0081)
Illness		0.3811**		0.2498**
		(0.0168)		(0.0172)
Constant	2.4490**	2.1813**	2.3956**	2.0171**
	(0.010)	(0.0213)	(0.0104)	(0.0217)
Observations	24,754	21,334	24,769	21,348
R-Squared	0.1858	0.3982	0.1697	0.3424
Number of households	233	201	233	201

Standard errors in parenthesis.

** and * indicate $p < 0.01$ and $p < 0.05$ respectively

The columns labelled 6.10.peak and 6.11.peak show the results of the models listed in equation 6.10 and 6.11 for the peak period only. The columns labelled 6.10.off-peak and 6.11.off-peak show the results listed in equation 6.10 and 6.11 for the off-peak period only.

The coefficients on LOW, MED and HIGH show how the group's logged quantity differed, on average, from the info-only group in 2008. There are clearly significant differences in mean consumption across groups. The coefficient on D2009 shows by how much the logged usage changed in 2009 for the info-only group. The coefficients on the terms where the year dummy, D2009, has been interacted with the groups are the parameters of interest when trying to determine if the households in the groups actually shifted their consumption from one period to another. They show how each group's consumption changed from year to year relative to the info-only group.

The results from the simple model for peak consumption suggest that those with low and medium price differences conserve electricity during peak hours relative to the info-only group. However once other factors are controlled for, the group with low price difference is no longer significantly different from the info group and only the group that did conserve during peak hours was the group with medium price difference. In both versions of the model, the group with the highest price difference appears surprisingly not to have conserved during peak times relative to the info-only group.

During the off-peak period the results from both models suggest that all the groups took advantage of the lower off-peak prices and consumed more electricity during off-peak hours. The group with low price difference consumed, on average, 4.5% more than the info-only group. The group with the medium price difference consumed, on average, 4.7% more than the info-only group and the group facing the highest price difference, hence the lowest off-peak price, consumed 13% more than the info-only group during those periods.

These results suggest that the only group that actually shifted consumption from one period to another was the group facing a 10c difference in price while the others mainly took advantage of the low off-peak prices.

Since the experiment ran over only one year, all the elasticities are short run. It might be that in the long run the household's ability to reduce peak consumption is improved and given a longer time frame an actual shift might take place.

7 SOCIAL BENEFIT

The reaction to the different price plans offered to households may potentially make a large difference to society as a whole. Time-of-use pricing influences how much households consume and when they consume it. The quantity consumed and the time of usage can improve efficiency in developing new power plants, and reduce the cost of transmission and distribution systems. However, when it comes to investigating the effect of such schemes another question pops up: How fair is a dynamic tariff? Does the system create winners and losers? This chapter reports simulations of the benefits to consumers and producers implied by the results reported previously. It also evaluates the impacts on consumers by income group.

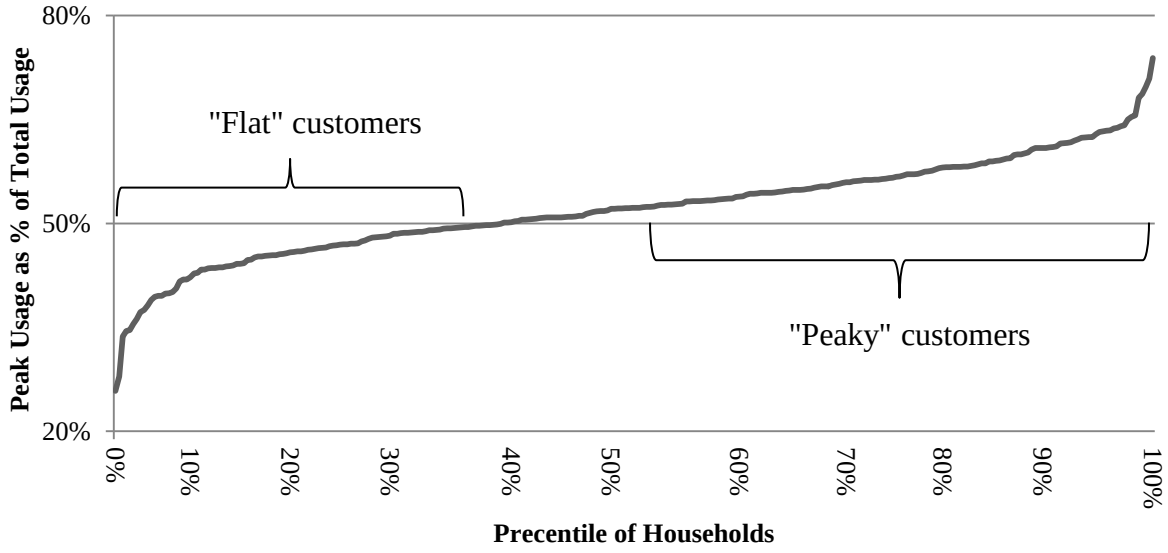
7.1 Consumer Benefit

In the 2010 paper "The Ethics of Dynamic Pricing" Faruqui et al. provide a simple, yet convincing, framework for how to answer such questions. According to their analysis a traditional fixed rate tariff system works like a subsidy from consumers who are less reliant on peak time electricity to those who tend to use more during peak time. If users who are being subsidised are on average poorer then there is a fairness argument based on the same principles as any income transfer programme. However, is there any reason to believe that households who earn less use more electricity during peak hours? In general, people who earn minimum wage and people who earn well above that tend to be away from home during similar hours. There is, however, a positive correlation in this sample between per capita earnings and hours spent away from home. While it is unknown if the people in the sample are away from home during peak hours it could be that people with lower incomes tend to be pensioners, unemployed or unable to work due to illness. In that case the transfer argument has some merit.

To begin to investigate it is possible to look at the daily load profile of the individual households in the sample and estimate savings and losses assuming no response to the semi-dynamic tariff. Figure 7.1 plots winter 2008 daily average household peak usage as a proportion of total usage in ascending order, i.e., lowest peak proportion to highest, for all households who completed both the pre and post-experiment surveys. Only April through July data were used and no school holidays or weekends were included in the calculation.

The vertical axis measures peak usage as a proportion of total usage. If a simple dynamic tariff, where a higher price is charged during the defined peak hours and a lower price is charged during off-peak hours and the average of the two prices equals the fixed current tariff, as is almost the case in the experiment, then the households with a relatively flat load profile—peak to total ratio lower than 50%—would save without any response to the time-varying price (and conversely for those with a "peaky" load profile with ratios of greater than 50%). In the experimental sample around 40% of the participants would have saved on their electricity bill simply by adopting the new plan while around 60% would have been worse off. However, the 60% could still be better off financially if they adjusted their behaviour in such way that the proportion used during peak time would be less than half of the total consumption.

Figure 7.1: Peak usage as a % of total usage for the participants of the experiment



Alternatively, we can look at the actual consumption by households in 2008 and compare how much more or less the households would have spent on electricity under a dynamic tariff compared with a flat rate tariff, again assuming the households do not responded at all to the time-variant prices. For example, assume that households paid a static tariff of 19 cents, the actual average rate in 2008 for the households in the experiment. Next, assume that a 10 cent peak/off-peak price differential is imposed, i.e., 14 and 24 cents charged during off-peak and peak times, respectively. The solid line in Figure 7.2 shows the distribution of the percentage

change in the monthly bill assuming no change in consumption, i.e., no response to the dynamic pricing. The dashed line shows the same distribution if all households responded to the dynamic pricing with elasticity of substitution -0.0508 (the average from the before). While the previous analysis could not confirm an actual substitution from peak to off-peak periods we will assume, for demonstrative purposes, in the following analysis that substitution took place.

Without any response to the variable pricing, only 36% of the participants would have paid less under a dynamic tariff. Assuming everyone has the average response to pricing, only 42% of the participants pay less under a dynamic pricing than under a flat rate design. In fact the overall average change in the electricity bill is economically insignificant at around 1%. This is not to say that the dynamic tariff is inefficient but rather a confirmation of the unfairness of a flat tariff where the households who are using the relatively plentiful off-peak electricity are subsidising those who prefer to use the relatively scarce peak time electricity.

Figure 7.2: Potential change in electricity bill with 10 cents price difference

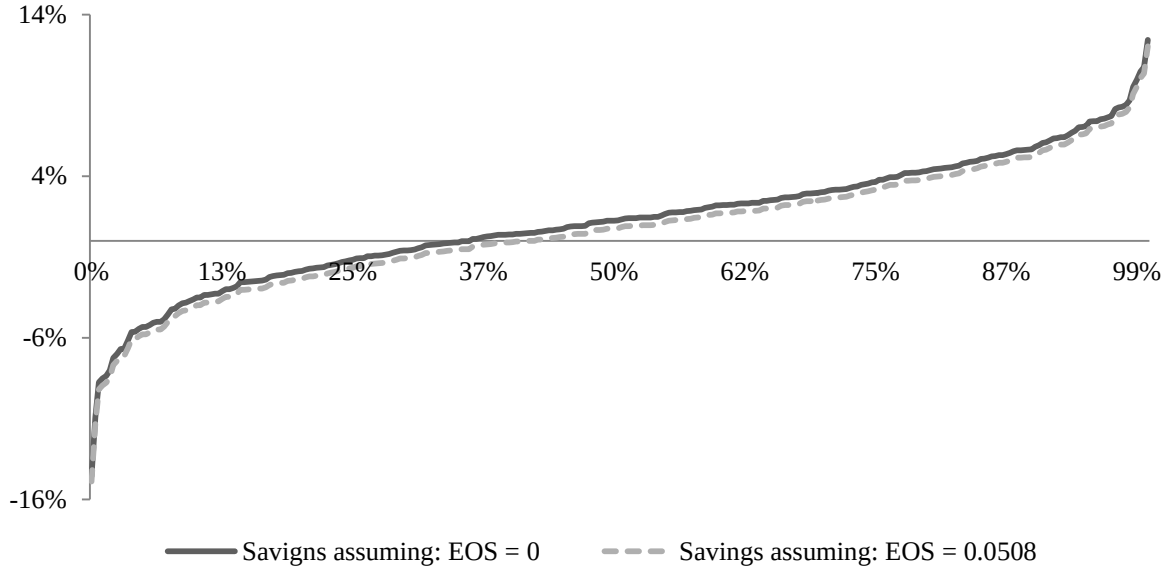


Figure 7.3: Potential change in electricity bill with 20 cents price difference

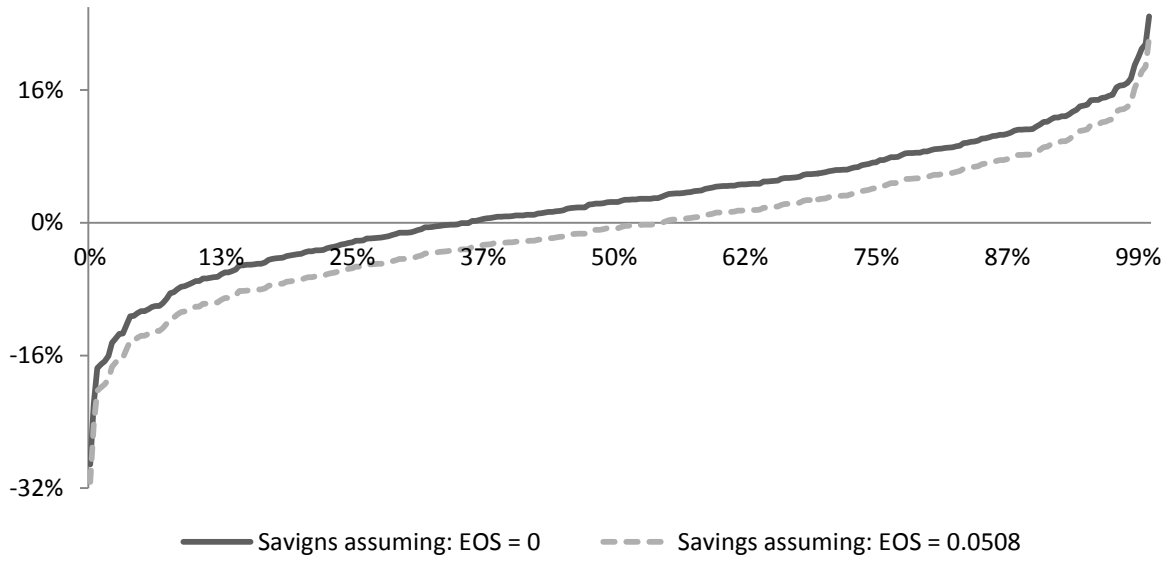


Figure 7.3 is produced using the same method as the figure before. The only difference is that in figure 7.3 the price difference for peak and off-peak electricity is 20 cents. The solid line assumes no response from the participants while the dotted line takes into account the substitution elasticity estimated in the previous chapter. An interesting result of looking at the change in the electricity bill after including the response with a 20 cent price difference is that now over 50% of the participants pay less for their electricity. Those who are more responsive and less dependent on peak electricity would certainly be the ones to gain most from such a plan while those who currently depend heavily on peak electricity would be the ones to lose from such a compulsory tariff. In the 20 cent price difference case the average change in the electricity bill was actually negative at around 1% (that is on average, the households could have saved only around 1% on the electricity bill). However, the EOS is likely to be larger in the long run and therefor consumer benefit would become larger as time passes.

7.2 Producer Benefit

The producer benefit is somewhat more difficult to investigate. Without any household response to the dynamic pricing a compulsory tariff would on average shift the revenue stream from one group of customers to the others without a major difference in revenues collected by the retailer. If, on the other hand, a system such as the one designed in the experiment were made optional (the likely scenario in practice in New Zealand), then those users who are less dependent on electricity during peak hours and those more willing and able to reduce peak consumption would adopt the new rate design. Without any adjustment by the consumers, in the short run, the profits for the producer might actually decrease if the time-invariant price is simply the average of the peak and off-peak prices.

Since electricity retailers compete aggressively for customers, in the long run, it would be expected that the customers who would be better off with a time-variant tariff would select any retailer that offers the most suitable time-variant tariff. This should incentivise most firms to offer a time-variant tariff. Since most customers who are better off with a dynamic rate are those who use more electricity during off-peak ("flat" customers, see figure 7.1) that would leave only the customers who use more during peak then during off-peak ("peaky" customers, see figure 7.1) on a time-invariant rate. This would probably result in the time-invariant rate being somewhat higher than the average of the time-variant rate.

If some households decide to go on a time-variant plan, then the producers could save if the need for buying expensive peak time electricity decreases. This is demonstrated by the following problem:

Problem 7.1: Producer profits and time-variant pricing

Assuming that the only cost to the retailer comes from buying electricity in the wholesale market and the only source of revenue comes from selling the electricity in the retail market, the profit received by the retailer, when charging a non-dynamic fixed price, from each individual household is simply the difference in the cost of obtaining the electricity in the wholesale market and the price received from the household. Formally it can be stated as:

$$\pi_{avg,i} = p_{avg,i} * q_{total,i} - c_{avg} * q_{total,i} = q_{total,i} * \left(p_{avg,i} - c_{avg}\right) \tag{7.1.1}$$

Where:

- $\pi_{avg,i}$: is the profit received by the retailer from household i,
- $p_{avg,i}$: is the standard time-invariant price paid by the household,
- $q_{total,i}$: is the total quantity consumed by the household, and
- c_{avg}: is the average price in the wholesale market paid by the retailers.

When the retailer charges different prices during peak and off-peak periods the profit received from individual household i, now depends on the new tariff and the cost of obtaining the electricity in the spot market during peak and off-peak hours:

$$\pi_{dyn,i} = p_{p,i} * q_{p,i} - c_p * q_{p,i} + p_{op,i} * q_{op,i} - c_{op} * q_{op,i} \tag{7.1.2}$$

Or

$$\pi_{dyn,i} = q_{p,i} * (p_{p,i} - c_p) + q_{op,i} * (p_{op,i} - c_{op}) \tag{7.1.3}$$

Where:

- $q_{p,i}$, $q_{op,i}$: is the quantity demanded during peak and off-peak hours, respectively
- $p_{p,i}$, $p_{op,i}$: is the price paid by the household during peak and off-peak hours, respectively, and
- c_p , c_{op}: is the price in the wholesale market paid by retailers.

If we subtract (7.1.1) from (7.1.3) we can compare how the profit would change for the retailers if a time-variant tariff is put in place:

$$\Delta\pi_i = \pi_{dyn,i} - \pi_{avg,i} = q_{p,i} * (p_{p,i} - c_p) + q_{op,i} * (p_{op,i} - c_{op}) - q_{total,i} * (p_{avg,i} - c_{avg}) \tag{7.1.4}$$

Since the average price that the households on the time-invariant plans pay is simply the average of the price charged during peak and off-peak, and the average cost for the producers of obtaining electricity in the wholesale market is simply the average of buying electricity in the wholesale market during peak and off-peak, if initially 50% of all electricity is consumed during peak, then the following most hold:

$p_{avg,i} = \frac{p_{p,i}+p_{op,i}}{2}$ and $c_{avg} = \frac{(c_p+c_{op})}{2}$ We can rewrite (7.1.4) as:

$$\Delta\pi_i = q_{p,i} * (p_{p,i} - c_p) + q_{op,i} * (p_{op,i} - c_{op}) - q_{t,i} * \left(\frac{p_{p,i}+p_{op,i}}{2} - \frac{c_p+c_{op}}{2}\right) \tag{7.1.5}$$

Rearranging terms, the change in producer profit can be written as:

$$\Delta\pi_i = (p_{p,i} - c_p) * \left(q_{p,i} - \frac{q_{t,i}}{2}\right) + (p_{op,i} - c_{op}) * \left(q_{op,i} - \frac{q_{t,i}}{2}\right) \tag{7.1.6}$$

And the aggregate change in profit can be calculated as:

$$\Delta\pi = \sum_{i=1}^{n} \left[(p_{p,i} - c_p) * \left(q_{p,i} - \frac{q_{t,i}}{2}\right) + (p_{op,i} - c_{op}) * \left(q_{op,i} - \frac{q_{t,i}}{2}\right)\right] \tag{7.1.7}$$

Equation (7.1.6) can be used to investigate conditions that yield a net gain for the retailer from switching to a dynamic pricing plan. In this particular example, the change in producer profit is determined by three factors: the difference in peak and off peak prices, the wholesale cost of electricity and the individual households' load profiles under the dynamic price system. If the households consume 50% during peak hours and do not adjust to the time-variant tariff, then profit is same across time-varying and time-invariant pricing.

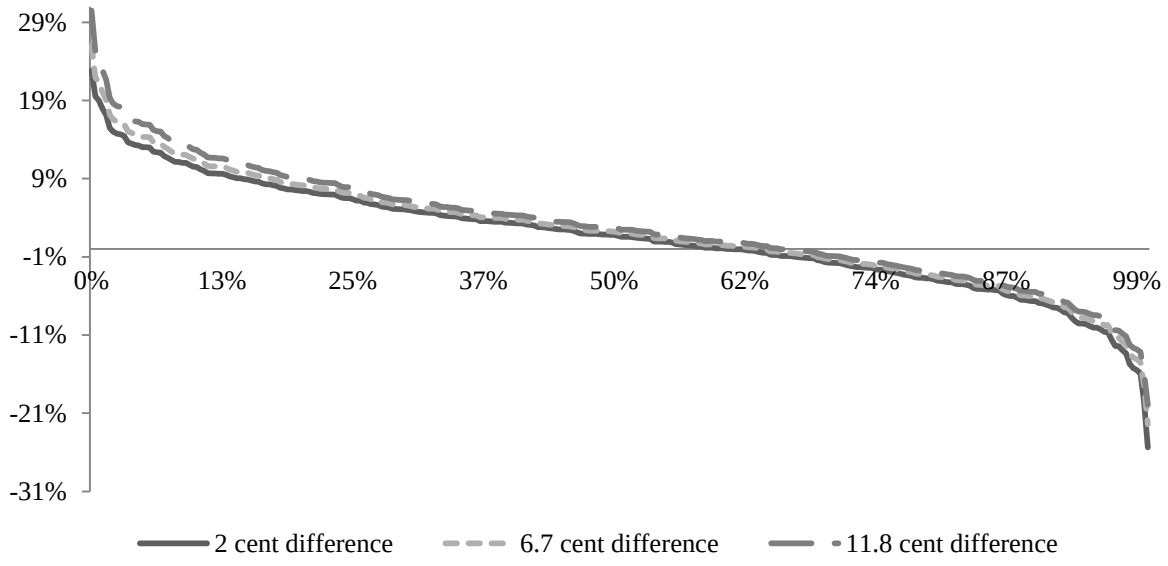
In the case of a single retailer who is a price taker in the wholesale market the cost of electricity would not vary with her changes in demand, making her control variable only the price. Therefore, the retailer can set the price to maximize her profits. Since quantity traded responds to the price, let the terms $\left(q_{p,i} - \frac{q_{t,i}}{2}\right)$ and $\left(q_{op,i} - \frac{q_{t,i}}{2}\right)$ vary with price. If households consume less during peak hours under a dynamic tariff than they did facing a fixed-average tariff, and conversely more during off-peak hours than before, then the retailer might be better off in the short run with dynamic pricing. That is because the term $q_{t,i}$ is the total quantity used if the household had been facing a fixed average price. The terms $q_{op,i}$ and $q_{p,i}$ are the quantities the households selects if a dynamic tariff is put in place, the dynamic tariff quantities can take on any value depending on the desired level selected by the households. Therefore, the producer's welfare depends on the tariff design and the demand response of the households.

In the long run, more retailers would offer time-varying pricing if such plans prove popular and that would change the dynamic of the simple example in problem 7.1. In that case, if consumers shift consumption, demand in the wholesale market in peak hours could decrease and reduce the equilibrium wholesale price during those hours.

Using the experimental data and substitution elasticities computed earlier it is possible to compute the short run producer benefit. This is purely a hypothetical analysis and no actual wholesale prices are used to compute the change in producer benefit. The purpose of doing this is simply to demonstrate the point of how changes in wholesale prices affect producers' profit. Three different wholesale price scenarios were selected to compute the change in retailer profit. They are:

- Low: 9.45 cents during peak and 7.45 cent during off-peak.
- High: 11.8 cents during peak and 5.1 cents during off-peak.
- Very High: 14.3 cents during peak and 2.5 cents during off peak.

Figure 7.4: Change in profits, by households (three wholesale cost difference scenarios)



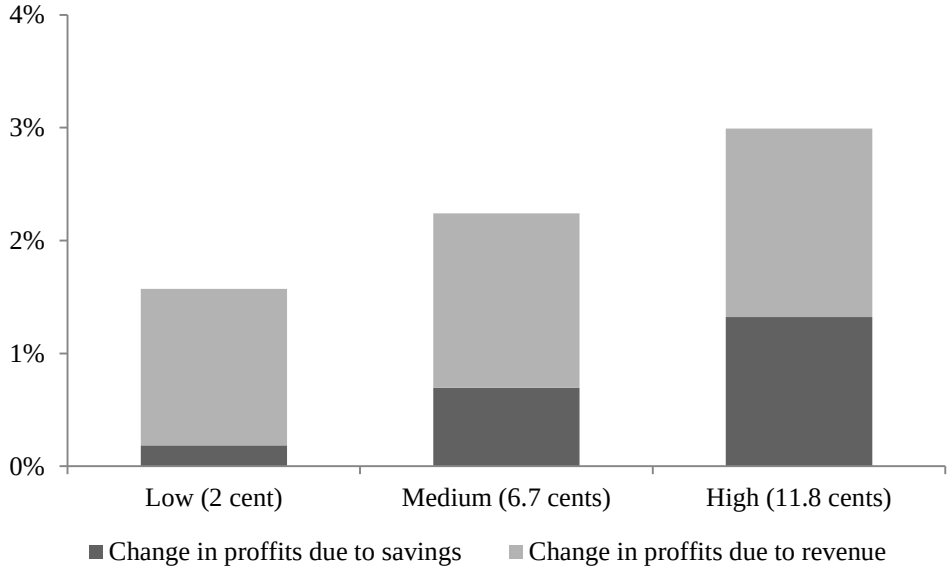
All the curves are estimated using the same usage data as in the analysis for consumer benefit, including the substitution elasticities. The solid line assumes a low peak/off-peak price differential, the short-dashed line assumes a high price differential and the long-dashed line

assumes a very high price difference in the wholesale market. All curves assume that all the participants had a 10 cent price difference between peak and off-peak (24 cents during peak and 14 cent during off-peak).

In the low-wholesale-price-differential scenario (2 cent difference), the producer receives 1.6% more profits after introducing the new plan. 88% of the change was contributed from higher rate charged during peak time while 12% of the change was contributed from savings in buying electricity from the wholesale market during peak time and a little bit is simply from increasing sales of electricity during off-peak time. Therefore, from the producer perspective this is definitely a pricing plan worth pursuing.

A higher price differential (6.7 cents) increases profits by 2.24%, supporting the argument that the benefit is greater to the producer if the wholesale price difference between peak and off-peak is greater. In that case a larger proportion of profits come from the peak time savings. Figure 7.5 shows how the profits could potentially change with three different peak and off-peak wholesale prices and the proportion of savings contributed to the change in revenue and wholesale electricity savings.

Figure 7.5: Sources of change in profit



This exercise demonstrates, at least in the short run, how the retailer's profits could increase when introducing such a plan. In the long run, however, it would be expected that other retailers would offer similar services and as a result the prices would adjust and the cost savings would eventually reduce the prices paid by consumers and equilibrate retailer economic profit to at zero, shifting the net benefit to consumers.

7.3 Social Benefit

Social benefit is simply the sum of producer and consumer benefits. So the social benefit boils down mostly to one thing: the savings made by suppliers (and, in the long run, passed on to consumers through competition) from acquiring electricity. This is demonstrated in problem 7.2.

Problem 7.2: Overall welfare and time-variant pricing

If the consumer benefit is just the savings made by households, as was done for the analysis earlier in the chapter, we can write down the change in consumer surplus as:

$$\Delta CS = \Delta Savings = \sum_{i=1}^{n}\left(p_{avg} * q_{,it} - \left[p_{p,i} * q_{p,i} + p_{op,i} * q_{op,i}\right]\right) \tag{7.2.1}$$

The total change in welfare is simply the sum of (7.1.7)[35] and (7.2.1) and can be written as:

$$\Delta W = \Delta\pi + \Delta CS = \sum_{i=1}^{n}\left[\left(p_{p,i} - c_p\right) * \left(q_{p,i} - \frac{q_{t,i}}{2}\right) + \left(p_{op,i} - c_{op}\right) * \left(q_{op,i} - \frac{q_{t,i}}{2}\right)\right] + \sum_{i=1}^{n}\left(p_{avg} * q_{,it} - \left[p_{p,i} * q_{p,i} + p_{op,i} * q_{op,i}\right]\right) \tag{7.2.2}$$

Once (7.2.2) is simplified the overall changes in welfare (excluding all other than monetary benefits) can be shown to be:

$$\Delta W = \sum_{i=1}^{n}\left(q_{t,i} * \frac{c_{p,i} + c_{op,i}}{2} - \left[c_{p,i} * q_{p,i} + c_{op,i} * q_{op,i}\right]\right) \tag{7.2.3}$$

[35] From the producer problem 7.1.

Therefore the total change in welfare boils down to the savings made from reduced need to buy more expensive peak time electricity, which is the point of peak-load pricing. The greater the participants' response, the greater the savings.

Table 7.1 shows the simulated additional welfare if the TOU pricing plan would have been implemented in 2008. The data and parameters are those used in the consumer and producer problems earlier. The substitution elasticities that were estimated in the previous chapter are employed to compute the change in peak and off-peak consumption and the three sets of wholesale prices, from the producer exercise, are used to give an idea of how the different wholesale prices could affect welfare under TOU pricing.

Table 7.1: Added welfare with TOU in the experiment

Wholesale price difference	Monthly added welfare (293 HH)	Annual added welfare (293 HH)
Low (2c)	$25.27	$303.28
Medium (6.7c)	$85.26	$1,023.11
High (11.8c)	$149.20	$1,790.44

Under a TOU rate the total added social welfare from 293 households is $25.27 per month or $303.28 per year. This is assuming a low difference between peak and off-peak prices in the wholesale market. Higher price difference yield higher social benefits from the experiment of $85.26 per month and $1,023.11 per year. When assuming a very high price difference (11.8 cents), the welfare starts to become to some extent economically significant.

To get a better idea of what the benefit could be if TOU pricing was implemented on a larger scale, the same exercise as before has been scaled for a larger population. Table 7.2 is computed using exactly the same data and method as the previous example. The only difference is that the welfare effect has been estimated as if there would have been 100,000 households in the experiment. This is not to be interpreted as the benefit from TOU if 100,000 households take up such tariff, rather what the potential effect of such plan could be under various TOU pricing scenarios.

Table 7.2: Added welfare from TOU with 100,000 households

Wholesale price difference	Monthly added welfare (100,000 HH)	Annual added welfare (100,000 HH)
Low (2c)	$8,625.65	$103,507.84
Medium (6.7c)	$29,098.70	$349,184.38
High (11.8c)	$50,922.72	$611,072.67

Table 7.2 helps explain how important it is to have many households take up a TOU for it actually to have an effect the, hypothetical, social benefit in this case is of a reasonable size for any type of wholesale price difference. Depending on the wholesale price difference the annual added benefit might have been between $103,507–611,072 in 2008.

Because the EOS reported earlier in the thesis were estimated over only one winter they are essentially short run elasticity's. However, in the long run the EOS would probably be larger. For example customers on a TOU plan could invest in appliances that make shifting load easier. This would be especially true for relatively wealthy households since they tend to have the funds to make such investments. Also, for people who have all their lives consumed electricity whenever they want to, it might potentially be that changing that habit might take longer than one winter. It could take some time before households get into the habit of consuming electricity at other times. If the EOS is larger in the long run the social benefit from a TOU plan would certainly be much greater in the long run.

7.4 Welfare by Income Groups

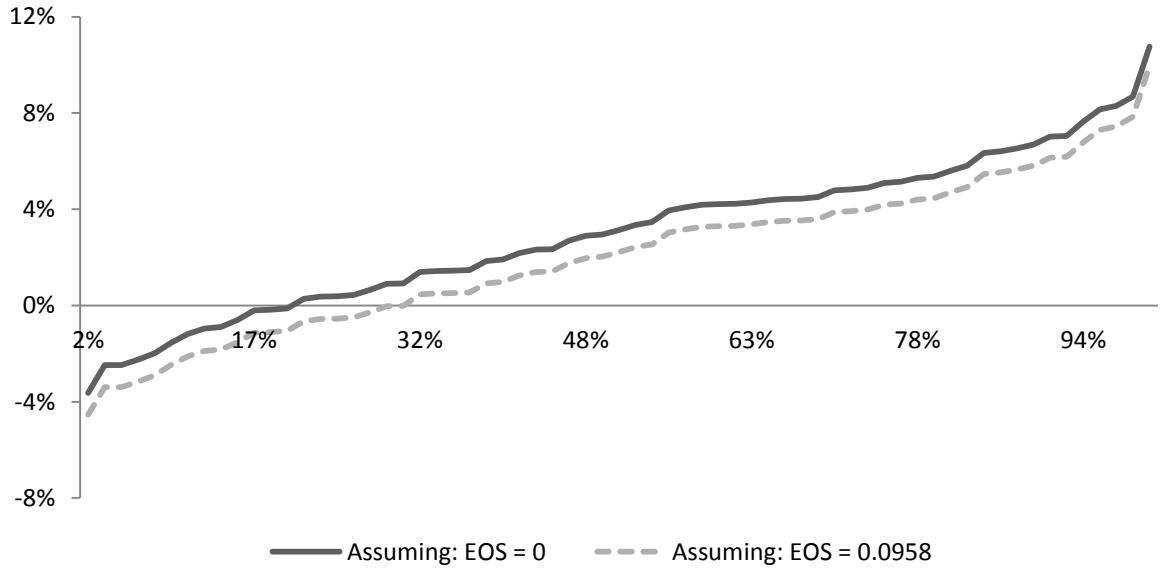
In the past, consumer watchdogs have been highly critical of any deviation from the status quo when it comes to electricity pricing. One argument is that low income people who do not hold a job, such as those who rely completely on some sort of government benefit, potentially spend more time at home during peak hours and could, therefore, be more negatively affected by the tariff. However, for low income households who work there is no reason to believe that they are more dependent on the peak time electricity than their richer counterparts in society. Using the 2008 data, it is possible to group the households into 3 groups: low-, medium- and high income.

Then as in the section before it is possible to see how the average change in the monthly electricity bill would have changed first without any response and second by using the substitution elasticities estimated earlier in the thesis.

When estimating the response to TOU pricing it is important to recognise that lower-income households tended to respond more to the pricing, i.e., had higher EOS, on average, than higher-income households. Therefore 3 sets of EOS are used to calculate the hypothetical change in the electricity bill. The rates used are -0.0958, -0.0589 and -0.0262 for low ($50,000 and less in total household income) medium ($50,000–100,000) and high income ($100,000 and more) household respectively. The values were selected based on the mean income in each income group.[36] This gives a more realistic estimate of the changes in participants' welfare.

Figures 7.6 through 7.8 demonstrate how the savings from the three income groups would have been distributed had they been on a dynamic rate in 2008. The solid line again represents the savings before any adjustments have been and the dashed line show the savings after accounting for the potential substitution.

Figure 7.6: Change in electricity bill (low income households in the sample)

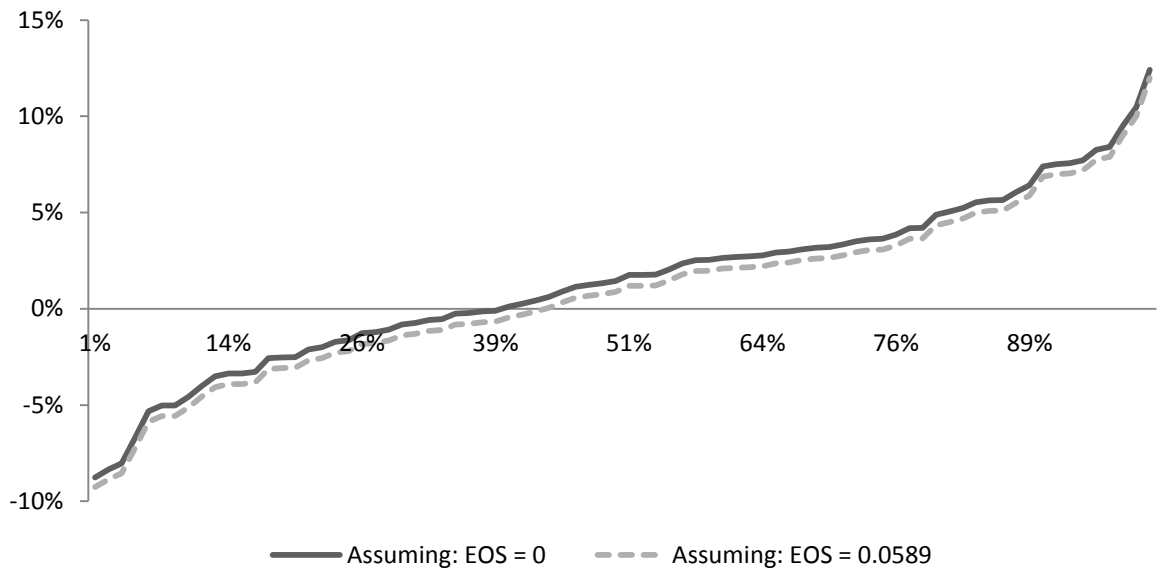


Despite the fact that lower-income households tend to respond more to dynamic pricing, they remain on average more dependent on peak-time electricity than the average- and high- income

[36] The income values placed on each income group; low, medium and high were 2.5, 7 and 11 respectively.

households. As figure 7.6 shows, only a small proportion of households with relatively low incomes, between $0 and $50,000, could have made savings from a dynamic rate design. In fact, only 20% of the low income households, before taking into account the response, would have been better off under a dynamic tariff. Since the low income households tend to be the most responsive to the tariff, when including the response to the dynamic tariff design, 31% of the low income participants would have paid lower bills.

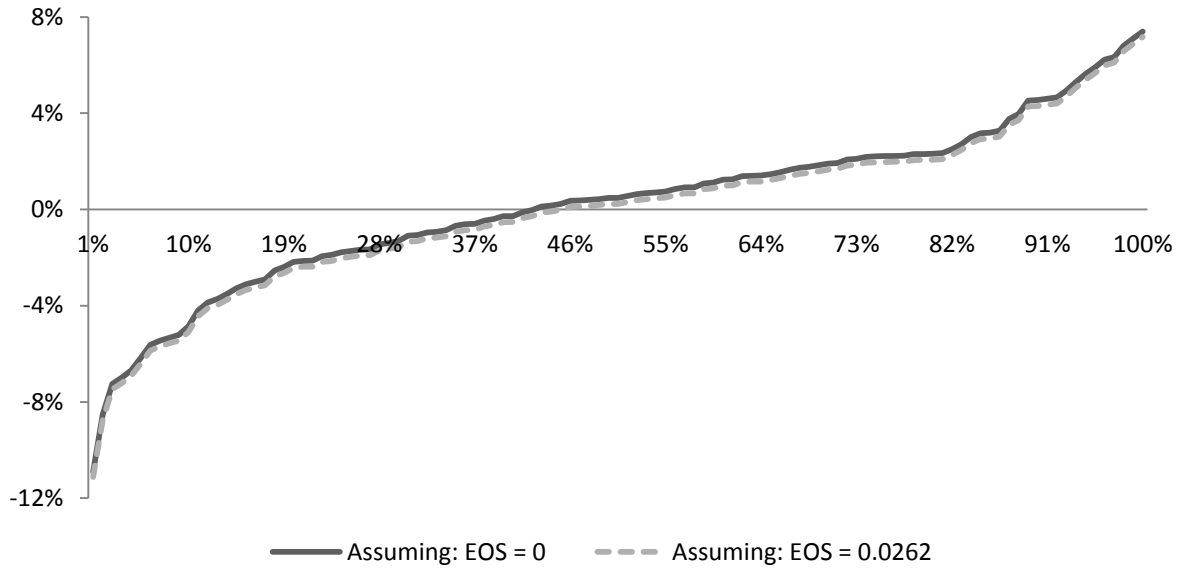
Figure 7.7: Change in electricity bill (medium income households in the sample)



The savings made by the medium-income households in the sample were greater than for the low income households and after including the response, over 43% of households could have made financial savings and 10% of the group would have saved more than 5% on their electricity bill (see figure 7.7).

As for the high-income households, the story is consistent with the medium-income households where the savings and cost from such a program is split almost in the middle. Just under half of the higher-income people in the sample would have been better off with a TOU tariff (see figure 7.8.

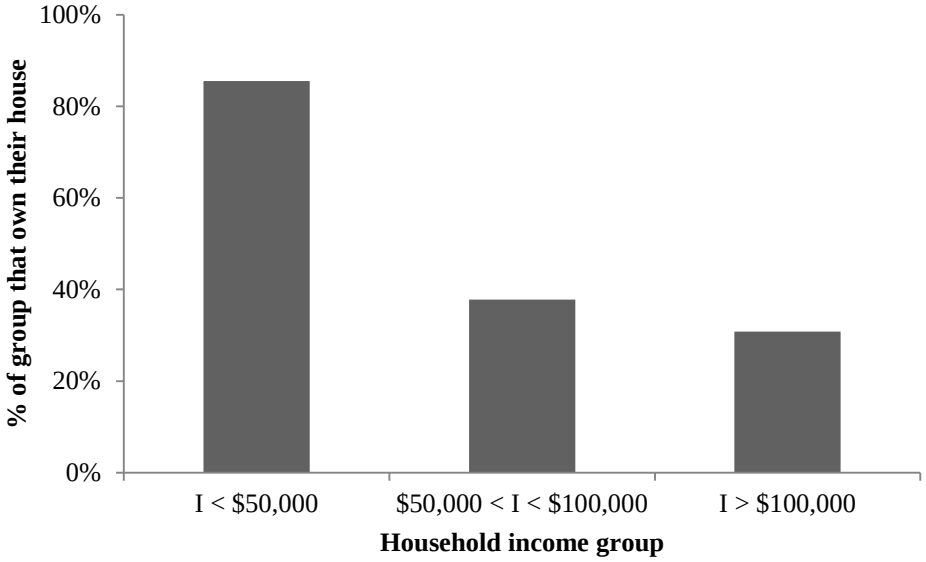
Figure 7.8: Change in electricity bill (high income households in the sample)



While at first it seems as if the households with lower incomes are worse off than the higher-income households in this sample, using annual household income might be misleading. Household income may not in some cases reflect accurately the household's disposable income or income per capita. For example a pensioner with low income is likely to have a larger stock of savings, own her home without a mortgage and have fewer dependents living in the house and has therefore higher disposable income.

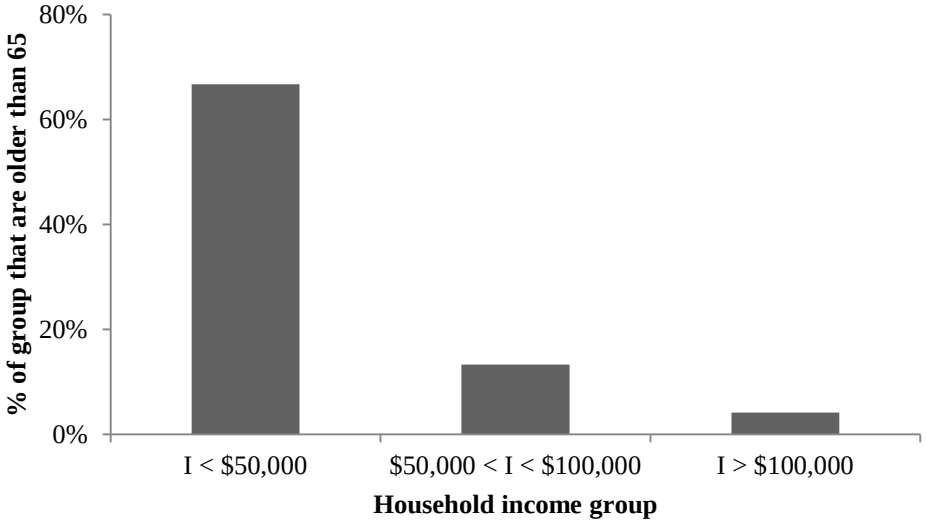
This is the case in the sample and the proportion of householders that own their house without a mortgage is shown in figure 7.9. The proportion of households where one household member is at least 65 years of age is shown in figure 7.10.

Figure 7.9: Proportion of participants that own their house by income groups



Over 85% of the households that have income of less than $50,000 per year (before taxes) own their own house without a mortgage. Those households in the higher income groups are much less likely to own their house. The fact that so many households that earn less income annually do not have to pay rent or make mortgage payments suggests that it might be misleading to use annual income to investigate the effect of the TOU on the people who are relatively poor in the sample.

Figure 7.10: Proportion of participants older than 65 by income groups



More than 65% of the households who earn less than $50,000 are more than 65 years old. For those earning more than that the proportion of people over 65 years old is much smaller. Since most people over 65 are either retired or working less than full time it is they who tend to have lower annual incomes in the sample, but they also tend to have a larger pool of savings (at least in the form of a mortgage-free house) and therefore the disposable income in that group might be higher than the annual income suggests.

Therefore, it is not that the poorer people in the sample are worse off under a TOU tariff but simply the people who are more at home during the peak hours. It could be that the people who, in the short run, are worse off under a TOU tariff might be able to invest in peak conserving technologies and adjust their consumption in the long run. In that case they would not be worse off under a TOU tariff.

8 CONCLUSION AND FURTHER WORK

This thesis reports analyses of data collected during a TOU pricing experiment conducted by Mercury Energy in 2008-09 in a suburban area of Auckland, New Zealand. The aim of the research was to estimate the (short-run) elasticity of consumer substitution and how household characteristics influence householder ability and willingness to shift consumption from higher-priced peak to lower-priced off-peak times.

The empirical model employed was a Constant Elasticity of Substitution (CES) model. The model was estimated using OLS with a cross-section of consumption data collected during the experiment. Peak/off-peak price ratios varied across four groups from 1:1 to about 3:1. As a robustness check, a household fixed-effects model was estimated using consumption data from the year before the experiment, which returned similar average estimates.

The average elasticity of substitution (EOS) was estimated to be -0.0508. The EOS varied systematically with house and household characteristics. Households with higher income and households with an ill household member responded less to the time-varying tariff. Large households, and households that, on average, spent more time away from home responded more to the time-varying tariff.

Of interest is whether or not the EOS represented an actual shift in consumption from peak to off-peak times. The own price elasticities were estimated using household fixed effects model. The results suggested significant off-peak own price elasticities at around -0.1047. The same model was estimated for the peak periods own price elasticity and the analysis found only significant elasticities when outside temperature was very low and suggested no response to the prices at more reasonable temperature levels. A further investigation was conducted into whether or not a shift from peak to off-peak took place and the data indicated that households' took advantage of the lower off-peak prices by consuming more during off-peak hours, but did not significantly decrease their higher-priced peak consumption. The only group that showed signs of an actual shift was the group facing a medium price difference (10 cents) between peak and off peak hours.

The responses estimated were then used to conduct a simulation to assess the potential social benefit of TOU pricing and of how those benefits are distributed. The social benefit depends on

the reduction in demand for relatively expensive peak electricity and is estimated in total for the 293 households to be between $303 and $1790 annually. The distribution of the benefit was investigated in the context of sample household income. Households with lower total income before tax tended to fare worse than those in the higher income brackets, largely because those in the sample with lower incomes tended to spend more time at home. However, this group's disposable income might be relatively high as many were either retired, probably with some savings, who own their home and have no dependents.

While the sample in the study represented a significant segment of the New Zealand population it was far from being representative of the population. It would be interesting to conduct a TOU experiment and try to get a more representative sample so the short run elasticities could be estimated in a representative way.

While the analysis found significant short run substitution elasticities there was no possible way of estimating the long run elasticities. The long run elasticities are expected to be higher and with higher substitution elasticities there are significantly higher gains to be achieved by a time-variant tariff.

The information feedback and electricity control was fairly simple in the experiment. The meters were simple and did not provide the participants with better real time information on electricity consumption, though participants were able to see their daily peak and off-peak consumption in their monthly bills. There were no time controlled appliances provided to participants (though some may have appliances with timers), and it would be interesting to investigate how and if better information feedback as well as time controlled appliances would affect the time of usage decision.

The study only focused on the effect of a very simple TOU rate. It would be interesting to investigate the effect of different rate designs such as CPP and RTP and investigate the effect such rate designs have on elasticities and customers interest.

Unlike where local monopolies have the power to impose a time-variant rate on their consumers, customers in this study opted in to the experiment. While the self-selection into the study might be considered a deficit it is a more realistic scenario in New Zealand than a compulsory time-variant tariff. Because time-variant tariffs are probably going to be offered alongside other tariff

designs it would be of interest to research what kind of households are likely to select the TOU, or other time-variant options. It would be logical that households with already relatively “flat” profiles would take up a dynamic rate, and households who have a greater control over their time of usage.

9 REFERENCES

Statisitcs New Zealand. (n.d.). Retrieved July 25, 2012, from Statisitcs New Zealand Web site: http://www.stats.govt.nz/

Allcott, H. (2011). Rethinking real-time electricity pricing. *Resource and energy economics, 33*(4), 820-842.

ATL. (n.d.). Retrieved April 20, 2012, from ATL Web site: http://www.atl.org.uk/

Aubin, C., Fougère, D., Husson, E., & Ivaldi, M. (1995). Real-time pricing of electricity for residential customers: Econometric analysis of an experiment. *J. Appl. Econ, 10*, S171-S191.

Ault, R. W., & Ekelund, R. B. (1987). The problem of unnecessary originality in economics. *Southern Economic Journal, 53*(3), 650-661.

Baumol, W. J., & Bradford, D. F. (1970). Optimal departures from marginal cost Pricing. *The American Economic Review, 60*(3), 265-283.

Boiteux, M. (1960). Revue generale de l'electricite. *The Journal of Business, 33*(2), 157-179.

Brandon, G., & Lewis, A. (1999). Reducing household energy consumption: A qualitative and quantitative field study. *Journal of Enviromental Psychology, 19*, 75-85.

Brown, Jr, G., & Johnson, M. B. (1969). Public utility pricing and output under risk. *The American Economic Review, 59*(1), 119-128.

Bye, R. T. (1929). Composite demand and joint supply in relation to public utility rates. *Quarterly Journal of Economics, 44*(1), 40-62.

Carlton, D. W. (1977). Peak load pricing with stochastic demand. *The American Economic Review, 67*(5), 1006-1010.

Caves, D. W., & Christensen, L. R. (1980). Econometric analysis of residential time-of-use electricity pricing experiments. *Journal of Econometrics, 14*(3), 287-306.

Caves, D. W., Christensen, L. R., & Herriges, J. A. (1984). Consistency of residential customer response in time-of-use electricity pricing experiments. *Journal of Econometrics, 26*(1-2), 179-203.

Coase, R. H. (1960). The problem of social cost. *Journal of Law and Economics, Vol. 3, 3*, 1-44.

Conchado, A., & Linares, P. (2012). The economic impact of demand-response programs on power systems. A survey of the state of the art. In P. M. Pardalos, *Handbook of Networks in Power Systems 1* (pp. 281-301). Springer Berlin Heidelberg.

Crew, M. A., Fernando, C. S. & Kleindorfer, P. R. (1995).The theory of Peak load pricing: a survey. *Journal of Regulatory Economics, 8*, 215-248.

Crew, M. A. & Kleindorfer, P. R. (1976). Peak load pricing with a diverse technology. *The Bell Journal of Economics, 7*(1), 207-231.

Dupont, B., De Jonghe, C., Kessels, K., & Belmans, R. (2011). Short-term consumer benefits of dynamic pricing. *8th international confrence on the european energy market (EEM)*, (pp. 216-221). Zagreb.

Electricity Authority. (2012). Retrieved May 12, 2012, from EA Web site: http://www.ea.govt.nz/

Faruqui, A. (2010). The ethics of dynamic pricing. *The Electricity Journal, 23*(6), 13-27.

Faruqui, a., & George, S. S. (2002). The value of dynamic pricing in mass markets. *The Electricity Journal, 15*(6), 45-55.

Faruqui, A., & Sergici, S. (2010). Household response to dynamic pricing of electricity: a survey of 15 experiments. *Journal of Regulaartory economics, 38*(2), 193-225.

Faruqui, A., & Sergici, S. (2011). Dynamic pricing og electricity in the mid-atlantic region: econometric results from the baltimore gas and electric company experiment. *Journal of regulatory economics, 40*, 82-109.

Faruqui, A., Harris, D., & Hledik, R. (2010). Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment. *Energy Policy, 38*(10), 6222-6231.

Faruqui, A., Hledik, R., Newell, S., & Pfeifenberger, H. (2007). The power of 5 percent. *The Electricity Journal, 20*(8), 68-77.

Haney, A. B., Jamasb, T., & Pollitt, M. G. (2009). Smart metering and electricity demand: technology, economics and international experience. *EPRG Working Paper EPRG0903, Cambridge Working Paper in Economics 0905*.

Hirst, E., & Kirby, B. (2001). *Retail-load participation in competitive wholesale electricity markets*. Washington, D.C.: Edison Electric Institue.

Holland, S. P., & Mansur, E. T. (2008). Is real-time pricing green? The environmental impacts of electricity demand variance. *The Review of Economics and Statistics, 90*(3), 550-561.

Kathleen, S., & Lave, L. B. (2007). Demand response and electricity market efficiency. *The Electricity Journal, 20*(3), 69-85.

National Institute of Water and Atmospheric Research. (n.d.). Retrieved April 15, 2012, from NIWA Web site: http://www.niwa.co.nz

Newsham, G. R., & Bowker, B. G. (2010). The effect of utility time-varying pricing and load control strategies on residental summer peak electricity use: A review. *Energy Policy, 38*, 3289-3296.

Ramsey, F. P. (1927). A contribution to the theory of taxation. *The Economic Journal, 37*(March), 47-61.

Sexton, R. J., Johnson, N. B., & Konakayama, A. (1987). Consumer response to continious-dispaly-electricity-use monitors in a time-of-use pricing experiment. *Journal of Consumer Research, 14*(1), 55-63.

Sherman, R. & Visscher, M. (1978). Second best pricing with stochastic demand. *The American Economic Review, 68*(1), 41-53.

Spees, K., & Lave, L. B. (2007). Demand response and electricity market efficiency. *The Electricity Journal, 20*(3), 69-85.

Steiner, P. O. (1957). Peak loads and efficent pricing. *Quarterly Journal of Economics, 71*(4), 585-610.

Varian, H. R. (2003). *Intermediate Microeconomics: a modern aprroach* . New York: W. W. Norton & Company Inc.

Visscher, M. L. (1973). Welfare-Maximizing Price and Output with Stochastic Demand: Comment. *The American Economic Review, 63*(1), 224-229.

WITS. (n.d.). *Free to air*. Retrieved July 7, 2012, from Wholesale Information Trading System Web site: http://www.electricityinfo.co.nz

World Bank. (n.d.). Retrieved April 6, 2012, from World Bank Web site: http://www.worldbank.org/